“The effect of optimal route planner on distance traveled by the fuel delivery truck : a case study at a road construction company.”

Master Thesis

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Abstract

This thesis explores how the introduction of optimal route planning tool implementation with and without capacity constraints affects the distance traveled by a fuel delivery truck at a road construction company in Latvia. The study is based on a case study conducted at road construction company “IGATE”, which at the time of research, managed fuel deliveries to multiple jobsites without the use of a route optimization tool. The current process relies on manual inputs and driver intuition, leaving room for inefficiencies and inconsistencies.

To explore this, two optimization methods were applied and compared against the current actual delivery data over a three-month period. Firstly, a classical vehicle routing problem (VRP) approach was implemented using Excel Solver to determine the most efficient delivery sequence without capacity constraints taken into account. Then, to see the additional value and make the case realistic, carrying capacity of the delivery truck was taken into account. This approach was based on a more advanced, capacitated vehicle routing problem (CVRP) model – the Google OR-Tools CVRP Python model. In between these approaches, a heuristic adjustment was introduced to better reflect operational reality and make the optimization results comparable. This was achieved by inserting manual returns to depot in those sequences where demand was higher than the capacity, and adjusting the distance traveled accordingly.

The findings of this case study indicate that both optimization approaches reduced the total distance traveled. Moreover, the optimization that considers capacity constraints further improved the uncapacitated case that was adjusted using the heuristic approach. Additionally, route consistency and predictability improved, as was observed by the reduction in variance and standard deviation of the kilometers driven. The results contribute to academic understanding of VRP applications in less-studied industries such as road construction. Moreover, the study offers actionable insights for companies aiming to introduce route optimization tools in their delivery planning as well as guidance on how even low-cost (free to use) solutions can lead to measurable improvements in efficiency, consistency and resource utilization.

Declaration of academic integrity

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Regarding the use of AI, I have used AI tools/websites – Chat GPT - in Chapter 3 for the purpose of understanding the Python code better. I accept full responsibility for all content presented, including its accuracy and reliability, and I acknowledge that I am aware of the sanctions regarding plagiarism and other forms of academic misconduct as outlined in the Academic Integrity policy (including but not limited to fraud, plagiarism, data fabrication/falsification, and personation).

Student Name: Kristofers Zvingelis

Date: 08.06.2025

Signature:

Preface

This thesis officially draws a close to my educational career (at least for now) at Tilburg University. From bachelor's to master's, what a journey this has been! Ups and downs along the way and none of this would have been possible without the belief and support of my family. Their support, love, encouragement, life lessons, sacrifices, advice has shaped the human I am today and helped me through yet another chapter of my life. For that I will forever be grateful to them. Thank You!

Also, my friends, those here in Netherlands and those back home in Latvia, have been a great support and motivator. Those friends I have made here - make being away feel like home. Those at home - make me want to miss home and give something to look forward to. To all of them – thank You!

I would also like to thank my supervisors. Firstly, Dr. Thomas Breugem who has been very helpful and involved in the thesis writing process. Thank You for giving good and honest advice about what is working and where improvements can be made in my work. This has made the thesis writing process less stressful and more enjoyable. Secondly, my company supervisor Evija Plaveniece for allowing me to conduct this case study at the company, helping with any information I needed and giving valuable advice along the way.

Finally, I would like to acknowledge the time and effort I have put into my studies. The challenges I have overcome and the successes I have celebrated along the way are reminders to me that everything will sort itself out in the end, and that patience and consistency is key. From the long study nights and a lot of confusion about the material, while trying to balance it with a part-time job, social life and sports activities, to being so close to the finish line feels great. Looking back - I would like to say that it was all worth it.

Kristofers

List of abbreviations

"VRP" - Vehicle Routing Problem

“CVRP” - Capacitated Vehicle Routing Problem

“VRPTW” - Vehicle Routing Problem with Time Windows

“SDVRP” - Split Delivery Vehicle Routing Problem

“DVRP” - Dynamic Vehicle Routing Problem

“km” - kilometer

Tables and figures

Table of Contents

CHAPTER 1: Introduction

1.1 Problem indication

Company Celu Buvniecibas Sabiedriba “IGATE” (Road Construction Company “IGATE”) is one of the leading road construction companies in Latvia. The company was established in 1995 and is located in Jelgava, Latvia. In 2024 the company employed 220 people, and its revenue reached more than 35 million euros in 2023. During the calendar year IGATE undertakes roughly around 50 projects (jobsites) per year. For those jobsites to perform their activities and work without trouble, many different machinery and equipment is used, which is provided by the technical department of the company. Furthermore, the technical department employs a designated fuel delivery truck to ensure that the machinery and equipment located at jobsites is always available for work. The fuel delivery to jobsites is a critical function to maintain the operations of IGATE uninterrupted. This has an impact on operational costs such as the fuel expenses and labor costs associated with the fuel deliveries.

Given the scale and frequency of these operations, the technical department is interested in exploring whether it is possible to reduce kilometers driven by the fuel delivery truck. These efforts are aimed at improving overall operational efficiency in terms of the time and costs incurred for the department and the company. Currently the delivery truck covers anywhere from 100 to 300 kilometers per day on average – a number that the technical department of the company would like to see decreased.

Currently the department has not yet implemented an optimal route calculator for the fuel deliveries. Instead, each morning the addresses of the jobsites that have requested fuel beforehand are written down in the waybill and handed over to the fuel truck driver. The driver then goes on his way to make deliveries following a route that makes sense to him. While it may do the job, it is not the most effective way to work.

Not choosing the most optimal route can lead to multiple drawbacks, including increased time spent on the road by the driver and increased fuel costs of the delivery truck to the department. Alzaman (2016) found that optimal route implementation leads to reduced fuel usage, CO_2 emissions and idle time in urban areas. Ferrão et al. (2024) add that implementation of an algorithm that optimizes routes led to a 25.44% reduction in distance traveled and 40 minutes less spent on the road in the waste management industry. Another study done by Bakhtiari et al. (2011) in the agriculture industry also found that the use of optimal route planning leads to reduced non-working distance, improves efficiency (reduced amount of time and fuel consumption) as well as offered route flexibility. All these academic findings are in line with what IGATE is aiming to achieve.

The route optimization challenge has been tackled in different industries such as waste management, agriculture, logistics and more, as indicated by the academic papers earlier. However, the academic use of route optimization in the road construction industry is scarce and inconcise. This implies that if a road construction company would like to implement a route planner, it would need to look at an industry similar to which it operates in, or which utilizes route planning, for example, construction, food delivery, postal services, public transportation industries. Moreover, the use of route optimization for fuel deliveries to jobsites in a road construction industry is, to the best of author's knowledge, very scarce and limited. Apaydin and Gonullu (2013) state that route optimization can reduce costs by 24% by minimizing "empty miles". Other studies revealed that route optimization has saved 17 hours on road, 2700 kilometers of unnecessary driving and up to 9% reduction in fuel consumption (Miller et al., 2018; Larson et al., 2013). Previously mentioned studies highlight the results that the company is aiming to achieve – reduced empty kilometers, reduced time on road and fuel costs. In other words, solve or at least make a step forward towards minimizing the vehicle routing problem at IGATE.

This research will thus investigate what are the effects of introducing an optimal route planner for a fuel delivery truck on the kilometers driven. This research will aim to analyze the current fuel delivery process, identify inefficiencies, and propose a solution to optimize routes for fuel deliveries to jobsites.

1.2 Theoretical contributions

In the literature the challenge that IGATE is facing is often referred to as *The Vehicle Routing Problem (VRP).* VRP is an optimization challenge that aims to design efficient routes, sequence of stops for one or multiple vehicles that serve customers (in the case of IGATE - jobsites) from a central depot, while at the same time aiming to minimize costs (Liu, 2009; Liong et al., 2008; Yadav et al., 2018). This describes the challenge that the company is trying to solve accurately.

Thus far route optimization benefits have been mentioned in the fields of agriculture, waste management, logistics and supply chain in general (Sulemana et al., (2019); Ferrão et al., (2024); Bakhtiari et al., (2011)). Although the underlying decision-making process might be similar to other industries, some key differences exist in the road construction industry. The main difference is that every day the number of stops, the jobsites that order the fuel, as well as the amount ordered changes. Thus, every day the delivery process can be a unique case, as there are many ways in which the jobsites can be visited and not all of them are visited every day. For comparison, in the waste management industry the route will be most likely optimized once, since waste needs to be collected from the same addresses over and over again, repeatedly. The same goes with the agricultural industry – the size of the field most likely will not change and the path of the optimal drive, therefore, will likely not change either. Thus, this case study can provide meaningful insights on how route optimization has an effect on operational costs of a company when the delivery route is not standardized and brings a new, unique case almost every time. Moreover, limited research has investigated the integration of route optimization within the road construction industry, more specifically for fuel deliveries. This may be the case due to multiple factors. Firstly, there are not that many road construction companies that perform academic research and, secondly, more trust may be put in practical experience rather than theoretical or academical research. This research aims to contribute towards the scarce amount of literature in this area and bridge this gap.

When looking at this challenge through the framework of Makadok et al. (2018) and what elements this research will contribute towards the theory, two levers stand out. Firstly, "where?" as in the industry of road construction and “how?" by the use of two different methods, one for each of the comparisons (with and without capacity constraints), to find the shortest route. To the best of the author’s knowledge, this study can provide novel perspective and practical implications in a specific area in a large industry.

1.3 Managerial implications

The findings of this research will provide useful and actionable information to the technical department of IGATE for improved operational efficiency. By introducing the optimal route planner several managerial implications can be expected, such as cost reductions, improved time management, scalability as well as improved decision-making.

Firstly, cost reduction in terms of lower fuel costs of the delivery truck due to minimized unnecessary travel distances. Reduced vehicle maintenance costs are also to be expected due to more efficient routes reducing the usage of the vehicle, thus leading to an extended lifespan and lowered depreciation. Secondly, improved time efficiency - improved delivery routes will allow to deliver the fuel in less time. Furthermore, time saved en route by the driver can be allocated to other activities engaged in by the technical department. Thirdly, scaling - the method and tools used for route optimization for fuel deliveries, could be implemented in other logistical areas such as material or equipment deliveries to jobsites. Finally, improved decision making. The company will have gained new tools and knowledge of their operations, as well as data-driven proof for an improved way of working in the future.

The findings could also be generalized to other companies engaging in fuel deliveries to jobsites, however the extent of applicability may depend on similarities in company size, planning structure and the resources available. Not only fuel, but material delivery routes to jobsites can be optimized using the same underlying principles and techniques.

1.4 Problem statement

"How does the introduction of optimal route planning with capacity constraints for fuel deliveries to jobsites affect distance traveled by the fuel delivery truck at a road construction company?"

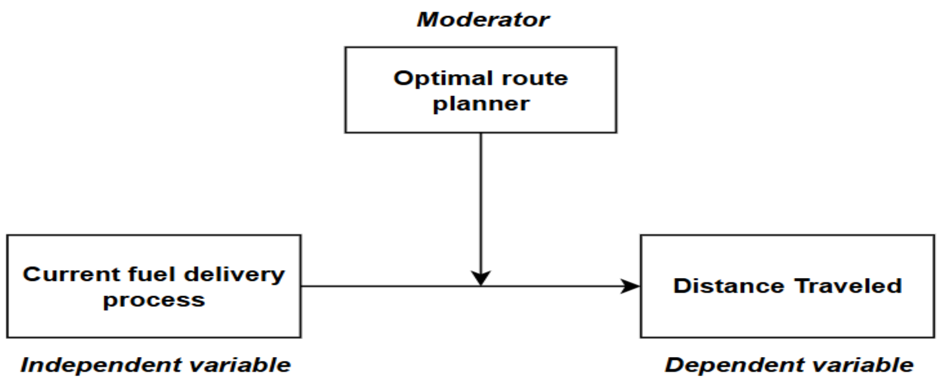

Figure 1. "Conceptual model"

The independent variable is "Current fuel delivery process". The dependent variable is "Distance traveled" and the model also contains a moderator – "Optimal route planner".

