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„Robot-based attended home deliveries"

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Abstract (English)

The retail sector is facing from year to year a higher demand for online shopping and home deliveries. Simultaneously there is an increase in urbanization and accessibility of cars to people, which leads to increased congestion in city areas. Consequently, the congestion leads to difficulties for retailers to reach their customers in an efficient and timely manner. In view of this, this master thesis refers to an alternative delivery tool which has the potential of becoming an alternative for home deliveries in urban areas. In this case, the robot-based delivery is considered as the potential for improving the urban deliveries compared to conventional delivery vehicles. Therefore, beside current global development related to trade and delivery, literature research on the current status of delivery robots has been conducted. The research includes issues related to the public acceptance of such a new technology andtechnical capabilities of delivery robots related to their limitations such as speed and capacity. In addition, economic and technical potentials are also part of the literature research, which argue the importance of such technology for finding a more economical and efficient delivery alternative in urban areas. On the other hand, the regulatory perspective as an important aspect when introducing new technologies on the market has also been considered. In this part, current policy status is elaborated, mostly related to responsibility in case of accidents. In addition, the theoretical findings have been used for a construction of a computational study, whose purpose was to support the research with exact numbers comparing potentials and shortcomings of delivery robots and conventional delivery vehicles. For this purpose, two static algorithms were developed, one for each of the approaches, whereas additional algorithm variants were part of each algorithm. The variants were meant to establish each of the algorithms with different characteristics, the change in characteristics enabled a comparison between each approach with itself under different circumstances (characteristics). The results were extracted to excel and accordingly, summarized in various diagrams (Appendix I).

Research question

Can robot-based deliveries improve attended home deliveries? (compared to conventional attended home deliveries)

Abstract (Deutsch)

Derzeitig steht der Einzelhandel jedes Jahr vor einer größeren Nachfrage nach Onlineshopping und somit Hauszustellungen von spezifischen Produkten. Gleichzeitig wird auch ein Anstieg an Urbanisierung und eine immer einfachere Lage für das Autoerwerb zu unserem Alltag. All dies, führt zu einem Anstieg an Verkehrsbelastung im täglichen Stadtverkehr. Folglich, die Verkehrsbelastung führt zu Staus und genauso zu immer größeren Schwierigkeiten für die Zusteller ihre Kunden effizient und rechtzeitig zu beliefern. In diesem Sinne, diese Masterarbeit bezieht sich auf die alternativen Zustellungstechnologien, welche ein Potenzial besitzen, die existierende Zustellfahrzeuge zu ergänzen oder komplett zu ersetzen. Die Zustellroboter sind eine der Alternativen die als ein potenzieller Fortschritt in dem Zustellsektor der „letzten Meile" in städtischen Gebieten angesehen werden. Das Thema über der globalen Entwicklung von Handel und Zustellung im Generellen und genauso die Zustellungsroboter wurden gemeinsam durch eine Literaturrecherche in dieser Arbeit befasst. Im engeren Sinne, die Themen beziehen sich auf die Akzeptanz der Technologie in der Öffentlichkeit, technische Fähigkeiten der Zustellroboter, wie limitierte Geschwindigkeit oder die reisende Distanz ohne Aufladung. Zusätzlich wurden die Themen wie ökonomische und technische Potenziale durch die Literaturrecherche bearbeitet, welche dann die Bedeutung von neuen effizienteren Zustellungsmethoden betonen. Auf der anderen Seite, die Wichtigkeit der regulatorischen Aspekte war auch Teil der Arbeit. Die Regulationen spielen eine bedeutende Rolle bei der Einführung von neuen Technologien auf den Markt. Somit wurden einige bestehende Gesetze erwähnt, Großteils in Bezug auf die Unfälle und bezogene Zuständigkeit bei einem Unfall während der Zustellung. Außerdem wurde der theoretische Teil mit dem quantitativen kombiniert, um einige Zahlen zu bekommen und Rückschlüsse ziehen zu können. Letzteres hat weiter ermöglicht die Daten zu Vergleichen und ein breiteres Verständnis über die Potenziale und Mängel von den Zustellroboter und genauso den konventionellen Zustellfahrzeugen. Für den Vergleich wurden zwei statische Algorithmen entwickelt, jeweils ein adaptiert auf jede der zwei erwähnten Zustellmethoden. Weitere Varianten waren Teil von jedem Algorithmus, die verschiedenen Charakteristiken an sich tragen und somit liefern verschiedene vergleichbare Ergebnisse. Die Varianten ermöglichten einen Vergleich von den zwei Algorithmen, die aus verschiedenen Perspektiven angeschaut werden und somit erreichen einen breiteren Verständnisspektrum über dem Thema. Letztendlich wurden die Ergebnisse in einer Excel Tabelle gefasst und dargestellt (Appendix I).

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Introduction

Nowadays, a lot of people have experienced the perks of home delivery. Reasons for choosing home delivery are plenty, including, among others, the lack of time, and motivation for leaving the house, being in a bad health condition, as well as the current world pandemic. This positive trend is impacted by a growing market share of internet shopping as well as a growing internet accessibility throughout the world (Vissera, et al., 2014). With the increased demand for home deliveries, the whole concept of city logistics is impacted as well. Not only the city traffic needs a more efficient functioning, but the transport companies have to adapt to the demand, increasing competition, customer service satisfaction sensitivity and other occurring challenges.

At the same time, with increasing greenhouse gas emissions, global warming and, subsequently various climate policies introduced all over the world, companies have to adapt their business models and transfer to more sustainable solutions. Hence, the importance of setting up an efficient home delivery transportation system is not only justified from an economic point of view, but also environmental.

In this regard, one of the solutions would be to transition from fossil fuel technologies to electric ones. Examples for such a practice include, among others, robot delivery vehicles, delivery drones, and a combination between fossil fuel vehicles and electric ones. Taking all of this into account, home delivery is becoming a global trend with an increased potential, followed by various challenges for which solutions should be found. Moreover, the electric delivery vehicles contain some advantageous characteristics compared to conventional delivery vehicles, which represent electric delivery vehicles such as drones and robots to be more suitable for deliveries under certain conditions. Knowing the potential of the electric delivery vehicles in theory, implies that also real numbers should be used to interpret the potential from another perspective. This computational part includes main results related to delivery time, capacity utilization, profit and cost occurring, and distance traveled, which will be further elaborated in this paper.

Global situation and developments concerning trade and delivery

Shopping, purchasing, and selling is part of everyday life for a lot of people. Everyone needs to wear clothes, eat food, use machines and furniture. However, not everyone is in a position to produce all the products by themselves, so societies are dependent on shops and stores where the products can be purchased. Nowadays, there are two types of shopping; online and traditional, so many people are in a position to decide which one to use. As the technology is developing with time, consequently, more and more people get the access to internet and have their own computers. Having such a trend in our societies, increasingly leads to a higher demand for online shopping opportunities (Reddy & Laxmi, 2014). In this regard, this chapter will focus on important state of the art and future developments of trade and delivery aspects.

E-commerce

In the year 2014 a double growth of e-commerce compared to the year 2011 was observed globally, with the amount of sales of about 1,9 trillion United States Dollars (Dollars) (Savelsbergh & Van Woensel, 2016). More recently, in 2019 the amount of sales using e-commerce reached 3 trillion Dollars, which is 20% growth per year (DHL, 2020). The great rise of the demand for e-commerce services was fundamental for approaching to a new and alternative business model era. The growth, however, is not at the same level in all regions of the world. While Europe and North America have an increase of about 13% in average, the Asia-Pacific region shows a growth of about three times more, with People´s Republic of China keeping the lead position. Not only in Asia, but China´s e-commerce turnover is higher than those from the United Kingdom and the United States (Savelsbergh & Van Woensel, 2016). In addition, the biggest players on the company level are Alibaba, Amazon, Mercado Libre. Not only specialized firm likes these are involved in the reshaping of the market, but also ones like Facebook and Instagram. Social media is contributing to the e-commerce services mostly through advertisements, by clicking on the commercial and redirecting customers to the place where the orders can be made. Developments in this branch have not yet reached the peak of potential, as not all areas of retailing are active in the e-commerce business. Since the limits for transferring businesses to online shopping practices are decreasing as time passes, it is predicted that more products will be available on online stores. The non-utilized potentials are mostly in the industrial sector, which is not adapted to the online retail service. In this context, it is expected in the future that the online retail expands to this type of products such as industrial equipment, car spare parts and other robust items (DHL, 2020). Notwithstanding the above, the more this type of business is developing, the better infrastructure and enhanced delivery technology on the market will be necessary. Modern way of delivery technologies such as robots, drones and automatized are one of the potential solutions, which are also a part of city logistics concept.

City Logistics

One of the most important components of e-commerce is city logistics, as without this component most of the e-commerce businesses would not be possible. One of the definitions for city logistics would be that it is trying to find the most efficient and most profitable delivery solutions while taking into account the effects on the environment, people and economy, which are occurring during the logistical operations. Taking into account the trends of the population growth and increased urbanization, it is obvious that the logistical services are increasing, and that the trend will continue in the future. Having said so, it will be necessary to organize the services in a different way, to reduce negative impacts on life quality. Along with the growing trends of increasing population and urbanization, increased sustainability requirements and the mentioned e-commerce growth, it is important to understand that the trends are also going towards an increased expectation of the delivery time as well as more opportunities for a shared economy (Savelsbergh & Van Woensel, 2016). In the recent years, home delivery was represented also as a same day delivery, upon a receipt of a customer order. The reason for retailers being willing to offer such services is market competitiveness, which is expected to have the same trend in the future as well. This will require a better coordination and will make the home delivery more problematic. However, those customers who are using the same day delivery services are not willing to pay extra money for it. According to the financial reasonability of the services, the service is only cost-effective if density of customers is high in the service area (Mueller, et al., 2013). Moreover, a collective business and consumption would be another important topic in order to understand future development and potentials. This trend leads to a higher aspiration to share a product or service, rather than having it only for yourself. This means that new business models are emerging, which will require new infrastructure as well as suitable online platforms. This will enable companies to have access to a broader spectrum of assets even if the company is not in a position to buy in its entirety (DHL, 2014).

Due to future trends the complexity of the delivery services will become more challenging, and it will be necessary to introduce new advanced technologies to facilitate the delivery and to mitigate the negative impact on people, environment and economy.

The digital world is one of the advanced technologies that will increase in the future. Considering city logistics, the reality is that the range of data types is huge and that the latter moves very fast. In order to make the collected data useful, it is necessary to accelerate the processing of the data. In this context, the current reality is that data can be used for a more efficient decision-making during city logistics operations. The dynamic update of the data is essential for an up-to-date data status. This rises the quality of the services and provides a higher level of autonomous vehicle control. More specifically, it allows a delivery vehicle to make decisions on the routes, accept delivery request, choose timeframes for pick ups and drop-offs - all based on the updated information like traffic status, capacity on the vehicle available and reachable range based on battery life.

Not only driverless vehicles are the future, but also several other such as vehicles powered by fuel substitutes, such as natural gas, hydrogen, batteries, which also have a way better treatment of the environment compared to conventional fuels. Market for the electric vehicles is expanding at the fastest rate. While for many it still seems to not happen in the near future, many big companies are developing the alternative vehicle solution or with some of them already having the plan for introduction of alternative solutions around the world; still not with a share of 100% of the world market, but with a significant share percentage (Savelsbergh & Van Woensel, 2016).

One less known invention that has been developed in the recent years is allowing access to deliver to car trunks of customers. It makes the delivery to the trunk of a car possible, without the owner being present and without the necessity to deliver until the home entrance. With this approach, the flexibility of a delivery receipt could be raised to a higher level (della Cava, 2015).

Having these improvements and innovations in the logistical sector it can be understood that the future of the city logistics possesses already a development direction. Going towards a more autonomous future, with the driverless delivery vehicles becoming the reality.

Notwithstanding the above, future city logistics will be characterized with the unmanned aerial vehicles. The vehicles are supposed to be controlled remotely and are not expected to rely on fixed ground but would rather float in the sky. Currently, the unmanned aerial vehicles are capable of delivering only small capacities, whereas the possible capacities are expected to be significantly increased in the future. A company Matternet ONE based in Silicon Valey is one of the companies that developed such a vehicle which is capable to travel distances up to 20 km with a single battery charge and which is adapted to different weather, terrain and air conditions.

For high quality, enhanced efficiency and lower costs, there are other important areas in the city logistics. One of them being the strategy concepts with multiechelon delivery concept considered as an advance strategy. The multiechelon is based on multiple levels of distribution. The distribution starts in distribution centers outside of urban areas and the shipments are distributed to urban areas using sustainable vehicles. This strategy can be implemented in different ways. One of them also being two tier delivery using robot-based vehicles for the last mile delivery. This concept is based on a two-level delivery, first level being delivered by a conventional delivery truck until certain hubs where robots are located and the second level being the last mile delivery, which is conducted with robots, from a delivery hub until a customer. While researching this delivery setup, it could be observed that the two tier robot delivery is much less cost expensive compared to the conventional direct customer delivery (Bakach, et al., 2020). Success of the strategy cannot be guaranteed as it is dependent on the characteristics of a delivery area as well as it is still not yet thoroughly researched. In order to further improve, it will require a detailed analysis related to real-life situations.

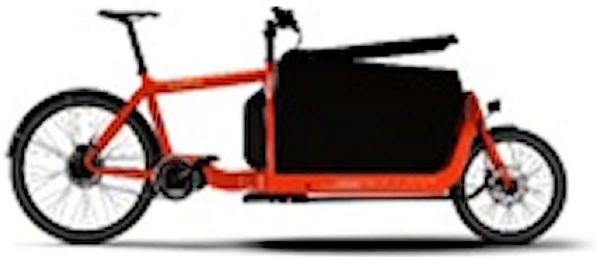
Additionally, an increased demand for the same day delivery is happening, and simultaneously the complexity of managing those deliveries is raising. There are two main challenges concerning this delivery setup: when a vehicle should depart from a depot and how to assign deliveries to an existing delivery route. It is also important to fulfill customers requests while assigning the deliveries - requests such as time and date of delivery as well as freshness of the delivered products mostly in case of food delivery.

Another and not the last solution, which could be also combined with robot deliveries are pick up boxes. With this time of pick up stations, some negative impacts on delivery can be mitigated. These boxes are impacting areas from environment to economic sector. Economic sector is impacted by an increased first delivery to the customer, so no missed deliveries are happening if the customer is not present at home or customer address was wrongly indicated, which causes lower operational costs. Secondly, the environmental sector in a way that due to a reduced mileage traveled, less energy is needed and lower amount of greenhouse gases are distributed. Not only the previously mentioned strategy concepts are existing, but many more. However, the impact of the city logistics on social, environmental and economic aspects are enormous and the real time data used for dynamic routing will be increasingly implemented in the future. This could facilitate the management of logistics and therefore offer new opportunities for mitigating the negative impact (Savelsbergh & Van Woensel, 2016).

Urbanization and home delivery

Current global trend about the increased urbanization and demand for online shopping is leading towards an increased demand for home delivery (Anderluh & Hemmelmayr, 2018). Currently, 75% of the European population is living in urban areas, whereas it is expected that this number will increase up to 84% until 2050 (Macharis & Kin, 2016). These developments have different effects on the environment, as well as on social and economical developments. Consequently, the latter causes various health issues for people. According to Anderluh and Hemmelmayr, 2018, one of the solutions for the respective issues in facing increased urbanization would be alternative means of delivery, such as electronic transportation bicycles. The positive side of such means of transport is that bicycles do not generate any noise, nor emit any polluting gases into the air. Moreover, due to their compact size, the latter can easily pass through tiny streets and, therefore, avoid congestion around the city, which increases economic efficiency and reduces operational costs and environmental and social damages (Anderluh & Hemmelmayr, 2018). These characteristics mirror the majority of the characteristics of a delivery robot. With regards to the cost of transportation, the latter accounts for approximately 10-15% of the total cost of a product, whereas the cost of the final stage of delivery, i.e. last mile delivery, accounts for 75% of the total delivery costs.

Picture 1 - Delivery bicycle
http://www.larryvsharry.com/



Picture 2 – Delivery bicycle
http://www.radkutsche.de/musketier/

Surveys also showed that such an alternative means of delivery in the core city areas, up to 50% of delivery services can be undertaken from the traditional delivery vehicles (Gruber, et al., 2013). Due to limited speed of the alternative delivery vehicles and their limited traveling distance as well as low capacity, it is necessary to build corresponding storage points in the core city areas, in a specified radius where the vehicles would be active. Types of storage points can differ, from storage boxes, large company owned facilities to mobile storage places such as transportation trucks (Anderluh & Hemmelmayr, 2018). Such a transition in the city area is not possible without governmental or municipality level support. Pointing at the urbanization plan that needs to be developed in this direction, or eventually the implementation of the necessary reforms to the existing regulations in order to adapt to the approach. The necessary adaptations would depend on the demographics, existing infrastructure, security regulations as well as on spatial planning so that the existing city architecture is not altered. For example, among others, the following would be taken into account when approaching mitigation measures for the reduction of urban congestion:

- the age of citizens when introducing such services in a specific area;
- the effect of costs for renting or buying property on cost effectiveness;
- the availability of place for storage purposes;
- the availability of long-term loading parking place for mobile storage vehicles; and
- the exterior of storage facilities

These would be some of the requirements that need to be taken into consideration when approaching the mitigation measures for urban congestion reduction.

Nonetheless, various challenges are present in this regard as it is not feasible to consider all three aspects (economic, environmental and social) at the same time. When considering adaptations in favor of environmental and social aspects, it will mostly be done by introducing different regulatory restrictions. The restrictions would include restricting time windows for deliveries, limiting weight and limiting stops only to parking zones and others. Taking the regulatory framework into account and the introduction of new limitations, it needs to be considered that the transportation sector is an important part of the economy with a significant number of employees and its requirements cannot be easily ignored. This indicates the importance of improvement of the delivery practices in a way that is beneficial for both; consumers and businesses (Macharis & Kin, 2016). In a research based on interviews with local authorities and freight transporters several assumptions on their relationship could be made. It was agreed by the transporters that the technical competency of authorities is not on a high level when it comes to freight. This might be the case, due to the fact that the authorities are mostly focused on the public transport and that the problem with freight services is not recognized as of high importance. For example, in the UK many interviewed personnel from the local authorities admitted that they are outsourcing the projects related to freight. A minor percentage of the local authorities could confirm their expertise on the issue. Since the freight transport issues are barely a concern for rural areas, the problem solving is mainly focused on urban areas, with freight business being one of the economical drivers in the urban areas. Despite the importance, freight is kept away from the development plans of the corresponding localities, except when it is about implementation of restrictions for the freight sector. Even though in some areas the understanding was achieved from both sides on the importance of the freight sector to the society, on the other hand it was also confirmed by both sides that reasonable measures are still lacking. It is the fact that freight is taken for granted by many people and that the negative impacts are rather observed than the problems occurring, which is a sign that an intensified cooperation between authorities and transportation companies is crucial for the improvement. Finally, it could be observed that obstacles are very common praxis in order to limit the freight sector. Some of them being one-way streets, pedestrian zones and even prohibition of deliveries during the weekend. Moreover, it is interesting to observe that many of the interviewed transporters have recognized time window regulations as having a negative impact on freight and not desirable. One of the main justifications for such an attitude is that the delivery volumes in urban areas are increasing. So, from hauliers perspective it would be more reasonable to have the deliveries spread through the day and not having limited service times. Taking into account the above mentioned statements that the local authorities does not have competent experts to approach the freight issues, it is most likely that the time window restrictions would not be implemented in a way to be advantageous to all stakeholders. However, it is necessary to maintain higher involvement in issue solving between authorities and service providers in order to achieve better conditions, which would benefit customers and suppliers. Contrary, most of the interviewed transportation companies answered to not have any contact with local authorities or the contract is very limited. Not necessarily it has to be direct contact between private transportation companies and public authorities but could be association that represents interests of freight companies. The communication would help the stakeholders to understand each other better. Consequently, the freight organization on the municipality level would reach a higher efficiency, law makers could better understand the priorities of different parties and therefore propose suitable regulations. This could be beneficiary for all types of delivery, so for the robot-based delivery (E.F. Ballantyne, et al., 2013).

Traffic congestion, its consequences and mitigation measures

In Europe, costs lost on traffic congestion are about 1% of the annual GDP of Europe, which amounts above 110 billion Euro. In some of the greatest cities in Asia, such as Singapore, Manila, Jakarta, Mumbai, the average vehicle speed is approximately 15 km/h (Chang, et al., 2017). In addition, it is said that larger cities with have high population density, the congestion level increases compared to lower density population cities. Some of the reasoning behind this is that in smaller cities there is more opportunity for changing the residence or job location, relocating companies itself and more choice on the road for avoiding congestion. (Gordon, et al., 1991). Further reason for that and one of the obvious reasons is population growth. As the population growth in urban areas is stronger, the predictions are that the traffic congestion would worsen in the future. Not only this, but also the increasing wealth and economic standards of the population are triggering a higher demand for transport services in a way that people are willing to pay more for transport and that the ability to be a car owner is increasing (Downs, 2004). Gordon, et at. 1991, came to an assumption in their research, concerning the size of cities and the relation to traffic congestion. The conclusion of the research was that developments in the congestion are different when looking at different sizes of cities. In simplified words, the bigger the city, the stronger the congestion consequences when a population growth is experienced.

Having congestion issues in various countries and cities, it automatically means that businesses and the economy are impacted in different ways. Taking into account different industrial sectors, a differentiated influence could be observed. The disadvantages of congestions are various and include, among others, increased operating costs, higher inventory costs, decreased trust from consumers, spoiling of food/drinks due to special storage conditions and reduced productivity that leads to a lower turnover. When it comes to the industrial sector and the impact of the congestion, businesses relying on truck transports and higher worker requirements experience higher downsides and benefit more from the reduction of congestion. The high impact includes also high skilled labour, whereas those requiring lower skilled labour are not so strongly impacted. It is also possible to alleviate the negative impact on the industry, which again depends on the industry sector or, more specifically, on the availability of the desirable market. This can be explained in a way that, if there are various opportunities for different industry needs on the market, then a producer is motivated to try with another supplier in order to reduce costs occurring during a congestion. Contrary, if the quality on the market shows high fluctuations (if the quality of goods and work is not always the same) a producer is less willing to switch a supplier in order to reduce the costs occurred during a congestion. In this context, the economic analysis shows that traffic delay is reducing business market of the urban areas, but also of the areas ranging to periphery of a city (Weisbrod, et al., 2003). Not only businesses and vehicle drivers stuck in a traffic jam are paying for the consequences caused by the congestion, but also population of certain areas, that are facing high traffic frequency. Translated it would mean that not only economic loses are occurring but also a lower living standard when it comes to environmental and social aspects. Some of the consequences of congestion, that cannot be represented by number but are a huge part of general well-being, are, among others, average increased fuel consumption and greenhouse gas emissions into the environment, higher noise in the affected areas and driver´s increased nervousness caused due to a loss of time (Bull & Thomson, 2002). The delivery vehicles are covering about 8 - 15% of the total number of vehicles active on the roads, and they cause a total of 20 – 30% of the emissions considering all vehicle´s emissions in total (MDS Transmodal, 2012).

To eliminate the congestion issues in its entirety would be very expensive and almost impossible. However, to mitigate the problem and therefore the consequences would be a desirable solution to the issues. Mitigation is possible by introducing a set of measures that would enhance city transport, such as management measures, more organized parking places, advanced public transport, security on the street, introduction of electric and autonomous vehicles, etc. (Bull & Thomson, 2002). In a research from Macharis and Kin, 2016 a concept for approaching this problem was developed, which includes Awareness, Avoidance, Act & Shift and Anticipation of new technologies.

