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List of Abbreviations

AFS....Alternative fueling stations
AFV.... Alternative-fuel powered vehicle
ALNS .... Adaptive Large Neighborhood Search
CMEM.... A Comprehensive Modal Emission Model
COPERT....Computer Program to calculate Emissions from Road Transport
CPU ....Central Processing Unit
CVRP .... Capacitated Vehicle Routing Problem
EVRP....Emissions Vehicle Routing Problem
G-VRP....Green Vehicle Routing Problem
LNS ....Large Neighborhood Search
MEET ....Methodology for Calculating Transportation Emissions and Energy Consumption
NAEI ....National Atmospheric Emissions Inventory
PRP....Pollution Routing Problem
TDP ....Truck Dispatching Problem
TDTSP....Time-dependent Traveling Salesman Problem
TDVRP.... Time-dependent Vehicle Routing Problem
TSP ....Traveling Salesman Problem
VRP .... Vehicle Routing Problem
VRPTW.... Vehicle Routing Problem with Time Windows

2 Introduction

Over the past decades, concerns about the environment have constantly increased (Min and Kim 2012). As a result of the ongoing man-made environmental destruction, climate change and global warming, many third-party logistics service providers and other companies have made tackling environmental sustainability issues their top priority (Evangelista et al. 2017). Notwithstanding, the increased environmental awareness at company level is above all a direct response to changing customer preferences. For instance, a survey conducted by the German Federal Environment Ministry on eco-consciousness in Germany in 2018 has shown that 64% of the German population attach considerable importance to environmental protection and climate change mitigation (BMU 2019). A majority (53%) of these respondents further support the claim that environmental concerns should be given more attention, especially in the area of transport policy (BMU 2019). Particularly the aim to mitigate pollution as much as possible was perceived as the most essential factor in the development of the transport sector (BMU 2019). To address the environmental concerns related to the transport industry, the objective of a 60% reduction of greenhouse gas emissions from transport by 2050 compared to 1990 levels was formulated in the EC White Paper on Transport (EC 2011). However, much remains to be done, as transport emissions, which are to the largest extent caused by road transport, are expected to still be around 10% above 1990 levels in 2030 (EEA 2021). Logistics service providers are therefore under high pressure to improve the sustainability of their transport activities by including the environmental impact in their cost evaluation, whilst maintaining a high level of operational efficiency in order to remain profitable (Dekker et al. 2012; Manerba et al. 2018).

Especially against the background of the remarkable growth of the e-commerce economy, carefully considering how to approach this challenge has become more important than ever. The surging demand in the area of online retail is mainly a result of the ongoing COVID-19 pandemic (Unnikrishnan and Figliozzi 2021). As a response to the numerous lockdowns and the associated safety concerns within the society, many customers have turned toward the online sales channel (Agatz et al. 2021). In this context, especially the e-grocery business has experienced enormous growth rates, as it is time-saving for customers to have groceries delivered directly to their homes and enables them to maintain social distance in times of the pandemic (Morganosky and Cude 2000). These trends not only created increased sales opportunities, but also massive logistical challenges (Agatz et al. 2021). In the pursuit of tackling these challenges, the success of e-commerce businesses mainly hinges upon their ability to handle the home delivery logistics of online shopping, referred to as *last-mile delivery* (Xu et al. 2008). Being the primary reason for failures of pioneering online retailers and substantial societal costs such as air pollution, traffic congestion and high levels of CO_2 emissions, logistics service providers have a strong incentive to optimize this highly inefficient and expensive, but crucial mode of transportation (Gevaers et al. 2011; Xu et al. 2008). In the realm of last-mile operations, especially attended home deliveries, which require the presence of the customer during delivery, bear the risk that delivery vehicles have to visit a similar location several times a day to serve customers within different delivery time windows (Agatz et al. 2021). Such challenges related to attended home deliveries on the one hand significantly jeopardize a company's operational efficiency through high expenses in lost productivity and fuel waste, and on the other hand strongly impede the achievement of environmental sustainability objectives (Agatz et al. 2021; INRIX 2018).

This demonstrates the importance of efficient time window management for attended home deliveries, which means offering the customers a set of feasible, profitable and suitable time windows to increase the likelihood of a successful delivery (Köhler et al. 2020). Although logistics service providers are increasingly responding to these issues by optimizing their supply-side processes, the potential that can be unlocked from influencing demand as means to improve system performance has long been overlooked (Agatz et al. 2021). In this context, especially the possibility of using non-financial incentives to motivate customers to choose delivery time windows that allow for both efficient and environmentally friendly route plans has been insufficiently studied.

This paper aims to close this gap. To scrutinize the impact of slot choice behavior on operational efficiency and environmental sustainability in the context of attended home delivery, a last-mile vehicle routing problem is simulated. Because transportation still relies nearly entirely on mineral oil products, carbon dioxide emissions are a direct reflection of fossil energy consumption and are thus used to assess the sustainability dimension of last-mile delivery operations (Borken 2003). The efficiency dimension of transport activities is usually measured by indicators such as vehicle miles and total costs, including both costs for the service provider and environmental costs (Agatz et al. 2021). Since, as shown later in this paper, these factors are closely linked, a reduction in CO_2 emissions is assumed to come along with an increase in efficiency.

As e-groceries typically require the presence of the customer upon delivery, this paper uses the time-window based delivery of groceries as an example for attended home delivery. For this purpose, three different scenarios are considered. In the first scenario, route plans for 20 customers with known locations and time window preferences are created. In doing so, the aim is to investigate how the operational efficiency and the expected level of CO_2 emissions of delivery routes change with increased time window length. In the second scenario, a closer look is taken at the impact of an individual customer's time window choice on the operational efficiency and environmental sustainability of the last-mile delivery route. Finally, a fully dynamic vehicle routing problem is imitated in the last part of the simulation. Thereby, the time window leading to minimum additional CO_2 emissions is determined incrementally and marked as environmentally friendly to each customer within a given route plan. Based on the results of the simulation, the previously identified, environmentally friendly time windows are incentivized in an experimental study via different non-financial approaches. Using a survey, the aim is to determine to what extent customers, under the presence of such incentives, are willing to choose more sustainable time windows.

The remainder of this paper is structured as follows. Chapter 2 covers the theoretical foundations for this work by illustrating the characteristics of attended home delivery and by providing an introduction into time window management, the Vehicle Routing Problem and Green Logistics. Furthermore, Chapter 2 reviews different types of financial and non-financial incentives. In Chapter 3, the research objective and the research questions of this work are formulated. Chapter 4 is dedicated to the simulation study and presents the results of the three scenarios. The experimental design, the participants and the outcomes of the online survey are featured in Chapter 5. Finally, Chapter 6 summarizes the main findings of this paper and Chapter 7 discusses some limitations of this work and provides an outlook.

3 Theory and Literature Review

3.1 Attended Home Delivery

A main reason why efficient time window management has become relevant in the first place is the rise of the e-commerce industry. Traditional brick-and-mortar stores have been facing increasing competition from online retailers in the past decades (Vojvodić 2019). This can be explained by rapidly changing consumer preferences of the millennial and post-millennial generation, who show a stronger demand for online retail when compared to the shopping behavior of Baby Boomers (Dhanapal et al. 2015). Since the demand for e-commerce experiences has even further increased throughout the COVID-19 pandemic, businesses and traditional retail stores have quickly realized the necessity to move to online channels (LaBerge et al. 2020).

The trend of customers turning to the online sales market to purchase goods easily and conveniently from home is reflected in the number of online sales in Austria. Statistics show that e-commerce sales have amounted to over 4 billion euros in 2020. When compared to 2006 levels, in which e-commerce sales in Austria accounted for only 700 million euros, this represents a six-fold increase. In terms of the number of consumers using the online channel to buy products, approximately 55% of Austrians aged 16 to 74 stated in an online poll conducted in 2021 that they had used the Internet for online shopping within the last three months before the time of the survey (Turulski 2022).

In the online retail environment, especially the e-grocery business has undergone a significant transformation (Agatz et al. 2021). Although traditional brick-and-mortar concepts are still prevailing in the grocery market, e-grocery sales have experienced a sharp increase in the past years (Hübner et al. 2016). In Austria, particularly the COVID-19 pandemic led to a boost of e-grocery purchases of 26% within a year, resulting in a total of 730.000 Austrian e-grocery buyers in 2020 (Austrian Retail Association 2020). At the peak of the pandemic, the sales from e-groceries were thus 37.9% higher than in the previous year of 2019 (Statista 2021). This trend persisted in the following year, in which the sales growth of e-groceries amounted to 12.3% from 2020 to 2021 (Statista 2021). This development is very positively received by customers, as having groceries delivered directly to their homes is convenient, saves time and increases overall customer satisfaction (Morganosky and Cude 2000).

At the same time, the growth of the e-commerce and, in particular, the e-grocery business have been the cause of rising concerns about the associated environmental impact when compared to offline shopping (Siragusa and Tumino 2021). In fact, e-grocery deliveries are assessed as particularly problematic in the context last-mile deliveries (Barnett and Alexander 2004). Contrary to other retail sectors, where orders are generally made up of one or a few pieces, the typical e-grocery order contains products from multiple single-piece lines (Agatz et al. 2008; Gee et al. 2019; Siragusa and Tumino 2021). Examples are dry, frozen and fresh items linked to perishability factors and strict health regulations (Siragusa and Tumino 2021). Additionally, groceries have relatively low value-to-bulk ratios, which is why delivered groceries are overall considered a low-margin business model (Barnett and Alexander 2004). Due to varying storage requirements for these different types of products and challenging timetabling, routing, storage, picking and packing methods, e-groceries are an extreme and sensitive system (Barnett and Alexander 2004). At the same time, e-grocery customers have very high expectations, as they typically buy fresh products for their daily needs and thus expect their delivery to arrive on the same day within a specified time frame (Barnett and Alexander 2004). This largely explains why last-mile fulfillment intricacies are considered as one of the biggest challenges for e-grocers (Weber-Snyman and Badenhorst-Weiss 2016).

Given these trends and challenges related to the e-commerce and, in particular, the e-grocery business, the success of online retailers largely depends on their ability to efficiently manage their online logistics planning processes. In the realm of online retail, the strategic planning framework for last-mile order fulfillment and delivery can be structured into back-end fulfillment, which is concerned with warehousing and in-store picking, and last-mile distribution concepts (Hübner et al. 2016). When executing this final step of the delivery process, one of the predominant last-mile solutions is home delivery. This delivery mode can be categorized into attended home delivery, which requires the customer to be at home at the point of delivery, and unattended home delivery (Hübner et al. 2016). This form of delivery is becoming increasingly popular among customers, as it is regarded as convenient, safe and secure (Hübner et al. 2016). The fulfillment process for attended home deliveries contains three main steps (Campbell and Savelsbergh 2005).

The first step of the process, order acceptance, takes place on the retailer's website. By selecting items and placing them in online shopping baskets, customers disclose their address or at least their ZIP code. To increase the likelihood of successful delivery, they are simultaneously offered a range of delivery time windows and asked to select one, which is then immediately confirmed by the retailer. In the second step, the placed order is assembled within the store or warehouse. Finally, the route plans are optimized, the main objective usually being on-time delivery at minimal cost (Köhler and Haferkamp 2019).

Unattended home deliveries, on the other hand, imply that the ordered products are delivered to the customer regardless of his or her physical presence. While the unattended delivery mode does not require the proposition of concrete time windows for a certain delivery date, delivery velocity becomes an essential criterion. This means that the retailer typically has to make a decision between offering same day delivery, next day delivery, or delivery within two or more days. As customer satisfaction and days until delivery after the order placement are negatively correlated, particularly in the case of online groceries, this creates a complex trade-off. The reason for this is that short delivery times and especially same-day delivery serve customer interests, yet pose great logistical challenges (Hübner et al. 2016).

3.2 Time Window Management

While attended home delivery accounts for the largest share of last-mile delivery in most countries, it also poses the problem that a considerable proportion of attended home deliveries fail since many people are not at home during a normal working day (Fernie and McKinnon 2009). In turn, unsuccessful deliveries have far-reaching consequences for the retailer. Not only do they increase costs for transportation, handling and storing of undelivered goods, they also confront the retailer with the time-consuming task of setting a new delivery date and carrying out an extra tour (Hübner et al. 2016). To reduce the number of failed deliveries, it has become common practice to offer the customers a selection of delivery time windows to choose from. The supermarket *Hofer* (Austria), for instance, offers deliveries between 8am and 6pm within non-overlapping one-, three- or ten-hour time frames at a delivery cost of € 5.90, € 4.90 and € 2.90, respectively. The hypermarket operator *Interspar* (Austria), on the other hand, offers only two-hour time windows from 9am to 9pm, which are all subject to fixed delivery fees of € 4,90. Overall, online grocery providers essentially differ in the time intervals in which they offer deliveries, the length of the time windows contained therein, the prices they charge for delivery within specific time windows as well as the order value from which the delivery costs are omitted. Additionally, differences exist in the minimum order values and whether or not overlapping time windows are offered. Figure 1 shows the time window offer set of the supermarket *Hofer* in Austria.

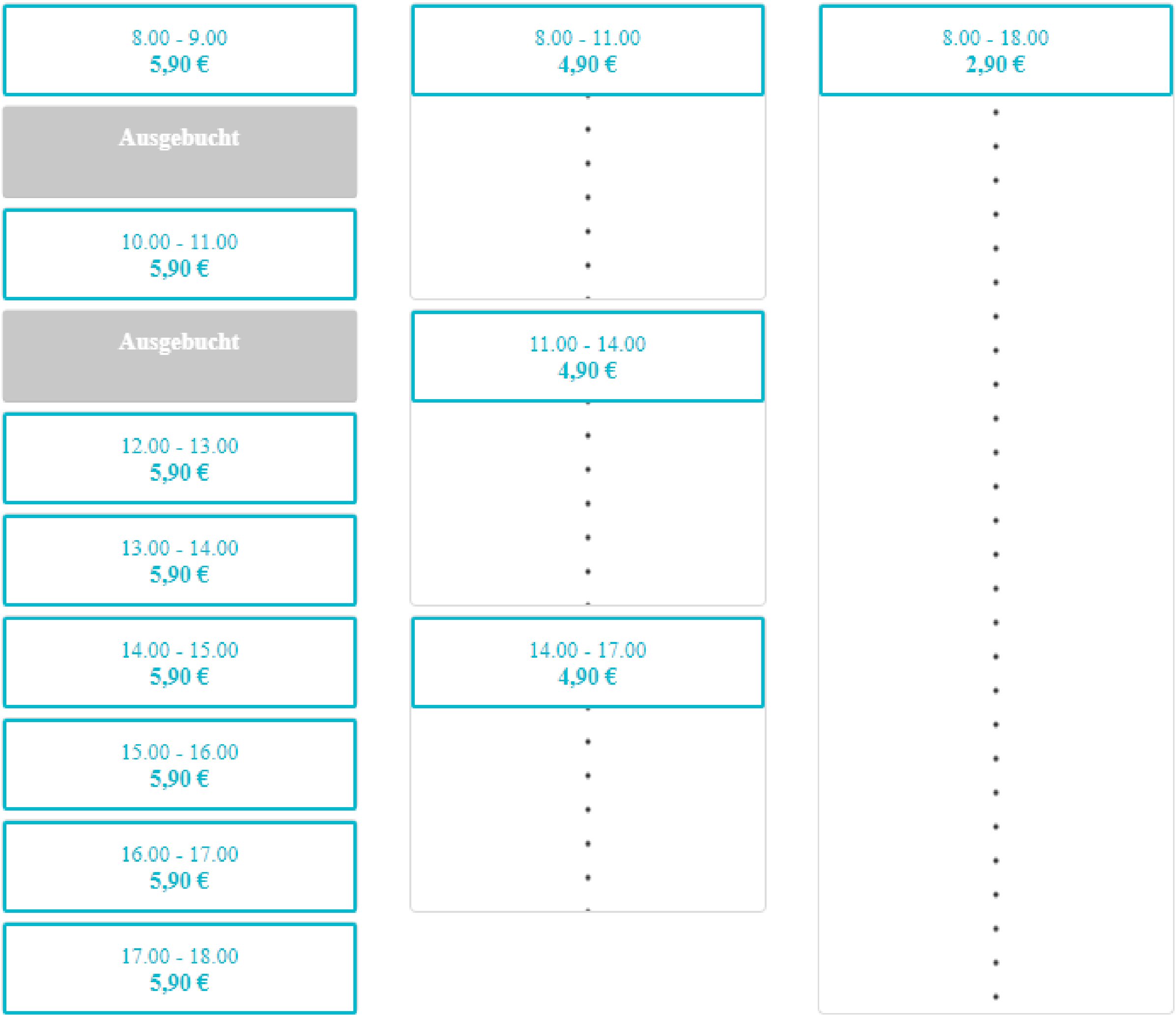


Figure 1: Time window offer set of Hofer

Source: https://www.roksh.at/hofer/anfangsseite (07.11.2021)

Given the high costs of attended home deliveries in combination with the low profit margin of e-grocers, the aim of most retailers is to maximize the number of customers served and the overall profit whilst minimizing delivery costs (Köhler et al. 2020). This places very high demands on effective and efficient time window management, that is to say, the process of offering delivery time windows that ensure a high level of customer satisfaction, while at the same time allowing for planning flexibility and routing efficiency (Köhler et al. 2020). Time window management thus describes the complex task of balancing marketing and operational considerations (Agatz et al. 2011).

To this end, a distinction has to be made between tactical and operational time window management. While the former is concerned with the tactical decision of which time windows to offer in each part of the delivery region, the latter describes the problem of managing the availability of the offered time windows. This happens after the tactical decisions have been made and the customer has placed the order (Agatz et al. 2011).

On the tactical level, the offered time windows have to be feasible, suitable and profitable. Feasibility refers to ensuring on-time deliveries, while suitability is concerned with meeting customers' window length expectations and time of day preferences. The latter implies that the time window offer set must be designed in a way that the customer is willing to accept at least one of the offered time windows. The profitability of a time window directly correlates with the achieved maximal profit, i.e., the ability to serve as many customers as possible under the given logistics capacity. Yet, given the highly competitive nature of online retail, the decision on the design and availability of delivery time windows is non-trivial (Köhler et al. 2020).

Notably, this decision becomes even more complex in the case of dynamic customer acceptance mechanisms. The crucial problem here is that customer requests are not known beforehand, as they arrive dynamically on the retailer's website during the booking process (Köhler et al. 2020). The dynamic approach thus creates tentative route plans based on customer locations and subsequently checks the feasibility of each particular time window in real-time (Köhler et al. 2020). Static approaches, in contrast, base the maximum number of customers that may be accepted per time window on past delivery performance from historical data or from tactical time window design (Köhler et al. 2020). Although this method does not consider information about customer locations and is therefore an inadequate reflection of complex, real-life conditions, it enables the creation of time window schedules that may serve as a good starting point for subsequent real-time adjustments (Agatz et al. 2011; Köhler et al. 2020).

A critical question arising in the context of time window management is related to the decision on time window length. Given the strong competition in the e-commerce industry, retailers have started to offer increasingly short time windows to their customers in order to improve customer service and strengthen customer loyalty (Köhler et al. 2020). Yet, offering the customer a large degree of control in the selection of time windows entails challenges associated with travel time uncertainties, fewer deliveries per vehicle, a lower degree of capacity utilization, the risk of tardy or failed deliveries and, consequently, high costs (Agatz et al. 2011; Hübner et al. 2016). This involves not only the delivery costs for the retailer, but also societal costs such as CO_2 emissions, air pollution and traffic congestions (Agatz et al. 2021). Therefore, offering home delivery within short time windows typically creates a number of inconveniences and complexities both for the retailer and the customer (Hübner et al. 2016). Most notably, the failure of several e-grocers strongly proves the theory that offering attended home delivery services with increasingly short time windows for all customers is a risky and unsustainable approach in the long-term (Köhler et al. 2020; Punakivi and Saranen 2001).

For this reason, it has become more and more common to offer customers a mix of both long and short time windows that are priced differently. Since increased time window length is often positively correlated with higher effectiveness of demand management systems, this can have a significant impact in the area of last-mile delivery (Agatz et al. 2021; Campbell and Savelsbergh 2005; Solomon 1987). While enlarged time windows of for instance five hours are less appealing for customers, as they have to wait at home for their delivery to arrive for a longer period of time, they provide the retailer with much more routing flexibility (Agatz et al. 2011; Köhler et al. 2020). Furthermore, longer time windows are associated with a higher number of accepted customers, lower delivery costs for the retailer and higher profits. Effectively, previous studies have shown that up to 15% more customers can be accepted when offering long instead of short time windows and the delivery costs for the retailer can be nearly cut in half (Ehmke and Campbell 2014; Gevaers et al. 2014; Köhler et al. 2020). Additionally, simply by extending a time window from 30 minutes to 3 hours, profits can be increased by 18% (Campbell and Savelsbergh 2005). Overall, incentivizing the choice of longer time windows allows for more optimized routes in last-mile delivery operations, which not only reduces costs, but also fuel consumption and emission levels (Agatz et al. 2021).

A factor that highly complicates efficient time window management and routing is that most customers tend to prefer after work deliveries, leading to uneven demand and capacity problems (Hübner et al. 2016; Köhler et al. 2020). Therefore, it is often necessary for delivery vehicles to visit several different geographical regions over long distances, resulting in unutilized vehicle capacities, inefficient routes, long working hours for the distributor and high delivery costs (Hübner et al. 2016). Escalating costs are in fact one of the greatest challenges in the area of attended home deliveries (Aspray et al. 2013). This applies in particular to e-grocery last-mile deliveries, as the arising costs in the fulfillment process for e-groceries are about 13% higher than for offline grocery shops in which the customer goes to the shop and performs the picking and final delivery him- or herself (Hays et al. 2005). To recoup these additional costs associated with picking online orders and tackling the challenges of last-mile deliveries, retailers have started to price time windows differently. The aim of this approach is to charge less for time windows that allow the retailer to create more efficient and cost effective schedules (Campbell and Savelsbergh 2005). Similarly, there is also the possibility to create specific time window offer sets for different geographical regions of the delivery area based on forecasted consumer demand. The primary objective here is not to assign specific time windows to a ZIP code in isolation, but rather simultaneously, considering the time windows that were allocated to neighboring customers (Agatz et al. 2011; Köhler et al. 2020). Knowing the estimated demand for each region can help create cost-minimal route plans and enhance decisions on the fleet size and -mix (Köhler et al. 2020).

Overall, the rise of the e-commerce industry has increased the need for deliberate time window management and has made it especially important for e-grocery retailers to find ways to encourage customers to choose delivery time windows that favor efficient and eco-friendly routing.

3.3 Vehicle Routing Problem

Capacitated Vehicle Routing Problem

In the past decades, a considerable body of research on the Vehicle Routing Problem (VRP) has evolved. The starting point for the formulation of the classical VRP was the introduction of *The Truck Dispatching Problem (TDP)* by Dantzig and Ramser (1959). As a generalization of the *Traveling Salesman Problem (TSP),* it is concerned with finding the shortest routes for a fleet of gasoline delivery vehicles between a bulk terminal and a large number of service stations (Dantzig and Ramser 1959). Acknowledging the challenge that a rising number of service stations increases the options of routes and thus complicates the task of finding an optimal solution significantly, an algorithm approach was developed based on a linear programming formulation to generate near optimal solutions (Dantzig and Ramser 1959; Lin et al. 2014).

As each carrier in the truck dispatching problem has a limited capacity, it is a version of the *Capacitated Vehicle Routing Problem (CVRP)*. The CVRP is characterized by the assumption that a preassigned fleet of delivery vehicles of uniform capacity must serve fixed customer demands. It is further assumed that each customer is visited exactly once by one delivery vehicle and that the corresponding purchase order quantity must not be split into several deliveries. The objective of the CVRP is thus to deliver the orders to the customers while adhering to the capacity restrictions (Ralphs et al. 2003).