1.5 Research questions

Answering the following research questions will ensure that the problem statement is explored and answered in a concrete and consistent way.

Theoretical questions

- What are the key factors influencing the efficiency of deliveries in the construction industry?

- What are the most common route optimization techniques used in logistics and transportation planning?
- How does route optimization contribute to reducing distance traveled and fuel consumption in delivery operations?
- What challenges are typically encountered when implementing route optimization tools?

Empirical questions

- What is the current procedure and its challenges for fuel deliveries to jobsites at IGATE?
- What are the current average and total kilometers driven for fuel deliveries to jobsites at IGATE?
- What is the effect of the introduction of the optimal route planner on average and total kilometers driven by the fuel delivery truck at IGATE under the Classical VRP optimization, when capacity constraints are not considered?
- What is the effect of the introduction of the optimal route planner on average and total kilometers driven by the fuel delivery truck at IGATE, under CVRP/SDVRP when capacity constraints are considered?

CHAPTER 2: Literature review and theoretical background

2.1 Key factors influencing the efficiency of material delivery in the construction industry

Efficient material delivery is crucial to projects' success. Especially in the construction industry as the deadlines are tight and the budget is very limited. Route optimizations in delivery processes can bring significant benefits to an organization. The name itself, *"route optimization",* provides a good enough explanation on how this procedure contributes towards the reduction of distance traveled and fuel consumption. Jovičić et al. (2010) found that route optimization led to cost reduction of 20%. Sulemana et al. (2019) state that route optimization in waste collection can decrease travel distance by 4.79%, travel time by 14.21%, and fuel consumption by 10.81%. A study done by Karimipour et al. (2021) reported that optimized routes for heavy vehicles generated a reduction in distance traveled by 60% and fuel consumption reduction by 62% per month. This is particularly relevant for IGATE as the case study will focus on the fuel delivery trucks which can be categorized as heavy vehicles. Not only that but correctly executed route optimization can provide opportunities for load optimization and better weight distribution, which also has an effect on fuel consumption.

Khade and Joshi (2024) state that one of the factors influencing delivery efficiency is distance to site. It is important as the distance directly influences the path the driver will drive – the shorter the distance the more likely it is that the stop will be at the beginning of the drive. This will be the main focus of the case study as it is also the main reason that the company wants to conduct this case study. Ocheoha and Moselhi (2013) identify that digitalisation and technology plays a crucial role in efficiency of material delivery in the construction industry. Thus far, IGATE has been using an "outdated" way of determining the fuel delivery path to jobsites. Therefore, engaging in increased use of technology and the use of digital tools to determine the optimal route will allow for improvements in IGATE's delivery procedure to jobsites and make them more efficient. The digitalization factor will be introduced in the case company by the use of two route generators which will use a distance matrix as input and provide a sequence of stops as an output. This will be a much more modern way of delivery route development compared to the current – hand-written and driver designed one. These will be the main factors considered during the case study on IGATE.

Other factors that influence the delivery efficiency also exist. Muya et al. (1997) state that delivery efficiency, supplier selection and use of information technologies are all important aspects to consider. This can be applied to the case of IGATE as the fuel delivery truck of the company is dependent on the big fuel companies to deliver the fuel in time to IGATE's depot where it can be further distributed to smaller delivery trucks. Thus, selecting a good and reliable partner for fuel procurement is important. Khade and Joshi (2024) add that the delivery efficiency for ready-mix concrete is influenced by traffic and weather. These are simple, yet very important aspects. Weather, for example, impacts the delivery efficiency because deliveries that are performed in dry and favourable conditions will be faster than those that will be made in, for example, heavy rainfall or snowstorms, as you must drive more carefully, slower. Also, effective and timely communication is a factor (Rajhans, n.d.). The faster the information flows from jobsites to the person who is responsible for material (fuel) allocation, the better the trip for the delivery can be planned and organized. Although the previously mentioned factors influence the material delivery to jobsites, they will not be the factors that will be looked into deeper for the case company. This is because, although the mentioned factors are important, they are not as relevant for the case of IGATE as the company wants to compare the current driven routes of the driver to the optimal routes provided by the optimization tools. Adding more variables could be an extension of this study to explore the route optimization challenge at the company on a deeper level.

2.2 Most common route optimization techniques used in logistics and transportation planning

Route optimization in logistics and transportation planning employs numerous techniques to minimize costs and improve efficiency. Ivanova et al. (2021) identifies common approaches such as greedy algorithm and simulated annealing. They also identify more complex methods, such as integer linear programming, that considers various factors such as fuel costs and travel time. While integer linear programming has higher accuracy, the greedy algorithm provides a faster computation (L. N. Ivanova & Ivanov, 2024). Malhotra and Khandelwal (2022) propose algorithms with specific constraints like vehicle capacity and signalized intersections.

VRP is an essential problem that these algorithms and methods are developed to solve. Algorithms such as Branch and Bound, Dijkstra's algorithm and the Clarke and Wright savings algorithm are among the most commonly used (Malhotra & Khandelwal, 2022). Malhotra and Khandelwal (2022) tackle the VRP from different angles and with different methods, with each getting more complex.

2.2.1 VRP key features, application areas, methods for analysis and common assumptions.

Vehicle routing problem is an optimization challenge that aims to design efficient routes, sequence of stops for one or multiple vehicles that serve customers from a central depot, while at the same time aiming to minimize costs (Liu, 2009; Liong et al., 2008; Yadav et al., 2018).

Over time many classifications of VRP have developed. Among those, the most commonly found in academic research are, to name a few, Capacitated Vehicle Routing Problem (CVRP), Vehicle Routing Problem with Time Windows (VRPTW), Split Delivery Vehicle Routing Problem (SDVRP), Dynamic Vehicle Routing Problem (DVRP), and many more (Zhang et al., 2021). In “Table 1” the most popular different types of VRP are listed. Alongside them their key features or description, areas of application, methods that are used to solve the specific VRP type and literature that provides information and more depth about each of the types.

Number.	VRP type	Key features/description	Application areas	Methods involved	Relevant literature
1.	Classical Vehicle Routing Problem	Meet the needs of customers with minimized distance, minimized cost and minimized time, while satisfying constraints. Each location is visited once. The vehicle returns to its starting point (depot/base).	Logistics, deliveries, waste collection, supply chain, postal & courier services.	*Classical heuristics models* Examples: The savings model, sweep algorithm, two phase approach Characteristics: Offer optimal computing time and applicable to real life constraints easily. *Metaheuristics* Examples: Tabu search, simulated annealing, genetic algorithms, ant systems, etc. Characteristics: emphasis on performing deep exploration of the most promising solution, takes more time, is more complex in general.	(Laporte, 2007), (Zhang et al., 2021), (Gendreau et al., 2002),
2.	Capacitated Vehicle Routing Problem	Based on Classical VRP – adds vehicle load constraints.	Logistics, deliveries, public transportation, waste collection.	*Precise algorithm* *Heuristic algorithm* (most commonly used)	(Baldacci et al., 2011), (Zhang et al., 2021), (Malhotra & Khandelwal, 2022)
3.	Vehicle Routing Problem with Time Windows	Based on Classical VRP – adds time window constraint to each demand point. Earliest and latest start of service for each of the demand points are set and respected. Involves complicated mathematical formulas.	Goods deliveries, service industry.	*Hard time window* Characteristics: Serve customer only in the specific time frame. Wait if arrive early. Gets rejected if arrives late. *Soft time window* Characteristics: Does not have a specific time frame to start serving customer. Gets punished if services outside of time window	(Zhang et al., 2021), (Solomon, 1987), (Bozkaya et al., 2010) (Malhotra & Khandelwal, 2022) (Desaulniers et al., 2014)

4.	Split Delivery Vehicle Routing Problem	Removes the constraint of each customer getting visited once. The customer demand can be larger than the vehicle capacity, thus leading to multiple visits by one or multiple vehicles for increased efficiency. Involves complicated mathematical models. Difficult balance computation time and optimization degree.	Deliveries of goods, logistics	*Accurate algorhitm* Examples: *-Branch and bound method* *-Dynamic programming* *-Cluster path* *-Column generation and section method* *Heuristic algorhitm* Examples: *-CW conservation nmethod* *-Tabu search* *-Particle size calculation method* *-Scanning algorhitn*	(Zhang et al., 2021), (Raff, 1983), (Moshref-Javadi & Lee, 2016), (Malhotra & Khandelwal, 2022) (Archetti & Speranza, 2008)
5.	Dynamic Vehicle Routing Problem	Considers changes in factors influencing the delivery. Factors such as customer demand, traffic, weather, vehicle state. Makes use of Internet of Things, artificial intelligence, sensors, etc. Constant replanning of the route to optimize and adapt to the new information obtained.	Deliveries of goods, logistics, transportation, taxi services.	*Dynamic demand* Characteristics: Demand fluctuates *Real time traffic information* Characteristics: routes update based on real life traffic updates such as accidents, traffic jams, speed limits, etc. *Dynamic demand & Real time traffic* Characteristics: combines the two types. Most complex.	(Zhang et al., 2021), (Bertsimas & Simchi-Levi, 1996), (Psaraftis, 1995), (Psaraftis et al., 2015), (Malhotra & Khandelwal, 2022) (Pillac et al., 2012)

Table 1. "Summary table of most popular VRP types – key features, application areas, methods for computing and relevant literature"

While the methods get increasingly more complex as more factors are introduced in the equation, common assumptions can also be found. All of the VRP methods have distance, time and cost minimization at their core. Moreover, the vehicle needs to return to its starting point - depot.

As the case study will be looking into how IGATE can reduce the amount of kilometers driven while making fuel deliveries to jobsites, this can be dealt with as a Classical Vehicle Routing Problem. This is the most simple form of VRP and assumes that that there are no capacity constraints, all customer orders are satisfied, while minimizing costs, distance and time (Zhang et al., 2021; Laporte, 2007). Gendreau et al. (2002) and Zhang et al. (2021) discuss several methods that can be used to perform Classical VRP analysis such as the savings model, sweep algorithm and two-phase approach. The case study will perform the classical VRP optimization by the use of Excel Solver. However, classical VRP lacks the limitations of the real world, such as capacity constraints.

The fuel delivery truck of the company has a capacity limit, thus the case study can be assigned to the Capacitated Vehicle Routing Problem (CVRP) and not just the Classical VRP (Zhang et al., 2021; Baldacci et al., 2011). The capacity consideration of 3000 liters will be taken into account (3000 liters is the maximum carrying limit of fuel allowed in the country) when performing the second optimization and comparison. Agarwal and Shinde (2022) found that the implementation of algorithm for route optimization resulted in improvements in load factors and 8% cost reduction. This can be applied to the case company as it is possible that the optimized route will first take the delivery truck to certain locations and on its way to other locations the depot of the company will be within route. This means that when on its way to making the first fuel deliveries the truck can carry less fuel with it, just what is necessary to satisfy the demand in the first section of the drive. Less fuel to carry means less weight on the truck, which in turn leads to the delivery truck itself consuming less fuel. While the CVRP approach is a good fit to the case study, it does not capture the real essence of how the company operates. Meaning that there are days in which the delivery truck visits one location multiple times, as a split delivery, due to ordered capacity exceeding the carrying capacity.

