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Optimizing Carbon Emissions for time-dependent Green Vehicle Routing Problem for Heterogeneous Vehicles

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Abstract

As climate change threatens to disrupt the lives of billions of people and cause severe economic consequences, a growing number of companies and governmental agencies are eager to reduce their environmental impacts and CO_2 emissions. The transportation sector accounts for 24% of global CO_2 emissions as of 2020, with 29.4% of this share emitted by road freight, including trucks and lorries. Reducing emissions in transportation not only mitigates climate change but also improves public health by decreasing air pollution, thereby lowering the incidence of respiratory and cardiovascular diseases. One way for companies or government agencies to achieve this is to optimize their vehicle routes to reduce emissions, which is also called the Green Vehicle Routing Problem (GVRP). Even though many papers have explored different variations and aspects of the GVRP, several research gaps remain; in particular, there is a lack of models that consider the effects of heterogeneous fleets, congestion, and customer time windows simultaneously. Given the magnitude of emissions emitted by the transportation sector, even small improvements in routing practices can have far-reaching positive effects. Therefore, using an objective function that minimizes energy consumption can provide more realistic results when aiming to minimize emissions. The objective of this master's thesis is to investigate the effect different fleets have on the GVRP's objective of reducing CO_2 emissions, while considering the effects of traffic congestion, and also adhering to customer time windows. In response to these gaps in the current body of research, this master's thesis aims to develop a mathematical model for the Green Vehicle Routing Problem (GVRP) that incorporates both heterogeneous fleets and time-dependency. A triple-objective model will be developed for optimizing carbon emissions in the context of time-dependent GVRP for heterogeneous vehicles, addressing the challenges of urban transportation while prioritizing a reduction in CO_2 emissions. After testing on the 1987 Solomon instances, real world distance and travel time data was gathered to demonstrate the effectiveness and applicability of this model on real world data. Numerous studies have significantly advanced the understanding and modeling of related problems, but the application of the HTDGVRP specifically to Vienna is a frontier yet to be fully explored. Developing both an exact approach as well as a genetic algorithm highlighted the effectiveness of metaheuristic approaches when tackling complex NP-hard problems. The results obtained while using real distance and travel speed data indicate that logistics planners may not have to compromise as much as previously thought in terms of travel times and thus labor costs when opting for more environmentally friendly vehicle fleets, which can help pave the way towards a carbon-neutral logistics sector.

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III. List of Abbreviations

CO_2	Carbon Dioxide
VRP	Vehicle Routing Problem
GVRP	Green Vehicle Routing Problem
TDGVRP	Time-dependent Green Vehicle Routing Problem
HTDGVRP	Heterogeneous Time-Dependent Green Vehicle Routing Problem
ALNS	Adaptive Large Neighborhood Search
PRP	Pollution Routing Problem
MILP	Mixed-Integer Linear Programming
GA	Genetic Algorithm
IIS	Irreducible Inconsistent Subsystem
RC101	Random Clustered 101 Instance
R101	Random 101 Instance

Contents

1 Introduction

As climate change threatens to disrupt the lives of billions of people, and cause severe economic consequences, a growing number of companies and governmental agencies are eager to reduce their environmental impacts and CO_2 emissions. The transportation sector accounts for 24% of global CO_2 emissions as of 2020, with 29.4% of this share emitted by road freight, including trucks and lorries (Ritchie, 2020). Reducing emissions in transportation not only mitigates climate change but also improves public health by decreasing air pollution, thereby lowering the incidence of respiratory and cardiovascular diseases. Furthermore, achieving emission reductions contributes to global climate goals, such as those outlined in the Paris Agreement. It supports sustainable development by preserving natural resources for future generations. One way for companies or government agencies to achieve this is to optimize their vehicle routes to reduce emissions, which is also called the Green Vehicle Routing Problem (GVRP). Solving the GVRP involves minimizing the distance traveled, energy consumption, or time spent in congested traffic. However, the GVRP is an NP-hard problem, meaning computational time grows exponentially as the number of nodes (i.e., customers) increases, making finding the optimal solution often not feasible (Asghari et al., 2021).

(Erdoğan and Miller-Hooks, 2012) formally introduced the Green Vehicle Routing Problem, and thus kicked off researchers' efforts to take environmental considerations into account in vehicle routing problems. However, their model does not consider heterogeneous fleets and time dependency, among other parameters. Additionally, their objective function aims to minimize the total distance, which is not the best measure to estimate CO_2 emissions, as the shortest route does not necessarily provide the lowest emissions, for example due to travel speed or road gradient.

Even though many papers have explored different variations and aspects of the GVRP, several research gaps remain; in particular, there is a lack of models that consider the effects of heterogeneous fleets, congestion, and customer time windows simultaneously. Addressing these gaps is essential for various stakeholders: companies can achieve significant cost savings and enhance their corporate social responsibility by adopting optimized routing practices, while government agencies can more effectively implement environmental policies and meet emission reduction targets. Society as a whole benefits from improved air quality and reduced environmental degradation, creating a healthier and more sustainable living environment. In view of the significant emissions of the transportation sector, closing these remaining gaps, and developing ever more realistic and better models, is crucial in reducing emissions. Given the magnitude of emissions emitted by the transportation sector, even small improvements in routing practices can have far-reaching positive effects. This is crucial, as the transportation sector has been unable to achieve a significant reduction in CO_2 emissions within the last 2-3 decades (Ritchie, 2020).

Therefore, choosing an objective function that minimizes energy consumption can yield more realistic results when aiming to reduce emissions. This approach, as implemented by (Kancharla and Ramadurai, 2018), provides valuable insights that help inform a model specifically designed to cut emissions. Given the similarity in research objectives, their work offers an excellent starting point for this study.

The central aim of this master's thesis is to explore how different fleet compositions influence the GVRP's ability to reduce CO_2 emissions, taking into account both traffic congestion and customer time windows. The outcomes of this research have the potential to assist logistics companies in lowering operating costs and boosting efficiency, while also supporting policymakers in shaping more effective environmental regulations. In addition, the findings contribute to the wider global endeavor of preserving the environment and mitigating climate change. To set a solid foundation, this thesis will begin by reviewing the existing literature, identifying what has already been studied, and determining how best to develop the model.

In response to the gaps in current research, this thesis presents a mathematical model for the Green Vehicle Routing Problem (GVRP) that includes both heterogeneous fleets and time-dependency. The chosen fleet—small gasoline-powered trucks, electric cars, and e-bikes—allows for more flexible and realistic routing, reflecting real-world scenarios where fleets are rarely uniform. The overarching objective is to assess how various fleet compositions affect CO_2 reduction efforts while factoring in the role of congestion.

A triple-objective model will be constructed to optimize carbon emissions in time-dependent GVRPs with heterogeneous vehicles, specifically addressing the challenges posed by urban congestion. Beyond lowering emissions, the model also focuses on distance and time optimization. This approach provides broader insights into how minimizing carbon emissions influences route efficiency and operating costs, enabling a more comprehensive understanding of the trade-offs inherent in eco-conscious vehicle routing.

After validating the algorithms using the well-known Solomon (1987) benchmark instances, the model will be tested with real-world distance and travel time data. This dual validation ensures that the model is not only theoretically sound but also robust, scalable, and suitable for practical application in various logistical settings.

Finally, the successful adoption of such optimized routing strategies can help drive innovation in logistics, encouraging the greater use of electric vehicles and the development of smart transportation systems. As urban centers become increasingly "smart," the need for efficient and sustainable logistics solutions will continue to grow, making this research both timely and forward-looking.

2 Literature review

2.1 Vehicle routing problem

The literature review for this thesis is designed to provide a comprehensive overview of the current research on the Green Vehicle Routing Problem (GVRP) and its various extensions, with a focus on heterogeneous vehicle fleets and time-dependent routing. The scope of the review includes traditional vehicle routing problems (VRP), green routing models, and recent innovations that address factors such as traffic congestion and emission minimization.

To ensure the relevance of the literature to this study, selection criteria were applied that focused on research published in recent years. The research papers examined broach the issues of the use of heterogeneous fleets in GVRP models, the incorporation of time-dependent variables, such as travel times and congestion patterns, objective functions that minimize carbon emissions, fuel consumption, or energy use. The review categorizes the literature into distinct themes, including traditional VRP approaches, time-dependent routing models, and GVRP with environmental objectives and special attention is given to studies that explore the use of alternative vehicle types (e.g., electric cars, e-Bikes) and those that incorporate real-time traffic data, as these are directly related to the model developed in this thesis.

Through this analysis, key research gaps were identified, particularly in the lack of models that simultaneously consider heterogeneous vehicle fleets, time-dependent traffic, and customer time windows. These gaps form the foundation for the development of the new model proposed in this thesis, which aims to address these limitations by integrating multiple fleet types and optimizing carbon emissions in time-dependent scenarios.

The concept of the vehicle routing problem was initially brought to light by (Dantzig and Ramser, 1959).

They addressed a practical issue relating to the distribution of gasoline from a major terminal to a vast number of service stations. As the number of service stations grew, the possible routing options increased exponentially, thereby complicating the task of identifying and evaluating an efficient route to achieve an optimal outcome. The challenge was significant enough that they sought to find a more effective method. As a result, Dantzig and Ramser developed an algorithmic solution that utilized integer linear formulation to attain a solution that was near-optimal.

A notable aspect of these problems is their inherent computational complexity. Despite their seemingly simplistic design, VRPs fall into the category of NP-hard problems, as demonstrated by (Lenstra and Kan, 1981). The complexity arises from the combinatorial nature of the problem, where the number of possible routes grows exponentially with the number of delivery locations. This complexity becomes even more pronounced when factors such as multiple depots, vehicle capacities, and time-dependent travel speeds are taken into account. Exact methods for solving the VRP such as branch and bound, branch and cut, dynamic programming, set partitioning and column generation are able to find optimal solutions to the VRP but only if the problem is relatively small i.e. not many customers (Laporte, 1992). Recognizing these challenges, researchers have employed a vast array of heuristics and metaheuristics to address VRPs. Classical approaches like the savings algorithm proposed by (Clarke and Wright, 1964) have been widely used in earlier studies. Meanwhile, metaheuristics, including genetic algorithms, tabu search techniques, and simulated annealing, have shown great effectiveness in solving VRPs (Asghari et al., 2020). These methods leverage sophisticated computational techniques to iteratively improve solution quality but do not guarantee to find an optimal solution as they may get stuck in a local optimum.