Time-dependent Vehicle Routing Problem

For a better reflection of real-life conditions, the traditional VRP, which draws on Euclidean distances for the determination of the optimal route plan, was extended to the *Time-dependent VRP (TDVRP)* (Lin et al. 2014). The work of Cooke and Halsey (1966) is among the first to critically question the hitherto existing assumption that the travel time between any two nodes is constant. For this purpose, they modified the classical shortest path problem by taking varying rather than static internodal time requirements into account (Lin et al. 2014). Yet, their study does not consider a mixed fleet of delivery vehicles, which is commonly used for contemporary standard deliveries. This shortcoming was addressed by Malandraki and Daskin (1992), who differentiate between two different versions of the TDVRP. In the classic case, they assume that customers are served by a vehicle fleet of fixed capacities. The basic assumption of the CVRP, namely that customers have fixed demands that may not exceed the preassigned capacity of the delivery fleet, is maintained. However, the crucial difference to the CVRP is that time minimization is included in the objective function. In doing so, the authors take into account that both distance traveled and daytime have an effect on the travel time between two customers or between a customer and the depot. The special case of the TDVRP, the so-called *Time-dependent Traveling Salesman Problem (TDTSP)*, differs from the classic case in that it assumes the availability of only one delivery vehicle with unlimited capacity. For both cases, mixed integer linear programming formulations are presented, in which the travel time is displayed as a step function conditional upon the time of day (Malandraki and Daskin 1992). Overall, the extension of the classical VRP to the TDVRP allows for a more accurate cost estimation, as it takes into account that vehicles are moving on a real road network that typically does not consist of Euclidean distances and emphasizes cost variability in relation to time (Lin et al. 2014; Polimeni and Vitetta 2013). This is especially relevant in urban areas, where frequent congestions and varying traffic density have a large impact on the traveling speed (Lin et al. 2014). Moreover, the increasing demand for attended home deliveries, which is associated with customers expecting punctual deliveries, makes it indispensable to carefully consider fluctuating travel times in network optimization problems.

Vehicle Routing Problem with Time windows

The efforts to improve the level of customer satisfaction through on-time delivery have put forth time window constraints as another VRP variant. Thanks to the impressive evolution in information technology, logistics service providers are better positioned to cope with the additional complexities arising from time window constraints (Kallehauge et al. 2005). In parallel, a growing body of literature has evolved that focuses on managing time window constraints in the VRP. The so-called *Vehicle Routing Problem with Time Windows (VRPTW)* is an extension of the classical VRP and, due to its practical relevance and applicability in various real-life scenarios concerning routing, is regarded as the most prevalent VRP variant in the extant body of literature (Lin et al. 2014). The crucial difference to previous VRP variants lies in the assumption that customers are served within a given time window. Such time windows can either be soft or hard (Lin et al. 2014). The former is the case when a violation of time window restrictions is acceptable at the price of some penalty (Kallehauge 2008). Hard time windows, on the other hand, must not be violated. This means that logistics service providers are bound to serve customers within their specified time intervals and have to wait for the time window to open in case of early arrival (Kallehauge et al. 2005). Overall, soft time windows are beneficial for the supplier, as they allow for more executable and better solutions in terms of the total distance traveled, the number of vehicles deployed and the resulting delivery costs (Figliozzi 2010b; Lin et al. 2014).

Recent studies of VRPTW clearly indicate a shift away from the one-sided focus on the minimization of transportation costs to more broader objectives. Figliozzi (2010a), for instance, introduces a new kind of VRPTW, the *Emissions Vehicle Routing Problem (EVRP)*. In this variant, the minimization of emissions and fuel consumption is regarded as the primary or secondary objective. For this purpose, Figliozzi (2010a) formulates a heuristic to reduce the level of emissions for a set of feasible routes under varying congestion levels and travel times. Similar to the VRPTW, the EVRP assumes time-dependent travel times and is subject to hard time windows and capacity constraints. However, the focus on reducing emissions clearly sets the EVRP apart from earlier VRP variants, in which primary and secondary objective are commonly the minimization of the number of vehicles and distance traveled, respectively. By comparing and analyzing the results obtained with the proposed EVRP solution approach for varying congestion levels, the author highlights the significant CO_2 savings potential that arises if emissions minimization is incorporated in the objective function of vehicle routing problems.

Green Vehicle Routing Problem

Although the body of literature that explicitly incorporates an emission-minimizing objective in the VRP is limited, the more general target of optimizing energy consumption in the field of vehicle routing has gained growing importance in recent studies (Lin et al. 2014). Commonly referred to as *Green Vehicle Routing Problem (G-VRP)*, this rather new variant of the VRP is a response to the overuse of energy and the associated fuel costs, air pollution and environmental degradation (Lin et al. 2014). The distinctive objective of the G-VRP is to minimize fuel consumption by taking into account the effect of factors such as vehicle load, distance traveled and travel speed on the total cost of transportation, all the while maximizing transportation efficiency (Kara et al. 2007; Xiao et al. 2012). This, in turn, is associated with a positive environmental impact, as the maximization of transportation efficiency generally goes hand in hand with a reduction of greenhouse gas emissions (Lin et al. 2014; Xiao et al. 2012).

In the field of the G-VRP, the number of studies reacting to the introduction of alternative-fuel powered vehicles (AFV) is still rather limited (Lin et al. 2014). Yet, the use of AFVs is becoming increasingly common due to environmental regulations or voluntary actions on the side of individuals or companies aiming to reduce pollution caused by road transport (Erdoğan and Miller-Hooks 2012). Along with Schneider et al. (2014), who extend the G-VRP with time windows, Erdoğan and Miller-Hooks (2012) pioneer the incorporation of additional complexities associated with operating a fleet of AFVs in the VRP. In this context, refueling techniques at alternative fueling stations (AFS) are proposed to both lower the risk of running out of fuel and to minimize routing costs (Erdoğan and Miller-Hooks 2012).

Overall, although the main objectives of the G-VRP, namely reducing fuel consumption and improving transportation efficiency, indirectly contribute to a decrease of CO_2 emissions, the associated environmental benefits are not directly measured. Yet, the dangerous impact emissions from transport activities have on humans and the entire ecosystem cannot be overlooked and call for VRPs that directly reflect societal and environmental costs in terms of environmental pollution (Lin et al. 2014).

The Pollution Routing Problem

To put a stronger focus on the pollution from carbon emissions and to find ways to reduce these in the road transport sector, the *Polluting Routing Problem (PRP)* was formulated. It is an extension of the classical VRP in that it includes broader objectives that reflect the social and environmental impact of transportation in the cost function (Lin et al. 2014). Among the authors who dedicate their work to the PRP are Sbihi and Eglese (2007), who examine the effect of avoiding congested areas in the route plan. They come to the conclusion that although this approach in some cases leads to longer travelling distances, it still reduces the overall emission levels. Maden et al. (2010) also describe a heuristic algorithm to measure the impact of congestion on traveling speed and, consequently, the total travel time. As travel time minimization remains their primary objective, the reported CO_2 emission savings potential of about 7%, which could be achieved by taking time-varying speeds into account, is seen as a positive side effect rather than the main target. Furthermore, the research of Palmer (2007) also recognizes the importance of finding ways to reduce the emission levels in the transport sector. To this end, a computer-based vehicle routing model is developed to measure and minimize the level of CO_2 emissions under varying congestion scenarios and minimization criteria. The results show that the implementation of the proposed vehicle routing heuristics may lead to a reduction of CO_2 emissions by up to 5%. A similar approach is followed by Ubeda et al. (2011), who examine how the incorporation of environmental management principles in the daily managerial decision-making process can yield both economic and ecological benefits. The novelty of their study lies in the formulation of a green optimization approach and the creation of an environmental matrix, which reflects the estimated CO_2 emissions between all delivery points and the depot. This method facilitates the design of routes that explicitly consider the minimization of CO_2 emissions in the objective function, which reinforces the shift away from the traditional target of solely minimizing delivery cost, distance or travel time. Another paper that includes a broader and more realistic estimation of costs from transportation is by Faulin et al. (2011). Apart from traditional logistics costs related to delivery processes, costs associated with environmental damage caused by logistic activities, such as pollution, noise, congestion and wear and tear on infrastructure are also considered.

The Pollution-Routing Problem by Bektaş and Laporte (2011) provides some of the most relevant findings for this study, as their mathematical model of the PRP with and without time windows expands the traditional VRP by not only taking into consideration the costs of the travel distance, but also those related to greenhouse gas emissions, fuel and travel time. The results show that in the presence of time restrictions, the implementation of a model with an energy-minimizing objective function reduces energy consumption rates by up to 10% when compared to a model with a traditional distance-minimizing objective. Notably, the savings potential is much lower in the case without time windows. However, the significance of the effect of energy reduction under time window constraints is eliminated in the case of overly tight time windows. The reason for this is that, especially in the case that only a single vehicle performs the delivery, over-restrictive time windows leave logistics service providers with a very limited margin for maneuver in terms of alternative routing solutions, often nearly dictating one sole optimal route (Bektaş and Laporte 2011).

Overall, the body of research aiming explicitly at reducing the environmental impact of transport activities is growing, but still rather limited. Further research work should thus be pursued to take full advantage of the potential of the PRP in conjunction with time windows.

3.4 Green Logistics

The different variants of the VRP that have evolved within the 50 years since it was first introduced show a clear shift from the pursuit of purely economic, cost-minimizing objectives to a reexamination of the VRP in the broader context of so-called *Green Logistics* (Lin et al. 2014). According to Wittenbrink (2010), Green Logistics is a sustainable and systematic process for recording and reducing resource consumption and emissions resulting from transport and logistics processes within and between companies. The relevance of this topic becomes clear when taking into account the absolute CO_2 emissions attributable to road transport. Although the emissions of freight transport per transport volume (measured in tonne kilometer) have decreased considerably throughout the past decades, this positive development through technological advances has been partly offset by the increase in traffic volume (Wittenbrink 2015). Effectively, the absolute CO_2 emissions of road freight transport even increased by 21% between 1995 and 2019, despite the aforementioned technological improvements (UBA 2021). Against this backdrop, the German Advisory Council on the Environment classified CO_2 emissions from road freight transport as one of the major unsolved problems of German climate policy (ACE 2012). In the light of the challenges that have become apparent through the Green Logistics debate, transport and logistics companies are under increasing pressure to anchor sustainability issues in their strategic planning framework (PwC 2009).

The three most relevant measures to reduce emissions are avoidance, shift to alternative modes of transport and diminution (Wittenbrink 2015). The first measure, avoidance, is concerned with providing incentives to reduce the demand for transport so that traffic can be circumvented as far as possible (Wittenbrink 2015). For this, it is necessary that the benefits of alternative logistics processes that may contribute to the avoidance of traffic need to be clearly communicated to the customer. In doing so, the associated ecological gains must be emphasized so that a potentially reduced service level will more likely be accepted. If the customer thinks a lower level of service only has benefits for the logistics service provider in terms of cost savings, it will be tolerated at most in combination with price reductions (Wittenbrink 2015). However, even if a part of the volume of traffic can be avoided or shifted to more sustainable modes of transport like rail or ship transport, finding new approaches to reduce the emissions for the remaining traffic is vital. Since there is a direct correlation between fuel consumption and CO_2 emissions, fuel savings are associated with a significant, yet insufficiently exploited CO_2 savings potential (Wittenbrink 2015). One of the main reasons for this unused potential is a general lack of knowledge about the far-reaching advantages a CO_2 reduction entails. It is often assumed that there is a conflict of objectives between environmental protection and economic efficiency, which in reality does not exist (Wittenbrink 2015). On the contrary, environmental protection activities can induce not only CO_2 emission savings, but also significant cost savings, especially if they are linked to reductions in energy consumption (Wittenbrink 2015).

Therefore, especially those logistics companies that are concerned with making their processes more environmentally friendly are moving toward recording their CO_2 balance and calculating the associated CO_2 footprint (Wittenbrink 2015). In this context, a distinction must be made between *Corporate Carbon Footprint* and *Product Carbon Footprint* (Wittenbrink 2015). Corporate Carbon Footprinting describes the process of calculating the level of greenhouse gas emissions for an entire company in order to take climate protection measures on this basis (Schmied and Knörr 2012). Product Carbon Footprinting, on the other hand, refers to calculation of the carbon footprint for individual transports, such as for selected customers (Schmied and Knörr 2012). A carbon footprint for time windows in the context of last-mile deliveries, on the other hand, has not yet been formulated. In any case, measuring and determining carbon footprints remains a challenge. However, a number of fuel consumption models exist that provide a solid estimation of network-wide emissions.

Fuel consumption models

With regard to fuel consumption models, a distinction must be made between macroscopic and microscopic models (Bektaş et al. 2016). While macroscopic models draw on average aggregate network parameters to estimate network-wide emissions, microscopic models calculate the instantaneous vehicle fuel consumption and emission rates at a given point in time in greater detail (Bektaş et al. 2016). Two of the most predominantly applied microscopic models are *An Instantaneous Fuel Consumption Model* by Bowyer et al. (1985) and *A Comprehensive Modal Emission Model* (CMEM) developed and presented by Scora and Barth (2006), Barth et al. (2005) and Barth and Boriboonsomsin (2008). The energy-related emissions estimation model by Bowyer et al. (1985) uses vehicle characteristics such as mass, energy or efficiency parameters to approximate the fuel consumption per second. It delivers best results when applied to estimate emissions for short trips at a micro-scale level (Bektaş et al. 2016). CMEM is a model for heavy-goods vehicles, which is based on second-by-second tailpipe emissions and requires detailed vehicle specific parameters for an accurate estimation (Bektaş et al. 2016). In this model, the total fuel consumption is calculated as a function of engine power requirement, vehicle speed and fuel rate (Bektaş et al. 2016).

Examples for macroscopic models include the *Computer Program to calculate Emissions from Road Transport (COPERT)*, the *National Atmospheric Emissions Inventory (NAEI)* model and the *Methodology for Calculating Transportation Emissions and Energy Consumption (MEET)* (Bektaş et al. 2016). COPERT estimates vehicle emissions for all major air pollutants for a number of vehicles classified by engine and vehicle type (Bektaş et al. 2016). To assess total fuel consumption, COPERT uses several regression functions, which are dependent on vehicle weight (Bektaş et al. 2016). Regarding the NAEI model, a distinctive feature is that it was developed for various pollutant categories, such as greenhouse gases, air pollutants, particulate matter as well as heavy metals and base cations. Additionally, it provides estimations of emissions in not only the transport sector, but also sectors like energy, agriculture and industrial processes (NAEI 2017). In the case of road transportation, emissions are estimated taking a combination of influencing factors into account, such as fleet composition, vehicle weight and temperature conditions (NAEI 2021).

The third listed macroscopic model, MEET, was developed by Hickman et al. (1999) and is deployed Europe-wide to calculate transportation emissions and energy consumption. The emission factors and functions of MEET refer to standard testing conditions and are typically calculated using a speed-dependent regression function. However, adjustments can be made to account for effects such as road gradient and vehicle load. To consider differences in the weight of different vehicle types, the model allows for an estimation of CO_2 emissions for several classes of vehicles (Bektaş et al. 2016).

Clearly, the MEET model has some drawbacks, especially in comparison with models that address dynamic or real-time problems. For instance, the fact that it does not take into account changing traffic conditions by using average speeds, as well as the assumption that all parameters are known with certainty contradict real-life conditions. Additionally, more qualitative parameters such as driver behavior are completely neglected. Lastly, since the parameters of MEET model were calibrated in 1999, updates would be necessary to take into account new engine technologies and aerodynamic vehicle designs (Bektaş et al. 2016).

However, the aim of this study is not to provide an exact calculation of CO_2 emissions for different real-life scenarios, but rather a good estimation on the basis of which appropriate environmentally friendly and efficiency-enhancing time windows can be identified and incentives formulated for customers. Therefore, the MEET model is well-suited for the purpose of this research.

3.5 Financial and Non-financial Incentives

In the area of Green Logistics, predominantly logistics service providers and retailers have been the stakeholders held accountable for the ecological footprint of their online activities and called on to optimize their supply-side processes (Buldeo Rai et al. 2021). Such optimization measures include the renewal of their vehicle fleet as well as processes of routing, loading and coordinating with other stakeholders (Mangiaracina et al. 2015). The role of consumers in the context of sustainable e-commerce deliveries, on the other hand, has been largely neglected. Yet, with the increasing number of online purchases, which was tremendously accelerated by the latest developments through the COVID-19 pandemic, it is now more important than ever to involve all relevant stakeholders in the process of reducing the environmental impact of e-commerce deliveries. Engaging customers in the decision-making process could make a big difference, as today's consumers are more environmentally conscious than ever (Buldeo Rai et al. 2021). Consequently, there is vast potential to be unlocked from both improving operational processes and investing in demand-side management to encourage online consumers to opt for more sustainable service options. This does not yet seem to have been fully recognized by most e-commerce players, who still focus mainly on increased delivery speed to gain a competitive edge (Buldeo Rai et al. 2021). Paradoxically, however, they are thereby satisfying customer expectations that are more attributable to ignorance than to actual desires. In fact, recent studies have shown that many customers are not categorically averse to longer delivery times (Buldeo Rai et al. 2019). A representative survey conducted in in 2021 by the market research institute GfK on behalf of Digitec Galaxus, in which customers in Switzerland were asked whether they were more interested in fast or environmentally friendly delivery when buying products online, has shown that for 32.2% of the respondents, both was equally relevant (Digitec Galaxus 2021a). At 24.3%, almost one fourth of the participants even rated an environmentally friendly delivery as more important (Digitec Galaxus 2021a). Yet, since nearly all large players are offering increasingly short delivery times, customers think that this is simply the norm (Buldeo Rai et al. 2021). That increased delivery speed, however, comes with a considerably higher environmental cost is something most customers are completely unaware of.

This is indirectly reflected in a survey asking European consumers which sustainable delivery options they expect large retail businesses to implement in 2021. At 54%, the largest share of respondents demanded sustainable packaging. Second and third most important for the respondents were the possibility to offset the delivery CO_2 footprint and a conversion of all delivery vehicles to electric, expressed by 48% and 47% of the respondents, respectively. Moreover, 44% of the participants were willing to accept a higher minimum number of items or value to qualify for free delivery and 42% would even like a minimum delivery fee to be implemented unconditionally. That the possibility of reducing the speed of delivery for the sake of the environment was not mentioned at all suggests a fundamental lack of knowledge on the negative correlation between increased delivery speed and sustainability (UPS 2021).

Therefore, to be able to effectively take advantage of the customers' intrinsic willingness to compromise on delivery time, it is crucial to better inform them about the environmental impact of the chosen delivery mode. In concrete terms, this means that online retailers need to find tools that facilitate the choice of eco-friendly delivery options and integrate them into the check-out page of their website (Buldeo Rai et al. 2021). Two basic approaches can be pursued for this purpose: The use of financial and non-financial incentives. Financial incentives typically take the form of discounts or extra charges on the delivery fee (Agatz et al. 2021). For instance, it is common for retailers to charge a higher delivery fee for popular delivery slots in the morning and evening rush-hour times in order to distribute demand evenly and avoid traffic congestions (Hübner et al. 2016). Additionally, since the location of a customer may have a great impact on the route plan and the generated vehicle miles, many retailers charge a location-based fee. This means that if a customer selects a time window that has already been selected by one or more customers from the same neighborhood, delivery fees are reduced for that specific time window (Hübner et al. 2016).

However, the use of financial incentives is problematic for several reasons. First of all, price incentives reduce profit margins, which can be particularly detrimental for low-margin business sectors like the e-grocery business (Srinivasan et al. 2002). Secondly, there is a risk that dynamic pricing strategies are greatly complicated since customers are inclined to postpone their order in the hope of receiving further discounts (Zhang et al. 2020). Additionally, dynamically assigning delivery fees based on already accepted orders often triggers a sense of injustice and may thus even have a deterrent effect on customers (Weisstein et al. 2013; Xia et al. 2004). For this reason, consumers are very price sensitive to delivery fees, leading to an overall aversion to bear the costs of delivery (Buldeo Rai et al. 2019; Nguyen et al. 2019). Overall, high delivery fees are the main cause for customer churn, which is why it is essential to investigate to what extent intrinsic, non-financial incentives are suitable alternatives to steer customers toward more environmentally friendly delivery options (Galante et al. 2013).

In this regard, a recent study by Agatz et al. (2021) provides meaningful insights. The authors examine the impact of green labels and price incentives on customers' time window choices. In their study, green labels present themselves as green markings of environmentally friendly time windows in combination with an information text indicating the associated environmental savings that can be achieved through the choice of these time windows. In this work, too, the notion of green labels will serve as an umbrella term for any kind of non-financial incentive that highlights certain time windows or time window lengths as environmentally friendly.[1] Agatz et al. (2021) show the effectiveness of green labels versus price incentives or no incentives in steering customers toward longer or more sustainable time windows using two experiments. Additionally, two simulation studies demonstrate the strong impact of the varied effects of green labels on downstream operational system performance (Agatz et al. 2021). Apart from the aforementioned study, there is only a small number of further studies that jointly address e-commerce delivery, sustainability and consumer behavior. Fu and Saito (2018), for example, question whether consumers even want convenient and fast delivery. The authors examine how many additional days customers would be willing to wait for their delivery in the presence of economic and environmental incentives. Similar to the approach of Agatz et al. (2021), the potential of environmental incentives such as a CO_2 equivalent to influence preferences for home delivery options is investigated. Ignat and Chankov (2020) also pick up the idea of providing additional information on the environmental impact of the chosen last-mile delivery option. They differentiate between same day delivery and delivery within 2-3 days and display the respective levels of CO_2 emissions ranging from 15 to 400 grams. In addition, Buldeo Rai et al. (2021) investigate the potential of different types of non-financial incentives to drive sustainable e-commerce delivery. Four non-financial incentives are considered in total, namely a positively formulated information message, placing the more

[1] Thus, the terms *(green) label(s)* and *(non-financial) incentive(s)* are used synonymously in this paper.

sustainable delivery options first, including a social media sharing option and providing a descriptive social norm pointing out the more environmentally friendly delivery option. Thereby, a distinction is made between the eco-friendly delivery mode of delivering within the next three days and the less sustainable next day delivery. It is concluded that informing customers about the ecological footprint of delivery options is the most effective of all non-financial incentives (Buldeo Rai et al. 2021).

After a close examination of the existing literature, it becomes clear that the focus lies on using monetary and environmental incentives to steer customers to wait a certain number of *days* longer. The role of non-financial incentives to motivate consumers to choose environmentally friendly *time windows* for a predetermined delivery day as well as the impact of slot choice behavior on operational efficiency and environmental sustainability is therefore somewhat neglected. Likewise, the line of research that directly quantifies and evaluates the carbon footprint of time windows in the context of last-mile deliveries is limited. The potential of sustainable time window management in combination with the effects of green incentives on customers' time window choices therefore needs to be extended.

4 Research Objective and Research Questions

With online retail increasing in its popularity, it has become an imperative for logistics service providers to find ways to make e-commerce deliveries more efficient and sustainable. Given the massive impact the last-mile has on the total logistics costs and the environment, the appropriate operational measures and incentives that can be implemented to steer customers toward more efficient and sustainable delivery choices are an interesting field of research. In this context, especially the potential that can be unlocked from time window management has long been overlooked. In light of changing customer behavioral patterns during COVID-19, in which working from home offices seems to be normalizing in many sectors, this topic is becoming increasingly relevant (EC 2020). Since more and more customers are at home most of the day, they are no longer tied to tight time windows for home deliveries. This may also allow them to select those time windows that allow for efficient and environmentally friendly route plans.

At this point, it is recalled that CO_2 emissions are prevalently used as a measure to assess the sustainability dimension of transport activities, and total vehicle miles for the efficiency dimension (Agatz et al. 2021; Borken 2003). To evaluate the relationship between distance travelled and carbon emissions and, consequently, between operational efficiency and environmental sustainability, reference is made to Ehmke et al. (2018). The authors demonstrate that with a distance minimizing objective, average distance, duration, and fuel consumption levels deviate from those in the case of a fuel minimizing objective. However, their results also show that in the presence of a distance minimization or fuel minimization objective, more similar delivery route plans are created than in the case of a time minimizing objective. As fuel consumption is mathematically directly related to CO_2 emissions, the findings can be applied to the objective function of minimizing the level of CO_2 emissions accordingly. The consequential assumption that distance and fuel minimizing objective functions generate relatively similar route plans is especially reasonable for urban, inner-city instances. The reason for this is that there is less distance between customers living in urban areas, which gives logistics service providers a more limited scope to use alternative routes that may allow for distance or fuel savings and thus create differences in the solutions resulting from a distance or fuel minimizing objective (Ehmke et al. 2018).

Thus, it is in this study argued that CO_2 reductions are automatically accompanied by distance reductions (or vice versa), which taken together directly affect the efficiency of a delivery route. This makes it possible to focus on determining the sustainability dimension of a route plan and simultaneously draw conclusions on the associated operational efficiency.

