Evaluation of the cost of time windows in home delivery applications

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Abstract

This thesis deals with a real-life business-to-consumer home delivery case that represents a classical example of Vehicle Routing Problem with Time Windows (VRPTW). There are several trade-offs that home delivery service providers need to face when designing their order fulfillment strategy.

Delivery time windows represent how long the customers have to stay at home waiting for their delivery. In the attended home delivery case, the customer service level is directly affected by time windows durations: providing convenient time windows improves customer’s satisfaction. However, offering high level of service by means of tight time windows often results in higher routing costs in terms of number of vehicles needed, time and mileage. Quantitative research on the last mile problem and the factors affecting the cost of home delivery has been scarce.

The scope of this project is twofold. First, the home delivery problem is introduced and an extensive literature review is presented. After that, the L’EASY real-life home delivery case study is described and the trade-offs that exist among different delivery strategies are examined by means of the following research questions: (1)How is the routing cost affected by the enlargement or shrinkage of time windows for all customers? (2)What is the effect on the routing cost of assigning different tight time windows to different shares of customers randomly selected? (3)What is the effect on the routing cost of assigning narrow time windows to those customers living in the biggest Danish cities?

Different scenarios for the L’EASY case study are modeled and solved using Route Planner, a commercial vehicle routing software from Transvision A/S. It is concluded that if the company was considering offering a tighter time window to all customers, then the 2-hour time slot represents an appealing alternative. On the other hand, if the company was considering offering a tight time window to a specific share of customers who place a higher value on their time and may be willing to pay more for a tighter time window, we could recommend different options. In particular, offering a higher level of service to the customers living in one of the major Danish cities represents a valid alternative.

Keywords: Vehicle routing, Time windows, Attended home delivery, Last mile logistics.
Foreword

This MSc thesis entitled "Evaluation of the cost of time windows in home delivery applications" has been prepared by Sara Zuglian during the period from 15th of April to 6th of October 2009 at the Department for Transport at the Technical University of Denmark (DTU), in collaboration with Transvision A/S.

The main advisor has been Associate Professor Stefan Repke from DTU Transport and from Transvision A/S Jakob Birkedal Nielsen supervised the project. The thesis has a scope of 30 ECTS points and is written in order to achieve the Master of Science degree in Transportation and Logistics at DTU.

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“When your determination changes, everything else will begin to move in the direction you desire. The moment you resolve to be victorious, every nerve and fiber in your being will immediately orient itself toward your success. On the other hand, if you think “This is never going to work out”, then at that instant every cell in your being will be deflated and give up the fight, and then everything really will move in the direction of failure.”
(Daisaku Ikeda)
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Chapter 1

Introduction

Nowadays Operations Research (OR) and Mathematical Programming techniques supply a number of tools that are used to model, solve and improve solutions to many real-life problems faced by companies. Very often these problems are in the areas of planning, logistics and distribution.

Problems that involve designing optimal delivery or collection routes from one or several depots to a number of geographically scattered cities or customers subject to operational constraints are usually denoted as Routing Problems and they do not occur solely in transportation companies. No matter what its business is, every manufacturing company needs to manage inbound of supplies and distribution of final products. Not to mention that the need of coordination and optimization of internal logistics among different sites of the factory increases quickly with the company size.

As the world economy turns more and more global, the transportation issue is a continuous battle to control costs while improving customer service. Indeed, the transportation process involves all stages of the production and distribution systems and represents a relevant component (generally from 10% to 20%) of the final cost of the goods [49]. Fuel costs can be as high as 10% to 15% of total operating costs [21]. Fleet operations improvements can be found through the practical application of route planning, optimization and real-time vehicle tracking. In addition, this technology can be instrumental in reducing mileage without impacting customer service - and in many cases, improving it.

Indeed, the development of computer systems on both hardware and software points of view has been a key success factor for the utilization of OR techniques in solving transportation problems. Thanks to this, models capable of handling real-world applications and algorithmic tools that find good solutions for real-life instances have been developed.

In modelling of routing problems terminology is to a great extent derived from graph theory. Notions like node, arc, path etc. will not be explained in this thesis. In general, the reader is assumed to be familiar with the concepts of graph theory and linear programming.
1.1 Background

Problems concerning the delivery and collection of goods or people are generally known as Vehicle Routing Problems (VRPs). The VRP is the problem of visiting a number of customers in the least expensive way, when a fleet of vehicles is given. Typical applications of this type are, for instance, solid waste collection, street cleaning, school bus routing, dial-a-ride systems, transportation of handicapped persons, routing of salespeople and of maintenance units [49]. The VRP and a number of its practical applications have been an area of research that has attracted many researchers in the last 50 years since Dantzig and Ramser introduced it in [19]. The book from Toth and Vigo [50] covers the state of the art of both exact and heuristic methods developed in the last decades for the VRP and some of its main variants.

The VRP generalizes the Traveling Salesman Problem (TSP). In the TSP a number of cities have to be visited by a salesman who has to return to the city where he started. The objective is to find the shortest such a trip. In the m-TSP there are m salesmen and each city has to be covered by exactly one salesman. Every salesman starts and ends its trip at the same city. The objective is to minimize the sum of the lengths of the m routes. Both the TSP and the m-TSP are pure routing problems in the sense that only the geographic component is taken into consideration.

The VRP is a m-TSP under capacity restrictions. A demand is associated with each city and vehicles have limited capacities. The objective is to minimize the total distance traveled ensuring that the sum of demands on each route does not exceed the capacity of the vehicle assigned to the route. This problem is also denoted as Capacitated Vehicle Routing Problem (CVRP).

More realistic routing problems also include a time component. In the Vehicle Routing Problem with Time Windows (VRPTW) in addition to the demand constraint, each customer can be served only during a specific time window. The vehicle is allowed to arrive before the customer becomes available but it can not start serving it until the time window opens. On the other hand, arrivals after the customer ended availability are prohibited.

The TSP was proven to be \( \mathcal{NP} \)-hard in 1972 by Karp. Therefore, also the VRP belongs to the class of problems "hard" to solve. It is difficult to solve the VRPTW exactly through classical simplex-based branch-and-bound methods, even for small instances. For solving the VRPTW, in the literature four main available approaches of exact solution methods can be found: dynamic programming, column generation, Lagrangian relaxation and branch-and-cut. Currently algorithms that use column generation give the best results and the VRPTW has been an important combinatorial optimization problem in the development of this type of algorithms.

Because of the complexity of the VRPTW and its practical importance, the field of non-exact algorithms for the VRPTW problem has been very active. There exist a wide body of research concerning the development of algorithms capable to
provide a good quality solution in short computing times. The three main classes of heuristics for the VRPTW are: construction heuristics that build a set of routes from scratch, improvement heuristics that try to produce an improved solution on the basis of an already available solution, and metaheuristics that continue the exploration of the solution space after a local minimum is encountered. Classical heuristics based on simple construction and local descent improvement techniques are easy to implement. However, in terms of solution quality, they do not compete with the best metaheuristic implementations but the price to pay is often coding complexity and computation time.

1.2 Motivation

Hereby a classical example of VRPTW is considered: the home delivery case also denoted as last mile logistics. In particular we focus on the business-to-consumer (B2C) orders and deliveries. Very efficient, reliable, low-cost freight transportation services are needed for customers with ever-increasing service level expectations. By service level we mean, for example, the delivery time window offered for the customer (i.e. how long the customer has to stay at home waiting for the delivery). Many people experienced, at least once in their life, to stay at home waiting for a delivery. In some cases customers have to take a whole day off from work, in the luckiest case they get their parcel within half an hour time window on a specific day. For the retailer or the logistic service provider there is a large cost involved in this choice.

Only few researchers studied the effects of introducing tight time windows in home delivery applications. The main contribution was given in Nockold [35], Lin and Mahmassani [34], Punakivi and Saranen [39], Punakivi et al. [41] and Punakivi and Tanskanen [40]. Their conclusion is that the more the customer is allowed to control the home delivery service and select the delivery time window the higher the number of vehicles needed and mileage. This, causing longer working hours for the staff, has an immediate and considerable effect on the total cost of the home delivery service. However, quantitative research on the last mile problem and the factors affecting the cost of home delivery has been scarce.

Therefore, this thesis deals with a simulation project based on real-life data about a last mile logistics case. The objective is to evaluate the cost of different home delivery solutions by mean of state-of-the-art vehicle routing software.

The Danish company Transvision A/S provides systems for planning and optimisation of road-based transport. It is Scandinavia’s leading provider of IT systems for transport and distribution planning and optimisation. Their core product is an advanced vehicle routing application and this product is used by a number of customers, mainly situated in Northern Europe. Transvision wishes to assess the cost of several home delivery concepts based on different time windows configurations using Route Planner, their commercial vehicle routing software and data from a real-life company: the L’EASY case. L’EASY A/S engages in telephone and online lease and sale of white goods (e.g. refrigerators, washing machines, tumble driers, dishwashers), brown goods (e.g. televisions, stereo, DVD players), digital cameras and videocameras, computers and mobile phones. L’EASY operates in the
Danish, Swedish, Norwegian and Dutch markets.

1.3 Purpose

The scope of this project is twofold in the way that it has both a qualitative and a quantitative research purpose.

First of all, the home delivery problem is introduced in great detail and an extensive literature review is presented since there seems not to be such a review in the literature.

In the second place, this is also a simulation project based on real-life data provided by L’EASY. The aim of our analysis is to compare different delivery time window policies and to assess the cost trade-offs that exist among them. These trade-offs are examined in chapter 7 by means of the following research questions: (1) How is the routing cost affected by the enlargement or shrinkage of time windows for all customers? (2) What is the effect on the routing cost of assigning different tight time windows to different shares of customers randomly selected? (3) What is the effect on the routing cost of assigning narrow time windows to those customers living in the biggest Danish cities?

Different scenarios for the L’EASY attended home delivery case study are modeled and solved using Route Planner, a commercial vehicle routing software from Transvision A/S. In this way, we provide also a quantitative analysis of the cost of tightening delivery time windows in order to meet precise delivery expectations of the customers and help the home delivery industry to quantify the impact of service level on transportation cost.

1.4 Outline of the thesis

In chapter 2 a mathematical model for the VRPTW is presented together with a brief review of the main optimal and approximation solution algorithms. After that, we provide an insight in the home delivery market in chapter 3. Chapter 4 presents a complete literature review on some of the most relevant issues related to the home delivery market which has lately been a subject of academic research to a notable degree.

The L’EASY case study and Transvision Route Planner are described in chapter 5. Chapter 6 deals with the research approach of our simulation project. Here we introduce the indicators used in order to compare different scenarios, the modelling assumptions and the setup used when running our simulations. The results of the extensive testing are presented and discussed in chapter 7 followed by conclusions and further work (chapter 8).
Figure 1.1 shows a graphical representation of the outline of this thesis:

![Figure 1.1: Outline of the thesis](image-url)
Part I

Problem description and literature review
Chapter 2

The Vehicle Routing Problem with Time Windows

In this chapter the description of the VRPTW presented in the Introduction is formalized. In section 2.2 a mixed integer programming model is first introduced according to Larsen [32] together with a brief review of the main optimal and approximation solution algorithms for the VRPTW (section 2.3). After that, real-life applications (section 2.4) and the importance of tightening time windows (section 2.5) are discussed followed by examples of commercial VRP software available (section 2.6). In fact, a wide body of research is available for the VRP and the amount of research done on the VRPTW is growing as an acknowledgement to the importance of the problem.

2.1 The VRPTW

As stated before, the VRPTW is an extension of the classical VRP problem in which capacity constraints on routes (vehicles) are imposed and each customer is associated with an availability time interval.

Beyond capacity and time windows constraints, several operational constraints may arise which depend on the specific application (nature of the transported goods, quality of the service level, characteristics of customers and vehicles, etc.). As an example, precedence constraints can be imposed on the order in which the customers served in a route are visited.

In the so-called VRP with Pickup and Delivery (VRPPD) vehicles (routes) can perform both the collection and the delivery of goods. Goods collected at the pickup customers are transported to the corresponding delivery customers by the same vehicle. Therefore precedence constraints ensure that the pickup is performed before the delivery. Another type of precedence constraint imposes the order in which different types of customers must be served. This is the case of the so-called VRP with Backhauls (VRPB) where, on each route, all deliveries must be performed before any pickup.
Several, and often contrasting, objectives can be considered for the vehicle routing problems. According to [49], examples of typical objectives are:

- Minimization of the global transportation cost, dependent on the global distance traveled (or on the global travel time) and on the fixed costs associated with the used vehicles (and with the corresponding drivers);
- Minimization of the number of vehicles (or drivers) required to serve all the customers;
- Balancing of the routes, for travel time and vehicle load;

In the following, a vehicle-flow formulation for the classical VRPTW is presented. The objective is to minimize the total transportation cost while the number of vehicles is fixed in advance.

2.2 A mathematical model for the VRPTW

The VRPTW can be defined by a fleet of homogeneous vehicles $K(|K| = m)$, a set of customers $1, 2, \ldots, n$ denoted as $C(|C| = n)$ and a directed graph $G = (N, A)$. $N$ is the set of vertices $0, 1, \ldots, n + 1$ so that $|N| = n + 2$. The depot is represented by the two vertices $0$ and $n + 1$ and a feasible route corresponds to a path starting at vertex 0 and ending at vertex $n + 1$. $A$ is the set of arcs between depot and customers and among customers. There is no arc ingoing in $0$ or outgoing of $n + 1$. A cost $c_{ij}$ and a time $t_{ij}$ (which may include the service time $s_{ik}$ at customer $i$, $k \in K$) is associated with each arc $(i, j) \in A$ where $i \neq j$.

Each vehicle has a capacity $q$ while each customer has a demand $d_i$ and a time window $[a_i, b_i]$. The vehicle is allowed to arrive before $a_i$ but it can not start serving it until the time window opens. On the other hand, arrivals after $b_i$ are prohibited (hard time windows). The scheduling horizon $[a_0, b_0] = [a_{n+1}, b_{n+1}]$ describes start and end of availability of the depot (both depots are assumed to be identical).

The model parameters $q, a_i, b_i, d_i, c_{ij}$ are non-negative integers while the $t_{ij}$’s are assumed to be positive integers. Moreover, zero demands and service times are defined for these depot, that is, $d_0 = d_{n+1} = s_{0,k} = s_{n+1,k} = 0, k \in K$.

The model involves two types of decision variables $x$ and $w$. For each arc $(i, j)$ where $i \neq j$, $i \neq n + 1$, $j \neq 0$, and each vehicle $k$ we define a binary variable $x_{ijk}$ as:

$$x_{ijk} = \begin{cases} 
1, & \text{if arc } (i, j) \text{ is traversed by vehicle } k \\
0, & \text{otherwise}
\end{cases} \quad (2.1)$$

The continuous decision variable $w_{ik}, \forall i \in C, k \in K$ defines the time at which the vehicle $k$ starts servicing customer $i$. If vehicle $k$ does not visit customer $i$ then $w_{ik}$ is undefined.
2.3 Solution methods for the VRPTW

The aim is to design a set of minimum cost routes, one for each vehicle, such that each customer is serviced exactly once while the time windows and capacity constraints are observed.

The MDVRPTW can be stated as a *arc formulation* as follows:

\[
\min \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ijk} \tag{2.2}
\]

subject to

\[
\sum_{k \in K} \sum_{j \in N} x_{ijk} = 1 \quad \forall i \in C \tag{2.3}
\]

\[
\sum_{i \in C} d_i \sum_{j \in N} x_{ijk} \leq q \quad \forall k \in K \tag{2.4}
\]

\[
\sum_{j \in N} x_{0jk} = 1 \quad \forall k \in K \tag{2.5}
\]

\[
\sum_{i \in N} x_{ihk} = \sum_{j \in N} x_{hjk} \quad \forall k \in K, h \in C \tag{2.6}
\]

\[
\sum_{i \in N} x_{i,n+1,k} = 1 \quad \forall k \in K \tag{2.7}
\]

\[
w_{ik} + t_{ij} - M_{ij} (1 - x_{ijk}) \leq w_{jk} \quad \forall k \in K, (i, j) \in A \tag{2.8}
\]

\[
a_i \leq w_{ik} \leq b_i \quad \forall k \in K, i \in N \tag{2.9}
\]

\[
x_{ijk} \in \{0, 1\} \quad \forall k \in K, (i, j) \in A \tag{2.10}
\]

\[
w_{ik} \in \mathbb{R} \quad \forall k \in K, i \in N \tag{2.11}
\]

The objective function (2.2) seeks to minimize the total routing cost. Constraints (2.3) ensure that each customer is served by exactly one vehicle route while (2.4) enforce the vehicle capacity restriction. Constraints (2.5)-(2.7) ensure that each vehicle is used exactly once and that flow conservation is satisfied at each customer vertex. Inequalities (2.8) state that a vehicle $k$ can not arrive at $j$ before $w_{ik} + t_{ij}$ if it is travelling from $i$ to $j$. Here $M_{ij}$ is a large scalar that can be replaced by $\max\{b_i + t_{ij} - a_j, 0\}, (i,j) \in A$. Finally, constraints (2.9) impose time windows while (2.10) and (2.11) are variable domain constraints. Note that an unused vehicle is modelled by an empty route $(0,n+1)$.

2.3 Solution methods for the VRPTW

The VRPTW is known to be $\mathcal{NP}$-hard. Indeed, even finding a feasible solution to the VRPTW with a fixed fleet size is itself an $\mathcal{NP}$-complete problem (Savelsbergh [45]). The VRPTW belongs to the class of problems "hard" to solve. However, when a VRPTW problem is sufficiently constrained (i.e., when time windows are sufficiently narrow), realistic size instances can be solved to optimality by mean of exact methods.
2.3.1 Exact algorithms for the VRPTW

The first paper proposing an exact algorithm for solving the VRPTW was published back in 1987 by Kolen et al. [30]. Since then the literature has proposed four main approaches of exact solution methods for solving the VRPTW: dynamic programming, column generation, Lagrangian relaxation and branch-and-cut. Currently algorithms that use column generation give the best results and the VRPTW has been an important combinatorial optimization problem in the development of this type of algorithms, closely followed by methods based on Lagrange relaxation. For a thorough survey on exact methods for the VRPTW see Cordeau et al. [17] and Cordeau et al. [18]. In 1987, Solomon [47] introduced 56 instances with 100 customers and only few of them remain unsolved. Recently Desaulniers et al. [20] succeeded in solving to optimality 5 previously unsolved Solomon’s problems and obtained substantial time reductions for the most difficult solvable 100-customer instances when compared to the best results found in the literature.

2.3.2 Heuristics for the VRPTW

Often a real-life case can not be solved to optimality due to the high number of customers and the complexity added by operational constraints. This is why several families of heuristics have been proposed for the VRPTW. The field of non-exact algorithms for the VRPTW problem has been very active - far more active than that of exact algorithms. A long series of papers has been published over the recent years (for a recent survey see on approximation methods for the VRPTW see Cordeau et al. [17], Larsen [32] and Cordeau et al. [18]). Heuristic methods produce good quality solutions (not necessarily optimal) within short computing times. These solutions can also be used as upper bounds for the exact algorithms. Heuristic methods can be classified into two main classes: classical heuristics developed mostly between 1960 and 1990, and metaheuristics, whose growth has occurred in the last two decades. Figure 2.1 describes the evolution of heuristic algorithms for the VRP:

![Figure 2.1: Evolution of heuristics for the VRP [24]](image)
Construction, two-phase heuristics and improvement heuristics belong to the first class. The former build a set of routes from scratch inserting one customer at a time into partial routes until a feasible solution is obtained. Among the others, some construction heuristics are the Clarke and Wright Savings Algorithm [15] (and its enhancements) that consists in merging existing routes using a savings criterion and insertion heuristics where vertices are gradually assigned to vehicle routes using an insertion cost. In two-phase heuristics, the problem is decomposed into two stages: clustering of vertices into feasible routes and actual route construction. Two-phase heuristics are divided into two classes: cluster-first, route-second methods where vertices are first organized into feasible clusters, and a vehicle route is constructed for each of them (e.g., Petal Heuristic [23] and Sweep heuristic [26]); and route-first, cluster-second methods where a tour is first built on all vertices and is then segmented into feasible vehicle routes (e.g., Giant-Tour heuristic [7]). Finally, improvement methods attempt to produce an improved solution on the basis of an already available solution performing a sequence of edge or vertex exchanges within or between vehicle routes. There exist two categories: single-route and multi-route improvement. Examples of simple neighborhoods for a multi-route improvement heuristic are string cross, string relocate and string swap. For recent surveys on classical heuristics for the VRPTW see Laporte and Semet [31] and Bräysy and Gendreau [10].

Classical heuristics perform a relatively limited exploration of the search space and typically produce good quality solutions within modest computing times. Moreover, most of them can be easily extended to account for the diversity of constraints encountered in real-life contexts. Therefore, they are still widely used in commercial packages.

On the other hand, metaheuristics continue the exploration of the solution space after a local minimum is encountered. The idea is to perform a deep exploration of the most promising regions of the solution space. These methods typically combine sophisticated neighborhood search rules, memory structures, and recombination of solutions. Examples of metaheuristics for the VRPTW are Tabu Search [16], Simulated Annealing [14], Adaptive Large Neighborhood Search [37] and Genetic Algorithm [48]. In a sense, metaheuristics are no more than sophisticated improvement procedures, and they can simply be viewed as natural enhancements of classical heuristics. For recent surveys on metaheuristics for the VRPTW see Gendreau et al. [24] and Bräysy and Gendreau [9].

Recalling Figure 2.1, it can be noticed that typically classical methods yield solution values between 2% and 10% above the optimum (or the best known solution value), while the corresponding figure for the best metaheuristic implementation is often less than 0.5% but the price to pay is increased computing time. Moreover, the metaheuristic procedures usually are context dependent and require finely tuned parameters, which may make their extension to other situations difficult [24].

### 2.4 Real-life applications

Much progress has been made since Dantzig and Ramser described the truck dispatching problem in 1959 [19]. They proposed a mathematical programming for-
imulation of the VRP for a fleet of gasoline delivery trucks between a bulk terminal and 12 service stations supplied by the terminal and solved it with an algorithmic approach. A few years later Clarke and Wright [15] proposed an effective greedy heuristic that improved on the Dantzig-Ramser approach. In the last 50 years, models, algorithms and computer hardware and software have come a long way and today vehicle routing is considered one of the great success stories of operation research. There have been a many successful real-life applications all around the world.