Archetti and Speranza (2008) and Zhang et al. (2021) describe Split Delivery Vehicle Routing Problem (SDVRP) as a process where each customer can be visited more than once, and the order capacity can be bigger than the vehicle capacity. Therefore, SDVRP is a subset of CVRP as capacity constraints are what drives the need for a split delivery, since the ordered amount cannot be delivered in one go. It is not uncommon that a jobsite orders an amount of fuel that exceeds the capacity of the delivery vehicle, especially if it is a larger jobsite, where many machines are working. As it will be seen in the case study of IGATE - while most of the jobsites order within the range of capacity of the vehicle, usually, that is almost every day, one of the jobsites orders an amount that exceeds the carrying capacity of the vehicle, especially as the road construction season intensifies. Therefore, a split delivery is required and will be the underlying method for the case study. SDVRP approach will be executed for the case study by the use of Python coding.

For Dynamic Vehicle Routing Problem (DVRP) Psaraftis (1995) mentions the use of intelligent vehicle highway systems, geographic information systems and electronic data interchange as some of the approaches towards DVRP. Psaraftis et al. (2015) add vehicle speed as a decision variable. Pillac et al. (2012) discuss the use of "Intelligent transport systems", modern software, sensors and indicators as enablers for dynamic real time changes in the routes driven. However, this does not currently apply to IGATE as the vehicles are old and not equipped with such technologies. This could be an option for the company if an investment into a new modern delivery vehicle would be made. The vehicle is, however, equipped with a tracking device, which provides real-time information, such as the location and the driving speed of the vehicle at any given moment. But this information alone is not enough to provide real time changes in routes as other factors such as traffic conditions, weather and more also need to be considered (Zhang et al., 2021).

Desaulniers et al. (2014), Zhang et al., (2021) and Solomon (1987) discuss Vehicle Routing Problem with Time Windows (VRPTW), which considers a time frame during which the vehicle must visit the customer. Bozkaya et al. (2010) state that VRPTW represents the majority of the cases found in practice. However, while prioritization of jobsite visits, such as bigger jobsite, more important jobsite or just an emergency situation, might be a case at the company, no strict time frame exists. Thus, VRPTW does not apply to the fuel delivery truck of the company as the delivery vehicle has all day to make the fuel deliveries. Of course, the deliveries have to be made as fast and efficiently as possible. However, no punishment will be given to the driver if the delivery is not made in a certain time frame as “punishments” are non-existent in the culture of the company.

2.3 Challenges of route optimization tool implementation

It has been widely discussed in academic articles how route optimization leads to a decrease in distance traveled and fuel consumption of the truck. However, the implementation of such systems can often be challenging.

For starters, for more complex systems, modeling challenges arise, and data management and availability also need to be considered (Assad, 1988; Rönnqvist, 2012). Dowd et al. (2020) bring up the problem of poor road quality and mixed vehicle fleet. Not only that but the fast pace of technological advancements means a constant need for learning new tools and always being up to date with the new technologies. Resistance to change also plays a big role. Ramadhani et al. (2024) state that resistance to change stems from insufficient skills, background, fear and culture. This could be one of the challenges that IGATE might face when introducing the route optimization tool. That is due to the fact that drivers of the fuel delivery truck are people of an older age, who are used to performing the same task the same way, and do not want anybody to intervene. Kot and Marczyk (2010) mention that the high investment costs necessary become a barrier to introduction. This is why the author wants to test and implement tools that cost nothing for the optimizations and comparisons, such as simpler tools like Google Maps and Excel for the first optimization and analysis. And, for the second optimization, which involves capacity constraints, a more complex coding tool Python will be implemented. This will allow the author and the company to see whether distance reduction is possible. And if true, the proof from the pilot route optimization program can be used as an argument for the purchase of a more complex and advanced system. Haughton (2002) adds that the introduction of such new tools will require training of drivers as well as managers. Mehdizadeh et al. (2008), Shin et al. (2019) and Shin et al. (2017) raise the challenge of data security and privacy as well as ways to protect this information. This is an important barrier to consider as route optimization deals with sensitive company data such as vehicle locations, jobsite addresses, delivery schedules, etc.

While the implementation of route optimization tools seems easy and fast, many barriers exist which need careful consideration. Not considering the risks that come with the introduction of such technologies can lead to severe difficulties strategically, financially and legally.

CHAPTER 3: Methodology

3.1 Research nature and strategy

As part of the case study at IGATE, the research focuses on the current fuel delivery process at the company, which can be characterized by manual and informal structure. Fuel orders are submitted via text messages and compiled on a daily waybill without optimization. This process allows the delivery driver to determine the route independently, often without regards to efficiency. This context illustrates the relevance of investigating the potential impact of the introduction of a route optimization tool

This research aims to compare, firstly, the kilometers driven by the driver, who has likely done some sort of optimization and logical thinking of the route driven currently (current route), with the kilometers driven on route that is optimized without capacity constraints of the vehicle (optimized-uncapacitated route). Then based on the optimized-uncapacitated route, by the use of a heuristic approach create an optimized-uncapacitated* routing, that considers returns to the depot to make it more realistic. And then, compare the optimized-uncapacitated* route results with kilometers driven when vehicle capacity is taken into consideration when optimizing the route (optimized-capacitated).

For this study, a deductive approach is chosen. Zhang et al. (2021) cover various types and classifications of VRP as well as the main implementation industries, key features and methods related to each type to VRP. In this study the base case of IGATE will be first treated as a Classical VRP and later as CVRP/SDVRP. The Classical VRP method assumes that each location is visited once, the route starts and ends at the same point, and the route is minimized in terms of kilometers driven, costs incurred, and time spent (Zhang et al., 2021; Laporte, 2007; Gendreau et al., 2002). While this method will be an improvement of the current state of the process, it will not be representative of the real world. That is, the carrying capacity of the delivery truck is not taken into account. This will yield improved but misleading results. Therefore, SDVRP, which is a subset of CVRP, will also be explored. SDVRP has mostly the same assumptions and goals as the Classical version of VRP, however it also considers the fact that the truck cannot carry an infinite amount of fuel to supply all the customers (jobsites) in one drive and multiple visits to one location are allowed (Zhang et al., 2021; Baldacci et al., 2011; Malhotra and Khandelwal, 2022). Archetti and Speranza (2008) and Zhang et al. (2021) state that SDVRP is applied in various industries such as goods delivery and logistics.

This study will look at the data of kilometers that would be traveled if the route calculator would not be used by IGATE and compare them to the data after the introduction of the optimal route planner with and without capacity constraints. Thus, this is a comparative research.

3.2 Data collection

This research will be conducted as a case study at IGATE. It will implement a quantitative approach. The advantages of using a case study are that they allow in-depth exploration of a specific topic in a specific context (Bennett, 2012). Drawbacks of this method involve reduced generalizability and potential for selection bias (Willis, 2020; Bennett, 2012).

The route planner will, firstly, be based on the minimized distance traveled generated by the Solver option on Microsoft Excel, and secondly, by the use of Python coding. Firstly, a distance matrix (Figure 2) that contains places from 1 to 10, which are all the current jobsites, will be created. Then, each of the jobsites will be assigned a number (starting from IGATE's depot = 1) and their distance from one another. That is, column numbers, 1 to 10, 1 being the starting point and 2 to 10 being jobsites will be set. And also in the rows, jobsites will be numbered from 2 to 10. In the corresponding cell, for example - column 1 and row 3, the distance between IGATE's base and jobsite 3 will be inserted. Each day a subset of these locations has to be visited. The distance will be taken from Google Maps. When all the locations and distances are added as numbers the optimization can be executed.

Location	Number		"Distance matrix : km between jobsites"									
			1	2	3	4	5	6	7	8	9	10
IGATE BASE	1	1	0	13.6	1.8	32.6	37.3	6.4	62.6	5.7	43.6	48.6
Jobsite 1	2	2	13.6	0	15.4	41.7	53	19.2	84.4	18.2	52.7	58.5
Jobsite 2	3	3	1.8	15.4	0	34.1	33	5.6	61.9	4.3	35.3	45.3
Jobsite 3	4	4	32.6	41.7	34.1	0	12	36.3	96.8	32.7	11.4	78
Jobsite 4	5	5	37.3	53	33	12	0	41	95	32.4	7.2	79.2
Jobsite 5	6	6	6.4	19.2	5.6	36.3	41	0	61.6	8	46.8	45.6
Jobsite 6	7	7	62.6	84.4	61.9	96.8	95	61.6	0	64.6	102	16
Jobsite 7	8	8	5.7	18.2	4.3	32.7	32.4	8	64.6	0	38.8	46.7
Jobsite 8	9	9	43.6	52.7	35.3	11.4	7.2	46.8	102	38.8	0	85.5
Jobsite 9	10	10	48.6	58.5	45.3	78	79.2	45.6	16	46.7	85.5	0

Figure 2. "Distance matrix "c" between jobsites"

For a given day, the jobsites that need fuel delivery are known and written on a waybill for each day. The last stop of the day will always be 1 because the delivery truck has to return to IGATE's base. The order of the places visited in a given day will be obtained from company's tracking system which precisely shows the location of the truck as well as records kilometers driven on a given day (Figure 3). This will be the base scenario, the current path of the driver, for a given day which will serve as input for the optimization. These stops will be collected in a table where each row represents a day (Figure 4).

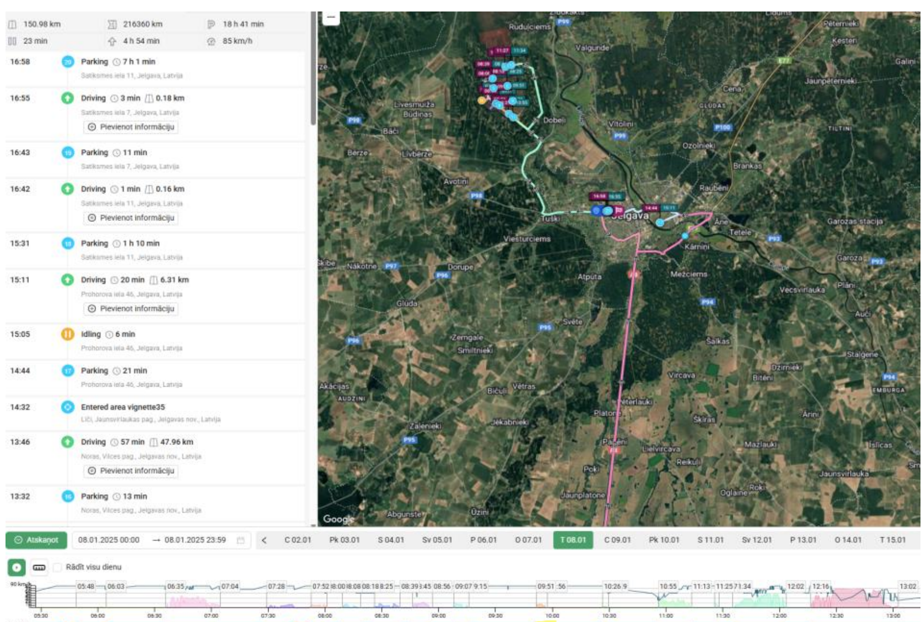

Figure 3. “Screenshot of company’s tracking system for the fuel delivery vehicle showing date, time and route”

