Autonomous Robots in Food Delivery:

a Simulation Study

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Index

Abstract

Autonomous Robots are an innovative technology deployed with the objective of alleviating the existing pressure on last mile delivery. In the study, the technology is studied under the logistic operations perspective in the context of Food Delivery industry. Operational and economic performance are studied though a simulation study highlighting the fundamental influential factors affecting the results and underlining the future required changes for a more widespread deployment of the technology.

1. Executive Summary

1.1 Introduction and Literature Review

In this study the technology of delivery Robots is studied under the logistic operations perspective. Autonomous Delivery robots are an emerging technology aimed at resolving complexity existing in the last phase of transportation to the final customer. Their application inserts in a complicated context in which a growing emerging awareness of a need of improvement of urban mobility is forcing companies to think to smarter and greener ways to complete deliveries. For these reasons, these fully electric vehicles are thought to operate on pedestrians' domain avoiding, and simultaneously limiting, the effects of last mile delivery on traffic. The autonomous solution at the same time clashes against existing walls of regulations influencing the conditions and Countries of deployment. Autonomous Delivery Robots are in the center of numerous themes concerning environmental sustainability, operational performance, urban mobility, AI and regulations which highlight the complexity and importance of the topic discussed in the thesis.

To guarantee pedestrians' safety and with the possibility of proceeding on pavements, the Robots are small in dimensions and must maintain low speeds of max 6 km/h. The low battery duration does not allow long trips highly limiting the range of the mission without recharging. These characteristics force the deployment of the technology in a context of local/hyperlocal delivery in which the goods delivered are small in volume and weight. Perfect in this sense are freight and food delivery in the e-commerce scenario. In Food delivery, operational excellence is fundamental to guarantee customers warm meals and short order cycle times. The industry has grown consistently in the recent years, and the Global market size is expected to reach 200 bn by 2025.

From the operational perspective, companies have noticed the potentialities of the technology and have started on field tests. Starship Technologies is currently the protagonist of the delivery robots' scene. Since 2016, the company has tested its vehicle in more than 100 cities across the world completing a total of 400.000 km of driving and more than 100.000 deliveries. The technology has also caught the attention of the e-commerce giant Amazon which deployed its version named "Scout" in 2019 and is conducting small field tests in 3 locations in the USA.

To guarantee pedestrian safety and the possibility of marching on pavements, the vehicles are small in dimensions and maintain low speeds (max 6 km/h). The low battery duration does not allow long trips highly limiting the range of the mission without recharging.

Scientific literature on the other hand has not fully addressed the topic. Among the most discussed technologies, unmanned Arial Vehicles (or drones) have received much attention, especially in their combined used with trucks. Most of the articles address the urban rather than rural delivery often considering the general e-commerce industry. Less attention has been received by the food delivery industry and other freight carriers such as delivery robots and autonomous vehicles. The focus of the study, especially in optimization articles, has been either on a time or economic dimension but never on both. Identifying as gaps the lack of articles focusing on Delivery robots and food delivery, the research question covers the understanding of the relevant parameters affecting the operational results of the technology and the study of their impact on key metrics for the industry. Besides an additional analysis of existing literature on food delivery and automated guided vehicles which DR belong to, a discussion with a manager of Deliveroo, one of the leading companies in the industry, has been conducted to capture the most characterizing elements of the industry.

1.2 Objective and Methodology

The key factors affecting vehicles performance have been identified in the size of the Area to serve, the number of Points of origin (POO or pickup points) and Points of Delivery (POD, customers), the speed, range and number of vehicles in the fleet. Moreover, a crucial role is played by the order profile, which in the food delivery industry is characterized by high peaks during mealtimes and lower requests in between. In order to answer the research question, given the complexity of elements included in modelling related for instance to the dynamicity of the requests and battery dynamics, a simulation model has been developed to flexibly conduct a sensitivity analysis on the previously identified factors.