Since its introduction in 1959, interest in this field of research has grown substantially and scholars have developed algorithms to solve a multitude of variations of the VRP which aim to account for more real life complexities (Asghari et al., 2020). The traditional vehicle routing problem has mostly been focused on reducing the cost of operations or the time traveled to serve customers. The Green Vehicle Routing Problem (GVRP), a variation of the VRP, however focuses on the environmental impacts of vehicle routing which is in most cases done by minimizing the energy consumption, the distance traveled, or time spent driving (Asghari et al., 2020). However minimizing the total distance or time spent driving does not necessarily provide the routes with the lowest emissions as the shortest may incorporate a significant road gradient, causing higher emission whereas fastest route may take vehicles on longer routes with higher travel speeds which also lead to more CO_2 being emitted.

2.2 Green vehicle routing problem

The Green VRP has the potential to significantly reduce the environmental impacts and has been of particular interest for researchers becoming one of the most studied variants of the VRP (Moghdani et al., 2021). Among the first to consider the environmental aspect of the vehicle routing problem was (Palmer, 2007) who was able to reduce emissions by 5% with his model, highlighting the effectiveness of an environmental approach to the VRP. Since then many researchers have studied the GVRP which has become one of the most studied variations of the VRP (Moghdani et al., 2021).

The term Green Vehicle Routing Problem was first coined by (Erdoğan and Miller-Hooks, 2012) who aimed at minimizing the fuel consumption and emissions of a fleet consisting of alternative fuel powered vehicles. They used a mixed integer linear programming model to compute a routing plan that minimizes the total amount of fuel consumed. This study paved the way for many other research efforts on the topic. However, they considered the fleet as homogeneous and their approach ignored other aspects such as traffic congestion i.e. time-dependent travel speeds which could significantly alter the route proposed by the algorithm and provide a more realistic model able to better improve energy consumption and consequently CO_2 emissions.

Developing a model that considers different vehicle types with different vehicle specifications and fuel consumptions, and subsequently varying emissions, has been to improve the overall CO_2 emissions when solving a GVRP. A significant contribution in this field was the work (Kopfer et al., 2014), who with their model, which considers vehicles of different sizes, shows that when optimizing for CO_2 emissions, vehicles are chosen that have lower fuel consumption, which, however, can lead to longer travel distances, travel time, and operational cost. The researchers have, however, highlighted these increased distances traveled by vehicles as well as more vehicles being used due to lower load capacities can lead to additional congestion.

The research on the effectiveness of heterogeneous approaches is further highlighted by the work of (Murakami, 2017), who considered both diesel as well as electric vehicles in their fleet to solve the Green Vehicle Routing Problem. Their model is quite realistic as they take into account road inclines, vehicle speed, acceleration, waiting times at traffic lights, as well as vehicle body and maintenance costs. Using a mixed linear programming approach, they are able to provide potential logistic operators an algorithm that can help them determine their optimal fleet mix of electric and diesel vehicles.

Despite the significant strides made in the exploration of the Green Vehicle Routing Problem (GVRP), it's noteworthy that the studies discussed in this chapter have not explicitly factored in the time-dependent variables. In real-world logistics and transportation, time-dependent factors play a pivotal role. These factors include elements like traffic congestion and varying vehicle speeds, which in turn directly influence fuel consumption and emissions (Luo et al., 2023).

It is important to underline that in practical scenarios, these elements do not remain constant, but vary depending on the time of day or prevailing road conditions. These temporal dynamics can significantly affect the environmental and cost efficiency of transportation routes. For instance, what may appear as the most efficient route in the early morning hours might not be the optimal choice during peak traffic hours. Incorporating these time-dependent parameters in the context of GVRP has the potential to yield more accurate, realistic, and environmentally beneficial solutions. For instance, it allows the algorithm to select slower, but more fuel-efficient routes during periods of high congestion. Therefore, acknowledging and integrating the time-dependent aspects within the context of GVRP, is a step toward more practical, adaptable, and sustainable route planning strategies.

2.3 Time-dependent green vehicle routing problem

Time-dependent Green Vehicle Routing Problems (TDGVRPs) are an extension of the traditional GVRP that take into account that travel speeds are not always constant, as assumed in many versions of the GVRP, but instead vary depending on the time of day and congestion patterns. Therefore, they are an important next step in environmentally focused vehicle routing, as they are able to provide even more detailed and realistic insights into carbon minimization for logistics companies, especially when considering city logistics. Among the first to take this time dependency into account was (Ichoua et al., 2003) and even though their objective was not to lower emissions but to reduce cost, they provide useful insights for others aiming to explore time-dependent vehicle routing. In their model, they considered a homogeneous fleet of vehicles with a fixed capacity and customer demands. They divided the time horizon into different intervals, i.e., time buckets, and used a time-dependent matrix to represent the travel time between each node pair in every time bucket, to ensure travel times don't need to be dynamically computed and allow for shorter runtime due to the precomputation of travel times. To represent real-world scenarios even more accurately, they also took into account changing speeds when vehicle trips extend across multiple time buckets. After testing their algorithm in both static and dynamic environments, i.e., changing travel speeds, they concluded that the time-dependent model provided significant improvements over the static model with fixed speeds, and encouraged further research into this area to allow for better routing decisions.

As mentioned, (Ichoua et al., 2003) laid the foundation for time-dependent vehicle routing; they, however, did not aim to consider the environmental aspects of vehicle routing. (Luo et al., 2023) combined both carbon minimization as well as varying vehicle speeds, providing key insights for research into the time-dependent Green Vehicle Routing Problem. They introduced an exact branch-and-price-cut algorithm to solve the TDGVRP, which was able to solve instances of up to 100 customers but given the NP-hard nature of the problem and the added complexity of considering congestion patterns, this approach is not suitable for solving larger customer instances in a reasonable amount of time. One study addressing this was published by (Keskin et al., 2019) who used Adaptive Large Neighborhood Search, a metaheuristic approach to find solutions for large customer instances for their homogeneous vehicle fleet consisting of electric vehicles, considering both time-dependent travel speeds and customer time windows.

Similarly, (Franceschetti et al., 2017) presented a metaheuristic for the Time-Dependent Pollution-Routing Problem. Their algorithm was based on an adaptive large neighborhood search heuristic, which incorporated new removal and insertion operators to enhance the solution quality. This research underscored the impact of traffic congestion on vehicle speeds and, consequently, greenhouse gas emissions. (Wang et al., 2019) introduced another perspective on the TDGVRP, focusing on reducing environmental impacts in freight distribution. Their research also highlighted how sharing transportation resources can lead to a more cost-effective and eco-friendly distribution network, noting that the shortest path does not always lead to minimum carbon emissions and operating costs.

Further expanding on the environmental aspects of TDGVRP, (Jabali et al., 2012) incorporated time-dependent travel times and the corresponding CO_2 emissions into vehicle routing problems. Their research demonstrated a reduction in emissions when compared to travel time and that reducing emissions can result in cost savings. (Poonthalir and Nadarajan, 2018) extended the GVRP to the Fuel efficient Green Vehicle Routing Problem (F-GVRP) with a varying speed constraint to emphasize the impact of speed on fuel consumption and carbon emissions, pointing out the importance of optimizing speed to achieve a greener solution in the TDGVRP.

Adding to the diverse range of studies focusing on the TDGVRP is the work (Zulvia et al., 2020). Their study brings a novel perspective to the domain, concentrating on the GVRP related to the transport of perishable goods, specifically food and medicine. The complexity of this problem lies in ensuring products are delivered within their shelf-life, the differing travel times during peak and off-peak hours, and constraints regarding drivers' working hours.

They propose a modified Gradient Evolution algorithm, transformed into a many-objective gradient evolution algorithm. This algorithm considers four objectives: operational costs, deterioration costs, CO_2 emissions, and service level. Furthermore, it includes a system for determining when to switch off the vehicle to reduce emissions and improve efficiency. The model was tested in a real-world scenario, with the results showing promise in terms of diversity and convergence when compared with other tested algorithms.

(Xu et al., 2019) made another significant contribution in the field of time-dependent GVRPs. They were able to incorporate time-dependent vehicle speeds as well as soft customer time windows adding another layer of complexity to the problem and making it more applicable in real world scenarios in which customers only have certain time windows in which they can receive goods. Using a multi-objective mixed integer nonlinear programming (MINLP) they can solve the model while considering the effect time varying vehicle speeds have on fuel consumption while also using fuzzy theory to determine customer satisfaction, which depends on the adherence of customer time windows. Ultimately, they were able to achieve a significant reduction in CO_2 emissions while only suffering a minimal decline in customer satisfaction.

Subsequent research by (Liu et al., 2023) which also takes a traffic avoidance approach was able to achieve CO_2 reduction using an adaptive large neighborhood search (ALNS) algorithm. Using this meta-heuristic approach, they were able to solve problem instances with up to 1000 customers, further highlighting their effectiveness for NP-hard problems like the time-dependent homogeneous GVRP.

While there is a rich body of research addressing the Time-Dependent Green Vehicle Routing Problem (TDGVRP), an underrepresented aspect of this domain is the specific focus on heterogeneous fleets. Much of the existing literature has simplified the problem by primarily considering homogeneous fleets, which overlooks the complexities and unique challenges posed by real-world fleet management, where logistics companies often operate a diverse range of vehicle types. Furthermore, heterogeneous fleets may provide additional advantages in the sense that different vehicles, such as e-Bikes, might be less affected by traffic congestion than conventional trucks.

The integration of customer time windows into the Heterogeneous Time-Dependent Green Vehicle Routing Problem (HTDGVRP) presents a critical enhancement in addressing real-world logistics complexities. This aspect is significantly highlighted in recent studies, underscoring the necessity to align vehicle routing schedules with specific customer service times, thereby ensuring both operational efficiency and environmental sustainability.

In their study (Yu et al., 2019) the focus is on the development of an improved branch-and-price algorithm tailored for HTDGVRP. This algorithm, integrating a multi-vehicle approximate dynamic programming method, considerably reduces computational complexity and time, specifically addressing the constraints of servicing customers within their designated time windows. This study highlights the necessity of accommodating such time windows to achieve minimal carbon emissions—an increasingly salient objective in green logistics.

Similarly, (Macrina et al., 2019) examined route optimization for mixed fleets of electric and conventional vehicles, underscoring the important role of customer time windows in driving energy efficiency and effective route design. Their matheuristic approach, embedded in a large neighborhood search framework, demonstrated that incorporating time windows contributes to minimizing costs associated with energy recharging, fuel consumption, and travel.

Further expanding on the time-dependency dimension, (Mazandaran, 2017) proposed a novel linear integer mathematical model that integrates customer time windows within HTDGVRP. This model explicitly accounts for urban traffic dynamics and places emphasis on optimizing vehicle routes, travel schedules, and fleet size while minimizing operational expenditures and CO_2 emissions. The findings underscore the importance of aligning route planning with time-sensitive urban conditions and rigid service schedules.