In the context of time window management, sustainability implies that the choice of certain time windows is associated with relative system-wide fuel savings and CO_2 emission decreases. In other words, from a time window offer set containing several time windows to choose from, the selection of environmentally friendly time windows leads to lowermost increase in CO_2 emissions and thus the highest relative CO_2 emission savings potential[2]. That being said, the sustainability dimension of time windows has two manifestations. In the case of a mixed time

[2] Since even the most environmentally friendly time windows inevitably lead to an increase in CO_2 emissions, the term CO_2 savings (potential) used in the further course of this paper always refers to the *relative* CO_2 savings (potential) compared to less environmentally friendly time windows.

window offer set, it is conditioned by time window length, i.e., longer time windows are more sustainable. When considering a set of time windows of uniform length, on the other hand, the environmental impact of a time window is largely dependent on whether a delivery truck is already in the vicinity of the customer during the selected time window. In this case, time windows that have already been booked by nearby customers, for example, are most sustainable. For both longer and the most environmentally friendly time windows from a set of time windows of uniform length, the synonym *green time windows* is used in this work.

Due to the limited body of literature on sustainable time window management, it is not yet clear to what extent green time windows contribute to more environmentally friendly and efficient route plans. Consequently, this study aims to fill this gap by focusing on the following research questions:

RQ 1: How high is the relative CO_2 savings potential that emanates from green time windows in last-mile deliveries?

Naturally, having determined green time windows has no practical relevance if these time windows are not selected by the customers. While the existing body of literature on last-mile delivery operations has shown that non-financial incentives generally work well to encourage customers to behave in a more environmentally friendly way (e.g., Agatz et al. 2021; Buldeo Rai et al. 2021), the full potential of using green incentives to steer customers toward more sustainable time window choices has not yet been fully explored. This leads to the following second research question:

RQ 2: How can service providers effectively steer consumers to choose green time windows as their preferred last-mile delivery option?

By better understanding to what extent the indication of the environmental impact of given time windows would convince e-commerce participants to choose a potentially longer or less convenient, but much more sustainable time window, logistics service providers could gain an important competitive advantage. This would enable them to design delivery methods that are not only environmentally friendly, but also appealing to customers in the long run (Ignat and Chankov 2020).

5 Simulation Study

In this section, a simulation of a vehicle routing problem with time windows is used to investigate the environmental implications of customer time window choices and, consequently, to answer Research Question 1. The simulation represents the following situation: A supermarket offers its customers a home delivery service for groceries. To increase the likelihood of successful delivery, all customers are presented with a set of time windows to choose from. Since the nature of a simulation does not require interviewing real customers, time window choices of fictitious customers are imitated under varying framework conditions and assumptions. Based on simulated time window choices in different scenarios, CO_2 minimizing route plans are created.

In order to identify green time windows in last-mile deliveries and to determine the associated CO_2 savings potential, the simulation is divided into three successive steps. In the first step, the sustainability dimension of time window choices is examined in view of *time window length*. Thereby, the aim is to identify whether the expected carbon footprint of the delivery route decreases significantly when *all* customers choose long instead of short time windows. The starting point for this is a selection of 20 fixed customer locations, as of now referred to as *baseline customers*, who are asked to choose a delivery time window between 10am and 8pm. This relatively small customer instance is chosen so that one delivery van is sufficient to serve all customers in a single delivery route. This allows for a much more direct assessment of CO_2 emissions resulting from customers' time window choices[3] than if the vehicle routing problem were to be expanded to heterogeneous vehicle fleets consisting of more than one delivery vehicle. For this customer base, the optimal route plans and the associated CO_2 emissions are determined in different scenarios taking time windows of varying lengths into consideration. The crucial assumption here is that in each scenario, the time window offer set only contains time windows of uniform length. After calculating the expected CO_2 emissions of the delivery route for all scenarios, a comparison of the results is used to determine the influence of time window length on the efficiency and sustainability of the delivery route. As all data on customer

[3] Clearly, given the nature of the simulation, CO_2 is not actually emitted. Hence, the specified CO_2 emissions refer to the expected CO_2 emissions associated with a (tentative) route plan.

locations and their time window preferences are assumed to be known at the beginning of the planning horizon, the time window allocation and determination of the route plans for the baseline customers is of static rather than dynamic nature. For this reason, the first part of the simulation is referred to as *static setting*.

To take a step toward dynamic time window management, the second part of the simulation is to determine how the route plan and the expected CO_2 emissions change when a 21st customer is inserted into the delivery system. In other words, after examining how the level of anticipated CO_2 emissions of a delivery route varies if all customers choose long instead of short time windows, the approach in the second step is to assess the environmental impact of the time window choice of an *individual* customer. In contrast to the static setting, in which the time window offer set in each scenario contains only one set of time windows of uniform length, the offer set in this scenario is divided into three subgroups of time windows of different lengths. The overall goal is to identify, for the additional customer, green time windows that generate the lowermost additional carbon emissions in last-mile deliveries. This is to be done in two ways, firstly by comparing the CO_2 emissions associated with each time window length, and secondly by juxtaposing the time windows within each subgroup to find out how even time windows of uniform length may differ in their CO_2 footprints. The assumption here is that the 21st customer is dynamically added to the delivery system only after the time window choices of the baseline customers, which are taken as given and known in advance, have already been confirmed in a binding manner. Therefore, the second step of the simulation is referred to as *partially dynamic setting*.

To investigate the potentially positive impact that could result from an identification and incentivization of green time windows in a more realistic context, a fully dynamic vehicle routing problem is simulated in the third and last step. Thereby, the baseline customers are assumed to place their orders dynamically, and the feasible time window leading to minimum additional CO_2 emissions is incrementally determined and marked as green for each newly arriving customer. Based on the simplifying assumption that all customers actually choose the incentivized time windows, it is then determined for the 21st customer which time windows can be offered to him or her and which can be marked as green. As the time windows are incentivized and allocated to all customers dynamically, the third step of the simulation is denoted as *fully dynamic setting*.

The existing literature on sustainable e-commerce deliveries has already shown that customers' time window choices impact last-mile delivery operations significantly. However, the focus to date has been almost exclusively on the influence of time window length, demonstrating that longer time windows are associated with increased planning flexibility, more efficient routing and reduced travel distances (Köhler et al. 2020). This study goes one step further by shedding light on the differences between both time windows of uniform length and time windows of different lengths in terms of their carbon footprint. To the best of the author's knowledge, this is among the first studies to calculate and evaluate the carbon footprint of time windows in the context of last-mile deliveries.

5.1 Simulation Setup

The delivery area is defined as a road network overlaying the city of Vienna, Austria, as it depicts a dense distribution of customers in an urban area. Within this area, 21 nodes are randomly selected, which display the 20 baseline customer locations as well as one fixed location for the depot. In order to determine how the expected carbon footprint of the delivery route carried out by one delivery vehicle changes with increasing time window length (static setting), four scenarios are considered for the baseline customers. All scenarios are run five times for different customer-time-slot-combinations to be able to calculate a representative average value of the respective level of CO_2 emissions for each scenario. In the first scenario, it is assumed that all 20 customers select *no time windows*[4], i.e., the logistics service provider is free to decide at what time which customer should ideally be supplied. The second scenario is used to represent the situation in which all customers exclusively choose *five-hour time windows*. Available for selection are the time windows from 10am to 3pm, 12pm to 5pm and 3pm to 8pm. Similarly, in the next scenario, the route plan is determined and the expected CO_2 footprint is calculated given the assumption that all 20 customers choose a time window from a selection of five consecutive, non-overlapping *two-hour time windows* from 10am to 8pm. The same is calculated in the fourth scenario for ten non-overlapping and consecutive *one-hour time windows* in the same period. For the sake of simplicity, the ten-hour, five-hour, two-hour

[4] Since choosing no time windows implies that the customer can be served at any time on the delivery day, it is equivalent to choosing a ten-hour time window from 10am to 8pm.

and one-hour time window scenarios from the static setting are denoted as S_{10}, S_5, S_2 and S_1, respectively. In all scenarios, the time windows available for selection are allocated to the customers on a random basis, sometimes requiring small manual adjustments to ensure that a feasible solution is created with the time window allocation.

In the partially dynamic setting, in which the carbon footprint associated with an *individual* customer's time window choice is determined, it is hypothesized that the vehicle deployed to deliver the baseline customers can only serve exactly one additional customer. The 21st customer thus marks the cut-off time, after which no further orders are accepted and the route for the considered delivery vehicle is finalized. It is further assumed that the baseline customers had already placed their orders and selected their preferred delivery time window from a range of time windows of different lengths. The time window offer set includes the same subgroups of one-, two- and five-hour time windows extending over a period from 10am to 8pm as defined in the static setting. The condition in which the 20 baseline customers make their slot choices from a mixed time window offer set in the partially dynamic setting is referred to as *baseline scenario (B_{20})*. The expected CO_2 emissions associated with the optimized tentative route plan in B_{20} represent a benchmark value, with which those of the final route plan after integration of the 21st customer are compared. For this customer, too, a location within Vienna is selected randomly, and the tentative route plan in B_{20} is updated and optimized for each of the one-, two- and five-hour time windows available for selection. This makes it possible to determine which individual time windows or time window lengths generate the lowest additional CO_2 emissions when compared to the benchmark value and can be labelled as environmentally friendly. The condition in which an additional 21st customer is included in the delivery system in the partially dynamic setting is referred to as PD_{21}. As to obtain robust and meaningful results that do not merely depend on the random location of the new customer, PD_{21} is run for a total of five different, randomly selected customer locations. This results in five distinct variants of PD_{21}, denoted as PD_{21A}, PD_{21B}, PD_{21C}, PD_{21D} and PD_{21E}, respectively. In each scenario, the carbon emissions associated with each of the ten one-hour, five two-hour and three five-hour time windows are calculated. This results in a total of 18 instances for each location, which, together with the baseline scenario, yields 91 instances altogether.

In the fully dynamic setting, the first step is to incrementally examine, for each customer separately, which time window from an offer set consisting exclusively of one-hour time windows leads to the lowest additional CO_2 emissions. This scenario in the fully dynamic setting is denoted as FD_A. Subsequently, the same is checked again for a time window offer set evolving with the arrival of new customers, temporarily including only five-, two- or one-hour time windows. This scenario is denoted as FD_B. In both cases, it is assumed that the first 20 customers all choose the time windows proposed to them, so that the time window that can be marked as green for the 21st customer is determined based on the dynamic time window allocation for the 20 customers arriving earlier in the booking process.

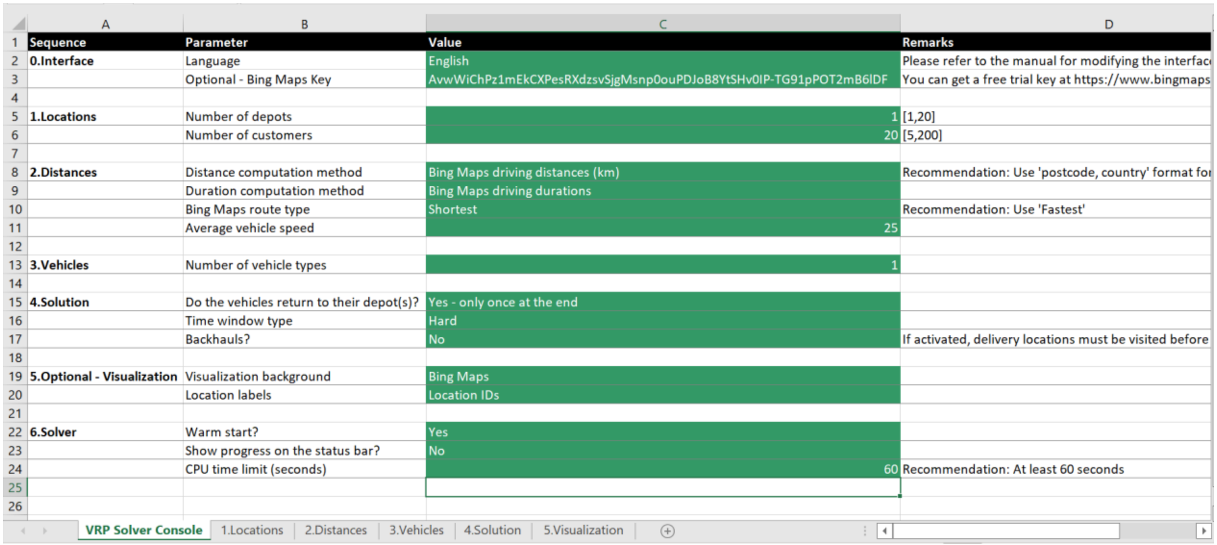
For the simulation of the vehicle routing problem and the calculation of the carbon emission values, the VRP Spreadsheet Solver is used. The structure of the worksheets is described in the following section.

5.2 VRP Spreadsheet Solver

The VRP Spreadsheet Solver was developed by Dr. Güneş Erdoğan and is a standard tool with which the results of VRPs are stated, solved, and visualized (Erdoğan 2020). The Excel tool is well suited for the purpose of this work, as it can solve the most studied basic variants of the VRP with up to 200 customers (Erdoğan 2017). Solving a vehicle routing problem with the VRP Spreadsheet Solver involves six steps. In the beginning, the Excel workbook only contains the worksheet named VRP Solver Console, in which all relevant data needs to be entered. Subsequently, the remaining worksheets 1.Locations, 2.Distances, 3.Vehicles, 4.Solution, and 5.Visualization are generated. Thanks to embedded features to query a GIS web service, the distances, driving times, and maps can be easily retrieved (Erdoğan 2017). For the final solution, a variant of the Large Neighborhood Search (LNS) algorithm is implemented within the Excel tool. In sum, the VRP Spreadsheet Solver stores the data about the components of a vehicle routing problem in separate worksheets and adopts an gradual information flow (Erdoğan 2020). In the following, each of the five worksheets are described in more detail.

VRP Solver Console

The VRP Solver Console contains relevant parameters about the size of the instance being solved, including the number of depots and customers. Köhler et al. (2020) show that three delivery vehicles operating from one fixed depot are sufficient to serve approximately 75 customers per day, which in turn means that each vehicle has the capacity to handle up to 25 customers daily. For this reason, one depot is selected and the number of customers to be served by one delivery vehicle is set to 20 or 21, depending on the scenario, as to allow for a certain buffer. For the population of the distances, Bing Maps driving distances (km) are selected. Accordingly, the duration computation method is set to Bing Maps driving durations. Since the objective of this VRP is to minimize the expected carbon emissions associated with a delivery route, which to a large extent depend on the distance traveled, the Shortest option is set for the parameter Bing Maps route type. Given that Vienna is a heavily congested city, especially at peak times, the average vehicle speed is set to 25 km/h. Moreover, a standard home delivery setting is assumed, in which the delivery van is loaded once in the beginning of the working day and returns to the depot only after all scheduled deliveries have been completed. As attended home deliveries generally do not include any pickups along the way, backhauls are not considered in this problem. Tardy deliveries often significantly reduce customer satisfaction, especially in the case of attended home deliveries, therefore only hard time windows are included. A Central Processing Unit (CPU) time limit of 60 seconds was found to be sufficient to for the program to find a good solution. Figure 2 shows a screenshot of the VRP Solver Console and the parameters entered in B_{20}.



	A	B	C	D
1	Sequence	Parameter	Value	Remarks
2	0.Interface	Language	English	Please refer to the manual for modifying the interfac
3		Optional - Bing Maps Key	AvwWiChPz1mEkCXPesRXdzsvSjgMsnp0ouPDJoB8YtSHv0IP-TG91pPOT2mB6lDF	You can get a free trial key at https://www.bingmaps
4				
5	1.Locations	Number of depots	1	[1,20]
6		Number of customers	20	[5,200]
7				
8	2.Distances	Distance computation method	Bing Maps driving distances (km)	Recommendation: Use 'postcode, country' format fo
9		Duration computation method	Bing Maps driving durations	
10		Bing Maps route type	Shortest	Recommendation: Use 'Fastest'
11		Average vehicle speed	25	
12				
13	3.Vehicles	Number of vehicle types	1	
14				
15	4.Solution	Do the vehicles return to their depot(s)?	Yes - only once at the end	
16		Time window type	Hard	
17		Backhauls?	No	If activated, delivery locations must be visited before
18				
19	5.Optional - Visualization	Visualization background	Bing Maps	
20		Location labels	Location IDs	
21				
22	6.Solver	Warm start?	Yes	
23		Show progress on the status bar?	No	
24		CPU time limit (seconds)	60	Recommendation: At least 60 seconds
25				
26				

Figure 2: Parameters entered in the VRP Solver Console (B_{20})

Locations

In the second step, the customer locations as well as the location of the depot are entered. For the depot, an address in the industrial park Inzersdorf in the 23rd district is chosen, as the logistics center of large food store chains like REWE group are also situated there. The 20 randomly selected customer locations for the baseline scenario cover all districts of Vienna except for the 6th, 12th, 14th, 15th, 18th and 20th district. After entering the addresses manually, the latitude and longitude of each coordinate is populated using the GIS web service and the following scatter chart displaying all customer locations as well as the location of the depot (represented as a black square in Figure 3) is generated:

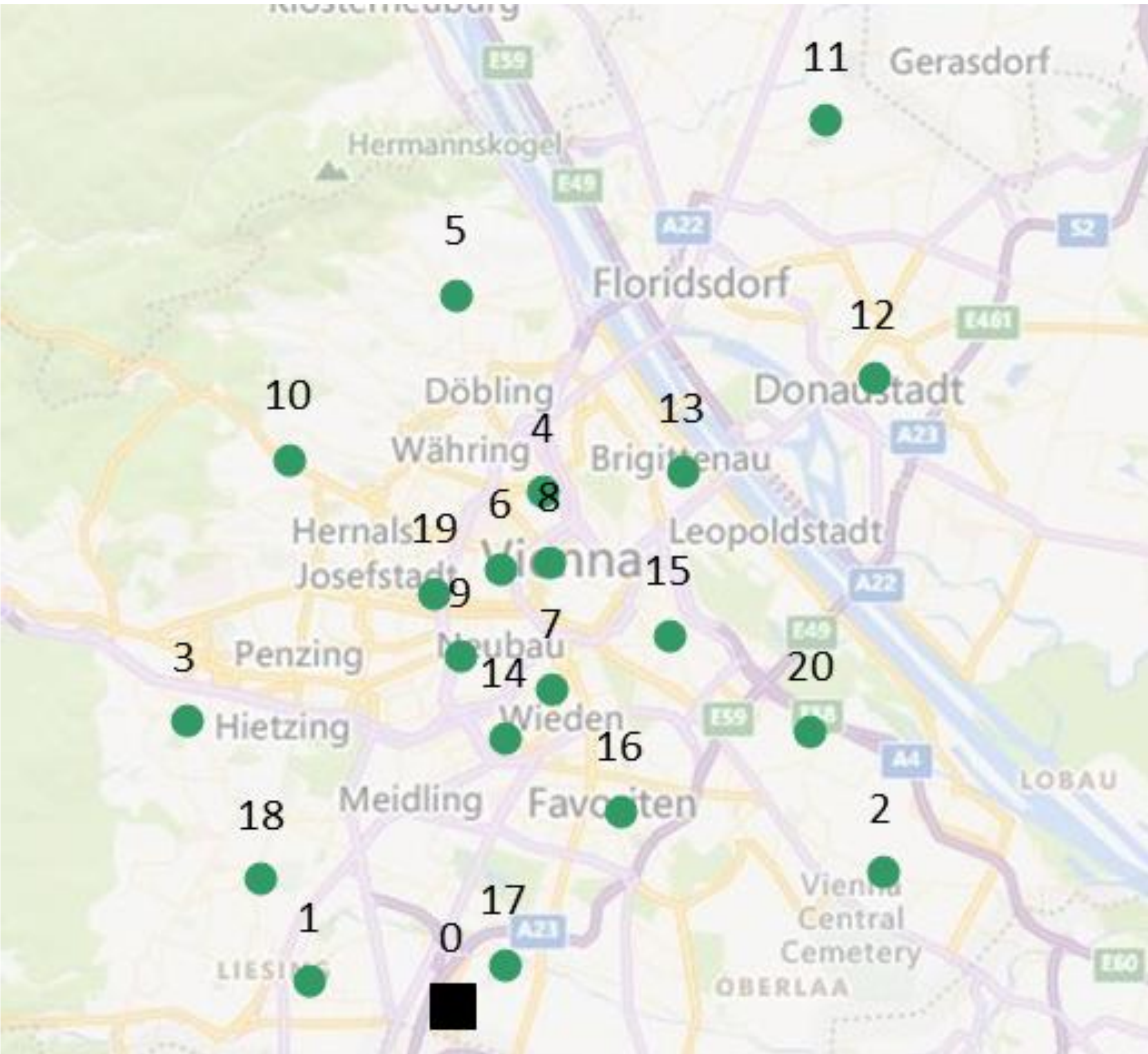


Figure 3: Locations of the 20 baseline customers and the depot

It is assumed that each customer has to be visited exactly once. The delivery time windows, which are entered separately for each customer, are readjusted for each scenario and simulation step. The service time is set to 150 seconds, which is for instance the target for the time in which a postman or postwoman should deliver a package (Kwasniewski 2016). As capacity should not be the limiting factor in this problem, the pickup and delivery amounts are considered to be zero. Additionally, as the center of attention lies on the environmental costs related to attended home deliveries within specific time windows rather than the financial return, the profit for each customer is also set to zero.

Distances

Using the coordinates of the customer locations, which are automatically calculated by the VRP Spreadsheet Solver, a distance matrix including the associated travel durations is created in the next step. However, as the central focus of this study is to compare the total carbon emission values associated with each feasible time window, distances between customers have to be quantified as the level of emissions generated, not distance travelled. In other words, the vehicle routing problem is optimized according to minimum CO_2 emissions rather than minimum distance. Here, it should be noted that even though the number of electric-powered delivery vehicles is increasing, this transition is happening very slowly, which is why the goal of minimizing CO_2 emissions in last-mile deliveries remains highly relevant. For the calculation of transport-related CO_2 emissions, the MEET model is used. Depending on the weight class of a vehicle, MEET suggests different functions for the estimation of the rate of CO_2 emissions per kilometer. For a standard grocery home delivery van, which typically weighs less than 3.5 tons, a speed-dependent regression function of the form

$$e(v) = 0.0617v^2 - 7.8227v + 429.51$$

is recommended (Hickman et al. 1999). Furthermore, the model proposes a number of correction factors depending on vehicle type and weight to include the effects of road gradient and vehicle load on the emissions into the equation. Yet, since these corrections only come into effect for vehicles weighing over 3.5 tons, they can be neglected for the purpose of this study. This results in a rather simple calculation of the CO_2 emission factor (in grams per kilometer) for a given speed v of

$$e(v) = 0.0617 \times 25^2 - 7.8227 \times 25 + 429.51 = 272.505\ g/km.$$

Subsequently, the total CO_2 emissions (in grams) for a given speed v and distance D are calculated as

$$E(v, D) = e(v) \times GC(v) \times LC(v) \times D,$$

where GC(v) is the gradient correction factor and LC(v) is the load correction factor (Bektaş et al. 2016). Since both factors can be neglected for vehicles weighing less than 3.5 tons, the total CO_2 emissions per kilometer add up to

$$E(v, D) = 272.505\ g/km \times D.$$

The distances D can be retrieved from the distance matrix generated by the VRP Spreadsheet Solver and displayed in the Distances worksheet. By multiplying all values in the distance matrix by *272.505*, a CO_2 matrix is created. Instead of showing the distances between all customers as well as the depot and the customers, the emissions emitted on the respective routes are specified in the CO_2 matrix.

Due to the linear relation between CO_2 emissions and distance travelled suggested in the formula of the MEET model, the solver comes to the same route plans when optimizing for minimum CO_2 emissions as for minimum distance. At this point, it must be noted that a perfect linear relationship between distance and CO_2 emissions is a simplifying assumption that does not exist in reality. Yet, with reference to Ehmke et al. (2018), a simplified linear relationship between distance and CO_2 emissions can be assumed for the purpose of this study.