Awareness

With the awareness all stakeholders of the delivery business should be made aware of the consequences and possible improvements. The stakeholders are customers, companies and lawmakers of certain countries. One way for raising awareness is to measure the amount of emissions that are being generated by current delivery practices, which should be compared to the emitted pollutants generated by more advanced future practices. In addition, a certain target for the decrease of pollutants should be introduced. Furthermore, certification standards are a possible option. The certificates determining certain standards that have to be implemented, not necessarily relating to the reduction of emissions. Certificates can emphasize or include codes of conducts, awards to companies when CO_2 emissions are reduced, labels that recognize silent vehicles suitable for rush hours, labels for required equipment and others. Corresponding certificates would increase the public image of the company. Consequently, a positive impact on the profitability is expected.

Avoidance

Avoidance means to avoid unnecessary traveling kilometers. The traveled kilometers can be reduced in several ways: some more recent solutions are instead of ordering physical books, CDs for movies and music, it could be simply downloaded and stored on computer or an USB. A further solution is using 3D printers - this approach is advantageous in a way that no storage space is needed until the order is set, as well as additional transportation to the storage place is avoided. One additional solution is compact packaging, with IKEA as the one widely known example, the way of packaging reduces volume and therefore, the amount of vehicles to transport certain number of products is reduced. One of the popular measures is the use of urban consolidation centers. These centers are easy to access, usually located close to main roads of the delivery areas, sometimes connected to railways and rivers. Notwithstanding the above, there are existing difficulties for the introduction of the centers, mainly represented through the operational costs. Costs for extra handling and administration, as well as property costs which are usually high in the areas appropriate for the centers. There are also other mechanisms, like ordering less frequently and by bundling orders summarized as a changed ordering delivery. A cooperative delivery solution between retailers, bundling transport, more direct communication between customers and suppliers who agree upon a night delivery. The concept of avoidance is not meant to stop the deliveries, but rather concentrate on necessary delivery services only.

Act & Shift

Act & shift is about two types of shifts, one being the modal shift and the other delivery shift during non-peak hours. The modal shift means shifting delivery methods from one end to another, while having an appropriate intermodal network of hubs. When having the appropriate infrastructure, this method can be efficient for all sizes of goods, from the remaining pieces of big infrastructural constructions to the fresh products. One of the modal shifts not being accessible at all locations is transportation of industrial waste, which is mostly done using railway transport and which requires, in this case, rail terminals to enable accessibility. However, the method of using modal shift transport can achieve significant benefits related to social and environmental aspects. For example, using cargo bikes in combination with small storage centers installed in the delivery areas, which are also very similar to the characteristics of robots.

The delivery shift during non-peak hours aims to avoid congestion by delivering in evenings, mornings or during nights when not many people are on the streets. As with most of the new inventions, this delivery method is also not lacking challenges that need to be addressed. For example, delivery outside of the peak hours causes notable noise, which is not acceptable by citizens, in a lot of cases. Taking this into consideration, a more advanced vehicle fleet is needed. Here, vehicles being noiseless and emitting less pollutants are of crucial importance but cause higher expenditures. However, the results show, despite additional capital expenditures, the total operational costs were decreased, as well as the impact on environment.

Anticipation of new technologies

The introduction of new technologies, includes, among others, autonomous and electric vehicles. The transition to new technologies in the transport sector is crucial for the reduction of negative impact on environment. Nowadays, electric vehicles are a major opportunity for sustainable delivery. However, such vehicles face several difficulties, including, among others, a limited range and a higher initial cost, whereas the operational cost are significantly lower than for conventional vehicles. Other alternative opportunities that are or could become competitors on the sustainable delivery market also exist. For example, vehicles using hydrogen or natural gas as fuel. Hydrogen is still not completely researched and difficulties can occur when it comes to storing processes and suitable storage tanks. Natural gas is a reasonable option, as it releases CO_2 but significantly lower amounts compared to diesel. Furthermore, autonomous vehicles are being developed and increasingly introduced to the market. However, many aspects concerning the autonomous vehicles are still not clear on the market, from the regulatory framework to the market share and implementation on the large scale (Macharis & Kin, 2016).

Relation between customers and retailers

In recent years, all generations began their online shopping journey; from older to younger generations, many are actively shopping online. Driven by the increased demand, retailers have also transformed part of their activities to the online retail in order to meet the demand. Retailers with different capacities, from those being micro and delivering five to 20 packages per day to those being enterprises and delivering from 20,000 to 100,000 packages per day (Temando, 2016).

Customer expectation

The gap between customers and retailers is constantly increasing in a way that consumers are expecting more than retailers could provide. In the year 2016, Temando did a research where it could be observed that the vast majority of customers in the UK would prefer to have certain delivery windows, whereas not a half of the retailers were providing this service at the point in time. The reason for the lack of time windows offered by retailers is mostly due to high delivery costs, where customers are not willing to pay for the service. Furthermore, customer expectation are also pointed towards an express as well as a standard shipping, same day delivery, pick up delivery from stores, afterwork pick up or during the weekend. In this regards, retailers are not capable to cover all the customer expectations. As regards the number of shipping options that a retailer can offer, the majority of customers would like to have several shipping options, whereas a low number of retailers could offer this concept.

There are also reasons why a customer would stop buying online. As mentioned throughout the paper, the cost of shipment has the highest negative impact on the online retail. Other lower negative impacts are, for example, late announcement about the shipping costs, or the process or shipping were too long. When a company generates negative shipment experience, it further causes reduced customer loyalty, negative impact on the brand image, increased costs of returns, poor public relations and others crucial aspects important for the success of a company (Temando, 2016).

Customer concerns

Another important topic for customers is the safety of customers data when buying online. The concern also occurs when buying in a store, but with a lower significance. In Deloitte´s research from 2015 it was found that people are more concerned about their personal data than years before, concerned about their privacy then retailers access their data over the phone and in case a breach of their data is experienced they would go for a different payment form. Moreover, customer is stronger convinced to buy in an online store if retailer is educating their customers on how to protect their personal data. Other methods that are building up a positive impression about the online retail are past positive personal experiences or positive experiences from close friends. Also familiarity with some brand that is trusted by customer has a strong influence as well as online security certificates and offers for free protection services (Deloitte, 2015).

Online shoppers attributes

An online shopper and a traditional one are differing in the attributes they possess. These differences affect motivation, time available for shopping, buying power, shopping frequency and others. Motivation of online shopping are mostly related to swiftness and practicability. Online shoppers prefer to shop fast, complete tasks quickly, avoid talking to a salesperson, travel from store to store and crowds of people. For some bargaining on the auction offers is one of the reasons to shop online, as well as surfing on interesting websites and being personally notified about new collection or sale offers. However, in the research from Ganesh, et al., from 2010, it could be observed, contrary to the existing research at this point in time, that online shoppers have more similarities to traditional shoppers than differences. One of the attributes which is specific for online shoppers is affinity to shop in a comfort zone, without getting in direct contact with other people and without facing any travel efforts (Ganesh, et al., 2010).

Retailers concerns

Notwithstanding the above, retailers have also their own concerns. As already mentioned, the customer expectation is in many cases above what a retailer can offer. In a research from Lowe and Rigb it was found out that beside the majority who thinks that online retail has improved their revenues, there is another third of the retailers who are convinced that online retail is decreasing their turnover. According to the research, problem with delivery during the peak season like Christmas or Easter is permanently occurring, which does not include problems with storage places. This issue is faced mainly through the uncertain forecast and therefore, uncertainty about meeting the expectations of customers. Handling returns is also one of the reoccurring problems, with clothing industry being one of the biggest parcel shippers. In the year 2013 about 128.9 millions clothes deliveries could be recorded, whereas due to the increased growth of the industry for 2018 the amount of parcels was estimated to double to 256 millions. When looking at the logistic firms, the biggest issue for them is a situation where the recipient is not present when the delivery is arriving. Among others, one of the solutions for the issue would be the attended home delivery (Lowe & Rigb, 2014). A further issue is outside of the retailer’s range of influence and concerns the logistic firms conducting deliveries for different retailers. In this case, the issue can occur when the logistical company is not performing well, so the parcels are not delivered on time (Stevens, 2015).

Modern delivery alternatives - strengths and limitations

Different deliveries concepts include a different performance for each of them. Not only the performance differs, but also types of vehicles that is being used. Excluding already discussed delivery robots, drones or so called unmanned aerial vehicles (UAVs) would be one of the future delivery solutions. Such vehicles can also be used in a combination with other vehicles in order to achieve a desirable delivery results, some of them being adapted costs, reduced emissions and noise, faster delivery and others. Each of the vehicles and concepts has its own purpose, with each of the having particular strengths and limitations. In this sub-chapter, some of the vehicles and concepts will be presented.

Unmanned aerial vehicles (UAVs)

The UAVs are not only used for delivery purposes but also for other services such as surveillance, usage in agriculture and video recording. Currently, it cannot be foreseen that drones will replace the ground delivery in its entirety, but rather a shortcut for the delivery vehicles in order to avoid downsides of the certain areas of the ground delivery route. Drones are bounded to a fixed place where they depart and land constantly. The concept on the delivery drones is actual for already several years and shows its opportunities and challenges, like the robot-based delivery. Currently, the greatest use of the delivery drones is for the surveillance services, whereas the development of the delivery is improving constantly. The development of the delivery drones has also experienced an accelerated expansion during the Covid-19 crisis, with workers being isolated and social contact reduced significantly. One of the sectors which are seen as potential field of integration for drones are intralogistics operations activities. Still, the challenges for UAVs in this sector are significant, however, the cost reduction is seen as a large potential which is one of the motivations for a continuous development in this sector. For the delivery drones an uncommon expansion has been experienced in the past three years. Companies from Australia, Finland and the USA are accomplishing over a thousand deliveries to online orders over two weeks time. Moreover, pharmaceuticals, different types of tests and transport of blood samples are also some of the implementations areas of delivery drones, which is under development and is expected to build up as a delivery alternative (DHL, 2020). The biggest advantages of drone´s are speed, ability to reach difficult terrains, avoiding of obstacles and limitations on the ground. This is mostly part of rescue activities, delivery of life saving medications and other urgent commodities. Whereas, on the other hand some drones face some limitations, similar to those of delivery robots, such as delivery capacity, limitation on the battery life, GPS uncertainty, lack of regulations on the market and one of the most controversial is injury to people in case of a fall on the ground. These are all limitations that need to be addressed in the future (Temando, 2016).

Two tier delivery

Two tier delivery is a so-called two-level delivery concept, which can be designed in different ways and with different vehicles being involved in the process. Bakach, et al., 2020, have been working on a paper which researched about the two-tier delivery involving delivery vans in a cooperation with robots (Bakach, et al., 2020). On the other hand, Anderluh, et al., (2017) have been working on a paper where the first instance of delivery was done by trucks and the last mile delivery was done with bicycles. Those living in city center were served by bicycles whereas those located outside of city areas were served by trucks. In addition, bicycles need to meet with truck in order to reload before continuing the delivery. Each bicycle is able to deliver up to three customers before reloading. Here the purpose of such a set up is to compare the reasonability of usage of the sophisticated delivery compared to the conventional delivery set up. The two-phase GRASP metaheuristic with path relinking has been used for the problem solving. First phase is constructing the bike routes a system of different rules, once this has been accomplished construction of van routes follows, with the depot being the starting point of each van. The results of the research show that in some occasions the more sophisticated delivery set up leads to lower delivery costs, whereas the sophisticated approach is beneficial in all cases when it comes to reduction of emissions. Contrary, the difficulty to synchronize bikes and vans lead to a cost increase in all cases (Anderluh, 2017).

Bakach, et al., 2020, have developed an approach where delivery trucks and delivery robots are cooperating during the delivery process. More specifically, the truck transport the parcels to be delivered to a robot hub, where all delivery robots for certain area are located. Once the parcels are delivered to the hub, they are automatically sorted to each robot. The robots can carry only one package during the delivery, whereas they can travel several times during the day between the hub and customer. Here, two different models can be observed, with and without time windows. Important aspects of the research that influence the final results are robot´s technical limitations such as low speed and low capacity compared to conventional trucks, type of time windows used, costs of robots, etc. The results of the two-tier based delivery show cost reduction. Whereas the cost reduction for the delivery without time windows occurs only in sub-urban areas, due to the density reduction as well as a higher willingness of customers to use this service. On the other hand, when using the time windows savings compared to conventional delivery vehicles are increasing significantly (Bakach, et al., 2020).

Problem description of the robot-based delivery

Public acceptance

Like for any other new technology coming to the market, public acceptance of ADRs is one of the most important aspects of a successful implementation of robots for commercial purposes. What are the preferences of a customer, how the trust is developed for a certain service, what is the amount of money one is willing to pay for the service are all questions that one could ask when developing a new business product. In the research conducted by A. Pani et al. in 2020 consumers were separated into six groups. A group of people, mainly living in suburb areas and focused on purchases in stores having a contact with employees, were skeptical about online shopping due to several reasons. Upon the outbreak of the Coronavirus (COVID-19) the group changed their mind and the skepticism for online shopping decreased by 20%, but the indicated reason for increasingly buying online at this point in time was not "due to Covid-19". The highest percentage of the researched people falling under this group of people were middle age female.

Contrary to the previously described group, the evaluation was conducted on a group with a majority of people having preferences for online shopping. Characteristics of those people are a high willingness for online purchasing, no concerns about delivery difficulties, no preference for going shopping in person. Most of the people sharing this opinion were male in the age between 25 and 40, having graduated from high school or with a university degree. Pattern with the location of living is very similar to the previous group; the majority of people live in the suburbs and prefer online shopping.

Groups with a preference to buy online only due to the outbreak of COVID-19 like to have live contact with sellers and their opinion is significantly influenced by the income level and gender.

When the willingness to pay is considered, the majority of the evaluated groups would prefer to use the services and pay for them, whereas 33% were against choosing this option. The reasons are different, one being that the current purchasing practice is good enough, while others believe that those services should be paid by the supplier of the goods, It could be concluded that those people who are labeled as "E-commerce supporters" are willing to pay the highest price of about three Dollars per delivery. The willingness to pay for the robot-based delivery decreases when the age of customer increases, people aged 65+ are significantly less interested in such kind of service. The lower interest is linked to a lower trust in new technologies, but also to a reduced source of income. Moreover, as regards general motivation to use the service, it plays a big role whether the customer has already used the service or whether the customer is familiar with the latter, if yes, the willingness to pay is much higher. Also, the location of the customer determines the motivation; it was observed that those living in urban areas are ready to spend some money for this service. Having researched groups such as online shoppers who developed the habit of online shopping due to Covid-19, it was possible to observe that those groups were one of the most willing to pay for the service - which was an interesting observation considering the great difference between the willingness to pay before and after.

In conclusion, a high level of education, familiarity with the technology and trust in the latter, geographic location in urban areas or areas located more than 8 km distance from the nearest shop are some indications for willingness to pay for the robot-based delivery concept (Pani, et al., 2020).

Technical capabilities

As the demand for online purchases is increasing, customer expectations with regards to the quality of the delivery services are growing along. This increases pressure on robot manufacturers to model robots with enhanced characteristics in order to be able to fulfil customer´s growing expectations. The enhancement is not an easy task, as the regulatory framework, safety measures and other limits need to be taken into account. Considering the regulatory system of the US and its states, the limits of different robot characteristics are set on different levels and are varying from state to state. The limits for weight carried by a robot are set from approximately 13 kg to 135 kg to no limits in certain states. The speed limit, for example, is set to 16 km per hour in most of the states (Jennings & A. Figliozzi, 2019).

In this context, a case study of Jennings and A. Figliozzi compares two different delivery concepts, one using a van and robots together for the delivery process and the other based only on delivery using a van. The important part from the paper are characteristics used to describe robots capabilities. In view of the above, when taking into account all assumptions, the robot is limited to a traveling range of 6.4 km before needing to be charged. Relying on

Amazon´s weight of each delivery, which is in average less than 2.3 kg, the assumption is made that a grocery basket pro delivery does not weigh more and therefore it is determined that the robot can carry up to six packages and, consequently, serve up to six customers in one go. Moreover, the robot does not have more than one locker, where all the packages are stored. The robot is also equipped with a security camera which records the whole delivery process and, therefore, protects the packages from being stolen. Furthermore, there is also a mapping system that steers the robots to the right address if it is being driven autonomously (without influence of a human controller). When it comes to the speed of robot, it is estimated to be 6.4 km/h, which is finally reduced by 30% to 4.5 km/h which represent s the waiting time on the street while waiting to cross the street or while waiting for people to pass and avoid causing an accident. In this regard, safety is one of the biggest problems concerning the use of delivery robots. According to Bogue´s research, Starship Technologies, an Estonian start-up company was the best and most famous producer of these type of robots in 2017. For the purpose of enhancing safety measures, their robots contain nine cameras that create situational awareness of the surrounding as well as ultrasonic sensors with the ability to detect an obstacle in the whole 360°. More specifically, the obstacle means in this case a pedestrian, an animal or a bicycle approaching closer. When detecting one of the obstacles, the robot stops at a distance of 30 cm away from it (Bogue, 2017).

Economic or technical potentials

Additionally, Jennings and A. Figliozzi researched in years 2019 and 2020 two types of delivery robots; sidewalk autonomous delivery robot (SADR[1]) and autonomous delivery robots (RADR), as well as their potentials.

It is said that SADR could increase the efficiency when the distance between a distribution center and customer is low by driving multiple tours in one day. The distance is to be low due to a restricted distance that a robot battery can endure without being recharged, as well as due to a limited capacity of a robot, which means a constant reloading of packages is required. Notwithstanding the above, SADR compared to typical delivery vehicles are in some cases time efficient and automatically cost efficient. Not only distance is crucial to experience the robot

[1] SADRs are pedestrian sized robots that deliver items to customers without the intervention of a delivery person. The SADR are being transported with a mothership van to a point in the delivery area, from where they operate autonomously or partially controlled by a person from control center.

efficiency potential, but also density in the customer area. This means, the higher the density, the greater the efficiency, which further implies that cities are a better surrounding in order to achieve the savings. Furthermore, the reduced traveling distance as a vital potential of the SADR leads further to a reduced traveling time a package would spend on the road. Consequently, certain harmful impacts on the delivered products would be mitigated. On the other hand, additional operational costs and cost of the acquisition of a robot are to be considered, which come as additional cost compared to the standard van delivery (Jennings & A. Figliozzi, 2019).

Concerning the RADR, which is currently being developed by several American companies, it is supposed to be able to travel longer distances which would contribute to the number of served customers significantly. However, the travel range compared to conventional delivery trucks would stay lower. The manufacturing costs of RADR are still significantly higher than the manufacturing cost of conventional trucks. The parts that make it expensive are certain sensors and softwares that would make the vehicles autonomous. However, the price for the latter could decrease by 50% once the market share of these vehicles becomes at least 10%. When considering the traveling time, it could be reduced under certain conditions which are like with SADR, a lower distance between depot and customer, whereas a higher density is not positively influencing RADR´s efficiency. This means that a higher number of customers can be visited with vans if the density is higher. The reason for that are higher safety measures, time spent in traffic and time used for searching for a place to park (Jennings & and A. Figliozzi, 2020).

An additional potential that could be attached to delivery robots is friendliness in regard to the environment and energy consumption. Figliozzi and Jennings worked in 2020 on the potentials of Autonomous Delivery Robots (ADRs) in relation to their emissions and energy consumptions. The ADR was divided into two types of delivery robots, SADR and RADR, as previously mentioned, but the emissions and the energy consumption of both were analyzed. Generally, for SADR two main assumptions could be made: compared to the mothership vehicle the eight SADRs consume significantly less energy and density of the delivery population has a great impact on the energy consumption. On the other hand, RADR´s main findings are that the energy consumption is significantly reduced. The influence of the density and range in the delivery area are influencing the energy efficiency differently, depending on which type of robot is being used. One robot shows efficiency when delivering with a range less than 10 km, whereas the other shows energy efficiency only when the density is high. Width is one of the characteristics that influence this outcome for the two types of robots. Despite a reduced range that a SADR travels and, consequently, reduced costs and delivery time, SADR is not that efficient in saving energy and reducing emissions like RADR, which however proves the potential in energy saving and reduction of the emissions when using ADRs (A. Figliozzi & Jennings, 2020).

Regulatory framework

Like in every field of our lives, the regulatory framework for the autonomous robot delivery vehicles is of an imposing importance when entering the global market and becoming a part of human everyday life. The modern concept of the industry, so called Industry 4.0 or 4th industrial revolution, is looking more and more towards sustainability in the whole product cycle, such as the efficient use of energy, increase in the productivity and resource efficiency. (Kagermann, et al., 2013). As a result, the new economical setup is leading towards ~~a~~ more complex value chains and, therefore, new business models, which open~~s~~, among others, new solutions for bridging already known last mile delivery problems, which include~~s~~ new experiences with autonomous delivery robots. (Prause, 2015) (SBS, 2016). The regulatory framework of the delivery robots business model is still an open topic in the global industry. In this paragraph the robots involved in the supply chain of the Industry 4.0 as well as last mile delivery will be considered. These robots are facing public areas, daily traffic, and people on the street - no robots in a private area are considered. The fact that the robots are facing public areas which are identified as pedestrian area says that it should be additionally regulated. Starting with the delict in a traffic accident and connected responsibility it is clear that the liability goes either to the corporation owing the robots or to a natural person being in charge for steering of the robot, as the robot is not entirely autonomous but needs to be controlled from a control center, which in addition requires a high exchange of data between robot and the center.

The data being exchanged are street maps used for improvement of the services, possible accident recordings, and personal data which are considered of a commercial value and need to be protected (Hoffmann & Prause, 2018). It could be summarized that two types of data occurs in this case, personal data such as name, address, bank information, consumption habits, whereas on the other hand data collected from robot´s starting point to the end location is much higher in amount. These data contain visual and audio recordings of natural persons recorded daily. Moreover, according to the General Data Protection Regulation (GDPR) approved by the European Union (EU) in 2016, this data is considered "personal data", which requires a higher courtesy in order not to violate the corresponding regulation. This means to know exactly what data to process, who is eligible to receive the information and how to safely store the data. For example, whether the company which received the data is responsible itself or the processor (employee) who was steering the robot and therefore the data. The GDPR contains various articles providing different requirements for data protection, for example, Article 28(1) requires assurance that certain technical and managerial measures are undertaken to ensure that data will be processed as regulated and that the data will be protected properly. Article 23 emphasizes that data should not be transferred to an indefinite number of people without the agreement of a natural person. There are also articles regulating the ability to restore data in case of a bad event.

Not only the does the owner of the robot and people controlling the latter from control centers need to comply with the GDPR, but also employees of telecommunication firms which have access to the data.

Fines for violation of the GDPR are expressed in financial manners and are ranging from 20 Mio. € and up to 4% of the corporate´s total turnover, which could be seen as a remarkable penalty (Hoffmann & Prause, 2018).

Notwithstanding the above, one more important aspect in legal terms is product liability. Here it is important to know that the manufacturer can be kept responsible for deviations in functionalities of a robot, meaning other than initially promised by the manufacturer. Manufacturer domains where the producer has a complete control over construction, manufacturing and instructions are responsibility of the manufacturer in the entirety.

In addition to the previously mentioned legal concerns it is crucial to know who is liable for accidents caused by the robots and under which laws a robot would fall according to regulations. For instance, it is not always clear whether the robot falls under same regulations as a car or transportation means like a wheelchair. In Germany, robots are considered as a wheelchair and are restricted to be driven only on pedestrian areas under a low speed. Moreover, the liability in an accident where damage is caused to an object, the owner of the robot is always held liable disregarding their non-involvement in the accident. Whereas the driver of the robot is not kept protected from liabilities but can also carry the responsibility for damages occurred. All these disadvantages are influenced by the technical abilities of a robot and the way of reaction in different circumstances (Hoffmann & Prause, 2018).