Agent Based simulation has been chosen as modelling methodology for its flexibility, ease and effectiveness of design in scenarios where interactions among the actors of a system are complex, discrete as well as when their position in space plays a crucial role (Bonabeau, 2002). ABM consists of modelling a system starting from its constitutive elements called Agents, through modelling their behavior and interaction with others in the environment. The modeler designs a system starting from understanding the behavior and states of each of the most relevant elements of a system and describing them through a state chart identifying the logic behind its actions. The model has been realized with Any logic, a java-based simulation software.

1.3 Model

The actors which have been modelled as agents are the following: Customers, Robots, Restaurants, Orders and the Platform. Each Agent type plays an important role in modelling reality. The following list describes the main actors and hypothesis of the model:

- Customer agents represent people requesting a meal to be prepared and delivered to their location;
- orders represent the meal/the products requested
- restaurants/points of origin are identified the location of preparation of the orders;
- robots are in charge pickup and delivery tasks;
- the platform is responsible for the order allocation process.
- The area offers the delivery service in a squared area;
- Time and position of requests are not known in advance (customers position is random uniform in the area);
- Customers can select from any of the randomly uniformly distributed restaurants in the area present on the Platform to have their order prepared.
- When the order is issued, the order allocation process is responsible of assigning it only to one of the Robots of the fleet which will pick it up at restaurant's location.
- After going through loading operations in which the order is loaded on the robot, the autonomous unit can proceed towards the final customer who will be picking it up unloading it.
- The starting node is a central depot/area located in the middle of the area and where battery swapping takes place to guarantee persistent delivery.
- No network exists linking nodes: distances considered are Euclidean adjusted with a circuit Factor to approximate network distance in an urban environment.

Order cycle time (OCT) is a fundamental KPI for the industry. It can be defined as the total time required for delivery from the moment of order issuing. When delivering food, the quality of products might be influenced by the time elapsed after preparation required to bring the meal to the final destination. Long OCT for this reason might lead to poor food quality, hungry and unsatisfied customers.

Another important element for customers is *Traceability*, the possibility of following the order during its phases, either with an expected delivery time or through GPS (or both), so to guarantee synchronization in the delivery phase. In this industry orders are rarely planned and are often requiring the service provider to deliver them as soon as possible. With this aim, the objective of the order allocation has concentrated on the concept of **Lateness**. Lateness can be defined as the delay of arrival to the pickup point by the Robot with respect to the earliest pickup time. In case of homogenous fleets, Lateness is the main driver affecting the OCT and influenced by order allocation policy. The lower the lateness, whose minimum value is formally set to 0 since it would not be possible for robots to start delivery without the order to be ready, the sooner the customer is served. OCT can be then be defined as the sum of travel time $(tt_{o,c})$ between restaurant and customer, lateness, preparation (pt), loading(lt) and unloading (ut) times.

$$OCT = Lateness + pt + lt + ut + tt_{o,c}$$

In order to quantitatively express the concept of order traceability an indicator considering the percentage of time between the issuing of the order $t_o$and the beginning of a mission t_m, determined by the time of final assignment to the robot has been considered t_f. This indicator called Traceability Index (*TI*) can be reconducted to the average time with which customer can know the delivery time and follow robot's movement on the support App.

$$TI = 1 - \frac{(t_f - t_o)}{(t_m - t_o)}$$

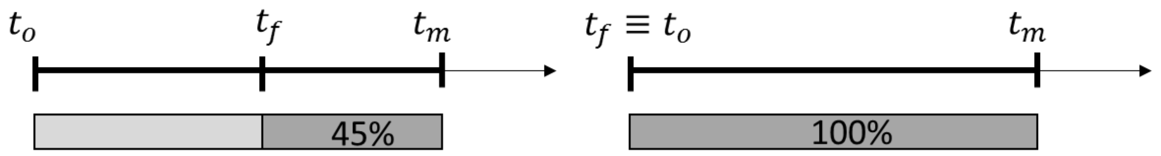


Figure 1 Graphical representation of Traceability index: in the first case the final assignment is between the ordering time and the start of the mission, while in the second case the final assignment coincides with the ordering time allowing the customers to follow the robot since the issuing of the order

1.4 Order Allocation

In order to effectively serve customers, two heuristic algorithms have been developed.