Adding another dimension to the literature, (Majidi et al., 2017) investigated GVRP under uncertain conditions by focusing on simultaneous pickup and delivery operations. Their fuzzy model accommodates imprecise customer demands and service time constraints, while an adaptive large neighborhood search heuristic effectively addresses the complexities posed by such uncertainties. This approach demonstrates how flexible methods can reconcile the need to manage fuzzy demands and time constraints with the pursuit of eco-friendly routing solutions.

Collectively, these studies highlight the growing recognition that customer time windows serve as a critical factor in HTDGVRP and illustrate how time-sensitive constraints shape both problem formulations and solution strategies, they reinforce the necessity of incorporating customer service times to achieve environmental sustainability, adapt to urban traffic variations, and enhance operational efficiency in green logistics. In this way, the existing scholarship on time-dependent green vehicle routing is significantly enriched, emphasizing the importance of customer-centric and time-sensitive planning in devising viable, low-emission distribution networks.

2.4 Time-dependent green vehicle routing problem with heterogeneous fleets

There exists a limited but growing body of research focused on the Heterogeneous Time-Dependent Green Vehicle Routing Problem (HTDGVRP). Ehmke et. al., 2018 embarked on a mission to optimize total costs, comprising driver and fuel costs, in urban vehicle routing, using a broad range of factors such as customer geographies, vehicle sizes, fleet compositions, and traffic congestion. Their analysis, based on extensive speed observation data and the road network of Stuttgart, revealed the inadequacy of traditional routing objectives such as distance and time in minimizing total costs. Specifically, their findings highlighted that optimizing for distance or travel time can significantly increase costs and fuel consumption, particularly with heterogeneous fleets.

In a related study, (Ehmke et al., 2016) investigated the impact of varying travel speeds and loads on emissions in urban areas. They proposed a method to keep the load and time-dependent Vehicle Routing Problem (VRP) tractable and analyzed how the structure of routes changes following varying speeds and loads. Their approach, which focused on minimizing CO_2 emissions in the routing of vehicles in urban areas, demonstrated that significant savings in emissions can be achieved when optimizing emissions for mixed customer instances. They found that it is also more important to minimize emissions when trucks are heavier and can potentially handle more load. This study further emphasized the importance of considering time-dependent factors and vehicle load in the context of green vehicle routing.

Adding another layer to the existing body of knowledge, (Xiao and Konak, 2016) introduced a mixed-integer linear programming (MILP) model for a Heterogeneous Green Vehicle Routing and Scheduling Problem under time-varying traffic conditions. Their comprehensive model accounted for a host of factors such as time-varying traffic congestion, the impact of vehicle load on emissions, and vehicle capacity/range constraints. It also allowed vehicles to idle/wait at any point during tours, which was shown to reduce emissions by up to 8% in simulated data. Their proposed hybrid algorithm, combined partial MILP optimization and iterative neighborhood search, and outperformed several well-known heuristics from the literature.

Lastly, the work by (Raeesi and Zografos, 2019) introduced the Steiner Pollution-Routing Problem (SPRP), a variant of the Pollution Routing Problem (PRP), aiming to provide a more realistic portrayal of the urban freight distribution conditions. Their multi-objective, time and load-dependent problem, integrated considerations of vehicle hiring cost, total fuel consumption, and total duration of the routes and tested their algorithm on the road network of Chicago's arterial streets. Despite the SPRP's complexity, particularly for larger practical instances, they suggested future studies to incorporate non-recurrent congestion in routing decisions and develop realistic problem instances reflecting daily congestion patterns.

Numerous studies have significantly advanced the understanding and modeling of the HTDGVRP, primarily in unique geographical contexts such as Stuttgart and Chicago (Ehmke et al., 2018; Raeesi and Zografos, 2019). It's also worth acknowledging the contributions of researchers who have applied various VRP models within the distinct environment of Vienna (Soriano et al., 2020; Kritzinger et al., 2012; Anderluh et al., 2020). However, the application of HTDGVRP specifically to Vienna is a frontier yet to be fully explored. Given the distinct traffic conditions and logistical challenges present in Vienna, there exists an opportunity to extend the reach of HTDGVRP research to this city. This study aims to navigate this uncharted territory by using traffic data from Vienna to develop a model that addresses the HTDGVRP. In doing so, this research contributes to the emerging field of study by providing insights from a previously unexplored context in this specific variant of VRP.

2.5 Research gaps in literature

Many researchers have tackled various variants of the Green Vehicle Routing Problem contributing to a wide body of research with the important goal of developing a more environmentally friendly freight sector. But as seen in the table 1 below there is little research looking at heterogeneous fleets, time-dependent routing and customer windows simultaneously.

Table 1: Overview of Research Gaps GVRP literature

Paper	Heterogeneous Fleets	Time-Dependent	Customer Time Windows
Ehmke et al. (2016)	✓	✓	✗
Xiao et al. (2016)	✓	✓	✗
Murakami et al. (2017)	✓	✗	✗
Franceschetti et al. (2017)	✗	✓	✗
Mazandaran et al. (2017)	✓	✓	✓
Majidi et al. (2017)	✗	✓	✓
Ehmke et al. (2018)	✓	✓	✗
Keskin et al. (2019)	✗	✓	✗
Wang et al. (2019)	✗	✓	✗
Xu et al. (2019)	✗	✓	✓
Yu et al. (2019)	✓	✓	✓
Macrina et al. (2019)	✓	✓	✓
Raeesi et al. (2019)	✓	✓	✗
Zulvia et al. (2020)	✗	✓	✗
Soriano et al. (2020)	✓	✓	✗
Asghari et al. (2020)	✓	✗	✗
Anderluh et al. (2020)	✓	✓	✗
Moghdani et al. (2021)	✓	✗	✗
Liu et al. (2023)	✗	✓	✗
Luo et al. (2023)	✗	✓	✗

To further improve the body of research regarding more sustainable vehicle routing, closing this research gap is the main focus of this thesis. It combines heterogeneous fleets, time-dependent speeds and customer windows to provide an even more realistic assessment of how emissions are emitted by transportation. More importantly, it can help reduce CO_2 emissions, by utilizing the effectiveness of a genetic algorithm, after testing and validating using an exact solver, to find more efficient routes and fleet compositions.

3 Problem description and formulation

3.1 Notations

To accurately model the time-dependent green vehicle routing problem, a multitude of variables are necessary. These variables, compared to those in the traditional vehicle routing problem, also include variables related to time dependency, customer time windows, and fuel consumption. The Table 2 below presents all the variables used in the mathematical formulation of the TDGVRP.

Decision Variables

x_{ijk}	Binary: 1 if vehicle k travels from node i to node j, 0 otherwise
τ_{ik}	Time bucket variable for vehicle k at node i
b_{ijk}	Binary: 1 if time bucket j is active for vehicle k at node i
f_{ijk}^{flow}	Flow variable to prevent subtours for customer i by vehicle k
l_{ik}	Load of vehicle k at node i
f_{ijk}^{fuel}	Cumulative fuel consumption for vehicle k at node i
z_{ik}	Binary indicator for the active time bucket based on τ_{ik}
$\delta(\tau_{ik}, l)$	Indicator function: 1 if τ_{ik} corresponds to speed bucket l, 0 otherwise

Non-Decision Parameters (Sets and Given Data)

N	Set of nodes
V	Set of vehicles
S	Set of time-dependent speed buckets
C	Set of customers
s_i	Start time at node i
e_i	End time at node i
u_i	Service time at node i
q_k	Capacity of vehicle k
F_k	Fuel capacity of vehicle k
g_{ijk}	Fuel consumed by vehicle k traveling from node i to node j
d_j	Demand at customer j

Table 2: Notation for the Green Vehicle Routing Problem: Decision Variables vs. Non-Decision Parameters

The binary decision variable x_{ijk} indicates whether vehicle k travels from node i to j, which works in conjunction with b_{ijk}, used to determine the currently active time bucket of vehicle k traveling between node i and j. f_{ik} is a decision variable used in the subtour constraint, ensuring each route is connected and starts and ends at the depot. f_{ik} is also used to track the fuel level of a vehicle, similar to how l_{ik} is used to monitor the load of a vehicle throughout its route.

3.2 Travel time calculation

The distance d_{ij} between two nodes i and j is calculated using the Euclidean distance formula:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of nodes i and j, respectively.

To provide a fleet with a high degree of heterogeneity, three types of vehicles i.e. cars, vans, and e-Bikes were chosen, which have distinct differences in key vehicle characteristics such as size, capacity, weight, type of fuel and perceived speed. To calculate the time-dependent travel times time-dependent speeds are required. Initially these speeds were self-defined based on the assumptions that speeds are slower during the morning and afternoon rush hour and speeds within the city do not exceed 50 km/h. Cars are the fastest, vans are a little slower than cars and e-Bikes are the slowest however they are not affected by traffic as much as elaborated in Section 4.3. In the model it is assumed that the speed during a trip between nodes remains constant even when traversing between time buckets. Thus speeds can be regarded as a stepwise function depicting the change in speed throughout a typical working day from 7am to 7pm, as can be seen below in 1.

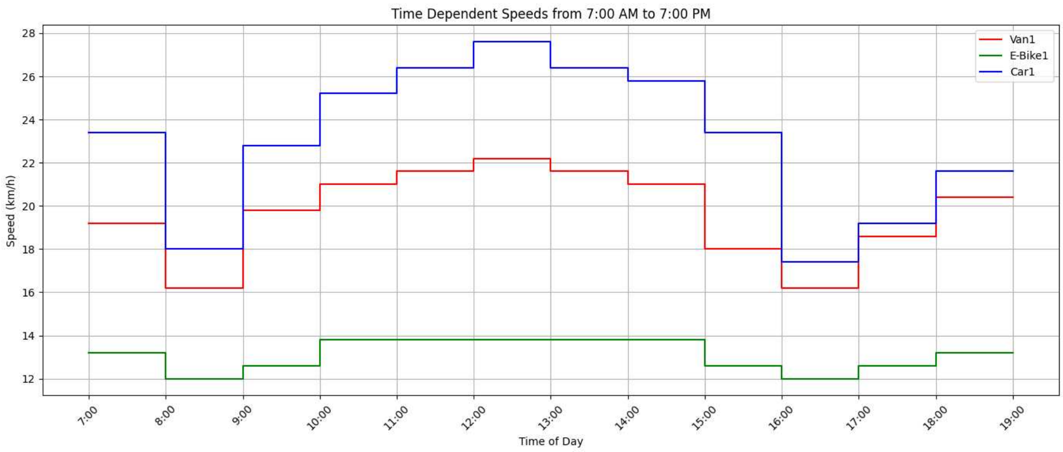

Figure 1: Vehicle Speeds from 7am to 7pm

The travel time t_{ijk} for vehicle k traveling from node i to node j during a specific time bucket is given by:

$$t_{ijk} = \frac{d_{ij}}{s_{ijk}}$$

where s_{ijk} is the speed of vehicle k during the active time bucket, calculated as:

$$s_{ijk} = \sum_{l \in S} s_{kl} \cdot \delta(\tau_{ik}, l)$$

Here, s_{kl} represents the speed of vehicle k for time bucket l, and $\delta(\tau_{ik}, l)$ is an indicator function that returns 1 if the time bucket l is active for vehicle k at node i, and 0 otherwise.