Attended home delivery

The last mile delivery is nowadays regarded as one of the most controversial delivery procedures. Facing a not impressive efficiency status, high service costs and emitting high number of pollutants such as CO_2 into the environment. Moreover, the last mile delivery is causing disturbance among the citizens due to the traffic noise as well as congestion and traffic accidents, all of these impacting human beings directly. Concerning this topic, the attended home delivery (AHD) is the one of the most utilized ways of doing this business. The business model of AHD includes specific time windows when deliveries arrive to customers, which also implies the requirement of the customer presence at the delivery location in a certain time. However, for the AHD the service costs are an important topic, as the more restricted delivery time windows are imposed, the more expensive the delivery process is becoming (Manerba, et al., 2018). Therefore, the design of delivery time windows is of a significant importance for such a business model. It means that a cost-effective approach has to be used, while at the same time keeping a high level of quality of the provided service to customers, in order to keep the level of satisfaction. This can be achieved by a well implemented tactical and operational management system. The tactical management is related to design of time windows, more specifically, on the length of time windows, on the cost of each time window that a customer needs to pay when ordering, on the possibility of overlapping the time windows as well as on the number of requests that can be accepted, etc. On the other hand, the operational part is to be considered once the tactical design is accomplished, the operational design has to manage the availability and allocation of the time windows as well as the creation of feasible and optimized delivery routes (Agatz, et al., 2011). An example for the operational design can be the dynamic delivery slot policy pricing, which determines and controls the allocation of the delivery requests (Xinan & Strauss, 2017). This part of dynamic policy pricing and other optimization processed for the delivery require a well-structured algorithms, task-courier matching and dynamic routing algorithms in order to ensure a sophisticated optimization process (Stanford Business, 2016). Therefore, below sections will give a more thorough insight into the AHD and corresponding important aspects of the business model as well as challenges and opportunities of the delivery approach.

Vehicle routing problem algorithm generally

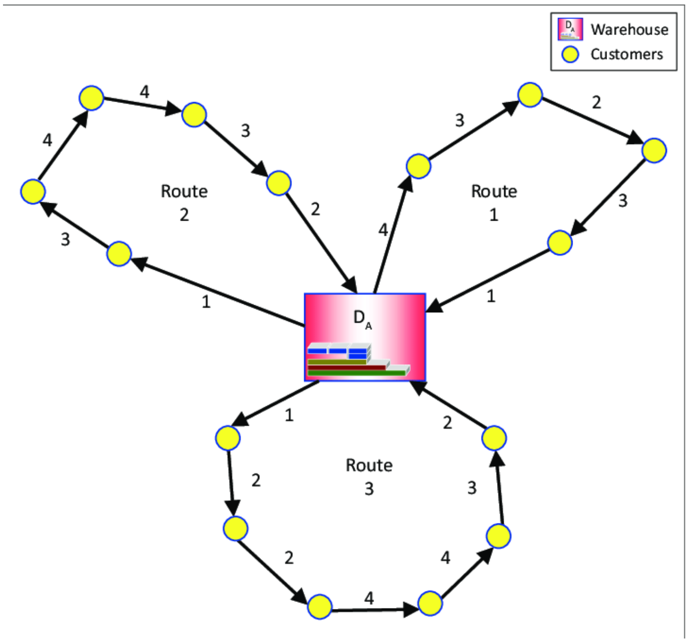
The vehicle routing problem is a wide known problem and widely used heuristic for routing problem solving. The VRP problems are different, including different characteristics and limitation to an algorithm. As there are many variants of the VRP heuristics some of them will be mentioned below:

- Vehicle Routing Problem with Profits (VRPP) – while for this approach delivery vehicles need to depart from a depo and to return to the same one, the aim of the heuristic is to visit all customers, taking into account the maximization of the profit while at the same time adhering to the time limits imposed by customers;
- Vehicle Routing Problem with Pickup and Delivery (VRPPD) – the objective of the heuristic is to move a specific amount of freight from one place to another one, while assuring the optimal routes;
- Vehicle Routing Problem with LIFO (last in, first out) – similar to the previously indicated heuristic, the difference is the unloading method, which foresees that the lately loaded parcel has to be the first one that is unloaded at the next drop-off location;
- Capacitated Vehicle Routing Problem/with Time Windows (CVRP or CVRPTW) – this heuristic contains a limitation in regard to the capacity to be transported and eventually time windows which would determine time of the delivery;
- Vehicle Routing Problem with Multiple Trips (VRPMT) – delivery vehicle that is capable of doing various routes instead of doing only a single one;
- Vehicle Routing Problem with Time Windows (VRPTW) – heuristic that is a part of the algorithm under this paper. This heuristic includes specific delivery time windows that are chosen by customers as a desirable delivery time. In addition, this heuristic like the other ones, can be combined with other specifications and limitations of other heuristics. More specifically, the algorithm of this paper will include certain capacity limitations, certain speed limitations as well as traveling time restrictions due to the robot battery that need to be recharged after certain traveling distance has been reached (Wikipedia, 2021).

Generally, the VRP is being widely used in industry sector, transportation is a part of costs of each purchased product in the amount of about 10 %, it also occupies a significant share of the GDP of the European Union equivalent to about 10 %, which imposes the potentials of computer optimizations in transportation sector. Savings in the transportation sector can achieve significant impact on community life standard, as even a saving in the amount of 5%

of the costs occurred in the European transportation sector, would amount to high amounts in monetary value.

As the transportation practices are high in number, the VRP is adjustable to the case. The costs under VRP can be represented as monetary values and distance. Vehicles are departing from one or several depots and they need to come back upon completion of the delivery to one of the depots. The main goal is to find feasible or optimal delivery routes for the given problem, these routes should satisfy required constraints as well as minimize the transportation costs. The routes can be represented graphically, using arcs and vertices, arcs symbolizing transportation roads and vertices being certain stops in between the roads, as represented in the picture 3 (Wikipedia, 2021).



Picture 3[2]

Furthermore, the numbers on the arcs represent costs in monetary value of distance that is occurring when traveling from vertex a to vertex b. This value is known for all combination of vertices between each other, but the graph shows only one feasible or optimal route and therefore the costs for a single route from vertex a to vertex b are shown and all other possibilities are not represented. Additional possibility is whether to direct arcs or not, which is depending on several aspects, one of them being the difference in the traveling costs, as

[2] *https://www.researchgate.net/profile/Jose-Luis-Flores/publication/326129926/figure/fig1/AS:644081285861380@1530572353872/Example-of-the-Capacitated-Vehicle-Routing-Problem-with-three-routes-served-by-three.png*

not always traveling costs are the same when traveling from vertex a to vertex b and from vertex b to vertex a, which are the same stops, but different route has to be applied.

Sometimes the feasibility of accomplishing all deliveries while at the same time satisfying every customer requirement is not possible. Therefore, several tools can be used to facilitate management of such deliveries as well as some customers might be underserviced. The tools for managing such cases are introduction of penalties for underserviced customers or prioritizing deliveries as per altitude value that would represent the priority of each customer. Having said so, the objectives of corresponding various VRPs can differ, which also influences the outcome of the computational results. Some of the possible objectives are such as those supporting the reduction of the transportation costs, some of them are trying to achieve a lower number of vehicles needed for serving customer, the other support a high service quality which is reflected through the penalties occurring during the optimization process, some want to maximize profit, etc.

Delivery routes are differing between dynamic and static ones. The main difference between these two approaches is the way of processing the information. While static route considers information only before the route is created and not while the delivery is being executed, the dynamic approach is taking into account also information that are upcoming during the delivery process. The received information for the dynamic routing have the purpose to improve the delivery process and achieve a higher customers satisfaction level, which requires an immediate optimization response using highly sophisticated optimization algorithms. While some concepts of dynamic routing allow to modify the route during the delivery process, as per newly received information, in other cases the restructuring of the route is not feasible but rather some improvements are allowed based on the availability of driver and capacity as well as requirements related to the delivery. A significant importance among the optimization algorithms with an increasing importance and implementation are related to the recently introduced additional constraints to the optimization process related to the delivery time windows. This higher flexibility of the dynamic routing supports suppliers to respond to customers expectations in a more efficient way, which is a consequence of route adaptations and corresponding share of information with drivers in timely manner. This approach with a high level accuracy information on when a delivery parcel is arriving to the customer´s address is valuable for customers as well as for the drivers, as drivers would know when a customer is not present at the delivery address and therefore, this customer can be skipped for the time being. This is the way, a delivery route is optimized even stronger and the delivery time could be saved.

Notwithstanding the above, the algorithms in the transportation sector are not only used to create and optimize delivery routes, but also for inventory management, product search and match, task courier matching, determination of delivery price, etc.

- Inventory management – suppliers are typically storing the inventory at several locations called distribution centers. In regard to the past inventory management and online shopping, the way of storing was done separately when looking at the online orders and the actual inventory. Contrary, the modern and more sophisticated way of inventory management is to show current status of the inventory to a customer when accessing the online shop and selecting a product to be bought. This approach enables a higher service quality, more accuracy to customers, reduced traveling time and consequently, emissions and costs.
- Product search and match – This system is used by the middleman companies, whose purpose is to process customer requests related to a product of another supplier/manufacturer in a way to promote products to be sold with a highest profit margin of the corresponding supplier/manufacturer.
- Task courier matching – is system that is locating available delivery personnel that is the best delivery option in the moment. In the moment a delivery request is posed, the task is allocated to a driver depending on the place of delivery and current driver location. For such an assignment of the delivery request there are two possible ways both depending on specific algorithms, one being an automatic assignment. One way being an automatic assignment of the request and the other relying on manual search by customer of possible driver allocation.
- Determination of delivery price – some suppliers allow price variability concerning the amount to be paid for the delivery service. The price variability depending on the order characteristics and can be of two types. One being auction where price is set according to the customer´s willingness to pay and the other calculated depending on the delivery distance or traveled time.

While these optimization algorithms are being advantageous for one group of suppliers, those that are accepting the new technologies, it can be also disadvantageous for the other suppliers that are not familiar with the new technologies and their potentials. The more advanced routing system would allow to the traditional companies to improve their services and to stay competitive on the market, which is unlikely to happen if there is no systematic transition to the modern optimization systems. Compared to the new types of delivery, as per above mentioned optimization techniques, many customers are still more trustful with the traditional delivery methods such as DHL, FedEx and UPS when it is about the delivery of important and valuable packages. In addition, the newly introduced concepts are still in their early stages, which means that their viability to stay on the market is still not completely integrated into the market (Stanford Business, 2016).

Challenges and opportunities of attended home delivery

As already mentioned, the attended home delivery is related to a type of delivery where customer have to be at the delivery address in the time the delivery arrives. This delivery method is characterized with time windows that each supplied have to offer to its customers, the length and design of time windows determines the effectiveness of the service as well as the delivery failures that are occurring. The reasons for customers to choose this type of delivery service are various, such as security related concerns of the high value electrical devices, food products with a special storage condition requirements like milk products, size related issues for massive products like furniture as well as when a specific service is to be performed like cleaning, repairs, etc. Contrary to the traditional delivery characteristics and an uncontrolled assignment of customer order request, where the possibility of acceptance of an unfeasible delivery request to the existing delivery portfolio is a usual occurrence, the electronically accommodated delivery requests are a way better optimized and assigned. With the algorithms for optimization numbers of time slots as well as pricing of each request can be adjusted in real-time and therefore, the avoidance of unfeasible requests in a specific route can be to some extent avoided. However, the challenges that are appearing when designing the concept of the attended home delivery are common and are mostly related to time slot scheduling design, dynamic time slotting and dynamic pricing (Agatz, et al., 2008).

Time slot scheduling design

A common practice for designing the time slot schedule is to customize time slots for various delivery areas. For this approach it is required to determine the shipping cost as well as the requirements of the service and in line with the requirement to assign the time slots to each specific delivery area. This scheduling has its challenges as well with determination tools being marketing and delivery routing models. It is not possible to offer all time slots in all delivery areas, as then there would be no need for the time slots. Therefore, in order to boost the demand, it is necessary to limit number of time windows per delivery area. The complexity to arrange this might be high, as a cost-effective solution has to be obtained which includes efficient and sustainable utilization of delivery personnel. In order to achieve the efficient and sustainable solution it is needed to consult marketing and operational practices and to balance between these two. The decisions to be made are about time slot length, time slot overlap, number of time slots offered and shipping costs. Taking these characteristics into account, it is important to assign them to the specific delivery areas, while at the same time considering perspective of a customer. The customer desires time windows to be smoothly spread over the whole week and to be available at all periods of a day (morning, afternoon and evening hours). Not only the smoothness of allocation of time slots is important, but even more significant is the allocation of the time slots according to the routing schedule, so that delivery areas are sequential visited where time slots are accordingly allocated. Having all this set up, then the quantity of orders and orders volume has to be taken into account and aligned with available capacities and already scheduled time slots. The quantity and volume of orders are highly influenced by the design of time slots as well as population density in an area, availability of internet access as well as provision of a solution for delivery requests that are rejected due to non-availability of certain time slot (Agatz, et al., 2008).

Dynamic time slotting

In addition to the previous subchapter, here the challenges and opportunities of real-time management of the previously elaborated time slot schedule will be formulated.

Once a customer request is posed on an online delivery platform, it also has to be allocated efficiently, which requires data available to be considered before offering time slot possibilities to a customer. Once the data is assessed, a variable set of time slots can be offered to the customer. In this point in time, customer has to decide whether to reject any of the offered time slots or to choose one of them. The design of the dynamic time slotting depends on customer´s aspiration for a specific delivery time as well as impression of a customer when in the offered set of time slots, the one with desirable time is not contained. Modelling itself is the most challenging part of the dynamic time slotting, with an advantage of customers buying online. The online purchasing enables modeler to get an insight into the customer attitude and to simplify the monitoring. The access to such information are valuable for marketing related issues as well as for the creation of delivery schedule. As already mentioned, strategies for such an approach are various, but the simplest one is to restrict time windows for any additional requests, as soon as a quota on accepted request under certain time window is achieved, relying on the collected statistics for certain zip code. Furthermore, another common challenge for the modelling is the short amount of time that is required to make decision on dynamic time slotting, which is measured in seconds. Time slot selection without previously selecting products and allowing the size of delivery to be known, is one of the difficulties that is occurring during the modelling time.

In order to facilitate the design process of time slots, various strategies with different outcome can be implemented. One of them being maximization of requests accepted, but without rejecting orders with high value products. Similarly, for solving the problem of short life products, a method related to limited time that products are allowed to stay in delivery vehicle is implemented. For request that are arriving several days before provision of services have to be efficiently allocated, which is the case of repair services, where the additional upcoming request are not known and therefore the schedule design faces difficulties. An estimation of the future demand is crucial for profit maximization. For example, if a customer request which entail high costs arrives and if at the same time is it known that a lower cost request will arrive for the same time slot in the future, the first request can be rejected and the other accepted. This approach enhances the cost optimization level of the delivery. Furthermore, a significant role plays the technology which decides whether a request can be accommodated according to it characteristic or not. With the advanced technology an increased number of accepted requests would be achieved. However, a highly sophisticated insertion algorithm with the VRPTW has to be used in order to reach efficient results (Agatz, et al., 2008).

Dynamic pricing

Dynamic pricing has the main purpose to change the offered delivery prices actively in order to influence customer choice of delivery time slots. The method is not based on forcing customers to choose a certain time slot, but rather to slightly adjust the prices of time slots which motivates customer to choose one time slot or another. Even a small price incentive of a few Dollars can change the customer opinion on the desired time window significantly. Prior to offering the incentives, some conclusion have to be performed related to:

- Not only direct price adjustment has to be an incentive, but also offering vouchers as well as free products could be one the possible influences on the customer choice.
- Implementation of penalties or only incentives to discourage customers from choosing certain time windows
- How to arrange price discounts on the delivery services if these are used as incentives. In such a case it could be distinguished between fixed discount and an incremental discount one, two or three Dollars depending on the purpose of the incentive to be made
- The amount of money to be secured for incentives purposes. This has to be decided prior to the beginning of the purchasing process out of the money that has been made available for the incentives, it has to be decided which amount to allocate to which customer.
- Considering that the sequence and characteristics of the upcoming request is unknown, the allocation itself becomes more complex. A trade-off has to be made between preferences of a customer and the expenses expected to appear for the certain delivery in a time slot compared to another one.

The dynamic pricing is an important topic in the recent years. More specifically, the revenue management which is directly responsible for management of prices as well as for the inventory of deficient products, all with a goal of profit maximization. The ability of estimation of the future demand and trends over the time is of a crucial importance for an efficient planning of the time slots. In addition, technology as well as mathematical softwares are improving with the time, therefore, the collection of required information and its editing will be favored more and more in the future. Consequently, the estimation quality will have the possibility to enhance relying on all the collected and edited information (Agatz, et al., 2008).

Example – Attended home delivery

Agatz et. al., 2008 have presented a real-world example on a retailer that is providing home delivery services to its customers. The company that was used as the example is called "Peapod" and is based in the United States (US) serving about 11 million families in 2008 around the US. The company was offering this service only five days a week in certain periods of the day. Morning service hours were from 6am until 1pm and the evening service hours were from 4pm until 10pm. Every day the company is confronted with decision making on how to structure the offered services and therefore the shipment schedule of the goods to be delivered. For a daily delivery the structuring includes determination of the amount of time slots (TS) during a day/week, length of each TS and specific times when the time windows are offered in different city areas. These parameters are determined according to the characteristics of different zip codes. In this way it was possible to increase the quality of the provided delivery services, due to the structuring of time windows according to the information related to a possible delivery demand in a certain zip code. A general setup of the time windows is that they are allowed to overlap as well as the price that a customer has to pay for the delivery is changing. In regard to the prices of delivery, Peapod decided to introduce a fix charges for the attended deliveries with a price level based on the economies of scale system. This means, the higher the total amount of the order, the lower is the delivery fee. The fees are ranging from 6.95 to 9.95 Dollars. Since the design of time windows offered influence among others, demand, service quality, costs occurring, the design is made according to characteristics such as population density, availability of internet connection as well as data of past demands for an area. In order to ensure enough time for the preparation of the delivery, a time window for delivery organizational purposes is a part of the strategy. In this context and depending on the time of delivery (evening/morning hours), a different ordering cut-off times are introduced, which allows time needed for the preparation of the orders. The specific times are allocated in a way to leave the same amount of the preparation time for both morning and evening deliveries, the orders cut-off time is at 8 pm for the morning deliveries and 12 am for the deliveries set for the evening hours at this day. Notwithstanding this, a cut-off time based on the capacity constraint can be introduced for certain regions, this type of cut-off occurs in case the available capacity is exceeded due to a higher demand at a point in time than usual. In this case, each closed time window is marked with “sold out”. Not only in case of exceeding the available capacity, but also in order to allow a balanced allocation of delivery requests through available time slot, which is based on forcing customers to use less popular delivery time slots (i.e. wide time window where delivery time is uncertain) instead of the popular ones (i.e. short time window with more exact delivery time). These or similar incentives helped Peapod to reach higher cost-efficiency in their delivery operations. Other incentives for balancing customer’s choice on time windows can be used, which would not require closure of time windows, but would rather be focused on price incentives like price discounts on time windows that are at the moment beneficial for the supplier. In this context it could be said that the tighter delivery time window the more expensive delivery will be, while on the opposite the wider the delivery time window the less expensive delivery will be. Some of the advantages of such an approach are that demand can be better balanced when customers tend to use wider time window and therefore the rush hours can be avoided. Consequently, number of packages delivered on time or within the time window would increase.

Following on the above and upon the cut-off time for orders submission, a routing plan need to be developed and a VRP method is used in this regard. Once the delivery route has been established, the arrival time can also be announced to the customers. Especially, those who have chosen a wider and more uncertain delivery time window can get more precise information about the arrival time, which is shorten to a two-hour delivery time window within the initially given time window of three and a half hours. In order to improve future delivery time window offers as well as the routing schedule for visiting customers, Peapod introduced GPS devices into their delivery trucks which enables a continuous improvement of the provided services as a result of constant collection of service information such as travel time, stop time and arrival time. Notwithstanding this, Peapod thought also how to avoid unnecessary additional deliveries and additional costs which occur when a customer is not present at his delivery address within the chosen delivery time window. In this context, customer has to pay an additional fee if not present at the delivery address at a specific time (Agatz, et al., 2008).

Time slot schedule design

Management of the time windows can be distinguished between tactical and operational, with the tactical management being related to the design of time slots. The design of the time slots includes decisions on the number of the offered time slots, on the possible overlapping and length of the time slots, which can be identical or which can differ depending on several aspects. The time slot schedule design should improve the cost-effective routing of delivery vehicles. Fundamental information for such an achievement is to obtain forecasting information about the overall demand expected for the next period, possibly known for each delivery area. The second part is that the expected demand shall be equally allocated through the offered time slots (Agatz, et al., 2008). The design of time slots is often a complex task, which need to balance between. The approach has usually to balance between marketing and operational issues. The time slot schedule has influences on both customer and supplier. Customer choice is influenced by the design of time slot, narrow time slots are more desirable by customers. On the other hand, the narrow time windows are more challenging to be accomplished correctly, which influences the effectiveness of the delivery service and supplier directly.

The research on time slot management in attended home delivery, conducted by Agatz et al., 2011, was based on, at this point in time, the only specialized internet retailer without physical presence of its stores in Netherlands, called Albert.nl. Albert.nl used 2 hours wide delivery time slots with each of them costing in a range from approximately four to nine Euro, depending on different characteristics. Moreover, a distinct time slots are used depending on delivery area. If in a delivery area demand is on a lower level, the number of the offered time slots will be lower as well, contrary the number of the offered time slots in a day will be increased. The Albert.nl approach had a significant time constraint, it was done manually, which requires several weeks to complete the assignment. With Agatz et at., the approach was improved using several techniques, one of them being a complete automatization of the computational work. Furthermore, the objective of the approach is to minimize the costs occurred during the delivery and consequently to the time slot choice. The assumption on a known upcoming demand and an independent set of time slots as well as on an equal allocation of the request to the offered time slots are made for this research. Translated it means that the adjustments on the offered time slots does not impose lost sales and that each time slot is equally desired by customers. Moreover, to simplify the computation, it is assumed that the upcoming requests are of a same size. For the comparison, an alternative integer programming approach was used including parameters that are typical for the continuous approximation method.

The continuous approximation method has a purpose of developing a model for calculating costs of each time slot related to several sets of delivery areas. To satisfy the results, the components of the continuous approximation were expanded to the following calculations:

- “the stem distance to or from the depot to a stop in a time slot;”
- “the distance between stops within a zip code within a time slot;”
- “the distance between stops in different zip codes within a time slot; and”
- “the distance between stops in consecutive time slots.”

The distances between the locations were calculated based on the local data and is calculated based on a combination of time slots under a delivery area. Having the computed set of distances, finally, a local assessment on the distance per order request is computed, aiming at several parameters for:

- "estimate the number of orders per route;"
- "estimate the number of time slots covered by a route;"
- "estimate the number of zip codes visited in time slot on a route; and"
- "estimate the number of orders delivered in a zip code in a time slot on a route."

Additionally, the distance related costs are calculated by multiplying cost per km traveled with total distance of a vehicle, which results into costs per order. These costs per order, summed up for all delivery areas and time slots, are further multiplied with the expected number of orders in order to obtain an approximation on the expected total costs of delivery. The costs of manpower are not included into the calculation as it is assumed that the labor costs are always equal. Once it is known how to calculate distances, the next important aspect is the number of vehicles demanded as well as the stem distances. The number of vehicles is highly dependent on several aspects, such as vehicle capacity and the number of deliveries possible to accomplish during a specific time slot. As the local estimate is available, the global estimate needs to be calculated in order to obtain an approximate number of routes. The demand-weighted average is applied over the local estimate in order to receive the global one. Dividing the expected shift demand by the global estimates gives the approximation on the number of delivery routes. In a comparable way, the number of vehicles required have been calculated. The estimated number of vehicles is representing the highest number of possible routes.