Vehicles

For the vehicle routing problem at hand, only one vehicle type, a standard food delivery van, is considered. The capacity dimension is irrelevant in this case, as it is assumed that the van has enough load capacity to execute all deliveries and pickup or delivery quantities are neglected in this problem. Additionally, since monetary costs are not of interest in this study, the fixed costs are set to zero. The costs per unit distance are the variable costs incurred on each delivery route. In the case of a CO_2 minimizing objective function, they represent the CO_2 emissions per kilometer as calculated using the MEET model. However, since these were already factored into the CO_2 matrix to be able to see the CO_2 emissions between all customers as well as the customers and the depot prima facie, the costs per unit distance are set to one. As only one vehicle type is considered and since the fact that delivery vans may drive slightly slower than normal cars was already taken into account by assuming an average speed of 25 km/h, the duration multiplier is not necessary to scale down the vehicle speed and is set to one. The distance limit in the Vehicles worksheet denotes the maximum distance a delivery vehicle can travel. However, since distances were transformed to carbon emissions, the parameter in this study indicates the maximum level of CO_2 emissions. It is assumed that the delivery vehicle is refueled during the night and that its range is enough to cover a day trip, so the distance travelled and the related CO_2 emissions are not a binding constraint. For this reason, the maximum CO_2 emissions are randomly set to a very high value of 2000000000 grams. The driver of the delivery vehicle is assigned a driving time limit of nine hours as per the European Union rules on drivers' hours and working time (DfT 2015). Since the time windows range from 10am to 8pm, i.e., a time span of ten hours, the working time is limited to ten hours. For the given scenarios with 20 and 21 customers, respectively, one delivery vehicle is deployed.

Solution

In this worksheet, the final route for each deployed delivery vehicle is detailed. As only one delivery vehicle is considered in this study, the sequence of customers to be served only concerns precisely that vehicle. With the help of the information on customer locations, service times, as well as the thereby populated distance and duration values, the departure and arrival times between customers are computed in the solution worksheet. If applicable, reasons for infeasibility are detected and specified. The latter is especially the case if the driver arrives after a time window has closed and thus violates the hard time window constraint, or if the maximum driving or working time is exceeded. In the third column, the cumulative travel costs are indicated. In this study, in which the VRP has a CO_2 minimizing objective, the travel costs are to be interpreted as cumulative CO_2 emissions. In addition, orange-colored cells provide warnings. These signals indicate that the delivery vehicle arrives before the start of the time window and therefore must wait, resulting in inefficient utilization of the driver's capacity. Since only the environmental costs incurred are of interest for the present research question and the profit remains constant at zero, the total profit can be translated into total environmental costs and arises from the negative value of the cumulative CO_2 emissions (in grams) of the respective solution. The values resulting from the generated routes in each simulation run can thus be compared straightforwardly and those leading to particularly unfavorable or favorable solutions in terms of their environmental impact can be directly identified.

Visualization

The last worksheet contains a scatter chart, which displays the customer locations and the route plan on a map of the delivery region retrieved from the GIS web service. While the Solution Worksheet allows for a straightforward assessment of the impact of customers' time window choices on the environmental sustainability associated with a delivery route, the Visualization worksheet is particularly useful for drawing conclusions on the corresponding operational efficiency. For example, long distances between customers, which are in large part a result of their respective time window choices, or routes that cross multiple times are clear indicatives of inefficient routes.

Figure 9, Figure 10, Figure 11 and Figure 12 in the Appendix show screenshots of the Distances, Vehicles, Solution and Visualization worksheets generated for B_{20}. In each scenario, the routes are optimized using the LNS algorithm implemented within the VRP Spreadsheet Solver.

5.3 Large Neighborhood Search Algorithm

To date, a large number of solution algorithms to solve different variants of the VRP have been developed. As the VRP Spreadsheet Solver by Erdoğan and Miller-Hooks (2012) was designed to solve over 64 VRP variants, the authors provide a formulation of the VRP that unifies all the variants the VRP Spreadsheet Solver can handle and incorporates their respective constraints (Erdoğan 2017). For a detailed formulation of the VRP including all relevant constraints, please refer to Erdoğan (2017).

The algorithm implemented in the VRP Spreadsheet Solver to solve the formulated problem is a version of the Adaptive Large Neighborhood Search (ALNS) of Pisinger and Ropke (2007), as ALNS can flexibly solve several variants of the VRP (Erdoğan 2017). The ALNS framework is a natural extension of the widely used Large Neighborhood Search formulated by Shaw (1998), in which an initial solution is gradually relaxed and reconstructed by modifying a significant number of variables in each iteration (Ancion and Dardenne 2016; Pisinger and Ropke 2007). The distinctive idea of ALNS is that the relaxation and reconstruction procedures are adapted or changed throughout the search (Ancion and Dardenne 2016). The neighborhoods are searched by several simple and fast algorithms that compete to change the incumbent solution. This means that in each iteration, heuristics are used to partially destroy and then repair the solution at hand (Pisinger and Ropke 2007).

The algorithm implemented in the VRP Spreadsheet Solver works accordingly. The exact steps, as specified by Erdoğan (2017), are as follows. An incumbent solution is generated by adding customers to the route and selecting, in each iteration, the customer that leads to the minimum increase in costs. In the case of this study, this would translate into a minimum increase in CO_2 emissions. Using a number of local search operators, the tentative solution is then improved and subsequently recorded as the best-known solution. Among the local search operators is the *EXCHANGE* operator, which searches all feasible customer pairings in an existing solution and evaluates whether exchanging them would improve the value of the objective function. The second operator, named *1-OPT*, tests whether better results can be achieved when every customer in a given solution is removed from the existing position and reinserted to an alternative position in the delivery sequence. To avoid inefficient crossings within the route, the *2-OPT* operator is applied, which simultaneously removes arcs between two customer pairings from the solution and reorders them in a way in which they do not intersect. The fourth operator in the algorithm, *VEHICLE-EXCHANGE*, does not come into play in the routing problem this study is concerned with, as only one delivery vehicle is considered. After improving and recording the incumbent solution as the best-known solution, it is once again destroyed and repaired by removing and adding vertices on a random basis. The incumbent solution is repaired using the greedy insertion and max regret heuristics, whereas for both heuristics, the probability of being selected is equal at each iteration. Greedy insertion subsequently inserts the customers on a random basis into the position of the route plan that minimizes the insertion cost (Hemmelmayr et al. 2012). With the max regret heuristic, the customer is chosen for whom the discrepancy between the cost of the cheapest and second cheapest insertion position is the greatest. In the next step, the incumbent solution is once again improved through the abovementioned local search operators and, in case it yields better results than the existing best-known solution, is recorded as the new best-known solution. A solution that does not improve the value of the objective function is accepted with a probability *p*. This process is repeated until the CPU time limit is reached. The probability of accepting a non-improving solution is 10% at the beginning of the runtime and reduces linearly to a probability of 0% as soon as the runtime is larger the CPU time allowed (Erdoğan 2017). For a high-level pseudocode implemented within the VRP Spreadsheet Solver, see Figure 15 in the Appendix.

5.4 Simulation Results

In each simulation run, all parameter settings remain the same, with the exception of the number of customers to be served and the time windows, which are reallocated in each scenario. All simulations are run on a Windows 10 Enterprise 64-bit operating system with an Intel Core i5-8365U processor and 16 GB of RAM.

5.4.1 Static Setting

Table 1: Average additional CO_2 emissions per time window length

Scenario	Average CO_2 emissions (in gm)
S_{10} (No time windows)	24176.10
S_5 (Five-hour time windows)	28772.39
S_2 (Two-hour time windows)	37490.58
S_1 (One-hour time windows)	42185.90

All scenarios in the static setting are repeated multiple times for different customer-time-slot-combinations to be able to calculate a representative average value of the CO_2 emissions associated with each time window length. Table 1 shows that in scenario S_{10}, in which none of the 20 customers are able to choose a time window and all customers can therefore be supplied at any possible time between 10am and 8pm, CO_2 amounting to 24.18 kilograms is emitted on average. This is about 4.60 kilograms (15.97%) less than in scenario S_5, in which all 20 customers are supplied in five-hour time windows and CO_2 emissions on average amount to

28.77 kilograms. Although associated with higher average CO_2 emissions than in the case in which no time windows are offered, S_5 leads to significantly lower CO_2 emissions on average than S_2. Effectively, the scenario in which all customers choose two-hour time windows results in average CO_2 emissions of 37.49 kilograms. This represents an increase of 8.72 kilograms (23.25%) in comparison with S_5. Compared to S_{10}, the difference elevates to 13.31 kilograms (35.51%). The increase in average CO_2 emissions is also large if instead of two-hour time windows, only one-hour time windows are chosen by all customers. In S_1, the average CO_2 emissions increase to 42.19 kilograms, which represents a difference of 4.70 kilograms (11.13%) compared to S_2. In comparison with S_5 and S_{10}, the increase amounts to 13.41 kilograms (31.80%) and 18.01 kilograms (42.69%), respectively. The fact that shorter time windows lead to significantly more inefficient solutions than longer time windows becomes evident when looking at the respective sample route plans as shown in Figure 13 and Figure 14 in the Appendix. For instance, while the scheduled delivery route in S_{10} only crosses once, it does so several times in S_5, which is a clear indication of a more inefficient route.

An overarching comparison of the scenarios shows that average CO_2 emissions can almost double, depending on whether no time windows or one-hour time windows are selected. But even when comparing one-hour and two-hour time windows, which seemingly differ only insignificantly in length, major differences in average CO_2 emissions emerge. This shows that the length of the time windows has a great impact on the expected carbon emissions associated with a delivery route and correspondingly the efficiency of the delivery system as a whole.

Since the choice of the time window length for a group of 20 customers leads to such varying levels of average CO_2 emissions, the question arises as to what difference the time window choice of a single customer can make. In this context, it is of particular interest to see how CO_2 emissions change not only when contrasting different time window lengths, but also when comparing the environmental impact resulting from time window choices of uniform length. To answer these questions, a simulation assuming a partially dynamic setting is conducted, which is described in the following chapter.

5.4.2 Partially Dynamic Setting

In this setting, all customer locations from the static setting remain the same, the crucial difference lying in their time window choices and the fact that an additional customer is inserted into the tentative route plan. To be able to evaluate the environmental impact of the time window choice of the 21^{st} customer, a baseline scenario with 20 customers has to first be established to serve as a reference point. The results of the baseline scenario are discussed in chapter 5.4.2.1. On this basis, it is possible to examine the effect of the integration of customer 21_A (corresponding to scenario PD_{21A}) into the delivery system, which is covered in chapter 5.4.2.2. A comparison of the additional CO_2 emissions associated with the selection of each of the feasible time windows makes it possible to identify those time windows that lead to the lowermost increase in the CO_2 benchmark value and can be labelled as green for the 21^{st} customer. In addition, the results obtained within the different subgroups of time window lengths are compared with each other. The aim is to find to what extent the additional CO_2 emissions associated with the 21^{st} customer's time window choice can be reduced through increased the time window length, i.e., when comparing one-hour and two-hour, one-hour and five-hour and two-hour and five-hour time windows. Apart from evaluating the environmental impact associated with the 21^{st} customer's time window choice, attention is paid to the extent to which the routes become more feasible through increased slot length. In chapter 5.4.2.3, the location of the 21^{st} customer is varied, and the results of PD_{21B}, PD_{21C}, PD_{21D} and PD_{21E} are evaluated in a more comprehensive manner.

5.4.2.1 Baseline Scenario

In the baseline scenario, it is assumed that all 20 customers choose a delivery time window out of a time window offer set consisting of three subgroups of one-, two- and five-hour time windows. The design of the time window offer set is made in accordance with the study of Agatz et al. (2021), however, a few adjustments regarding the length of the available time windows were made. Table 2 in shows an overview of the time windows offered, including an indication of how many customers they are allocated to.

Table 2: Mixed time window offer set in the partially dynamic setting

SlotID	One-hour		Two-hour		Five-hour	
1	10am to 11am	3x	10am to 12pm	1x	10am to 3pm	
2	11am to 12pm	2x	12pm to 2pm	1x	12pm to 5pm	1x
3	12pm to 1pm	1x	2pm to 4pm		3pm to 8pm	4x
4	1pm to 2pm		4pm to 6pm		-	
5	2pm to 3pm	2x	6pm to 8pm	2x	-	
6	3pm to 4pm	1x	-		-	
7	4pm to 5pm		-		-	
8	5pm to 6pm	1x	-		-	
9	6pm to 7pm	1x	-		-	
10	7pm to 8pm		-		-	

The time windows are assigned to the customers on a random basis, with the majority of assigned slots (11) being one-hour time windows. The underlying assumption is that most customers prefer short over long time windows. In the baseline scenario, the expected total CO_2 emissions associated with the tentative route plan amount to 40922.08 grams or approximately **40.92 kilograms**. In the given solution, all customers can be served within their chosen time windows, therefore leading to a feasible route plan.

The total CO_2 emissions in the baseline scenario serve as a benchmark value in the further course of this study, with which all values of PD_{21} are compared. The time window choices of the first 20 customers in the baseline scenario are assumed to be fixed and immutable. In order to comply with the hard time window condition, the 21st customer can thus only be offered those time windows that lead to a feasible solution, i.e., a route plan in which each customer can be supplied within the selected time window. If the simulation shows that the choice of a certain time window leads to one or more customers receiving their deliveries late, it is assumed to be unavailable for the 21st customer.

5.4.2.2 Scenario PD_{21A}

The location chosen for customer 21_A is Bambergergasse 41 in the 22nd district, which is one of the outer districts of Vienna. There are no other customers in immediate proximity and the depot is also relatively far away. The scatter chart in Figure 4 shows the location of the 21st customer highlighted in red.

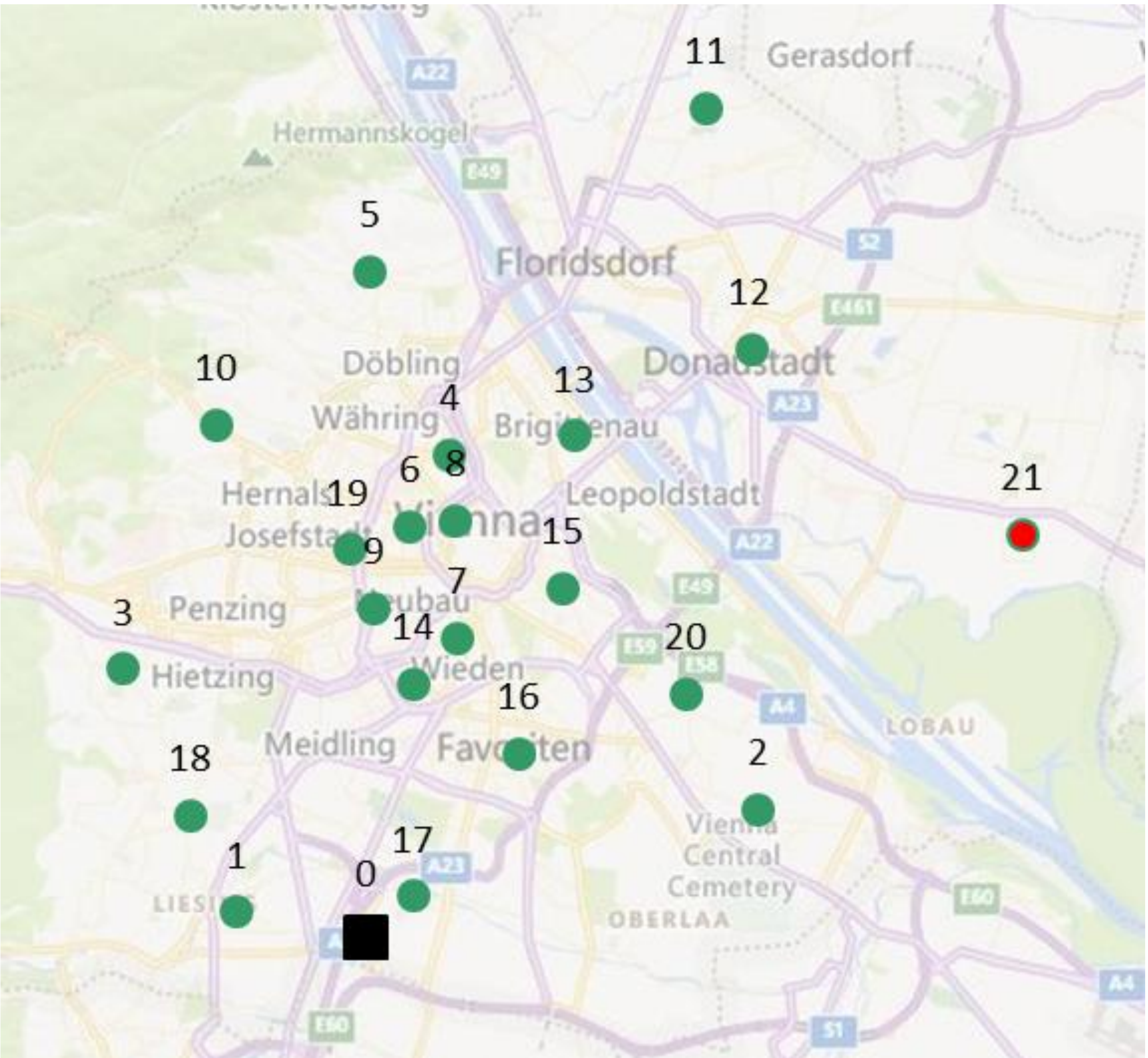


Figure 4: Location of customer 21_A in the partially dynamic setting

Table 3 depicts the environmental implications associated with each feasible time window that can be offered to the 21st customer. Thereby, the minimum and maximum CO_2 emissions as well as the minimum and maximum CO_2 increase compared to the benchmark and the corresponding time windows are specified. Additionally, the CO_2 savings potential within each of the three subgroups is indicated to demonstrate how much CO_2 can be saved at most when choosing the most environmentally friendly instead of the most environmentally harmful one-, two- or five-hour time window. Moreover, cross-comparisons are made between the different time window lengths to calculate the CO_2 savings potential from choosing longer instead of shorter time windows. In this context, is important to recall that the 21st customer in the partially dynamic setting marks the cut-off time, after which no further customers are integrated into the delivery schedule. As the route plan is thus finalized with the 21st customer's order placement, it can be determined at which position precisely he or she should be integrated in the delivery sequence to minimize the overall level of CO_2 emissions, whereby maintaining flexibility for the integration of future customers becomes irrelevant. The key difference between the time window sets of different lengths thus lies in the maximum rather than the minimum CO_2 emissions resulting from the selection of the time windows contained therein. Therefore, the choice of longer time windows makes the greatest difference if the delivery time is irrelevant for the customer and he or she has no information on the environmental impact of the available time windows. The CO_2 savings potential emanating from longer time windows is thus calculated through cross-comparisons of the CO_2 emissions resulting from the longer time window and the maximum CO_2 emissions associated with the shorter time windows contained within the same time period.

Table 3: Results for PD_{21A}[5]

	One-hour time windows	Two-hour time windows	Five-hour time windows
Min. CO_2 emissions	44192.95	44192.95	44192.95
Time window	4pm to 5pm	4pm to 6pm	12pm to 5pm; 3pm to 8pm
Max. CO_2 emissions	48248.92	46277.20	45197.41
Time window	7pm to 8pm	2pm to 4pm	10am to 3pm
CO_2 savings potential (within subgroup)	4055.96 (8.41%)	2034.25 (4.40%)	1004.45 (2.22%)
Min. increase to B_{20} (40922.08 gm)	3270.88 (7.40%)	3270.88 (7.40%)	3270.88 (7.40%)
Max. increase to B_{20} (40922.08 gm)	7326.84 (15.19%)	5305.13 (11.48%)	4275.33 (9.46%)
CO_2 savings potential (vs. one-hour time windows)	-	2357.99 (4.89%)	4055.96 (8.41%)
CO_2 savings potential (vs. two-hour time windows)	-	-	2034.25 (4.40%)
Infeasible time windows	3	1	0

One-hour time windows

To evaluate the impact of the available one-hour time windows on the route plan's sustainability and efficiency, the first column of Table 3 is used. Because of the long distances that need to be covered in addition to be able to deliver the 21st customer, the time windows from 10am to

[5] All values on CO_2 emissions, increases to B_{20} and the CO_2 savings potential in this table as well as the following tables in this chapter are consistently expressed in grams.

11am, 11am to 12pm and 2pm to 3pm become infeasible and cannot be offered to customer 21_A.

Depending on the selected feasible one-hour time window, the CO_2 emissions generated range from 44.19 kilograms to 48.25 kilograms, which is a difference of 4.06 kilograms. In other words, up to 8.41% of CO_2 emissions can be saved, solely depending on which of the ten one-hour time windows is chosen by the customer. The highest value is induced when the time window from 7pm to 8pm is chosen, as the delivery van must take the longest diversions to comply with this time window. The lowest additional CO_2 emissions are generated when the 4pm to 5pm time window is selected. Thus, choosing one of the ten one-hour time windows increases the CO_2 benchmark value by a minimum of 3.27 kilograms (7.40%) and a maximum of 7.33 kilograms (15.19%).

Two-hour time windows

The second column in Table 3 shows that amongst the two-hour time windows, only the time window from 10am to 12pm is not available for selection, as it would require 21_A to be served in midst of the already very tightly scheduled morning hours and lead to an infeasible route plan.

Examining the feasible two-hour time windows at hand, the minimum and maximum emissions that result from their selection are 44.19 kilograms, as in the one-hour case, and 46.28 kilograms. Compared to the benchmark value, this results in a minimum and maximum increase in CO_2 emissions of 3.27 kilograms (7.40%) and 5.31 kilograms (11.48%), respectively. Within the two-hour time windows, up to 2.03 kilograms (4.40%) of CO_2 emissions can be saved depending on which time window is chosen.

A comparison of the results of the two-hour with the one-hour time windows reveals that the two-hour time windows perform better with regard to maximum CO_2 emissions. In this scenario, for example, supplying the 21^{st} customer between 7pm and 8pm leads to particularly high CO_2 emissions of 48.25 kilograms. In the neighboring time window from 6pm to 7pm, they amount to only 45.89 kilograms. Thus, if a two-hour instead of a one-hour time window is chosen, the logistics service provider can schedule the deliveries in such a way that eliminates delivering the 21st customer between 7pm and 8pm and instead allows for suppling him or her between 6pm and 7pm. This makes a difference in CO_2 emissions of 2.36 kilograms (4.89%).

Five-hour time windows

When analyzing the third column in Table 3, it becomes apparent that each of the three five-hour time windows from 10am to 3pm, 12pm to 5pm and 3pm to 8pm lead to feasible solutions and can therefore all be offered to the 21st customer.

Through the selection of a five-hour time window, it can be ensured that the 21st customer is supplied at a feasible time window that furthermore results in relatively low additional CO_2 emissions. The three five-hour time windows available for selection lead to CO_2 emissions amounting to 45.20 kilograms, 44.19 kilograms and 44.19 kilograms, respectively. This represents a minimum increase in CO_2 emissions of 3.27 kilograms (7.40%) and a maximum increase of 4.28 kilograms (9.46%) compared to the benchmark value. Within the five-hour time windows, up to 1.00 kilogram (2.22%) of CO_2 emissions can be saved depending on which time window is chosen.

When comparing the five-hour with the one-hour time windows, the highest CO_2 savings potential results from the selection of the time window from 3pm to 8pm, associated with CO_2 emissions of 44.19 kilograms. During this period, all one-hour time windows are feasible and lead to minimum and maximum CO_2 emissions of 44.19 kilograms and 48.25 kilograms, respectively. Consequently, up to 4.06 kilograms (8.41%) can be saved through the selection of the 3pm to 8pm time window. Not only in comparison with the one-hour time windows, but also with the two-hour time windows, a considerable amount of CO_2 can be saved through the selection of five-hour time windows. The highest savings potential results from the choice of the time windows from 12pm to 5pm and 3pm to 8pm, as both allow for up to 2.03 kilograms (4.40%) of CO_2 savings.

To summarize, the results show that the time window choice of the 21st customer located in Bambergergasse 41 in the 22nd district entails direct, far-reaching effects on the sustainability and the efficiency of the route plan. Depending on the time window choice, the levels of CO_2 emissions range from 44.19 kilograms to 48.25 kilograms, which is a difference of 4.06 kilograms and 8.41%, respectively. The increase compared to the benchmark value is thus between 3.27 kilograms (7.40%) and 7.33 kilograms (15.19%). The savings potential resulting from the choice of two-hour instead of one-hour time windows is up to 2.36 kilograms (4.89%). In contrast to the one-hour scenario, where three different time windows cannot be offered to the 21st customer, this is the case for only one time window in the two-hour scenario. When one of the five-hour time windows is chosen, the maximum CO_2 savings potential in comparison with one-hour time windows increases to 4.06 kilograms (8.41%). Compared to two-hour time windows, the values change to 2.03 kilograms (4.40%). The five-hour scenario furthermore stands out against the other two scenarios in that it is the only one in which none of the time windows have to be removed from the time window offer set due to infeasibility. Arguably, while the number of five-hour or two-hour time windows offered is much lower compared to one-hour time windows, customers may feel less constrained in their decision-making ability if they can choose from a more restricted number of longer, but feasible time windows than if several shorter time windows have to be eliminated from the time window offer set altogether due to infeasibility.