The successful implementation of vehicle routing applications has been aided by the exponential growth of computer power since 1950, the emergence of accurate geographic information systems (GIS) technology and easy-to-use interface software that enables the customer to integrate routing with other key functions such as billing, inventory tracking and forecasting. Vehicle routing software can integrate directly with enterprise resource planning (ERP) systems.

Many interesting applications of vehicle routing are surveyed in Golden et al. [27] where the authors focus on three industries: solid waste; beverage, food, and dairy; and newspaper distribution. Other VRP applications span a broad variety of industries. These involve the commercial distribution of a wide range of products, delivery of mail, school bus routing, street sweeping, bank deliveries and so on.

2.5 Tightening time windows

As stated before, only few researchers studied the effect of offering a higher level of customer service by means of tighter time windows in vehicle routing problems. The literature review is presented in chapter 4. In general, the few studies concluded that the more the customer is allowed to control the level of service and select the delivery time window the higher the number of vehicles needed and mileage. This, causing longer working hours for the staff, has an immediate and considerable effect on the total cost of the transportation service. However, quantitative research has been scarce in this field.

We can see in the purpose of this project an opportunity to quantify the impact of service level on transportation cost for different industries that deal with time constrained vehicle routing problems. As an example, in the mail delivery case it is clear that companies (public and private ones) would benefit from having an idea of what the cost associated with tightening time windows to meet customers’ expectations is. In this thesis we research the impact of enlarging or shrinking delivery time windows durations using a real-life last mile logistics case. We aim at providing a complete overview of the problem and a quantitative assessment of the trade-offs associated with different time windows scenarios.

2.6 Commercial VRP software

In their 2008 survey of vehicle routing software Hall and Partyka [29] had sixteen software vendors participating. The questionnaire was divided into sections covering platform, algorithmic capabilities, interfaces and features, applications, system
2.6 Commercial VRP software

integration and background information. All responses were self-reported by the software vendors and unverified. The authors comment on the answers and provide some interesting conclusions.

Generally speaking, vehicle routing software provide a set of common capabilities:

- Geocoding of addresses through integration with GIS technology, i.e., locating the latitude and longitude by matching the address against data contained in a digital map database;
- Determining the best paths through street networks between pairs of geocoded points;
- Solving vehicle routing problems, entailing an assignment of stops to routes and terminals, sequencing stops and routing vehicles between pairs of stops;
- Displaying the results in both graphical and tabular forms in such a way that dispatchers can guide the solution process and communicate results to drivers, loaders and other personnel.

Hall and Partyka [29] describe how in the last 10 years digital maps have migrated to mobile phones and other portable devices providing the tools for location-based-service as vehicle routing. Wireless connections enable fleets to link routing optimization with satellite navigation and proof of delivery. As an example, integrating VRP software with mobile devices allows the dispatch office to track drivers’ location. Thus providing better and faster information for delivery status update for customers or real-time/dynamic fleet management.

Concerning the algorithms underlying vehicle routing software, vendors usually declare them proprietary. Even though they generally involve a combination of integer programming methods and heuristics. With regard to the user interface, most applications provide the possibility to show routes and stops on digital maps that can be edited by dragging-and-dropping stops to other locations on the map. Thus enabling the planner to modified the algorithm-based routes.

Although vendors claim that their VRP software are suitable for a wide range of applications, most of them are specialized in a specific industry being private truck fleets management for markets as food, beverage and consumer products. They also claim that they can do both node and arc routing along with real-time routing, daily routing and route planning. Moreover they generally claim unlimited problem size capabilities for their products. However, Hall and Partyka remind that a single routing package is unlikely to be adept at all of these functions and computation time, memory size and disk space bound product performance. So it is important to select a vendor that has experience in the planned application and test software on actual problems.
Finally, Hall and Partyka [29] remind the importance of discussing the following issues before purchasing a vehicle routing software:

- How big of a problem will be solved (vehicles, stops and terminals)?
- How frequently will the solution be updated, and how quickly must the software generate a solution?
- Who will use the software, how is the information best presented to the user, and are the users distributed among many locations?
- Who will install and maintain the software? Which other software systems must the routing system interact with?

Not to mention the importance of comparing the full installed cost (licence fees, installation, maintenance, hardware and digital maps) before making a choice. They suggest that vendors should demonstrate that they are experienced serving other customers with similar requirements, and they should provide references so that you can verify claims.
Chapter 3

The home delivery market

Studies about the VRPTW have found a practical application in the home delivery market that is the subject of this thesis. In this chapter we present the home delivery market, also known as last mile logistics.

We start introducing definitions in section 3.1 and examples of products in section 3.2. Afterward, we introduce some home delivery issues (section 3.3) and present interesting findings from a survey about time windows preferences (section 3.4). In section 3.5 we provide an insight in the e-grocery market.

3.1 Definitions

As stated before, in this thesis we focus on the B2C home delivery case. Indeed, the home shopping market is not a new concept. It has a long history in mature markets such as catalogue shopping and door-to-door selling and over the last 20 years, the parcel distribution market has experienced a large growth.

The Post Danmark Group - Annual Report 2008 [5] states that letters, magazine mail and newspapers, magazines and periodicals account for 67% of their revenue. However, in recent years, the volume of letters has gone down, and the composition of revenue from the various services has changed towards an increase in direct mail (e.g. an individual sales letter, a newsletter or a promotional gift) and magazine mail (e.g. shipped catalogues, brochures or magazines to the same target group each time).

Figure 3.1 shows the revenue composition for Post Danmark Group in 2008 and the increase in the number of parcels distributed by the same company in the period 2004-2008. It can be noticed that in the examined four-years period the number of parcels handled by the Post Danmark Group has increased by about 19%. 

Next-day and overnight delivery services have helped industries revolutionize manufacturing processes and cut inventory cost through just-in-time techniques, and permitted the rapid delivery of documents around the world. Additionally, the development of new technologies such as Internet and e-commerce has created new opportunities, methods and products offer making the home shopping market attractive to millions of new users. As an example, the Danish Institute for E-commerce - Annual Report 2008 [22] states that 47.5% of their respondents has shopped online an average of 5.31 times during the past three months before the interview. The same figures for the year 2007 were 47.2% and 5.06 times.

Hereby, we define *home delivery operations* and *home shopping* according to [1] and [2]. These are two interesting studies about the home delivery market in the UK that were commissioned back in 2001 by the Retail Logistics Task Force - DTI Foresight and the Freight Transport Association - FTA.

*Home shopping* refers to the means by which the order is placed and paid for by the customer, and includes purchasing by mail order, by telephone and fax, door-to-door selling, and orders placed over the Internet (e-commerce or online shopping).

*Home delivery* refers to all goods delivered to customers’ homes (or another location of the customers’ choice) rather than the customers having to collect the goods in-person from the point of purchase and transport them home themselves. This holds regardless of the ordering system that includes orders made in-person by customers in retail premises as well as home shopping.

Therefore in a home delivery operation the physical distribution of the goods from the point of purchase to the customer is organised and carried out by specialist companies, also known as home delivery services (HDSs), rather than by the customer. Home delivery can take place for several reasons including:

- Additional service provided by the shop (i.e. if the customer does not wish to take the goods with him at the point of purchase or if the goods are currently out-of-stock and home delivery will prevent the need for the customer to make another visit to the shop);
3.2 Products and market size

- Customer convenience in terms of wider products offer and availability, price comparison, price discounts;
- Size and/or weight of the purchased products make it impossible for customers to transport the goods by themselves (e.g. furniture, white goods);
- Because the retailer does not operate physical shops and there is no possibility for the customers to collect the goods themselves.

However, the increase in the number of home shopping transactions entails even greater challenges in optimizing last mile logistics operations while ensuring sustainable development of urban freight transport (city logistics).

3.2 Products and market size

The range of products that can be delivered to the customers’ site is extremely wide. The research and the literature has been focusing mainly on groceries, small packages and large items. However, there are several other product classes that take part in the home delivery business, for example [2] mentions: goods sent through the existing postal service and other products that fit through letter-boxes (e.g. mail and newspapers), delivery of cooked meals (e.g. pizzas, take-aways etc.), florist deliveries, informal home delivery services offered by local shops (e.g. a local independent chemist who can arrange for prescription drugs to be delivered by taxi or in-person), products supplied electronically via computers (such as computer software, music and digital books and newspapers), products bought and sold by consumers on Internet auction sites (C2C e-commerce).

The Danish Institute for E-commerce - Annual Report 2008 [22] distinguishes the following categories of products for the e-commerce market:

**Physical products** customers buy physical products through the internet that are then delivered to the customers’ place or collected by them at an agreed collection point. Examples are clothing, electronics, books, magazines, music, movies, groceries;

**Service products** customers book and/or buy the service online and this is later supplied and consumed at a place other than the internet. Examples are theater/concert tickets, flight/train tickets, holidays;

**Online products** customers buy products online and get the product through the internet. Examples are music, computer games, e-books, software.

Figure 3.2 shows that the purchase of physical products represents 54% of the Danish e-commerce market, followed by service (31%) and online products (8%).
Moreover [22] states that e-shoppers most frequently buy clothing (21%) in the physical products category. Similarly, flight tickets count for 21% among the services purchases and music files for 37% in the online products category.

Figure 3.3 concerns the UK home delivery market. It shows that around 420 million home deliveries of physical products were made in the UK in the year 2001, over 90% of them generated by the primarily small package-based home shopping market. This sector has been steadily growing over the last decade mainly due to online purchasing. Home delivery of large items and groceries follow with 2% and 5% market share respectively.

The core of the home delivery market remains the agency mail order business and the delivery of high-value household items such as electrical appliances, furniture, clothing and footwear. These services have been expanding over the last decades and new forms of "remote" shopping (e.g. Internet and interactive television) have emerged which also require home delivery [1].

According to Cairns [11], delivering goods to the customer’s place is an increas-
3.3 Home delivery issues

The growth of the home delivery market is responsible for part of the increase in van traffic in residential and urban areas. Quak [42] focuses on the e-grocery market and distinguishes three sustainability issues: social sustainability, economic sustainability and environmental sustainability. Retailers and carriers are keen to exploit new commercial opportunities in the home delivery market, while local authorities are considering the resulting impact on the transport system and society.

Moving goods over the last mile to the consumers’ home in a manner that reconciles social, economical and environmental issues is not an easy task. It provides a great increase in service for customers but also creates a huge logistics challenge for companies [12].

Last mile logistics operations are very problematic and extremely expensive. There are several trade-offs between often contrasting objectives. Home shopping fulfillment and delivery systems need to be able to supply the right goods at the right time to suit the customers’ expectations - but at the same time, efficiently and cost effectively enough to make home delivery profitable for the supplier. Typical logistics key factors are:

- Size of the service area;
- Number of customers, demands size and order frequency;
- Number of depots and number of vehicles at each depot;
- Duration and number of time windows;
- Service, loading and unloading times;
- Vehicle fill rate;
- Capital investment;
- Average distance from the warehouse or store to the customers, average distance between customers;
- Road network topology and long journey distances in rural areas;
- High congestion levels in urban areas often worsened by preferred delivery times;
- High customer expectations about short delivery lead time versus customer reluctance to pay a premium for attractive delivery options;
- Redelivery cost due to customer’s absence;
- High rate of goods returns in some product categories;
• High logistical cost of some deliveries compared to the value of the product being delivered.

For example, having more vehicles would allow each of them to serve fewer demands and to meet tighter time windows for each customer thus improving customer service. Of course, there exists a trade-off between the improved level of service and the resulting operation cost of the larger fleet, which will ultimately be passed on to the customer. The effect of these factors on the level of service and the economics of the operation depends on the overall level of demand, as well as on the customers' spatial distribution or clustering and respective value of the orders being delivered. In general, greater demand normally implies a larger number of vehicles to meet that demand. Whereas spatial clustering (i.e. grouping customers according to the promised time window and location) would allow efficient delivery routes, with lower travel time between consecutive delivery destinations and more time spent delivering revenue-generating loads to customers [34].

3.4 Delivery time windows preferences

Those home deliveries where the customer must be present at home (or at the delivery point) are also called attended. This may be necessary for security reasons, because goods are perishable or because goods are being picked up or exchanged. In order to avoid redelivery cost due to customer’s absence, to provide a high service level and to avoid poor customer image of the company, usually retailer and customer mutually agree on a day and (narrow) delivery time window. Generally speaking, the attended home delivery concept is a VRPTW application where time windows constraints are likely more critical than are vehicle capacity restrictions. This is due to the fact that in most cases the size of parcels is rather small compared to vehicles capacity (except in the case of large items) while promised delivery time windows are often required to be as narrow as possible in order to meet customer’s expectations. Attended delivery is often the case for large and heavy items (such as furniture and white goods) because it is very inefficient to have to load and unload these type of products more than necessary.

Often HDSs offer to the customer the possibility to select a time slot for the delivery. This is because customers would rather prefer to be able to choose the time slot instead of having it imposed by the retailer. The combination of stringent time constraints, uncertain demand and the pressure to control costs, create quite a challenge.

According to 17 [2], in the UK over 50% of houses are empty in the time frame between 9 and 16. This is due to several factors such as the increasing number of single households, flexible working patterns, trends in female employment, people spending more of their free time away from home. Being the standard delivery time between 8 and 17, the vehicle routing and scheduling difficulties are obvious. If the customer is not in when the delivery attempt is made, and the goods can not be left with a neighbour, then the goods have to be redelivered at a later time and/or date. The "At Your Home" [2] report presents some interesting findings concerning customers’ preferences: deliveries on a Saturday afternoon, which was traditionally a
3.4 Delivery time windows preferences

Convenient time for making home deliveries, are also becoming more difficult due to the number of people who are out; failed deliveries in small package operations (and other delivery systems) where no delivery time/date arrangement is made with the customer prior to delivery can be as high as 60% thus involving high redelivery cost.

As an example, Figure 3.4 shows the results of a survey where RAC (UK’s motoring organisation) asked 317 motorists who bought goods over the Internet or telephone or by mail order when they would like to receive their products:

![Figure 3.4: Preferred delivery times - RAC 2001 [2]](image)

It can be noticed that the early evening time slot (6pm-8pm) is far the most favourite one with a 34% of preferences. In general, morning deliveries are preferred over afternoon ones, even though it is not clear whether the respondents prefer the early (8-10) or the late morning (10-12). The "By arrangement" option consists of an agreed date and time for the delivery that suits best the customer and gets 17% of the respondents’ preferences. Finally, the least preferred time slots are the early afternoon, the very early morning and the late evening.

A way of analyzing the trade-offs between delivery cost and customer service is by highlighting the significant cost impact of tight delivery time windows. This can be done by using vehicle routing software to evaluate different delivery policies based on different time window configurations. Here we briefly present some design decisions:

**Time slot length.** A shorter time slot implies higher customer service, but reduces the delivery flexibility and therefore may lead to higher delivery costs;

**Time windows can or not overlap.** For example, to cover the four hours period from 8 to 12, it may be possible to offer two 2-hour time slots from 8 to 10 and from 10 to noon. Alternatively, three overlapping 2-hour time slots from 8 to 10, from 9 to 11, and from 10 to noon. Overlapping might provide marketing advantages since it offers customers more choices;

**Number of time slots offered.** A larger number of time slots offered increases customer service, but may also increase distribution costs since the retailer
The home delivery market

may have to make far away deliveries more often. Note that the number of
time slots offered does not have to be the same for every customer. Customers
far away from the distribution center or living in areas with low population
densities may be offered fewer time slots so as to artificially increase their
density [3].

In the customer’s point of view, a well-balanced offering of time slots over a
day (i.e. morning, afternoon and early evening) and over the week (i.e. weekdays
and weekends) is required. From a company perspective smooth demand patterns
and its smooth geographical distribution over a day and the week tends to facilitate
cost-effective picking and delivery. In light of this, it is clear that time slot design
is likely to influence the customer demand in a specific area while, contemporane-
ously, expected demand affects time slot design in that area.

Therefore, analyzing demand is crucial. First of all demand is characterized by
its size (number and volume of orders). Then home delivery sales volume in the
specific area is related to the population density, the average income, the average
age, the Internet penetration, etc. It is also necessary to understand the preva-
ient desired delivery times in terms of preferred days and times of delivery. The
final issue is about what happens when the customer’s preferred delivery time and
day is not available. Will he withdraw the order or will he choose another time slot?

In order to facilitate cost-effective routing, the HDS provider can choose the
time slots that are offered to the different customers and the fees associated with
deliveries during these time slots. Obviously, the closer the delivery locations are
for orders due in a given time slot (or consecutive time slots), the easier it will be
to schedule the deliveries and the cheaper it will be to carry them out. However,
without specific dynamic pricing schemes there is little motivation for consumers to
choose time slots that are convenient for the retailer. In other words, the dynamic
order promise process in the home delivery case can be described as follows. Before
placing the delivery request, the customer can see a price that includes the value
of the purchased goods and a fixed delivery fee. He then places a delivery request
and the HDS suggests the set of feasible time slots (i.e. at the phone or through
a website). The idea behind maximizing profitability through the implementation
of pricing policies is to propose delivery discounts along with feasible time slots
depending on the location of the customer, the order size and the time slot. This
entails a reduction of distribution cost and profit maximization. Then the customer
can select one of the offered time windows or decide to cancel the delivery request.

On the other hand, considerable investment and research has gone in the di-
rection of finding acceptable means of delivering goods when there is no one at
home. Unattended delivery increases flexibility but is only suitable for products
that can be safely deposited at the customer’s site. Yet by far the most popular
option for home-shoppers is for a next-door neighbour to receive the goods, with
the main alternative being to leave them in the garage. Both of these options, how-
ever, raise security issues and have implications for retailer and carrier liability [2].
Using facilities enabling unattended reception, the customer is relieved of the need
to be present to receive the goods ordered. Unattended reception may be based on
reception boxes, delivery boxes, shared reception boxes or collection and delivery
points (CDP).

From a VRPTW point of view, unattended delivery can be modelled as an open time window that would span the entire day meaning better routing optimization and substantial cost savings. However this involves also remarkable investments and further research is needed. To conclude, Figure 3.5 shows the delivery factors that determine whether or not the customers has to be present to receive the delivery:

![Figure 3.5: Delivery factors that determine whether attended or unattended delivery is necessary](image)

Research is emerging that analyzes routing strategies for unattended home deliveries where time slots are not of concern. Several papers related to the ECOLOR project of the University of Helsinki ([39], [41], [40] and [38]) present simulation based analyses of different delivery strategies for e-groceries. In the next chapter we will present that together with the academic research that has recently emerged about home delivery services especially concerning the e-grocery market.

### 3.5 E-grocery

Over the last few years electronic commerce has undergone growing pains and experienced a dramatic evolution. Many dotcoms had a spectacular rise and sometimes no less spectacular subsequent fall. Nonetheless, electronic commerce continues to grow and evolve under different models. As presented for the Danish market in section 3.2, currently e-commerce activity is concentrated on items such as clothing, books, hardware, software, music, travel and electronics. The e-grocery sector is also growing and developing.
In the e-grocery commerce customers shop for groceries on the Internet, agree with the grocer on a delivery date and time window and this then delivers the parcel to the customers’ place. This is a typical example of home delivery service and it is the most studied case in the academic literature. In light of this, we will briefly introduce the concept and some real-life cases to illustrate the complexity of this VRPTW application.

Figure 3.6 shows a comparison between traditional grocery shopping and e-grocery:

![Comparison of traditional and home delivery grocery channels](image)

**Figure 3.6:** Comparison of traditional and home delivery grocery channels [8]

It can be noticed that the e-grocery framework requires new operating models in the supply chain. In the traditional grocery supply chain, goods are delivered to the store from a distribution centre and customers perform the picking and final delivery to their home. The e-grocer also grounds his activities on a distribution center. However, in this case the e-grocer is in charge of picking, packing, and home delivery transportation that are the major cost drivers. Therefore, the challenges for an e-grocer are to achieve cost-efficient operating models and to provide more convenience to consumers. The e-grocery home delivery model is based on unattended reception, which enables the a more cost-efficient routing and scheduling of delivery vehicles [38]. Many of the difficulties in managing such a business come from a mismatch between marketing and operations strategies.

In fact, the groceries market is characterised by highly perishable products, customers expecting very short lead times (i.e. time between order placement and delivery), widely changing customer tastes, products with low value to size ratio and low profit margins. It is therefore very competitive. In the customer’ point
of view online conveniences consist in the ability to add to the saved shopping list over several days, email lists to other family members, comment on items, receive personalized coupons, sort items by calorie count or nutritional information such as sodium content and order the ingredients for "one click meals" automatically from online recipes [26]. Moreover, food is fresher and higher quality when processed under the strict temperature control and shorter supply chain in online grocers’ distribution centers.

During the dotcom boom, pioneers in online groceries were pure play firms that used venture capital to experiment with innovative ideas. However, unconstrained spending and slower than expected consumer adoption of buying groceries over the Internet resulted in most pure play pioneers being acquired or closed down during the dotcom bust. For example, Safeway acquired GroceryWorks, Ahold USA acquired Peapod and Streamline, and Shoplink and Webvan closed down [46].

Despite many innovations, pioneer pure play e-grocer startups’ distribution centers were much too costly and had far too much capacity for the demand at that time. Webvan, for example, aspiring to leverage the “last mile” spent over $1.2 billion on huge highly automated warehouses. However, Webvan failed from overestimating the demand for buying groceries online and underestimating the logistic problems.

The three most dominant surviving business models for e-grocery home deliveries are:

- Fulfillment from stores by "brick-and-click" supermarkets, such as Tesco and Safeway. Also known as multi-channel business model. This is a decentralized model that involves conventional stores (or facilities immediately adjacent to stores) for picking, packing and delivery of Internet grocery orders;
- Fulfillment from distribution centers, such as FreshDirect in New York and Ocado in London. Also called pureplay model. This is a centralized model based on dedicated fulfillment centres (warehouses) that enables efficient picking and packing operations and can handle a larger number of orders and supply goods to a wider area;
- Hybrid strategies such as used by Peapod and Sainbury’s.