The first algorithm named Look Ahead Immediate Permanent Assignment (LAIPA) considers the future status of robots after deliveries assigns a just received order. Considering a customer ordering, the objective function allows to select the best Robot minimizing Lateness and battery consumption. Battery consumption is expressed as a function of the distance that the robot *r* travels to serve customer *c* and safely return to the depot called Worst Case Trip Distance (WCTD). In the expression two weighting factors are used to favour Lateness over battery consumption.

$$\min_r \; w_1 L_{r,c} + \; w_2 WCTD_{r,c}$$

$L_{r,c}$: $is\ the\ value\ of\ Lateness\ calculated\ for\ robot\ r\ and\ customer\ c$

$WCTD_{r,c}$: $is\ the\ worst\ case\ trip\ distance\ for\ robot\ r\ and\ customer\ c$

$$w_1\ and\ \ w_2\ are\ the\ weighting\ factors$$

In case two or more robots present the same Lateness value in serving a customer, the robot requiring the least energy is selected. When assigned, the customer is added as last in the list of orders of the robot (processed with a FIFO logic) and two important parameters called *available Time* and *Battery Level* are updated. Available time identifies the moment of end of the last assigned mission, while battery level identifies the status of the battery in terms of left charge (expressed in km). In case a new order arrives, this two information are used as inputs to evaluate each of the Robots selecting the best candidate for delivering it as soon as possible. The calculation of Lateness is then based on the time and position the end of last mission (or its current time and position in case no orders have been assigned) and the feasibility of immediate start without need for battery swap. This algorithm leads to high traceability from the customer since it is possible to immediately know the time and the robot responsible for delivery.

In systems when the degree of dynamicity is high, i.e most of the requests are not known in advance by the dispatcher, an immediate and permanent allocation might not be optimal. For this reason, a second algorithm which leverages on the possibility to reallocate not processed orders based on new information has been developed.

In the Single order Queue Permutation algorithm (SQP), with *n* robots in the system, the possibility of reallocation is limited to the first *n* non processed orders, which will be assigned based on an objective function considering the average Lateness and battery consumption of each allocation. The optimization is combinatorial considering all *n!* possible assignments of orders to robots, limiting the queue of orders to one for each robot. The combinatorial nature of the method is related to the evaluation of all possible permutations of an array (*a [ ]*) storing the information of the element in queue for each robot. For example, the i^{th} element of the array *a[i]* contains the index of the customer of the i^{th} Robots queue. The best permutation of the elements of the array, computed through Heap's algorithm[1],is evaluated averaging the results of the objective function used in case of LAIPA, and the minimum is selected. The fact the array has a fixed size equal to the number of robots in the systems

[1] It generates all possible permutations of *n* objects recursively swapping elements in the set.

leads to additional not required computations also in cases when no elements are in the queue of the robot.

The two methodologies have been compared in terms of Lateness and Traceability in small experiment involving from 1 to 7 robots, serving from 5 to 35 customers ordering with a triangular profile of demand in 2 hours. A random allocation policy, which assigns the order to a random robot has been used as base of comparison to prove the effectiveness of the two proposed algorithms (on average reduction of lateness of 48%). SQP algorithm has led to better results in terms of Lateness reduction (lower by 5.5% on average), but at the same time to worse results in traceability from customers. The strength of this methodology relies on the possibility to allocate orders based on progressive information, leveraging on an objective function including the average Lateness of (at most) *n* orders instead of one at a time as in the case of LAIPA. The possibility of reassignment on the other hand leads to dynamic changes in robots responsible for the delivery leading to lower traceability. For instance, in the experiment with 7 robots and 35 orders, customers on average know 16 minutes prior to the start of the mission the time of delivery compared to the 28 minutes of notice possible in case of maximum traceability. The computational complexity related to the combinatorial nature of the algorithm has shown an increase in computational time with the impossibility to study systems with more than 7 robots. For this reason, LAIPA algorithm has been chosen to study the performance of the system in larger experiments.