DATE (DD.MM.YY)	CURRENT PATH (from company records)										DISTANCE (km)
02.01.2025	1	2	9	1							111.94
03.01.2025	1	2	6	9	1						131.47
04.01.2025	1	2	5	1							97.87
06.01.2025	1	2	9	6							144.46
07.01.2025	1	2	10	9	4	1					220.4
08.01.2025	1	2	5	9	6	1					150.98
09.01.2025	1	2	10	9	1						211.73
10.01.2025	1	2	1	9	1						136.08
11.01.2025	1	2	9	1							104.7
13.01.2025	1	2	9	10	1						219.88
14.01.2025	1	2	9	1	6	1					143.44
15.01.2025	1	2	9	1							125.95
16.01.2025	1	2	9	6	1						150.99
17.01.2025	1	2	9	1							128.6
18.01.2025	1	2	1								45.14
20.01.2025	1	2	9	6	1						140.2
21.01.2025	1	2	9	5	1						123.22
22.01.2025	1	2	9	6	1						146.09
23.01.2025	1	2	9	1							117.72
24.01.2025	1	2	9	6	1						133.66
25.01.2025	1	2	1								30.76
27.01.2025	1	2	9	1							117.44
28.01.2025	1	2	9	5	1						136.91
29.01.2025	1	2	9	1							117.08
30.01.2025	1	2	3	6	9	1					131.31
31.01.2025	1	2	9	1							124.47
										Average	132.40
01.02.2025	1	2	1								38.74
03.02.2025	1	2	1	2	3	6	1				85.02
04.02.2025	1	2	4	9	1						123.57
05.02.2025	1	2	3	6	9	1					135.83
06.02.2025	1	2	1	4	5	9	1				130.81
07.02.2025	1	2	1	3	6	9	1				135.39
08.02.2025	1	2	9	1							112.67
10.02.2025	1	2	1	3	5	9	1				145.35
11.02.2025	1	2	1	3	6	4	9	1			146.36
12.02.2025	1	2	1								45.76
13.02.2025	1	2	4	1	3	6	1				139.31
14.02.2025	1	2	9	5	1						126.34
15.02.2025	1	2	1								43.34
17.02.2025	1	2	3	4	9	1					150.21
18.02.2025	1	2	1	9	1						128.76
19.02.2025	1	2	9	1							136.74
20.02.2025	1	2	1	5	9	1					128.05
21.02.2025	1	2	1	3	9	1					148.06
22.02.2025	1	2	9	1							125.24
24.02.2025	1	2	1								54.74
25.02.2025	1	2	1	5	9	1					133.22
26.02.2025	1	2	9	1							136.9
27.02.2025	1	2	1	9	1						139.45
28.02.2025	1	2	1	5	9	1					141.17
										Average	117.96

Figure 4. “Table containing current path sequence of stops and kilometers driven in each of the corresponding days”

Since there will be a double comparison, one between the current route and optimized route based on a Classical VRP approach with greedy method applied, and another between the optimized Classical VRP approach with greedy method applied and SDVRP approach, two different constraint combinations and two different optimization approaches will be used.

C. E. Miller et al. (1960) formulate and provide constraints for the first optimization, called the *MTZ formulation*, and will be used as a reference study for the first optimization of the case study. For the first optimization, between the current route and optimized route based on a Classical VRP approach, Excel Solver will be used as it is powerful enough to perform this analysis and it is free of charge. In a separate sheet four tables are created. First contains the distance matrix "c" (Figure 2). The second contains the constraints matrix "x" and controls the constraints such that each stop can be visited only once. The sum of the row and the sum of corresponding column should equal to 1 if the stop must be included in the final optimization sequence (Figure 5).

$$\sum_{i=1,i\neq j}^{10} x_{ij} = 1 \text{ for j} = 1, \ldots, 10$$

$$\sum_{j=1,j\neq i}^{10} x_{ij} = 1 \text{ for i} = 1, \ldots, 10$$

$$x_{ij} \epsilon \left\{ \begin{matrix} 1 & \textit{the path goes from stop i to stop j} \\ 0 & \textit{otherwise} \end{matrix} \right\}$$

Where "j" is the place of arrival, or stop, and each of the stops is visited at most once. And where "i" represents the place the truck leaves from, also maximum of only one exit from each of the stops in the sequence is allowed. "i" represents rows and "j" columns. $i \neq j$ holds in order for the calculation to exclude leaving and arriving in the same spot, which would result in 0. If the stop is in the sequence, it colors the field red and changes the number of the cell from 0 to 1, indicating that the stop is indeed included. The solution indicates only those locations that are visited, which can be less than total amount of locations, depending on which jobsites have ordered the delivery.

	1	2	3	4	5	6	7	8	9	10	
1	0	1	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	1	0	1
3	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	1	0	0	1
6	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	1	1
9	0	0	0	0	1	0	0	0	0	0	1
10	1	0	0	0	0	0	0	0	0	0	1
	1	1	0	0	1	0	0	1	1	1	

Figure 5. "Constraint matrix "x""

The third table is a multiplication between the first and the second table, which ultimately provides the total number of kilometers that are driven in the sequence (Figure 6).

	1	2	3	4	5	6	7	8	9	10	
1	0	13.6	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	52.7	0	
3	0	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	
5	0	0	0	0	0	0	0	32.4	0	0	
6	0	0	0	0	0	0	0	0	0	0	
7	0	0	0	0	0	0	0	0	0	0	
8	0	0	0	0	0	0	0	0	0	46.7	
9	0	0	0	0	7.2	0	0	0	0	0	
10	48.6	0	0	0	0	0	0	0	0	0	
											201.20

Figure 6. "Matrix "cx""

Thus, the following minimization formula holds for the first optimization:

$$min \sum_{i=1}^{n} \sum_{j \neq i, j=1}^{n} c_{ij} x_{ij} :$$

$$x_{ij} \epsilon \{0,1\} \qquad \text{i, j} = 1, \ldots, \text{n}$$

The green cell in Figure 6 represents a minimized total number of kilometers that are driven if route optimization without capacity constraints is applied for a given day.

The fourth table (Figure 7) ensures that the output provided is a global tour rather than a local tour, meaning that it includes all the necessary stops in one sequence rather than splitting them up into multiple small trips. This table holds for each i = 1, …, 10 a dummy variable u_i , which keeps track of the order in which stops are visited in the green line. The constraints below ensure the route connectivity, meaning that if the vehicle arrives at a certain stop, it must leave from the same stop to proceed on the route, it removes subtours.

$$u_i - u_j + 1 \leq (n-1)(1 - x_{ij}) \qquad 2 \leq \text{i} \neq \text{j} \leq \text{n}$$

$2 \leq u_i \leq \mathrm{n}$ $\qquad\qquad$ $2 \leq \mathrm{i} \leq \mathrm{n}$

9		5	3	2	2	2	2	2	4	2
	1	2	3	4	5	6	7	8	9	10
1										
2			-7	-6	-6	-6	-6	-6	-8	-6
3		-11		-8	-8	-8	-8	-8	-1	-8
4		-12	-10		-9	-9	-9	-9	-11	-9
5		-12	-10	-9		-9	-9	-9	-11	-9
6		-12	-1	-9	-9		-9	-9	-11	-9
7		-12	-10	-9	-9	-9		-9	-11	-9
8		-12	-10	-9	-9	-9	-9		-11	-9
9		-1	-8	-7	-7	-7	-7	-7		-7
10		-12	-10	-9	-9	-9	-9	-9	-11	

Figure 7. "Matrix "u""

Therefore, the full mathematical model representing the first optimization in the case study can be shown as:

$$min \sum_{i=1}^{n} \sum_{j \neq i, j=1}^{n} c_{ij} x_{ij} :$$

$$x_{ij} \epsilon \{0,1\} \qquad \mathrm{i, j = 1, \ldots, n ;}$$

$$\textstyle\sum_{i=1, i \neq j}^{10} x_{ij} = 1 \text{ for j = 1, …, 10}$$

$$\textstyle\sum_{j=1, j \neq i}^{10} x_{ij} = 1 \text{ for i = 1, …, 10}$$

$$x_{ij} \epsilon \begin{Bmatrix} 1 & the\ path\ goes\ from\ stop\ i\ to\ stop\ j \\ 0 & otherwise \end{Bmatrix}$$

$$u_i - u_j + 1 \leq (n-1)(1 - x_{ij}) \qquad 2 \leq \mathrm{i} \neq \mathrm{j} \leq \mathrm{n}$$

$$2 \leq u_i \leq \mathrm{n} \qquad 2 \leq \mathrm{i} \leq \mathrm{n}$$

In order for the second optimization (from optimized-uncapacitated* to optimized-capacitated) to be comparable to the first optimization (from the current state to the optimized-uncapacitated*) a greedy approach will be first taken to create *optimized-uncapacitated* path*. Meaning, for those days in which the demand was bigger than the carrying capacity of the truck, a return to the depot will be manually put in the optimized-uncapacitated sequence and the additional kilometers driven adjusted accordingly (Figure 8). This approach will ensure that both of the optimizations are comparable with each other and also allow to see the value that the second optimization brings when capacity is taken into consideration. As it can be seen in Figure 8, the days in which jobsites or a single jobsite ordered more than or equal to 3000 liters of fuel (in orange), a manual return to the depot has been inserted to satisfy the future demand of the next stop(s) and the optimized-uncapacitated* case is created.

OPTIMIZED-UNCAPACITATED PATH							
10.01.2025	1	2	9	1			109.9
11.01.2025	1	2	9	1			104.7
13.01.2025	1	2	9	10	1		219.88
14.01.2025	1	6	9	2	1		119.5

OPTIMIZED-UNCAPACITATED WITH RETURNS TO DEPOT /heuristic*							
10.01.2025	1	2	1	9	1		114.4
ordered amount (l)		3000		500			
11.01.2025	1	2	9	1			104.7
ordered amount (l)		1500	500				
13.01.2025	1	2	9	10	1		219.88
ordered amount (l)		2000	500	500			
14.01.2025	1	6	9	1	2	1	124
ordered amount (l)		500	500		2500		

Figure 8. "Example of heuristic approach"

For the second optimization, from the optimized-uncapacitated* approach to optimized-capacitated, Python coding will be implemented. Google's "OR-Tools" offer already existing codes in different coding languages and for different scenarios, such as VRP and CVRP. "OR-Tools" stands for operations research tools, and it is an opensource guide on how to use computer coding to solve different problems, including routing, packing, integer and linear optimization, and more (*Google OR-Tools*, n.d.). Alves et al. (2021) found that OR-Tools combined with google maps showed promising results in minimizing route distances. This fits the case of IGATE well, as the distances between jobsites are also obtained from google maps and the second optimization model from Google OR-Tools. Moreover, Kristina et al. (2021) report that OR-Tools reduced delivery distances by 18.18% using the CVRP model. Ren (2011) formulates and provides constraints as well as will be used as a reference study for the second optimization in the case study. Google's OR-Tools, more specifically the CVRP Python model will be used as the underlying principle to study the second optimization. The Python model will be adjusted to fit the case of IGATE accordingly. That is - parameters like vehicle capacity, number of vehicles and data source will be adjusted. The adjusted Python code from Google's OR-Tools will be used in combination with the PyCharm Community Edition software, which is a free of charge software that allows users to execute Python codes for practice as well as to gain insights into the coding process.