There are several trade-offs that online grocers need to face in their fulfillment strategy. In summary, distribution centers enable more efficient inventory control, picking, packing and delivery than store fulfillment. On the other hand, distribution centers require a higher fixed investment cost, and a longer lead-time to set up. Currently, only highly populated cities like New York and London have proven to have enough concentrated demand to justify large distribution centers. Hybrid business models attempt to capture the advantages of both stores and distribution centers. The trade-offs among the alternatives can be modeled using management science [26].

In the last ten years most academic research concerning the home delivery market has used the e-grocery concept as case study. Among the others, Gillett
and Miller [26], Punakivi [38], Punakivi [38], Cairns [11], [1] and [2] provide an extensive review of models and issues concerned with it. We refer to these studies for a more complete problem description.
Chapter 4

Literature review

This chapter presents a complete literature review on some of the most relevant issues related to the home delivery market which has lately been a subject of academic research to a notable degree (especially about the e-grocery business). Therefore, we have concentrated this review on literature concerning the last mile logistics market leaving out the massive study of the pure vehicle routing problem.

This literature study starts with an extensive discussion of issues and results for different attended and unattended home delivery concepts for the e-grocery market (section 4.1). Next, section 4.2 describes a research project that deals with orders acceptance or rejection while section 4.3 presents several questions and methods proposed in the literature for pricing of home delivery services. Then two specific studies about the effect of tight delivery time windows on delivery costs are introduced in section 4.4. Finally social, economical and environmental sustainability issues are discussed in 4.5 while the interesting driver familiarity concept is proposed in 4.6.

4.1 Attended or unattended deliveries

As stated in the previous chapter, as many as 60% of small package deliveries may fail due to the absence of the customer from the home, causing increased costs to the distributor and inconvenience to the consumer [2]. In order to reduce redelivery costs and increase customers’ service level, the scheduling of deliveries tends to be preferred over the promise to deliver "on Wednesday". Retailer and customer mutually agree on a delivery time window that is how long the customer has to stay at home waiting for the delivery.

However, in general attended deliveries are the cause of high operating costs. This is because, generally speaking, the more the customer is allowed to control the home delivery service by selecting the time window, the higher is the number of vans required, the working hours for the drivers and the mileage. On the other hand, unattended home deliveries correspond to time windows spanning over the entire day. From the retailer's point of view relaxing the time window constraints would allow more optimal routing and scheduling, maximum utilization of transportation capacity as well of the staff involved. Moreover, from the customer’s perspective
unattended delivery increases convenience since customers would be totally independent of the delivery time slot.

These issues are discussed in Punakivi and Saranen [39], Punakivi et al. [41], Punakivi and Tanskanen [40] where the authors provide an extensive description of the unattended home delivery concept for the e-grocery market and compare transportation costs for different attended and unattended delivery set-ups and assess the impact of varying delivery time window lengths. They also analyse what level of investments the cost savings due to unattended delivery justify from the retailer’s point of view. Issues like initial investment, low utilisation rate and slow growth of demand are addressed. The simulation results presented hereby were based on point-of-sale data from Finnish grocery stores. The RoutePro VRP software from CAPS Logistics was used. First of all, the delivery of goods when there is no one at home can be ensured by one of the following solutions:

Reception box is installed at the customer’s home yard or garage and is equipped with a refrigerator-freezer unit and a room temperature compartment;

Delivery box an insulated box with a docking mechanism that is delivered to the customer’s house and collected empty on the day following delivery or later;

Shared reception box (or collection and delivery points (CDP)) may be placed in a location that is convenient for the customers such as gas stations, bus or metro stations, post offices, local shops, parking lots. They may have various amounts of separate lockers, which may contain freezer, chilled, and room temperature compartments. The separate lockers have electronic locks with a changing opening code to enable shared usage of the lockers using a mobile phone.

Punakivi and Saranen [39] compares four existing home delivery concepts (two attended and two unattended - reception box) using real-life point-of-sale data. They are also compared with the case where the customer uses his own car for shopping for groceries (Case 5). The population density in the considered service area is 1496 inhabitants per square kilometre (the same figure for the Greater Copenhagen area was about 1830 inhabitants per square kilometre in 2003\textsuperscript{1}). The simulation results are presented in Figure 4.1:

In the comparison the cost of the time spent shopping has been left out. This is because the cost of the customer doing the picking and packing in the store can be compared to the costs of the logistics center in the e-grocery supply chain. It can be noticed that the delivery concept offering a 1-hour delivery time window (Case 2) is 54\% more expensive than Case 5 (own car). Moreover the home delivery transportation cost in Case 2 is 2.7 times greater than in Case 4. This demonstrates that unattended home delivery always leads to better vehicle routing optimization in terms of transportation cost.

Case 1 represents a three 2-hour delivery slots concept(17-19, 18-20 and 19-21) and allows to gain efficiency enabling better route and schedule optimisation thus

\textsuperscript{1}http://www.oresund.com/oresund/facts/copcap3.htm
4.1 Attended or unattended deliveries

Figure 4.1: The indexed transportation cost of different home delivery concepts [39]

leading to a significant (54%) cost reduction if compared to Case 2. This operating concept is, cost wise, the same as in "self service" (Case 5).

From a retailer’s point of view remarkable cost reductions can be found using a reception box that allows unattended delivery. In fact, Figure 4.1 shows that an open (from 8 to 18) delivery time window (Cases 3-4, unattended delivery) enables the best possible optimisation of the routing and delivery schedule. In Case 4 orders are sorted by zip code and divided evenly among the six delivery days of the week so that customers can receive their purchases once a week on a fixed customer chosen day. On the other hand in Case 3 orders are delivered on the original shopping date (next day).

Actually, Case 4 simulates the best attainable situation in the home delivery transportation. According to the simulations, in Case 4 the cost level drops dramatically, by 43%, compared to the cost level of ”self service” (Case 5). In real life, this kind of situation can be reached by effective service area pricing policy by the service provider. However, if the optimal situation (Case 4) can not be reached, the cost level of Case 3 will still be 27% better than Case 5.

Punakivi and Saranen identify the critical key factor behind the cost base as the density of stops on the route. This dependency is shown in Figure 4.2 where it can be noticed that the cost efficiency of a home delivery concept is based on decreasing average mileage per order and simultaneously increasing number of stops per hour:
Figure 4.2 shows that the results of the simulations for Case 5 (customers visiting the store using their own cars) report an average round trip length of 6.9 km. This validates the research by Granfelt et al. [28] that stated that in Finland the average one-way distance to the grocery store is 3.5 km.

However, in their study Laseter et al. [33] demonstrated that even in the larger US cities, the density of population will not allow for a low cost provision of home delivery services if the customer decides the timing (narrow delivery time window) of the service.

Considering the investments required, for reception boxes high investments are involved and the payback period, based on the cost savings, is 6-13 years [38]. The delivery box concept potentially enables a faster growth rate and higher flexibility of the investments because a smaller investment is required per customer. Punakivi et al. [41] estimate a payback time of 2 years. The drawback is the additional cost of collecting the empty boxes [41] that weakens its operational efficiency to the level of attended reception [40] (see also Figure 4.3 where Case 4 is 46-54% less expensive compared to Case 3B).

Reception and delivery box solutions are customer-specific solutions for unattended delivery. Reception boxes are well suited to customers living in one-family houses or rows of houses in a suburban area. On the other hand, shared reception boxes are a good solution for blocks of flats in the city centre and for rural areas. Shared reception boxes are also well suited for one-family houses or rows of houses but this depends on the customer’s willingness to pick up the parcel instead of having it delivered at his place. In general, the utilisation level of shared reception boxes ought to be higher. Punakivi and Tanskanen [40] address this issue and
4.1 Attended or unattended deliveries

present the results of a simulation project that was carried out using point-of-sale data from one of the largest grocery retailing companies in Finland. In their research Punakivi and Tanskanen present 5 cases. Case 1 describes attended 2-hour time window home delivery concept. Case 2, 3A and 3B represent unattended delivery. In particular Case 2 describes the reception box concept with delivery between 8 and 16. While Cases 3A and 3B depict the delivery box option with delivery between 8 and 16. Cases 3A involves pick-up of the box on the next delivery and Case 3B does it on the next day. Finally Case 4 represents the shared reception box solution. Figure 4.3 presents the results of Punakivi and Tanskanen’s simulations:

![Figure 4.3: The operational cost levels of home delivery concepts [40]](image)

It can be seen that home delivery transportation costs using the shared reception box concept (Case 4) are 55-66% lower than those of the standard home delivery model with attended reception and 2-hour delivery time windows (Case 1). This cost saving is based on an operational efficiency approximately three times higher and the fact that a smaller number of vehicles are needed when the shared reception box solution is simulated. This cost reduction alone justifies the two-to-five-year payback period of the investment required for the shared reception box concept, even if there is only a fairly small number of deliveries per day [38]. Similarly, the comparison on the same data of attended reception and 2-hour delivery time windows (Case 1) against customer-specific reception boxes (Case 2) or de-
livery boxes with pick-up on next delivery (Case 3A) leads to a cost reduction of 44-53%. In this case the cost saving is based on operational efficiency that is 1.9 times higher Punakivi and Tanskanen [40].

However, when choosing a shared reception box solution, goods are delivered only "half way" and the customer has to pick up the goods within the pick-up time window defined by the service provider. This does not provide total independence of delivery time slot as in the case of customer-specific unattended delivery solutions (reception or delivery box). Moreover, Punakivi and Tanskanen [40] present also some key questions to be resolved: the accepted distance from home to the CDP, the accepted price level for using the service, and how much additional traffic this concept may generate. Moreover, theoretically the CDP concept opens up new business opportunities for the retailer in the way that it expands the retailer’s coverage area more cheaply than investing in a new store.

Finally, these results illustrate the efficiency gains of relaxed time constraints in the way that fully flexible, unattended delivery reduces costs by up to a third, relative to attended delivery within 2-hour time slots. Moreover, there is notable potential for traffic reduction when compared to the situation in which customers visit the shop using their own cars. Punakivi [38] presents reductions up to 12%, depending on the home delivery model used. Of course, this results would largely depend on the context (i.e. actual mode choice for grocery shopping related trips). We can conclude saying that unattended reception is better and economically feasible when reaching for repetitive purchasing customers, stable demand of goods [41] and depends very much on the e-grocery market share in the future.

4.2 Dynamic order acceptance or rejection

Depending on the requested delivery time and location, serving some customers may be more expensive than serving others. Thus, if capacity is limited, order-acceptance decisions must be taken in order to maximize the overall profit. Campbell and Savelsbergh [13] explicitly address this issue. They examine which deliveries to accept or reject. Their approach exploits stochastic information about future requests to decide on requests under consideration. The objective is to maximize profit even if it may not be possible to satisfy all requests due to limited capacity or time. Requests are accepted or rejected and assigned to a specific time slot considering the option of rejecting an "expensive" delivery to preserve resources for more, future deliveries. Their analysis is based on insertion heuristics for a vehicle routing problem. As each order arrives, they compare the value of inserting that particular order versus inserting potential future orders that are properly discounted based on their probability of being realized. They also suggest several variants for incorporating expected future orders. A experimental study compares these variants and underlines their superiority over a simple first-come-first-serve order acceptance.

4.3 Static and dynamic pricing

Pricing decisions play a key role in any business. In the home delivery market, companies need to set prices both for the physical products and for the delivery
service. Common policies often combine both price elements, e.g. in the form of free delivery of sufficiently large orders [4].

As stated in Section 3.4, prices can also be used to encourage customers to opt for broader time windows or time slots outside rush hours when the roads are less congested, or to shop on particular days (to artificially increase demand density for particular areas at most convenient times). As highlighted above, offering customers delivery on a given day could reduce delivery company costs quite substantially compared with allowing them to opt for specific time windows. Cairns [11] describes the following examples of pricing policies from UK supermarkets that should contribute to service efficiency while improving operations cost performance:

- At Asda, deliveries of home shopping orders over £99 are free. At Ocado, deliveries of orders over £75 are free. At Iceland, deliveries of orders over £40 are free;
- At Tesco, pricing policy varies with individual stores, and time slots are charged at £3.99, £4.99 or £5.99 to try and spread demand;
- At The Food Ferry, customers choosing a 3/4-hour time slot receive free delivery, or they can pay £5.50 for a 2-hour time window or £7.50 for a 1-hour slot.

Each home delivery service provider needs to choose an appropriate level of delivery service and a corresponding price. At the same time, they need to manage efficiently the necessary resources, meaning transportation capacity, to provide this service in a profitable way.

Basu et al. [6] explores a multizone pricing plan for home delivery applications. They introduce an \textit{N}-zone extension of uniform pricing (i.e. same delivered price, irrespective of delivery cost, to all customers who buy the same product or service). Multizone pricing plans are widely used in practice, especially by retailers of heavy or bulky goods; by mail order and electronic commerce firms; by freight intermediaries; and by taxis and airport shuttles. The authors prove that the optimal number of zones varies with the level of demand relative to the spatial dispersion of customers, and with the cost of implementing a zonal plan. They also demonstrate that a small number of zones captures almost all the profit attainable with a spatially discriminatory plan (i.e. this policy maximizes profit from each customer perfectly discriminating between them because the price rises with distance from the origin at a fixed rate).

In the logistics literature, the primary objective in most of the VRP models is to minimize the total route length (cost). These models usually require the fulfillment of the pre-determined demand for deliveries of a pre-determined set of customers. However, in the planning phase demand for deliveries depends on prices. Therefore it is useful to understand how pricing decisions influence demand (and the costs associated with meeting demand) and how prices and demands combine to determine profitability. Geunes et al. [25] specifically address the delivery pricing problem when both the size of demand and the demand frequency is price sensitive by mean of an approximation model. The focus is on the question of which customer regions
to serve, at which price, in order to maximize profitability.

Moreover, recently academic research on dynamic pricing has grown considerably. A related field of research is revenue management, which concerns the management of prices and inventory of scarce goods in order to maximize profits. As an example, Agatz et al. [4] see the development of revenue management approaches for home delivery operations among the most relevant current research issues in e-fulfillment. This is due to the particular pricing flexibility in online sales where demand is most likely stochastic. Agatz et al. [4] provide a review of models and applications and expect significant additional contributions in the future. The most studied application area of revenue management is the airline industry. Obvious similarities, but also significant differences, exist between the application of revenue management concepts in the airline industry and home delivery environments. The key difference concerns the cost of using inventory (i.e. seats in the context of airlines and a delivery in a certain time slot in the context of home delivery). The cost of a seat is independent of who gets the seat; instead, the cost of a delivery in a certain time slot depends on the location of the customer as well as on the location of other customers requiring a delivery in that time slot Agatz et al. [4]. In fact, the design of a dynamic pricing policy depends on the assumptions regarding: the desired delivery time slot of a customer; the reaction of a customer when presented with a particular set of delivery charges for the time slots.

For instance, Campbell and Savelsbergh [12] provide an example of how a customer’s reaction can be modeled and how such a model can be used to compute incentives. They suggest that in the e-grocery market potentially significant improvements in routing costs can be achieved by influencing customers’ choices of delivery windows. This means that if customers select better time windows, not only will total distance travelled be less, but a more efficient use of resources may increase the number of orders that can be accepted, thus creating higher revenues. In their paper an incentive scheme specialized for home delivery service is proposed. The developed online algorithm allows the shipper to offer delivery time slots with cheapest insertion costs and it is based on an algorithm used to solve the dynamic routing and scheduling problem. A simulation analysis indicates that the suggested incentive schemes can significantly enhance profit.

4.4 Tightening time windows

Only few studies specifically address the performance assessment of distinct home delivery concepts based on different time window designs. The main contribution is given in Nockold [35] and Lin and Mahmassani [34]. These are two simulation projects that use VRP software in order to compare different attended home delivery policies.

Nockold [35] is a study that was carried out in 2001 by Paragon Software Systems, a company that develops software for transport optimization and execution systems. The aim was to help the Internet-based home shopping sector quantify the impact of service levels on transport costs and understand the real cost of meeting customers’ e-service requirements in home delivery operations. In other words, they aimed at objectively assess the cost of the tightening of time windows and quantify
4.4 Tightening time windows

the potential benefits of alternatives.

To form the basis for his study, Nockold created a typical London-based home delivery operation offering all customers 3-hour time windows whose profile across the day reflected preference for delivery during the early morning and evening time slots. This is denoted as variable time window in Figure 4.4 and is according to the results of the survey presented in Section 3.4. Then the Paragon vehicle routing and scheduling software was run on the dataset as if it were being used to plan the daily operation. Nockold studied the effect of a number of time window scenarios. This meant assigning completely open time windows to varying proportions of customers under different assumptions. It can be seen that time window opening corresponds to adopting the unattended home delivery concept.

Figure 4.4 presents the transport cost reductions calculated for different percentages of customers with open time window. It also shows the effect of higher drop densities and increased number of drops per vehicle:

<table>
<thead>
<tr>
<th>% of customers with open time windows</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>300 calls with variable time window profile, max 14 drops per vehicle</td>
<td>6%</td>
<td>17%</td>
<td>24%</td>
<td>34%</td>
</tr>
<tr>
<td>600 calls with variable time window profile, max 14 drops per vehicle</td>
<td>9%</td>
<td>18%</td>
<td>22%</td>
<td>31%</td>
</tr>
<tr>
<td>1200 calls with variable time window profile, max 14 drops per vehicle</td>
<td>9%</td>
<td>17%</td>
<td>22%</td>
<td>27%</td>
</tr>
<tr>
<td>300 calls with even time window profile, max 14 drops per vehicle</td>
<td>10%</td>
<td>17%</td>
<td>27%</td>
<td>36%</td>
</tr>
<tr>
<td>300 calls with even time window profile, max 26 drops per vehicle</td>
<td>14%</td>
<td>22%</td>
<td>27%</td>
<td>38%</td>
</tr>
<tr>
<td>300 calls with variable time window profile, max 30 drops per vehicle</td>
<td>12%</td>
<td>23%</td>
<td>28%</td>
<td>36%</td>
</tr>
</tbody>
</table>

Figure 4.4: Transport cost reductions [35]

It can be noticed that a substantial cost benefit can be gained by increasing the proportion of customers with open time windows. Depending on drop density and number of drops per vehicle, for 25% of 3-hour time windows would reduce transport cost by 6-14%. Removing 50% would reduce transport costs by 17-24%; removing 100% would increase this to 27-38%. Moreover, the percentage saving varies as drop density increases, although savings are still at similar levels. The percentage saving generally increases as the number of drops per vehicle increases. [35] also demonstrated that the conclusions are not significantly affected by making different assumptions about the time window profile. Changing the base variable profile of 3-hour time windows to an even time window distribution (i.e. customers evenly distributed among the different time slots throughout the day), or biasing the enlargement of time windows to those shoppers requesting very early or very
late deliveries did not mean significant difference. Finally, according to what presented previously in this Chapter, Nockold suggests unattended delivery and the use of incentive pricing schemes to influence customers’ choices of delivery windows as solutions for cost efficient e-fulfillment operations.

Similarly, Lin and Mahmassani [34] use simulation to evaluate the impact of different delivery policies on the operations of an e-grocer. Among their research questions, they illustrate the trade-off between delivery cost and customer service by highlighting the potentially significant cost impact of tight delivery time windows. They first survey and summarize the delivery policies for many online grocers in the U.S. and then use vehicle routing software (TransCAD GIS) to evaluate the impact of some of these policies on a few realistic instances of the problem.

Tailored datasets were produced for two cities (Boston and Washington D.C.). The number of customers was split evenly within the selected window duration. Different delivery policies were defined by unique combination of number of vehicles used, number and duration of the time window, number of depots, number of customers to serve, and road network on which they serve their customers. These different scenarios were used in order to address the impact of the following issues: one open time window for all customers, different time windows of the same duration, and different time windows of different duration. The comparative analysis presents, among other results, the number of customers served/not served, the total miles traveled and the idle (loss) time for all scenarios. This allows conclusions regarding system performance and economic implications for the business operator. Figure 4.5 summarizes how an increase in one of the factors determining the home delivery policy, all the others being constant, affects the operating performance of an e-grocer represented by Proportion of Customers Served, Total Miles Traveled and Idle Time:

<table>
<thead>
<tr>
<th>Factors</th>
<th>Proportion of Customers Served</th>
<th>Total Miles Traveled</th>
<th>Idle Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand</td>
<td>--</td>
<td>+</td>
<td>--</td>
</tr>
<tr>
<td>Vehicle</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Number of time window</td>
<td>--</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Duration of time window</td>
<td>+</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Depots</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Service area and network size</td>
<td>--</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Figure 4.5: Effect of significant increase in each factor on the operating performance [34]

For example, it can be noticed that providing the high level of service and convenience (in the form of specific and tight delivery time windows) desired by online customers often results in higher delivery costs, which directly affect the profitability of the operation. In fact, an increase in the duration of time windows entails better flexibility in terms of larger proportion of customers served and better vehi-
4.5 Sustainability issues

The environmental and sociological consequences of the increase of the home delivery market are beyond the scope of this thesis. However, these issues are very important and have received a quite remarkable attention from researchers from all over the world. Hereby we present some interesting papers that deal specifically with the UK and Dutch markets.

First of all, a major issue which the Retail Logistics Task Force (UK) has considered in [2] is the likely effect of the growth of home shopping on traffic levels. In the optimistic scenario, one van journey will replace several car shopping trips resulting in a significant net reduction in road traffic. The pessimistic view is that people will substitute other forms of car travel for shopping trips which, when combined with van deliveries to the home, will generate a net increase in traffic. Cairns [11] concerns the e-grocery sector in the UK context. The author examines a range of international evidence, including the results of nine modelling assessments, undertaken by different researchers, at different scales, and using a range of different methods and scenarios. The paper examines the evidence about the trade-off between increasing delivery movements and the potential for reduced private car travel. By looking at the effects of straightforwardly substituting personal car trips for goods transport by delivery vehicles, the results suggest that if such a straightforward substitution occurred grocery home deliveries should probably be given a cautious welcome, since the traffic increases from additional delivery movements are likely to be substantially outweighed by reductions in personal car travel such that the total relevant traffic could more than halve.