3.3 Fuel consumption calculation

The fuel consumption FC_k for a vehicle can be calculated with the following formula which is based on (Franceschetti et al., 2013):

$$FC_k = (\lambda \cdot k \cdot N_e \cdot V + \gamma \cdot \beta)\,\frac{d}{s} + \gamma \cdot (\beta \frac{d}{s^2} + \alpha \cdot (\mu_k + L)$$

Symbol	Description
d	Distance traveled
s	Speed of the vehicle
λ, k, N_e, V	Engine parameters
γ, α, β	Fuel consumption coefficients
μ_k	Mass of vehicle k
L	Load factor

Table 3: Parameters for the Fuel Consumption Calculation

The fuel consumption f_{ijk}^{fuel} for vehicle k traveling from node i to node j within a specific time bucket is calculated and stored in a lookup table as follows:

$$f_{ijk} = fc(d_{ij}, s_{ijk}) \cdot x_{ijk} \cdot b_{ijk}$$

Where:

- fc(d_{ij}, s_{ijk}) represents the fuel consumption calculation based on distance d_{ij} and speed s_{ijk}.
- x_{ijk} is the binary decision variable, indicating whether vehicle k travels from node i to node j.
- b_{ijk} is the binary variable that is 1 if the time bucket j is active for vehicle k at node i, ensuring the computation is relevant for the specific time period.

This formula integrates the distance and speed to compute fuel consumption, modulated by the route decision (x_{ijk}) and the active time bucket (b_{ijk}), highlighting the time and vehicle dependency of fuel usage.

In this model the fuel type varies depending on the vehicle as cars and vans use diesel whereas e-Bikes use electricity. Thus to weigh the environmental impact appropriately the fuel consumption has to be multiplied by an emissions factor which determines the environmental impact, in terms of CO_2 emitted, of 1 liter of diesel (Ministry for the Environment, 2024) or 1 kWh of electricity consumed by the vehicle. In June 2024, the CO_2 emission factor for electricity in Austria was obtained from Electricity Maps an application providing real-time CO_2 intensity data per country.

$\text{GV}_k = fc_k \times ef_k$
where

$$\text{ef}_k = \begin{cases} 2.68 \text{ kg } CO_2 \text{ per liter of diesel} & \text{if } k \text{ uses diesel} \\ 0.262 \text{ kg } CO_2 \text{ per kWh of electricity} & \text{if } k \text{ uses electricity} \end{cases}$$

3.4 Model formulation

The first objective focuses on minimizing the total distance traveled by the vehicles:

$$\min \sum_{i,j \in N, k \in V} d_{ij} \cdot x_{ijk} \tag{1}$$

The second objective seeks to minimize the total travel time, considering time-dependent travel speeds:

$$\min \sum_{\substack{i,j \in N, i \neq j \\ k \in V \\ l \in S}} t_{ijl} \cdot x_{ijk} \cdot b_{ijk} \tag{2}$$

The third objective aims to minimize fuel consumption based on time-dependent fuel rates:

$$\min \sum_{\substack{i,j \in N, i \neq j \\ k \in V \\ l \in S}} f_{ijl} \cdot x_{ijk} \cdot b_{ijk} \tag{3}$$

The model is subject to the following constraints:

$$\sum_{j \in N, k \in V} x_{ijk} = 1, \quad \forall i \in C \tag{4}$$

$$x_{iik} = 0, \quad \forall i \in N, k \in V \tag{5}$$

$$\sum_{j \in N \setminus \{i\}} x_{ijk} = \sum_{j \in N \setminus \{i\}} x_{jik}, \quad \forall i \in C, k \in V \tag{6}$$

$$f_{ik} - f_{jk} + N \cdot x_{ijk} \leq N - 1, \quad \forall i, j \in C, i \neq j, k \in V \tag{7}$$

$$\sum_{i \in C} x_{0ik} \leq 1, \quad \forall k \in V \tag{8}$$

$$\sum_{i \in C} x_{i0k} \leq 1, \quad \forall k \in V \tag{9}$$

$$s_i \leq t_{ik} + \sum_{j \in N \setminus \{i\}, l \in S} t_{ijl} \cdot b_{ijk}, \quad \forall i \in N, k \in V \tag{10}$$

$$t_{ik} \leq e_i - u_i - \sum_{j \in N \setminus \{i\}, l \in S} t_{ijl} \cdot b_{ijk}, \quad \forall i \in N, k \in V \tag{11}$$

$$z_{ik} = \sum_{l \in S} b_{ijkl} \cdot \delta(\tau_{ik}, l), \quad \forall i \in N, k \in V \tag{12}$$

$$t_{0k} = 0, \quad \forall k \in V \tag{13}$$

$$l_{0,k} = q_k, \quad \forall k \in V \tag{14}$$

$$l_{jk} \geq l_{ik} - d_j \cdot x_{ijk}, \quad \forall i, j \in C, i \neq j, k \in V \tag{15}$$

$$l_{ik} \geq 0, \quad \forall i \in N, k \in V \tag{16}$$

$$l_{ik} \leq q_k, \quad \forall i \in N, k \in V \tag{17}$$

$$f_{0k} = F_k, \quad \forall k \in V \tag{18}$$

$$f_{jk} \geq f_{ik} - g_{ijk}, \quad \forall i, j \in N, i \neq j, k \in V \tag{19}$$

$$f_{ik} \leq F_k, \quad \forall i \in N, k \in V \tag{20}$$

To ensure that the routes found by the Gurobi solver adhere to real world limitations of vehicle routing, constraints are necessary. Constraint (4) ensures that each customer is visited by one vehicle so that all customers are served, and their demands are met. To prevent vehicles from traveling from a node to itself constraint (5) is applied to avoid any self-loop routes this works in conjunction with constraint (6) which makes sure that if a vehicle arrives at a node, it must also depart it, ensuring the continuity of a vehicles tour. To avoid any subtours (i.e., small loops) that don't start and end at the depot a flow conservation constraint (7) is implemented in combination with constraint (8) and (9) which force a vehicle to start and end at the depot if it is used. In this time-dependent Green vehicle routing problem customer time windows are considered. To make sure they are adhered to constraints (10) and (11) enforce that the service of a customer starts and ends within the customers given time window. Time consistency of vehicles and the effect the current time has on vehicles' speed and subsequently time-dependent fuel consumption is handled through constraint (12) which ensures that the correct time bucket is active for a node- vehicle combination. Additionally, constraint (13) regulates the departure time from the depot making sure vehicles leave the depot at the start of their routes. Each vehicle has a different load capacity, vans having the most capacity and e-Bikes. Constraint (14) sets each vehicle's load to its maximum capacity at the beginning of the day. Each vehicle's load is then reduced by the demand of the customer visited by constraint (15). To ensure the feasibility of routes constraint (16) prevents negative load values whereas constraint (17) makes sure that the load does not exceed the vehicle's capacity. Fuel management is handled quite similarly to load management where constraint (18) sets the fuel level to each vehicle's maximum fuel capacity. Subsequently the fuel level is reduced by the fuel used to travel a given arc at a given time by constraint (19) and does not go below zero. Lastly constraint (20) ensures that the fuel level does not exceed the vehicles fuel capacity.

4 Exact approach

4.1 Description of the model

The goal of the Gurobi model is to solve the time-dependent GVRP for small customer instances to allow for some comparability between the GA and the exact approach, and establish a unified approach to tackle this time-dependent GVRP that also includes customer time windows. The model has three objective functions for the user to choose from to solve the model, which include distance, time, and CO_2 minimization, which are defined in a linear fashion using decision variables and problem-specific parameters. To ensure real-world feasibility, such as limits to how much load a vehicle can transport or fuel limitations, Gurobi allows for the use of constraints, which can be implemented quite similarly to how they are defined within the mathematical model.

4.2 Implementation of commercial solver

The Gurobi model for this TDGVRP is set up to extract data from an XML file, which includes information about customers, demands, locations, and time windows. The user can choose the number of customers to be considered for the optimization and, based on this information, distances, travel times, and time-dependent fuel consumption are precomputed to avoid having to calculate this dynamically, which would increase the run times significantly, and makes them easier to access for analysis of the model and its interpretation. The Gurobi solver then tries to find an optimal solution based on the objective and explores the solution space, which is limited by the constraints, until either an optimal solution is found or a predefined time limit is reached. The results are then displayed, which includes vehicle-specific results and overall results regarding distances covered, time traveled, and CO_2 emitted. In case no feasible solution was found, an IIS report is generated to help troubleshoot the cause for infeasibility.

A wide range of parameters are necessary to accurately model the complexities that arise when developing both an exact approach as well as a genetic algorithm for a time-dependent heterogeneous green vehicle routing problem. These parameters include basic definitions of depots, customers, and nodes, vehicle-specific attributes, time-dependent factors such as travel speeds at different times of the day, and detailed engine parameters which are necessary for the calculation of the time-dependent fuel consumption.

The model consists of one single `Depot` ($[0]$) and customer nodes which are pulled from a .xml file and stored in the model as `customers` which together are stored within "nodes" to provide a list of all relevant locations to solve the routing problem. In this heterogeneous version of the Green Vehicle Routing Problem 3 different types of vehicles are considered: Vans, e-Bikes, and Cars and are stored in the list of `Vehicles` like e.g., 'Van1', 'E-Bike1'. Each type has a detailed profile which specifies vehicle specific attributes such as load capacity, maximum travel time, and fuel capacity. These parameters are defined in a way, so they depict real world constraints such as limited load capacity of e-Bikes compared to Vans. To model the time-dependent nature of the problem and provide the algorithms the necessary information to guide vehicles to avoid traffic time-dependent speeds are defined. These speeds are defined for each vehicle type and for 12 time buckets representing a typical working day from 7am to 7pm. The vehicles travel significantly slower during the morning and evening rush hour however the difference in speed for the E-Bike is not as substantial because it is assumed to not be affected by traffic as the Van and Car. These travel speeds in conjunction with (d_{ij}) which stores the distance between nodes is used to calculate time-dependent travel times and store them in (t_{ij}). The time-dependent fuel consumption (f_{ij}) is calculated on vehicle specific attributes such as weight and fuel type. These calculations of (d_{ij}), (t_{ij}), and (f_{ij}) are essential for modeling the fuel consumption dynamics of the heterogeneous time-dependent green vehicle routing problem.