5.4.2.3 Variation of the Customer Location

Since the final route plans and the associated CO_2 emissions depend significantly on the location of the 21st customer, it stands to reason that the previously discussed, pronounced results in scenario PD_{21A} are partly due to the customer's remote location. Therefore, it is interesting to see how the findings change as the location of the 21st customer varies. For this purpose, four additional locations are randomly selected for the remaining scenarios PD_{21B}, PD_{21C}, PD_{21D} and PD_{21E}:

- PD_{21B}: Wilhelminenstraße 84, 1160 Vienna, Austria
- PD_{21C}: Alma-Rosé-Gasse 2, 1100 Vienna, Austria
- PD_{21D}: Neulinggasse 29, 1030 Vienna, Austria
- PD_{21E}: Andersengasse 9, 1120 Vienna, Austria

As in the previous chapter, a tabular view is used to highlight the environmental implications of each feasible time window that can be offered to the 21st customer across all customer locations. For the sake of completeness, the previously discussed results in scenario PD_{21A} are also displayed with a grey background.

One-hour time windows

Table 4: Results for the alternative customer locations – One-hour time windows

	PD_{21A}	**PD_{21B}**	**PD_{21C}**	**PD_{21D}**	**PD_{21E}**
Min. CO_2 emissions	44192.95	40925.89	42436.39	40922.08	41486.97
Time window	4pm to 5pm	2pm to 3pm	6pm to 7pm; 7pm to 8pm	6pm to 7pm; 7pm to 8pm	7pm to 8pm
Max. CO_2 emissions	48248.92	42238.28	45898.29	43345.19	44522.14
Time window	7pm to 8pm	1pm to 2pm	3pm to 4pm	3pm to 4pm	3pm to 4pm
CO_2 savings potential (within one-hour time windows)	4055.96 (8.41%)	1312.38 (3.11%)	3461.90 (7.54%)	2423.11 (5.59%)	3035.16 (6.82%)
Min. increase to B_{20} (40922.08 gm)	3270.88 (7.40%)	3.82 (0.01%)	1514.31 (3.57%)	0.00 (0.00%)	564.90 (1.36%)
Max. increase to B_{20} (40922.08 gm)	7326.84 (15.19%)	1316.20 (3.12%)	4976.21 (10.84%)	2423.11 (5.59%)	3600.06 (8.09%)
Infeasible time windows	3	2	3	2	3

Comparing the results of the one-hour time windows across the four alternative locations of customer 21 presented in Table 4, it stands out that particularly low minimum CO_2 emissions can be achieved in scenario PD_{21B} and PD_{21D}. In $PD_{21B,}$ it is noticeable that if customer 21 is supplied from 2pm to 3pm, almost no additional distances have to be covered and the CO_2 emissions generated in this case are only 40.93 kilograms. It is striking that this value is only marginally higher than the benchmark value of 40.92 kilograms. In concrete terms, the benchmark value increases by only 3.82 grams (0.01%) when the most environmentally friendly time window is chosen. An even more optimal solution in terms of minimum CO_2 emissions can be achieved if the 21st customer in scenario PD_{21D} is served in the time window from 6pm to 7pm or from 7pm to 8pm. In both cases, CO_2 emissions amount to 40.92 kilograms, which corresponds exactly to the benchmark value. This is possible since customer 21 is located on a direct route between customer 7 and customer 15, who need to receive their groceries in a two-hour time window from 6pm to 8pm and a one-hour time window from 6pm to 7pm, respectively. Hence, if customer 21 also chooses to be supplied within this period of time, no additional distances need to be travelled. At this point, it must be mentioned that supplying an additional customer could in reality not lead to such a negligible or even zero increase in CO_2 emissions. The search for a parking space alone, for instance, induces longer distances that need to be travelled and thus contributes to CO_2 emissions that are higher than those calculated by the VRP Spreadsheet Solver. However, since neglecting these factors leading to an additional increase in CO_2 emissions does not distort the basic results of this work, such small deviations from real-life conditions can be accepted.

The highest possible level of CO_2 emissions within the one-hour time windows occurs in PD_{21C} in the 3pm to 4pm time window. In this scenario, the maximum CO_2 emissions amount to 45.90 kilograms, which depicts a CO_2 increase of 4.98 kilograms (10.84%) compared to the benchmark value. In turn, the relatively high level of CO_2 emissions in this scenario associated with the choice of the 3pm to 4pm time window also suggests a high savings potential emanating from the selection of alternative one-hour time windows. Since only 42.44 kilograms of CO_2 are emitted if the greener time windows from 6pm to 7pm or from 7pm to 8pm are chosen, which both represent an increase of the benchmark value by 1.51 kilograms (3.57%), 3.46 kilograms (7.54%) of CO_2 can be saved compared to the 3pm to 4pm time window.

A cross-locational examination of the feasibility of the time windows shows that a minimum of two and a maximum of three of the one-hour time windows cannot be offered since they would lead to infeasible routes.

Two-hour time windows

Table 5: Results for the alternative customer locations – Two-hour time windows

	PD_{21A}	PD_{21B}	PD_{21C}	PD_{21D}	PD_{21E}
Min. CO_2 emissions	44192.95	40925.89	42436.39	40922.08	41486.98
Time window	4pm to 6pm	2pm to 4pm	6pm to 8pm	6pm to 8pm	6pm to 8pm
Max. CO_2 emissions	46277.20	42225.47	45898.29	41604.97	44522.14
Time window	2pm to 4pm	12pm to 2pm	2pm to 4pm	2pm to 4pm	2pm to 4pm
CO_2 savings potential (within two-hour time windows)	2034.25 (4.40%)	1299.58 (3.08%)	3461.90 (7.54%)	682.90 (1.64%)	3035.16 (6.82%)
CO_2 savings potential (vs. one-hour time windows)	2357.99 (4.89%)	354.26 (0.86%)	38.70 (0.09%)	1740.22 (4.01%)	2118.45 (4.82%)
Min. increase to B_{20} (40922.08 gm)	3270.88 (7.40%)	3.82 (0.01%)	1514.31 (3.57%)	0.00 (0.00%)	564.90 (1.36%)
Max. increase to B_{20} (40922.08 gm)	5305.13 (11.48%)	1303.39 (3.09%)	4976.21 (10.84%)	682.90 (1.64%)	3600.06 (8.09%)
Infeasible time windows	1	1	1	1	1

Table 5 shows that if the 21st customer chooses to be served within one of the feasible two-hour time windows, the same minimum and maximum CO_2 emissions as in the one-hour case arise when comparing the results across the four scenarios. Accordingly, the minimum and maximum increase to the benchmark value as well as the minimum and maximum CO_2 savings potential within the two-hour time windows remain unchanged. The highest CO_2 savings potential compared to the one-hour time windows is possible in scenario PD_{21E}. Here, up to 2.12 kilograms (4.82%) of CO_2 emissions can be saved when a two-hour instead of a one-hour time window is selected by customer 21_E.

In the scenarios PD_{21B} to PD_{21E}, one of the two-hour time windows each cannot be offered to the 21st customer because these time windows would lead to infeasible route plans.

Five-hour time windows

Table 6: Results for the alternative customer locations – Five-hour time windows

	PD_{21A}	**PD_{21B}**	**PD_{21C}**	**PD_{21D}**	**PD_{21E}**
Min. CO_2 emissions	44192.95	40925.89	42436.39	40922.08	41486.98
Time window	12pm to 5pm; 3pm to 8pm	10am to 3pm; 12pm to 5pm	3pm to 8pm	3pm to 8pm	3pm to 8pm
Max. CO_2 emissions	45197.41	41280.15	43756.95	41065.69	41861.40
Time window	10am to 3pm	3pm to 8pm	10am to 3pm	10am to 3pm; 12pm to 5pm	10am to 3pm; 12pm to 5pm
CO_2 savings potential (within five-hour time windows)	1004.45 (2.22%)	354.26 (0.86%)	1320.56 (3.02%)	143.61 (0.35%)	374.42 (0.89%)
CO_2 savings potential (vs. one-hour time windows)	4055.96 (8.41%)	1312.38 (3.11%)	3461.90 (7.54%)	2423.11 (5.59%)	3035.16 (6.82%)
CO_2 savings potential (vs. two-hour time windows)	2034.25 (4.40%)	1299.58 (3.08%)	3461.90 (7.54%)	539.29 (1.30%)	3035.16 (6.82%)
Min. increase to B_{20} (40922.08 gm)	3270.88 (7.40%)	3.82 (0.01%)	1514.31 (3.57%)	0.00 (0.00%)	564.90 (1.36%)
Max. increase to B_{20} (40922.08 gm)	4275.33 (9.46%)	358.07 (0.87%)	2834.87 (6.48%)	143.61 (0.35%)	939.32 (2.24%)
Infeasible time windows	0	0	0	0	0

Analyzing the results presented in Table 6, it becomes evident that there is further significant potential for a more efficient and environmentally friendly delivery route if a five-hour instead of a one- or two-hour time window is chosen by the 21st customer. Because the delivery times leading to routes associated with the highest levels of CO_2 emissions can largely be avoided for deliveries in a five-hour time frame, the maximum CO_2 emissions across all customer locations are only 43.76 kilograms and arise if the time window from 10am to 3pm is chosen by customer 21_C. The maximum level of CO_2 emissions within the five-hour time windows is thus 2.83 kilograms (6.48%) above the benchmark value and, accordingly, 2.14 kilograms (4.67%) below the maximum value for the one-hour and two-hour time windows. Since the minimum CO_2 emissions among the five-hour time windows in PD_{21C} are 42.44 kilograms, up to 1.32 kilograms (3.02%) of CO_2 can be saved within this time window length, depending on the time window choice of customer 21_C. A cross-comparison of the results in PD_{21C} with the one- and two-hour time windows even shows a CO_2 savings potential of up to 3.46 kilograms (7.54%) in each case. This saving is made possible if the five-hour time window from 3pm to 8pm is selected, making it possible for the logistics service provider to avoid supplying the 21st customer in the most unfavorable delivery times between 2pm and 4pm, which lead to CO_2 emissions of 45.90 kilograms. However, one of the most notable benefits associated with the five-hour time windows again lies within the minimization of the number of infeasible time windows. In all four scenarios, none of the five-hour time windows lead to infeasible solutions. Consequently, the logistics service provider can supply all customers within their selected time window.

Overall, the results of the partially dynamic setting show that the time window choice of an individual customer has a significant influence on the environmental sustainability and consequently the efficiency of a delivery route in the context of last-mile deliveries. However, customers cannot know on their own which time window is the most environmentally friendly and will place them in a favorable position in the delivery sequence. Detailed information on how strongly CO_2 emissions can vary depending on the choice even among time windows of uniform length is withheld from them. Consequently, customers who want to contribute to an environmentally friendly delivery route can, without receiving decision support from logistics service providers, only do so by choosing longer time windows. In this chapter, it could be shown that long compared to short time windows hold considerable CO_2 savings potential. The key point in the preceding scenario, however, is that only the time window choice of the 21st customer, who is the last customer to be integrated in the delivery sequence, was considered. Therefore, longer time windows outperform shorter time windows only in terms of lower maximum CO_2 emissions. In other words, the minimum CO_2 emissions resulting from the most favorable one-, two- or five-hour time windows are the same in all three cases and the CO_2 minimizing one-hour time window is just as green as the CO_2 minimizing two- or five-hour time window. Yet, the situation may be completely different for customers arriving earlier in the order stream, as maintaining flexibility for the integration of future customers becomes crucial. Thus, the next step is to check in a dynamic setting how much the expected CO_2 emissions of the delivery route can be reduced if green time windows are marked and incentivized dynamically for each customer and to examine how longer time windows perform compared to shorter ones under such dynamic framework conditions.

5.4.3 Fully Dynamic Setting

In the fully dynamic setting, it is assumed that the first 20 customers place their order in the sequence of their numbering in the VRP Spreadsheet Solver. In contrast to static settings, in which all customer locations and their time window preferences are known in advance, customers in dynamic settings may place their order at any time during the evolution of the route plan (Köhler et al. 2020). This means that service providers need to constantly check in which position a newly arriving customer should be inserted into the delivery sequence. Transferred to the vehicle routing problem this study is concerned with, this requires checking for each individual customer incrementally which time window leads to the lowest additional CO_2 emissions. Those time windows are then allocated to each customer, as the simplified assumption is made that all customers are willing to choose green time windows when marked accordingly. Since the VRP Spreadsheet Solver can only generate routes starting from five customers, a tentative route plan is built for the first five customers. The time windows allocated to them on this basis embed the point in time at which they are to be supplied according to the tentative route plan. Subsequently, it is checked for the 6th customer which delivery time leads to minimal additional CO_2 emissions, taking into account the first five customers and their fixed time window choices. The corresponding green time window is then allocated to him or her accordingly. Following this approach, green time windows are step by step determined for and allocated to all 21 customers. Due to the dynamic setting, the time window allocation to each individual customer is significantly influenced by the locations and time window choices of customers who had placed their order at an earlier point in time. Overall, the aim is to examine whether it makes sense to incentivize time windows based on already accepted customer requests, even if future customer requests are unknown and it is unclear to what extent the previously incentivized time windows can still be considered as environmentally friendly after all customer requests are known.

In the first step of the fully dynamic setting (FD_A), only one-hour time windows are considered. The development of the cumulative CO_2 emissions in FD_A is shown in Figure 5. The tentative route plan that emerges after the incremental allocation of incentivized one-hour time windows to the first 20 customers results in CO_2 emissions of 34.53 kilograms. Due to the route inefficiency and the long distances that have to be travelled in some cases, the CO_2 value is 10.35 kilograms (29.98%) higher than in scenario S_{10}, in which all customer locations were known beforehand, and a CO_2 minimizing route plan could be determined based on complete information. Nevertheless, the CO_2 emissions resulting from the dynamic allocation of one-hour time windows are 7.66 kilograms (18.15%) lower than the average CO_2 emissions in S_1, where the one-hour time windows were allocated to customers purely randomly.

Especially toward the end, the route plan is characterized by increased inefficiency, with more and more time windows becoming infeasible. Effectively, only the afternoon and evening time windows from 4pm to 5pm, 5pm to 6pm, 6pm to 7pm and 7pm to 8pm can be offered to the 21st customer, the last three being undesirable because of the long waiting times involved. All three time windows lead to an increase in CO_2 emissions by 5.60 kilograms (13.97%), i.e., from 34.53 kilograms to 40.13 kilograms.

To better reflect reality, in which it rarely occurs that only one-hour time windows are offered, a second dynamic route planning scenario with mixed time windows of five hours, two hours and one hour (FD_B) is considered. The time windows are allocated to customers according to the following logic: The first seven customers are offered only five-hour time windows, the next seven only two-hour time windows and the last seven, including the 21st customer, only one-hour time windows. This approach is based on the findings of Köhler et al. (2020), who show that offering long time windows to early arriving customers and shorter time windows to customers placing their order later in the booking process can contribute to flexible route plans and significantly increase the availability rate of time windows throughout the booking process. As noted by Köhler et al. (2020), customers normally expect to receive rewards when booking early, which is why this approach of offering early birds longer time windows could cause resentment among customers. This could be particularly problematic when customers realize that they would be provided shorter time windows the longer they wait and thus decide to delay the order placement for as long as possible. In order to provide customers with an incentive to book early even under these circumstances, they could in the beginning of the booking process be guaranteed to receive an update on their delivery time upon finalization of the route plan. This could be implemented by sending an e-Mail or SMS, in which the guaranteed delivery period is reduced to 20 or 30 minutes exclusively for early birds (Köhler et al. 2020).

The approach of how the green time windows are determined for each customer is the same as in FD_A. The only difference here is that the CO_2 minimizing delivery times are not only embedded in one-hour time windows, but also in two- or five-hour time windows. In this case, a much more flexible and environmentally friendly route plan is created when compared to FD_A. Figure 5 demonstrates that the emissions generated amount to 30.29 kilograms, which is 4.24 kilograms (12.29%) lower than in FD_A. Due to the increased flexibility, all baseline customers can be served four hours before the maximum working time is reached. Thus, the dynamic approach FD_B allows for a lot of free capacity to deliver additional customers. When integrating the 21st customer, he or she can be supplied in all one-hour time windows except those from 10am to 11am, 11am to 12pm and 3pm to 4pm. The time window that leads to the lowermost additional CO_2 emissions of 30.29 kilograms and can be labeled as environmentally friendly is from 2pm to 3pm. Strikingly, the level of CO_2 emissions in context with this precise time window remains the same as in the case of the delivery of 20 customers, i.e., no additional CO_2 emissions are generated through the insertion of the 21st customer into the route plan. At this point, reference must be made to chapter 5.4.2.3, in which a zero increase in CO_2 emissions following the integration of an additional customer is critically questioned. Here too, however, small deviations from real-life conditions do not distort the basic results of this work and can thus be accepted. The highest level of CO_2 amounting to 33.74 kilograms is emitted if the one-hour time window from 4pm to 5pm is chosen. Depending on the slot choice of the 21st customer, this results in a CO_2 savings potential of up to 3.45 kilograms (10.23%). When comparing FD_A and FD_B, it becomes evident that while the curve progression shown in Figure 5 is quite similar in the beginning of the route plan, the cumulative CO_2 values in FD_A are significantly higher and lead to much more erratic increases than in FD_B especially toward the end of the route plan. These results show that, even if customers are given information on the carbon footprint of their time window choices, it is a largely unsustainable approach to only offer one-hour time windows to customers. Rather, it makes sense to offer early arriving customers long time windows and customers appearing later in the order stream short time windows, as this greatly contributes to reduced CO_2 emissions and increased operational efficiency.

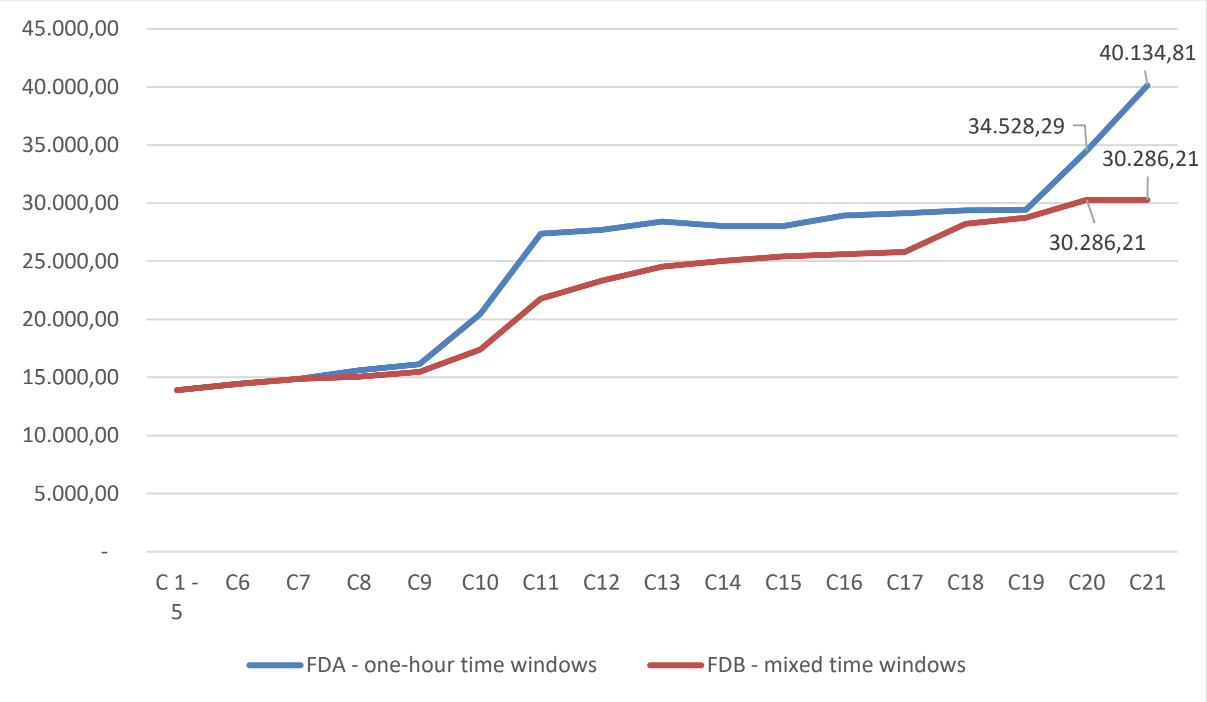


Figure 5: Development of cumulative CO_2 emissions (in grams) in FD_A and FD_B

5.5 Analysis

Three main conclusions can be drawn from the simulation. Firstly, it has been shown that the level of CO_2 emissions can be significantly reduced if all customers choose longer instead of shorter time windows. The level of CO_2 emitted varied between 24.18 kilograms, 28.77 kilograms, 37.49 kilograms and 42.19 kilograms on average, depending on whether no time windows or five-, two- or one-hour time windows were allocated to the baseline customers, respectively.

Secondly, as it is unlikely that all customers agree to choose long time windows, the next part of the simulation showed that even the time window choice of a single customer can make a big difference. By simulating a more realistic scenario in which customers could choose from different time windows of varying lengths, it was possible to demonstrate that the expected CO_2 emissions for a tentative delivery route remained at the same level in the best case and increased by about 7.33 kilograms or 15.19% in the worst case after integrating the 21st customer. The findings of the simulation clearly show how essential it is to inform customers about the environmental impact of the chosen time window, both within uniform time window lengths, and when comparing time windows of different lengths. Many customers are unaware that, as for example in PD_{21A}, up to 4.06 kilograms (8.41%) of CO_2 can be saved, solely depending on whether a one-hour time window favorable to an efficient and CO_2 minimizing delivery route is chosen. Furthermore, there is no clear picture of how much CO_2 can be saved by extending a narrow time window of for instance one hour to two or five hours. This is because most customers are not familiar with the complexities associated with route planning and tight time windows. Hence, they are unable to assess that simply extending a time window for one individual customer from one hour to two hours can, as for instance in PD_{21A}, save up to 2.36 kilograms or 4.89% of CO_2 emissions. That this value can, again as shown in PD_{21A}, be increased nearly twofold to up to 4.06 kilograms (8.41%) if a customer gives the logistics service provider even more flexibility by choosing a five-hour instead of a one-hour time window is equally difficult to estimate for laymen. Notably, the additional savings potential that would result when a customer is not the last to arrive in the order stream and maintaining flexibility for future requests becomes crucial is not even included these figures.

To pick up on this aspect, a dynamic route planning scenario was illustrated in the third step. When designing delivery routes, it is never certain which customers will place an order further down the line. Accordingly, time windows that are the most environmentally friendly for a particular customer at a certain point in time and thus labeled as green may no longer be favorable at a later stage and consequently lead to higher costs and CO_2 emissions. Overall, however, the last part of the simulation demonstrated that the CO_2 savings resulting from a dynamic incentivization of time windows strongly outweigh the CO_2 increases that may arise in some cases. Even in the case in which only one-hour time windows were considered, the level of CO_2 emitted was almost eight kilograms lower than in the case in which one-hour time windows were allocated randomly. However, since the number of customers that can be served if only one-hour time windows are offered is restricted significantly, it is a better approach to offer time windows of varying lengths. As shown in FD_B, offering early arriving customers long time windows and customers arriving later in the order stream short time windows can help maintain flexibility and create a more efficient and environmentally friendly route plan. This also allows for a much higher number of customers being served than when green time windows are not incentivized. These findings indicate the potential that would result if all customers were incentivized to choose green time windows.

Overall, many customers may be under the impression that they are just a small, insignificant link in a complex delivery system and that their time window choice has hardly any influence on the sustainability of the delivery route as a whole. But this, as the simulation has highlighted, is a fallacy that urgently needs to be addressed. Since even a single customer can make a big difference through thoughtful time window choices, the potential is considerable if selecting green time windows becomes the norm for more and more customers. This requires, first and foremost, that customers are directly informed about the carbon footprint of their time window choice. How to appropriately educate customers about the CO_2 footprint of time windows and how this may contribute to the choice of greener time windows is explored in the next part of the paper.

6 Empirical study – Incentivizing Green Time Windows

After having shown that an incentivization of green time windows can help reduce last-mile emissions significantly, the purpose of the following survey is twofold: On the one hand, the aim is to examine the different ways in which green time windows can be incentivized, and on the other hand, to determine to what extent customers under the presence of such incentives are willing to choose them. Consequently, the objective of the following chapter is to answer the second research question:

RQ 2: How can service providers effectively steer consumers to choose green time windows as their preferred last-mile delivery option?