Of course, urban freight transport is recognized to be fundamental to the economic vitality and competitiveness of industrial, trade and leisure activities which are essential to wealth generation. Rapid and reliable goods distribution supports urban lifestyles and is an important element of the urban economy. However, it is also recognized as one of the most significant sources of unsustainability in urban areas. It is responsible for environmental unsustainability (global and local pollutant emissions, fossil fuel usage, global warming) and for decreasing social sustainability due to its contribution to noise, visual intrusion, vibration, reduction in city accessibility, increase in congestion and traffic accidents.

Time-access regulations and vehicle restrictions are increasingly used, especially in western Europe, to improve sustainability in urban areas. Quak and de Koster [44], Quak and de Koster [43] and Quak [42] deal with urban policy restrictions and their effect on retailers’ distribution organisation and distribution costs and on...
the environment. In other words, these studies primarily consider the impacts on environmental and economic sustainability due to improvements of social sustainability by time windows and vehicle restrictions.

In particular, Quak and de Koster [44] study the impact of governmental time window pressure on retailers’ logistical concepts and the consequential financial and environmental distribution performance. Time-access restrictions force the distribution activities to take place within a specified period of the day. The objective is to improve the shopping climate in shopping areas and to separate the freight carriers from the shopping public who use cars to visit the shopping areas. Time window restrictions are becoming increasingly popular in western Europe. For example Quak and de Koster [44] says that, in the Netherlands, only 41% of the municipalities used time windows in 1998; this increased to 53% in 2002. The larger municipalities in particular use time windows: 71% of the top 100 largest municipalities and all top-20 municipalities in the Netherlands use them. At the same time, the average time window length decreases. Many forwarders consider time windows to be one of their most urgent problems in distributing goods in urban areas. Moreover, local authorities have substantial autonomy, time window restrictions differ per municipality and are not harmonized. Although carriers operate in different cities and are therefore confronted with a wide range of local restrictions making the problem even more complicated. In their research Quak and de Koster [44] determine which dimensions in the retailer’s logistical concept determine its cost and emission sensitivity to increasing time window pressure. The research is based on a multiple case study of fourteen Dutch retail cases in different sectors and with different store formulas. The authors conclude that time windows cause an increase in the amount of global (CO₂) and local (PM₁₀, NOₓ, and CO) emissions. Time windows also cause an increase in retailers’ distribution costs. When time window lengths decrease, the financial and environmental performances deteriorate more than proportionally. In other words, the relaxation of the time window restrictions would immediately relieve retailers’ cost-increase, as well as the environmental burden. The total percentage increase in costs and emissions depends on the retailer’s logistical concept and the exact time window pressure. For example, supplying more stores during the time window hours enabled by short distance, short unloading time, and larger drop size, reduces sensitivity to time window pressure. Again, these results depend very much on the specific socio-economic conditions and the overall context.

Similarly Quak and de Koster [43] extend the work studying the impact of governmental time windows, vehicle restrictions, and different retailers’ logistical concepts on the financial and environmental performance of retailers. Vehicle restrictions can apply to length, width, height, axle pressure, weight, engine type, and load factor. They usually aim at avoiding traffic problems due to roundabouts, narrow streets, etc. However, in the urban freight transportation context, they are also considered to improve livability, reduce environmental impacts, and reduce perceived large-vehicle impacts. Currently, about 35% of Dutch municipalities use vehicle restrictions [43]. Again, the authors conclude that positive impacts of time windows on social sustainability issues come at the expense of environmental performance. Also vehicle restrictions also have a negative environmental effect. Most decisions that are cost efficient for retailers are also desirable from an environmental
4.6 Driver familiarity

point of view (e.g. reducing the number of kilometers traveled is cost efficient for
retailers and is also the best way to lower transport emissions). Therefore, Quak
and de Koster conclude that both time windows and vehicle restrictions result in
a cost increase for retailers. The magnitude of the cost increase depends on the
distribution characteristics of the retailers such as average drop size per delivery
and average load factor of a vehicle when it leaves the distribution center.

4.6 Driver familiarity

Finally, Zhong et al. [51] introduce a very interesting concept, the so-called driver
familiarity or driver learning. The authors study the case of local delivery of pack-
ages where customer locations and demands vary from day to day. The objective
is to provide realistic models to optimize vehicle dispatching while maintaining
driver familiarity with their service territories, hence dispatch consistency. Driver
familiarity is achieved by assigning the same driver to the same set of customers
every day and tends to create fixed routes (service territories). On the other hand,
classical route optimization tends to assign drivers to variable routes every day.
Therefore, a good dispatching systems should balance these trade-offs. Under spe-
cific assumptions Zhong et al. develop a two-stage vehicle-routing model. They
solve it by mean of a tabu search metaheuristic and build low-cost yet consistent
dispatch plans.
Part II

Simulations
Chapter 5

Model and Data

In this chapter we first introduce the real-life case on which this simulation project is based (section 5.1). In section 5.2 we describe the vehicle routing software used to model and solve our real-life problem instances. The given dataset, a collection of L’EASY’s customer orders, is presented in section 5.3.

5.1 The L’EASY case

L’EASY A/S specialises in telephone and on-line lease and sale of brown and white goods to private addresses (B2C). All orders are delivered to the customer’s place (attended delivery concept). Delivery and installation fees are included in the price. Typical products are televisions and refrigerators, washing machines, dishwashers that require a significant service time at the customer’s site.

The company’s business is based on a call centre that receives requests and information inquiries from consumers by telephone. Distribution planning is a complex matter for L’EASY because of a large number of unique order requirements and high demands for precisely timed deliveries. Usually, L’EASY’s call center agents offer to their customers good suggested time slots while the customer is on the phone. These time slots consist of a specific day (from Monday to Sunday) and a time window. L’EASY currently offers three time windows: Morning (M) - 8 to 12; Afternoon (A) - 12 to 16; Evening (E) - 16 to 21. The company’s goal is to ensure a high customer service level while maintaining distribution cost efficiency.

We do not have exact information about how this real-time component of the L’EASY’s decision support system works. In particular, we do not know exactly what kind of algorithms are used. However, we guess that the system is based on insertion cost calculation carried out by a heuristic solution method. Such a system could work as follows. L’EASY call center agents receive customer requests (consisting mainly of product specification and address for the delivery). They immediately pass that information to the real-time decision support system that, within a very short time (approximately 5 seconds), calculates what the cost of feasibly assigning (inserting) the customer order to each scheduled route would be. This calculation should be done for each day of delivery. After that, the feasible route assignments (day of delivery and time window) are shown to the call center agent.
larly, the system could highlight the first 3 best (less costly) assignments so that
the agent could offer them first to the customer on the phone. In section 6.4 we
show that suggesting a time slot while the customer is on the phone entails a more
efficient scheduling. In fact, the randomization of time windows assignment for the
dataset we used entails a worsening in the overall operational performance. The
number of necessary vehicles (routes) increases by 7.1% while the total time driv-
ing and waiting increases by 8.2%. Likewise the total distance driven raises by 10%.

In our case study customers and vehicles are associated with an availability
time interval of the hard type (see section 2.2). Each vehicle is assigned to a
specific depot and routes have the characteristic that the driver returns to the
same home base at the end of the work period. In Section 3.4 we stated that
the attended home delivery concept is a VRPTW application where time windows
constraints are likely more critical than are vehicle capacity restrictions. This is
true also for the L’EASY case and it is the reason why capacity constraints are
not taken into account either for vehicles or for terminals. Therefore, the L’EASY
case is a typical example of Multiple Depot Vehicle Routing Problem with Time
Windows application (MDVRPTW, see Cordeau et al. [17], p. 178) characterized
by 3 depots and a ”weakly homogenous” fleet of vehicles. With this we mean that
the vehicle types are not strictly identical but they differ solely in their availability
time windows.

5.2 Modelling tool used

In this dissertation the modelling and simulation work was performed using a com-
mercial vehicle routing tool, Route Planner (RP) from Transvision A/S. The soft-
ware was used in order to model and solve different scenarios for the L’EASY
attended home delivery case study. Additionally, a spreadsheet program was used
for data processing and for analysing the simulation results.

With over 30 years of experience, Transvision is Scandinavia’s leading provider
of transport planning and optimisation systems. Their products are used in a wide
range of industries, such as oil and gasoline distribution, timber transportation,
furniture and cement distribution, waste and bulky refuse collection.

Transvision Route Planner is a general planning and analysis tool for the dis-
tribution of goods from terminals to customers. It can handle a range of different
types of distribution problems. The optimization of the instances is done through
the use of up-to-date metaheuristics (see Section 2.3). The user can build an ap-
proximate distribution model that resembles the real-life problem at hand. This
is done by defining, among other data, the problem specific characteristics about
customer orders, depots, vehicles and respective time windows.

Additionally, Route Planner uses digital road maps in the vehicle routing:
graphical maps for visualizing information and road network for calculating dis-
tances between points. This makes possible to take into consideration, for exam-
ple, different road characteristics like speed limits and rush hours for different road
types and allows the visualisation of routing results on a map.
5.3 Data

This case study is based on a dataset containing L’EASY’s customer orders from 4179 customers located in Denmark, that were served during weeks 13, 14, 15 and 16 of the year 2009. Each customer order is defined by order ID, XY-coordinate, time window start and end, scheduled week and day, estimated service time and ZIP code. Service times range from a minimum of 2 to a maximum of 146 minutes with an average service time of 31 minutes. Table 5.1 presents four examples of customer orders, one for each week:

<table>
<thead>
<tr>
<th>OrderID</th>
<th>X</th>
<th>Y</th>
<th>Start TW</th>
<th>End TW</th>
<th>Day</th>
<th>Duration</th>
<th>Week</th>
<th>ZipCode</th>
</tr>
</thead>
<tbody>
<tr>
<td>34871</td>
<td>580340</td>
<td>61390677</td>
<td>08:00</td>
<td>11:59</td>
<td>Mon</td>
<td>300</td>
<td>13</td>
<td>5250</td>
</tr>
<tr>
<td>35061</td>
<td>510111</td>
<td>6221869</td>
<td>16:00</td>
<td>20:59</td>
<td>Mon</td>
<td>7200</td>
<td>14</td>
<td>7430</td>
</tr>
<tr>
<td>38102</td>
<td>723683</td>
<td>6177334</td>
<td>08:00</td>
<td>11:59</td>
<td>Wed</td>
<td>300</td>
<td>15</td>
<td>2200</td>
</tr>
<tr>
<td>40760</td>
<td>717508</td>
<td>6176462</td>
<td>16:00</td>
<td>20:59</td>
<td>Tue</td>
<td>6840</td>
<td>16</td>
<td>2610</td>
</tr>
</tbody>
</table>

Table 5.1: Examples from the L’EASY customer orders dataset

Transvision provided also data about depots (section 5.3.2), vehicles (section 5.3.3) and all the relevant information about road network such as velocity profiles and digital maps.

First of all, we present a preliminary analysis of the structure of the orders dataset. Figure 5.1a shows that week 14 is the one with the highest number of scheduled orders (1123) while week 15 has the lowest (870), since the Easter vacations fell in it. Similarly, Figure 5.1b shows that in the four considered weeks most orders were scheduled on Wednesday, followed by Tuesday and Monday.

(a) Orders distribution within weeks  
(b) Orders distribution within days

Figure 5.1: Orders distribution

Figure 5.2 shows a map visualization of the 1123 L’EASY’s customer orders scheduled on week 14:
It can be noticed that the requests are mainly located in the København, Odense, Århus and Ålborg areas.
Figure 5.3 represents L’EASY’s customers’ preferences for each of the three time windows currently offered by the company:

![Time window preferences](image)

**Figure 5.3:** L’EASY customers’ time window preferences

It can be noticed that the A time slot is far the most favourite one with a 43% of preferences followed by M (35%) and E (22%) deliveries.

### 5.3.1 Customer orders

Given its XY-coordinate each customer order is geocoded in Route Planner so that orders can be displayed on a map and the real distances can be calculated. Figures 5.5 and 5.4 show an example of how customer orders are modelled and visualized on a map in Route Planner.

Figure 5.4 shows a map visualization of the customer orders scheduled on Monday - week 14 in the Odense area. Customer order number 3251 (Paarup Kirkegård area) is highlighted with the symbol on the right.

Figure 5.5 shows how the same customer order is modelled into Route Planner. It can be noticed that for this case study some information are not relevant and the correspondent entries are left empty. Instead, as stated above, customer orders are characterized by Order ID, XY-coordinate, time window, scheduled week and day, service time (*Extra time in RP*) and ZIP code. The *House no.* actually defines the modelling scenario that the selected order belongs to.
Figure 5.4: L’EASY customer orders - RP Map visualization

Figure 5.5: L’EASY customer orders - RP Modelling
5.3.2 Terminals

As stated before, L’EASY’s business is based on 3 depots. These are located in Hobro, Odense and Tåstrup and each terminal is associated with a fleet of vehicles and is modelled as XY-coordinate so that it can be displayed on a map. Figures 5.6 and 5.7 refer to our case study and present how terminals are modelled and visualized in RP:

![Figure 5.6: L’EASY terminals - RP Map visualization](image)

Figure 5.6 is a map visualization of the L’EASY terminals. The Odense depot is selected and Figure 5.7 illustrates how the same item is modelled into Route Planner. Terminals are characterized by their number and name, address information and time window. Again, some of the entries (e.g. capacity and cost) are left empty because that data is not used in this particular modelling framework.
Figure 5.7: L'EASY terminals - RP Modelling
5.3 Data

5.3.3 Vehicles

In the L’EASY case there are two types of vehicles at each terminal, each of them with different working shifts (Table 5.2):

<table>
<thead>
<tr>
<th>Vehicle type</th>
<th>Shift start</th>
<th>Shift end</th>
</tr>
</thead>
<tbody>
<tr>
<td>L’EASY Early Shift Truck</td>
<td>07:30</td>
<td>16:30</td>
</tr>
<tr>
<td>L’EASY Late Shift Truck</td>
<td>12:30</td>
<td>21:30</td>
</tr>
</tbody>
</table>

Table 5.2: L’EASY trucks types

It can be noticed that the model assumes extra capacity for the A time slot being that the L’EASY Early Shift Truck and the L’EASY Late Shift Truck are overlapping in the hours between 12.30 and 16.30. This is in line with the time window customer preferences shown in Figure 5.3. Concerning the fleet size, we can say that L’EASY has as many vehicles as needed. This means that if their fleet was not big enough to fulfill all orders, they would hire third party logistic (3PL) providers. Later in this project we will discuss this issue. For example, in section 6.5 we present the effects that the reduction in the number of vehicles has on the planning outcome.

Figure 5.8 illustrates how vehicle types are modelled into Route Planner:

Vehicle types are described by their number (ID), name, time window, terminal and velocity profile that they must obey (different speed limits on different road types). Our model does not include capacity constraints. Moreover, Route Planner allows the minimization of total cost (sum of all vehicle costs) as optimization criteria. Vehicle costs would be specified in the right part of Figure 5.8. Each vehicle
has its own cost profile. The cost profile consists of a start-up cost, a distance cost and a time cost. The start-up cost is added to the total cost of the plan, if the vehicle is active in the plan as well as the distance cost (cost/km driven by the vehicle) and the time cost (user-defined piecewise linear function which provides a cost depending on the total time spent by the vehicle). However, we do not have these cost figures. Therefore, in our study the routing optimization will consider the minimization of total time and number of vehicles (see section 6.1).
Chapter 6

Research approach and preliminary testing

In this chapter we first present the research approach of our simulation project: section 6.1 describes purpose and methodology of our study, section 6.2 describes the cost figures used in order to compare different scenarios while section 6.3 outlines modelling assumptions and setup that will be later used in the Testing chapter. In sections 6.4, 6.5 and 6.6 we present some preliminary testing where we aim at introducing some of the features of Transvision Route Planner and run some introductory simulations.

6.1 Research approach

As we discussed in the literature review (chapter 4), in a distribution case like the L’EASY one, the more the customer is allowed to control the service by selecting the delivery time window, the higher is the number of vehicles required, the working hours for the drivers and the mileage. However, quantitative research on the last mile problem and the factors affecting the cost of home delivery has been scarce. In this simulation project we use the L’EASY case and a state-of-the-art vehicle routing software (Transvision Route Planner, RP) to evaluate the impact of tightening delivery time windows on the the operational performance.

From an operational point of view, L’EASY’s goal is to daily plan its routes so that all customer orders are fulfilled while minimizing the number of vehicles and the total time.

Transvision Route Planner was used in order to model and solve different scenarios for the L’EASY attended home delivery case study. The operational planning is where the actual orders are being assigned to resources. Therefore, we focused on one planning day at a time and each of our scenarios consists of a set of customer orders to be served within the same day and a specific RP planning set up.
When using Transvision Route Planner, the planning can be based on the following optimization criteria:

**Total Time** the algorithm only tries to minimize the total time;

**Total Distance** the algorithm only tries to minimize the total distance driven;

**Total Cost** the algorithm only tries to minimize the total costs (sum of all vehicle costs: start-up costs, distance related costs and time related costs).

In order to evaluate and compare the different scenarios, Transvision Route Planner provides the following plan key performance indicators (KPIs):

**Total Routes** number of routes;

**Total Time Driving** total time spent on driving [hh:mm:ss];

**Total Time Waiting** total time spent on waiting [hh:mm:ss];

**Total Time At Customer** total service time spent at the customers' sites [hh:mm:ss];

**Total Time** the total sum of the time spent on driving, waiting and at the customers' sites [hh:mm:ss];

**Total Distance** total distance driven [km].

Later in this report, we will use these KPIs in the tables used to present and compare different routing scenarios.

*Since L’EASY’s goal is to minimize the number of vehicles and the total time spent in the system, we have chosen total time and minimization of the number of routes as optimization criterions throughout all the simulations - if not otherwise specified. Consequently, we focused our analysis of the optimization outcome on KPIs such as total routes and total time.*

As we stated before, for each plan, the total time is the total sum of the time spent by the vehicles in the plan on driving, waiting and serving the customers. The total time spent at customer would be exactly the same for two scenarios fulfilling the same customer orders thus becoming a constant in the sum. In such a case we will focus our analysis only on the sum of total time driving and waiting hence making the comparison of different scenarios more sound.

When evaluating and comparing different scenarios we will also consider the number of unplanned orders (**Orders in Orderbank** in RP). If the planning process failed in assigning some of the orders in a scenario to a route, the unplanned orders are kept in the orderbank. Generally speaking, unplanned orders are the result of unfulfilled restrictions (e.g. too little capacity on the vehicles, impossible to arrive within the time window, long distance from the depot).
6.2 Cost figures

In order to measure the operational efficiency of different delivery plans we also define the following Distribution efficiency KPIs that, later in this report, we will use to compare different scenarios:

**Orders/Hour** average number of customer orders served per hour in the plan, calculated as $\frac{\text{Number of Requests}}{\text{Total Time}}$.

**Orders/Route** average number of customer orders assigned to each route in the plan, calculated as $\frac{\text{Number of Requests}}{\text{Total Routes}}$.

**Km/Order** average mileage (in km) per order in the plan, calculated as $\frac{\text{Total Distance}}{\text{Number of Requests}}$.

**Time/Order** average time (in hours) spent per order in the plan, calculated as $\frac{\text{Total Time}}{\text{Number of Requests}}$.

In chapter 4 (section 4.1) we mentioned that Punakivi and Saranen identify the critical key factor behind the cost base in the density of stops on the route. This dependency was shown in Figure 4.2 where it could be noticed that the cost efficiency of a home delivery concept is based on decreasing average mileage per order and simultaneously increasing number of stops per hour. With our study we will compare scenarios also on the base of the average time per order since time is a key factor for L’EASY.

The purpose of the preliminary tests is to present some features of Transvision Route Planner and describe the simulations setup that has been used in the following extensive testing section (chapter 7). Therefore, in this chapter we examine the following preliminary research questions:

1. Suggestion of time slots while the customer is on the phone: how does this contribute to efficient routing (see section 6.4)?

2. What would be the performance improvement if an optimal assignment of the day of delivery was possible (see section 6.4)?

3. Fleet size: what are the effects of its reduction (see section 6.5.1)?

4. How are KPIs such as the number of vehicles (routes) and the total time affected by different time windows durations? And which tight time window durations is it worth to investigate? (see section 6.6)

### 6.2 Cost figures

In the next chapter, when evaluating and comparing different scenarios we will also attempt to evaluate the impact of tightening time windows on the routing cost. For this purpose, in the next chapter we will make use of two cost indicators. First of all we will look at the Total Cost of the plan (in DKK). This is calculated as the sum of total hourly and total mileage costs that depend on Total Distance and
Total Time respectively. Therefore, for each scenario, the Total Cost is calculated as:

\[(\text{Total Time} \cdot \text{Cost per hour}) + (\text{Total Distance} \cdot \text{Cost per km})\].

Since the specific L’EASY’s cost figures were not available, we decided to use the ones presented in Table 6.1:

<table>
<thead>
<tr>
<th>Cost per hour</th>
<th>Cost per km</th>
</tr>
</thead>
<tbody>
<tr>
<td>[DKK/hour]</td>
<td>[DKK/km]</td>
</tr>
<tr>
<td>250</td>
<td>1.55</td>
</tr>
</tbody>
</table>

Table 6.1: Cost figures

These cost figures are in 2003 level market prices (including taxes) and are taken from the "Key Figure Catalogue - Usage within socio-economic analysis in the transport sector. Danish Ministry of Transport (2006)" [36]. As indicated in the catalogue, the hourly cost includes depreciation, wage, maintenance and overhead costs [36, p. 12]; the mileage cost includes depreciation, fuel, lubricant, tires and maintenance [36, p. 27]. Therefore, these include also the costs associated with the vehicles.

We will also compare different scenarios based on the Cost per Order (in DKK/order) calculated as:

\[
\frac{\text{Total Cost}}{\text{Number of orders served in the plan}}
\]

Finally, in chapter we will provide all the simulation results necessary for the cost comparison. Therefore, it would be easy for the company to compare the different delivery scenarios on the base of its specific cost figures.

6.3 Scenarios definition and simulations setup

In section 5.3 week 14 was shown to be the one with the highest number of customer orders (1123). In order to decide which day to choose for our preliminary analysis we examined the distribution of customer orders in week 14 (Figure 6.1).