4.3 Data preparation and preprocessing

To test the effectiveness of the developed algorithms for the time-dependent, heterogeneous GVRP, the widely recognized Solomon, 1987 instances were used, as they provide the necessary data to model this version of the GVRP, and allow for the comparison of results. The datasets are structured in an XML format containing information about customers, their locations, which are given in x and y coordinates, demands, time windows, and service times.

These customer time windows are given in integer values for the starting and ending times. To make these fit this model's characteristics, they had to be scaled accordingly. Given that the model considers a day that starts at 7am, 420 was added, which is the number of minutes past midnight, to each time value to make the time windows fall in the range between 7am and 7pm.

$$(\text{new\_start}, \text{new\_end}) = \text{adjust\_time\_window}(\text{start}, \text{end}) \tag{21}$$

$$\text{adjust\_time\_window}(\text{start}, \text{end}) = \begin{cases} \text{start\_minutes} = \text{start} + 420 \\ \text{end\_minutes} = \text{end} + 420 \\ \text{new\_start} = \max(420, \min(1140, \text{start\_minutes})) \\ \text{new\_end} = \max(420, \min(1140, \text{new\_start} + \text{duration})) \end{cases} \tag{22}$$

This ensures all time-related data are properly scaled and adjusted to match the operational hours and conditions specified in the model.

The different Solomon datasets vary in terms of the number of customers and their specific demands and time windows. The key difference between the considered R and RC datasets is the location of customers, as in the R datasets, customers are randomly distributed throughout the map, whereas for the RC datasets, there is a random aspect to customer locations, however, these customers are clustered together in groups.

4.4 Optimal results from commercial solver

For the non time-dependent distance minimization the Gurobi Solver found the optimal solution in less than a second, however an increase in the number of customers drastically increased the run time from 0.35 seconds to more than 7 minutes as can be seen in 4 while all test were carried out using a MacBook Air (Retina, 13", 2020), 1.1 GHz Quad-Core Intel Core i5. This highlights the nature of NP hard problems and demonstrates the need for metaheuristic approaches to increasingly complex problems.

As discussed in Section 3 the minimization of time and CO_2 is time-dependent i.e. takes into account varying traffic speeds throughout the day and their effect on fuel consumption. This further complicates the problem by adding another layer of complexity to the GVRP, which leads to even longer run times for the same number of customers compared to the non-time-dependent distance minimization. As shown in 5, this added layer increased the search duration for the optimal solution for 5 customers 60-fold when comparing the minimum distance and minimum time objectives.

No of customers	Objective	Distance (km)	Vehicles used	Runtime (seconds)
5	Min Distance	84.27	Car, E-bike	0.35
10	Min Distance	137.78	Van	428.53

Table 4: Distance minimization with constant travel times

The Gurobi solver was also unable to find an optimal solution for the minimum time and minimum emission objectives for 15 customers within 2 hours, thus indicating the necessity of a metaheuristic approach to find a good solution within a reasonable time frame.

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used	Runtime (seconds)
5	Min Time	11.91	84.27	18.32	Car, E-bike	20.48
10	Min Time	23.81	137.78	29.95	Car, E-bike	908.47
5	Min Emissions	2.98	84.27	36.34	Car	15.46
10	Min Emissions	6.90	137.78	59.90	E-bike	1124.36

Table 5: Emission minimization with congestion avoidance

Using Matplotlib the routes can be plotted and visualized as seen in 2 giving a better picture of the vehicles' behavior. The arrows indicate the direction of travel and the vehicles are clearly differentiated by e-Bikes being depicted as green, cars as blue, and vans as red.

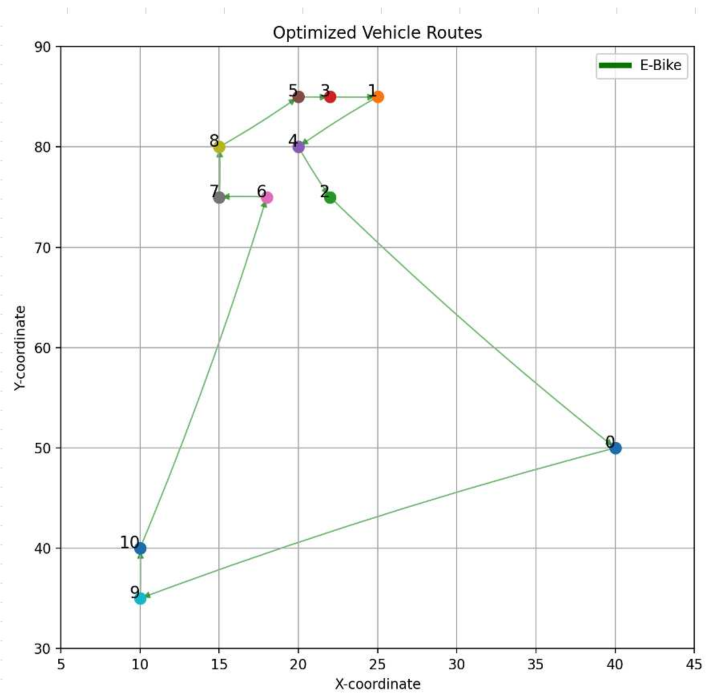

Figure 2: Visualization of the minimum emissions objective

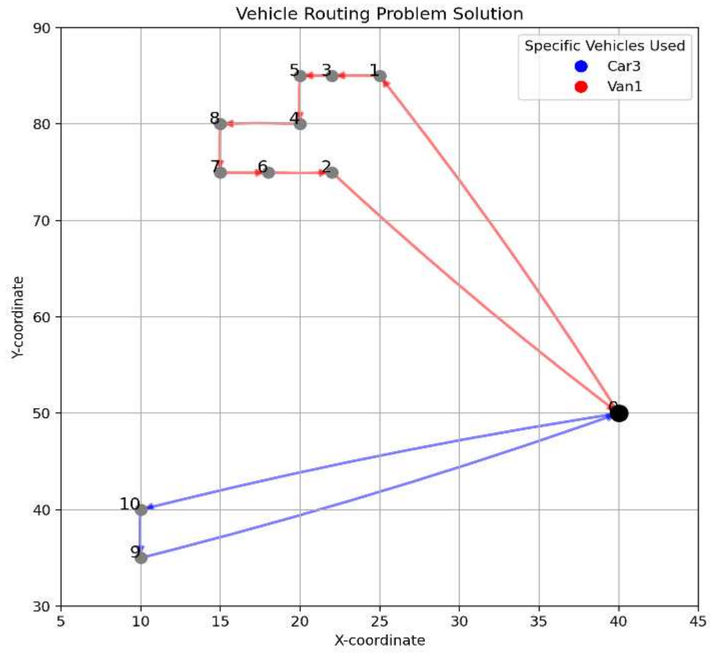

Figure 3: Visualization of the minimum time objective

5 Metaheuristic approach

This chapter presents the implementation of a Genetic Algorithm (GA) for solving the heterogeneous time-dependent green vehicle routing problem (HTDGVRP). The GA is designed to optimize routing solutions based on various criteria such as distance, time, and fuel consumption which represent the GA's objective functions. Key to its design is the consideration of operational constraints and real-world complexities associated with vehicle routing problems through penalty functions and operators that include feasibility checks and repair functions.

5.1 Methodology

The GA is crafted with a focus on generating high-quality solutions that adhere to the constraints of the HTDGVRP in a similar way they were handled in the Gurobi model. Several original constraints, such as ensuring all customers are visited and that routes start and end at the depot, are inherently handled within the solution generation process, whereas some are handled by the operators. This is achieved by carefully structuring the genetic operators to maintain the validity of the routes throughout the evolution process.

- **Solution Representation:** The GA uses a sophisticated representation of solutions that encapsulates the routes for each vehicle. This representation is designed to naturally adhere to many of the routing constraints, such as visiting all customers and maintaining valid start and end points at the depot.
- **Genetic Operators:** Key operations such as selection, crossover, and mutation are tailored to respect and maintain the routing constraints. Load constraints, for instance, are considered within these operators to ensure that generated routes are feasible in terms of vehicle capacity.

- **Fitness Evaluation:** The fitness functions are developed to evaluate the total fitness based on distance, total time, and total fuel consumption of the routes, incorporating penalty factors for constraint violations such as exceeding fuel capacity or not adhering to customer time windows. The fitness functions are designed in a way so, that when distance minimization is the goal the fitness level decreases, which is better, if the total route taken by all vehicles is shorter. On the other hand the fitness level is increased if fuel limitations or customer time windows are not respected.
- **Constraint Handling:** The GA uses both penalty functions as well as feasibility checks in combination with repair functions within the evolutionary process to make sure all real world constraints such as vehicle capacity, limited fuel or customer time windows are respected.
- **Initialization and Evolution:** The initial population is generated at random with a variety of routes, ensuring a diverse starting solution for the GA. The evolution process then iteratively improves the population throughout the predefined number of generations by the application of genetic operators, guided by the fitness evaluations and consideration of real world limitations i.e. constraints.

This design of the GA allows it to find good and viable solutions to complex NP-hard problems like this time-dependent heterogeneous GVRP with time windows in a reasonable amount of time.

The Genetic Algorithm used to solve the heterogeneous, time-dependent green vehicle routing problem utilizes a comprehensive encoding scheme to represent the solutions, which encapsulate a set of routes for a fleet of vehicles which is necessary to allow the GA to deal with the intricacies of the TDHGVRP and its real-world limitations i.e., constraints. In this GA, solutions are represented as dictionaries, with vehicle identifiers as keys and lists of nodes as values where each list signifies the route for a respective vehicle, starting and ending at the depot node. With this initial solution representation and generation some constraints and basic routing requirements are already handled.

The initial starting population for the GA is created randomly by the `generate_initial_population` function and produces solutions with a unique vehicle to customer assignments. This provides a diverse starting solution space for the GA to build upon throughout the evolutionary process. The way in which solutions are initially created already incorporates some of the basic constraints of the TDHGVRP such as all customers being served, or routes having to start and end at the depot. Other constraints such as customer time windows or time-dependent elements of the model like the time-dependent speeds are handled through fitness evaluations or other genetic operators.

The fitness evaluation is based on the objective criteria, which depend on the GA's objective, which is either distance, time, or minimum emissions. The fitness value of a solution is, however, reduced by penalty functions that add a penalty to the fitness value if the solution found by the GA violates fuel or customer window constraints. This guides the GA towards solutions that have a lower fitness value while still respecting the feasibility in real-world operations. Since the GA is being used to handle more complex scenarios and handle more customers, finding a global optimum is rather difficult and unlikely. Thus, a stopping criterion in the form of a maximum number of generations is implemented to provide a good solution in a reasonable amount of time. This encoding scheme is the basis for the GA to explore a wide range within the solution space and ensure that the intricacies of a time-dependent heterogeneous green vehicle routing problem are considered.