In the research field of sustainable e-commerce deliveries, there is a fundamental lack of studies that examine the potential of online consumers' decision-making. In this regard, especially the environmental implications associated with customer time window choices in the context of attended home deliveries have long been overlooked. This is partly due to the fact that attended home deliveries are a relatively young phenomenon. Germany's leading supermarket chain REWE, for example, has only started offering an online delivery service for groceries in 2011 (REWE Group 2011). Accordingly, the approach of offering customers time windows as part of home deliveries is also relatively novel, as is an increased awareness of how this is to be assessed in terms of environmental sustainability. Yet, particularly in times of the COVID-19 pandemic, more and more people have chosen to have their orders delivered directly to their homes. This trend suggests that attended home deliveries will continue to play an important role in the future, which is why efficient and sustainable time window management will ultimately become indispensable (Leyerer et al. 2020).

As relatively few studies to date have examined how steering demand in last-mile delivery impacts the operating system of attended home delivery and thus also the sustainability of the delivery system as a whole, conducting further studies in this research area is essential. However, some significant foundations have already been laid, including the work of Agatz et al. (2021) and Buldeo Rai et al. (2021). Both studies provide strong support for the effectiveness of the use of non-financial incentives in steering customers toward choosing more environmentally friendly delivery options. Consequently, this study also assumes that providing customers with information on the environmental impact of their decisions will help to steer them toward more sustainable delivery choices. Since the focus in this work is on attended home delivery of groceries, the delivery options at hand present themselves as a set of time windows. While the framework conditions are thus similar to those in the study by Agatz et al. (2021), the main research contribution of this survey lies in three essential points. First, since Agatz et al. (2021) show that green labels are more effective than price incentives in nudging customers toward more environmentally friendly time windows, financial incentives are neglected in this survey. Second, all environmentally friendly or green time windows in this work are consistently determined and incentivized to the participants in the survey based on concrete calculations in the simulation. Third, the aim of the survey is to examine customers' time window choices in a context in which they can choose from not only one, but two alternative time window lengths in addition to the one-hour time windows. Since one-, two-, and five-hour time windows were examined in the simulation, these three time window lengths are also considered in the first part of the survey. In doing so, the gradations that exist between varying time window lengths in terms of their environmental friendliness are highlighted and clearly communicated to the customers. Based on the calculations and the assumptions made in the static setting of the simulation, the first step in the survey is to examine to what extent an accentuation of longer time windows is suitable to convince customers to select them. This leads to the following first hypothesis:

H1: If customers are informed about the environmental benefits of longer versus shorter time windows, more customers will choose two-hour or five-hour instead of one-hour time windows than if they are not given any information on the associated environmental benefits.

Furthermore, the partially dynamic setting has shown that amid time windows of equal length, there are also significant differences in terms of the associated environmental impact. This finding suggests that a dynamic incentivization of green time windows may be a desirable measure to reduce last-mile CO_2 emissions. The second hypothesis is thus as follows:

H2: Last-mile CO_2 emissions will be significantly lower if delivery time windows are labeled according to their environmental impact than in the case of no labels.

To examine alternative ways in which customers can be steered to choose green time windows, the survey builds on a study by Demarque et al. (2015). The authors emphasize the potential of descriptive norms as effective ways to incentivize sustainable choices in an online grocery shopping context. Thereby, they highlight that including reference points such as numerical quantifiers in descriptive norms strengthens their effect of encouraging customers to make environmentally friendly delivery choices. For this reason, two different versions of green labels, which vary in the information content provided for the customer, are examined in this study. Thereby, the focus is on investigating whether providing customers with concrete, numerical information on the impact of their time window choice has an additional effect on their slot choice behavior. This leads to the following, third hypothesis:

H3: The more numerical reference points customers receive on the environmental impact of their time window choices, the lower last-mile CO_2 emissions will be.

6.1 Method and Research Design

6.1.1 Research Design

To answer the research question and to test the hypotheses, an experimental, quantitative study was conducted using a survey that imitated a shopping basket. The survey was developed in the online survey tool Google Forms and a total of 137 participants took part. They were contacted via social media and were encouraged to forward the survey to their contacts as well. The respondents were randomly allocated to one of three groups, namely one control group (N = 49) and two experimental groups (EG_A, N = 33 and EG_B, N = 43). The general approach was to ask participants in the control group to choose their preferred delivery time window from two sets of ordinary, unincentivized time windows. Simultaneously, participants from the experimental groups were shown the same time window sets, however, their presentation was slightly adapted. For both EG_A and EG_B, the more sustainable time windows or time window lengths were visually highlighted, and the associated environmental benefits were explained in a short information text. The main difference between the two groups is that all participants in EG_A received concrete, numerical information on the CO_2 footprint of their time window choice, whereas those in EG_B received the relevant information in a more general manner. The data of the study was collected within a period of two weeks (02.02.2022 to 16.02.2022). The design and sample of the survey are specified in the next sections.

6.1.2 Online Survey and Data Collection

The experiment was conducted using a between-subjects experimental design to avoid carryover effects. In doing so, the participants were randomly assigned to one of the three groups. To educate participants about the frame conditions of the survey, an introduction specifying the research context and guaranteeing participants' protection of anonymity preceded the actual study. Since the results from the simulation were to be used as a baseline for the design of the survey, the same framework conditions had to apply here as well. Accordingly, it was assumed that in the first part of the survey, each participant embodied one of the baseline customers. In the second part of the survey, the participants presented the 21st customer, who was assigned the same fictitious location in Bambergergasse 41 in the 22nd district in Vienna as already used in the simulation. Respondents were encouraged to truthfully state their real preferences, meaning that they were asked to choose only those time windows they would also select in a real-life context when ordering groceries online. It was emphasized that they would have to be at home during the entire duration of the time window to be able to accept their order. At the end of the survey, participants were asked about a set of socio-demographic characteristics, namely year of birth, gender, country of residence and educational background.

The three groups were asked about their time window preferences in two consecutive steps. In the first step, all participants were shown a mixed time window offer set containing ten one-hour, five two-hour and three five-hour time windows from 10am to 8pm and asked to choose one. Participants in the control group were shown the mixed offer set without any incentives, whereas for EG_A and EG_B, the offer set was visually slightly adapted using two distinct green label designs:

Label 1a: For participants in EG_A, the two-hour and five-hour time windows were accompanied by a green label in the form of one or two green leaves, respectively. The design was inspired by the online shop of the grocery supplier *Gurkerl* (Austria), which also uses green leaves to highlight the most environmentally friendly time windows. Moreover, a note was added informing the participants that longer time windows allow for more routing flexibility as well as distance and emission savings. The exact wording was as follows (translated from German to English):

"The ***longer*** *your chosen time window, the more you contribute to higher* ***routing flexibility*** *as well as* ***distance and emission savings****. Why not choose a longer time window and help* ***save the environment****?"*

Label 1b: For participants in EG_B, longer time windows were also accompanied by one or two green leaves, however, the information text was slightly modified. Instead of stating the environmental benefits of longer time windows in general terms, the exact CO_2 savings potential was specified. The values included in the incentive are based on the calculations in the static setting of the simulation, which examines the environmental impact of longer versus shorter time windows. In particular, the following text was used (translated from German to English):

"The more customers choose ***longer*** *time windows, the higher the contribution to more* ***routing flexibility*** *and* ***distance and emission savings****. Why not choose a* ***five-hour*** *time window and help save up to* ***31% of*** CO_2 ***emissions*** *or a* ***two-hour*** *time window and help save up to* ***11% of*** CO_2 ***emissions*** *on average?"*

A screenshot of the presentation of the three mixed time window sets can be seen in Figure 16, Figure 17 and Figure 18 in the Appendix.

The design of the second part of the survey was based on the results of the fully dynamic setting. Thereby, it is recalled that scenario FD_B validated the theory that dynamically incentivizing short time windows only to customers arriving latest in the order stream is highly beneficial for the creation of sustainable route plans. Referring to this finding, it was assumed that the respondents of the survey, who were to represent the 21^{st} customer, could choose from a time window offer set consisting exclusively of one-hour time windows. Based on the calculations in FD_B, some time windows were no longer available for the 21^{st} customer due to the time window choices of the first 20 customers. Participants in the control group were presented with the available one-hour time windows without any labels. For participants in the experimental groups, the time windows were ranked according to their environmental impact as calculated in FD_B. The following labels were used for this purpose:

<u>*Label 2a:*</u> For participants in EG_A, the one-hour time windows were color-coded and presented in ascending order of their additional CO_2 footprint as computed in FD_B. For visual emphasis, tones ranging from different shades of green to an orange-red color were used. For clarification, an arrow was added next to the time windows to show that the sequence in which the time windows are presented corresponds to increasing additional CO_2 emissions. Additionally, the following information text was added:

*"During the **greener** time windows, the delivery vehicle will already be **in your area**. Why not choose one to help **reduce CO_2 emissions** and **save the environment**?"*

<u>*Label 2b:*</u> For participants assigned to EG_B, too, the time windows were color-coded and sorted according to their environmental impact and the same note was added as for participants in EG_A. The only difference to EG_A is that a CO_2 label was also attached to each time window, which indicated the associated additional CO_2 emissions as calculated in FD_B. The design of the time window offer sets presented to each group are shown in Figure 19, Figure 20 and Figure 21 in the Appendix.

By comparing the time window choices and the associated average CO_2 increases of all three groups, it can be investigated to what extent green labels can help service providers to steer customers toward choosing environmentally friendly and efficiency-enhancing time windows. Thereby, the aim is to determine whether customers are more responsive to green labels if they include numerical reference points. For this purpose, contingency tables are created and Chisquare tests as well as Cramer's V tests are performed in the statistical program R to measure both the relationship between the variables and the strength of the relationship.

Based on the existing literature, three main results are predicted. First, more respondents in the control group are expected to choose shorter time windows than in the experimental groups. It is also hypothesized that more participants in EG_B than in EG_A choose longer time windows, as they have more concrete information on the environmental benefits emanating from longer time windows. Additionally, as respondents do not know the level of CO_2 emissions each of the one-hour time windows generate unless labeled accordingly, more participants in the control group are expected to select less favorable one-hour time windows associated with higher additional CO_2 emissions on average than in the experimental groups. Because there is a gradation of time windows in terms of their environmental impact, respondents in the experimental groups have greater scope for choosing an environmentally friendly one-hour time window. In concrete terms, this means that even if the greenest time window does not suit the participant, he or she still has the option to switch to the second or third most environmentally friendly window. Again, it is presumed that more participants in EG_B than in EG_A choose greener time windows. This is because they can make their choice not only based on the colors and the order of the available time windows, but also on the basis of the labels specifying the precise CO_2 footprint associated with each one-hour time window.

6.2 Participants

From the 137 participants who took part in the survey, 12 were not taken into consideration because they did not select a valid time window. Accordingly, 125 completed surveys could be incorporated into the analysis. Among the participants, 63% are female, 36% male and 1% diverse. Since the focus of this study is on German-speaking customers, all respondents live in Austria or Germany. At this point, it should be noted that female participants from Germany are clearly overrepresented, which may bias the results and lead to a limited generalizability. Table 7 specifies the average age and the number of female, male and diverse participants in the control group and the experimental groups as well as their country of residence.

Table 7: Sample composition per group

Group	N	Avg. age	Female	Male	Diverse	Austria	Germany
Control Group	49	37	33	16	0	10	39
Experimental Group A	33	40	24	9	0	8	25
Experimental Group B	43	38	22	20	1	15	28

6.3 Results

The aim of the survey is to examine whether the applied green labels work well to steer customers toward longer time windows (Hypothesis 1) or more environmentally friendly one-hour time windows (Hypothesis 2) and to test whether the effectiveness of such incentives is increased through the integration of numerical reference points in the information text (Hypothesis 3).

Incentivizing longer time windows

To examine whether green labels increase the likelihood of longer time windows being chosen, the percentage of one-, two- and five-hour time windows selected in the experimental groups is directly compared to the time window choices in the control group. The percentage of how often each of the three time window lengths were opted for in the control group and the experimental groups is shown in Figure 6.

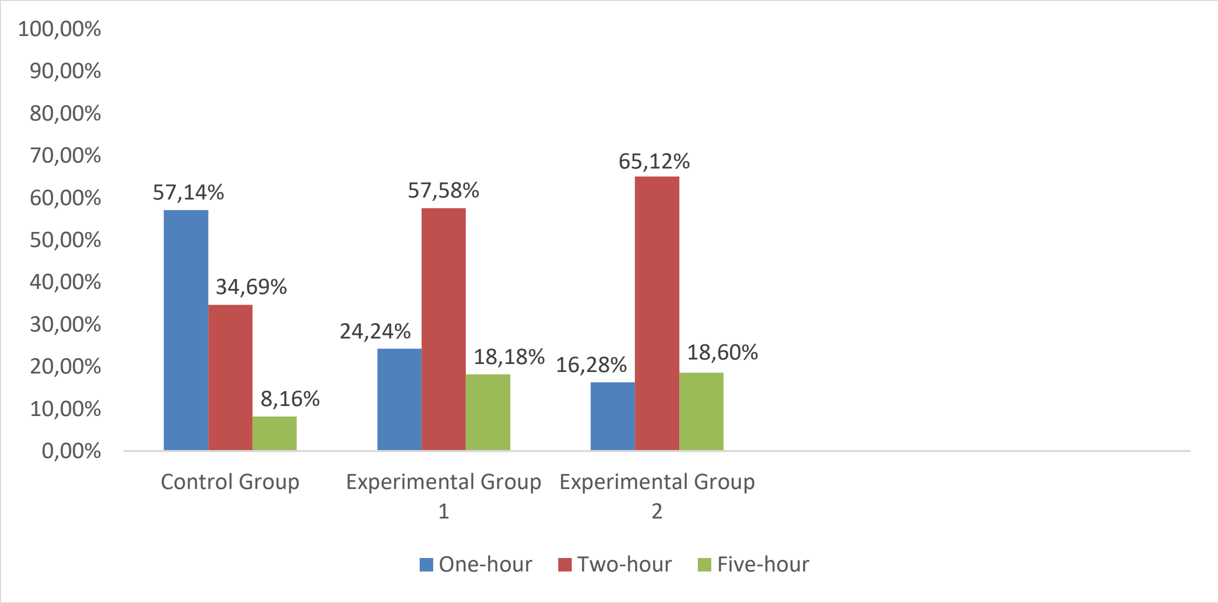


Figure 6: Percentage of selected one-, two- and five-hour time windows across groups

At first sight, it seems that green labels are well suited in steering customers away from one-hour and toward two-hour and five-hour time windows. In the control group, it is particularly noteworthy that at over 57%, the largest proportion of participants opted for one-hour time windows. Two-hour time windows were chosen by 34.69% and five-hour time windows by only 8.16% of the respondents. In EG_A, in which the environmental benefits of the two-hour and five-hour time windows were highlighted using Label 1a, a completely different trend can be observed. Chosen by less than one fourth of the participants, the percentage of selected one-hour time windows could be more than halved. In contrast, two-hour time windows were chosen by 57,58% of respondents and the percentage of selected five-hour time windows more than doubled to over 18%. The analysis of the survey answers shows that the difference in the slot choice behavior between the control group and EG_A is significant and that the relationship between Label 1a and the choice of a longer time window is moderately strong ($p = 0.01205$; Cramer's $V = 0.328$). It can thus be concluded that visually highlighting longer time windows and including a short information text about the associated environmental benefits can motivate consumers to choose longer delivery time windows.

When comparing the control group and EG_B, even greater differences become apparent. Chosen by only 16.28% of respondents, the one-hour time windows were particularly unpopular among respondents in EG_B. The two-hour time windows, on the other hand, were by far the most preferred and therefore selected by 65.12% of the participants. At 18.60%, the percentage of five-hour time windows chosen in EG_B again more than doubled compared to the control group. The statistical analysis of the results reveals significant differences in the slot choice behavior between the control group and EG_B, showing a moderately strong relationship between Label 1b and the choice of a longer time window ($p = 0.0002887$; Cramer's $V = 0.421$). It is therefore again argued that accentuating longer time windows through visual stimuli such as green leaves and adding an information note including straightforward and numerical reference points can be a powerful tool to motivate consumers to choose longer delivery time windows.

When comparing the time window choices of EG_A to those of EG_B, the differences do not appear to be major, which is validated by the results obtained through the statistical analysis. Effectively, there are no significant differences in the time window choices between EG_A and EG_B and the relationship between the design of the green label and the choice of a longer time window is weak ($p = 0.6793$; Cramer's $V = 0.101$). Based on these results, it is thus concluded that there is little added value in including numerical reference points in the information text on the environmental benefits of longer time windows. Rather, a more general statement that longer time windows are preferable with respect to environmental criteria seems sufficient to achieve the desired effect.

A cross-age and cross-gender analysis provides further meaningful insights. Table 9 in the Appendix provides a detailed breakdown of the results of the first part of the survey by gender and age group. In both the control group and the two experimental groups, a larger percentage of male participants were willing to choose five-hour time windows and the proportion of men choosing one-hour time windows was also lower than the corresponding proportion of female participants[6]. In all three groups, there is also a tendency of younger participants being more inclined to choose five-hour rather than one-hour or two-hour time windows. Against the background of extant literature measuring differences in environmental consciousness across socio-demographics, the findings of this study are rather surprising. Hiramatsu et al. (2016), for instance, found elderly people to be more ecologically aware than younger people when asked about their environmental consciousness in daily activities. This clearly deviates from the results of this study, in which younger participants displayed more environmentally friendly

[6] Since only one person indicated "diverse" as their gender status, this is not included in the cross-gender analysis.

behavior. In addition, the term *Eco-Gender Gap* commonly used in the existing body of literature essentially suggests that women on average show more eco-friendly behavior than men (Normandin 2020). Specifically related to differences between men and women in their preferences for green delivery options, recent studies have found trends contrary to those observed in this work. A study conducted in 2021 by the market research institute GfK on behalf of Digitec Galaxus, for instance, shows that 24.38% of men preferred fast over environmentally friendly delivery when shopping online. On the contrary, only 14.61% of female participants prioritize fast delivery (Digitec Galaxus 2021b). These findings again conflict with the results of this study. It therefore seems that although elderly people or women on average behave in a more environmentally friendly way than younger people or men, this does not appear to be the case in the context of attended home delivery of groceries, where environmentally friendly behavior is expressed purely through customers' time window choices.

Incentivizing greener one-hour time windows

To assess whether green incentives work well to steer customers toward more environmentally friendly one-hour time windows (Hypothesis 2), the additional CO_2 emissions associated with each available time window are first translated into ranks to facilitate interpretation. That is to say, the time window that leads to the lowest additional CO_2 emissions is assigned rank 1, the one associated with the second lowest additional CO_2 emissions rank 2, and so on. Since the three time windows from 10am to 11am, 11am to 12pm and 4pm to 5pm were already marked as booked out and could thus not be selected by the 21st customer, seven time windows remain to be ranked. Because the 5pm to 6pm, 6pm to 7pm and 7pm to 8pm time windows all result in the same additional CO_2 emissions, they receive the same ranking with the additions a, b and c to be able to distinguish them from one another. An overview of the one-hour time windows offered, the associated additional CO_2 emissions and the respective ranks is provided in Table 8.

Table 8: Ranking of the available one-hour time windows

Time window	Additional CO_2 emissions (in kg)	Rank
2pm to 3pm	≈ 0[7]	#1
12pm to 1pm	2.21	#2
1pm to 2pm	2.44	#3
5pm to 6pm	3.44	#4a
6pm to 7pm	3.44	#4b
7pm to 8om	3.44	#4c
4pm to 5pm	3.45	#5

Based on the ranking of the time windows, the effectiveness of the incentives can be tested by comparing the percentage of the higher and lower ranked time windows chosen in each group. Figure 7 illustrates the percentage of each ranked time window chosen in the control group and the two experimental groups.

[7] At this point, it is important to repeat that a zero increase in CO_2 emissions, as calculated by the VRP Spreadsheet Solver, would not be possible under real-world conditions. However, for the sake of simplicity, this zero value is used for the analysis of the survey results.

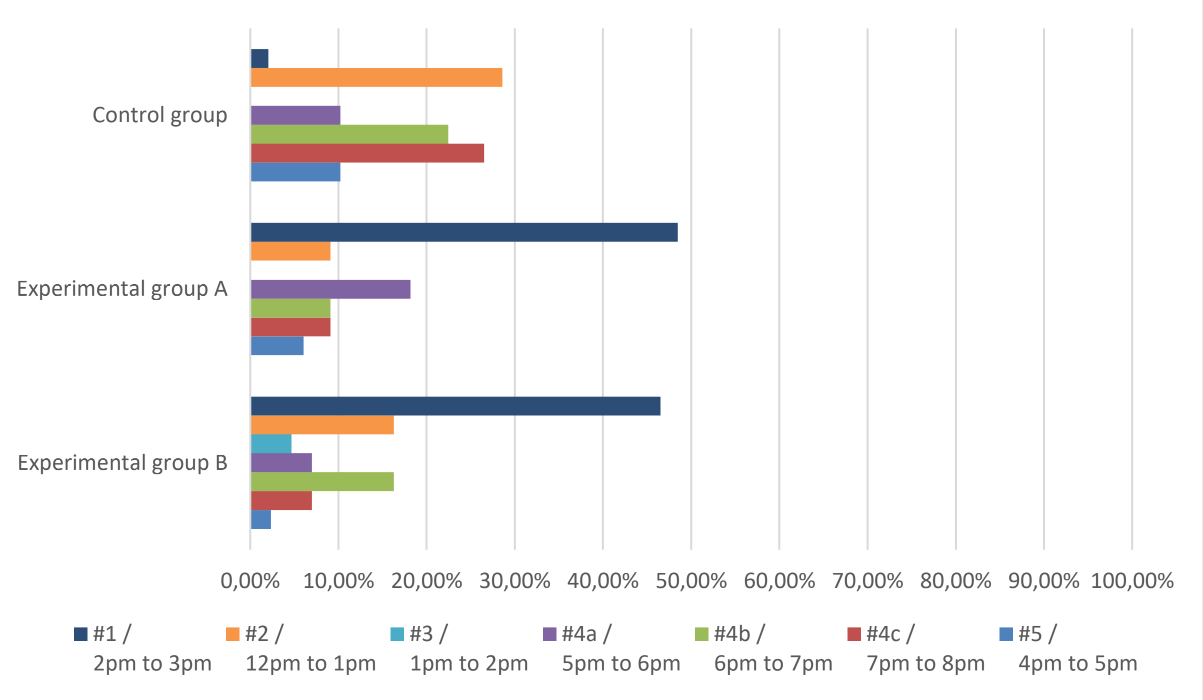


Figure 7: Comparison of the chosen one-hour time windows across groups

In the control group, in which the respondents were not given any information on the environmental impact of their time window choices, the most frequently selected time window was the 12pm to 1pm / #2 time window. Similarly popular among participants were the evening time windows from 6pm to 7pm / #4b and from 7pm to 8pm / #4c. Possibly as many people are not home throughout the day, the 1pm to 2pm / #3, the 4pm to 5pm /#5 and the 5pm to 6pm / #4a time windows were relatively unpopular. The former was not selected once by participants in the control group and the latter each by only 10.20% of the respondents. The most environmentally friendly time window from 2pm to 3pm was selected by only 2.04% of the respondents. This is most likely because customers had no information on how the time window performs in terms of environmental impact, and without such information preferred to choose time windows that are not in the middle of the day, but rather in the evening or during lunch break when they are more likely to be at home anyway.

In EG_A, the ratios change substantially. Here, the most environmentally friendly time window from 2pm to 3pm was chosen by almost half of the respondents. Yet, the second most popular time window was the one from 5pm to 6pm, which only ranks #4a in terms of environmental impact. The evening 6pm to 7pm / #4b and 7pm to 8pm / #4c time windows as well as the 12pm to 1pm / #2 time window were each chosen by only 9.09% of the participants. Again, the 4pm to 5pm / #5 time window, chosen by 6.06% of the respondents, was relatively unpopular. As in the control group, the 1pm to 2pm / #3 time window was selected by none of the customers. The statistical analysis of the survey answers of the control group and EG_A shows that the difference in the slot choice behavior between the control group and EG_A is significant and that the relationship between label 2a and the choice of a more environmentally friendly time window is strong ($p = 0.01205$; Cramer's $V = 0.569$). It is therefore argued that color coding each available time window according to the associated environmental impact along with a short information text works well to steer customers toward more sustainable time windows.