The CVRP Python model obtains the necessary data for the optimization from an Excel file. Similar to the first optimization, a distance matrix in Microsoft Excel is used as an input, only now the distance is shown in meters not kilometers (Figure 9). This is due to the fact that the Python model is an integer solver, thus only round numbers are accepted in the optimization. For a given day a known demand of fuel that is required can be inserted in the *demand* row (Figure 9) precisely to which jobsite made the order. Also, an Excel Macro function is used to streamline the creation of the data that will be used as input for the Python model, such as output of distances (Figure 10) and output of demand (Figure 11). The OR-Tools Python model follows the underlying minimization function:

$$Z = Min_{X_{ijk}} \left\{ Max_k \sum_{i \in S} \quad \sum_{j \in S} \quad \sum_{k \in V} \quad x_{ijk} d_{ij} \right\}$$

Decision Variable: $x_{ijk} = 1$, if travel vehicle "k" moves from "i" to "j", i $\neq$ j $\in$ S, k $\in$ V; or $x_{ijk} = 0$ otherwise.

Where "i", again, represents the place the truck leaves from and "j" the place of arrival or stop. "x_{ijk}" represents a route from "i" to "j" by vehicle or in route "k". "k" is the number of vehicles, while it can also be seen as routes. That is because, as it can be seen in Figure 14 and Figure 15, the presented number of routes in the output is equal to the number of vehicles specified in the code. Even though IGATE has only one delivery truck, this method still works, as it does not matter if one delivery truck drives two paths, or two delivery trucks drive one path each (Figure 15). By combining the output paths, the result is still an optimized path, with returns to the depot and capacity consideration now taken into account, that can be used by the company's single delivery truck. Using a single vehicle in the vehicle constraint and 3000 as capacity for case in which demand exceeded 3000 resulted in a failure of the code, thus the minimum amount of vehicles and the minimum amount of capacity in the CVRP Python model constraint lines is 2 and 3000, 3000 respectively, for cases where demand exceeds 3000. "S" represents all the possible places of stops, that is depot and all the jobsites. "V" represents all the tours possible. Finally, "d" represents the distance between jobsites. This formula's goal is to minimize the longest route. That is the "Max_k" part of the function takes out the longest distance "d" between the jobsites "i" and "j" for the vehicle/route "k" and "$Min_{X_{ijk}}$" finds the shortest path possible between those places. The formula keeps doing it until it can no longer shorten any of the paths involved in a single route.

	0	1	2	3	4	5	6	7	8	9	
0	0	13600	1800	32600	37300	6400	62600	5700	43600	48600	run
1	13600	0	15400	41700	53000	19200	84400	18200	52700	58500	
2	1800	15400	0	34100	33000	5600	61900	4300	35300	45300	
3	32600	41700	34100	0	12000	36300	96800	32700	11400	78000	
4	37300	53000	33000	12000	0	41000	95000	32400	7200	79200	
5	6400	19200	5600	36300	41000	0	61600	8000	46800	45600	
6	62600	84400	61900	96800	95000	61600	0	64600	102000	16000	
7	5700	18200	4300	32700	32400	8000	64600	0	38800	46700	
8	43600	52700	35300	11400	7200	46800	102000	38800	0	85500	
9	48600	58500	45300	78000	79200	45600	16000	46700	85500	0	
demand	0	2500	0	500	0	0	0	0	600	0	3600

Figure 9. "Distance matrix for second optimization"

0	1	3	8
0	13600	32600	43600
13600	0	41700	52700
32600	41700	0	11400
43600	52700	11400	0

Figure 10. "Macro output 1: output of distances"

0	1	3	8
0	2500	500	600

Figure 11. "Macro output 2: output of demand"

As mentioned, the obtained results from the Excel Macro output serve as data that is being used by the CVRP Python model for the optimization (Figure 12; Figure 13)

```
data01 = pd.read_excel( io: 'C:/Users/krist/Downloads/cvrp_v01/kristofers_20250415.xlsm',
    sheet_name=['out.distance'])
```

Figure 12. "Distance data input in the CVRP Python model from Excel"

```
data02 = pd.read_excel( io: 'C:/Users/krist/Downloads/cvrp_v01/kristofers_20250415.xlsm', sheet_name=['out.demand'])
```

Figure 13. "Demand data input in the CVRP Python model from Excel"

To ensure that a particular tour visits a stop:

$$\sum_{k \in V} Y_{ik} = 1 \text{ , i} \in \text{H}$$

Where "Y_{ik}" equals to 1 if "k" serves a stop and 0 otherwise, and where "H" represents all the stops that are in the route of "k". This is like an indicator for the truck, for those stops that it visits. It denotes which stops a particular tour visits.

For any given day, the vehicle capacities and number of vehicles need to be adjusted according to the demand of the specific day. The demand cannot exceed the 3000 capacity of the truck while only 1 vehicle is used as a constraint, otherwise the optimization leads to failure. Thus, at all times, at least 2 vehicles and 3000 and 3000 capacities were used as constraints for the second optimization (Figure 14). Logically, for a case where demand would exceed 6000, the number of vehicles would be set to 3 and the vehicle capacities 3000, 3000 and 3000, in order for the demand to be satisfied, as that would imply that at least 2 returns to the depot, or 3 different trips (paths) have to be taken.

$$\sum_{i \in s} \sum_{j \in S} q_i \, x_{ijk} \leq W_k, \qquad k \in V$$

The above constraint is responsible for keeping the optimization within the capacity limits of the truck. "q_i" represents the demand of a certain stop and "W_k" represents the capacity of a vehicle or route "k".

```
data["vehicle_capacities"] = [3000,3000] #data["vehicle_capacities"]
data["num_vehicles"] = 2 #data["num_vehicles"]
```

Figure 14. "Vehicle capacity and number of vehicle specification line in Python code example"

Just like in the first optimization, also here the optimized sequence need to leave from and visit the prespecified locations no more than once. Therefore, the following constraint holds:

$$i \in s \quad xijk = Yjk \textstyle\sum_{i \in s} \quad x_{ijk} \; = \; Y_{ik} \,, \mathrm{j} \in \mathrm{S} \,, \;\; \mathrm{k} \in \mathrm{V}$$

The above specifies that from every starting point "i" a truck can leave no more than once in a single route ("k") and:

$$\textstyle\sum_{j \in s} \quad x_{ijk} \; = \; Y_{ik} \,, j \in S \,, \;\; k \in V$$

specifies that at every stop "j" a truck can arrive no more than once in a single route ("k").

Also, similarly to the first optimization there needs to be a constraint that ensures route connectivity, meaning that the route is a global tour visiting all the destinations specified, eliminating subtours. Moreover, it also ensures that once the vehicle arrives at a stop it also must leave from that stop and in the end of the tour return to the depot. Therefore, the following constraint holds:

$$\sum_{i \in s} \sum_{j \in s} x_{ijk} \leq |\mathrm{m}| - 1, \forall \mathrm{m} \subseteq \{2,3,\ldots,\mathrm{n}\}, k \in V$$

Where "|m|" represents the number of jobsites in the subset m.

As displayed in Figure 15, the output of the Python model shows the most optimal paths for the delivery, the total distance to be traveled (in meters) as well as the total demand (load) satisfied at each stop and in total.

```
Route for vehicle 1:
 0 Load(0) ->  2 Load(500) ->  3 Load(1100) ->  0 Load(1100)
Distance of the route: 87600m
Load of the route: 1100

Route for vehicle 2:
 0 Load(0) ->  1 Load(2500) ->  0 Load(2500)
Distance of the route: 27200m
Load of the route: 2500

Total distance of all routes: 114800m
Total load of all routes: 3600
```

Figure 15. "Output of Google's OR-Tools CVRP Python model example"

Therefore, the full mathematical model representing the second optimization in the case study can be shown as:

$$Z = Min_{X_{ijk}} \left\{ Max_k \sum_{i \in S} \sum_{j \in S} \sum_{k \in V} x_{ijk} d_{ij} \right\}$$

Decision Variable: $x_{ijk} = 1$, if travel vehicle "k" moves from "i" to "j", $i \neq j \in S$, $k \in V$; or $x_{ijk} = 0$.

Constraints:

$$\sum_{k\in V} Y_{ik} = 1 \text{ , i} \in \text{H ;}$$

$$\sum_{i\in s} \sum_{j\in S} q_i\, x_{ijk} \leq W_k,\ k \in V\ ;$$

$$\sum_{i\in s} x_{ijk} = Y_{ik} \text{ , j} \in \text{S , k} \in \text{V ;}$$

$$\sum_{j\in s} x_{ijk} = Y_{ik}\ , j \in S\ ,\ k \in V\ ;$$

$$\sum_{i\in s} \sum_{j\in s} x_{ijk} \leq |\mathrm{m}| - 1, \forall \mathrm{m} \subseteq \{2,3, \dots, \mathrm{n}\}, k \in V$$

As the fuel deliveries to jobsites are a daily practice at IGATE, the data is available from the first working day of the year. Therefore, there is enough valuable data for the analysis that can be, with the approval of the company, extracted from the company's database. This makes this a longitudinal study - data will be collected from the same source over a longer period of time. An advantage of longitudinal study is that it allows for observing patterns of change over a longer period of time as well as the level of this change (Schouten & Tager, 1996). This is relevant for the thesis, as data collected in January differs significantly to the data that is collected in February and March, due to the road construction being a seasonal industry. Time frame of the data collection will be from beginning of January 2025 until the end of March 2025. This should give the study enough valuable data and information in order to make meaningful conclusions and recommendations to the company.

3.3 Measurements

Dependent variable is "Distance traveled". This is a quantitative, metric value and falls under the ratio category because it has a meaningful true zero, meaning that time and fuel costs cannot be negative (Ciliska et al., 1999). It can be measured in concrete numbers and will be obtained from the company reports.

Independent variable is "Current fuel delivery process". This is a nominal, non-metric, variable that reflects the current state of the fuel delivery process without numerical or ordered value (Ciliska et al., 1999).

Moderator variable "Optimal route planner". This is a nominal, non-metric, variable that reflects the new state of the fuel delivery process without numerical or ordered value.

3.4 Data Analysis

Data will be stored in four tables with each day as a row. First table will contain the "Current path" with each location represented by a number and the distance traveled for each delivery day reflecting the current delivery process. Second table will contain the "Optimized-uncapacitated path" for each delivery day, also represented by numbers corresponding to each jobsite location and the distance which could have been traveled if the optimization without capacity constraints had taken place. The third table will contain the "Optimized-uncapacitated* path", which, by the use of greedy approach will contain the manually adjusted distance traveled for those days in which a return to the depot is required in the optimized-uncapacitated path due to orders exceeding the carrying capacity of the truck. For this approach the amount ordered by each of the jobsites is relevant, thus the amount will be presented in a row under each location (amount presented in liters). Finally, the fourth table will, again, have each day as a row and contain the "Optimized-capacitated path" and the distance that would have been covered if the CVRP/SDVRP method would have been applied. Also here, the amount ordered by each of the jobsites is presented in a row under each location. After all the optimizations will have finished the change in distance, percentage change in distance, variance and standard deviation will be calculated and stored in a separate tables for each month and discussed accordingly. Change in distance, percentage change in distance, variance and standard deviation will be calculated using the following formulas:

$$Change\ in\ distance = \frac{Distance_t - Distance_{t-1}}{Distance_{t-1}}$$

$$Percentage\ Change\ in\ distance = \frac{Distance_t - Distance_{t-1}}{Distance_{t-1}} * 100$$

$$\text{Variance; } \sigma^2 = \frac{\sum(ai-\bar{a})^2}{b-1}$$

$$\text{Standard deviation; } \sigma = \sqrt{\sigma^2 = \frac{\sum(ai-\bar{a})^2}{b-1}}$$

Where "$Distance_t$" is the total kilometers driven in a specific month, " $Distance_{t-1}$" is the total kilometers driven in the previous month, "ai" is the individual data point (kilometers driven) in a specific day in a month, "$\bar{a}$" is the sample mean or the average of all the individual data points and "b" refers to the total number of data points in the sample.