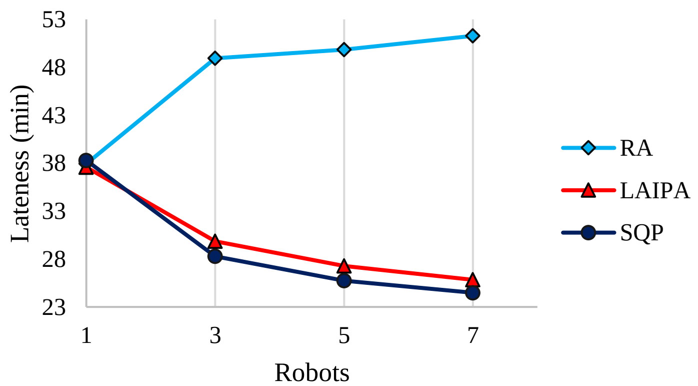


Figure 2: Different Allocation methods and their impact on Lateness

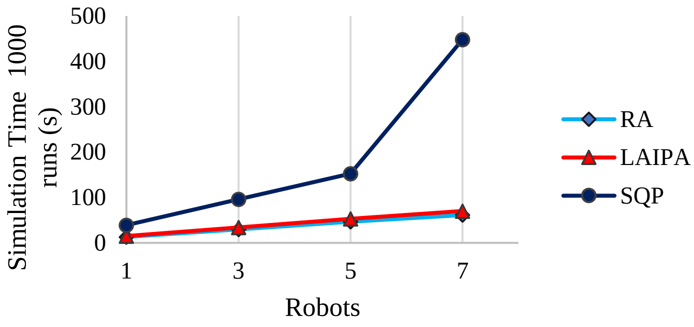


Figure 3:Different allocation methods and the required simulation time

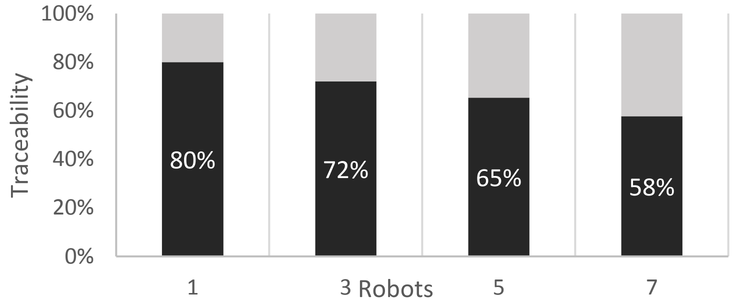


Figure 4 Traceability index for SQP

1.5 Simulation Results

The experiments are set from a starting scenario considering a central depot operating for 12 hours, 120 customers, 4 restaurants 10 robots travelling at speed of 3 km/h and a maximum range of 6km providing the service to an area of 1 km^2. A sensitivity analysis on each of these factors has been conducted to show their impact on the OCT and Lateness. Moreover, two order profile distributions have been included: a uniform (UNI) and a custom distribution made of two equal triangular distributions (DTRI) aimed at recreating the peaks during lunch and dinner time. In all the experiments conducted the uniform distribution allows the system to reach lower values of lateness and consequently of order cycle time. The starting results of average OCT and Lateness have been 35.23 and 2.63 minutes for DTRI distribution and 32.95 and 0.37 for UNI distribution. In the base cases considered 96.7% of the orders are delivered within 1 hour in case of DTRI and 99.85% for the case of UNI distribution.

Number of Restaurants/Points of Supply

In the case of DTRI distribution the increase of Points of supply in the area allows to reduce lateness reaching values of 2.14 minutes and 0.35 minutes in the case of 16 restaurants. The reduction is especially visible in the average OCT reduction during peak hours, while remains the same in off-peak time fig (6).