In EG_B, similar tendencies as in EG_A can be observed. Again, the 2pm to 3pm / #1 time window was selected by the largest share of respondents. Surprisingly, at 46.51%, it was chosen slightly less often than in EG_A. In this group, the second most frequently chosen time windows were the 12 pm to 1pm / #2 and 6pm to 7pm / #4b time windows, each selected by 16.28% of the participants. Contrary to the results in EG_A, the 5pm to 6pm / #4a and 7pm to 8pm / #4c time windows were each only chosen by approximately 6.98% of the participants. In this group, the 1pm to 2pm / #3 time window was for the first time chosen by some participants. However, it was only selected by 4.65% of the respondents. In this case, the label marking the 4pm to 5pm time window as the most harmful to the environment seemed to have had an additional effect on respondent's slot choices, as only 2.33% chose to receive their ordered groceries in this time window. A statistical comparison of slot choices of the participants in the control group and those in EG_B reveals that the difference in the slot choice behavior between the two groups is significant and that the relationship between Label 2b and the choice of a more environmentally friendly time window is strong ($p = 0.0002887$; Cramer's $V = 0.571$).

When comparing the results of EG_A and EG_B, however, the difference between the time window choices of participants within the two groups is insignificant and the relationship between label design and the choice of a more environmentally friendly time window is weak ($p = 0.6793$; Cramer's $V = 0.204$). Looking at the average additional CO_2 emissions resulting from the participants' time window choices within the different groups, these findings are confirmed.

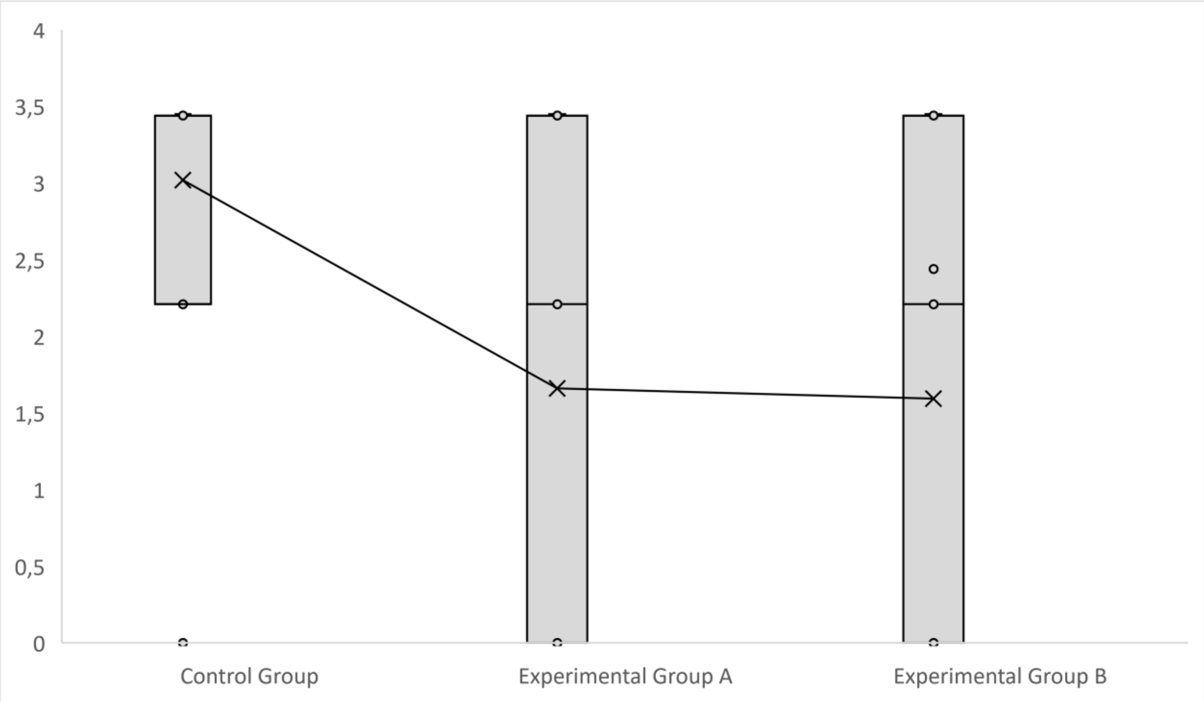


Figure 8: Average additional CO_2 emissions (in kilograms) per group

Figure 8 shows that the average additional CO_2 emissions resulting from the time window choices of the participants are significantly lower in the experimental groups than in the control group. In concrete terms, they amount to 3.02 kilograms in the control group, whereas in EG_A and EG_B, the average additional CO_2 emissions are only 1.66 kilograms and 1.59 kilograms, respectively. Thus, the environmental impact expressed as additional CO_2 emissions resulting from the participant's time window choices in the experimental groups could be almost halved compared to the control group. The difference between the average additional CO_2 emissions in the experimental groups, on the other hand, is only 67.42 grams. Overall, the findings suggest that color-coding and ordering time windows according to their environmental impact can help to significantly reduce additional CO_2 emissions per customer. However, labels that specify the exact amount of additional CO_2 emissions resulting from each time window choice do not need to be included, as they do not appeal to customers' environmental concerns in a significantly stronger way than if no such numerical labels are added.

A cross-age and cross-gender analysis once again provides interesting insights. For a detailed breakdown of the results by gender and age group, please refer to Table 10 in the Appendix. In the control group, the average additional CO_2 emissions resulting from the time window choices of the respective group members are nearly the same when comparing the choices of male and female participants. In both EG_A and EG_B, however, male participants' time window choices once again lead to lower additional CO_2 emissions than those of female respondents. Observing the differences in the time window choices across age groups also yields noteworthy findings. In the control group, the average additional CO_2 emissions resulting from the time window choices of the respective age groups range from 2.21 kilograms to 3.36 kilograms, the lowest value occurring in the 35 – 49 age group and the highest in the 50 – 64 age group. In both EG_A and EG_B, the lowest additional CO_2 emissions on average resulted from the time window choices of participants older than 64 and the second lowest from the 20 – 34 year old participants. The greatest negative environmental impact was in both groups caused by the time window choices of the 35 – 49 year old respondents. In sum, the youngest and oldest participants seemed to be most inclined to choose environmentally friendly time windows, while the middle-aged respondents were less likely to do so. This can possibly be explained by the fact that among the youngest participants are many students who, due to their flexible lifestyles, are able to make more compromises when it comes to time window selection. The same applies to participants from the highest age group. Since most people aged 65 and over are already retired and thus spend much of their time at home, they are also not bound to a few specific time windows.

7 Discussion and Conclusion

In this work, a simulation study and a survey were conducted to estimate and assess the impact of customers' time window choices on the operational efficiency and environmental sustainability of delivery operations in the context of attended home delivery of groceries. From the simulation, three main conclusions can be drawn. First, it was demonstrated that, if all customers within a given delivery route choose longer rather than shorter time windows, CO_2 emissions can be greatly reduced. This could be the case, for example, if one-hour time windows were removed from online supermarkets' time window offer sets altogether. The online shop of the globally operating supermarket *Spar*, for instance, offers its customers a time window set consisting exclusively of two-hour time windows, i.e., there is not even the option of choosing environmentally harmful one-hour time windows. However, given the large number of customers who are only at home at certain times of the day and hence rely on more narrow time windows, as well as the fierce competition among retailers, one-hour time windows are unlikely to be eliminated across the board at all online supermarkets. In the second step, it was thus demonstrated that even a single customer's time window choice can have a significant effect on the efficiency and sustainability of the delivery route. To be able to calculate the exact CO_2 savings potential resulting from the 21^{st} customer's time window choice, the customer under consideration was assumed to be the last to place an order and join the delivery system in an existing order stream. Thereby, it was demonstrated how much CO_2 could be saved both if the customer chooses a longer time window, or a one-hour time window during which the delivery truck is already in the area. Because the route plan is practically complete by the time the last customer places his or her order and selects the preferred time window, choosing a longer time window in this case only makes sense if no information is available on the most environmentally friendly one-hour time window. Effectively, the advantage of choosing longer time windows only becomes truly visible when a customer request is followed by unknown future requests, i.e., when maintaining flexibility for the route plan becomes essential. To pick up on this aspect, the third part of the simulation demonstrated that dynamically arranging routes based on an incremental incentivization of green time windows can reduce CO_2 emissions substantially. In this context, the approach of offering customers arriving early in the order stream long time windows and those placing their order at a later point in time short time windows has proven to be particularly effective. Altogether, the results of the simulation point out the considerable potential that can be realized if more customers select greener time windows. For this, however, it is important that customers are supported in their decision-making to the greatest possible extent. This means that the environmental impact resulting from their time window choice must be incentivized and communicated to them directly. Only in this way do customers have the opportunity to contribute effectively to greater delivery efficiency and reduced CO_2 emissions in the context of attended home deliveries.

Consequently, the second section of this work studied the impact of educating customers about the CO_2 footprint of their time window choices using an online survey. The results of the survey emphasize the potential of using green labels as means to increase customers' intrinsic motivation to select greener delivery time windows in two significant ways. First, when presented with a mixed time window offer set containing one-, two- and five-hour time windows, a considerably larger number of participants opted for longer time windows when one of the green labels was involved. Longer time windows can only be expected to be chosen by customers who have some knowledge on the complexity of last-mile delivery processes and understand how difficult it is to reconcile meeting short time windows with the design of an environmentally friendly delivery route. In reality, however, most customers are not aware of how constraining shorter time windows can be for the flexibility of the route plan and how this in turn has a highly negative impact on the sustainability of such last-mile operations. In line with the findings by Buldeo Rai et al. (2021), this suggests a major consumer awareness gap on the impact each individual time window choice has on the sustainability of the entire delivery chain. This may to a certain extent explain the results of the survey, which show that there is little added value in including numerical reference points in the information text pointing out the more sustainable delivery option. When concrete numbers are involved, customers often do not know how to interpret them. It is therefore sufficient to visually highlight green time windows combined with a brief information text without any numerical reference points. This also makes implementation much easier, as service providers are not required to calculate the potential environmental impact associated with the time window choice for each customer individually.

Second, when having to decide between time windows of uniform length, customers indeed seem to be willing to shift their time window preferences to greener time windows in the presence of green labels. Without incentives, customers cannot possibly know how each available one-hour time window performs in terms of environmental friendliness, which is why the average additional CO_2 emissions resulting from the participants' time window choices were significantly higher in the control group than in the two experimental groups. Again, however, the numerical CO_2 tags included in the incentive for EG_B did not produce significantly better results than the green label applied for EG_A. This again highlights that customers do not have sufficient knowledge on the complexities of last-mile delivery operations to be able to effectively interpret quantitative information as provided through the numerical CO_2 labels in the survey. Hence, it is sufficient if customers are made aware of which time windows perform better from an environmental perspective using visual and easily understandable labels combined with a brief explanation.

Overall, the findings of this work contribute to extant literature in several different ways. This is, to the best of the author's knowledge, the first paper to calculate and evaluate the carbon footprint of time windows in the context of attended home deliveries. The study thus stands out from similar lines of research in that it clearly highlights the extent to which a customer's time window choice at an individual level impacts the operational efficiency and environmental sustainability of home delivery operations. Additionally, the two-pronged approach of using a survey, in which customers are offered incentivized time windows on the basis of preceding, concrete calculations in a simulation, is also novel. This study thereby complements the work of Agatz et al. (2021) and confirms the finding that green labels are an effective tool to intrinsically motivate customers to choose a more environmentally friendly delivery option. Most importantly, this study provides a very practical contribution on how to design and manage the offer of time windows in the context of attended home deliveries in the future. Especially Label 1a and Label 2a presented in this study are easy to implement and can significantly reduce the carbon footprint of even a single customer's time window choice. Extrapolated to the number of customers demanding home deliveries of groceries on a daily basis, the approach of encouraging customers to choose longer time windows or the method of dynamically incentivizing green time windows could result in massive cumulative CO_2 savings and associated increases in operational efficiency. Therefore, service providers should take advantage of customers' willingness to choose more environmentally time windows and focus on incentivizing green time windows to contribute to more sustainable last-mile delivery operations.

8 Limitations and Outlook

When interpreting the study results, the limited scope of this work and the necessary compromises made in the simulation and the survey must be taken into account. In the simulation, for instance, the maximum number of customers was set to 21. In this respect, it would be interesting to investigate alternative scenarios considering a larger number of customers, varying pickup and delivery quantities or more delivery vehicles and depots. Thereby, it would also be useful to examine how the results change when not only the location of a single customer is varied, but the position of all customers in a predetermined delivery area. Additionally, some factors influencing the level of CO_2 emissions were neglected in the VRP Spreadsheet Solver, such as how the negative environmental impact associated with a delivery route increases when a delivery vehicle parks, switches off the engine and starts up again. Furthermore, the Bing maps route type in the Solver Console of the VRP Spreadsheet Solver was set to Shortest, as to allow for a straightforward translation of the travel distances into CO_2 emissions using the MEET model. On the one hand, it should in this context be noted that the MEET model itself can lead to inaccurate results, as it categorizes vehicles into weight classes and neglects factors such as vehicle load and road gradient up to a certain weight category. On the other hand, the parameters set in the VRP Spreadsheet Solver made it impossible to investigate how external factors such as real time traffic affect the delivery route and the resulting CO_2 emissions. It would therefore be intriguing to see how the results obtained through the VRP Spreadsheet Solver change through the use of an alternative, more precise emission model. Finally, it must be noted that the dynamic incentivization of green time windows and the calculation of the associated CO_2 emissions in the last part of the simulation were based on the assumption that all customers are actually willing to choose these time windows. More realistic results could be achieved if each time window was assigned a certain probability of being booked or rejected and if the route plan was incrementally designed on that basis.

With regard to the survey, it must be pointed out that at N = 125, the number of participants is rather low, which suggests limited representativeness. In addition, the advantages of an online survey, which in particular lie in the possibility of testing of causal effects, are offset by possible validity problems. For example, there is a risk that participants, even if prompted otherwise, did not reveal their true time window preferences. Regarding the design of the green label, investigating alternative forms of incentives might provide further useful insights. For example, it could be examined whether an information text is even necessary to motivate customers to choose greener time windows, or if visual effects are sufficient. Moreover, the only partially representative socio-demographics of the respondents of the survey can potentially be attributed to the fact that the study participants were primarily recruited in the author's own social environment and via online channels, leading to the fact that more women and German participants took part in the study and that many of the participants have a similar age and educational background. In this respect, it would be interesting to test whether the tendency of especially men and young participants being prone to choose greener time windows as observed in both experimental groups still prevails in a larger and more representative study.

Overall, this study shows how effective it can be to pay more attention to the CO_2 emissions associated with customers' time window choices and highlights the importance of giving customers a better understanding of the impact of their decisions on environmental sustainability and operational efficiency of last-mile delivery operations. It is to be hoped that more scientists will continue this line of research in the coming years and contribute to more efficient and sustainable time window management in the context of attended home deliveries.

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Appendix

A. Abstract

Abstract (English)

This paper investigates the effect of customers' delivery time window choices on the operational efficiency and environmental sustainability of the last-mile delivery system in the context of attended home delivery of groceries. Although these two parameters are argued to be closely interlinked, especially the sustainability dimension of offering customers delivery time windows during the online ordering process has been insufficiently studied so far. Yet, the significant increase in home deliveries, particularly during the COVID-19 pandemic, makes it essential to rethink the existing concept of time window management. To illustrate and quantify the effects of customers' time window choices on the last-mile delivery system, a simulation of a vehicle routing problem is conducted using the VRP Spreadsheet Solver. Subsequently, a survey is carried out to examine the propensity of customers to select the thereby defined environmentally friendly and efficiency-enhancing time windows when marked as such through the use of green labels. The results of the simulation provide strong support for the positive effect of longer versus shorter time windows and further highlight the effectiveness of dynamically identifying and incentivizing the most environmentally friendly time windows for each individual customer in a given route plan. The outcome of the survey suggests that significantly more customers choose longer or more environmentally friendly time windows in the presence of green labels and that additionally including numerical reference points in the incentive has little added influence on customers' slot choice behavior. Overall, the results of the study suggest that each customer's time window choice has a significant impact on the operational efficiency and environmental sustainability of the last-mile delivery route. Consequently, providing customers with information on the environmental impact of their time window choice is a cost-effective and easy-to-implement way to contribute to more efficient and sustainable last-mile operations.

Abstract (German)

In dieser Arbeit wird untersucht, wie sich die Wahl von Lieferzeitfenstern im Rahmen der Hauszustellung von Lebensmitteln auf die operationelle Effizienz und die ökologische Nachhaltigkeit des Liefersystems auswirkt. Obwohl diese beiden Parameter eng miteinander verknüpft sind, wurde insbesondere die Nachhaltigkeitsdimension des Ansatzes, Kunden im Rahmen des online Bestellprozesses Lieferzeitfenster anzubieten, bisher unzureichend untersucht. Durch den massiven Anstieg an Hauszustellungen, der insbesondere auf die COVID-19 Pandemie zurückzuführen ist, ist es jedoch dringend notwendig, das bestehende Konzept des Zeitfenstermanagements zu überdenken. Zur Veranschaulichung und Quantifizierung der Auswirkungen der Zeitfensterpräferenzen einzelner Kunden auf das Liefersystem wird eine Simulation eines Tourenplanungsproblems anhand des VRP Spreadsheet Solvers durchgeführt. Anschließend soll eine Umfrage untersuchen, inwiefern Kunden im Beisein von grünen Labels verstärkt dazu geneigt sind, die dadurch definierten umweltfreundlichen und effizienzsteigernden Zeitfenster auszuwählen. Die Ergebnisse der Simulation untermauern die positive Wirkung von längeren gegenüber kürzeren Zeitfenstern. Sie zeigen außerdem die Effektivität des Ansatzes, die umweltfreundlichsten Zeitfenster für jeden einzelnen Kunden in einer bestimmten Lieferroute dynamisch zu identifizieren und Anreize für die Wahl solcher Zeitfenster zu schaffen. Die Ergebnisse der Umfrage lassen darauf schließen, dass sich deutlich mehr Kunden für längere oder umweltfreundlichere Zeitfenster entscheiden, wenn diese durch grüne Labels hervorgehoben werden, und dass es keinen signifikanten Mehrwert bringt, numerische Referenzpunkte in die Labels mit einzubeziehen. Insgesamt deuten die Ergebnisse der Studie darauf hin, dass die Zeitfensterpräferenzen von Kunden einen erheblichen Einfluss auf die operationelle Effizienz und die ökologische Nachhaltigkeit der Lieferroute haben. Folglich stellt die Aufklärung der Kunden über die Umweltauswirkungen ihrer Zeitfensterwahl eine kosteneffiziente und einfach umzusetzende Möglichkeit dar, zu einem effizienteren und nachhaltigeren Liefersystem beizutragen.

B. Spreadsheets in the VRP Spreadsheet Solver

From	To	Distan	Duratic	Metho	Bing Maps driving distanc	(km) / Bing Maps driving durations
Depot	Depot	0	0:00			
Depot	Customer 1	1411,3	0:12			
Depot	Customer 2	3147,71	0:22			
Depot	Customer 3	2494,51	0:20			
Depot	Customer 4	3221,55	0:35			
Depot	Customer 5	4333,1	0:47			
Depot	Customer 6	3050,42	0:34			
Depot	Customer 7	1955,5	0:17			
Depot	Customer 8	2821,79	0:30			
Depot	Customer 9	2317,11	0:24			
Depot	Customer 10	3585,08	0:31			
Depot	Customer 11	6541,48	0:35			
Depot	Customer 12	4697,71	0:22			
Depot	Customer 13	3533,3	0:34			
Depot	Customer 14	1822,79	0:17			
Depot	Customer 15	2618,77	0:22			
Depot	Customer 16	1839,14	0:13			
Depot	Customer 17	532,202	0:05			
Depot	Customer 18	1711,06	0:12			
Depot	Customer 19	2665,64	0:27			
Depot	Customer 20	2860,48	0:14			
Customer 1	Depot	1448,91	0:12			
Customer 1	Customer 1	0	0:00			
Customer 1	Customer 2	3907,18	0:29			
Customer 1	Customer 3	1820,06	0:20			

... 1.Locations | 2.Distances | 3.Vehicles | 4.Solution | 5.Visualization

Figure 9: Distances worksheet (B_{20})

Starting depot	Vehicle type	Capacity	Fixed cost per trip	Cost per unit distance	Duration multiplier	Distance limit	Work start time	Driving time limit	Working time limit	Return depot	Number of vehicles
Depot	T1	1	0,00	1,00	1,00	2000000000,00	10:00	9:00	10:00	Depot	1

... 1.Locations 2.Distances **3.Vehicles** 4.Solution 5.Visualization

Figure 10: Vehicles worksheet (B_{20})

Total net profit:	**-40922,08**							
Vehicle:	**V1**	**Stops:**	**21**	**Net profit:**	**-40922,0759**			
Stop count	**Location Name**	**Distance travelled**	**Driving time**	**Arrival time**	**Departure time**	**Working time**	**Profit collected**	**Load**
0	Depot	0,00	0:00		10:00	0:00	0	0
1	Customer 17	532,20	0:05	10:05	10:07	0:07	0	0
2	Customer 12	5193,40	0:27	10:29	10:32	0:32	0	0
3	Customer 4	7450,56	0:51	10:56	10:58	0:58	0	0
4	Customer 6	8067,51	1:01	11:08	11:11	1:11	0	0
5	Customer 1	10764,22	1:31	11:41	11:43	1:43	0	0
6	Customer 18	11813,09	1:42	11:54	11:57	1:57	0	0
7	Customer 9	13633,97	2:02	12:17	12:19	2:19	0	0
8	Customer 13	15773,41	2:30	12:47	12:50	2:50	0	0
9	Customer 20	17692,11	2:49	13:09	14:02	4:02	0	0
10	Customer 2	18796,85	2:59	14:12	14:15	4:15	0	0
11	Customer 10	22843,28	3:38	14:54	14:56	4:56	0	0
12	Customer 5	24834,20	4:00	15:18	15:21	5:21	0	0
13	Customer 11	28002,34	4:23	15:44	15:46	5:46	0	0
14	Customer 14	32161,31	5:03	16:26	16:29	6:29	0	0
15	Customer 16	33039,32	5:16	16:42	17:02	7:02	0	0
16	Customer 7	33902,07	5:29	17:15	18:02	8:02	0	0
17	Customer 15	34805,16	5:41	18:14	18:17	8:17	0	0
18	Customer 8	35815,33	5:55	18:31	18:33	8:33	0	0
19	Customer 19	36721,68	6:08	18:46	18:49	8:49	0	0
20	Customer 3	38521,31	6:29	19:10	19:12	9:12	0	0
21	Depot	40922,08	6:48	19:31		9:31	0	0
Detected reasons of infeasibility								

... 1.Locations 2.Distances 3.Vehicles **4.Solution** 5.Visualization

Figure 11: Solution worksheet (B_{20})