Sample variance and standard deviation will be calculated, as the study treats the dataset as representative of a broader context. Meaning that the analysis focuses on a limited time period (three months), rather than the entire operational history of the company, and does not include every fuel delivery IGATE has ever made.

The path optimization and comparison will be done in two runs. Microsoft program Excel, Solve function under the Data tab will be used to generate the first optimized path. Solver function will be implemented to generate the optimal sequence of locations to visit in a specific order for the first optimization from current path to optimized-uncapacitated. This optimal sequence will result in minimized travel distance for the optimized-uncapacitated path. The results obtained from the optimization will be stored in a table in Excel. Built-in Excel formulas will be used to analyze and conclude from the obtained data in the first comparison run.

Python coding will be used to generate the second optimized sequence with capacity constraints taken into account. Excel Solver cannot be used to perform this optimization due to there being more constraints necessary than it is actually possible to insert in the Solver's constraint tab. Therefore, a more advanced solution is necessary. Google's "OR-Tools" offers an already existing code which can be tailored to the case study of IGATE to represent the challenge accordingly. The execution of the code will provide an optimal sequence of stops, while also considering capacity constraints of the truck. The results obtained from the optimization will be stored in a table in Excel. And built-in Excel formulas will be used to analyze and conclude from the obtained data in the second comparison run.

The solver function in Microsoft Excel has been chosen to do the analysis for the current path to optimized-uncapacitated path of IGATE because, firstly, excel is freely available for Tilburg University students. Secondly, the author already has previous knowledge on how to use Solver. Finally, it is a simple, yet an effective tool to use and see whether the optimization challenge can be implemented for the selected case.

Google's OR-Tools CVRP Python model in combination with PyCharm software has been chosen to improve the optimized-uncapacitated* path to optimized-capacitated path because, firstly, the code for similar CVRP problems is provided by Google's OR-Tools and it is fully customizable to fit the case study of IGATE. Secondly, Excel Solver cannot perform computations with as many constraints as are necessary for the second optimization, due to the constraint amount limit in Excel. Thirdly, studies done by Alves et al. (2021) and Kristina et al. (2021) serve as proof that the tools offered by Google have real life impact and that they perform accordingly. Lastly, the Python code and the PyCharm software are both free of charge, and the author has previous knowledge and skills working with Python codes.

3.5 Reliability and Validity

Reliability refers to the consistency and accuracy of the data used in the analysis (Mohajan, 2017). Since the case study is based on fuel delivery records, route data and waybills directly obtained from the company records, the data sources are consistent, systematically recorded and present the actual operational activity. This ensures that, if the same methodology were to be applied to a different time period or repeated by another researcher using the same records, the results would likely be the same or very similar. Therefore, the reliability of the data can be considered as high.

Validity refers to how accurately the data and methods used capture the actual phenomena that is being studied (Mohajan, 2017). In the case of IGATE, the use of real operational data and jobsite distances, fuel delivery routes, as well as routing decisions display a strong internal validity. This is because the variables (e.g. kilometers driven, fuel consumption) are directly related to the research questions and are company specific. However, due to the fact that the study focuses on a single company and a specific operational process, the external validity is limited. Nevertheless, the insights remain highly relevant and valid within the context of IGATE and other companies which engage in similar activities.

As this research is based on a single case study conducted at IGATE, a road construction company in Latvia, the findings are context specific. Therefore, the generalizability of the results to other companies, sectors, or geographical locations is limited. However, the underlying concept explored within the study – how route optimization can influence delivery distances – is applicable to other firms facing similar logistical challenges. As such, while the numerical results may not be directly transferable, the insights gained, and the methodology used can serve as a reference or a great starting point for related studies in other construction or logistics-based environments.

CHAPTER 4: Results and Findings

4.1 Current procedure and its challenges for fuel deliveries to jobsites at IGATE.

The current fuel delivery process at the company is very simple and primitive. Firstly, when a jobsite needs fuel, it alerts the technical department of IGATE by the means of a text message that it requires a certain amount of fuel in the next day. The message must be delivered no later than 4:30 PM on the previous day of the delivery. This message is then processed by the department and the required amount is noted in the waybill, as is the location of the corresponding jobsite. When all the jobsites have made their orders and the waybill has been filled, it is then handed over to the delivery truck driver. However, the locations on the waybill are listed in the order in which the fuel was requested, most likely not in the most efficient way for the delivery. Thus, the driver is the main decision maker regarding which jobsites get visited in which sequence. And, therefore, an opportunity for an improved sequence of jobsite visits arises every day but goes unnoticed since no route optimization tool is in place at the company. Currently there are several challenges that exist at the company regarding the current fuel delivery system. Firstly, the way the route is created is solely up to the human mind. While some logical sequence of stops is most likely applied, this does not guarantee that the most efficient and optimized route has been chosen. This can lead to an increased number of kilometers driven every day which in turn causes higher fuel consumption and, thus, increased operational costs of the delivery truck. Secondly, a lack of standardized processes for delivery routing exists within the company which results in constant inefficiencies regarding the deliveries. Any new or substitute delivery driver would drive even less efficient routes without the lack of reference to past experience and benchmarks. Finally, there is limited transparency, since the route decision is mostly up to the driver and not based on a system. This makes it difficult for management to not only track or benchmark the process but also to identify room for improvement. Despite the current limitations and challenges, the existing system provides a clear opportunity for improvement regarding the current fuel delivery procedure at the company. By first examining the existing performance, average and total kilometers driven per day, valuable information can be gained that supports the introduction of an optimization tool for the delivery routes.

4.2 Current average and total kilometers driven for fuel deliveries to jobsites at IGATE.

During the writing of this thesis and data collection period the company is engaged in 10 jobsites which make fuel orders independently of each other. In the data collection period, from the 2^{nd} of January until the 31^{st} of March 72 fuel deliveries have been made and all 10 of the jobsites have ordered fuel delivery at least once. As it can be seen in Figure 16, In January the minimum number of kilometers that the delivery truck drove in a single day was 30.76 km while the maximum number of kilometers made in a single day was 220.40 km. The average number of kilometers driven per day in January was 132.40 km. In February the minimum number of kilometers that were driven in a day were 38.74 km and the maximum number of kilometers driven in a day were 150.21 km. Average kilometers driven per day by the delivery truck in February were 117.96 km. March was the busiest of the months that were part of the data collection process. The lowest number of kilometers that were driven in a single day in March was 78.30 km and the highest number of kilometers driven in a single day was 410.60 km. March also saw the highest average number of kilometers driven out of the three months that were analyzed, with the average kilometers driven equaling to 203.77 km.

	JANUARY	FEBRUARY	MARCH
	current	current	current
min	30.76	38.74	78.3
max	220.40	150.21	410.6
average	132.40	117.96	203.77
sum total km	3442.49	2831.03	4482.86

Figure 16. "Table of current state of deliveries"

This makes sense since road construction is a very seasonal industry, therefore, the closer the summer, the busier the company gets as more jobsites are beginning or continuing their work. These are the real and unoptimized figures that represent the current delivery process accurately. It is worth exploring whether the introduction of optimal route generation benefits can be achieved, firstly, by optimizing the current process with no capacity constraints with Excel Solver and, secondly, to make the optimization representative of the real world – with capacity constraints by the use of Python code.

4.3 The effect of the introduction of the optimal route planner on average and total kilometers driven by the fuel delivery truck at IGATE under the Classical VRP optimization, when capacity constraints are not considered.

As mentioned, the first optimization from the current path to optimized-uncapacitated path was achieved by the means of Excel Solver. The results are as expected, and the optimization has led to a decrease in the kilometers driven by the delivery truck. For the month of January, if the Excel Solver would have been used for route optimization and there were no capacity constraints on the delivery truck, the minimum number of kilometers (compared to the same day as in current path) would not have changed as the number of jobsites that ordered a delivery was only one. However, when comparing the day in which the maximum number of kilometers was driven in the current path with the same day in the optimized-uncapacitated path a decrease of 19.6 km can be observed, that is an 8.89% decrease. The total kilometers driven in January decreased by 332.61 km and the average kilometers driven decreased by 12.79 km. That is a decrease of 9.66% for both – on average and total amounts (Figure 17).

JANUARY		
	current	uncapacitated
min	30.76	30.76
max	220.40	200.80
average	132.40	119.61
sum total km	3442.49	3109.88
change in min	-	0.00
change in max	-	-19.60
change in average	-	-12.79
change in total km driven	-	-332.61
% change in min	-	0.00
%change in max	-	-8.89
% change in average	-	-9.66
% change in total km driven	-	-9.66
Variance	1765.37	1536.50
Standart deviation	42.02	39.20

Figure 17. "Table of January comparing current and optimized-uncapacitated paths"

In February the optimization also yielded results. The day on which the most kilometers were driven in the current path saw a reduction of 46.41 km or 30.9%. The total amount of kilometers driven in February decreased by 478.77 km, from 2831.03 km to 2352.26 km, while the average kilometers driven decreased by 19.95 km. That is a decrease of 16.91% (Figure 18).

FEBRUARY		
	current	uncapacitated
min	38.74	38.74
max	150.21	103.80
average	117.96	98.01
sum total km	2831.03	2352.26
change in min	-	0.00
change in max	-	-46.41
change in average	-	-19.95
change in total km driven	-	-478.77
% change in min	-	0.00
%change in max	-	-30.90
% change in average	-	-16.91
% change in total km driven	-	-16.91
Variance	1270.93	829.25
Standard deviation	35.65	28.80

Figure 18. "Table of February comparing current and optimized-uncapacitated paths"

In March the biggest changes in performance can be observed. The day on which the least amount of kilometers were driven in the current path saw a reduction of 42.6 km or 54.41% decrease when compared to the optimized-uncapacitated path. The day with the most kilometers driven in the current path in March resulted in a 174.1 km reduction, a 42,4% decrease. Finally, the total and average amount of kilometers driven in the current path, when compared to the optimized-uncapacitated path, saw a decrease of 832.79 km and 37.85 km respectively, or a decrease of 18.58% (Figure 19).

MARCH		
	current	uncapacitated
min	78.30	35.70
max	410.60	236.50
average	203.77	165.91
sum total km	4482.86	3650.07
change in min	-	-42.60
change in max	-	-174.10
change in average	-	-37.85
change in total km driven	-	-832.79
% change in min	-	-54.41
%change in max	-	-42.40
% change in average	-	-18.58
% change in total km driven	-	-18.58
Variance	7163.27	2685.15
Standard deviation	84.64	51.82

Figure 19. "Table of March comparing current and optimized-uncapacitated paths"

When looking at variance and standard deviation for the three months a decrease can be observed in all of the months analyzed. In January, variance in kilometers driven decreased from 1765.37 km² in the current path to 1536.50 km² in the optimized-uncapacitated path, and standard deviation decreased from 42.02 km to 39.20 km. February saw a decrease from 1270.93 km² to 829.285 km² in variance and a decrease in standard deviation from 35.65 km to 28.80 km. Variance decreased from 7163.27 km² to 2685.15 km² and standard deviation from 84.64 km to 51.82 km in March. This indicates that the delivery distances are not only lower on average (as seen in the reduction in average kilometers driven) but also more consistent, meaning that the delivery distances deviate less from the average. A decrease in standard deviation demonstrates a narrower spread of delivery distances leading to more predictable and stable delivery routes (Figure 17; Figure 18; Figure 19).