The genetic algorithm uses a range of genetic operators throughout its evolution, such as selection, crossover, and mutation, which play a pivotal role in balancing the exploration and exploitation of this metaheuristic approach. In this implementation of the Heterogeneous Time-Dependent Green Vehicle Routing Problem (HTDGVRP), tournament selection is used to select parent solutions to improve upon. For this, a pool of parent solutions, which were previously generated by the `generate_random_solution_function`, are chosen from the initial population to participate in the tournament selection. The initial population is ranked according to their fitness value to then choose a select pool of parents which consist to 60% of the best solutions, to 10% of the worst solutions and 30% of parent solutions are chosen at random. This approach of selecting parents ensures a mix of high-quality solutions while also preserving genetic diversity by keeping the strong individuals and weaker ones to maintain a level of diversity and escape local optima.

A key aspect of the evolutionary nature of genetic algorithms is the crossover, which combines parent solutions to produce new offspring. In this implementation, a single point crossover was implemented, where a point within the parents' solution is randomly chosen at which the parents' genes, i.e., the order in which customers are visited, is chosen and then combined with the cutoff segment of a different parent. This crossover is effective at diversifying the solution space and escaping local optima; however, given that the segments of routes that are combined are determined by a randomly chosen point within the genes of parents, combining these route segments, infeasibility may arise. To tackle this, feasibility checks and repair functions are employed to ensure that the offspring solutions do not violate load or time window constraints.

Mutation of solutions is another method employed in this implementation of the TDGVRP that fosters diversity within the evolutionary process of the genetic algorithm. In this particular case, swap mutation is used to randomly select two nodes, which are swapped. The chance of this happening is determined by the mutation rate, which has to be accurately balanced to prevent premature convergence to a local optimum, but also not diverge away from good solutions that may need to be explored further to find even better results.

Fitness functions are a core aspect of Genetic Algorithms that help determine the fitness of a solution, i.e., how good that solution is at achieving the desired objective, which in this implementation can either be minimizing the distance traveled, the time traveled by all vehicles, or the total CO_2 emitted when serving all customers. This is assessed fitness value then helps guide the Genetic Algorithm towards improving upon the good throughout its evolutionary process.

The first fitness function implemented in this TDGVRP aims to minimize the total distance traveled by all vehicles. Within the fitness function the starting hour is set to 7am and the total distance, which in this case reflects the fitness, is initialized to 0. The fitness function then iterates over each vehicle's route, calculating the total distance of the route. Thus, a shorter route has a lower fitness score which is better. It also updates the current time depending on the arcs traveled to accurately reflect the impact the time of the day has travel times and therefore fuel consumption. A penalty is added to this total distance, making the fitness of a solution worse, if the fuel or load constraints are violated ensuring that the GA is guided towards feasible solutions.

The second fitness function which aims to minimize the total travel time works in a similar fashion as the distance minimization. In this second objective the total time represents the fitness of a solution which is initially set to 0. It then iterates over each vehicles route to calculate the total travel time vehicles travel which depends on the time bucket, i.e., time of the day a vehicle travels a specific arc. Similarly, to the distance minimization fitness function penalties are added to make sure the GA avoids solutions that violate operational constraints.

To minimize the CO_2 emissions when solving this VRP a third objective function is introduced. It assesses the fitness value i.e., total emissions by iterating through all the vehicles and determining the emitted carbon emissions based on the time bucket an arc was traveled in. Similar to the other objectives this is done by setting the starting time to 7am and then updating it along the way using the tij lookup table to accurately model how fast vehicles move on their routes in this time-dependent GVRP. This approach as well as the added penalties in case operational constraints are violated ensure that the GA finds feasible solutions that emit as little carbon emissions as possible.

As previously mentioned, the fitness functions include penalties that penalize solutions found by the GA that conflict with operational constraints. The fuel consumption penalty ensures that the fuel level of a vehicle does not go negative when trying to serve all its assigned customers. This works by assigning a penalty factor that also scaled as the problem instances increase. The penalty function iterates over each vehicle and calculates the time-dependent fuel consumption to see if the expected fuel consumption exceeds the vehicle's fuel capacity. If the solution found by the GA does in fact violate this constraint a penalty factor is applied depending on the degree of this violation. Therefore, solutions that require vastly more fuel than available are heavily penalized whereas solutions that only use a little more fuel are only penalized a little. This approach enables initially unfeasible solutions to be carried on over to the next generation, which with some adjustment might become feasible instead of directly discarding them, possible missing out on an even better solution.

The same logic is applied to the customer time window penalty function. This penalty function iterates over each vehicle's assigned route to determine if either the start or the end of the customer's service time lies outside the bounds of the customer's time window, while taking the time-dependent travel times into consideration. Similarly, to the fuel constraint this customer time window penalty is applied dynamically depending on the size of the problem size and the degree of the violation to help the GA found good solutions that respect the operational constraints of time-dependent green vehicle routing.

5.2 Implementation

Developing a genetic algorithm for a time-dependent green vehicle routing problem is a complex undertaking, requiring the consideration and integration of numerous real-life conditions into the genetic algorithm's logic to find feasible solutions that achieve their respective objectives while complying with the defined constraints. The pseudocode below provides an overview of how the algorithm in this implementation is structured.

Algorithm 1 Genetic Algorithm for the time-dependent Green Vehicle Routing Problem

Input: Population size P, crossover rate CR, mutation rate MR, elitism size E, number of generations G or time limit T, vehicle profiles, demands, travel times t_{ij}, fuel consumption f_{ij}.
Output: Best solution, best score.
Initialize population P randomly with valid routes.
Set the start time t_0.
while generation $< G$ **or** time elapsed $< T$ **do**
    Evaluate fitness of each solution based on the selected objective: *distance*, *time*, or *fuel consumption*.
    For each solution, calculate penalties for:
    - Time window violations.
    - Load violations.
    - Fuel consumption violations.
    Select P parents using **tournament selection**.
    for each pair of parents **do**
        Perform **crossover** with probability CR to generate offspring.
    end for
    for each offspring **do**
        Apply **mutation** with probability MR.
    end for
    Add top E solutions to the next generation (elitism).
    Update population with new offspring and elites.
    Evaluate fitness and penalty-adjusted scores of the current generation's solutions.
    if best solution in current generation is better than global best solution **then**
        Update global best solution and best score.
    end if
    Increment generation.
end while
Return: Best solution and best score.

The implementation of a heterogeneous time-dependent GVRP requires both operational and vehicle parameters that define the environment of the model such as customer or depot locations, as well as genetic parameters that control the evolutionary behavior of the genetic algorithm.

The model consists of three different vehicle types which are e-Bikes, Cars, and Vans which are identified as follows 'Van1', 'E-Bike1', and 'Car1' and have their own specific vehicle profile that includes type specific attributes regarding load and fuel capacities. These different vehicle specific parameters enable the simulation of realistic limitations and capabilities of different vehicle types and heavily influence the behavior of the GA.

Given that this implementation of the GVRP takes different speeds and therefore time-dependent fuel consumption some additional parameters are needed to accurately model this behavior. Speeds are defined in time buckets ranging from 1 to 12 representing a working day form 7am to 7pm where each vehicle type has its own speed. These speeds vary throughout the day and are slowest during the morning and evening rush hour. However, it is assumed that the e-Bikes are not affected by traffic as much, as the cars or vans and thus their speeds do not change as much throughout the day.

In order to calculate the emissions weighted fuel consumption in additional parameters are introduced. These include parameters related to the engine- speed, -displacement, and friction in addition to each vehicle type's curb weight. Since the fuel types vary between vehicles, cars and vans using diesel and the e-Bikes running on electricity, emission factors are used to weigh the fuel consumption calculation based on the environmental impact a vehicles fuel consumption has. This emission factor is based on how much CO_2 is emitted per liter diesel and kWh used which for diesel is 2,68kg and for kWh is 0,262kg of CO_2.

The Genetic parameters other had control the behavior and evolutionary process of the genetic algorithm. The population size determines how many different solutions are evaluated every generation based on their fitness. How many times this evaluation is done is determined by the number of generation parameter. The crossover rate as well as the mutation rate dictate the possibility of a mutation, or a crossover being performed whereas the tournament specifies how many parents are selected to be considered for the next generation. To keep the best solutions the elitism size determines how many of the elites are carried over to the next generation.

These Genetic parameters were initially set to values commonly used in the context of VRPs, however, given the increased complexity of a time-dependent, heterogeneous GVRP that also considers time windows, specifically tailored parameters can improve the performance of the GA. This can be either done manually by testing how changing specific parameters affect the performance of the genetic algorithm, which is quite time-consuming, or by implementing auto parameter tuning. To find the best or close to the best parameters for this specific GVRP, Bayesian Optimization was implemented using the bayes_opt library. It works by predefining a range for each parameter, where, for instance, the crossover rate is set to vary between 0.3 and 1.0, the mutation rate between 0.01 and 0.3, the tournament size between 2 and 100, the number of generations between 20 and 100, and the elitism size between 0 and 30. The optimization process starts with a few initial evaluations using randomly chosen parameters within the range to gather data on their performance. Using this information on the performance of these initial sample parameters, the probabilistic model, i.e., Gaussian process, is fitted to this collected data, allowing for predictions of the performance of different combinations of parameters. Thereafter, an acquisition function, which balances exploration and exploitation, is used to suggest the next set of parameters to evaluate based on the probabilistic model's predictions, which are then tested and used to update said model. This process is repeated until a defined iteration limit or convergence criteria is met. For the optimization of genetic parameters of this time-dependent, heterogeneous green vehicle routing problem, `n_iter`, which defines the number of iterations of the optimization, was set to 25, and `init_points`, which determines the number of steps of random exploration, was also set to 25. This ensures the model has enough data points to suggest parameters that fit the complexity of the problem.

Each parameters bounds and the results found by the Bayesian optimization can be found in the table below:

Parameter	Bounds	Optimized Value
Crossover Rate	0.3 - 1.0	0.8829
Mutation Rate	0.01 - 0.3	0.1774
Tournament Size	2 - 100	31.6532
Number of Generations	20 - 150	149.9217
Elitism Size	0 - 30	5
Population Size	100-200	162

Table 6: Bounds and Optimized Values for Genetic Algorithm Parameters

5.3 Data preparation and real world instance characterization

To test the validity of the genetic algorithm the same Solomon instances were preprocessed identically to the exact approach as described in 4.3.

For the real world data different DHL locations and their addresses were gathered from the DHL websites to use as customer locations within the city of Vienna. The customers were subsequently divided into the inner districts (1.-9.) and the (10.-23.) districts which seen as in figure x constitute the outer districts.