Regarding the stem distance, first, the range between depot and first customer is to be calculated. This is done by taking into account all distances between depot and delivery areas, which is the average distance. Moreover, other calculations such as number of vehicles required in a time slot and total stem distance.

The complexify further emerges with the overlapping setup of the time windows, which can be mitigated by introducing the non-overlapping time slots. The approach to transfer the overlapping to non-overlapping time slots while satisfying the customer demand was done in a way to allocate the overlapping part of the window to one or the other non-overlapping time slot relying on the expected demand of each time slot. More specifically, the allocation was done proportionally to the expected demand. Once all the costs are estimated and a draft of the time slots design is available, the second step toward solving the issue is the optimization. Due to the complexity of the case, a simple greedy algorithm was used for the optimization, which can start from any feasible schedule. Time slots are allocated in a way to achieve low delivery costs. Once the time slot schedule is established, it is further adjusted in order to achieve a lower expected delivery costs, this approach is replicated either until the minimum cost is achieved or until the highest number on allowed iteration is achieved. The continuous approximation can be considered as an approach based on consequence, translated it would mean that no direct routing optimization has been conducted, but rather cost based decision making with a main goal to satisfy the requirements and to reduce the costs. Whereas a direct routing optimization can be done using the integer programming alternative approach. Characteristics which increase the complexity of the approach are the number of time slots and the number of delivery areas that have to be visited by a vehicle and in some cases several delivery areas in a time window (Agatz, et al., 2011). For this approach the delivery costs were obtained using the delivery seed-scheme. The seed is represented as a middle point of a group of customers who are surrounded with a circle that represents a time slot (Fisher & Jaikumar, 1981). By means of using the seed, two different type of expenses can be evaluated. First, a seed related to a specific time slot obtaining the route costs and; Second, a plain evaluation of the costs that arise while visiting customers under each time slot based on the distance to the seed. Moreover, some variables are represented by integer variables, such as if a vehicle is used or not, if a zip code is visited or not and other variables are included such as distance between delivery areas and distance between seeds. The distance is estimated by the calculations of the distances between seeds. The estimated distances are further used for calculations of the delivery costs, which are composed of tours between different seeds, between different delivery areas as well as costs occurred through usage of vehicles. Contrary to the continuous approximation approach, the integer programming has an objective to conduct feasible routing schedules in addition to the cost reduction. To achieve the feasibility of each route, other specific variables have to be introduced such as travel time calculation between two delivery areas as well as between customers in the same delivery area and specific number of time slots assigned to each delivery area. Number of time slots in the delivery areas does not vary but is rather fixed for all delivery areas. Depending on the number of vehicles, the demand of the delivery areas is equally distributed to all vehicles foreseen to serve the specific delivery area. An additional constraint is the capacity of the parcels to be delivered, which shall not exceed the available delivery vehicle capacity. Contrary to the continuous approximation method, the constraint for a limited number of feasible deliveries for each time slot causes difficulties to the integer programming method due to the fact that the length of the time slots can differ. It is also presumed that the vehicles are traveling from the depot and back to the depot outside of the given time slots, which is the reason for not including this travel time into the model. However, segregation of the three types of time windows is part of the methodology, it is differentiated between early time slots, time slots in the middle and late time slots. In regard to the early time slots, a limitation related to the time invested to conduct deliveries is limited. Moreover, the overlapping time slots are regulated in a way to consider only the total length of all time slots in one of the three periods. More specifically, if two or more time slots are overlapping, one time slot is considered in total, which has the length ranging from the beginning of the first time slot to the end of the last time slot. Last constraint included into the method is related to the allocation of request according to the index level of a vehicle, the lower the index level the more requests are assigned to the vehicle. The constraint is not determining for the correctness of the model but supports the model to achieve better optimized solutions.

In the following part of the chapter, the efficiency of the two methodologies will be elaborated. This computation part has computed the methodologies considering different characteristics with the objective of evaluating the impact of the methodology. The approach comprehends a delivery area in the amount of 1000 m^2 which is divided into 30 delivery areas. Two shifts are considered, morning and afternoon shift, which also vary in the length, number of time slots and the structure of the overlapping time slots. Out of the 30 delivery areas, 24 receive only one time slots, whereas three of them are assigned three time slots and the remaining three are not given any of the time slots. Time slots schedule was observed according to several methods with different characteristics, as follows: using continuous approximation, integer programming, schedule used by Albert.nl, schedule where a high service is represented including high number of time slots and schedule where no time slots are included, but the whole shift is considered as time window. Delivery costs are considered as parameters for determination of the service level. A staring number of available delivery addresses is 448 addresses in a broad delivery area, which is further segregated into small delivery areas. In each delivery area, a specific number of random addresses from the delivery area is chosen for the calculation purposes. The chosen addresses are considered as customer orders and the number of chosen addresses is based on the expected demand of a certain delivery area. This procedure is repeated 20 times, each with different numbers, which are memorized and used for the other comparisons in order to reduce the variations between computations and therefore, to achieve comparable results among the computation methodologies. Application of the procedure means that only the allocation of time slots is different but the addresses representing customers have to be visited in the same schedule. The different time slot schedule leads to different average costs, average number of vehicles needed to provide the service as well as different average traveling distance and average time needed to complete the service. A significant cost difference between the methodology including the high number of time slots and the one without time slots could be observed. The cost advantage is on the side of the methodology without time slots, which is at the same time more inconvenient for customers as they should reserve the whole day at home to ensure a safe receipt of the delivery. The same holds for the number of vehicles required, which is lower in case of the methodology without time slots. Additionally, a different behavior related to the customers assignment can be observed when comparing continuous approximation and integer programming methodologies. More specifically, the continuous approximation is based on a more clustered allocation of the time slots, in a way to assign the identical time slots to the delivery areas that are close or bordering each other. Whereas, with the integer programming this is not the case in its entirety. Using this methodology, vehicle routes are established without an intent to create geographically related groupings. An explanation for this difference can be the distinct aims, where the aim of the continuous approximation is to raise the demand compactness within a time slot for each delivery area, which leads to the creation of delivery groups. On the other hand, the integer programming is focused on the number of zip codes that can be visited with a vehicle through the whole delivery time period. Moreover, two comparisons with different capacity availability have been considered, one with an increased vehicle capacity for 25% and the other with a reduced vehicle capacity of 25%. This is direct influence on the number of deliveries feasible for a vehicle. The change in vehicle capacity influences differently different computation methodologies. It appears that the no time slot methodology and the optimization methodologies sense the effect of the change with a higher intensity, as well as the morning shift due to the longer service time compared to the evening shift. In addition, service level was manipulated in order to observe behavior when introducing an additional time slot and when reducing the number of time slots in a delivery area. Expected computational results were observed after the computation, the increased number of time slots experienced stronger impact compared to the reduced number of time slots. Other attractive observation was contradicting the assumptions, which was an increase in the total service cost after a removal of the time slot from the early shift. The reduction of time slots leads the demand to be spread to a fewer time slots and to obtain higher flexibility for the delivery services, which leads to a lower capacity utilization and less balanced amount of work. Translated it means that the balanced amount of work is beneficial to the capacity utilization and influences costs. Regarding the set of time slots, overlapping and non-overlapping time slots were compared. The non-overlapping time slots starting at 8am in the morning until 2pm in the afternoon inclusive of four non-overlapping time slots and the afternoon shift starting at 4pm until 9pm inclusive of three time slots that are not overlapping. On the other side, the overlapping time slots range from 30min until 60min overlaps, but include two same shifts that start and end at the same time like the non-overlapping time slots. It can be said that the overlapping time slots are more challenging when it comes to the modeling structure. On the other side, the non-overlapping time slots with a shorter timeframe face higher costs. Contrary, the overlapping time slots are considered to obtain a higher delivery flexibility as well as a higher service level, which leads the approach to a cost decrease and therefore, a lowest cost solution (Agatz, et al., 2011).

Incentives to influence customer time window choice

Due to the complexity of arranging the attended home deliveries while taking into account time windows, vehicle constraints and availability of resources, incentives to manage customer´s decision making was developed. The incentives that affect customer decision making related to the attended home delivery. The approach of the customer incentives and its tactical design is partially based on opportunity costs of the upcoming requests. The opportunity cost supports the incentive´s design to the time windows. The selection of the time window stimulated by the certain incentive would have several benefits for the supplier, such as reduced traveling distance and the delivery cost reduction (Campbell & Savelsberg, 2006). The customer time window choice is influenced in a way to choose the cheapest delivery option, which falls under supplier´s desirable delivery arrangement (Vinsensius, et al., 2020). In the approach developed by Campbell & Savelsberg, 2006, time windows offered were non-overlapping and one-hour delivery time windows. In addition, a probability for choosing a specific time window is incorporated. For each received request, a maximum monetary incentive shall not be exceeded, which is defined initially. Translated, the incentive relates to discounts when choosing a specific delivery time window, at the same time with the assumption that a minor price incentive can influence customers decision making significantly (Yang, et al., 2016). Moreover, for the requests that would not fit into any of the offered time windows due to the time windows constraints, a solution had to be provided. One of the simplified solutions is that the customers with the unfeasible request would give up its order and finally cancel the purchase request. Any stochastic evaluation is excluded from the incentive approach in order to facilitate the calculation process.

Notwithstanding the above, it is complex and important aspect to make decision on which time slots shall receive the incentive and which level of the incentive should be allocated. An example can be observed, where no incentive to two single time windows has been provided, however, if the two single time windows are merged, a probability of receiving the incentive in a situation where it could be beneficial, is more likely to happen compared to the single time window. This approach shows the importance of a specific time window, even if initially it was not chosen for the incentive. The impact of the incentives is evaluated based on the figures received without indicating any of the incentives to the time slots. The incentives are not incorporated into the computation, if every time slot has the same opportunity costs, which implies to a lack of benefits for supplier. The examination also proves that the simple incentives, based on the simple price discounts with the goal to influence customer behavior by selecting the cheapest time window, do not operate economically when the amount of the incentives to the offered time windows is increasing. Contrary, when the amount of the incentives related to the offered time windows is lower, about one or two time windows, the economical performance increase. One of the important aspects under the incentive concept, is to develop a solution on how to reduce the number of customers who are leaving without posing any order. The customer behavior is caused due to the non-availability of the desirable service at this moment in time. The reduction of the left customers can lead to a significant cost reduction and profit gain. Furthermore, the length of time windows measured in hours has a significant impact as an incentive and in the total profit for the deliveries. As deliveries under tight time windows are difficult to arrange and accomplish within the offered time, the incentives are used to motivate customers to choose wider time windows. The wider time windows characterize the time windows as more flexible and cost efficient. In the research, the wider time windows are characterized with the two hours length. First, it is assumed that the probability of a customer choosing the wider time window is zero, whereas the probability increases once the incentive is offered to the customer. At the same time the probability of choosing the tighter time window of one hour is decreasing. The wider time windows are not always practical for the incentives and can be removed from consideration if they are not feasible to the supplier. Decision on the allocation of incentives depends on the cost as well as the initial probability values. The overview about the incorporating of the incentives shows the possible reduction in the expenses and rise in the profit, the reduction in canceled orders, it is sufficient to include only few incentives to the existing time windows, when more incentives are to be incorporated to the time windows it is important to use more upgraded incentive schemes. Moreover, it could be observed that it is simpler to motivate customers to choose a wider time window compared to a specific time window and the use of incentives in early stages of computation method can negatively impact the demand (Campbell & Savelsberg, 2006).

Dynamic time slotting and dynamic pricing

The dynamic times slotting and pricing are methods which assist the decision making during the whole booking process, with the advantage of considering specific order characteristics of each upcoming in order to obtain a broader picture of the current situation and to make decision about the time slotting and pricing for each request individually. On the other hand, the static method provides a decision only once before the arrival of the delivery requests, which holds for all upcoming requests without any additional adaptations. This includes the slot pricing, length, availability in certain days (Mackert, 2019).

Delivery charges are an important decision-making factor to customers when choosing delivery services. Even minor price deviation can have an influence on customer decision making (Yang, et al., 2016). A way to obtain efficient and profitable delivery schedules is by using the dynamic slot management and dynamic customer incentives, which is dependent on the dynamic calculations. One of the examples would be, dynamic price incentives, a process that considers the opportunity cost of a time slot. More specifically, this opportunity cost considers the future lost orders if certain time slot is selected, which is not an easy task. When the opportunity costs are calculated the remaining task is to evaluate the feasibility of the allocation (Xinan & Strauss, 2017). According to. Yang et., al, 2016, demand is not being considered during any other day except the day when the request is posed (Yang, et al., 2016). When a customer reaches the delivery online platform, the availability of the time slots is screened among all existing time slots. Once this step is completed, the corresponding prices are assigned to the available time slots. It is assumed that the loading of a vehicle is happening only once per day, before the vehicle dispatches. In this approach, it is determined that the delivery time needed to accomplish all accepted order shall not exceed the duration of the assigned time slot. Since there is service time included, it is assumed that the average service time is used for each request as well as the average speed of the vehicle is included in the computation process. Moreover, distance that a vehicle is supposed to drive through is known and used for all calculations. Capacity is one of the constraints, that like the delivery time, which should not be exceeded when accepting requests compared to the available capacity of a vehicle. As in this case, the objective of the methodology is to maximize profit, cost approximation is part of the computational process, which is linked to the traveling distance and estimated accordingly. The traveling distance is the only parameter that is being considered for the cost approximation due to the reason that other costs such as driver salaries and costs to obtain vehicles are same for all methodologies and are not influencing the results.

When it comes to the real time management of the upcoming requests, at the moment a request arrives, it has to be assigned to a feasible vehicle. The feasibility of the vehicle is checked for the already assigned delivery capacity as well as for the maximum number of orders in a certain slot which are already accepted for the delivery. The customers data is taken from a real-world retailer, where each customer must have a registered account, which encloses its zip code and therefore, the address of living. Not only the customer´s address is stored, but also other order specification such as average purchasing amount, preferable time windows and size of the order. The data was distinguishing between customers that have a yearly subscription who would not pay any price for the delivery and those who are paying for each delivery. Because those customers who pay for their delivery are more influenced by the time slot design compared to those who do not pay for the delivery. Therefore, only the customers without the subscription were taken into consideration for the optimization. It was considered that no cancelled orders were occurring, more specifically, the cancelled orders were removed without further consideration and to obtain simpler results. Time window variation was constant and depending on the period that a request is posed in advance. If a request was received some time in advance, time windows were wider, whereas if it was received shortly before the delivery, the time window tightened. Coming back to the delivery address of each customer which was known prior to proceeding with the delivery request, this was used for the estimation of the probability that a request from certain zip code will be received. The probability is based on the proportion of the requests from a certain zip code compared to requests from other zip codes. Finally, the average order size for each zip code is known (Xinan & Strauss, 2017).

Furthermore, Mackert, 2019, has conducted a research for the approximation of the opportunity costs, which is directly influencing the demand through the dynamic time slotting. The requests are arriving in a stochastic manner and the booking time frame has a predefined booking time limit. The allocation of the time slots is dependent on the value of the chosen products to be purchased and is allocated prior to the delivery. This approach leads to an approximation of the opportunity costs before accepting a specific request and arrange the time slot allocation in this way. Normally, a beneficial time slots to be proposed to customers is achieved if the profit of an accepted request exceeds the opportunity costs of the request being accepted. The opportunity costs result from the scarcity of resources for providing the delivery service related to some future upcoming request, resources such as lack of available vehicles, vehicle capacity shortage, vehicle time limitations, etc. Since it is related to the future request, the approximation on the opportunity costs cannot be completely accurate. However, the approximation of the opportunity costs as well as the time slot allocation have to be completed in real time, as each customer that poses a request is also awaiting the decision on the requested time window and products ordered. The process of the decision making starts with customer submitting a delivery request for a certain time window, once the request arrived the supplier has to distribute the time slots, where the customer is responsible for the final decision making on the choosing the time slot in line with its own aspirations. Moreover, the multinominal logit approach that is the most frequently used choice model was not included in this approach, but rather the approach relied on the generalized attraction model, which allows to mirror customer´s frustrations related to the offered time slots (Gallego, et al., 2014). As already mentioned, the time slots offered depend on the approximation of the opportunity costs, which approximation is based on the mixed-integer linear program. The time slots offered by supplier can be offered only to a group of customers located in a certain area, which ensures feasibility of the request influence by the range of the delivery vehicle.

Modeling of the customer choice behavior based on the generalized attraction model considers different characteristics while decision making. First, a sign of attraction is assigned to each upcoming request, which is based on the location of the customer which is already assumed to belong to the group of feasible delivery areas. Second, each customer is assigning a number to each time slot which represents a level of dissatisfaction if a certain time slot is not under offered time slots. Based on the dissatisfaction level, a probability of customer rejecting the offered time slots can be understood, in case the time slots offered which were not considered as desirable from the customer point of view. Furthermore, the dynamic seed based method is applied for the approximation of delivery costs. The method differentiates between customers that have already provided their request with the customers that will provide the requests in the future. Consequently, the important data obtained from already accepted request are the exact location for the delivery, the selected time slot and the distance between the two customers. This collected data is further used to solve the VRPTW with the support of an insertion heuristic (Campbell & Savelsbergh, 2004). However, from the starting period of the booking cycle which is characterized as t + 1, until the end of the booking cycle characterized as T, the exact customer´s addresses information are not known. Knowing this, for every vehicle a delivery tour is generated once the booking period is finished, indicated as T + 1, the insertion algorithm can be used to solve the insertion heuristic. In addition to the insertion algorithm, a dynamic seed-based scheme is used for determination of the average traveling distance of a specific order, which is based on the chosen time slot, delivery address and the vehicle being responsible for the delivery. The seeds used for the determination are dynamically computed in each booking cycle, which are dependent on the already scheduled delivery route, and the allocation of the delivery areas and time slots. From all traveling distances computed, an average distance is being kept as well as the exact location of the customer which took a part in the delivery process. Having all this data, a so called "area-time slot combination" seed is established, which can be used to serve the customers in a specific time slot and the delivery area. Distance for a specific delivery is computed by combination of two components: average value of the area-time slot combination and the precise location where a customer form the specific area in the past was located. In all delivery areas, customers are assigned to specific time slots and the seed for

each vehicle is calculated, which is represented as a central point when considering all assigned customers form a certain specific delivery area (area-time slot combination). In a situation where no assigned customers for a delivery are available, the central point in an area is created, based on the past customers locations. Traveling costs are obtained in a way to calculate the traveling distance, which is multiplied with a factor *c,* that is equal for all delivery areas. Therefore, the costs of deliveries are related to the traveled distance (Mackert, 2019).
Concerning the mathematical approximation related to the opportunity cost computations. More specifically, the consequence when a customer terminates the order without ordering anything and the relation on how a customer from an area is served in a specific time slot. Whenever a request is assigned to a specific time slot and area, the binary value one is assigned to the decision variable representing the assignment matrix, alternatively, the binary value 0 is assigned to the decision variable. In addition, also other binary decision variables are included in the model, such as if a vehicle travels to a specific area and if a request is assigned to a vehicle. Additional computational figures such as, expected distance, capacity and time constraints have to be considered and managed in order not to exceed their capacities. More specifically, the time constraint is managed in a way to check the availability by monitoring the number of already assigned customers under a specific vehicle and a specific time slot. Following this approach, it is assumed that the profit can be maximized once the booking timeframe has passed. To calculate the profit expected number of customers under a time slot is multiplied by the expected profit per customer. In this context, the obtained costs are deducted from the calculated profit, which gives the total profit for all deliveries. It is also considered that the number of customers leaving without placing any orders or conducting any purchase is equal to the amount of the expected customers. Using the computational constraints, it is restricted that a customer request can only be assigned to one vehicle, as well as that it was controlled, when necessary, to assign specific request to a certain vehicle if the customer is located in a specific area and if the request is posed in the specific time window. The sum of the traveling distances to serve all accepted customer requests is used for calculating the total distance that a vehicle travels during a time window and for the entire delivery day (Mackert, 2019). Moreover, the insertion algorithm is used for the optimization of the requests allocation, which is at the same time used for feasibility check of the already active time slots regarding the remaining capacity and routing applicability. The insertion heuristic first decide on which are remaining feasible time slots and used them for

further computing. The feasible time slots are further used for the profit maximization, which are evaluated for the opportunity costs of assigning a request to a feasible time slot. The opportunity costs approximation is done in two phases, first phase is consideration of the already assigned requests to the existing time slots, whereas in the second phase the future approximated upcoming request are taken into account. This is done by taking the mean cost value of the previous ten assigned deliveries (Yang, et al., 2016). Finally, it could be concluded that this approach resulted in a higher profit maximization compared to other approaches. The improvement could be observed for every capacity level as well as every number of time slots. The reasons for the maximized profits, among others, are the capacities that are being saved for the future and due to the increased profit at the stage when the available capacity is squeezing (Mackert, 2019).

Home delivery request acceptance mechanism

Once time slot design is completed as part of the tactical management, the dynamic slotting is accomplished and the incentives have been incorporated, the operational management, more specifically, accepting of the orders is also on the mechanism needed to finalize the service provision. In this regard, Ehmke and Campbell, 2014 worked on a mechanism for accepting of customers in metropolitan areas, with a goal to maximize the number of accepted request while at the same time considering the feasibility of requests. Consequently, a different amount of travel time information has been used to understand possible improvements on the feasibility check methodology. The process is based on a customer who optionally chooses a time window, which simultaneously generates a request including the earliest and latest possible starting date of the requested service. The requests can be either accepted or rejected, with an instant response to the customer informing about the final decision. Whereas the accepted request are fixed into the list of the accepted requests and are not subject to the removal from the list in order to include another request. For the rejected requests, prior to canceling them completely, another alternative time slot is being offered at the same day. Moreover, in the research it was distinguished between static and dynamic acceptance mechanism, with the main difference being the amount of travel information that have been used. Both mechanisms provide a quick response on the feasibility of the request and are based on the already accepted requests. Static estimation contains less

real time travel information used for the decision making, whereas the dynamic acceptance mechanism relates to the real time and stochastic travel time information.
The static approach is based on a maximal number of requests that can be accepted for a single time slot. The maximal number of requests is calculated based on the supplier´s belief on the number of manageable requests per time window, for the decision the supplier considers number of time slots offered, length of the time slots and time needed to provide the service for each request. Therefore, the upcoming request would be accepted in a certain time window whenever the number of the already accepted requests is lower than the maximal number of acceptable requests under a specific time window. If the request cannot be accommodated, an alternative is checked, if still not feasible, the request is rejected. As a solution to improve the delivery efficiency in the city, taking into account the congestion periods of the day, the length of the time slots was not identical for all of them. The length was adapted depending on the time of the day, as during rush hours less requests could be accommodated, due to the larger amount of time spent in traffic, the maximum number of feasible requests per time window was reduced compare to the time with no traffic congestion. Since the computation is not directly based on the delivery information such as capacity, distance, service time, it has to be considered that the accepted requests under a time window can prove to be infeasible and the possibility of having an inefficient delivery schedule is present.
Contrary, the dynamic approach diminished the downsides of the static approach using an advanced feasibility check. Like for the static approach, each request is checked for feasibility, based on the calculation it is accepted or rejected. For the feasibility check a time dependent heuristic is being used including three variants for the mechanism. One of them being based on the number of vehicles, where a maximum number of vehicles is given which cannot be exceeded for the purpose of allocating additional request whose allocation would require an extra vehicle to be added to the fleet. Additionally, in order to reduce the lateness of the tour, buffer time has been included to each customer. This means that the scheduled start of a specific service has to take a part at least a specific time before the latest possible start time that would ensure feasibility of the request. The same specific buffer time is used for all requests independent on the customer location. While constructing the problem, it has been distinguished between urban and suburban areas. This means that computational distances between customers were different, with customers in urban areas being in a closer proximity

to each other compared to the customers in suburban areas being located more distant to each other. To calculate distances between customers a method is used where straight distance between customers is multiplied with 1.5, which calculates distance between customers. Moreover, in order to represent different travel frequencies in different times of a day, varying multiplier values have been used, which simulate slower or faster traffic in a day. It is also defined for each delivery area a specific number of requests arriving, whose selection represents at the same time the order of request´s arrival. More specifically, number of requests that a supplier an accommodate in a business day is indicated. The number of feasible requests in a business day is calculated by multiplying number of feasible requests per time slot multiplied with number of time windows. One of the significant differences for the static approach is that the tour is not created until the feasible number of requests is received. Contrary, the dynamic approach is constantly developing delivery routes, during requests arrival. From the scheduled routes different statistics can be generated, such as number of required vehicles, departure and arrival times as well as total distance and total travel time and number of late deliveries inclusive of the total lateness average. Also statistics on the initially accepted requests, requests with no offered alternative time window or rejected requests, are being stored (Ehmke & Campbell, 2014).