Monday resulted to be the day with the highest share (243 orders) and was chosen as planning day. Figure 6.2 shows a map visualization of the 243 L’EASY’s customer orders scheduled on Monday - week 14.

Again, it can be noticed that the requests are mainly located in the København, Odense, Århus and Alborg areas.

The different scenarios for the preliminary testing were designed using those 243 customer orders and setting up different plans depending on the subject of the analysis. On the other hand, in the next chapter (7) we will present the results of a larger number of simulations (one for each day of week 14 - except for Sunday). This will ensure more significant results and a more robust analysis.
The different scenarios that we designed for the preliminary analysis were generated either by modifying: the time window and/or day of assignment; the number of vehicles; or the time windows duration (enlargement or shrinkage). When changing the time windows durations, customer orders were split evenly among the new time slots.
Concerning the planning setup, the following stop criteria was defined - if not otherwise specified:

**Maximum Total Planning Time** maximum total time allowed where the optimization engine tries to improve the solution, set to 30 minutes.

With regard to the number of vehicles at each of the 3 depots - if not otherwise specified - it was set to 10 for each type (for a total of 60 available vehicles). This fleet size was determined according to the results of a preliminary planning test on the customer requests due on Monday - week 14.

Finally, we selected the *Use Customer Time Window* and *Use Vehicle Time Window* plan restrictions for all plans in Transvision Route Planner. And - if not otherwise specified - we selected the *Fewer routes better than optimization criteria* planning option. Meaning that, if this option is selected, the optimization process will consider the minimization of the number of vehicles better than the optimization of the optimization criteria (total time in our case - for more details see section 6.5).

### 6.4 Randomization of time windows and/or day assignment

In order to investigate preliminary research question number 1 - *Suggestion of time slots while the customer is on the phone: how does this contribute to efficient routing?* - we first examined the effect of randomizing the assignment of time windows within the same day. After that we considered the effect of randomizing the assignment of the day of delivery for the whole week.

First of all, we varied the time windows assignment within Monday - week 14 holding all other data (ID, XY-coordinate, scheduled week and day, service time and ZIP code) constant. Recalling the results presented in Figure 5.3, we kept the share of customers assigned to M, A and E time slots constant. We first randomized the order in which the 243 customer requests appeared in the dataset. After that we modified their time window start and end so that 35% of customers were assigned the M time slot, 45% the A one and 22% the E one. This will be later called *scenario 2* while the original dataset for requests due on Monday - week 14 constitutes the benchmark dataset later called *scenario 1*.

Table 6.2 summarizes the computational results for scenarios 1 and 2:

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>28</td>
<td>0</td>
<td>6.261</td>
<td>229:07:00</td>
<td>107:36:00</td>
<td>121:31:00</td>
</tr>
<tr>
<td>S2</td>
<td>30</td>
<td>0</td>
<td>6.883</td>
<td>237:55:00</td>
<td>116:23:00</td>
<td>121:31:00</td>
</tr>
</tbody>
</table>

**Table 6.2**: Computational results for scenarios 1 and 2
6.4 Randomization of time windows and/or day assignment

It can be noticed that the randomization of time windows assignment for the 243 requests due on Monday - week 14 entails a worsening in the overall operational performance. The number of necessary vehicles (routes) increases by 7.1% while the total time driving and waiting increases by 8.2%. Likewise the total distance driven raises by 10%.

Additionally, Table 6.3 shows that in scenario 2 the number of orders served per hour decreases by 3.7% together with the number of orders per route (-6.7%). At the same time, there is an increase in both the mileage per order (+9.9%) and the time per order (+3.8%). Thus demonstrating that suggesting a time slot while the customer is on the phone entails a better scheduling.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Orders/Hour</th>
<th>Km/Order</th>
<th>Time/Order</th>
<th>Orders/route</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1.06</td>
<td>25.8</td>
<td>0:56:34</td>
<td>8.7</td>
</tr>
<tr>
<td>S2</td>
<td>1.02</td>
<td>28.3</td>
<td>0:58:45</td>
<td>8.1</td>
</tr>
</tbody>
</table>

Table 6.3: Comparison of scenarios 1 and 2

We also examined the effect of randomizing the assignment of the day of delivery for all the 1123 customer orders due in week 14. The original dataset of requests due in week 14 constitutes the benchmark dataset: 6 scenarios were created (scenarios 3-8), one for each day of week 14 where a suggestion of day and time window had been done while the customer was at the phone. then, we created scenarios 10-15 by grouping all orders due in week 14, randomizing their order of appearance and then reassigning the day of delivery. Of course, the original distribution of requests in week 14 (see Figure 6.1) was kept constant.

Tables 6.4 and 6.5 show the effect of randomizing the assignment of the day of delivery for all the requests due in week 14. In all scenarios all orders were scheduled. Hence resulting in no orders in the orderbank.

<table>
<thead>
<tr>
<th>Day</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mon</td>
<td>S3</td>
<td>28</td>
<td>6.261</td>
<td>229:07:00</td>
<td>107:36:00</td>
<td>121:33:00</td>
</tr>
<tr>
<td>Tue</td>
<td>S4</td>
<td>26</td>
<td>6.886</td>
<td>212:40:00</td>
<td>109:39:00</td>
<td>103:00:00</td>
</tr>
<tr>
<td>Wed</td>
<td>S5</td>
<td>29</td>
<td>6.959</td>
<td>238:11:00</td>
<td>114:24:00</td>
<td>123:46:00</td>
</tr>
<tr>
<td>Thu</td>
<td>S6</td>
<td>28</td>
<td>6.706</td>
<td>225:45:00</td>
<td>109:58:00</td>
<td>115:47:00</td>
</tr>
<tr>
<td>Fri</td>
<td>S7</td>
<td>13</td>
<td>3.030</td>
<td>98:20:00</td>
<td>51:29:00</td>
<td>46:51:00</td>
</tr>
<tr>
<td>Sat</td>
<td>S8</td>
<td>19</td>
<td>4.840</td>
<td>142:42:00</td>
<td>76:13:00</td>
<td>66:28:00</td>
</tr>
<tr>
<td>Week 14 - original</td>
<td>143</td>
<td>34.681</td>
<td>1146:45:00</td>
<td>569:19:00</td>
<td>577:23:00</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.4: Computational results for scenarios 3-8

By looking at the weekly totals, it can be seen that the randomization of the assignment of the day of delivery entailed again a worsening in the overall operational performance. The number of necessary vehicles (routes) increases on average
Research approach and preliminary testing

Table 6.5: Computational results for scenarios 10-15

<table>
<thead>
<tr>
<th>Day</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mon</td>
<td>S10</td>
<td>31</td>
<td>7.332</td>
<td>245:06:00</td>
<td>122:42:00</td>
<td>122:24:00</td>
</tr>
<tr>
<td>Tue</td>
<td>S11</td>
<td>27</td>
<td>6.722</td>
<td>228:40:00</td>
<td>113:30:00</td>
<td>115:10:00</td>
</tr>
<tr>
<td>Wed</td>
<td>S12</td>
<td>30</td>
<td>7.665</td>
<td>242:27:00</td>
<td>124:40:00</td>
<td>117:47:00</td>
</tr>
<tr>
<td>Thu</td>
<td>S13</td>
<td>28</td>
<td>6.894</td>
<td>235:21:00</td>
<td>115:06:00</td>
<td>120:14:00</td>
</tr>
<tr>
<td>Fri</td>
<td>S14</td>
<td>14</td>
<td>3.589</td>
<td>107:29:00</td>
<td>58:21:00</td>
<td>49:08:00</td>
</tr>
<tr>
<td>Sat</td>
<td>S15</td>
<td>15</td>
<td>3.621</td>
<td>114:27:00</td>
<td>61:46:00</td>
<td>52:40:00</td>
</tr>
<tr>
<td>Week 14 - randomized days</td>
<td></td>
<td>145</td>
<td>35.823</td>
<td>1173:30:00</td>
<td>596:05:00</td>
<td>577:23:00</td>
</tr>
</tbody>
</table>

Table 6.6: Comparison of scenarios 3-8 and 10-15

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Orders/ Hour</th>
<th>Km/ Order</th>
<th>Time/ Order</th>
<th>Orders/ Route</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 14 - original</td>
<td>S3-S8</td>
<td>0.98</td>
<td>30.9</td>
<td>1:01:16</td>
</tr>
<tr>
<td>Week 14 - randomized days</td>
<td>S10-S15</td>
<td>0.96</td>
<td>31.9</td>
<td>1:02:42</td>
</tr>
</tbody>
</table>

Figures 6.3 and 6.4 present the graphical comparison of the results shown in Tables 6.4 and 6.5 concerning total routes and total time driving and waiting.

It can be noticed that this kind of randomization implies better results for the scheduling of customer orders on Saturday. In this case, the number of routes decreases by 21.1% while the total time driving and waiting decreases by 19%. This might mean that in the original dataset L’EASY scheduled on Saturday - week 14 some difficult requests either in terms of geographical location or time window. However, we do not have access to this kind of information and can not be sure about the reasons behind this result.
6.4 Randomization of time windows and/or day assignment

**Figure 6.3:** Comparison of scenarios 3-8 and 10-15 - Total routes

**Figure 6.4:** Comparison of scenarios 3-8 and 10-15 - Total time driving and waiting
After that, we investigated preliminary research question number 2 - *What would be the performance improvement if an optimal assignment of the day of delivery was possible?* - by grouping all the customer orders of week 14 in one single planning day. The resulting scenario 41 consists of 1123 customer requests where we varied only the scheduled day of delivery holding all other data constant. In this scenario the number of vehicles at each of the 3 depots was increased in order to handle the increased daily demand. It was set to 50 vehicles for each type for a total fleet size of 300 vehicles. Scenario 41 was compared with the results for Week 14 - Randomized days (scenarios 10-15). Table 6.7 shows the computational results from Transvision Route Planner (of course the Time at Customer was the same):

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Total Routes</th>
<th>Total Distance</th>
<th>Total Time Driving &amp;Waiting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 14 - randomized days</td>
<td>S10-S15</td>
<td>145</td>
<td>35.823</td>
</tr>
<tr>
<td>One single planning day</td>
<td>S41</td>
<td>132</td>
<td>26.911</td>
</tr>
</tbody>
</table>

**Table 6.7:** Comparison of scenarios 10-15 and 41

It can be seen that grouping all orders due in week 14 in one single planning day entails a much more efficient scheduling from an operational point of view: all the KPIs relevant for our study see an improvement (number of routes -9%, total time driving and waiting -26,6% and total distance driven -25%). Contemporaneously, Table 6.8 shows that the number of orders served per hour improves by 15.6% as well as the number of orders per route (+10.5%), the mileage per order (-24.9%) and the time per order (-13.5%).

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Orders/ Hour</th>
<th>Km/ Order</th>
<th>Time/ Order</th>
<th>Orders/ Route</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 14 - randomized days</td>
<td>S10-S15</td>
<td>0.96</td>
<td>31.9</td>
<td>1:02:42</td>
</tr>
<tr>
<td>One single planning day</td>
<td>S41</td>
<td>1.11</td>
<td>24.0</td>
<td>0:54:13</td>
</tr>
</tbody>
</table>

**Table 6.8:** Comparison of scenarios 10-15 and 41

These are the possible savings that the company could achieve if an optimal assignment of the day of delivery was possible, no matter what the customer preferences were. In practice, these savings could be obtained by assigning 22 of the total 132 routes to each day of delivery (from Monday to Saturday, 6 days).

Finally, we compare the computational outcome for scenario 41 and the results presented in 6.4. These show that if an optimal assignment of the day of delivery was possible L’EASY could achieve a much more efficient scheduling compared to what they currently do. In fact, all the KPIs relevant for our study would see an improvement (number of routes -7.7%, total time driving and waiting -23.2% and total distance driven -22.4%).
6.5 Testing of different Plan setups

In this section we present the study carried out in order to investigate preliminary research question number 3 - Fleet size: what are the effects of its reduction?. We used scenario 2 as customer orders dataset (243 requests).

6.5.1 Fleet size

We first modified the fleet size with respect to the basic scenario 2 where we had a total of 60 available vehicles (10 for each type at each depot). We created 6 scenarios where we gradually reduced the number of vehicles at each depot.

From Figure 6.3 we can see that the calculated number of daily routes was never higher than 31 (for scenario 10). Therefore we created the new scenarios starting with 6 available vehicles at each depot (scenario 21 - for a total of 36 available vehicles) an decreased it down to 1 (scenario 26 - for a total of 6 available vehicles).

Table 6.9 presents the computational results for scenarios 21-26. These were compared to scenario 2 that was used as benchmark.

<table>
<thead>
<tr>
<th>Number of vehicles per type</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp;Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>S2</td>
<td>30</td>
<td>0</td>
<td>6.883</td>
<td>237:55:00</td>
<td>116:23:00</td>
<td>121:31:00</td>
</tr>
<tr>
<td>6</td>
<td>S21</td>
<td>30</td>
<td>0</td>
<td>7.186</td>
<td>238:12:00</td>
<td>116:40:00</td>
<td>121:31:00</td>
</tr>
<tr>
<td>5</td>
<td>S22</td>
<td>29</td>
<td>6</td>
<td>7.129</td>
<td>234:49:00</td>
<td>116:30:00</td>
<td>118:18:00</td>
</tr>
<tr>
<td>4</td>
<td>S23</td>
<td>24</td>
<td>30</td>
<td>5.960</td>
<td>203:20:00</td>
<td>100:27:00</td>
<td>102:53:00</td>
</tr>
<tr>
<td>3</td>
<td>S24</td>
<td>18</td>
<td>74</td>
<td>5.219</td>
<td>155:47:00</td>
<td>82:39:00</td>
<td>73:07:00</td>
</tr>
<tr>
<td>2</td>
<td>S25</td>
<td>12</td>
<td>106</td>
<td>2.836</td>
<td>104:39:00</td>
<td>50:29:00</td>
<td>54:09:00</td>
</tr>
<tr>
<td>1</td>
<td>S26</td>
<td>6</td>
<td>159</td>
<td>1.232</td>
<td>51:37:00</td>
<td>21:44:00</td>
<td>29:53:00</td>
</tr>
</tbody>
</table>

Table 6.9: Computational results for scenarios 2 and 21-26
Figure 6.5 presents the graphical comparison of the results shown in Table 6.9 concerning the number of orders in the orderbank:

It can be seen that the number of unplanned orders increases rapidly when reducing the fleet size. With a total number of 60 and 36 vehicles (scenarios 2 and 21) the number of unfulfilled orders is equal to zero. However, as soon as we reduce the fleet size to 30 vehicles (scenario 22) we get 29 routes and 6 unplanned orders (2.5% of the total requests) meaning that some of the orders become impossible to serve. This is due their time windows and geographical location and to the fleet size.

For example, Figure 6.6 shows the map visualization of 5 of the 29 routes calculated for scenario 22. These 5 routes are located in Sealand and are served by the only 5 L’EASY Early Shift Trucks based at the Tastrup depot. It shows also the 6 unplanned orders highlighted with the symbol on the right.

These orders were all assigned a M time window (8-12) but since the number of L’EASY Early Shift Trucks is limited and capacity has already been taken by other routes, they result impossible to serve.
6.5 Testing of different Plan setups

Figure 6.6: Scenario 22: the 6 unplanned orders and 5 of the 29 routes
6.5.2 Optimization criteria

Additionally, the following plan settings in Transvision Route Planner all influence on how the optimization builds the final routes:

**Use All Assigned Vehicles** if selected, all the available vehicles will be used in the plan. Otherwise the optimization process outcome could use fewer vehicles than the number of available ones;

**Fewer routes better than optimization criteria** if selected, the optimization process will consider fewer routes better than the optimization criteria (total time in our case).

Naturally, in Transvision Route Planner these two options are mutually exclusive: the planner can unmark both or select one of them at a time. When selecting the **Fewer routes better than optimization criteria** option, the planning will always try to reduce the number of used vehicles, while if this option is unmarked the algorithm will only try to reduce the number of vehicles in use if this results in a lower value of the optimization criteria.

Earlier in this chapter we stated that L’EASY’s goal is to daily plan its routes so that all customer orders are fulfilled while minimizing the number of vehicles and the total time. In this section we want to research the effect of the use of these two plan setup options on the optimization outcome. We use the customer orders dataset from scenario 2 and define 3 new scenarios: scenario 18 where both options were unmarked; scenario 17 where the **Fewer routes better than optimization criteria** option was selected; and scenario 19 where **Use all assigned vehicles** option was selected. As for scenario 2, the fleet consists of a total of 60 vehicles.

Table 6.10 presents the simulation results for scenarios 17-19. Again, all orders were planned in all the scenarios. Thus the time at customer was the same for the three of them (121:31:00).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
</tr>
</thead>
<tbody>
<tr>
<td>S18</td>
<td>32</td>
<td>0</td>
<td>6.498</td>
<td>232:31:00</td>
<td>110:59:00</td>
</tr>
<tr>
<td>S17</td>
<td>30</td>
<td>0</td>
<td>6.883</td>
<td>237:55:00</td>
<td>116:23:00</td>
</tr>
<tr>
<td>S19</td>
<td>60</td>
<td>0</td>
<td>6.873</td>
<td>243:03:00</td>
<td>121:31:00</td>
</tr>
</tbody>
</table>

Table 6.10: Computational results for scenarios 17-19
Figure 6.7 presents the graphical comparison of the same scenarios:

It can be noticed that when none of the examined planning options was selected (scenario 18) Transvision Route Planner optimized the planning with 32 routes. On the other hand it used all available vehicles in scenario 19 and optimized the plan with only 30 routes when the Fewer routes better than optimization criteria option was selected (scenario 17). This means that the latter planning option entailed a decrease in the number of routes of -50% with respect to scenario 19 and -6.3% compared to scenario 18.

On the other hand, with regard to the total time driving and waiting, the selection of the Fewer routes better than optimization criteria option led to an improvement by 4.2% compared to scenario 19 while it entailed an increase of 4.9% with respect to scenario 18. This is because in scenario 17 we are prioritizing the minimization of the number of vehicles with respect to the total time.
6.6 Which tighter time windows durations is it worth to investigate?

Finally, in order to investigate preliminary research questions number 4 - *How are KPIs such as the number of vehicles (routes) and the total time affected by different time windows durations? And which tight time window durations is it worth to investigate?* - we modified time windows durations holding all other data constant. To do so, we assigned the same time window width to all customer orders due on Monday - week 14 (243). We first assigned to all requests a 13-hour wide time slot (8-21) and then tightened it down to 0.5-hour. This gave us a total of 14 scenarios. However, these were in fact 28 since we chose to run them both selecting the Fewer routes better than optimization criteria option (scenarios 27a-40a) and the Use all assigned vehicles option (scenarios 27b-40b). As for scenario 2, the fleet consisted of a total of 60 vehicles. As stated before, when modifying the time windows durations, customer orders were first randomized and then split evenly among the new time slots. Table 6.11 presents the simulation results for the aforementioned scenarios:

<table>
<thead>
<tr>
<th>Selected option</th>
<th>Time windows width [hours]</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer routes better than optimization criteria</td>
<td>13</td>
<td>S27a</td>
<td>23</td>
<td>-</td>
<td>4.563</td>
<td>200:58:00</td>
<td>79:27:00</td>
</tr>
<tr>
<td>12</td>
<td>S28a</td>
<td>24</td>
<td>-</td>
<td>4.668</td>
<td>202:38:00</td>
<td>81:06:00</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>S29a</td>
<td>25</td>
<td>-</td>
<td>4.717</td>
<td>203:05:00</td>
<td>81:34:00</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>S30a</td>
<td>25</td>
<td>-</td>
<td>4.669</td>
<td>202:52:00</td>
<td>81:21:00</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>S31a</td>
<td>26</td>
<td>-</td>
<td>4.839</td>
<td>205:37:00</td>
<td>84:05:00</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>S32a</td>
<td>26</td>
<td>-</td>
<td>5.036</td>
<td>208:09:00</td>
<td>86:37:00</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>S33a</td>
<td>27</td>
<td>-</td>
<td>5.203</td>
<td>211:55:00</td>
<td>90:23:00</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>S34a</td>
<td>27</td>
<td>-</td>
<td>5.649</td>
<td>219:01:00</td>
<td>97:29:00</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>S35a</td>
<td>28</td>
<td>-</td>
<td>5.959</td>
<td>224:18:00</td>
<td>102:46:00</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>S36a</td>
<td>29</td>
<td>-</td>
<td>6.416</td>
<td>231:49:00</td>
<td>110:18:00</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>S37a</td>
<td>31</td>
<td>-</td>
<td>7.267</td>
<td>245:43:00</td>
<td>124:11:00</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>S38a</td>
<td>33</td>
<td>2</td>
<td>8.744</td>
<td>261:43:00</td>
<td>144:04:00</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>S39a</td>
<td>39</td>
<td>7</td>
<td>9.909</td>
<td>280:51:00</td>
<td>167:10:00</td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>S40a</td>
<td>46</td>
<td>12</td>
<td>11.408</td>
<td>324:45:00</td>
<td>213:12:00</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Use all assigned vehicles</th>
<th>Time windows width [hours]</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>S27b</td>
<td>60</td>
<td>-</td>
<td>5.535</td>
<td>219:50:00</td>
<td>98:19:00</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>S28b</td>
<td>60</td>
<td>-</td>
<td>5.645</td>
<td>221:21:00</td>
<td>99:50:00</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>S29b</td>
<td>60</td>
<td>-</td>
<td>5.796</td>
<td>223:29:00</td>
<td>101:58:00</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>S30b</td>
<td>60</td>
<td>-</td>
<td>5.999</td>
<td>229:22:00</td>
<td>107:00:00</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>S31b</td>
<td>60</td>
<td>-</td>
<td>6.210</td>
<td>232:40:00</td>
<td>111:08:00</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>S32b</td>
<td>60</td>
<td>-</td>
<td>6.375</td>
<td>235:39:00</td>
<td>114:07:00</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>S33b</td>
<td>60</td>
<td>-</td>
<td>6.813</td>
<td>241:31:00</td>
<td>120:00:00</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>S34b</td>
<td>60</td>
<td>-</td>
<td>7.412</td>
<td>248:33:00</td>
<td>127:01:00</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>S35b</td>
<td>60</td>
<td>-</td>
<td>7.763</td>
<td>255:29:00</td>
<td>133:57:00</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>S36b</td>
<td>60</td>
<td>-</td>
<td>8.214</td>
<td>264:00:00</td>
<td>142:28:00</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>S37b</td>
<td>60</td>
<td>-</td>
<td>8.819</td>
<td>276:12:00</td>
<td>154:41:00</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>S38b</td>
<td>60</td>
<td>2</td>
<td>9.892</td>
<td>288:10:00</td>
<td>170:32:00</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>S39b</td>
<td>60</td>
<td>7</td>
<td>11.114</td>
<td>316:22:00</td>
<td>202:41:00</td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>S40b</td>
<td>60</td>
<td>12</td>
<td>11.933</td>
<td>345:43:00</td>
<td>234:09:00</td>
<td></td>
</tr>
</tbody>
</table>

**Table 6.11:** Computational results for scenarios 27a-40a and 27b-40b
6.6 Which tighter time windows durations is it worth to investigate?