While a huge change can be observed in all of the metrics used for describing the change from the current state to the optimized-uncapacitated state of the system, an important element must be remembered. The Classical VRP model does not take capacity into consideration and each location can be visited only once, meaning that some improvements are not actually feasible. Thus, a greedy approach has been taken and manual returns to depot have been inserted and distance traveled adjusted accordingly for those day in which the capacity ordered exceeded the carrying capacity of the truck. The carrying capacity of the truck is a maximum of 3000 liters at any single moment of time. Therefore, it is worth looking at all three months to assess how the adjusted routing performs under more realistic conditions and how it compares to the actual current path driven by the driver.

In January the least amount of changes can be observed. This is due to the fact that in January the jobsites have barely started or restarted their works, therefore, also the ordered fuel amounts are lower, and thus returns to depot are a lot less likely. However, some changes can be observed. Average kilometers driven still decreased when compared to the actual path driven, by 12.24 km, and total kilometers driven decreased by 318.41 km, that is a 9.25% decrease. Variance and standard deviation dropped from 1765.37 km² and 42.02 km to 1529.15 km² and 39.10 km respectively (Figure 20).

JANUARY			
	current	uncapacitated	uncapacitated*
min	30.76	30.76	30.76
max	220.40	200.80	200.80
average	132.40	119.61	120.16
sum total km	3442.49	3109.88	3124.08
change in min	-	0.00	0.00
change in max	-	-19.60	-19.60
change in average	-	-12.79	-12.24
change in total km driven	-	-332.61	-318.41
% change in min	-	0.00	0.00
%change in max	-	-8.89	-8.89
% change in average	-	-9.66	-9.25
% change in total km driven	-	-9.66	-9.25
Variance	1765.37	1536.50	1529.15
Standart deviation	42.02	39.20	39.10

Figure 20. “Table of January comparing current, optimized-uncapacitated and optimized-uncapacitated* paths”

February was no different and changes can be observed. Average kilometers driven decreased from 117.96 km to 113.12 km driven. That is a decrease of 4.84 km or 4.11%. Total kilometers driven decreased by 116.25 km, which is also a decrease of 4.11%. Interestingly, variance and standard deviation increased from 1270.93 km² and 35.65 km to 1710.08 km² and 41.35 km respectively (Figure 21). This indicates that while the optimization led to the truck driving less kilometers overall, some trips have become longer and others shorter, thus creating more imbalance in the paths taken. This can be explained by the returns to the depot taken into account.

FEBRUARY			
	current	uncapacitated	uncapacitated*
min	38.74	38.74	38.74
max	150.21	103.80	103.80
average	117.96	98.01	113.12
sum total km	2831.03	2352.26	2714.78
change in min	-	0.00	0.00
change in max	-	-46.41	0.00
change in average	-	-19.95	-4.84
change in total km driven	-	-478.77	-116.25
% change in min	-	0.00	0.00
%change in max	-	-30.90	-30.90
% change in average	-	-16.91	-4.11
% change in total km driven	-	-16.91	-4.11
Variance	1270.93	829.25	1710.08
Standart deviation	35.65	28.80	41.35

Figure 21. "Table of February comparing current, optimized-uncapacitated and optimized-uncapacitated* paths"

Also, in March changes can be seen and are greater in numbers than in the previous two months, due to there being more work. Therefore, also more fuel gets ordered, which in turn requires more returns to the depot if capacity is exceeded. As shown in Figure 22, average kilometers driven decreased from 203.77 km to 170.08 km, which is a decrease of 16.53% when compared to the current path of deliveries. Total kilometers driven decreased by 741.16 km, from 4482.86 km to 3741.70 km. Variance decreased from 7163.27 km² to 2604.42 km², and standard deviation from 84.64 km to 51.03 km accordingly. This signals that the optimized-uncapacitated delivery routes for March, under the heuristic approach, are more consistent and closer to the average values, which also provides a more stable and balanced workload for the driver.

MARCH			
	current	uncapacitated	uncapacitated*
min	78.30	35.70	53.80
max	410.60	236.50	241.00
average	203.77	165.91	170.08
sum total km	4482.86	3650.07	3741.70
change in min	-	-42.60	-24.50
change in max	-	-174.10	-169.60
change in average	-	-37.85	-33.69
change in total km driven	-	-832.79	-741.16
% change in min	-	-54.41	-31.29
%change in max	-	-42.40	-41.31
% change in average	-	-18.58	-16.53
% change in total km driven	-	-18.58	-16.53
Variance	7163.27	2685.15	2604.42
Standart deviation	84.64	51.82	51.03

Figure 22. "Table of March comparing current, optimized-uncapacitated and optimized-uncapacitated* paths"

4.4 The effect of the introduction of the optimal route planner on average and total kilometers driven by the fuel delivery truck at IGATE, under CVRP/SDVRP when capacity constraints are considered

As mentioned, the second optimization, from the optimized-uncapacitated* to optimized-capacitated, was accomplished by the use of Google's OR-Tools CVRP Python model coding. The results are as expected, meaning that improvements have been achieved, however the magnitude of the improvements was less than what was achieved by the first optimization from current path to optimized-uncapacitated*. This makes sense as it is harder to further improve an already optimized sequence than to improve a non-optimized one. Nevertheless, improvements can be observed.

In January, after the implementation of CVRP Python model, the minimum and maximum kilometers driven in a single day remained unchanged. Average kilometers driven per day decreased slightly – by 2.13 km or 1.77%. Also, the total kilometers driven in the whole month of January decreased. A decrease of 55.38 km or 1.77% can be observed for the total kilometers driven. Lower variability and standard deviation was also observed. From 1529.15 km^2 and

39.10 km in the optimized-uncapacitated* case to 1372.88 km² and 37.05 km in the optimized-capacitated case. This indicates that delivery distances have become even more consistent and more predictable (Figure 23). While the capacitated optimization outperforms the uncapacitated approach with the greedy method (uncapacitated*) the improvements made in January are relatively small. This suggests that the greedy approach already captures most of the efficiency gains (at least this in this month).

JANUARY				
	current	uncapacitated	uncapacitated*	capacitated
min	30.76	30.76	30.76	30.76
max	220.40	200.80	200.80	200.8
average	132.40	119.61	120.16	118.03
sum total km	3442.49	3109.88	3124.08	3068.7
change in min	-	0.00	0.00	0.00
change in max	-	-19.60	-19.60	0.00
change in average	-	-12.79	-12.24	-2.13
change in total km driven	-	-332.61	-318.41	-55.38
% change in min	-	0.00	0.00	0.00
%change in max	-	-8.89	-8.89	0.00
% change in average	-	-9.66	-9.25	-1.77
% change in total km driven	-	-9.66	-9.25	-1.77
Variance	1765.37	1536.50	1529.15	1372.88
Standart deviation	42.02	39.20	39.10	37.05

Figure 23. "Table of January comparing current, optimized-uncapacitated, optimized-uncapacitated* and optimized-capacitated paths"

In February the impact of CVRP Python model on the path driven was stronger. Average kilometers driven in February decreased by 9.06 km or 8.01%. Total kilometers driven were reduced from 2714.78 km to 2497.36 km or, also, a decrease of 8.01%. This demonstrates a stronger optimization performance when compared to optimized-uncapacitated* method. A sharp drop can also be observed in the variance and standard deviation. From 1710.08 km² and 41.35 km to 953.11 km² and 30.87 km respectively (Figure 24). This suggests that the paths produced by the CVRP Python model yield more consistent and predictable trip lengths, which can be seen as operational benefit. This is because, as workload for staff becomes more predictable, improved scheduling and easier resource planning opportunities arise, such as staffing, maintenance, etc. In February the optimized-capacitated model clearly outperforms the optimized-uncapacitated* method.

FEBRUARY				
	current	uncapacitated	uncapacitated*	capacitated
min	38.74	38.74	38.74	38.74
max	150.21	103.80	103.80	103.80
average	117.96	98.01	113.12	104.06
sum total km	2831.03	2352.26	2714.78	2497.36
change in min	-	0.00	0.00	0.00
change in max	-	-46.41	0.00	0.00
change in average	-	-19.95	-4.84	-9.06
change in total km driven	-	-478.77	-116.25	-217.42
% change in min	-	0.00	0.00	0.00
%change in max	-	-30.90	-30.90	0.00
% change in average	-	-16.91	-4.11	-8.01
% change in total km driven	-	-16.91	-4.11	-8.01
Variance	1270.93	829.25	1710.08	953.11
Standart deviation	35.65	28.80	41.35	30.87

Figure 24. "Table of February comparing current, optimized-uncapacitated, optimized-uncapacitated* and optimized-capacitated paths"

In March the performance improvement from optimized-uncapacitated* to optimized-capacitated was slight. The average kilometers driven per day decreased by only 0.64 km and the total amount driven in March decreased by 14 km – from 3741.70 km to 3727.70 km. That is a reduction of 0.37%. Additionally, the variance in the optimized-capacitated model decreased from 2604.42 km^2 to 2560.35 km^2 and standard deviation decreased from 51.03 km to 50.60 km. This similarity in standard deviation and variance suggests that both optimizations produced almost equally consistent routes. This also suggests that the optimized-uncapacitated method, at least for the month of March, effectively captures nearly all the potential efficiency gains (Figure 25).

MARCH				
	current	uncapacitated	uncapacitated*	capacitated
min	78.30	35.70	53.80	53.80
max	410.60	236.50	241.00	241.00
average	203.77	165.91	170.08	169.44
sum total km	4482.86	3650.07	3741.70	3727.70
change in min	-	-42.60	-24.50	0.00
change in max	-	-174.10	-169.60	0.00
change in average	-	-37.85	-33.69	-0.64
change in total km driven	-	-832.79	-741.16	-14.00
% change in min	-	-54.41	-31.29	0.00
%change in max	-	-42.40	-41.31	0.00
% change in average	-	-18.58	-16.53	-0.37
% change in total km driven	-	-18.58	-16.53	-0.37
Variance	7163.27	2685.15	2604.42	2560.35
Standart deviation	84.64	51.82	51.03	50.60

Figure 25. “Table of March comparing current, optimized-uncapacitated, optimized-uncapacitated* and optimized-capacitated paths”

CHAPTER 5: Discussion, Limitations & Recommendations

5.1 Theoretical contributions

All routing scenarios across the three-month period have been optimized and analyzed, allowing for a clear comparison between the outcomes. The study has evaluated how different optimization approaches and the presence of capacity constraints would have affected the current fuel delivery process to jobsites. The results demonstrate that both – the optimized-uncapacitated* method, which is the result of Excel Solver's optimized-uncapacitated method adjusted by the use of a greedy approach, as well as the optimized-capacitated method generated by Google's OR-Tools CVRP Python model can reduce the total distance driven by the delivery truck and improve delivery route consistency. This chapter summarizes the main findings of the case study by presenting them as theoretical and managerial contributions, presents the limitations of the study, as well as offers recommendations for future research.