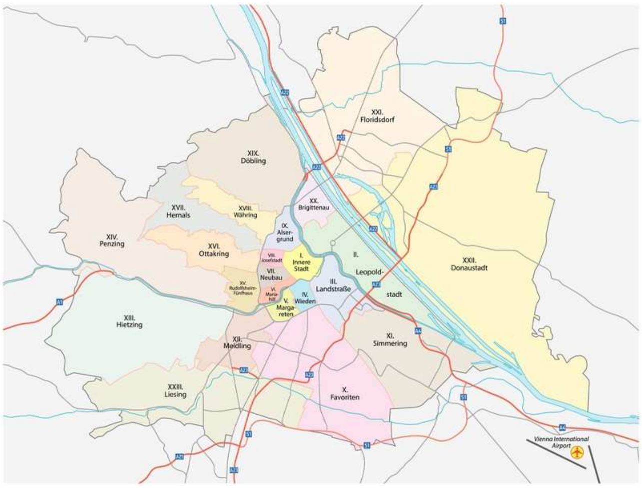

Figure 4: Map of Vienna's districts

The distances between customers were retrieved using a Graphhopper API (GraphHopper) which provides very precise distance information. To get realistic speed profiles for the different vehicle types, a multitude of travel time observations were made to collect information on travel times throughout the day using traffic data provided by google maps for Bikes and Cars. As there is no travel time information available for vans, the assumption is made that they are 20% slower than cars based on their increased size, weight and difficulty of finding a parking spot. The average speed of each vehicle type can be seen in table was calculated based of these observations and assumptions is depicted in table 7.

	Car	**E-Bike**	**Van**
Average Speed in km/h	16,76	17,76	13,41

Table 7: Daily Average Speeds for Car, E-Bike, and Van

To better represent a realistic situation in the morning more observation were made from trips form the outer to the inner districts, whereas for the evening more trips from the inner to the outer districts were observed. Based of these travel times and the distance provided vehicle speeds were calculated using a similar approach to (Ehmke and Campbell, 2014) where the average speed is multiplied by a multiplier indicating the change in speed throughout the day.

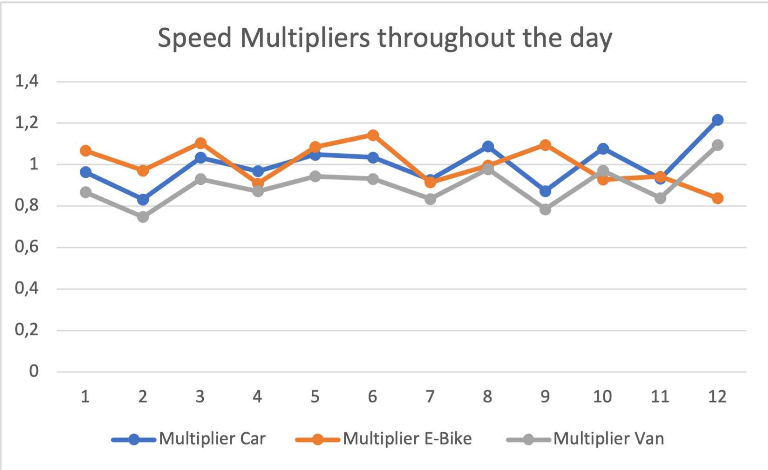

Figure 5: Speed Multipliers from 7am to 7pm

To test the real distance and travel time data the Solomon instances were still used but the coordinates and distances were replaced by the real world data. The demands and the time windows remained the same when the testing on real world data was performed.

5.4 Computational results

The RC101 dataset consists as described in chapter 4.3, of customers that are distributed randomly on the map but still clustered together on a map. The results from 8, 9, 10 show that the genetic algorithm as desired finds the shortest route when minimizing for distance, the fastest travel time when minimizing for time and the lowest amount of CO_2 emitted when optimizing for emissions.

From the tests performed some trends can be observed and are also prevalent in the best found solutions depicted in the tables below. For distance minimization the GA tends to favor using Vans which likely happens as they have the largest load capacity. This effect is however not that pronounced and the GA still provides a multitude of solutions that incorporate other vehicle types. For the 5 customer instances a vehicle's maximum load capacity is irrelevant as all three vehicle types can serve the first 5 customers demands with a single load. Using vans can help the GA find routes that satisfy all customers demands, this however comes at the trade off of vans being slower and having a high environmental impact leading to higher CO_2 emissions and increased travel times as shown in table 10.

Additionally, it can be observed in table 8 that the best found distances match that found by the Gurobi solver as can be seen in table 4 thus proving that the GA is able to find the optimal solution for distance minimization. The distance of the three objectives for 5 customers is identical, therefore demonstrating that the GA is able to find the optimal order of customers for all three of its objectives.

Even though the distance values found are identical between the objectives some key differences in emissions and travel time can be observed. For the 5 customer instance similar to the 10 and 15 customer instances when minimizing for time the GA tends to choose the car as expected given its faster speed and therefore shorter travel times. This however results in increased CO_2 emissions compared to the minimum emissions objective given the increased environmental impact of cars compared to e-Bikes.

When minimizing for emissions the GA heavily favors e-Bikes over car and vans, since when the fuel consumption is weighted by the fuel type's emission factor the difference in environmental becomes even more significant. Consequently not just the best found solutions depicted in the table below but the vast majority of solutions found by the GA for minimum emissions exclusively used e-Bikes to service the customers.

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
5	Min Distance	29.18	84.27	26.33	Van
5	Min Time	11.5	84.27	21.61	Car, E-bike
5	Min Emissions	3.07	84.27	38.3	E-bike

Table 8: Results for Solomon instances RC101

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
10	Min Distance	42.77	166.05	47.95	2 Cars, 1 Van
10	Min Time	23.33	170.19	43.64	2 Cars, 1 E-bike
10	Min Emissions	7.31	200.73	91.24	2 E-bikes

Table 9: Results for Solomon instances RC101

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
15	Min Distance	45.62	186.94	53.31	Car, 2 Vans
15	Min Time	25.5	186.94	47.93	2 Cars, 1 Van
15	Min Emissions	9.23	253.29	115.13	Car, E-bike

Table 10: Results for Solomon instances RC101

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
5	Min Distance	41.37	119.48	37.34	Van
5	Min Time	16.3	119.48	30.64	Car, E-bike
5	Min Emissions	4.35	119.48	54.31	E-bike

Table 11: Results for Solomon instances R101

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
10	Min Distance	41.69	198.21	74.29	Car, Van
10	Min Time	27.04	198.21	50.82	2 Cars, E-bike
10	Min Emissions	8.01	220.01	100.00	2 E-bikes

Table 12: Results for Solomon instances R101

The results for the R instances, where customers are distributed randomly but not clustered together provide similar insights to the RC instances and validating the designed code works as expected. For the distance minimization vans are favored, time minimization cars as are preferred given they are the fastest vehicle type and for carbon minimization the GA almost exclusively uses e-Bikes due to their drastically lower environmental impact. However due to the increased distances between customers and them not being grouped together for the 10 and 15 customer instances more vehicles were needed to serve all customers as seen in table 12 and 13.

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
15	Min Distance	98.76	285.22	89.13	Car, 2 Vans
15	Min Time	55.00	294.87	79.56	2 Cars, Van
15	Min Emissions	11.05	303.48	137.95	Car, 2 E-bikes

Table 13: Results for Solomon instances R101

Throughout testing the importance of fleet composition became evident. As previously discussed the genetic algorithm favors different types of vehicles depending on the objective. These findings could be used to further improve the results by adjusting the available fleet of vehicles that the GA can choose from to guide it towards a better solution. If for example the time minimization objective is applied the available vehicle pool could be adjusted to include more cars than e-Bikes or vans thus already pointing the GA in the right direction of choosing cars and ultimately improve solution quality. Additionally, the number of vehicles could be adjusted based on the number of customers and their combined demand beforehand. If the objective were to minimize the distance, the total demand of customers could be assessed to determine the minimum number of vehicles required to satisfy this demand. For some customer instances where the best found solution by the GA used two vehicles, one van would have sufficed. Thus, if the vehicle pool was adjusted before running the GA to only include one van the best found result would likely improve.

Another aspect in favor of adjusting the vehicle pool based on objective and total customer demand before running the GA, apart from potentially improved solution quality are shorter run times. As previously discussed one of the main reasons for choosing a meteheuristic approach over an exact approach like the Gurobi solver is the ability to find a good solution within a feasible time frame. If fewer vehicles are available in the vehicle pool, the solution space is reduced as the number of possible combinations and permutations of routes decreased. Additionally, the fitness evaluation can be performed quicker and fewer vehicle specific constraints have to be considered. This in conjunction with the reduced crossover and mutation complexity leads to a significantly lower computational load resulting in less time needed to complete the same amount of generations if fewer vehicles being used. Ultimately, assessing the objectives, and the total customer demands and adjusting the vehicle pool beforehand can improve both solution quality and runtimes of the GA when solving a time-dependent heterogeneous GVRP.

Below as seen in Figure 6 the genetic algorithm find logical and efficient routes for 15 customers in a reasonable time, considering the complexity of the problem.

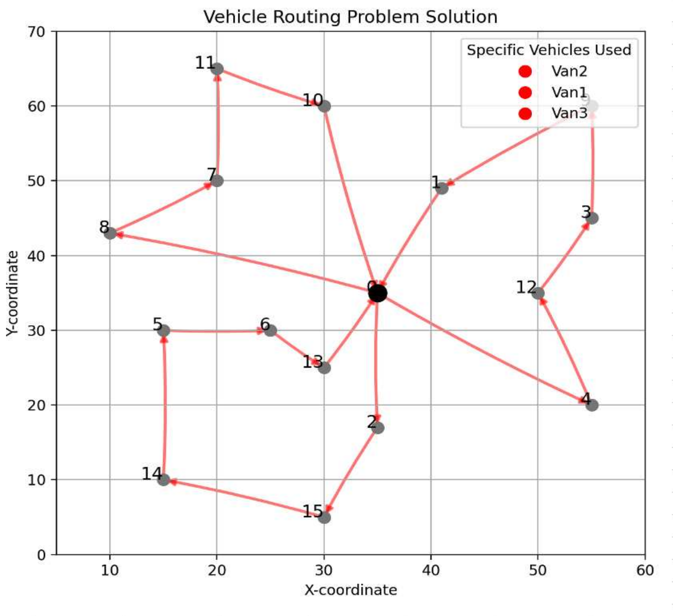

Figure 6: Minimum distance 15 customer visualization

Van Routes:

Van 1: 0 → 5 → 6 → 0

Van 2: 0 → 12 → 3 → 9 → 1 → 0

Van 3: 0 → 8 → 7 → 11 → 10 → 0

As previously mentioned in 4.3, to test the genetic algorithm instances of packaging locations within the city of Vienna were chosen of which a sample route visualization containing 5 packaging locations is depicted below in figure 7.