When looking at the number of unplanned orders we can see that in scenarios 38, 39 and 40 some requests appear impossible to fulfill. This is true for both the examined planning options. In fact, the unplanned orders are the same respectively in scenarios 38a and 38b, 39a and 39b, and 40a and 40b. Thus we do not present the time at customer that is exactly the same in each pair of a and b scenarios.

Instead, we focus on the unplanned orders. Figures 6.8 and 6.9 show the map visualization of the planning results for scenarios 39a and 39b. They both show the same unplanned orders (7, highlighted) while the plan for scenario 39a consists of 39 routes and the one for scenario 39b involves all 60 vehicles.

![Map visualization of the planning results for scenario 39a](image)

Figure 6.8: Map visualization of the planning results for scenario 39a

When examining the dataset and looking at the time windows for the unfulfilled requests we noticed that 4 out of 7 were assigned a 20-21 time slot. For example, the request located in the Helsingør area was assigned such a time window and the service time was estimated in 55 minutes.

This suggests that that customer order was impossible to serve within the L’EASY Late Shift Truck time window (12.30-21.30) being that the distance Tastrup-
Research approach and preliminary testing

Figure 6.9: Map visualization of the planning results for scenario 39b

Helsingør is approximately 64 km. We examined all the unplanned orders and concluded that they were impossible to fulfill due to distance from the depot and/or time window constraints.

Finally, when looking at the number of routes (Figure 6.10) it can be noticed that when we selected the Use all assigned vehicles option Transvision Route Planner naturally always optimized each plan on 60 routes no matter how long the customer time window was. This means that the number of routes for scenarios a where on average 51.3% better (lower) than the ones for scenarios b (min. 23.3% and max 61.7%). For those scenarios where the Fewer routes better than optimization criteria option was selected, we can see that the number of routes increases rapidly when decreasing time windows widths. In particular, we observe that the number of routes increases by 6.9% when passing from 4 to 3-hour time slots.

Similarly, Figure 6.11 shows the graphical comparison of the computational results obtained for scenarios 27a-40a and 27b-40b concerning total driving and waiting time. Generally speaking, we can observe that the values for the scenarios where all vehicles were used are on average 26.1% higher than the ones for scenarios 27a-40a (min. 9.8% and max 32.8%). In particular, we observe that for
6.6 Which tighter time windows durations is it worth to investigate?

Figure 6.10: Comparison of scenarios 27a-40a and 27b-40b - Total routes and orders in orderbank

the *a scenarios* the total driving and waiting time steeply increases by 7.9% when passing from 7 to 6-hour time slots. Similarly the trend suddenly breaks between 8 and 7-hour for the *b scenarios* (increasing by 5.2%).

Figure 6.11: Comparison of scenarios 27a-40a and 27b-40b - Total driving and waiting time
Finally, we present the comparison on the total distance results (Figure 6.12). Again, we can observe that the values for the scenarios $b$ are on average 22.9\% higher than the ones for scenarios $a$ (min. 4.6\% and max 31.2\%). In particular, we observe that for the $a$ scenarios the total distance steeply increases by 8.6\% when passing from 7 to 6-hour time slots. Similarly the trend suddenly breaks between 8 and 7-hour for the $b$ scenarios (increasing by 5.9\%).

![Figure 6.12: Comparison of scenarios 27a-40a and 27b-40b - total distance](image)

In this chapter we presented our research approach by introducing Transvision Route Planner features and the scenarios definition. We recalled the scope of our project and described KPIs and simulation setup that we will later use for our analysis. We also presented the results of some preliminary testing that aimed at introducing the reader to the dataset structure and at providing some practical examples about Transvision Route Planner outcome.

In the next chapter we will introduce the three main research questions by which we aim at comparing different delivery time window policies and to assess the cost trade-offs that exist among them. L’EASY’s goal is to ensure a high customer service level while maintaining distribution cost efficiency by minimizing the number of vehicles and the total time. Our purpose is to quantify the impact of increasing the customer service level (in terms of tighter time windows width) on operational performance and transportation cost. Therefore we will research the impact of open time windows (when enlarging them) or, more specifically, either 3, 2, 1 or 0.5-hour wide time slots (when tightening them).
Chapter 7

Testing

After having introduced some of the features of Transvision Route Planner and
the simulation approach and setup, in this chapter we present the results of the
extensive testing we carried out holding the same simulation setup presented in
section 6.3. As stated before, in this chapter we will not focus only on one planning
day (Monday - week 14). Instead we will present a larger number of simulations
(one for each day of week 14). This will ensure more significant results and a more
robust analysis.

First of all, in section 7.1 we research the impact on the operational performance
of providing to all customers the same time window width. In section 7.2 we
examine the effect of assigning different tight time windows to different shares of
customers. Finally we investigate the outcome of imputing narrow time windows
only to those customers living in the major cities (section 7.3). In each section, we
compare different delivery policies based on the KPIs and the cost figures introduced
in chapter 6.

7.1 Time windows of uniform duration for all cus-
tomers

In this section we examine the following research question: how is the routing cost
(in terms of total time and number of routes) affected by the enlargement or shrink-
age of time windows for all customers?

The idea behind this kind of analysis is that some customers are not likely to
spend 4 hours of the day waiting for their goods to be delivered. They would rather
prefer a tighter time window (e.g. 3, 2, 1 or 0.5-hour). On the other hand, when
reducing the time window width thus increasing the level of service, we expect a
worsening from an operational (number of vehicles needed and total time) and cost
performance points of view.

The original dataset - collection of L'EASY's customer orders due in week 14
(see Figure 5.2), each of them assigned a M/A/E time window - was used as bench-
mark. In fact, according to the results presented in section 6.4, we varied the time
Testing

windows assignment holding all other data (ID, XY-coordinate, scheduled week and day, service time and ZIP code) constant. In this way, the quality of those 6 delivery plans (scenarios 50-55, one for each day in week 14) is not affected by the suggestion of time slots done while the customer was on the phone.

Thereafter, we created 6 new scenarios (56-61) on the base of scenarios 50-55 where we assigned an open time window (8-21) to all L’EASY’s customer orders due in week 14.

After that, we created other 24 scenarios where we assigned a uniform time window duration to all requests due in week 14. We used the following durations: 3-hour (scenarios 62-67), 2-hour (scenarios 68-73), 1-hour (scenarios 74-79) and 0.5-hour (scenario 80-85).

When reassigning time windows the customer requests were split evenly among the new time slots. For example, Table 7.1 presents the number of customer orders due on each day of week 14:

<table>
<thead>
<tr>
<th>Week 14</th>
<th>Number of customer orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>243</td>
</tr>
<tr>
<td>Tuesday</td>
<td>214</td>
</tr>
<tr>
<td>Wednesday</td>
<td>236</td>
</tr>
<tr>
<td>Thursday</td>
<td>228</td>
</tr>
<tr>
<td>Friday</td>
<td>94</td>
</tr>
<tr>
<td>Saturday</td>
<td>108</td>
</tr>
<tr>
<td>Total</td>
<td>1123</td>
</tr>
</tbody>
</table>

Table 7.1: Number of customer orders due on each planning day - week 14

As an example, when we assigned 3-hour long time windows we had 11 available time slots (8-11, ..., 18-21). Consequently, in that case, for each planning day we divided the number of customer orders by 11 and then split them evenly among the new time slots. Table 7.2 shows an example of assignment of uniform time windows duration for Friday - week 14.

We also thought over assigning more customer orders to the afternoon hours, between 12 and 16 being that the A time slot is the preferred one (see Figure 5.3). However, we finally disregarded that possibility and opted for the easier to implement option where customer orders are split evenly among the new time slots.
7.1 Time windows of uniform duration for all customers

<table>
<thead>
<tr>
<th>Time slot</th>
<th>Number of customer orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>8-11</td>
<td>8</td>
</tr>
<tr>
<td>9-12</td>
<td>8</td>
</tr>
<tr>
<td>10-13</td>
<td>8</td>
</tr>
<tr>
<td>11-14</td>
<td>8</td>
</tr>
<tr>
<td>12-15</td>
<td>8</td>
</tr>
<tr>
<td>13-16</td>
<td>9</td>
</tr>
<tr>
<td>14-17</td>
<td>9</td>
</tr>
<tr>
<td>15-18</td>
<td>9</td>
</tr>
<tr>
<td>16-19</td>
<td>9</td>
</tr>
<tr>
<td>17-20</td>
<td>9</td>
</tr>
<tr>
<td>18-21</td>
<td>9</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>94</strong></td>
</tr>
</tbody>
</table>

**Table 7.2:** Number of customer orders assigned to each of the 11 3-hour long time slots. Friday - week 14

After designing all the 36 instances (6 planning days, 6 uniform time windows durations) we imported them in Transvision Route Planner and ran the simulations with the same setup described in section 6.3. Table 7.3 shows the complete outcome for scenarios 50-55:

<table>
<thead>
<tr>
<th>Time windows width [hours]</th>
<th>Day</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Mon</td>
<td>S50</td>
<td>31</td>
<td>0</td>
<td>7.866</td>
<td>243</td>
</tr>
<tr>
<td></td>
<td>Tue</td>
<td>S51</td>
<td>28</td>
<td>0</td>
<td>6.602</td>
<td>214</td>
</tr>
<tr>
<td></td>
<td>Wed</td>
<td>S52</td>
<td>30</td>
<td>0</td>
<td>7.861</td>
<td>236</td>
</tr>
<tr>
<td></td>
<td>Thu</td>
<td>S53</td>
<td>31</td>
<td>0</td>
<td>7.141</td>
<td>228</td>
</tr>
<tr>
<td></td>
<td>Fri</td>
<td>S54</td>
<td>14</td>
<td>0</td>
<td>3.668</td>
<td>94</td>
</tr>
<tr>
<td></td>
<td>Sat</td>
<td>S55</td>
<td>15</td>
<td>0</td>
<td>3.777</td>
<td>108</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td>149</td>
<td>0</td>
<td>36.914</td>
<td>1123</td>
</tr>
</tbody>
</table>

**Table 7.3:** Computational results for scenarios 50-55

These results were later used as benchmark since they represent L’EASY’s actual practice - the basic scenario. On the other hand, Table 7.4 shows the aggregated results for scenarios 50-85 in terms of weekly totals. These are the results that we
used for comparison in our analysis:

<table>
<thead>
<tr>
<th>Time windows width</th>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>56-61</td>
<td>121</td>
<td>0</td>
<td>25.679</td>
<td>1021:58:00</td>
<td>444:34:00</td>
<td>577:23:00</td>
</tr>
<tr>
<td>4</td>
<td>50-55</td>
<td>149</td>
<td>0</td>
<td>36.914</td>
<td>1189:56:00</td>
<td>612:30:00</td>
<td>577:23:00</td>
</tr>
<tr>
<td>3</td>
<td>62-67</td>
<td>157</td>
<td>0</td>
<td>42.255</td>
<td>1262:04:00</td>
<td>684:38:00</td>
<td>577:23:00</td>
</tr>
<tr>
<td>2</td>
<td>68-73</td>
<td>180</td>
<td>7</td>
<td>47.780</td>
<td>1355:44:00</td>
<td>786:29:00</td>
<td>569:13:00</td>
</tr>
<tr>
<td>1</td>
<td>74-79</td>
<td>207</td>
<td>38</td>
<td>57.080</td>
<td>1499:32:00</td>
<td>951:03:00</td>
<td>548:25:00</td>
</tr>
<tr>
<td>0.5</td>
<td>80-85</td>
<td>234</td>
<td>69</td>
<td>64.025</td>
<td>1671:02:00</td>
<td>1143:29:00</td>
<td>527:29:00</td>
</tr>
</tbody>
</table>

Table 7.4: Computational results for scenarios 50-85 - weekly sums

Figures 7.1, 7.2 and 7.3 present the graphical comparison of scenarios 50-85 concerning, respectively, total routes and orders in orderbank, total driving and waiting time and total distance. We have decided to examine both weekly sums (scenarios 50-55, 56-71, 62-67, 68-73, 74-79, 80-85) and a single planning day for each uniform time window duration (Mondays - scenarios 50, 56, 62, 68, 74, 80). In each of the following figures, the basic scenario is emphasized with a lighter colour.

For example, Figure 7.1a shows the comparison of the total routes weekly sums presented earlier in Table 7.4 while Figure 7.1b focuses on the same results for Mondays only:

![Figure 7.1: Comparison of scenarios 50-85 - Number of routes and unfulfilled orders](image)

The basic scenario is denoted with a light green column. In both charts it can be noticed that both the number of routes and the number of unfulfilled orders...
7.1 Time windows of uniform duration for all customers

increase considerably as the time windows width decreases. On the other hand, the same figures saw an improvement when we assigned one time window for the entire day (13-hour). Figure 7.1a shows that, with regard to the basic scenario, the number of routes decreases by 18.8% when assigning an open time window while it increases up to 57% when tightening the time windows duration down to 0.5-hour. Likewise, the number of unfulfilled orders increases noteworthy when diminishing the time windows width. On a weekly basis we get 0.6% of unfulfilled orders when passing to a 2-hour time window and, respectivley, 3.4% with 1-hour and 6.1% with 0.5-hour.

Similarly, Figure 7.2a shows the comparison of the total time - weekly sums presented in Table 7.4 while Figure 7.1b focuses on the same results for Mondays only:

Likewise, the basic scenario is denoted with a light red column. It can be noticed that the total time increases notably as the time windows width decreases. As an example, Figure 7.2a concerns the weekly sums and ut shows that the total time increases by 40.4% when passing from a 4-hour to a 0.5-hour time window duration. On the other hand, the same KPI saw an improvement by -14.1% when we selected 13-hour time slots.
In addition, Figure 7.3a shows the comparison of the total distance weekly sums presented in Table 7.4 while Figure 7.3b focuses on the same results for Mondays only:

(a) Weekly totals
(b) Mondays

Figure 7.3: Comparison of scenarios 50-85 - Total distance

It can be noticed that the trend followed by the total distance driven is very similar to the one followed by the total time: with regard to the basic scenario it increases by 73.4% when selecting a 0.5-hour time window while it decreases by 30.4% when assigning open time windows.

In Figure 7.4 we present a graphical summary of the comparison of the uniform duration time window scenarios (weekly sums presented in Table 7.4). The results obtained for scenarios 50-55 are again used as benchmark:

In Figure 7.1 we pointed out that the number of unfulfilled orders rapidly increases when tightening the time windows width down to 2, 1 and 0.5-hour. Correspondingly, Figure 7.4 shows that the total time at customer also decreases.

Figure 7.4 shows also the very interesting trend followed by the total time spent on waiting by the vehicles in the system. This is the only KPI that is plotted on the secondary axis (on the right). When describing the VRPTW in chapter 2 we stated that in the hard time windows case each customer has time window \([a_i, b_i]\) and the vehicle is allowed to arrive before \(a_i\) but it can not start serving it until the time window opens. On the other hand, arrivals after \(b_i\) are prohibited. Therefore, if deliveries are made to all the customers within their availability time window, and the time for the subsequent delivery has not started, the vehicle will have to sit idle until it is time for the next time window.

Consequently, the idle time is appreciably decreased by 91.6% as the time windows duration increases (scenarios 56-61, 13-hour). The wider time slots allow the
7.1 Time windows of uniform duration for all customers

Figure 7.4: Comparison of scenarios 50-85 - weekly sums

Table 7.5 presents the actual figures for driving and waiting times for scenarios 50-85. Again, it can be noticed that the total time waiting increases much faster than the total time driving (as presented in Figure 7.4). Additionally, looking at these results we can see that in the 13-hour time window scenario the total waiting time is not avoided. This is due to the fact that, in the L’EASY case, vehicles must leave the depot at the beginning of their availability time window (either 7.30 or 12.30). Therefore, if the time for the first delivery has not started yet they can not sit idle at the depot. Instead they will have to leave the depot at the beginning of their availability time window and then wait at the customer’s site. Thus the company will have to pay the drivers for the time spent waiting.
<table>
<thead>
<tr>
<th>Time windows width [hours]</th>
<th>Scenario</th>
<th>Total Time Driving</th>
<th>Total Time Waiting</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>50-61</td>
<td>443:54:00</td>
<td>0:40:00</td>
</tr>
<tr>
<td>4</td>
<td>50-55</td>
<td>604:32:00</td>
<td>7:58:00</td>
</tr>
<tr>
<td>3</td>
<td>62-67</td>
<td>669:55:00</td>
<td>14:43:00</td>
</tr>
<tr>
<td>2</td>
<td>68-73</td>
<td>750:22:00</td>
<td>36:07:00</td>
</tr>
<tr>
<td>1</td>
<td>74-79</td>
<td>846:43:00</td>
<td>104:20:00</td>
</tr>
<tr>
<td>0.5</td>
<td>80-85</td>
<td>926:33:00</td>
<td>216:56:00</td>
</tr>
</tbody>
</table>

**Table 7.5:** Driving and waiting times for scenarios 50-85 - weekly sums

In Figure 7.5 we compare the uniform duration time window scenarios on the base of the distribution efficiency KPIs introduced in section 6.1. The time per order is here plotted on the secondary axis.

**Figure 7.5:** Comparison of scenarios 50-85 - distribution efficiency KPIs

It can be noticed that all indicators get worse when adopting tighter time windows. In particular, the number of stops per hour and density of stops on each route decrease while the average mileage and time per order see an increase.
7.1 Time windows of uniform duration for all customers

Table 7.6 presents the relative comparison of the uniform time windows duration scenarios with regard to the basic scenario:

<table>
<thead>
<tr>
<th>Time windows width [hours]</th>
<th>13</th>
<th>3</th>
<th>2</th>
<th>1</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orders/Hour</td>
<td>16.4%</td>
<td>-5.7%</td>
<td>-12.8%</td>
<td>-23.3%</td>
<td>-33.2%</td>
</tr>
<tr>
<td>Km/Order</td>
<td>-30.4%</td>
<td>14.5%</td>
<td>30.2%</td>
<td>60.0%</td>
<td>84.8%</td>
</tr>
<tr>
<td>Time/Order</td>
<td>-14.1%</td>
<td>6.1%</td>
<td>14.6%</td>
<td>30.4%</td>
<td>49.6%</td>
</tr>
<tr>
<td>Orders/Route</td>
<td>23.1%</td>
<td>-5.1%</td>
<td>-17.7%</td>
<td>-30.5%</td>
<td>-40.2%</td>
</tr>
</tbody>
</table>

Table 7.6: Comparison of distribution efficiency KPIs with respect to the basic scenario

Again, these results show that wider time slots allow the trucks greater flexibility in optimizing the sequence of deliveries and improve routing efficiency. In fact, we can see that when assigning open time windows the average time per order sees a decrease of and -14.1% while the density of stops on each route increases by 23.1%. On the other hand, when tightening the time slots durations down to 0.5-hour the density of stops on each route decreases respectively 40.2% while the average time per order increases by 49.6%. From an operational point of view this means that tight time windows mean lower time and vehicle utilization rates.

Figure 7.6 shows the cost comparison of scenarios 50-85 based on the assumptions described in section 6.2. For each time window width we present both the total cost (in DKK per week) and the average cost per order (in DKK):

![Cost comparison](image)

**Figure 7.6:** Cost comparison of scenarios 50-85

Being that the total cost depends on total time and total distance, we can see that it increases when tightening time windows durations; at the same time the
number of fulfilled orders decreases. Therefore, also the average cost per order sees a notable increase. Actually, when passing from the basic scenario to a 0.5-hour time window for all customers serving each order becomes 175 DKK more expensive. On the other hand, assigning open time windows to all requests means an average saving of 53 DKK.

Finally, if the company was considering offering a tighter time window to all customers, then the 2-hour time slot seems to be a good compromise. It represents an appealing tight time window that requires 31 extra routes per week and entails an increase in the average cost per order by 54 DKK.

However, in the next two section we will research the effect of tightening time windows durations for a lower share of customers. This is because, from a practical point of view, we assume the share of customers willing to pay an extra fee for a tighter time window to be between 10 and 40%.

Before that, in the next subsection we examine the effect on the number of unfulfilled orders of increasing number of vehicles and/or extending vehicles availability.

### 7.1.1 Unplanned orders

The quantitative research that we have presented so far is in collusion with the theory and the results from the literature review. However, there is an issue concerning the fact that we got some unplanned orders when tightening time windows. In the worse case (scenarios 80-85, 0.5-hour) we got up to 69 out of 1123 unplanned orders.