The results of this case study support, strengthen and extend the already established findings in the academic literature on VRP and optimization in logistics. Various studies have emphasized that route optimization has a significant impact on operational efficiency, mostly by reducing total distance driven, fuel consumption and time spent on road (Jovičić et al., 2010; Sulemana et al., 2019). The results from the case study of IGATE are in alignment with these conclusions. For instance, Sulemana et al. (2019) identified that optimized routing in waste collection resulted in reduced travel distance by 4.79%. In the case of IGATE the optimized-uncapacitated* path saw a reduction of 9.25% in January, 4.11% reduction in February and 16.53% reduction in March when compared to the current path. Moreover, these reductions were further reduced by the capacitated model. January saw a further 1.77% decrease, February 8.01% and March 0.37% when compared to the optimized-uncapacitated* model. While these improvements vary from month to month, it can be clearly observed that they indicate a trend of operational improvements and confirm that similar efficiency gains are achievable in the road construction industry, where the application of VRP optimization is relatively underexplored. Additionally, in line with Karimipour et al. (2021), who observed 60% reduction in kilometers traveled by heavy vehicles, improvements of the variance and standard deviation in this study also reflect an enhanced predictability. In January variance decreased from 1765.37 km² to 1529.15 km² and standard deviation from 42.02 km to 39.10 km, increased from 1270.93 km² and 35.65 km to 1710.08 km² and 41.35 km in February, and decreased from 7163.27 km² and 84.64 km to 2560.35 km² and 50.60 km in March, when comparing the variance and standard deviation of the current path to the optimized-uncapacitated* scenario. What is more, these changes where further affected by the optimized-capacitated case scenario. In January variance decreased to 1372.88 km² and standard deviation to 37.05 km, in February to 953.11 km² and 30.87 km, and in March to 2560.35 km² and 50.60 km. This indicates that under the optimization scenarios the delivery routes become usually (in all except one case) became more stable and consistent. This also supports the literature's claim that optimized routing improves route regularity and consistency, while also allowing for better resource allocation (Wang et al., 2021; Helvaci et al., 2008). Furthermore, the distinction between uncapacitated and capacitated routing revealed new implications. While classical VRP method (as the one simulated in Excel Solver) offers an initial understanding of the optimization potential, the optimized-uncapacitated scenario, followed by the more complex Google OR-Tools CVRP Python model, show the change from what would be an idealized and unrealistic optimization to a much more precise and accurate real-world representation. This confirms claims of Zhang et al. (2021) and Baldacci et al. (2011) who argue that the real-world implementation of VRP models, namely the more advanced models (such as those that account for capacity constraints) provide a more realistic and effective solution, especially in scenarios where split deliveries are necessary, such as in the case of IGATE on multiple occasions over the period of the three studied months.

5.2 Managerial contributions

The findings of this case study also provide several practical insights as well as conclusions for manager that are directly applicable to IGATE as well as potentially to other companies involved in fuel deliveries, road construction industry or construction industry in general. Firstly, it can be concluded that the company should adopt a route optimization tool. IGATE should consider implementing a route optimization tool or software, such as Excel Solver or the CVRP Python model. While the Excel Solver is a relatively simpler tool to learn, it is also a lot less fast in computation and each case takes more time to set up. On the other hand, Python is a lot faster in computation, however, learning Python coding basics will be a must for the managers that will be using the CVRP Python route optimization tool. Both of these tools have their own benefits and drawbacks, nevertheless these tools allow the company to plan routes in a more standardized way by minimizing the manual decision-making process currently done by the driver, while also ensuring more optimal sequence of stops. Secondly, capacity constraint integration should be done. As seen in both the optimized-uncapacitated* and optimized-capacitated cases, the most optimal paths were generated after the introduction of capacity limits. That is, total and average kilometers driven reduced in January, February and March, as well as the variance and standard deviation decreased in all cases, except when applying greedy approach to the optimized-uncapacitated case in February. This can be explained by some routes becoming a lot longer and some significantly shorter when compared to the original route driven. Nevertheless, the main goal of the total distance reduction was achieved also in February. Capacity considerations become increasingly important as the road construction season intensifies and more jobsites become active. As it can be in the numbers of fuel ordered and total kilometers driven when comparing January and March. This difference tends to become even larger as the industry approaches summer months, when most of the job gets done, and tends to slow down as autumn approaches. Thirdly, the company should engage in benchmarking these optimized route performances. Regular tracking and comparison with benchmarks will allow the company and its management to effectively evaluate the performance of the optimized routes as well as identify any further possibilities for improvement.

It is also worth performing a cost-benefit analysis to further evaluate the impact of the optimization tool on the company (Table 2).

Costs	Benefits
Setup costs – initial setup costs of the route optimization tools. Potentially free if Excel Solver or Python code implemented, but more advanced tools should also be considered, which are not free.	**Reduced distance traveled** – optimized routes lead to less kilometers driven between the stops in a sequence.

Training costs – training managers and key staff that will be the main users of the tool to use it and read result will take some time and money (wages).	**Reduced fuel costs –** less kilometers driven, less fuel spent, therefore reduced fuel costs for the truck.
Operational process change – implementation of an optimization tool will require to change the current routine of the delivery process. Data input, route generation and capacity allocation will be affected.	**Lower vehicle wear and maintenance costs -** the less the truck drives, the less likely it is that it will break down. Reducing the distance driven, reduces the maintenance frequency.
Upkeeping – occasional adjustments and updates to the models (such as adding new locations in the distance matrix).	**Time savings** – more efficient routes mean less driving per day.
Resistance to change – potential hesitation of the employees to use a new system/tool, and potential hesitation of drivers to drive new/unfamiliar routes.	**More predictable deliveries** – route optimization and standardization of the process can increase consistency, which allows for better planning.
	Reduced reliance on driver's judgement – reduces operational dependency on an individual's experience and uses mathematical calculations for precision every time.
	Data – provides data for performance evaluation and improvement opportunities.

Table 2: "Cost-Benefit Analysis"

If the company decides to implement one of the methods used in this study, then the benefits would highly outweigh the costs, since the methods used in this study are free of charge and the monetary costs that would be incurred are purely employee related. However, if the company decided to look into other, more sophisticated tools, a more serious evaluation should be done to compare the monetary costs of the tool, as well as other costs involved, such as the ones mentioned in the cost-benefit analysis, to the savings on fuel, time and maintenance costs generated by this investment. While operational process change is a barrier that needs to be overcome, the implementation of such optimization tools will also come with increased predictability of the routes, thus also increasing the consistency of work. And, while there might be resistance to change from both, the office employees as well as from the delivery truck drivers, the tool implemented will reduce the operational dependency on the driver to figure out the sequence of stops, as well as allow the employees to evaluate and look for improvements in the performance of the optimization.

While tailored to IGATE the findings are also relevant to other firms that are engaged in fuel or material deliveries to jobsites. Companies in construction and road construction industries can also gain benefits of route optimization without high initial costs. A commitment to create and take a standardized approach towards optimizing the current delivery process must be taken by utilizing available tools, such as Excel, Python and Google OR-Tools which are free of charge. The transition to an algorithm-based route planning is especially relevant to those industries and companies, where the driver-based planning is common, and delivery amounts are high, for example food deliveries and postal services.

5.3 Limitations

Despite the valuable insights and improvements in the delivery process that this case study has generated, there are also several limitations that are worth acknowledging, which could impact on the broader interpretation and application of the findings. Firstly, the scope of the data. This study is based on three months of fuel delivery data. While this time period provides a representative case of daily operations, it does not capture the long-term trends, such as seasonality fluctuations (summer and autumn/winter periods). Secondly, single company focus. This study is a case study conducted at a specific road construction company in Latvia. Therefore, the findings are context-specific and affected by the company’s size, structure, geographical location and operational specifications. This limits the direct transferability of conclusions to other companies that do not have similar characteristics. Thirdly, the use of manual heuristic adjustments. While the optimized-uncapacitated* (created by the greedy approach) model generated valuable optimization results, the need to manually adjust for return trips (to make the case more realistic and comparable) introduced subjectivity. Although these adjustments are reasonable, they are not based on real-time capacity tracking and, therefore, may not accurately reflect the true operational constraints. Fourthly, simplified modeling assumptions. The study used fixed distance matrixes as inputs for the optimization. A single point, in the middle of the jobsite was selected on Google Maps to represent the whole jobsite. While representative, in a real-world scenario, it might be the case that the delivery truck must drive further into the jobsite or less, leading to different fuel delivery offloading places, which in turn affects the distance traveled. Moreover, variables like traffic patterns and refueling time were not incorporated into the study in order to make it feasible to perform. Lastly, optimization tool limits. The optimizations were executed using the Excel Solver and Google's OR-Tools CVRP Python model. While these tools are free of charge and accessible, they are limited in handling larger-scale routing complexity. For example, Excel Solver was unusable to perform the second optimization that involves capacity constraints due to the Solver's constraint tab having a limit on how many constraints can be put on a single model. Moreover, both of the tools do not take dynamic, real-time updates on, for example, traffic, weather and jobsite situations into account. More advanced logistics platforms may offer stronger performance, however, they were outside the scope of this thesis.

5.4 Recommendations for future research

Building on the limitations discussed above, several directions for future research can be suggested to expand, strengthen and solidify the understanding of route optimization in the road construction industry and construction logistics in general. For starters, it would be interesting to see the results of a similar experiment done by extending the data scope. That is to explore a case in which a full year of operational data are included. This would allow to capture seasonal variations and better showcase the long-term delivery patterns. Moreover, it would also be interesting to see the results the implementation of route optimization would have in the summer months when the road construction industry's operations are at its peak. Secondly, it is worth performing a study in which multiple case companies are included. By conducting a comparative study across several road construction or logistics companies, engaging in fuel or material deliveries to jobsites or similar operations, increased external validity would be achieved. Also, this approach would allow to analyze how results differ across different organizational contexts as every company has its own way of engaging in business activities. Thirdly, the possibility for future research potential could be to explore more advanced optimization tools. While the tools used in this case study offer optimization benefits and are free of charge, optimization tools that take into account more variables to generate optimized routes should also be explored. For example, dynamic updates such real-time traffic conditions and weather conditions could be considered. Another possibility for a future research would be to decide on a single location in a jobsite in which the fuel would be delivered to. This would allow for accurate measurement of the distance that needs to be traveled from one jobsite to another, as currently (in this case study) the delivery point is set in the middle of the jobsite, while it may not always be the exact offloading place of the delivery.

5.5 Conclusion

This thesis set out to explore how the introduction of route optimization tools could affect the efficiency of the fuel deliveries to jobsites at a road construction company. In the case study, performed at IGATE, two different routing optimizations where introduced. Firstly, the current delivery paths driven were optimized in Excel Solver by not taking capacity constraints of the delivery truck into account. This allowed to see whether optimization was possible, which resulted in the optimized-uncapacitated case, however the case was not realistic and representative of the real world. To make it more realistic, a heuristic, greedy approach was taken. A manual return to the depot was inserted in the optimized sequence and kilometers driven were manually adjusted, which resulted in the optimized-uncapacitated* case. Secondly, Google's OR-Tools Python model was used to further optimize the optimized-uncapacitated* case to see what the effect of and what value does including capacity constraints in the optimization models brings. This resulted in the optimized-capacitated case. After comparison, the results demonstrated that route optimization in both cases lead to meaningful reductions in average and total kilometers driven, as well as improved consistency of the delivery routes was achieved. While the heuristic approach already provided noticeable gains, the capacitated approach brough further improvements. Although the study faced several limitations such as its scope, single company focus, etc., it clearly highlighted the operational and strategic potential of free-to-use optimization tools. Moreover, the case study's results contribute to both the academic understanding of VRP applications in underexplored sectors such as road construction and provide practical guidance that companies can implement to improve routing efficiency, reduce costs, and enhance the consistency of their delivery operations. With further enhancements and broader applications, such optimization practices can support smarter, more sustainable delivery systems in construction logistics and beyond.

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