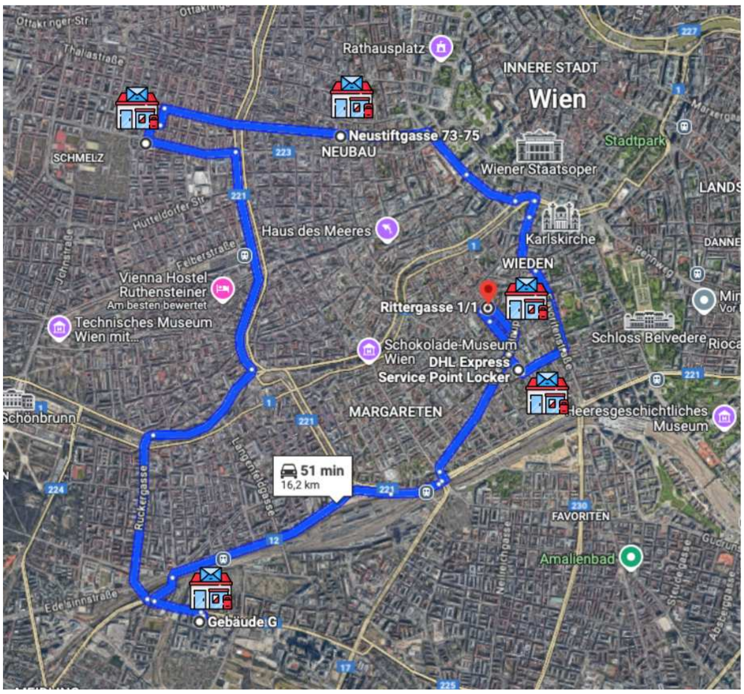

Figure 7: Real world visualization of route connecting 5 packaging locations

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
5	Min Distance	4.41	8.01	29.76	Car
5	Min Time	1.37	8.01	25.35	E-Bike
5	Min Emissions	1.37	8.01	25.35	E-Bike

Table 14: Genetic Algorithm Results for real instances

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
10	Min Distance	8.71	15.82	58.76	Car
10	Min Time	3.13	18.29	57.85	2 E-Bikes
10	Min Emissions	3.39	19.8	62.25	3 E-Bikes

Table 15: Genetic Algorithm Results for real instances

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
15	Min Distance	18.42	22.41	105.38	Car, Van
15	Min Time	9.13	22.41	78.57	Car, E-Bike
15	Min Emissions	5.75	27.29	87.89	Car, 2 E-Bikes

Table 16: Genetic Algorithm Results for real instances

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
25	Min Distance	38.03	52.17	242.98	Car, 2 Vans, E-Bike
25	Min Time	20.48	51.2	188.38	Car, E-Bike
25	Min Emissions	13.92	62.36	202	3 E-Bikes, Van

Table 17: Genetic Algorithm Results for real instances

No of customers	Objective	Emissions (kg)	Distance (km)	Time (min)	Vehicles used
50	Min Distance	129,86	179,75	757,59	2 E-Bikes, 2 Cars, 2 Vans
50	Min Time	101,63	198,35	729,92	2 E-Bikes, 2 Cars, 2 Vans
50	Min Emissions	76,62	224,23	801,38	5 E-Bikes, 2 Cars, 2 Vans

Table 18: Genetic Algorithm Results for real instances

No. of Customers	Savings vs. Distance (%)	Savings vs. Time (%)
5	68.9	0.0
10	61.1	-8.3
15	68.8	37.0
25	63.4	32.0
50	41.0	24.6

Table 19: Percentage CO_2 emission savings when choosing the Min Emissions objective

The results from the real world show that the genetic algorithm designed for this time-dependent, heterogeneous green vehicle routing problem is able to find a solution for up to 50 instances within a reasonable time frame of 15-20 minutes, while also respecting customer time windows. Similar to the Gurobi instances, the algorithm was able to either find the shortest distance, total travel time, or lowest emissions, depending on the chosen objective. However, given the new real-world data, in particular updated speed profiles as depicted in 7, the results in terms of the vehicles chosen vary. Given that the car is no longer significantly faster than the other two types of vehicles, it is not favored as much by the minimum time objective. E-Bikes are still heavily favored when optimizing carbon emissions, as they are still significantly more environmentally friendly compared to cars and vans. For distance minimization, no vehicle in particular was chosen more often than others, but a slight trend towards vans could be observed, as they are able to service more customers at once, therefore reducing the number of vehicles needed.

Given the significantly lower carbon footprint of e-Bikes and their ability to match and even exceed the speed of cars and vans, which were previously assumed to be faster, logistics companies should look further into expanding their vehicle pool to include more e-Bikes.

These results indicate that significant reductions can be made when logistics companies shift their objectives towards reducing their CO_2 emissions by substantial magnitudes exceeding 50%, as seen in 19. This, however, does not come at significant cost in terms of labor costs, as the time to serve customers may even be reduced when opting for the more environmentally friendly e-Bikes. Policymakers should take notice of this and further expedite the development of bike infrastructure to encourage a shift towards carbon-friendly modes of transportation, not just for the general population but also for businesses.

6 Conclusions and future work

The goal of this thesis was to close some of the remaining research gaps regarding environmentally conscious vehicle routing which included considering heterogeneous vehicle fleets, time-dependent travel times and customer time windows simultaneously. This added another layer of complexity to the already difficult to solve NP-hard problem but provides more realistic insights as to how logistics companies may be able to reduce their carbon emissions. Developing both an exact approach as well as a genetic algorithm highlighted again the effectiveness of metaheuristic approaches when tackling complex NP-hard problems.

The implementation of three different objectives offers additional insights into which vehicles are used and favored depending on the objective by the genetic algorithm and allows for comparisons as to how the total distance, time traveled and CO_2 emissions vary depending the chosen objective. The results obtained while using real distance and travel speed data indicate that logistic planners may not have to compromise as much as previously thought, in terms of travel times and thus labor costs when opting for more environmentally friendly vehicle fleets which include more e-Bikes. This resulted in a 24.6% reduction in CO_2 emissions when compared to the minimum time objective and 41% when compared to the minimum distance objective in the 50 customer instances.

Despite these advancements, some limitations need to be acknowledged as for example all of the testing was not done on a computationally strong device and thus resulting in longer runtimes and potentially worse results within the maximum time limit. Additionally, more real world data, especially regarding travel times, would be beneficial to depict congestion patterns more realistically. To do this even more accurately in future work the speed of vehicles could be adjusted when traveling while crossing into a new time bucket which as of now remains constant. Splitting the day into even more time buckets would result in more of a continuous function instead of a stepwise function mimicking traffic more realistically.

It would also be interesting to tune the GA to handle even larger customer instances or see how the changing the starting times, which are currently fixed in this implementations would affect the solution found. Even though the green vehicle routing problem is one of the most studied variations of the VRP, given the urgency of reducing CO_2 emissions, and logistics' significant role in total global carbon emissions, adding to this body of knowledge in green logistics can provide substantial benefits in the total amount of greenhouse gas emitted, even if the environmental impact is reduced by a few percent. This thesis can be a promising step towards a carbon-neutral logistics sector and encourage more research into this promising field of environmental research.

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Abstract

Da der Klimawandel das Leben von Milliarden von Menschen bedroht und schwerwiegende wirtschaftliche Folgen nach sich ziehen kann, legen immer mehr Unternehmen und Behörden Wert darauf, ihre Umweltbelastung und insbesondere ihre CO_2-Emissionen zu senken. Der Verkehrssektor verursacht weltweit rund 24% der gesamten CO_2-Emissionen (Stand 2020), wobei etwa 29,4% dieses Anteils auf den Straßengüterverkehr, einschließlich Lkw, entfallen. Eine Reduzierung der Emissionen im Transportwesen trägt nicht nur zum Klimaschutz bei, sondern verbessert auch die öffentliche Gesundheit durch geringere Luftverschmutzung und damit weniger Atemwegs- und Herz-Kreislauf-Erkrankungen. Ein vielversprechender Ansatz für Unternehmen und Behörden ist dabei die Optimierung ihrer Fahrzeugrouten – auch als Green Vehicle Routing Problem (GVRP) bekannt.

Obwohl zahlreiche Studien bereits verschiedene Aspekte und Varianten des GVRP beleuchtet haben, gibt es nach wie vor deutliche Forschungslücken. Insbesondere fehlen Modelle, die heterogene Fahrzeugflotten, Verkehrsstaus und Kundenzeitfenster gleichzeitig berücksichtigen. Angesichts des erheblichen Anteils des Transportsektors an den globalen Emissionen können selbst kleine Verbesserungen in der Routenplanung große positive Auswirkungen haben. Eine Zielfunktion, die den Energieverbrauch minimiert, führt dabei häufig zu praxisnäheren Lösungen, wenn es um eine realistische Verringerung der Emissionen geht.

Diese Masterarbeit untersucht den Einfluss unterschiedlicher Fahrzeugflotten auf das Ziel der Emissionsreduktion im GVRP unter Berücksichtigung von Verkehrsstaus und vorgegebenen Kundenzeitfenstern. Um den bestehenden Forschungslücken entgegenzuwirken, wird ein mathematisches Modell entwickelt, das sowohl heterogene Flotten als auch zeitabhängige Bedingungen einbezieht. Dieses Modell verfolgt drei Ziele, darunter die Optimierung von Kohlenstoffemissionen im zeitabhängigen GVRP, wobei insbesondere städtische Verkehrsverhältnisse berücksichtigt werden. Zur Validierung wurden zunächst die bekannten Solomon-Datensätze von 1987 herangezogen, bevor anschließend reale Entfernungs- und Fahrzeitdaten verwendet wurden, um die praktische Anwendbarkeit des Modells zu demonstrieren.

Zahlreiche Studien bereits das Verständnis und die Modellierung vergleichbarer Probleme vorangebracht haben und in anderen Städten angewandt haben, ist die Anwendung des HTDGVRP auf Wien jedoch bislang weitgehend unerforscht. Sowohl ein exakter Lösungsansatz als auch ein genetischer Algorithmus erwiesen sich bei der Bewältigung dieser komplexen, NP-schweren Aufgabe als hilfreich. Die mit realen Entfernungs- und Geschwindigkeitsdaten erzielten Ergebnisse deuten darauf hin, dass sich der Einsatz umweltfreundlicherer Flotten nicht so stark auf Fahrzeiten und damit verbundene Personalkosten auswirkt wie befürchtet. Dies kann einen wichtigen Schritt hin zu einem kohlenstoffneutralen Logistiksektor darstellen.