When looking at the routes we could see that, again, some requests are impossible to fulfill because of their time window, service time and geographical location. In particular, we observed that increasing the number of vehicles and/or extending the vehicles availability of 1.5 hours on each side may help. Therefore we defined the following new L'EASY truck types:

<table>
<thead>
<tr>
<th>Vehicle type</th>
<th>Shift start</th>
<th>Shift end</th>
</tr>
</thead>
<tbody>
<tr>
<td>L'EASY Early Shift Truck</td>
<td>06:00</td>
<td>16:30</td>
</tr>
<tr>
<td>L'EASY Late Shift Truck</td>
<td>12:30</td>
<td>23:00</td>
</tr>
</tbody>
</table>

**Table 7.7:** New L'EASY trucks types

After that we defined 15 new scenarios where we introduced more capacity on the vehicles side either in terms of longer time windows or higher number of trucks:

- **scenarios 80a-85a:** 15 vehicles for each original type (see Table 5.2) at each of the 3 depots (for a total of 90 available vehicles);
- **scenarios 80b-85b:** 10 vehicles for each new type (see Table 7.7) at each of the 3 depots (for a total of 60 available vehicles);
- **scenarios 80c-85c:** 15 vehicles for each new type (see Table 7.7) at each of the 3 depots (for a total of 90 available vehicles).
The aim was to investigate whether or not Transvision Route Planner could assign all orders to a route. Table 7.8 presents the computational results:

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-85</td>
<td>234</td>
<td>69</td>
<td>64.025</td>
<td>1671:02:00</td>
<td>1143:29:00</td>
<td>527:29:00</td>
</tr>
<tr>
<td>80a-85a</td>
<td>235</td>
<td>69</td>
<td>63.862</td>
<td>1674:52:00</td>
<td>1147:20:00</td>
<td>527:29:00</td>
</tr>
<tr>
<td>80b-85b</td>
<td>242</td>
<td>7</td>
<td>71.414</td>
<td>1823:23:00</td>
<td>1255:01:00</td>
<td>568:17:00</td>
</tr>
<tr>
<td>80c-85c</td>
<td>243</td>
<td>7</td>
<td>69.686</td>
<td>1820:32:00</td>
<td>1252:12:00</td>
<td>568:17:00</td>
</tr>
</tbody>
</table>

Table 7.8: Unplanned orders. Increase in the number of vehicles and/or availability time windows - computational results

Table 7.9 shows that introducing longer availability time windows for the vehicles (scenarios b) results in a very good improvement on the service level - with only 7 unserved orders. On the other hand, when increasing the number of vehicles of the original type (scenarios a) both the number of routes and the total time see an increase. This can be explained by the fact that Transvision Route Planner makes use of a heuristic solution method.

<table>
<thead>
<tr>
<th>Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving &amp; Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>80a-85a</td>
<td>0.4%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>0.2%</td>
<td>0.3%</td>
</tr>
<tr>
<td>80b-85b</td>
<td>3.4%</td>
<td>-89.9%</td>
<td>11.5%</td>
<td>9.1%</td>
<td>9.8%</td>
</tr>
<tr>
<td>80c-85c</td>
<td>3.8%</td>
<td>-89.9%</td>
<td>8.8%</td>
<td>8.9%</td>
<td>9.5%</td>
</tr>
</tbody>
</table>

Table 7.9: Unplanned orders. Increase in the number of vehicles and/or availability time windows - comparison of different solutions

Therefore, we conclude that introducing more capacity by increasing the number of vehicles does not help the problem of unserved orders. On the other hand, enlarging their availability time windows helps even though it does not solve the problem. This is due to the fact that some customers are impossible to reach because of their tight time windows, handling times and distances from the closest depot. In order to fulfill all customer requests even larger availability time windows are required.
7.2 Mixed time windows for different durations and different shares of customers

In this section we examine the following research question: what is the effect on the routing cost (in terms of total time and number of routes) of assigning different tight time windows to different shares of customers randomly selected?

Again, the idea behind this kind of analysis is that some customers would prefer a smaller time window. Actually, some customers who place a higher value on their time may be willing to pay more for a tighter time window. And on the other hand L’EASY may realize a lower delivery cost from customers that pick the larger time slots (4-hour).

Again, when increasing the level of service for different shares of gold customers, we expect a rapid increase in number of routes, total time and cost.

In this case we decided to investigate 4 tight time windows durations (3-hour, 2-hour, 1-hour and 0,5-hour) and 4 different shares of customers (10%, 20%, 30% and 40%).

As in the previous section, the original dataset - collection of L’EASY’s customer orders due in week 14, each of them randomly assigned a M/A/E time window - was used both as benchmark and as starting point for the creation of instances. In this way, the quality of the 6 daily delivery plans (scenarios 50-55) is not affected by the suggestion of time slots done while the customer was on the phone.

Thereafter, we created 96 new scenarios (86-181) one for each day of week 14, tight time window and share of gold customers combination.

We created these scenarios on the base of scenarios 50-55 where all customers have a 4-hour time slot and the time windows assignment is according to the preferences shown in Figure 5.3. When creating a new scenario we randomly selected the gold customers and then assigned the new time slots. When reassigning time windows the customer requests were split evenly among the new time slots.

For example, we created the scenario where 10% of customer requests due on Saturday - week 14 were assigned a 0,5-hour wide time window as follows. First of all, we randomly selected 10% of customer orders due on Saturday - week 14 (Table 7.10):
7.2 Mixed time windows for different durations and different shares of customers

<table>
<thead>
<tr>
<th>OrderID</th>
<th>X</th>
<th>Y</th>
<th>StartTW</th>
<th>EndTW</th>
<th>Day</th>
<th>Duration</th>
<th>Week</th>
<th>ZipCode</th>
</tr>
</thead>
<tbody>
<tr>
<td>38725</td>
<td>631454</td>
<td>6173731</td>
<td>08:00</td>
<td>11:59</td>
<td>Sat</td>
<td>600</td>
<td>14</td>
<td>4400</td>
</tr>
<tr>
<td>37587</td>
<td>720478</td>
<td>6175346</td>
<td>08:00</td>
<td>11:59</td>
<td>Sat</td>
<td>1560</td>
<td>14</td>
<td>2000</td>
</tr>
<tr>
<td>39660</td>
<td>697517</td>
<td>6200843</td>
<td>08:00</td>
<td>11:59</td>
<td>Sat</td>
<td>600</td>
<td>14</td>
<td>3320</td>
</tr>
<tr>
<td>39314</td>
<td>535548</td>
<td>6151502</td>
<td>08:00</td>
<td>11:59</td>
<td>Sat</td>
<td>900</td>
<td>14</td>
<td>6000</td>
</tr>
<tr>
<td>38441</td>
<td>701322</td>
<td>6155060</td>
<td>08:00</td>
<td>11:59</td>
<td>Sat</td>
<td>2280</td>
<td>14</td>
<td>4600</td>
</tr>
<tr>
<td>38560</td>
<td>714719</td>
<td>6169628</td>
<td>12:00</td>
<td>15:59</td>
<td>Sat</td>
<td>1560</td>
<td>14</td>
<td>2660</td>
</tr>
<tr>
<td>37796</td>
<td>589125</td>
<td>6142650</td>
<td>12:00</td>
<td>15:59</td>
<td>Sat</td>
<td>1500</td>
<td>14</td>
<td>5000</td>
</tr>
<tr>
<td>34135</td>
<td>587737</td>
<td>6139841</td>
<td>12:00</td>
<td>15:59</td>
<td>Sat</td>
<td>2220</td>
<td>14</td>
<td>5000</td>
</tr>
<tr>
<td>37451</td>
<td>550791</td>
<td>6084506</td>
<td>12:00</td>
<td>15:59</td>
<td>Sat</td>
<td>720</td>
<td>14</td>
<td>6400</td>
</tr>
<tr>
<td>38460</td>
<td>604272</td>
<td>6151866</td>
<td>12:00</td>
<td>15:59</td>
<td>Sat</td>
<td>1500</td>
<td>14</td>
<td>5370</td>
</tr>
<tr>
<td>36922</td>
<td>596778</td>
<td>6252876</td>
<td>16:00</td>
<td>20:59</td>
<td>Sat</td>
<td>1920</td>
<td>14</td>
<td>8581</td>
</tr>
</tbody>
</table>

Table 7.10: Random selection of 10% of the customer orders due on Saturday - week 14. Original time window assignment

We then modified the time windows assignment for these orders randomly assigning a 0.5-hour time slot. When doing this we made sure that customers originally assigned to a morning time window (8-12) will still be assigned a morning 0.5-hour wide time window. The same for afternoon (12-16) and evening (16-21) reassignments. Table 7.11 presents the new time windows assignment:

<table>
<thead>
<tr>
<th>OrderID</th>
<th>X</th>
<th>Y</th>
<th>StartTW</th>
<th>EndTW</th>
<th>Day</th>
<th>Duration</th>
<th>Week</th>
<th>ZipCode</th>
</tr>
</thead>
<tbody>
<tr>
<td>38725</td>
<td>631454</td>
<td>6173731</td>
<td>08:00</td>
<td>08:29</td>
<td>Sat</td>
<td>600</td>
<td>14</td>
<td>4400</td>
</tr>
<tr>
<td>37587</td>
<td>720478</td>
<td>6175346</td>
<td>09:00</td>
<td>09:29</td>
<td>Sat</td>
<td>1560</td>
<td>14</td>
<td>2000</td>
</tr>
<tr>
<td>39660</td>
<td>697517</td>
<td>6200843</td>
<td>09:30</td>
<td>09:59</td>
<td>Sat</td>
<td>600</td>
<td>14</td>
<td>3320</td>
</tr>
<tr>
<td>39314</td>
<td>535548</td>
<td>6151502</td>
<td>10:00</td>
<td>10:29</td>
<td>Sat</td>
<td>900</td>
<td>14</td>
<td>6000</td>
</tr>
<tr>
<td>38441</td>
<td>701322</td>
<td>6155060</td>
<td>11:30</td>
<td>11:59</td>
<td>Sat</td>
<td>2280</td>
<td>14</td>
<td>4600</td>
</tr>
<tr>
<td>38560</td>
<td>714719</td>
<td>6169628</td>
<td>12:30</td>
<td>12:59</td>
<td>Sat</td>
<td>1560</td>
<td>14</td>
<td>2660</td>
</tr>
<tr>
<td>37796</td>
<td>589125</td>
<td>6142650</td>
<td>13:00</td>
<td>13:29</td>
<td>Sat</td>
<td>1500</td>
<td>14</td>
<td>5000</td>
</tr>
<tr>
<td>34135</td>
<td>587737</td>
<td>6139841</td>
<td>13:30</td>
<td>13:59</td>
<td>Sat</td>
<td>2220</td>
<td>14</td>
<td>5000</td>
</tr>
<tr>
<td>37451</td>
<td>550791</td>
<td>6084506</td>
<td>14:00</td>
<td>14:29</td>
<td>Sat</td>
<td>720</td>
<td>14</td>
<td>6400</td>
</tr>
<tr>
<td>38460</td>
<td>604272</td>
<td>6151866</td>
<td>14:30</td>
<td>14:59</td>
<td>Sat</td>
<td>1500</td>
<td>14</td>
<td>5370</td>
</tr>
<tr>
<td>36922</td>
<td>596778</td>
<td>6252876</td>
<td>17:00</td>
<td>17:29</td>
<td>Sat</td>
<td>1920</td>
<td>14</td>
<td>8581</td>
</tr>
</tbody>
</table>

Table 7.11: Random selection of 10% of the customer orders due on Saturday - week 14. New time window assignment

After designing all the 96 instances (6 planning days, 4 tight time windows and 4 different shares of gold customers) we imported them in Transvision Route Planner and ran the simulations with the same setup described in section 6.3. As an example, Table 7.12 shows the complete outcome (for each day and the weekly sum) for the scenarios where we assigned a 3-hour time window to a random selection of 10% of the customer orders due in week 14:
Table 7.12: Assignment of 3-hour time windows to 10% of the customer orders due in week 14. Daily plans and weekly sum - Computational results

Tables 7.13 and 7.14 present the aggregated computational results for the gold customers scenarios in terms of weekly sums. In Table 7.13 we first report total time driving, total time waiting and total time at customer:

Table 7.13: Computational results for the gold customers scenarios. Time driving, waiting, at customer and total time - weekly sums

As benchmark results for our analysis we used what we earlier called the basic scenario (scenarios 50-55 - L’EASY’s actual practice). Moreover in this section we also used the computational results that we got when we assigned time windows of uniform duration to all customers - 3-hour (scenarios 62-67), 2-hour (scenarios 68-
7.2 Mixed time windows for different durations and different shares of customers

<table>
<thead>
<tr>
<th>Time window width [hours]</th>
<th>Share of gold customers</th>
<th>KPI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10%</td>
<td>20%</td>
</tr>
<tr>
<td></td>
<td>Tot. Routes</td>
<td>Tot. Orders In Orderbank</td>
</tr>
<tr>
<td>3</td>
<td>151</td>
<td>152</td>
</tr>
<tr>
<td></td>
<td>37.528</td>
<td>37.963</td>
</tr>
<tr>
<td></td>
<td>Tot. Routes</td>
<td>Tot. Orders In Orderbank</td>
</tr>
<tr>
<td>2</td>
<td>151</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>37.376</td>
<td>38.002</td>
</tr>
<tr>
<td></td>
<td>Tot. Routes</td>
<td>Tot. Orders In Orderbank</td>
</tr>
<tr>
<td>1</td>
<td>153</td>
<td>155</td>
</tr>
<tr>
<td></td>
<td>38.475</td>
<td>40.550</td>
</tr>
<tr>
<td></td>
<td>Tot. Routes</td>
<td>Tot. Orders In Orderbank</td>
</tr>
<tr>
<td>0.5</td>
<td>156</td>
<td>158</td>
</tr>
<tr>
<td></td>
<td>39.438</td>
<td>40.420</td>
</tr>
</tbody>
</table>

Table 7.14: Computational results for the gold customers scenarios. Number of routes, unfulfilled orders and total distance - weekly sums

73), 1-hour (scenarios 74-79) and 0.5-hour (scenario 80-85). These last cases can be seen as scenarios where we assigned a tight time window to a share of customer corresponding to 100%. Table 7.15 summarizes the computational results earlier presented in Tables 7.4 and 7.5 for the basic scenario (first row in Table 7.15) and the other 100% benchmark scenarios.

<table>
<thead>
<tr>
<th>Time windows width [hours]</th>
<th>Scenario Total Routes</th>
<th>Total Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time Driving</th>
<th>Total Time Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>50-55</td>
<td>149</td>
<td>0</td>
<td>36.914</td>
<td>604:32:00</td>
<td>7:58:00</td>
</tr>
<tr>
<td>3</td>
<td>62-67</td>
<td>157</td>
<td>0</td>
<td>42.255</td>
<td>669:55:00</td>
<td>14:43:00</td>
</tr>
<tr>
<td>2</td>
<td>68-73</td>
<td>180</td>
<td>7</td>
<td>47.780</td>
<td>750:22:00</td>
<td>36:07:00</td>
</tr>
<tr>
<td>1</td>
<td>74-79</td>
<td>207</td>
<td>38</td>
<td>57.080</td>
<td>846:43:00</td>
<td>104:20:00</td>
</tr>
<tr>
<td>0.5</td>
<td>80-85</td>
<td>234</td>
<td>69</td>
<td>64.025</td>
<td>926:33:00</td>
<td>216:56:00</td>
</tr>
</tbody>
</table>

Table 7.15: Benchmark scenarios - Basic and 100% ones

In order to analyze the results that we obtained for the new scenarios we first present a graphical comparison (Figures 7.7, 7.8, 7.9, 7.10 and 7.11). Each of these figures shows the results we got for the benchmark scenarios together with the ones for the gold customers cases. For each tight time window width (horizontal axis) we present the computational results for the 4 different shares of gold customers. The last bar in each group represents the 100% scenarios while the red line represents the value for the basic scenario. Later in sections 7.2.1 and 7.2.2 we will present a percentagewise comparison of the results focusing on number of routes and total time.

The following figures concern, respectively, number of routes (Figure 7.7), total driving time (Figure 7.8), total waiting time (Figures 7.9) and total distance (Figure 7.10):
**Figure 7.7**: Gold customers scenarios. Comparison of total routes with regard to the benchmarks

**Figure 7.8**: Gold customers scenarios. Comparison of total driving time with regard to the benchmarks
7.2 Mixed time windows for different durations and different shares of customers

Figure 7.9: Gold customers scenarios. Comparison of total waiting time with regard to the benchmarks

Figure 7.10: Gold customers scenarios. Comparison of total distance with regard to the benchmarks
Generally speaking, for all the KPIs presented it can be noticed that the tighter the time window the larger the gap with respect to the basic scenario. Likewise, it can be seen that for the scenarios where we assigned 0.5-hour wide time windows to different shares of customers the worsening when increasing the percentage of randomly selected \textit{gold} customers is much more severe than for the cases where we assigned larger time windows (e.g. 3-hour).

For example, looking at Figure 7.8 we can see that having 100% of customers assigned 3-hour time slot entails an increase of 9.3% in the total driving time with regard to the case where we had only 10% of \textit{gold} 3-hour customers. On the other hand, having 100% of customers assigned 0.5-hour time slot requires a total driving time 47.9% higher than in the case where we had a mere 10% of \textit{gold} 0.5-hour customers.

Likewise, when comparing the total distance (Figure 7.10) it can be noticed that having 100% of customers assigned 3-hour time slot requires a total distance traveled 12.6% higher than in the case where we had 10% of \textit{gold} 3-hour customers. On the other hand, having 100% of customers assigned 0.5-hour time slot entails a worsening in the total distance traveled by 62.3% with regard to the case where we had 10% of \textit{gold} 0.5-hour customers.

Finally, Figure 7.11 concerns the number of unfulfilled orders:

![Number of unfulfilled orders](image)

**Figure 7.11:** \textit{Gold} customers scenarios. Comparison of total number of unfulfilled orders with regard to the benchmarks.
This figure shows once more that the number of unserved customers rapidly increases when tightening time windows durations. Again, we can see that the tighter the time window the larger the gap with respect to the basic scenario. Moreover, we can notice that the higher the percentage of gold customers and the steeper the curves are. Meaning that, assigning 1-hour time window to 10, 20 or 30% of the customer orders does not make that big difference while when the share of gold customers increases (40 and 100%) the number of unserved orders increases swiftly.

As a general comment to Figures 7.7, 7.8, 7.9, 7.10 and 7.11 we can see that the optimization engine is based on heuristic solution methods and that the scenarios that we are attempting to compare constitute completely different problem instances. This is the reason why for some of the scenarios we can see that increasing the share of gold customers actually entails a better routing performance. An example can be seen in Figure 7.7 where we obtain a better result when assigning a 2-hour time window to 20% of the customers (150 routes) than when the share was 10% (151 routes). Similarly, in Figure 7.8 we obtain a better result when assigning a 3-hour time window to 30% of the customers (615:05:00) than when the share was 20% (615:10:00). Therefore, in the next subsection we will concentrate on KPIs relevant for our case study such as number of routes and total waiting time focusing and on the overall trends rather than on the single scenario figures.

Finally, we can see that the gaps between the 40% gold customer scenarios and the 100% ones are quite impressive, especially for the tighter time windows. From an academic point of view, it would have been interesting to see what the effect of having higher shares (60 and 80%) of gold customers would be. However, from a practical point of view, we assume the portion of customers willing to pay an extra fee for a tighter time window to be lower, between 10 and 40%.

### 7.2.1 Comparison with the basic scenario

In this section we present the comparison of the results obtained for the scenarios we designed using mixed time windows for different durations and different shares of customers with the basic scenario.

First of all, Figure 7.12 concerns the number of routes. In the data table column headers represent the different tight time window durations (TW) while row headers identify the different shares of gold customers. The entries in the data table represent a percentagewise comparison of the results. Each entry is calculated as follows:

\[
Entry_{TW,share} = \frac{Routes_{TW,share} - Routes_{Basic}}{Routes_{Basic}}
\]

where \( Routes_{Basic} = 149 \) (Table 7.15) and

\( Routes_{TW,share} \) are the results presented in Figure 7.7.

It can be noticed that the curves have different trends: the 30 and 40% share of randomly selected gold customers ones see a much more rapid increase than the...
Figure 7.12: Gold customers and basic scenarios. Comparison of number of routes lower shares ones. This means, for example, that when assigning a tight time window to 10 or 20% of the customer orders the corresponding curves increase quite slowly. On the other hand, when the share of gold customers increases to 30 and 40% the number of routes with regard to the basic scenario increases rapidly.

Likewise, except for the 0.5-hour time window width, we can see that assigning a tight time slot to either 10 or 20% of the customers does not make that big difference (the percentagewise comparisons with regard to the basic scenario are quite close). While, for the scenarios where we assigned a tight time slot to either 30 or 40% of the customers the corresponding figures are more distant.

Finally, for the scenarios where we assigned a tight time slot to 10% of the requests, the number of routes compared to the basic scenario is lower where we used 0.5-hour time windows (153) than when we used the 1-hour ones (154). We can see the same situation when looking at the 20% tight time slot cases: the number of routes compared to the basic scenario is lower where we used 2-hour time windows (150) than when we used the 3-hour ones (152). Again, this is due to the fact that we are using an optimization engine based on heuristic solution methods and that the scenarios constitute completely different problem instances.

Figure 7.13 concerns the total time spent by the vehicles. As earlier, in the data table column headers represent the different tight time window durations (TW) while row headers identify the different shares of gold customers. The entries in the data table represent a percentagewise comparison of the results. Each entry is
7.2 Mixed time windows for different durations and different shares of customers

Calculated as follows:

\[
Entry_{TW, share} = \frac{TotalTime_{TW, share} - TotalTime_{Basic}}{TotalTime_{Basic}}
\]

where \(TotalTime_{Basic} = 1189 : 56 : 00\) (Table 7.15) and \(TotalTime_{TW, share}\) are the results presented in Figure 7.9.

![Total time graph](image)

**Figure 7.13:** Gold customers and basic scenarios. Comparison of total time

Generally speaking, the figure shows again that the total time increases when tightening time windows durations with regard to the basic scenario. As for the number of routes, we can see that the curves have different trends and the ones representing higher shares of gold customers see a much more rapid increase than the lower shares ones.

Again, due to the heuristic solution methods and scenarios that constitute completely different problem instances, we get some odd results. That is the case for the scenario where we assigned 2-hour time slots to 20% of the requests. In fact, for the scenario where we assigned 2-hour time slots to 20% of the requests we get a lower total time (1195:10:00) than for both the scenario where we assigned the same time window width to 10% of customers (1999:35:00) and the scenario where we assigned 3-hour time slots to the 20% of the requests (1201:32:00).
7.2.2 Comparison with the 100% scenarios

In this section we present the comparison of the results obtained for the scenarios we designed using mixed time windows for different durations and different shares of customers with the 100% scenario for each time window duration.