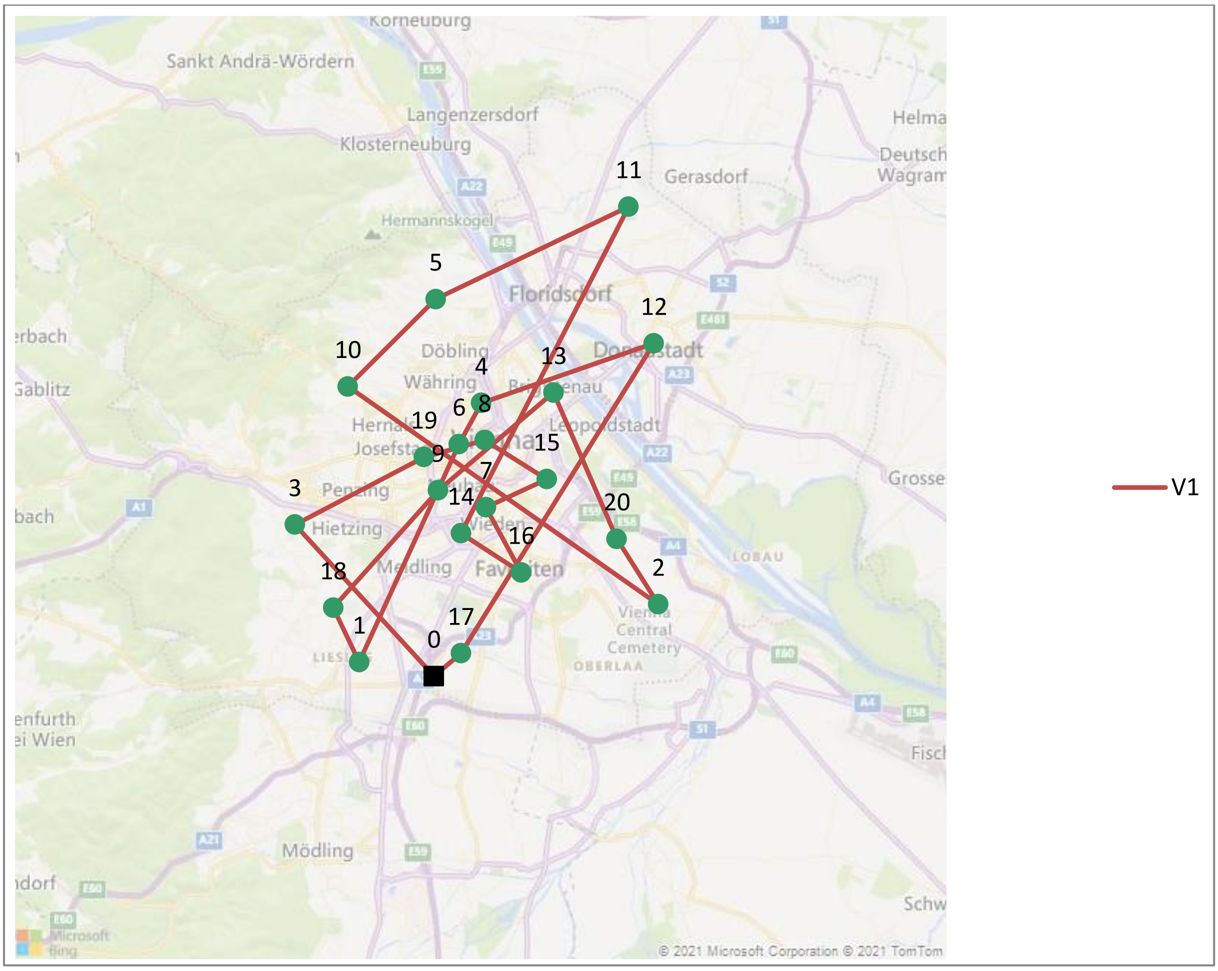

Figure 12: Visualization worksheet (B_{20})

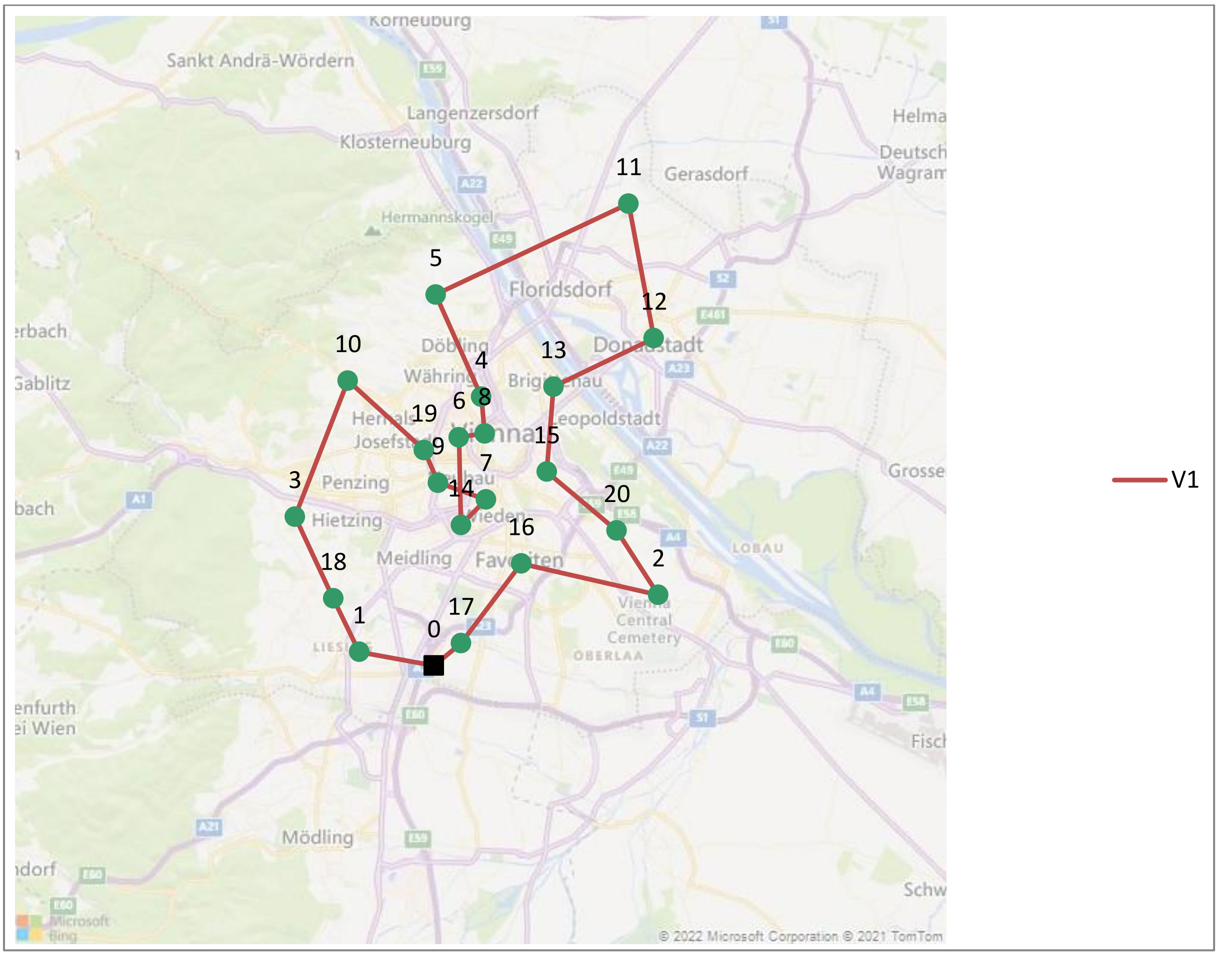

Figure 13: Visualization of the route plan in S_{10}

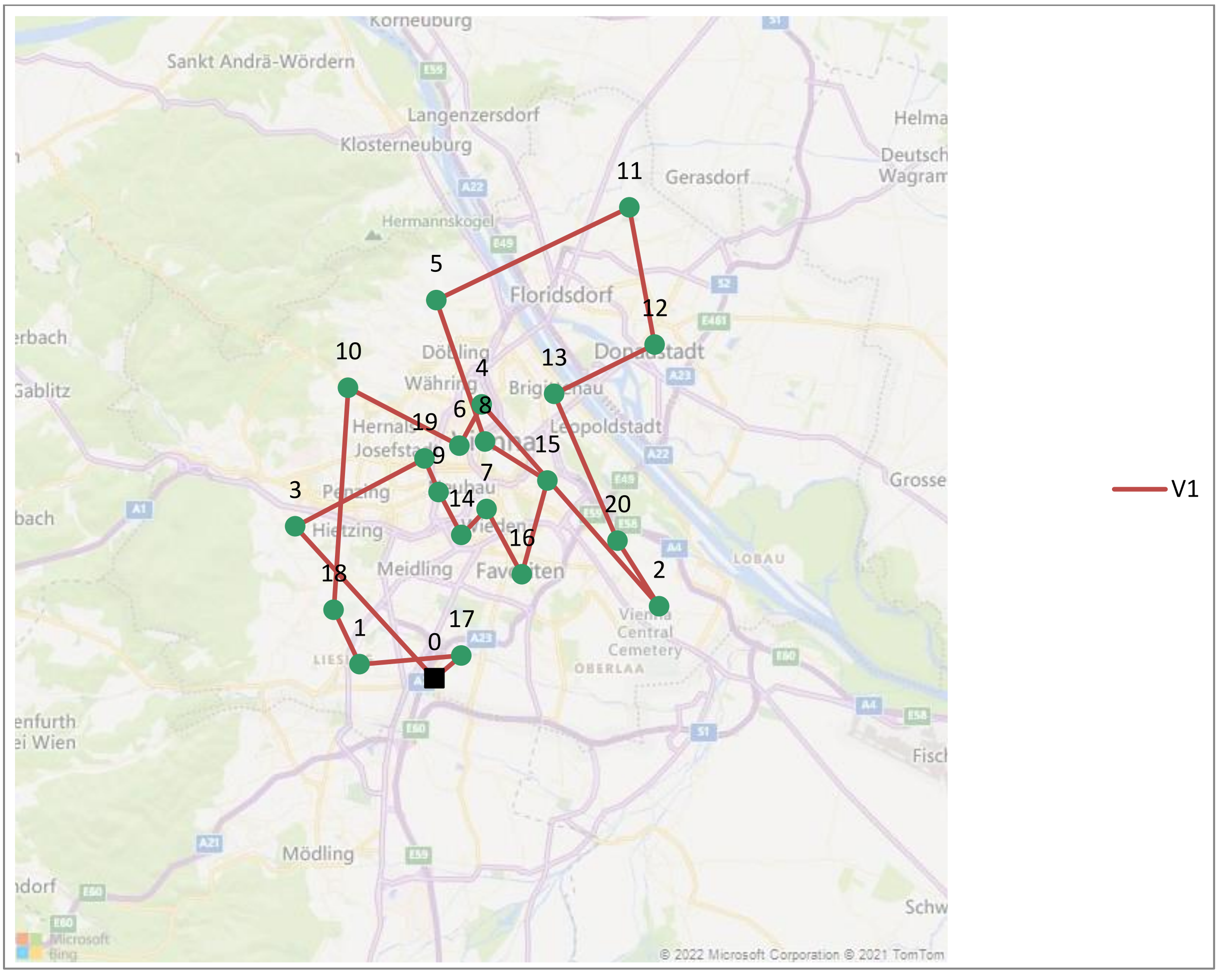

Figure 14: Visualization of the route plan in S_5

C. Pseudo-code of the LNS algorithm

Algorithm 1 LNS algorithm implemented within VRP Spreadsheet Solver.

procedure LNS(depots, customers, distances, durations, vehicles)
Construct an *incumbent* solution by adding customers to the routes, choosing the customer that results in the maximal profit increase (equivalently, minimal cost increase) at every step
Improve the *incumbent* solution using local search with the EXCHANGE, 1-OPT, 2-OPT, and VEHICLE-EXCHANGE operators
Record the *incumbent* solution as the *best known* solution
repeat
    Destroy the *incumbent* solution by randomly removing vertices
    Repair the *incumbent* solution heuristically by adding vertices
    Improve the *incumbent* solution using local search with the EXCHANGE, 1-OPT, 2-OPT, and VEHICLE-EXCHANGE operators
    if the *incumbent* solution is better than the *best known* solution **then**
        Record the *incumbent* solution as the *best known* solution
    else
        Replace the *incumbent* solution by the *best known* solution with probability p
until time elapsed is larger than the CPU time allowed
return best known solution
end LNS

Figure 15: Pseudo-code implemented within the VRP Spreadsheet Solver

Source: Erdoğan (2017)

D. Online survey design

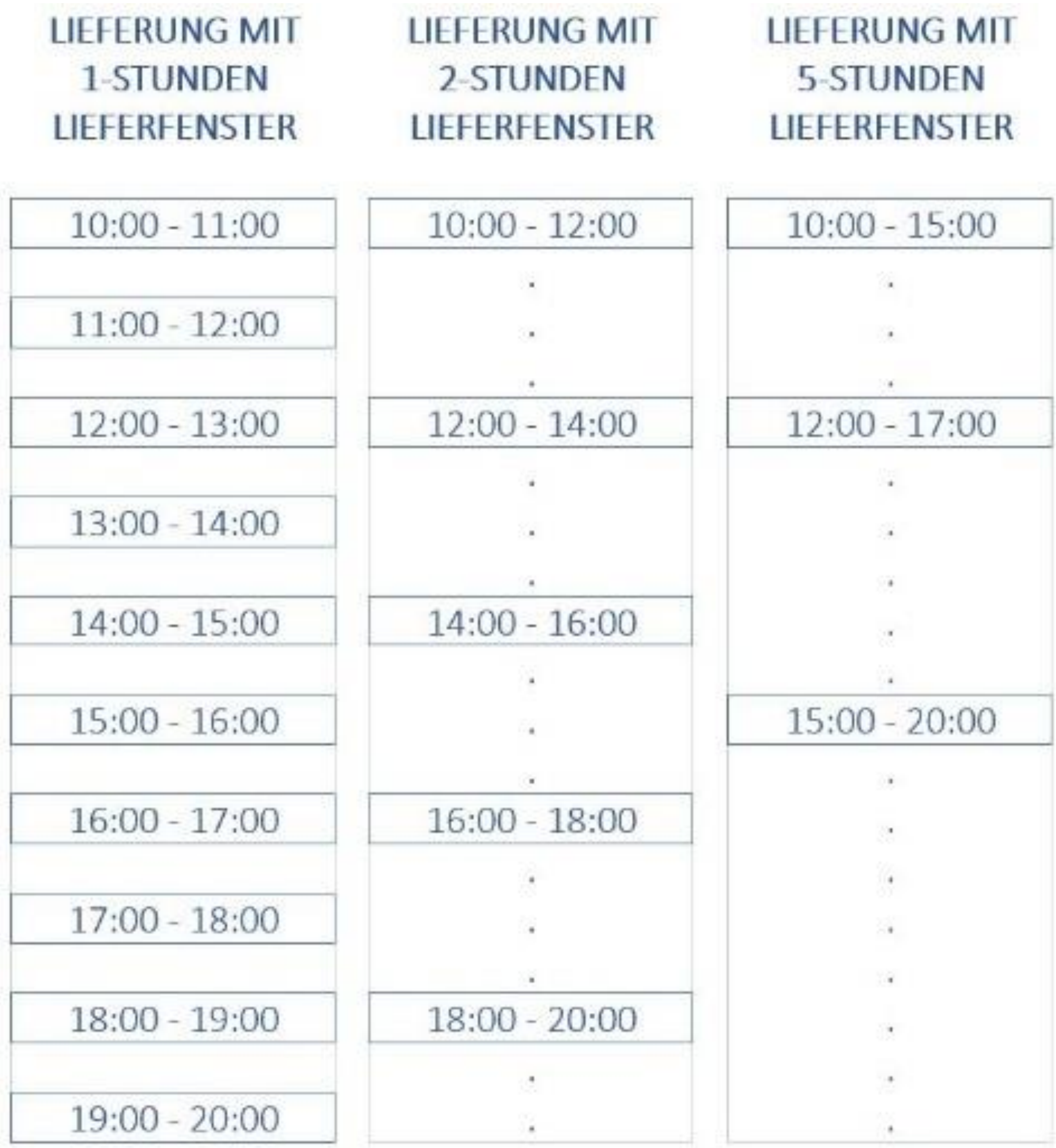

Figure 16: Mixed time window offer set shown to the control group

Figure 17: Mixed time window offer set shown to experimental group A

Figure 18: Mixed time window offer set shown to experimental group B

Figure 19: One-hour time window offer set shown to the control group

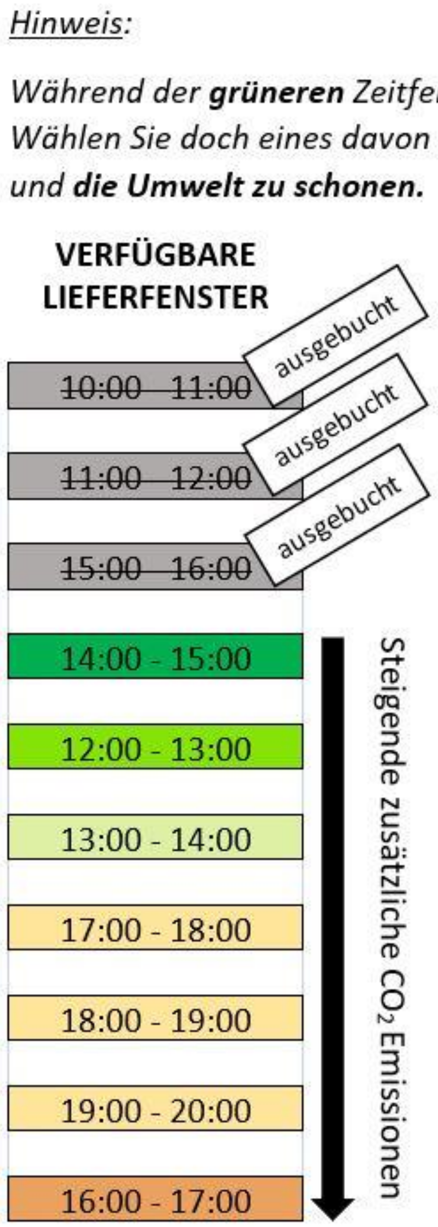

Figure 20: One-hour time window offer set shown to experimental group A

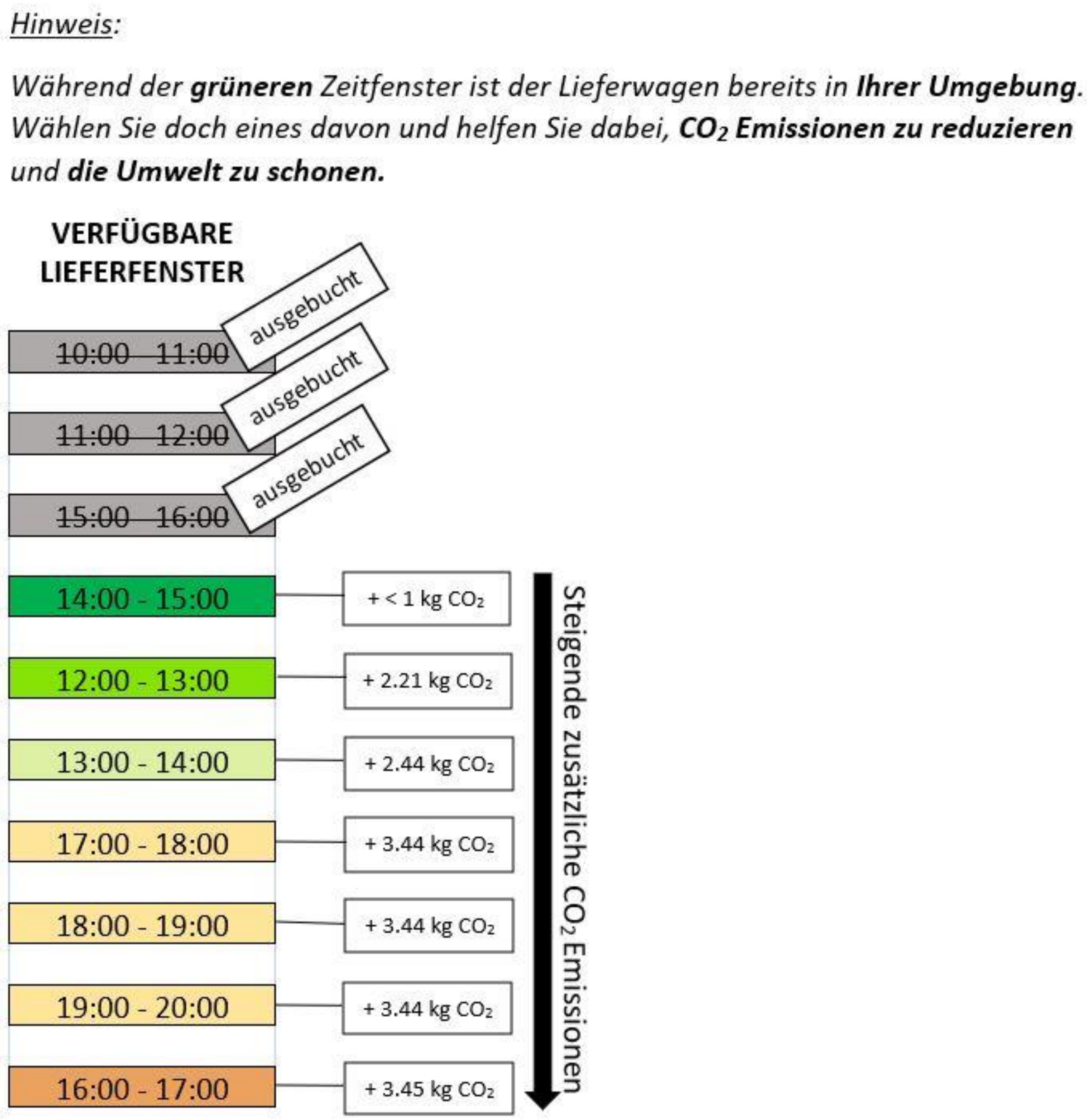

Figure 21: One-hour time window offer set shown to experimental group B

E. Cross-age and cross-gender analysis

Table 9: Cross-age and cross-gender analysis of the percentage of time window lengths chosen in each group

	One-hour	Two-hour	Five-hour
Control Group			
Male	**9/16 = 56%**	**5/16 = 31%**	**2/16 = 13%**
20 - 34	5/9 = 56%	2/9 = 22%	2/9 = 22%
50 - 64	4/7 = 57%	3/7 = 43%	0/7 = 0%
Female	**19/33 = 58%**	**12/33 = 36%**	**2/33 = 6%**
20 - 34	12/21 = 57%	7/21 = 33%	2/21 = 10%
35 - 49	2/2 = 100%	0/2 = 0%	0/2 = 0%
50 - 64	4/8 = 50%	4/8 = 50%	0/8 = 0%
65 - 79	1/2 = 50%	1/2 = 50%	0/2 = 0%
Experimental Group A			
Male	**2/9 = 22%**	**5/9 = 56%**	**2/9 = 22%**
≥ 80	0/1 = 0%	1/1 = 100%	0/1 = 0%
20 - 34	1/6 = 17%	4/6 = 67%	1/6 = 17%
50 - 64	1/2 = 50%	0/2 = 0%	1/2 = 50%
Female	**6/24 = 25%**	**14/24 = 58%**	**4/24 = 17%**
20 - 34	2/14 = 14%	8/14 = 57%	4/14 = 29%
35 - 49	0/2 = 0%	2/2 = 100%	0/2 = 0%
50 - 64	4/4 = 100%	0/4 = 0%	0/4 = 0%
65 - 79	0/4 = 0%	4/4 = 100%	0/4 = 0%
Experimental Group B			
Divers	**0/1 = 0%**	**0/1 = 0%**	**1/1 = 100%**
50 - 64	0/1 = 0%	0/1 = 0%	1/1 = 100%
Male	**2/20 = 10%**	**14/20 = 70%**	**4/20 = 20%**
20 - 34	1/13 = 8%	9/13 = 69%	3/13 = 23%
50 - 64	1/5 = 20%	3/5 = 60%	1/5 = 20%
65 - 79	0/2 = 0%	2/2 = 100%	0/2 = 0%
Female	**5/22 = 23%**	**14/22 = 64%**	**3/22 = 14%**
20 - 34	3/15 = 20%	9/15 = 60%	3/15 = 20%
50 - 64	2/5 = 40%	3/5 = 60%	0/5 = 0%
65 - 79	0/2 = 0%	2/2 = 100%	0/2 = 0%

Table 10: Cross-age and cross-gender analysis of the average additional CO_2 emissions resulting from the one-hour time windows chosen in each group

	Percentage	Avg. additional CO_2 emissions (in kg)
Control Group		
Male	**16/49 = 33%**	**3,06**
20 - 34	9/16 = 56%	2,76
50 - 64	7/16 = 44%	3,44
Female	**33/49 = 67%**	**3,00**
20 - 34	21/33 = 64%	2,98
35 - 49	2/33 = 6%	2,21
50 - 64	8/33 = 24%	3,29
65 - 79	2/33 = 6%	2,83
Experimental Group A		
Male	**9/33 = 27%**	**1,39**
≥ 80	1/9 = 11%	0,00
20 - 34	6/9 = 67%	2,09
50 - 64	2/9 = 22%	0,00
Female	**24/33 = 73%**	**1,76**
20 - 34	14/24 = 58%	1,55
35 - 49	2/24 = 8%	3,44
50 - 64	4/24 = 17%	3,44
65 - 79	4/24 = 17%	0,00
Experimental Group B		
Diverse	**1/43 = 2%**	**0,00**
50 - 64	1/1 = 100%	0,00
Male	**20/43 = 47%**	**1,14**
20 - 34	13/20 = 65%	1,23
50 - 64	5/20 = 25%	0,88
65 - 79	2/20 = 10%	1,22
Female	**22/43 = 51%**	**2,08**
20 - 34	15/22 = 68%	1,98
50 - 64	5/22 = 23%	2,75
65 - 79	2/22 = 9%	1,11