Experiment on robot-based delivery vs. conventional vehicle-based delivery

In addition to the previous chapters, a combination of some of the previously mentioned vehicle characteristics and the attended home delivery optimization models have been used to develop a method for simulation of two computational models with seven variants in total. One of the computational models is tailored to represent the delivery robots with their typical characteristics, whereas the other model represents conventional delivery vehicles with their tailored characteristics. Both models have several variants, which are supposed to present different outcomes, and which were used for the comparison of results. Having the several variants for both algorithms a more reasonable understanding of the outcomes is achieved. Each variant has been run in Phyton for 10 times to obtain differentiated results for each variant. These results are further used for getting average values for each of the variants, which is considered as a more precise outcome compared to the results of only one run. The received results have been compiled in Excel and, accordingly, diagrams for various results presentation have been created. Finally, two visualization samples for the robot-based algorithm as well as for the conventional vehicle algorithm and their generated routes have been created in six-time windows. For this purpose, a map not exceeding radius of 3 km was used.

Algorithms

Delivery robot-based algorithm

Regarding the robot-based delivery algorithms, three variants of the algorithm have been used. Each of the variants differentiated from the other two in a different number of available delivery robots. The number of delivery robots was ranging from two to four (two, three and four), as indicated in the below paragraph "Variables". The approach was structured this way to enable observing of different data developments, when different number of delivery robots are on duty. Having the data ("Results" as per below paragraph) for different numbers of delivery robots on duty, a conclusion on a desirable number of delivery robots in a specific delivery area can be made. Beside the optimal utilization of each delivery robot based on demand, an optimal number of delivery robots in a specific area is important to be considered also due to high market acquisition costs per delivery robot. Moreover, the data ("Results") obtained was used for reaching other conclusions about the robot-based delivery, such as its characteristics, efficiency, advantages, and downsides, etc.

The algorithm is based on the Capacitated Vehicle Routing Problem with Time Windows. This means that beside assigning six-time windows to each robot, being operational timeframes for delivery, a capacity constraint is an important algorithm characteristic. The algorithm (incl. all three variants) is conceived to be used in an online shopping process for products that are not of a heavy weight, like food. It is designed to receive customer requests from a certain area with specific characteristics related to each request, which are checked for feasibility and either allocated to a robot or rejected as non-feasible. Customer requests are received all together and once received, the allocation (feasibility check) starts, as per the below paragraph "Feasibility check".

The characteristics of each received customer request contain delivery location, request capacity and desirable time window. On the other hand, delivery robot characteristics, which

are considered during the allocation (feasibility check) of the received requests, include constraints for limited capacity of each robot, low limited speed as well as limited distance that a robot can travel before being recharged. In addition, another constraint is part of the algorithm, which is not a real robot characteristic, but rather introduced to limit number of accepted requests per time window to three. With this constraint, acceptance of a high number of requests with a small capacity under a time window is prevented, as the probability to deliver the high number of accepted requests in a time window is low. Along with the specific number of delivery robots on duty (the three algorithm variants), the number of feasible requests per time window is predetermined (in a real world determined by the retailer). Depending on the algorithm variant (number of delivery robots on duty), the number of upcoming requests is automatically determined and received.
The previously mentioned low limit speed (delivery robot characteristic), is further reduced in the algorithm to reflect the minor delivery delays and time losses that can occur during the delivery process, such as waiting for the green traffic light as well as while waiting for pedestrians to pass to avoid collision. The traveling speed is indicated in the below paragraph "Variables", however, the reduction is not significant compared to the conventional delivery vehicle, as delivery robots are not expected to face greater time delays resulting from traffic congestion; robots are of a small size, travel over pedestrian zones and are not expected to lose any time on searching for a parking spot, which is considered as an advantage for robot-based delivery and a difference in algorithm structure compared to the conventional delivery vehicle algorithm.

Conventional delivery vehicle-based algorithm

Additionally, the conventional vehicle delivery algorithm was differentiated into four variants, one more compared to the robot-based algorithm. Two of them with a different number of acceptable requests per time window. More specifically, the first variant included the number of requests per time window equal to four, whereas in the other variant the number of acceptable requests per time window was equal to five. The two different variants were introduced with an idea of obtaining computational data, which would allow a comparison between the two variants and a conclusion on the sensitivity of conventional delivery vehicles when it comes to changing number of requests per time window. More specifically, when several acceptable requests per time window are increased from four to five or reduced from five to four, what would be the outcome related to traveling time and consequently, to the number of overdue time windows.

Furthermore, the other two variants (out of the four) were related to changes in capacity of the upcoming requests. One variant included capacity per request being 1-3 units, whereas the other variant had a different capacity per request which was equivalent to 4-7 units. For simplicity reasons, instead of kilogram (kg), in both algorithms (all seven variants) units were used as measurement for weight. Reason for choosing the two variants related to requests capacity is a significantly higher available capacity of delivery vehicle compared to delivery robot. In view of this, the intent was to compare how request´s capacity influences computational data. Beside the data obtained such as, traveling time, delivered capacity per time window, a conclusion related to cost and profit when using both robot delivery versus conventional vehicle was made. Unlike the robot-based algorithm, here the number of delivery vehicles did not change, as it was considered that more than one vehicle would strongly exceed robot capacity and other characteristics, which would make the two algorithms less comparable.

The idea of the algorithm is the same as of the robot-based algorithm, which means that the algorithm is made for online shopping. The customer requests are first received and afterwards, an allocation of the request is conducted, like under the robot-based algorithms. Moreover, as the robot-based algorithm, each customer request has individual characteristics, such as capacity, customer location and desirable time window, which are used for the feasibility check.

On the other hand, beside the four variants and non-changeable number of conventional delivery vehicles (limited to one vehicle) being considered as differences compared to robot-based algorithm, there are also several other characteristics that are tailored to a conventional delivery vehicle. These characteristics are related to an unlimited capacity that can be accepted per time window, as in reality the accepted requests (four or five requests per time window with capacity of each request being 1-3 or 4-7 units, as per the above-mentioned variants) would not exceed the available capacity of a delivery vehicle per time window. Moreover, unlike the robot-based algorithm, for conventional delivery vehicles, there is no distance limitation, as a vehicle does not need to be recharged after a few kilometers. The speed limit is also not on a low level like for robot-based algorithms, however, the average speed was reduced compared to the speed limits in the area (30 - 50 km/h). The average speed variable was reduced in the algorithm for a certain percentage, which represents time spent in a traffic congestion(while waiting for traffic lights and pedestrians to cross the street). Moreover, for each delivery a 10 minute time is added on the delivery time. The 10 minutes represent the time of each delivery that is spent on looking for a parking spot and walking to the customer location from the parking spot. This is not the case under the robot-based algorithm, as robots do not spent time looking for a parking spot and drive directly to customer location. The next paragraph refers to variables used in both algorithms, whereas the results received from both algorithms were presented in form of diagrams attached below in Appendix 1.

Variables

Another important part of the computation is related to different variables, which in some cases vary in values when comparing the two delivery methods. The latter appears due to the different characteristics previously described. The only variable that is not influenced by the difference in delivery robot and conventional vehicle characteristics is the number of time windows, which stays the same throughout the algorithms and their variants. Whereas when looking at the variants of the algorithms, in case of robots, as already mentioned the number of delivery robots change from two to four, which automatically influence total feasible delivery capacity per day as well as the number of upcoming requests. All other variables stay the same and will be represented in the below table 1. Moreover, the variables related to upcoming request´s capacity as well as the number of acceptable requests per time window change. While the first does not influence number of upcoming and feasible requests, the number of acceptable requests influence the number of requests. Other variables are indicated in the table 1.

Table 1

Characteristics	**Robot**	**Vehicle**
A. Available no.	2, 3 and 4	1
B. No. of time windows per robot/vehicle	6	6
C. Speed (km/h)	4.5	28.2
D. Capacity (units)	5	unlimited
E. Request´s capacity (units)	1-3	1-3 and 4-7
F. No. of acceptable requests per time window	3	4 and 5
G. Max. traveling distance per time window (km)	6	unlimited

H. Feasible no. of delivery requests	A*B*F	A*B*F
I. No. of upcoming requests	1.25*A*B*F	1.25*A*B*F

Upcoming requests and locations

Number of upcoming requests is automatically generated and is based on the previously determined number of robots/vehicle, number of time windows and number of feasible requests per time window. These three parameters are multiplied, and the result of the multiplication is multiplied by 1.25, which represents 25% more upcoming requests compared to what is feasible. This approach is meant to represents a realistic number of upcoming requests, where several requests are rejected due to the computational constraints, which are afterwards considered as lost customers. It is further assumed that requests for both vehicle/robot-based code are coming in a sequence and are assigned in the same sequence to a delivery vehicle/robot. The route for each vehicle/robot in each time window is built according to the sequence of assigned requests. A robot/vehicle starts delivery only once all the upcoming requests have been allocated, either accepted or rejected. Additionally, depot location as well as the location of upcoming requests has been determined. Depot is considered to be located on the border of the second and third district (Anderluh & Hemmelmayr, 2018), whereas customers were considered to be located in second and third district while not being located on an address which is more than 3 km away from the depot. If a customer would be located more than 3 km away from the depot, it would not be feasible for the robot to deliver to the location, as the robot traveling distance per time window is limited due to battery capacity. This means that certain coordinates from the second and third district have been collected and each coordinate represents a customer location. Having a high number of coordinates, it ensures a diversity in received requests. However, same coordinates are always part of the algorithm, but a random shuffle function is included in the algorithm to ensure a different sequence of upcoming requests for each algorithm run. Moreover, Euclidean distance is used in the algorithm to calculate distance between each of the respective coordinates, which is further organized in a matrix representing kilometers between each of the coordinate positions.

Buffer time

It is also important to mention the incorporated buffer time to each delivery variant under each time window. Starting with robots, the buffer time represents the availability of all robots in the beginning of each time window, which excludes time needed for a robot to be recharged and in case of a late delivery, provides the robot with enough time to travel back to the depot. Furthermore, the delivery process starts always exactly in the beginning of each time window, as there is enough buffer time between time windows for recharging and traveling back. In this way, the same number of robots can be used under each time window, which also simplifies the structure of the algorithm and results understanding. More specifically, it is assumed that there is enough buffer time between offered time windows, consequently lateness in delivery in time window A cannot be transferred to starting point of time window B, but lateness under each time window is recorded and is presented in a form of a diagram. Similarly, the buffer time for vehicles is introduced for the same purposes alike for the robot-based delivery. Whereas, the vehicle related buffer time is needed to enable timely delivery start, which otherwise, could have been delayed due to traffic congestion circumstances. In the same way, lateness occurred during vehicle delivery in time window A cannot be transferred to starting point of time window B. Here, the lateness under each time window is recorded and presented like in case of delivery robots.

Feasibility check

More specifically, the idea of the algorithm for robot-based delivery is that certain number of requests with random characteristics are received. The specific characteristics for each request would include capacity, delivery location and desirable time window. After a customer has placed an order, the algorithm must immediately compute whether the order can be delivered to the customer in a certain time window, considering the characteristics of the request. In this context, the request is checked for feasibility, if its capacity, time window and location fit with the limits of a robot (such as capacity, number of requests already accepted under a certain time window, battery durability) which represent the distance that a robot can travel prior to being recharged and to reach the delivery location. It is assumed that the same number of robots is used in each time window. After each acceptance of a customer request, robot characteristics are updated. This means that capacity, number of assigned requests and distance are added to the current statistical figures of a delivery robot, which are considered while conducting further feasibility checks for the upcoming requests. Moreover, the characteristics are used for limitation of accepted requests per robot, in order not to exceed the feasible robot capacity. Concerning the sequence of the feasibility check for the acceptance, first it is checked if the initially chosen time window can be assigned to a customer, and, if not feasible, alternatively two closest time windows are checked for the feasibility. If still the request is not feasible under the offered alternative option, all the other time windows are checked. If none of them feasible, the request is rejected. Contrary, if any of the checked time windows is feasible, the request is assigned to the feasible time window.

Results structure

Once the execution of the program is completed, various results for a single delivery day are obtained, such as total lateness time, number of violated time windows, number of rejected and accepted requests, maximum and minimum traveling distance, average used time per time window. Using the obtained results, cost and profit calculations for each algorithm variant were calculated. Having an overview about the costs of each of the delivery methods, a more representative comparison of the delivery methods can be achieved. After collecting all the data in excel sheet, all the data was summarized in diagrams. Each variant has its own label, which was used for marking the diagrams to achieve a better understanding of the results presented on, the specific labels can be seen in the Table 2 below.

Table 2

Robot		**Vehicle**	
Variants	Diagram Label	Variants	Diagram Label
No. robots = 2	R2	No. requests per TW = 4 Capacity = 1-3	C2
No. robots = 3	R3	No. requests per TW = 5 Capacity = 1-3	C1
No. robots = 4	R4	No. requests per TW = 4 Capacity = 4-7	C3a
N/A	N/A	No. requests per TW = 5 Capacity = 4-7	C3b

Results

Time windows

When observing the result related to the used time per time window, it was noticed that the change in number of acceptable requests per time window had influenced the time window delivery time significantly. More specifically, when the number of acceptable requests related to delivery vehicle is increased from four requests per time window (Diagram 1) to five requests per time window (Diagram 2), the number of overdue delivery time windows increased to 95%. The reason for the change can be a low flexibility of avoiding traffic congestion due to the size of vehicle, as well as the difficulties to park in urban areas. In order to have control over the sensible delivery times related to delivery vehicles, the number of deliveries per time window plays an important role. On the other hand, the result related to robot delivery does not show significant difference between the three variants, but rather similarities to one another. Therefore, only one diagram has been included in the paper. The Diagram 3 shows a situation when four delivery robots are available and acceptable number of requests under each time window is three. In this case, it appears that most of the time under time windows has been used reasonably. This means that under the time window with a length of one hour, a robot uses 30 to 60 minutes to deliver all accepted requests, which shows a good utilization of time windows. Whereas, on the other hand, it is shown that about 23% of time windows have overdue deliveries. This means that accepted requests under a time window, need more than one hour to be delivered. As the number of requests per time window is low, it is not optimal to decrease it further to reach a lower level of overdue deliveries. Therefore, different alternative solutions (i.e., customer incentives, discounts for late deliveries, etc.) to influence customers choice could be implemented, which could be a solution to lower the number of overdue reports.

In addition, when looking at the traveling distances of variant C1 and variant C2, it can be observed that the average traveling distance per vehicle and day increases in case of a higher number of requests (C1) per time window. The average traveling distance per vehicle increases from 39,49 km/day for C2 to 49,86 km/day for C1, the increase in the traveling distance is expected due to the increased number of requests per time window. Whereas, on the other hand, the traveling distances for robot variants R2, R3 and R4 do not differentiate significantly from each other. One of the reasons for not having changes in the traveling

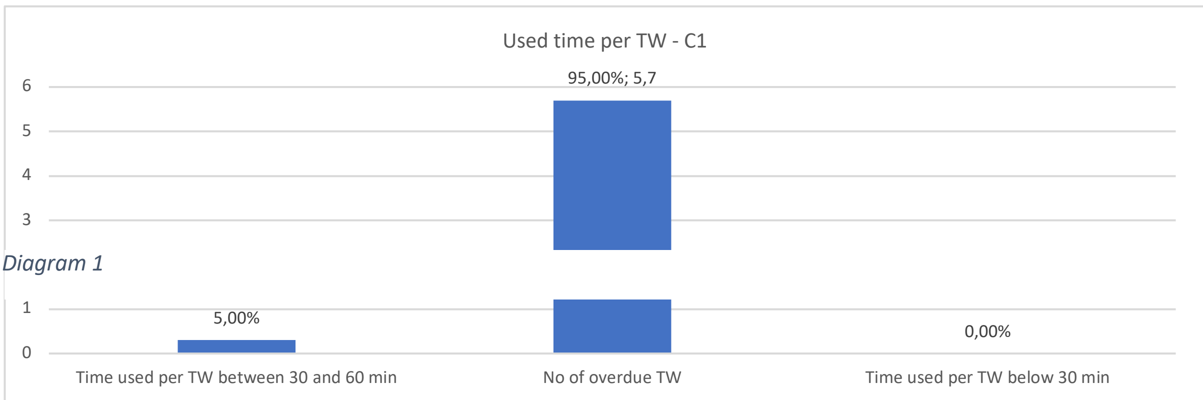


Diagram 1

distance in robot algorithm is the number of feasible requests per robot and time window, which does not change for the three robot variants.

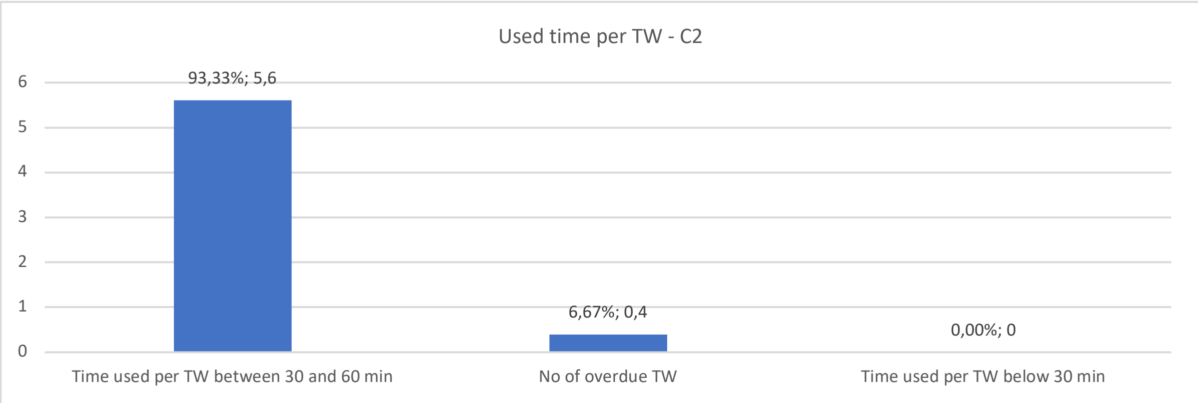
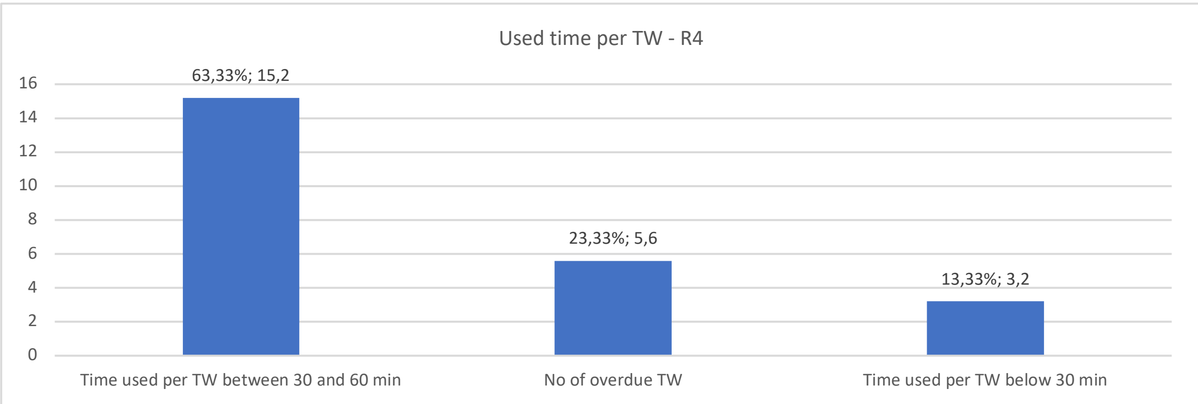


Diagram 2

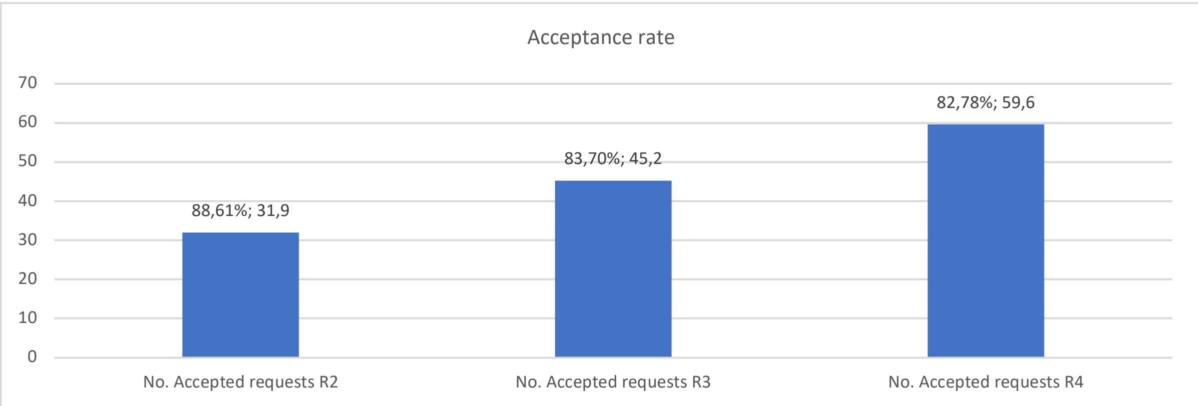
Diagram 3



Acceptance rate

One of the obtained results are different acceptance rates when comparing delivery robots as well as the delivery vehicles. In the diagram 4 the differences between acceptance rates for different number of delivery robots can be observed. The result in the diagram shows an increasing acceptance rate when number of available delivery robots is decreasing, whereas the number of accepted deliveries increases with the number of available delivery robots. The decrease in the acceptance rate can be understood as an occurrence influenced by the higher number of delivery robots and accordingly a higher number of upcoming requests. The higher number of requests, each having different characteristics, could lead to a more complicating computation, which as a result, has to reject more requests due to robot constraints. Keeping a low number of delivery robots in order to achieve a higher acceptance rate is not considered as the most desirable solution to the issue, as a low number of robots would not be able to serve various customers and would not acquire a high profit rate. Therefore, solution to the issue could be an increasing number of depots (robot bases) and a spread out of the available robots to the depots. Each depot would cover a specific delivery area and accordingly, the upcoming delivery requests would be checked for feasibility only under the robots available at the depot that covers customer´s delivery region. Moreover, diagram 5 compares the acceptance rates between four delivery robots and a delivery vehicle. In diagram 5, a very high acceptance rate related to delivery vehicle can be observed, with a number of rejected requests below 1% of all received requests, whereas the number of rejected request related to delivery robots is about 17%. The rejected requests mean that the customers are lost, and

Diagram 4



it is not known whether these customers would request the same service again. However, important part for delivery businesses is to avoid lost customers and to increase the acceptance rate. In this case, the vehicle-based delivery has advantage related to the number of accepted requests. The reason for such a high acceptance rate is related to loss constraints such as no capacity and no maximum distance that a vehicle can travel per time window. On the other hand, in this case the number of accepted requests is more than double higher for the robot variant (R4) compared to delivery vehicle, which lead to a higher profit related to the variant R4. Knowing the two aspects for both delivery types, it can be said that delivery robots are a reasonable delivery tool when delivery distances are shorter and delivery capacity is low. In such circumstances delivery robots can use their ability to easily avoid congestion and conduct delivery smoothly.