First of all, Figure 7.14 concerns the number of routes. The entries in the data table represent a percentagewise comparison of the results. Each entry is calculated as follows:

\[ \text{Entry}_{TW,\text{share}} = \frac{\text{Routes}_{TW,100\%} - \text{Routes}_{TW,\text{share}}}{\text{Routes}_{TW,\text{share}}} \]

where Routes\(_{TW,100\%}\) are the computational results presented in Table 7.15.

![Number of routes](image)

**Figure 7.14:** Gold customers and 100% scenarios. Comparison of number of routes

We can see that, for each tight time window width, having a lower share of randomly selected gold customers always entails a more efficient scheduling with regard to the 100% case. Moreover, the curves follow approximately the same quite smooth trend and the tighter the time slot the bigger the relative difference compared to the corresponding 100% scenarios. This means that assigning to all customers a 0,5-hour time slot involves an increase in the number of routes by 52.9% compared to the scenario where we assigned such a tight time window
7.2 Mixed time windows for different durations and different shares of customers

to only 10% of the requests. On the other hand, assigning to all customers a 3-hour time slot involves an increase in the number of routes by 4% compared to the scenario where we assigned such a tight time window to a mere 10% of the requests.

Figure 7.15 concerns the total time. Each entry in the data table is calculated as follows:

\[
Entry_{TW,\text{share}} = \frac{\text{TotalTime}_{TW,100\%} - \text{TotalTime}_{TW,\text{share}}}{\text{TotalTime}_{TW,\text{share}}}
\]

where \(\text{TotalTime}_{TW,100\%}\) are the computational results presented in Table 7.15.

Figure 7.15: Gold customers and 100% scenarios. Comparison of total time

We can see that the total time sees a considerable increase when tightening time windows durations for all customers with regard to the case where we randomly do it for a lower share of requests. Again, the curves follow approximately a quite smooth trend and the tighter the time slot the bigger the relative difference compared to the corresponding 100% scenario. Additionally, the tighter the time slot the bigger the relative difference compared to the corresponding 100% scenario. This means that assigning to all customers a 0.5-hour time slot involves an increase in the total time by 37.6% compared to the scenario where we assigned such a tight time window to a mere 10% of the requests. On the other hand, assigning to all customers a 3-hour time slot involves an increase in the total time by 5.2%
compared to the scenario where we assigned such a tight time window to 10% of the requests.

Figures 7.16 and 7.17 show the cost comparison of Gold customer and benchmark scenarios based on the assumptions described in section 6.2. For each time window width and share of gold customers we present both the total cost (in DKK per week) and the average cost per order (in DKK):

![Cost comparison graph]

Figure 7.16: Gold customers and benchmark scenarios. Cost comparison - Total cost

Again, given that the total cost depends on total time and total distance, we can see that for each tight time window duration it increases when increasing the share of gold customers. It can be noticed that the tighter the time window and the larger the difference with regard to the basic scenario. This means that the impact on the routing costs is much more severe when we assign 0.5-hour time windows compared to 3-hour time slots.

Finally, if the company was considering offering a tight time window to a specific share of customers we could recommend different alternatives. For example,
assigning 2-hour wide time slots to 40% of randomly selected requests represents an appealing *tight* time window that requires 10 extra routes per week and entails an increase in the average cost per order by 18 DKK. At the same time, offering a 0.5-hour time window to 20% of randomly selected customers requires 9 extra routes per week and entails an increase in the average cost per order by 19 DKK. Recalling the conclusions from the previous section (7.1) we can also notice that offering a 0.5-hour time window to 40% of randomly selected customers is, on average, cheaper than assigning 2-hour time slots to all customers (20 versus 31 extra routes per week and 48 versus 54 DKK per order).
7.3 Geographic areas

In this section we investigate the effect on the routing cost (in terms of total time and number of routes) of assigning narrow time windows to those customers living in the biggest Danish cities.

In Figure 5.2 we showed that the Storkøbenhavn (Greater Copenhagen), Odense, Århus and Ålborg areas are the denser ones in terms of customer orders. In this section of our simulation project we are interested in analyzing what the effect of assigning tight time windows to the customer requests located in those areas would be from an operational point of view.

In this case, we know that improving the level of service by means of tighter time windows entails a worsening from a routing cost perspective. However, we are interested in comparing the effect of narrowing time windows for a selected portion of customers with the results we presented in sections 7.1 and 7.2.

Table 7.16 presents the actual number of L’EASY’s customer requests due in week 14 located in each major Danish city. It shows that, on a total number of 1123 customer requests due in week 14, 42.7% were located in a major Danish city:

<table>
<thead>
<tr>
<th>City</th>
<th>Number of customer orders</th>
<th>Share of the total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ålborg</td>
<td>36</td>
<td>3.2%</td>
</tr>
<tr>
<td>Århus</td>
<td>51</td>
<td>4.5%</td>
</tr>
<tr>
<td>Odense</td>
<td>82</td>
<td>7.3%</td>
</tr>
<tr>
<td>Storkøbenhavn</td>
<td>310</td>
<td>27.6%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>479</strong></td>
<td><strong>42.7%</strong></td>
</tr>
</tbody>
</table>

Table 7.16: Number of requests located in the major Danish cities. L’EASY customer orders, week 14 (1123 orders)

We designed the new scenarios by assigning the same tight time window to all customer requests located in on of the aforementioned Danish cities. We used 2, 1 or 0.5-hour time slot durations and will later call these the cities scenarios.

As benchmark results for our analysis we used what we earlier called the basic scenario (L’EASY’s actual practice) and the computational results from the scenarios where we assigned time windows of uniform duration (2, 1 or 0.5-hour) to all customers - the so-called 100% scenarios. Moreover, we compared the new scenarios with the ones where we assigned a tight time window (2, 1 or 0.5-hour) to 40% of the customer requests - the so-called gold customers scenarios.
Table 7.17 presents the complete outcome obtained for cities and benchmark scenarios:

<table>
<thead>
<tr>
<th>Time windows width [hours]</th>
<th>Total Routes</th>
<th>Orders In Orderbank</th>
<th>Total Distance</th>
<th>Total Time</th>
<th>Total Time Driving</th>
<th>Total Time Waiting</th>
<th>Total Time At Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Basic scenario</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>149</td>
<td>0</td>
<td>36.914</td>
<td>1189:56:00</td>
<td>604:32:00</td>
<td>7:58:00</td>
<td>577:23:00</td>
</tr>
<tr>
<td>0.5</td>
<td>169</td>
<td>16</td>
<td>47.210</td>
<td>1318:24:00</td>
<td>725:23:00</td>
<td>29:10:00</td>
<td>563:49:00</td>
</tr>
<tr>
<td>1</td>
<td>165</td>
<td>10</td>
<td>44.113</td>
<td>1281:44:00</td>
<td>694:27:00</td>
<td>17:39:00</td>
<td>569:33:00</td>
</tr>
<tr>
<td>2</td>
<td>159</td>
<td>0</td>
<td>40.918</td>
<td>1245:35:00</td>
<td>654:12:00</td>
<td>13:57:00</td>
<td>577:23:00</td>
</tr>
<tr>
<td><strong>40% of gold customers scenarios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>234</td>
<td>69</td>
<td>64.025</td>
<td>1671:02:00</td>
<td>926:33:00</td>
<td>216:56:00</td>
<td>527:29:00</td>
</tr>
<tr>
<td>1</td>
<td>207</td>
<td>38</td>
<td>57.080</td>
<td>1499:32:00</td>
<td>846:43:00</td>
<td>104:20:00</td>
<td>548:25:00</td>
</tr>
<tr>
<td>2</td>
<td>180</td>
<td>7</td>
<td>47.780</td>
<td>1355:44:00</td>
<td>750:22:00</td>
<td>36:07:00</td>
<td>569:13:00</td>
</tr>
<tr>
<td><strong>100% scenarios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>163</td>
<td>4</td>
<td>44.061</td>
<td>1291:45:00</td>
<td>693:33:00</td>
<td>25:13:00</td>
<td>572:56:00</td>
</tr>
<tr>
<td>1</td>
<td>159</td>
<td>3</td>
<td>41.731</td>
<td>1256:26:00</td>
<td>669:03:00</td>
<td>12:23:00</td>
<td>574:57:00</td>
</tr>
<tr>
<td>2</td>
<td>153</td>
<td>0</td>
<td>39.695</td>
<td>1228:18:00</td>
<td>643:50:00</td>
<td>7:02:00</td>
<td>577:23:00</td>
</tr>
</tbody>
</table>

Table 7.17: Computational results for the benchmark and cities scenarios. Weekly sums

Likewise, Figures 7.18, 7.19 and 7.20 show the graphical comparison of the same results. In each chart, bars represent either the cities, the 40% of gold customers or the 100% scenarios for each tight time window and the red line represents the value for the basic scenario.

Figure 7.18 concerns the total number of routes while Figure 7.19 concerns the number of unserved customer requests and Figure 7.20 refers to the total time.

The comparison of the 3 cities scenarios with the basic one shows that tightening time window durations for those customers located in the main cities entails an overall worsening from an operational point of view. In fact, all the KPIs relevant for our analysis (number of routes, total time and number of unfulfilled orders) see an increase. In particular, the tighter the time window and the larger the effect. This is in line with the results presented in Sections 7.2 and 7.2.1 where we concluded that assigning a tight time window to a randomly selected 40% portion of the requests leads to an overall increase in the number of unserved customers, number of routes and total time. This is due to the fact that the problem instances become harder to solve in the way that customer time window constraints are more difficult to obey. Therefore the number of vehicles needed to fulfill the operational constraints increases together with the total time spent in the system.
Figure 7.18: *Cities* and benchmark scenarios. Comparison of number of routes.

Figure 7.19: *Cities* and benchmark scenarios. Comparison of number of unfulfilled orders.
On the other hand, we can see a good improvement in the number of routes, total time and number of unfulfilled orders when comparing the computational results obtained for the cities scenarios with the scenarios where we assigned the same tight time window to a randomly selected share of 40% of the customer orders. This is due to the fact that assigning a tight time window to those customers living in one of the main cities (42.7% of the total) results in dense clusters of gold customers. By this we mean that in the cities scenarios the "difficult" gold customers are located quite close to each other (at least within the same city area). Therefore the problem instance becomes easier to solve - with regard to the case where we randomly selected the gold customers - in the way that customer time window constraints become easier to fulfill because the gold requests are concentrated in specific areas.

Likewise, we can notice an even better improvement in the number of routes, total time and number of unfulfilled orders when comparing the computational results obtained for the cities scenarios with the scenarios where we assigned time windows of uniform duration (2, 1 or 0.5-hour) to all customers - the so-called 100% scenarios. This is due to the fact that in the cities scenarios the share of gold customers is lower and, again, to the fact that they are clustered around the major cities.

As a confirm, in Table 7.18 we compare the cities and all the benchmark scenarios on the base of distribution efficiency KPIs introduced in section 6.1.

Generally speaking, it can be noticed that all indicators get worse when adopting tighter time windows: the number of stops per hour and density of stops on each
<table>
<thead>
<tr>
<th>Time windows width</th>
<th>Orders/ Hour</th>
<th>Km/ Order</th>
<th>Time/ Order</th>
<th>Orders/ Route</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Basic scenario</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.94</td>
<td>32.9</td>
<td>1:03:35</td>
<td>7.5</td>
</tr>
<tr>
<td><strong>100% scenarios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>0.63</td>
<td>60.7</td>
<td>1:35:08</td>
<td>4.5</td>
</tr>
<tr>
<td>1</td>
<td>0.72</td>
<td>52.6</td>
<td>1:22:55</td>
<td>5.2</td>
</tr>
<tr>
<td>2</td>
<td>0.82</td>
<td>42.8</td>
<td>1:12:53</td>
<td>6.2</td>
</tr>
<tr>
<td><strong>40% of gold customers scenarios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>0.84</td>
<td>42.6</td>
<td>1:11:27</td>
<td>6.6</td>
</tr>
<tr>
<td>1</td>
<td>0.87</td>
<td>39.6</td>
<td>1:09:06</td>
<td>6.7</td>
</tr>
<tr>
<td>2</td>
<td>0.90</td>
<td>36.4</td>
<td>1:06:33</td>
<td>7.1</td>
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<tr>
<td><strong>Cities scenarios</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>0.5</td>
<td>0.87</td>
<td>39.4</td>
<td>1:09:16</td>
<td>6.9</td>
</tr>
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<td>1</td>
<td>0.89</td>
<td>37.3</td>
<td>1:07:19</td>
<td>7.0</td>
</tr>
<tr>
<td>2</td>
<td>0.91</td>
<td>35.3</td>
<td>1:05:38</td>
<td>7.3</td>
</tr>
</tbody>
</table>

Table 7.18: Cities and benchmark scenarios. Distribution efficiency KPIs

route decrease while the average mileage and time per order see an increase. We can also notice that the cities scenarios are preferable to the 40% gold customers ones. By providing better time slots to the customers living in the major cities we obtain more efficient distribution with regard to the 40% gold customer scenarios especially for the 0,5-hour time windows duration.

Therefore, when evaluating the opportunity of providing a higher level of service in terms of tighter time windows to a selected share of customers who place a higher value on their time and may be willing to pay more for a tighter time window, we conclude that the cities scenarios are the most efficient alternative from a routing point of view because cheapest in terms of number of routes and total time. Moreover, it is more realistic to assume that 40% of customers are willing to pay an extra price rather than all of them. Especially under the assumptions of a pricing policy based on higher prices for tighter time windows.
Finally, in Figure 7.21 we present the cost comparison of Cities and all benchmark scenarios based on the assumptions described in section 6.2. For each time window width we present both the total cost (Figure 7.21a, in DKK per week) and the average cost per order (Figure 7.21b, in DKK):

![Graph showing total cost and cost per order for different time window widths.](image)

**Figure 7.21:** Cities and benchmark scenarios. Cost comparison

By looking at the results presented in Figure 7.21b we can again see that, when considering the opportunity to provide a tight time window to a selected share of customers, the cities scenarios are preferable to the 40% gold customers ones. In fact, by providing better time slots to the customers living in the major cities we obtain more cost-efficient routing compared to the 40% gold customer scenario. This is true especially for the 0.5-hour time windows width.

In conclusion, we would like to remark that when offering the same time window width to all customers, urban requests are cheaper to serve because clustered and located in areas close to distribution centres. Therefore, in the basic and 100% scenarios the customers located in denser areas are "subsidizing" the rural ones with regard to the routing cost.

On the other hand, when comparing the assignment of different tight time windows to different shares of customers (40% gold customers and cities scenarios with the basic one - Figure 7.21a) we can assume the cost of serving those customers assigned a 4-hour time window to be as much as in the basic scenario (316 DKK/order). Instead, for each gold and urban gold request we can calculate the actual additional cost with regard to the basic scenario (Table 7.19):

These figures represent how much more expensive is to serve a gold (resp. urban gold) customer in each of the 40% gold (resp. cities) scenarios with regard to the basic scenario (316 DKK/order).
Time windows width

<table>
<thead>
<tr>
<th></th>
<th>0,5</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>100% scenarios</td>
<td>491</td>
<td>427</td>
<td>370</td>
</tr>
<tr>
<td>40% gold customers</td>
<td>423</td>
<td>392</td>
<td>360</td>
</tr>
<tr>
<td>Cities scenarios</td>
<td>392</td>
<td>366</td>
<td>345</td>
</tr>
<tr>
<td>Basic</td>
<td>316</td>
<td>316</td>
<td>316</td>
</tr>
</tbody>
</table>

Table 7.20: Cities and benchmark scenarios. Comparison of actual cost per order

These figures are calculated adding the actual cost differences presented in Table 7.19 to the basic cost per order (316 DKK/order).

In addition, Figure 7.22 shows the total cost figures (in DKK per week) earlier presented in Figure 7.21a. Figure 7.22a concerns the 40% gold customers scenarios while Figure 7.22b concerns the cities one.

In these figures we present the cost distribution among normal and gold customers (Figure 7.22a) and among rural and urban gold customers (Figure 7.22b).

At last, by comparing the new cost estimations from Table 7.19 and 7.20 we can again conclude that the cities scenarios are preferable to the 40% gold customers ones. Within the framework of our research the cities scenario represent the cheapest alternative when evaluating the opportunity of offering a better level...
7.3 Geographic areas

Figure 7.22: Cities and 40% gold customer scenarios. Cost distribution - rural and urban customers of service to a selected share of customers who place a higher value on their time and may be willing to pay more for a tighter time window.
Chapter 8

Conclusions

The home delivery market is a VRPTW application that has a long history in mature markets such as catalogue shopping and door-to-door selling. Moreover, the parcel distribution market has experienced a large growth over the last two decades. The development of new technologies such as Internet and e-commerce has created new opportunities, methods and product offers making the home shopping market attractive to millions of new users.

In this thesis we amply analyzed the home delivery market and concluded that moving goods over the last mile to the consumers’ home provides a great increase in customer service level but it also creates a huge logistic challenge for the suppliers. We described the existence of several trade-offs between often contrasting objectives and concluded that delivery systems need to be able to supply the right goods at the right time to suit the customers’ expectations while focusing on efficiency and cost effectiveness in order to guarantee profitability.

In order to reduce redelivery costs and increase customers’ service level, the scheduling of deliveries tends to be preferred over the promise to deliver “on Wednesday”. Therefore, retailer and customer mutually agree on a delivery time window that is how long the customer has to stay at home waiting for the delivery.

In general, the attended home delivery concept is a VRPTW application where time windows constraints are likely more critical than vehicle capacity restrictions are. This is because promised delivery time windows are often required to be as narrow as possible in order to meet customer’s expectations while in most cases the size of parcels is rather small compared to vehicles capacity (except in the case of large items). According to [2], in the UK over 50% of houses are empty in the time frame between 9 and 16. Therefore, the combination of stringent time constraints, uncertain demand and the pressure to control costs, create quite a challenge for the retailers.

Decisions about time windows policy are strategic for any company in the distribution business. Time slots length is one of the design decisions involved. Using the L’EASY real-life case study, we analyzed the trade-offs between delivery cost and customer service level by highlighting the significant cost impact of tight de-
livery time windows.

L’EASY’s goal is to minimize the number of vehicles and the total time spent in the system. Therefore we have chosen total time and minimization of the number of routes as optimization criterions throughout all the simulations and focused our analysis of the optimization outcome on KPIs such as total routes and total time. Moreover we compared different time windows scenarios on the base of distribution efficiency KPIs such as orders/hour, Km/order, orders/route and time/order.

We defined different delivery time windows scenarios for the L’EASY case and solved them using Transvision Route Planner, a commercial vehicle routing software. We addressed the following research questions: (1) How is the routing cost affected by the enlargement or shrinkage of time windows for all customers? (2) What is the effect on the routing cost of assigning different tight time windows to different shares of customers randomly selected? (3) What is the effect on the routing cost of assigning narrow time windows to those customers living in the biggest Danish cities?

We provided an extensive comparison of the scenarios based on both optimization criterions values and distribution efficiency KPIs. We also compared different time windows policies on the base of routing cost and cost per order using cost figures from the "Key Figure Catalogue - Usage within socio-economic analysis in the transport sector. Danish Ministry of Transport (2006)” [36] since we did not have the case specific ones. Tightening time windows always entails an overall worsening from an operational performance point of view. This is according to the VRPTW theory and literature and due to the fact that the problem instances become harder to solve in the way that customer time window constraints are more difficult to obey.

It is concluded that if the company was considering providing a higher level of service to its customers by offering a tighter time window to all requests, then the 2-hour time slot represents an appealing alternative. However, this scenario would entail a significant worsening in the operational performance with regard to L’EASY’s actual practice. The number of weekly routes would increase by 20.8% and the total time would rise by 13.9%. Thus meaning an increase in the average cost per order by 54 DKK.

From a practical point of view, we assume the share of customers willing to pay more for a tighter time window to be between 10 and 40%. Therefore, we examined the effect of assigning different tight time windows (2, 1 or 0.5-hour) to different shares of customers randomly selected. Moreover, we also researched the effect of assigning the same tight time window only to those customers living in the major Danish cities (42.7% of the total).

We concluded that, if the company was considering improving the customer service level by offering tighter time windows then it should opt for the cities scenarios. In fact, we noticed a good improvement in the number of routes, total time and number of unfulfilled orders when comparing the computational results obtained for the cities scenarios with the scenarios where we assigned the same tight time window to a randomly selected share of 40% of the customer orders. This is
because in the cities scenarios the "difficult" gold customers are located quite close to each other (at least within the same city area). Therefore the problem instance becomes easier to solve - with regard to the case where we randomly selected the gold customers - in the way that customer time window constraints become easier to fulfill because the gold requests are concentrated in specific areas. This is true especially for the 0.5-hour time slots.

From a cost perspective, the cities scenarios result in an actual extra cost per urban customer of 75 DKK for the 0.5-hour time slot duration, 50 DKK for the 1-hour one and 29 DKK for the 2-hour one. Thus representing the most appealing option.

8.1 Further work

First of all we believe that this kind of research could possibly benefit from having longer computation time available. In our simulation setup the maximum total time allowed where the optimization engine tried to improve the solution for each scenario was set to 30 minutes. Some testing is needed in order to determine what is the effect of increasing the computation time on the solution quality. However, we can say that an increase from 30 to 90 minutes per scenario would definitely make a difference.

Moreover, the robustness of this kind of analysis would benefit from using a larger number of test instances. In our tests we used 6 instances for each time window scenario (one for each weekday from Monday to Saturday) and compared scenarios on the basis of the the weekly sums. Again, we cannot say which would be the best number of test instances. However, we suggest the testing extension to at least 30 instances for each time window scenario. Of course, there is a trade-off between robustness/solution quality and assigned resources (such as computation time, instances generation) that needs to be balanced.

We also believe that this kind of assessment would benefit from a survey about customers’ willingness to pay an extra fee for a tighter time window. The survey should investigate which is the share of customers that place an higher value on their time, which is the actual extra fee that they are willing to pay for a higher level of service and where they are located (urban or rural areas).

Finally, when comparing different delivery time windows scenarios it would be interesting to have the actual L’EASY’s cost figures at disposal even though we can see the obvious difficulties that exist in their estimation.
Conclusions
Bibliography