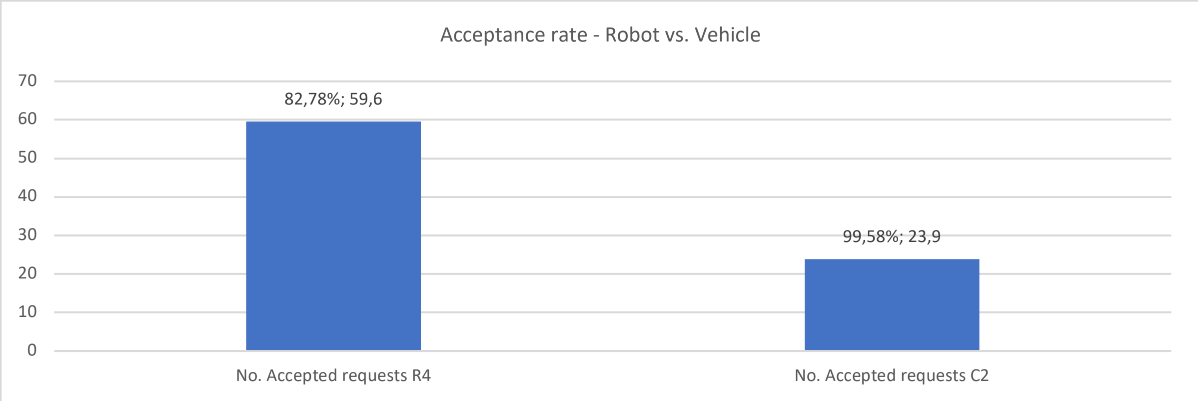


Diagram 5

Capacity utilization

In addition to the acceptance rate, capacity utilization of each variant is part of the observation, which is presented in diagrams 6 and 7. Indiagram 7, the used capacity rate increases with the number of available delivery robots. The reason for this occurrence can be the increased number of available robots, which establish a better condition for the allocation of upcoming request´s capacities. In this way, the upcoming requests can be more optimally allocated and therefore, the used capacity rate increases. Moreover, it is interesting to observe the relation between the capacity usage of delivery robots and delivery vehicles. The relation between the two algorithms is represented in diagram 6 where the increased capacity of the upcoming requests related to vehicle delivery show an increase in the capacity used per vehicle (C3a and C3b). In the conventional vehicle variant C2 it can be observed that the capacity used is far below the capacity used in case of robot delivery, whereas when looking at variants C3a and C3b where request capacities are 4-7 instead of 1-3 units for all other variants, it is observable that the capacity used outrages the capacity used related to robot delivery. It should also be noted that despite the increased capacity requests, there is still available vehicle capacity. This represents the conventional vehicle capacity advantage compared to robots, which leads to a higher profit in case of high delivery capacities and high distances, which robots are not able to endure without recharging.

Diagram 6

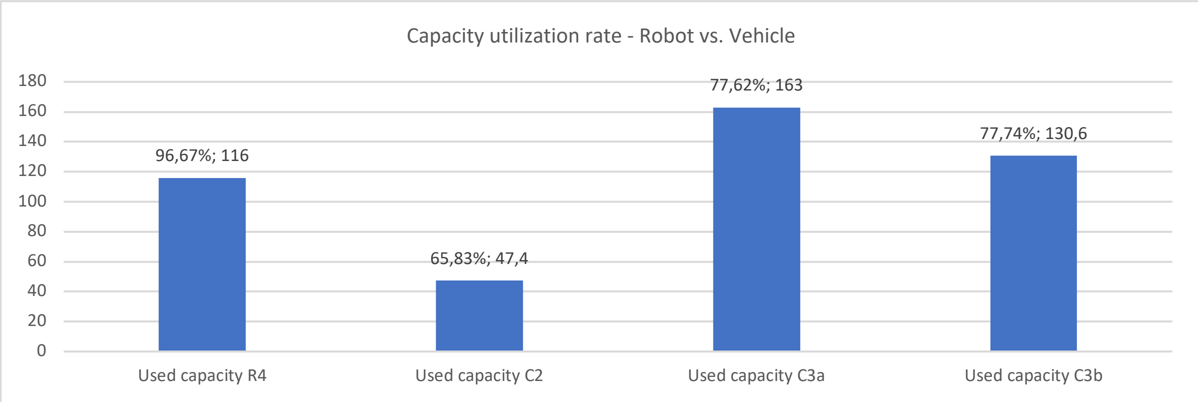
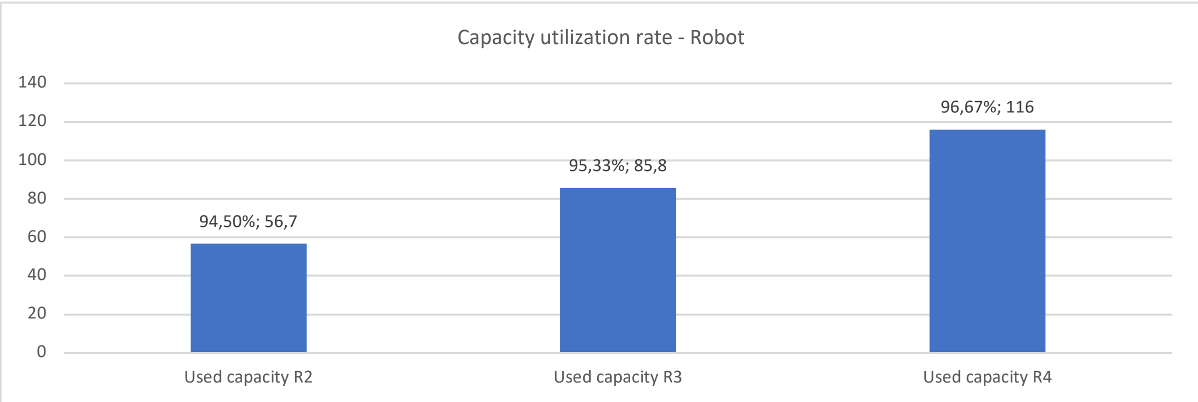


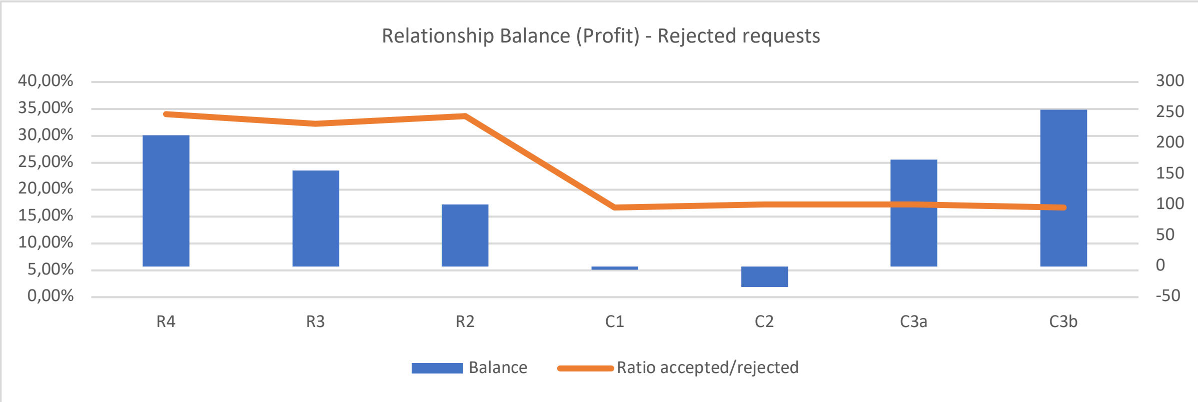
Diagram 7



Monetary values

Lastly, important aspect of the results received is related to profit (revenue – cost excl. acquisition cost) and cost of the delivery variants, which are represented in diagrams 8 and 9. Diagram 8 shows the profit achieved by each variant computed. Here it can be observed that robot related profit is the highest in case of more available delivery robots, whereas delivery vehicle shows a profit increase when the capacity of requests increase. Moreover, it is shown that using delivery vehicles when requests capacity is low does not appear as optimal, but rather as non-competitive on the market due to a significantly low profit or even loss compared to other variants. Contrary, when the request capacity is increased, the profit increases considerably. More specifically, at a certain request capacity it outranges the profit of the robot-based delivery. However, it is important to emphasize that even with the increased requests capacity (C3a and C3b), the full capacity of the vehicle has not been reached. This leaves more space to further increase profit of vehicle-based delivery. Finally, from the profit related results, it can be concluded that robots are advantageous in city areas when request capacity is low as well as when traveling distance is shorter, whereas the delivery vehicle shows advantage when request capacity high and delivery distance longer, above robot feasible range.

Diagram 8

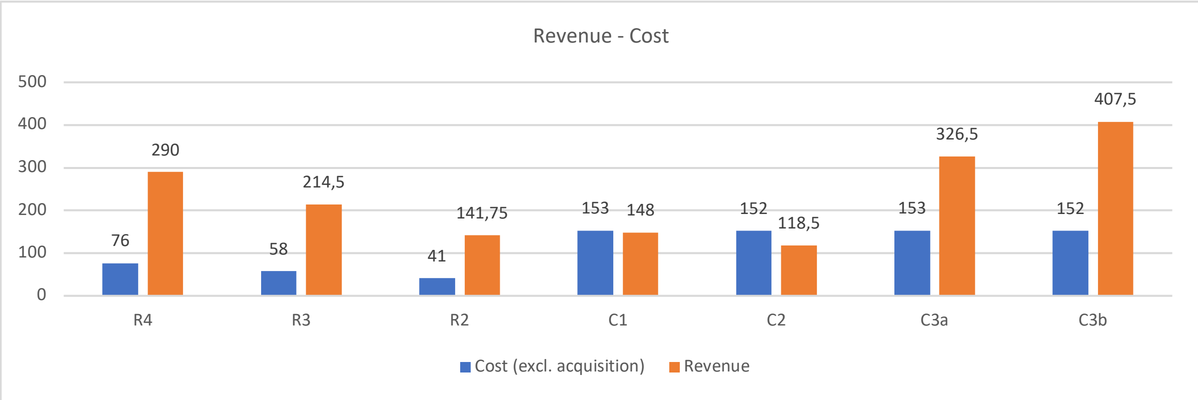


Additionally, diagram 8 shows the relation between total revenues and costs (excl. acquisition costs), which gives insight into profit related aspect from a different perspective compared to diagram 7. However, it shows a cost increase related to robot-based delivery when number of robots raises, while the vehicle cost does not change significantly. The delivery robot related cost increase is based on a simultaneous increase in electricity and operational costs, whereas the vehicle cost does not change as the driver working hours does not change nor the vehicle traveling distance, but only the request capacity which does not influence these two cost factors. The considered costs for both robot delivery and vehicle delivery are shown in table 3.

Table 3

Costs in EURO	**Robot**	**Vehicle**
Acquisition cost per unit	4,550	18,000
Cost for gas per km	N/A	0.06
Electricity costs per TW	0.08	N/A
Hourly cost for driver	N/A	25
Operational cost per delivery (cost to operate robots)	1.25	N/A

Diagram 9

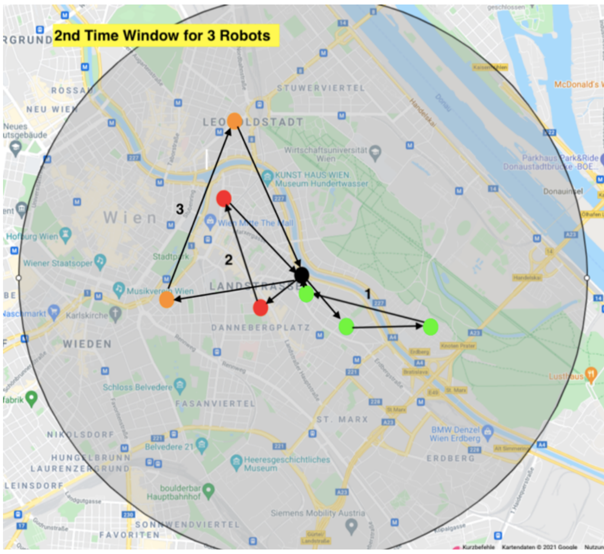


Visualization

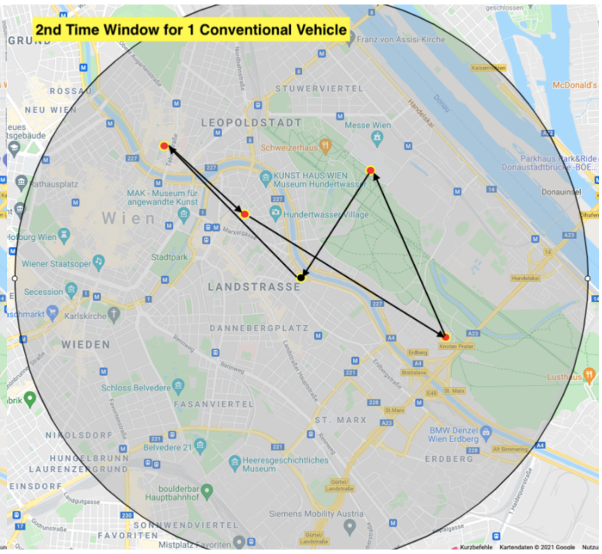
The visualization of two variants is represented, one from delivery robot algorithm and the other from the conventional vehicle algorithm. This visualization has been made by introducing an additional function in the two algorithms, which included a 3D array for recording of the sequence of customers. According to the recorded sequence, the correct locations of each customer could have been drawn and, accordingly the arrows representing the traveling direction were incorporated. Moreover, an online map has been used, where a depot on the border of the second and third district is represented as a middle point. Out of the depo, a radius circle is drawn to present an area of 3 km starting from the depot. The 3 km radius would be the last point a robot could reach while being able to travel back to the depot without recharging.

Here, it has to be taken into account that only an open area, without any obstacles (i.e. houses, streets, cars, people), would make it feasible for a robot to reach the end of the circle and retour to the depot without being recharged.

In this regard, in the pictures 4 and 5 and related pictures under appendix I, the allocation of routes for both robot and conventional vehicle delivery, for all considered time windows (incl. appendix 1) has been visualized. In the pictures it can be observed that delivery does not happen 3 km away from the depot, but rather at places closer to the depot. It can also be seen that the customer location for robot and conventional vehicle delivery does not differentiate significantly, however, the distance that a robot or a vehicle travels in one time window, seems to be significantly longer when looking at the conventional vehicle visualization. Furthermore, it can be observed that the sequence of allocated customers per robot or vehicle can be done in a more optimized way. To achieve a desirable level of optimization, a sophisticated optimization heuristic should be included in the algorithm. Moreover, the pictures visualize the number of customers that are served within one time window, where it is shown that robots serve more customers under a time window compared to a vehicle. Notwithstanding the above, the visualized pictures show the feasibility of the routes, however, certain measures could lead to a route optimization, which would further improve the customer allocation and delivery sequence. With the optimized routes, profit maximization and cost reduction could be achieved.



Picture 4



Picture 5

Conclusion

Technology is becoming more and more an unavoidable part of our everyday life. The technological transition in Europe and the rest of the world enable access to different technologies to an increasing number of people. These technologies are also used in transportation services, which include home delivery of goods. The robot-based delivery is one of the technologies that found its place within the delivery tools, and which also has a potential for further development and implementation. When implementing robots for delivery services, it is important to consider different limitations which change from place to place. These limitations are related to legislative regulations, delivery infrastructure, public acceptance of the technology, safety measures, speed, and capacity limitations, etc. Knowing that the technology has future potentials, it is expected that the limitations would be overcome in future.

Computation conducted as part of the paper shows different results and leads to different conclusions. It had been observed that delivery vehicles are sensitive to changes of allowed number of requests to be accepted in one time window. More specifically, an increase of the requests per time window for only 1 unit, can increase the number of overdue time windows significantly, which leads to an enormous raise in customer requests rejection rate. On the other side, the rate of overdue time windows related to delivery robots does not exceed 25%, however, it is considered to be high. An answer to this delivery robots related issue could be solved by introducing different alternative solutions which would incentivize customers to choose specific time windows which would influence the number of overdue time windows in a positive manner. Moreover, acceptance rates related to robots show that a low number of available delivery robots lead to a higher acceptance rate. Whereas, when looking at the acceptance rate of delivery vehicles the acceptance rate is almost at 100% due to no limitations related to capacity and traveling distance. However, the four delivery robots accept almost three times more requests compared to one vehicle, which implies that using robots is more profitable when requests of low capacity are considered. Contrary, when requess capacity is increased until a certain level, the profitability aspect would prevail to delivery vehicles. The comparison between four robots and one vehicle has been made based on a similar level of acquisition costs for both. Additionally, while available capacity of robots is used almost until its full limit, vehicle capacity still shows available space even after an increase in requests capacity. In view of these aspects, robot-based delivery is advantageous when low-capacity delivery is needed as well as when short distances are characteristic for the delivery area and traffic congestion occurs regularly. The congestion does not influence robots operation significantly compared to vehicles, as robot size and other characteristics allow robot movement over pedestrian zones. Contrary, advantages related to delivery vehicles prevail when request capacity as well as traveling distances stay high.

Finally it is important to highlight that static algorithms were used for computation and, perhaps, a more sophisticated dynamic algorithm might provide different results and more precise outcomes. Other, more sophisticated algorithms could possibly provide more precise results for all algorithm variants. This should be a part of future research on the robot-based delivery topic in order to ensure results from a more sophisticated algorithm perspective. The sophisticated algorithms might lead to more accurate results, which could be directly implemented in real life and in the business development sector. Such algorithms should consider circumstances of real traffic in specific areas such as traffic lights, people on street, one-way streets, different day time which influence traffic density, etc., which is contrary to using Euclidean distance for calculating distance. Moreover, time windows could be structured in a more complex and customer desirable way, which would include overlapping time windows, availability of time windows according to demand and customer density per area. Furthermore, the acceptance mechanism could be based on real time data, where the data is constantly being updated and represents real time situation, instead of the static data management, which requires allocation of all requests in one round and before the delivery starts. Notwithstanding the above, the future of delivery robots and unmanned vehicles supporting sustainable transportation seem to have a bright future. However, to reach a satisfactory level of implementation of such delivery technologies, improvements and industry transition should progress further.

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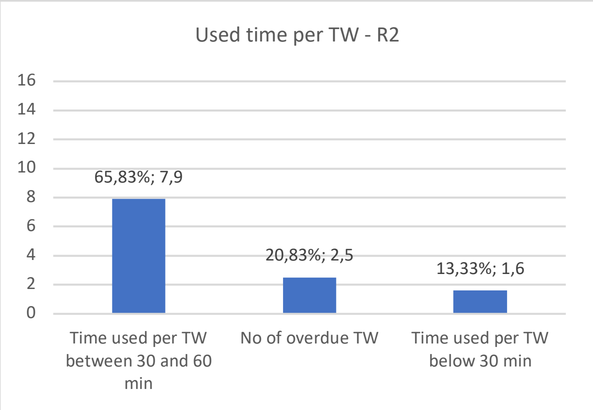
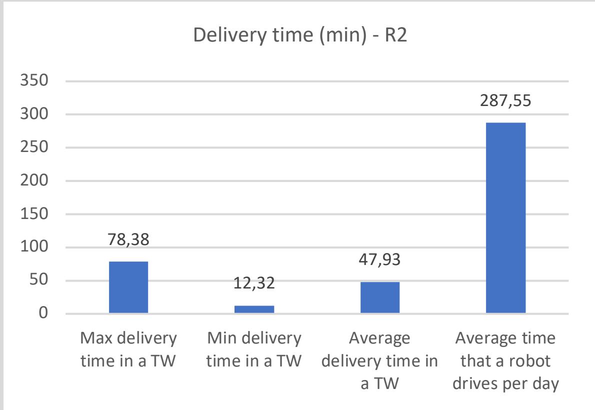
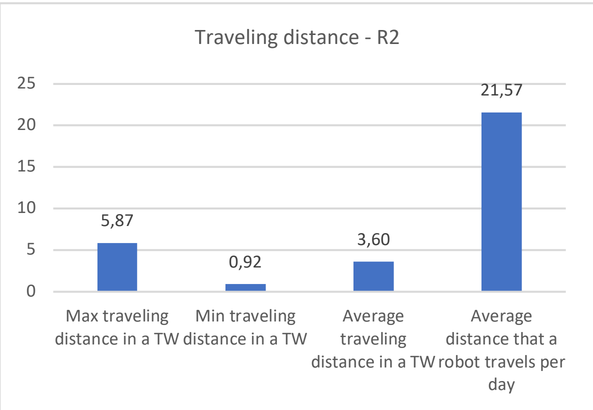
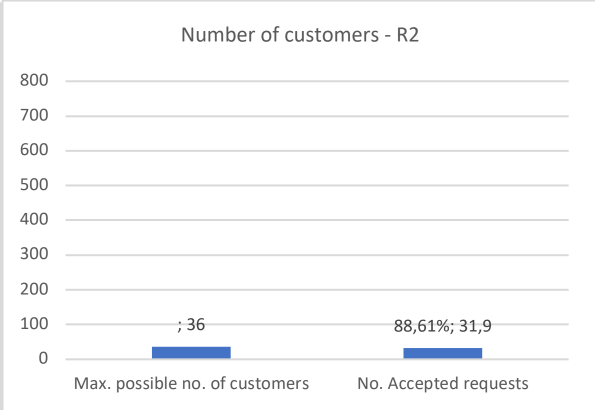
Appendix I

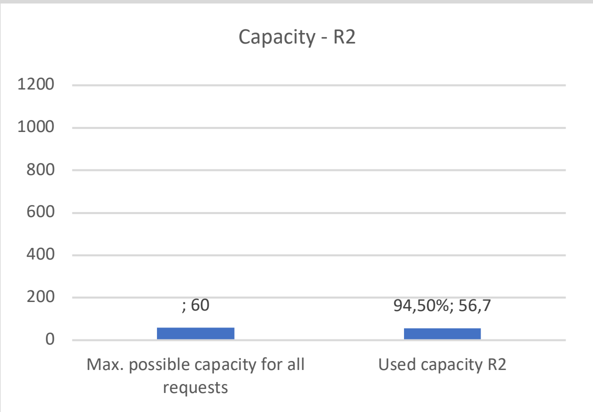
Results – R2

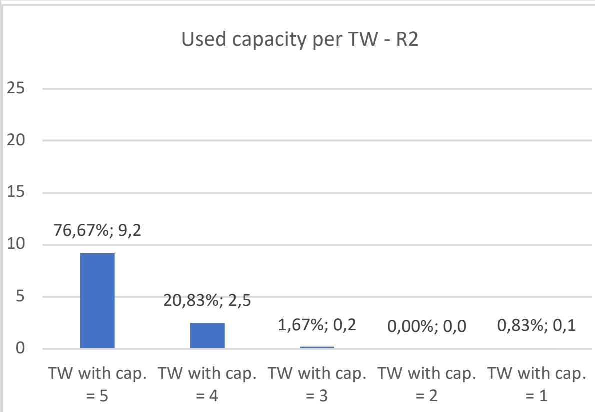




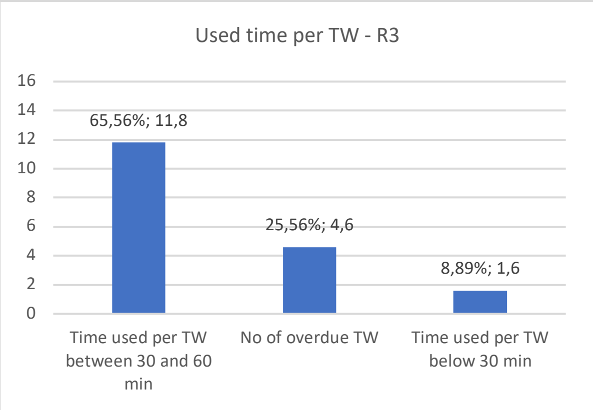




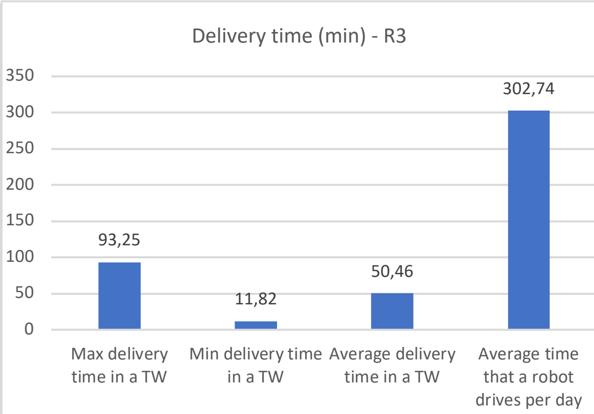




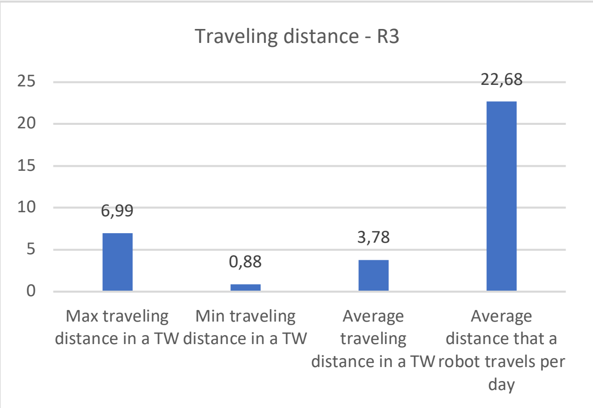
Results – R3



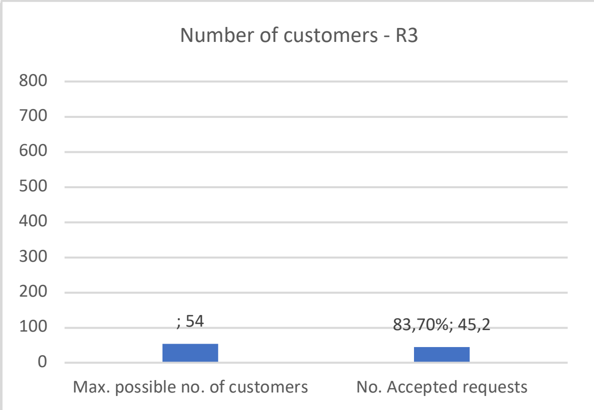
Used time per TW - R3
16
14
12
10
8
6
4
2
0
65,56%; 11,8
25,56%; 4,6
8,89%; 1,6
Time used per TW between 30 and 60 min
No of overdue TW
Time used per TW below 30 min



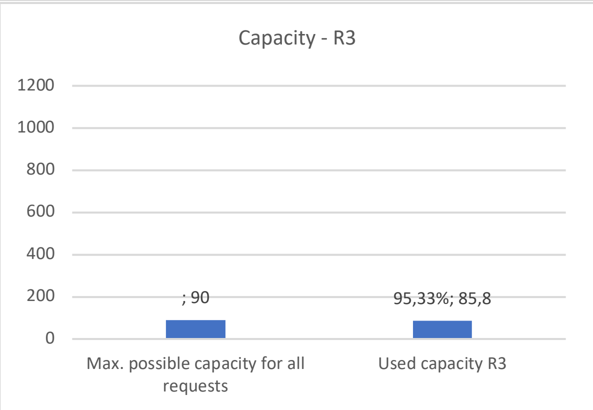
Delivery time (min) - R3
350
300
250
200
150
100
50
0
93,25
11,82
50,46
302,74
Max delivery time in a TW
Min delivery time in a TW
Average delivery time in a TW
Average time that a robot drives per day



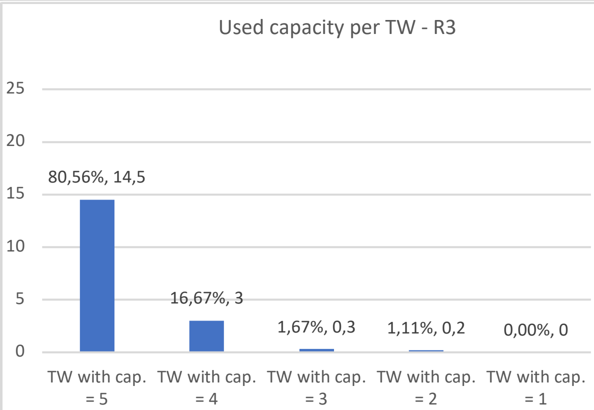
Traveling distance - R3
25
20
15
10
5
0
6,99
0,88
3,78
22,68
Max traveling distance in a TW
Min traveling distance in a TW
Average traveling distance in a TW
Average distance that a robot travels per day



Number of customers - R3
800
700
600
500
400
300
200
100
0
; 54
83,70%; 45,2
Max. possible no. of customers
No. Accepted requests

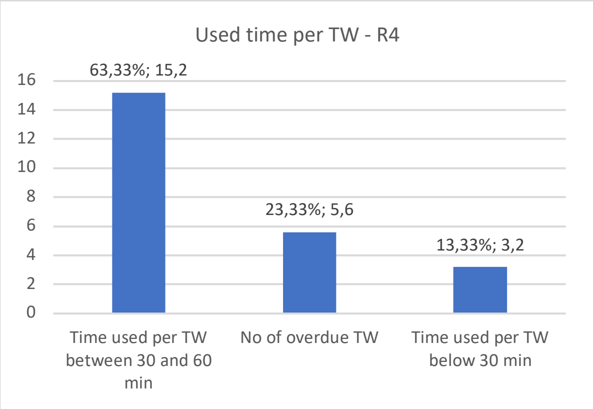


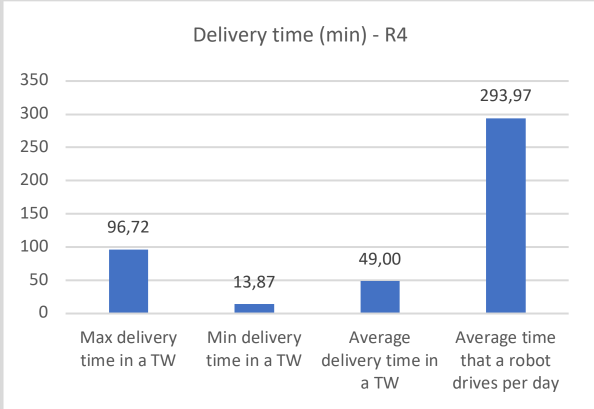
Capacity - R3
1200
1000
800
600
400
200
0
; 90
95,33%; 85,8
Max. possible capacity for all requests
Used capacity R3

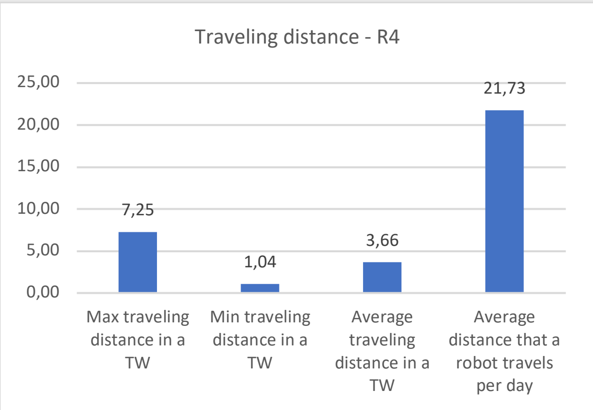


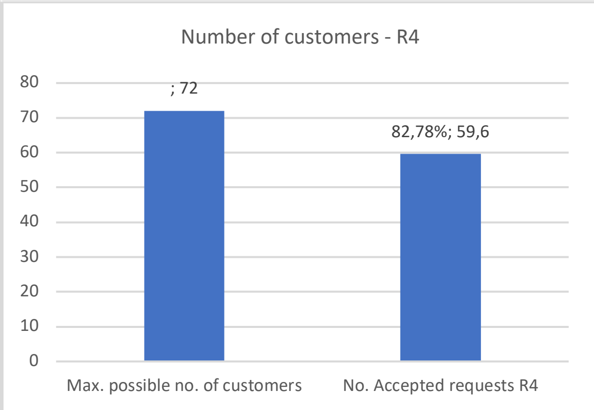
Used capacity per TW - R3
25
20
15
10
5
0
80,56%, 14,5
16,67%, 3
1,67%, 0,3
1,11%, 0,2
0,00%, 0
TW with cap. = 5
TW with cap. = 4
TW with cap. = 3
TW with cap. = 2
TW with cap. = 1

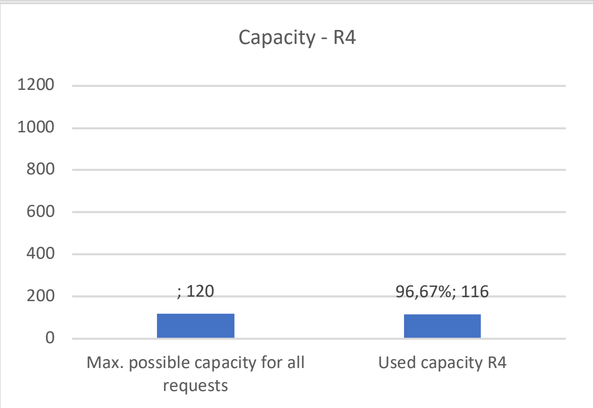
Results – R4

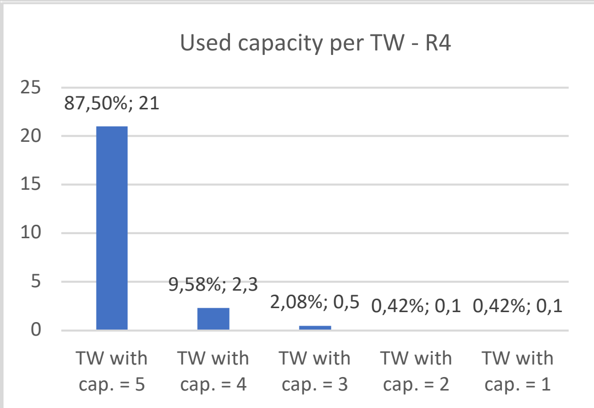

Used time per TW - R4
16
14
12
10
8
6
4
2
0
63,33%; 15,2
23,33%; 5,6
13,33%; 3,2
Time used per TW between 30 and 60 min
No of overdue TW
Time used per TW below 30 min


Delivery time (min) - R4
350
300
250
200
150
100
50
0
96,72
13,87
49,00
293,97
Max delivery time in a TW
Min delivery time in a TW
Average delivery time in a TW
Average time that a robot drives per day

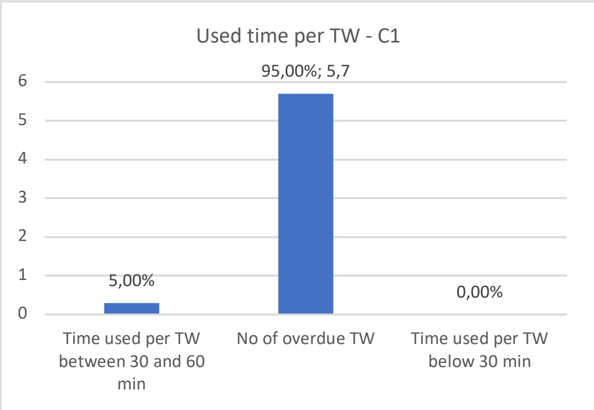

Traveling distance - R4
25,00
20,00
15,00
10,00
5,00
0,00
7,25
1,04
3,66
21,73
Max traveling distance in a TW
Min traveling distance in a TW
Average traveling distance in a TW
Average distance that a robot travels per day

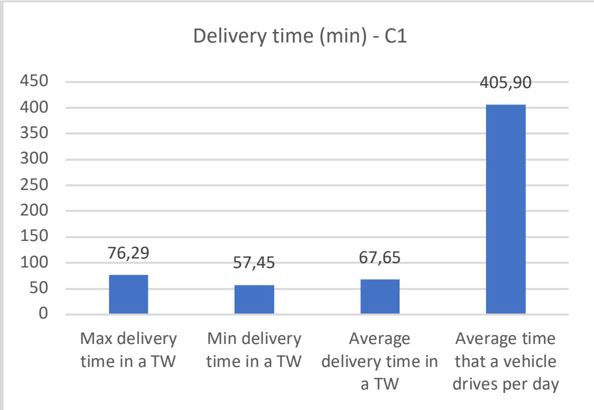

Number of customers - R4
80
70
60
50
40
30
20
10
0
; 72
82,78%; 59,6
Max. possible no. of customers
No. Accepted requests R4

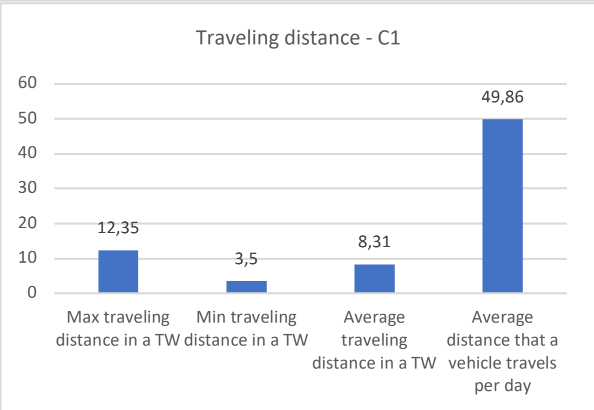

Capacity - R4
1200
1000
800
600
400
200
0
; 120
96,67%; 116
Max. possible capacity for all requests
Used capacity R4

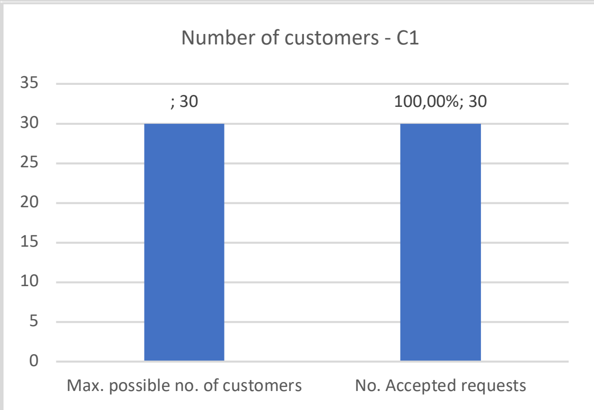

Used capacity per TW - R4
25
20
15
10
5
0
87,50%; 21
9,58%; 2,3
2,08%; 0,5
0,42%; 0,1
0,42%; 0,1
TW with cap. = 5
TW with cap. = 4
TW with cap. = 3
TW with cap. = 2
TW with cap. = 1

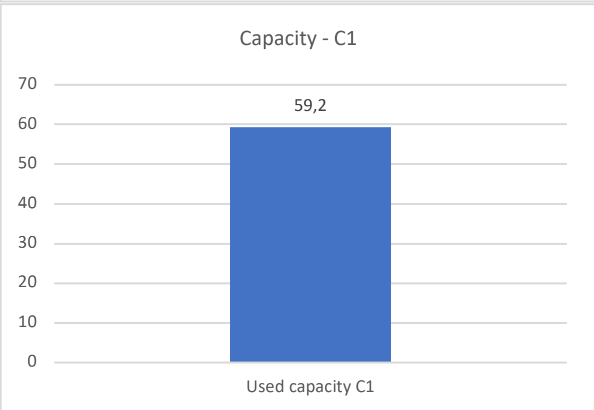
Results – C1

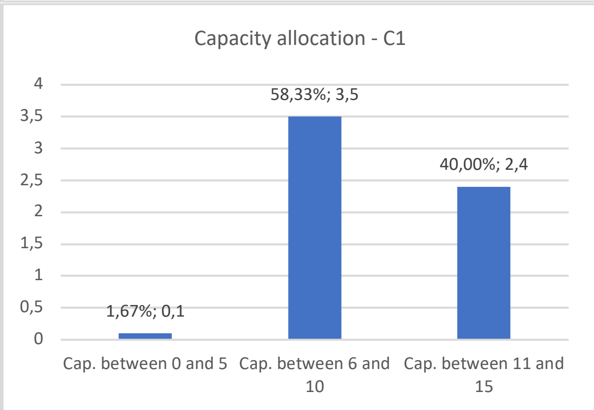

Used time per TW - C1
6
5
4
3
2
1
0
95,00%; 5,7
5,00%
0,00%
Time used per TW between 30 and 60 min
No of overdue TW
Time used per TW below 30 min


Delivery time (min) - C1
450
400
350
300
250
200
150
100
50
0
76,29
57,45
67,65
405,90
Max delivery time in a TW
Min delivery time in a TW
Average delivery time in a TW
Average time that a vehicle drives per day

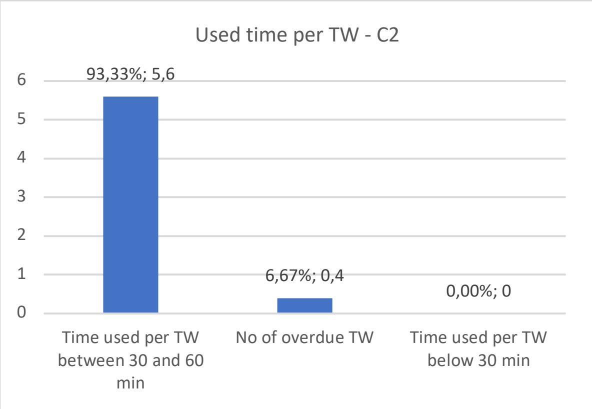

Traveling distance - C1
60
50
40
30
20
10
0
12,35
3,5
8,31
49,86
Max traveling distance in a TW
Min traveling distance in a TW
Average traveling distance in a TW
Average distance that a vehicle travels per day

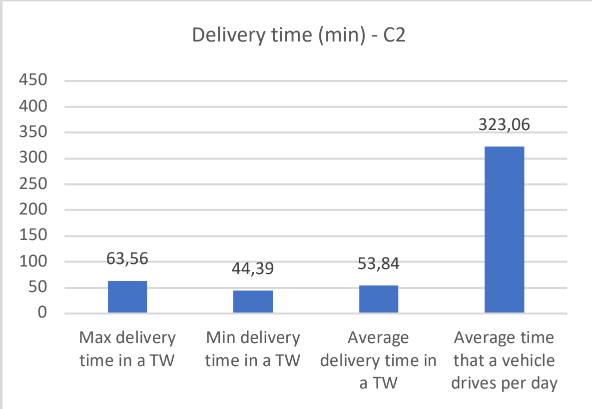

Number of customers - C1
35
30
25
20
15
10
5
0
; 30
100,00%; 30
Max. possible no. of customers
No. Accepted requests

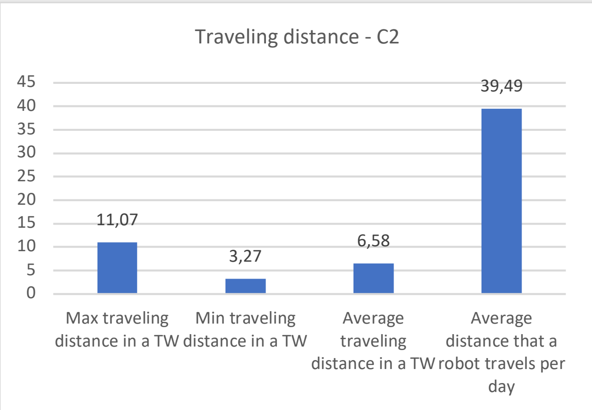

Capacity - C1
70
60
50
40
30
20
10
0
59,2
Used capacity C1

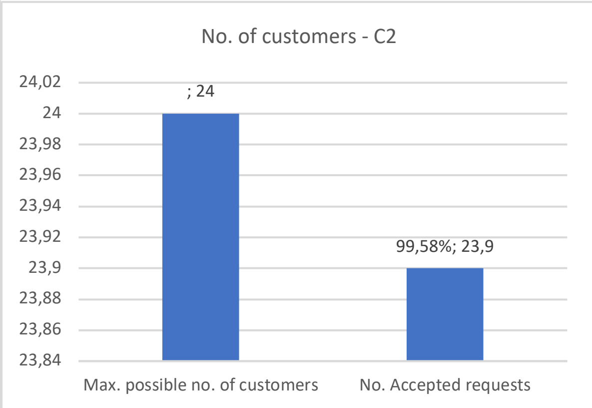

Capacity allocation - C1
4
3,5
3
2,5
2
1,5
1
0,5
0
1,67%; 0,1
58,33%; 3,5
40,00%; 2,4
Cap. between 0 and 5
Cap. between 6 and 10
Cap. between 11 and 15

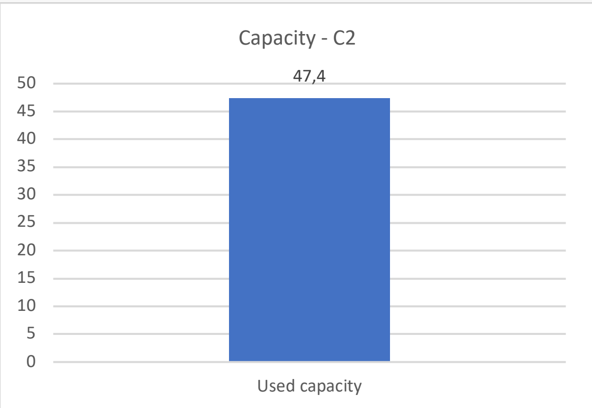
Results – C2

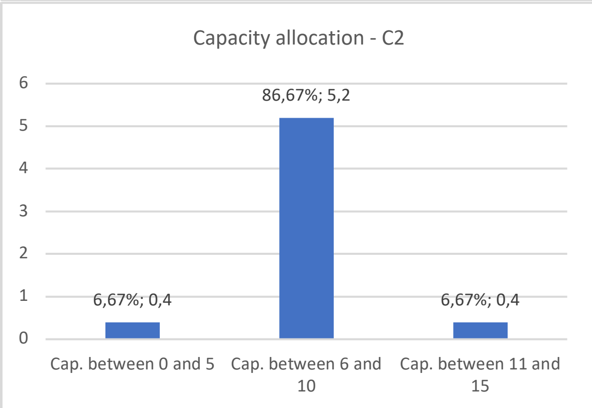

Used time per TW - C2
93,33%; 5,6
6,67%; 0,4
0,00%; 0
Time used per TW between 30 and 60 min
No of overdue TW
Time used per TW below 30 min


Delivery time (min) - C2
63,56
44,39
53,84
323,06
Max delivery time in a TW
Min delivery time in a TW
Average delivery time in a TW
Average time that a vehicle drives per day


Traveling distance - C2
11,07
3,27
6,58
39,49
Max traveling distance in a TW
Min traveling distance in a TW
Average traveling distance in a TW
Average distance that a robot travels per day

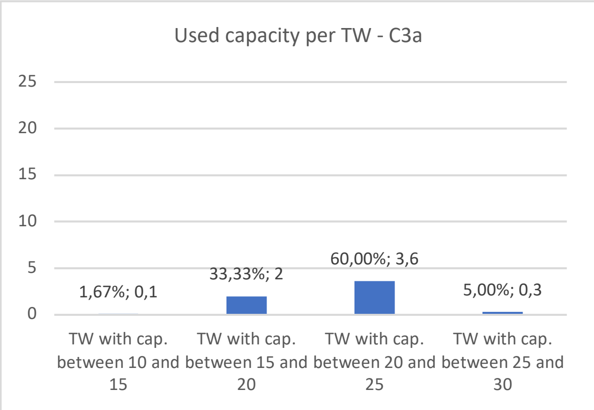

No. of customers - C2
; 24
99,58%; 23,9
Max. possible no. of customers
No. Accepted requests

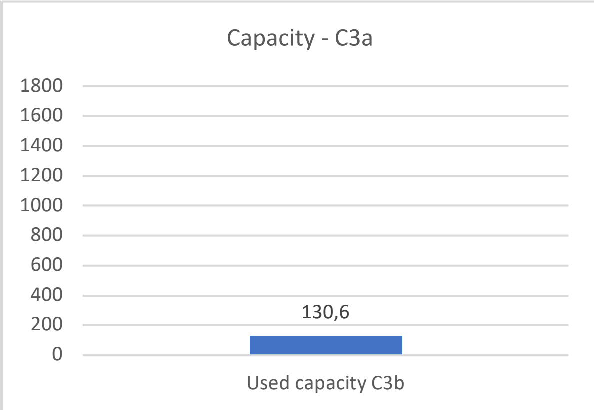

Capacity - C2
47,4
Used capacity

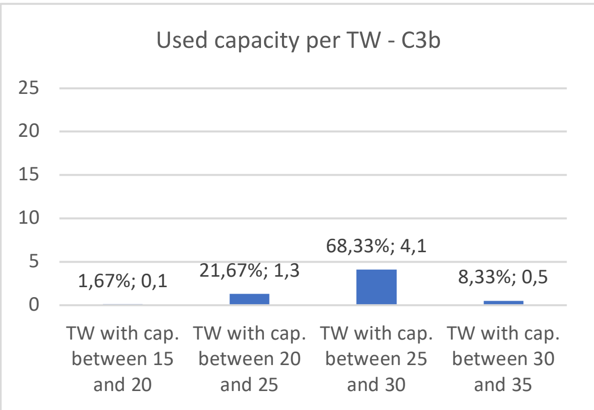

Capacity allocation - C2
6,67%; 0,4
86,67%; 5,2
6,67%; 0,4
Cap. between 0 and 5
Cap. between 6 and 10
Cap. between 11 and 15

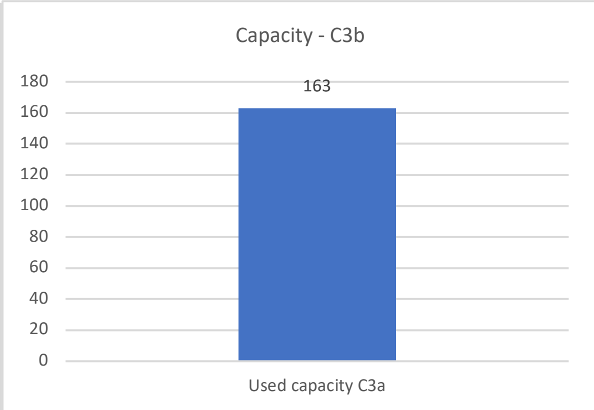
Results – C3a and C3b

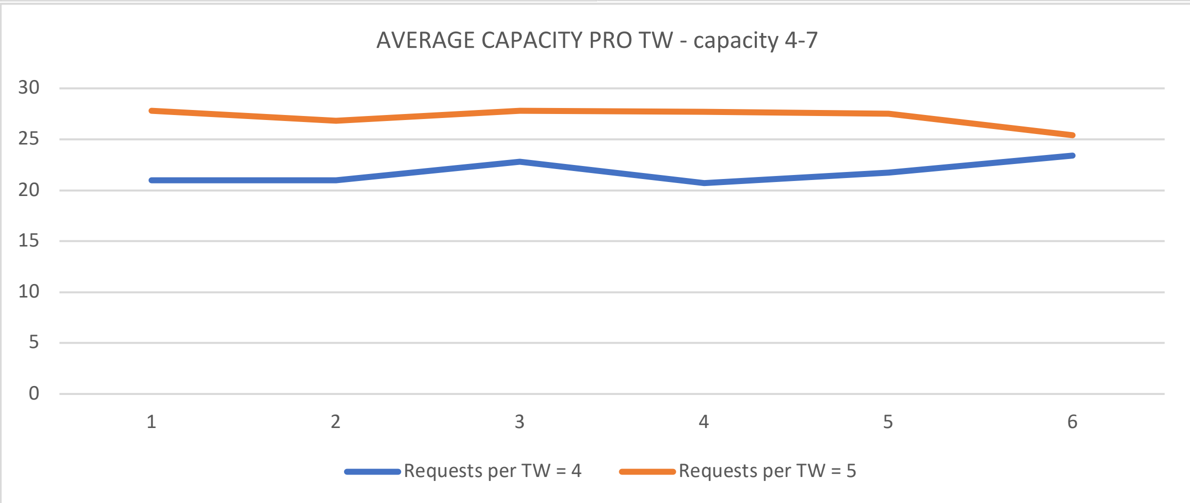
- Other diagrams identical to C1, respectively C2. Therefore, only below diagrams presented to avoid duplications



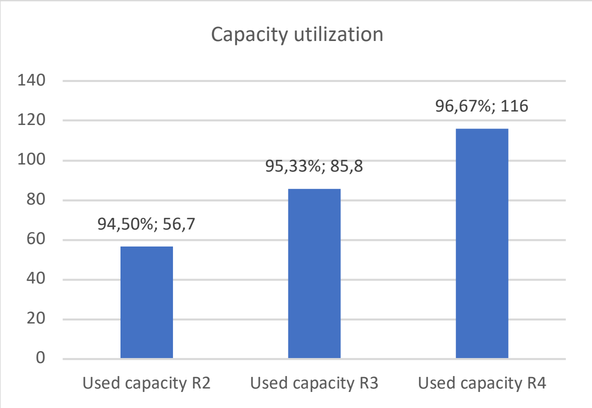


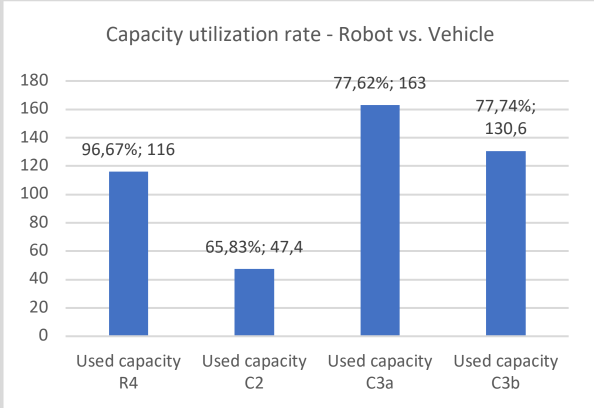


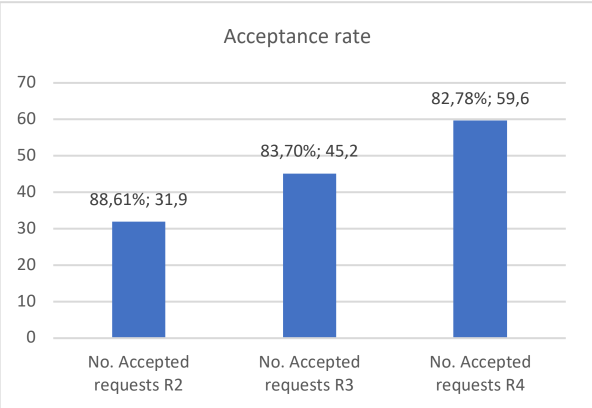


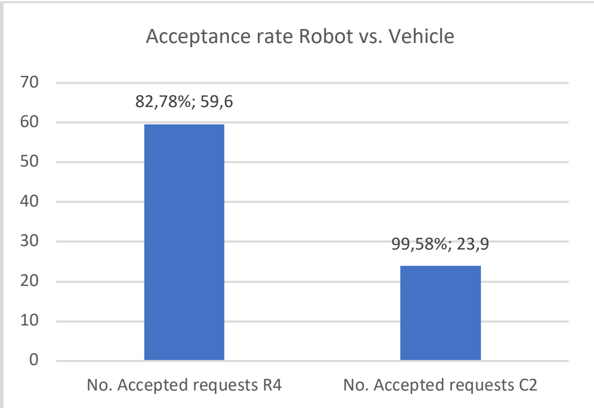


Results – Comparison Delivery Robot and Delivery Vehicle

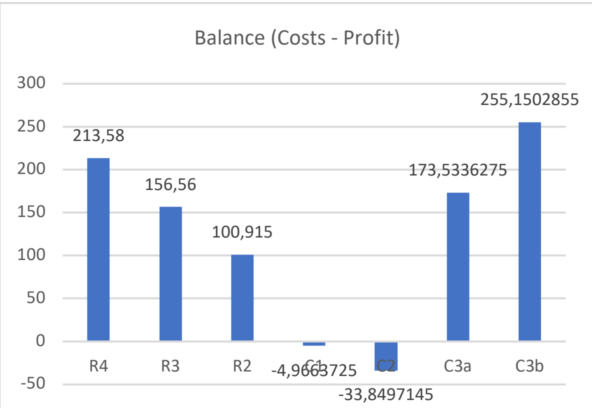


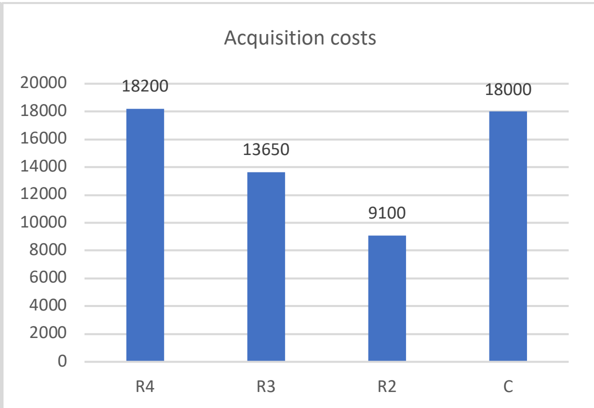


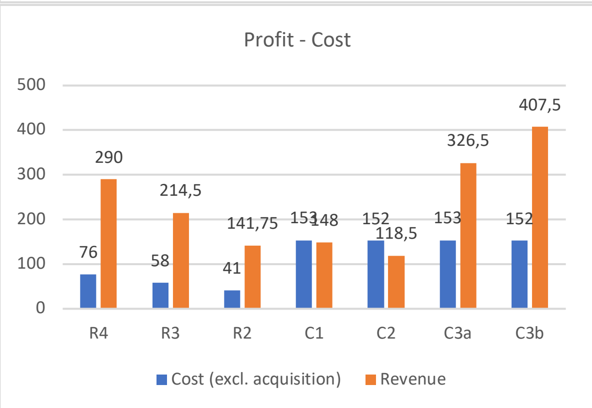


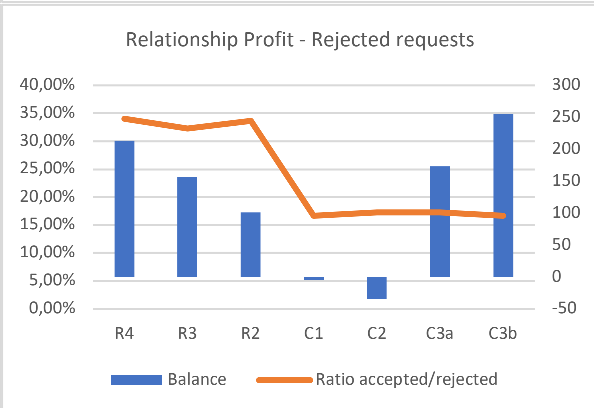


Results – Cost and Profit

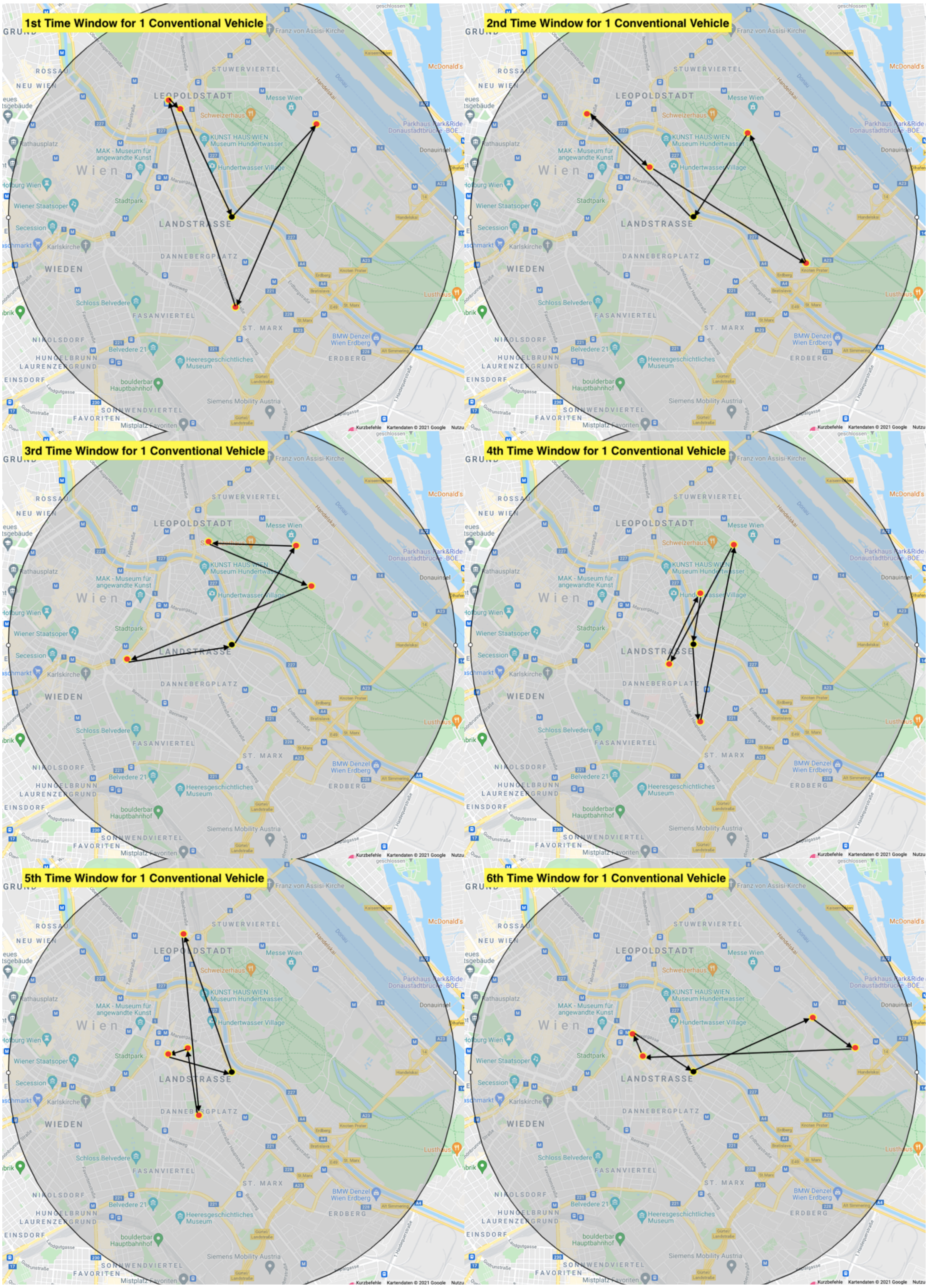




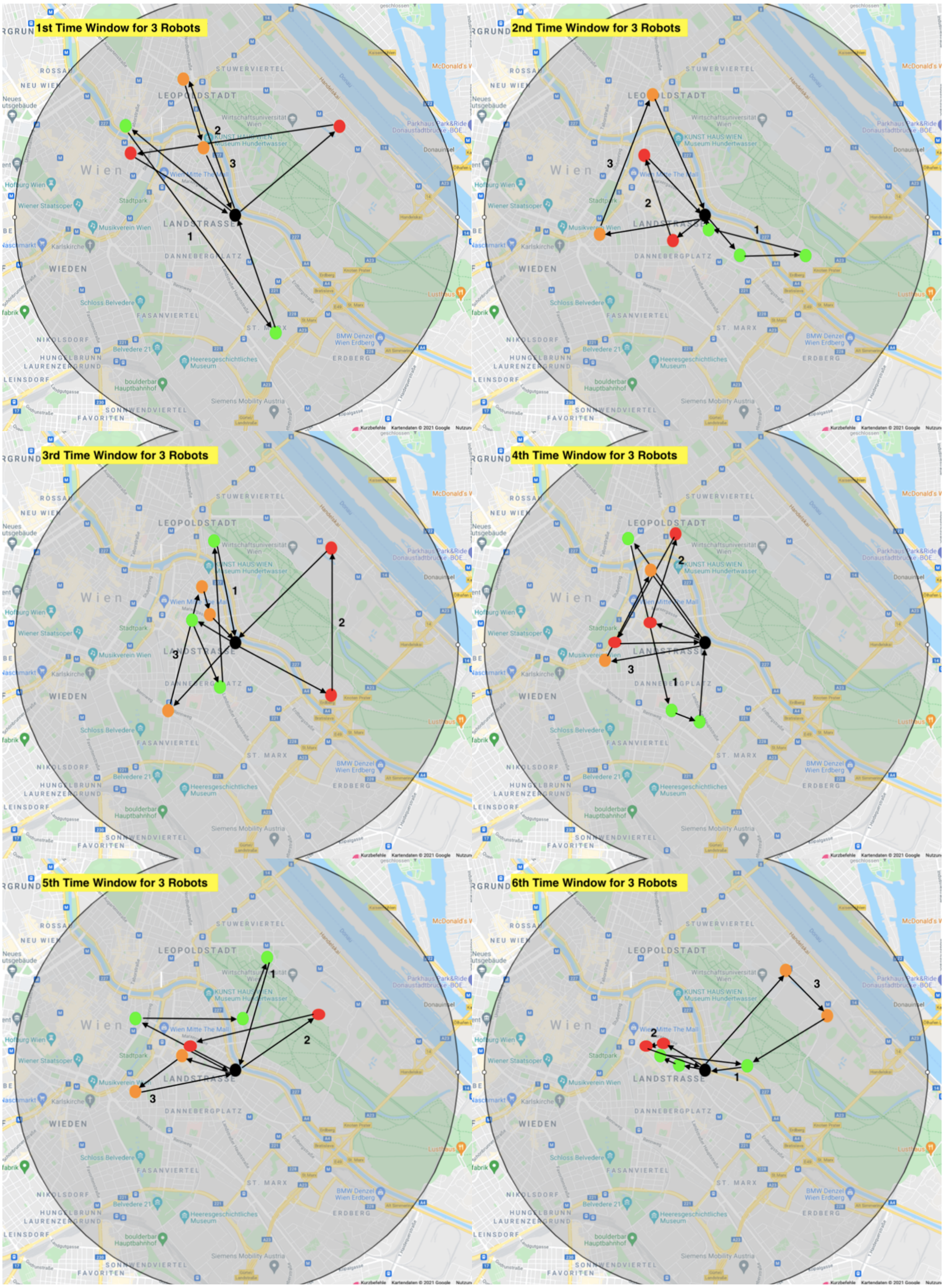




One conventional vehicle visualization – 6 time windows



Three delivery robot visualizations – 6 time windows



Randomly generated coordinates used for visualization

Conventional delivery vehicle

1. [48.213839 16.413952]
2. [48.209227 16.419492]
3. [48.19354 16.399417]
4. [48.193405 16.397001]
5. [48.215237 16.379069]
6. [48.21454 16.409193]
7. [48.214245 16.405263]
8. [48.216157 16.386273]
9. [48.21485 16.387622]
10. [48.199511 16.393818]
11. [48.208393 16.391789]
12. [48.204849 16.427516]
13. [48.203102 16.389997]
14. [48.197477 16.416211]
15. [48.215095 16.393876]
16. [48.209677 16.398908]
17. [48.218772 16.389462]
18. [48.212991 16.407809]
19. [48.20982 16.411849]
20. [48.197198 16.392886]
21. [48.206654 16.387027]
22. [48.200395 16.378185]
23. [48.205522 16.391335]
24. [48.205752 16.386496]
25. [48.213582 16.416668]
26. [48.195315 16.383895]
27. [48.210535 16.381752]
28. [48.215095 16.389584]
29. [48.205953 16.38939]
30. [48.209992 16.38737]
31. [48.207934 16.380416]
32. [48.208898 16.388128]
33. [48.208971 16.4129]
34. [48.195016 16.391466]
35. [48.200987 16.388338]
36. [48.210948 16.417333]
37. [48.202148 16.408692]
38. [48.196665 16.380749]
39. [48.217383 16.389339]
40. [48.214245 16.405263]
41. [48.205707 16.389476]
42. [48.198042 16.378875]
43. [48.203443 16.393811]
44. [48.212096 16.389643]

Delivery robots

1. [48.215237 16.383442]
2. [48.197453 16.404914]
3. [48.205522 16.391335]
4. [48.200116 16.391294]
5. [48.213846 16.376883]
6. [48.203948 16.390846]
7. [48.203624 16.394057]
8. [48.196964 16.395287]
9. [48.206024 16.390414]
10. [48.207934 16.380416]
11. [48.215056 16.411904]
12. [48.208971 16.4129]
13. [48.212695 16.418174]
14. [48.195016 16.391466]
15. [48.204865 16.387645]
16. [48.213582 16.416668]
17. [48.205953 16.38939]
18. [48.216484 16.392282]
19. [48.196327 16.416162]
20. [48.209677 16.398908]
21. [48.197477 16.416211]
22. [48.200395 16.378185]
23. [48.188598 16.40517]
24. [48.194103 16.386192]
25. [48.21631 16.403714]
26. [48.210601 16.379069]
27. [48.203092 16.381814]
28. [48.215095 16.393876]
29. [48.218772 16.389462]
30. [48.193405 16.397001]
31. [48.208393 16.391789]
32. [48.200659 16.379743]
33. [48.212096 16.389643]
34. [48.204405 16.393345]
35. [48.209992 16.38737]
36. [48.203446 16.405588]
37. [48.209227 16.419492]
38. [48.204849 16.427516]
39. [48.217383 16.389339]
40. [48.201039 16.398224]
41. [48.20489 16.389673]
42. [48.203102 16.389997]
43. [48.210834 16.392547]
44. [48.196665 16.380749]

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62. [48.215941 16.411904]
63. [48.206024 16.390414]
64. [48.204689 16.389202]
65. [48.203446 16.405588]
66. [48.199147 16.399906]
67. [48.194103 16.386192]
68. [48.204865 16.387645]
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80. [48.201039 16.398224]
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82. [48.20489 16.389673]
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86. [48.210413 16.390653]
87. [48.196961 16.389654]
88. [48.205095 16.399738]
89. [48.197028 16.407871]
90. [48.197009 16.380363]
91. [48.203092 16.381814]
92. [48.194003 16.39909]

45. [48.215095 16.389584]
46. [48.216015 16.405872]
47. [48.193465 16.388106]
48. [48.20982 16.411849]
49. [48.192444 16.400493]
50. [48.210918 16.387496]
51. [48.19354 16.399417]
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53. [48.20313 16.427999]
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72. [48.213765 16.410853]
73. [48.214245 16.405263]
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75. [48.195315 16.383895]
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89. [48.21485 16.387622]
90. [48.214245 16.405263]
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92. [48.208898 16.388128]

93. [48.197453 16.404914]
94. [48.192936 16.40143]
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