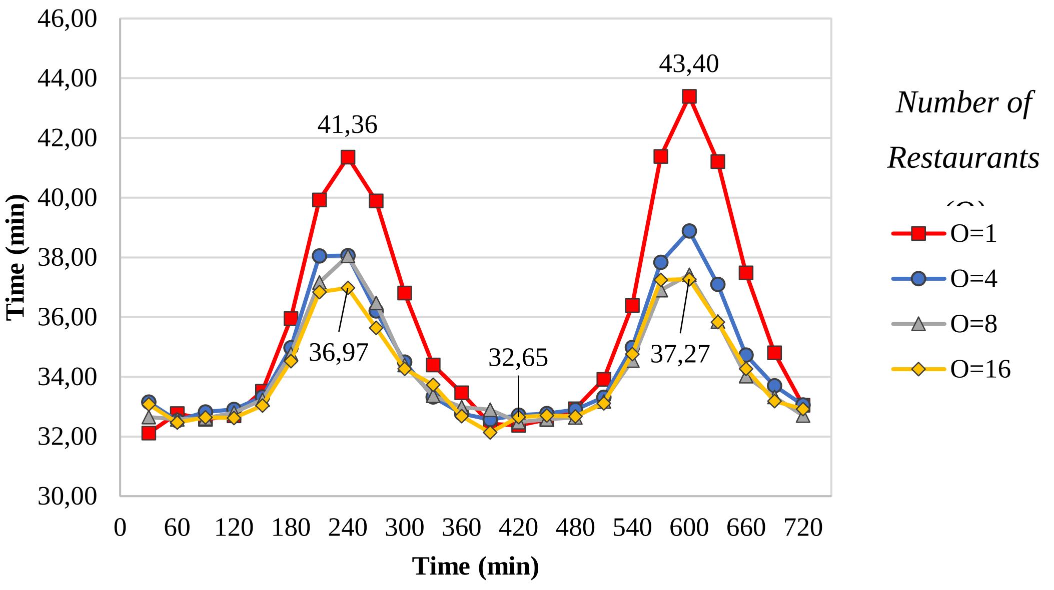


Figure 5 Average order cycle time as a function of the ordering hour in the case of DTRI distribution. Sensitivity analysis conducted on the number of restaurants (O.)

Number of Customers and Robots

The sensitivity analysis on Customers and Robots has demonstrated the consequences of unbalanced systems under the capacity perspective. With the progressive accumulation of requests, the average OCT increases dramatically in peak hours impacting especially on ordering windows immediately following (fig.8). The results show how the exponential growth of Lateness mainly affects DTRI distribution with average OCT ranging from 32 to 62 mins in the case of 80 and 200 customers, but severely influences the results also in the case of UNI distribution. In the latter considering the experiment with 200 customers, the average OCT increases during the ordering hours reaching a steady state around 42mins after the 200th minutes. At the same time, changing the number of robots in the system (in the analysis from 8 to 14), has shown similar trends to the sensitivity analysis conducted on customers. Considering the reduction to 8 robots operating in the area, the average OCT has been of 42 mins for DTRI and 33 mins for UNI, while the same results have been reached considering 14 robots with an average OCT of 32.89 mins, showing how with higher number of robots, the demand profile is not seen as differential. An additional experiment in which the ratio between customers and robots has been kept constant to show the advantages in higher densities of customers properly met by increases in the number of delivery robots.

Size of the Area

The area of operations is another fundamental parameter studied in the analysis. Areas from 0.5 to 1.5 km^2 have been considered. Larger areas could not be studied to guarantee the feasibility of all deliveries for which the robots autonomously return to the depot after completing the mission. Large areas affect not only the value of Lateness, which increases in both DTRI and UNI distribution, but also the travel time between restaurants and customers. The connected distance, which can be reconducted to the distance between two randomly selected points inside a square, increases leading to travel times ranging from 9.55 (A=0.5 km^2) to 16.62 (A=1.5 km^2) minutes highly impacting on the Order Cycle Time. The contribution of these increases makes the changes in lateness almost irrelevant for their weight on the overall result.

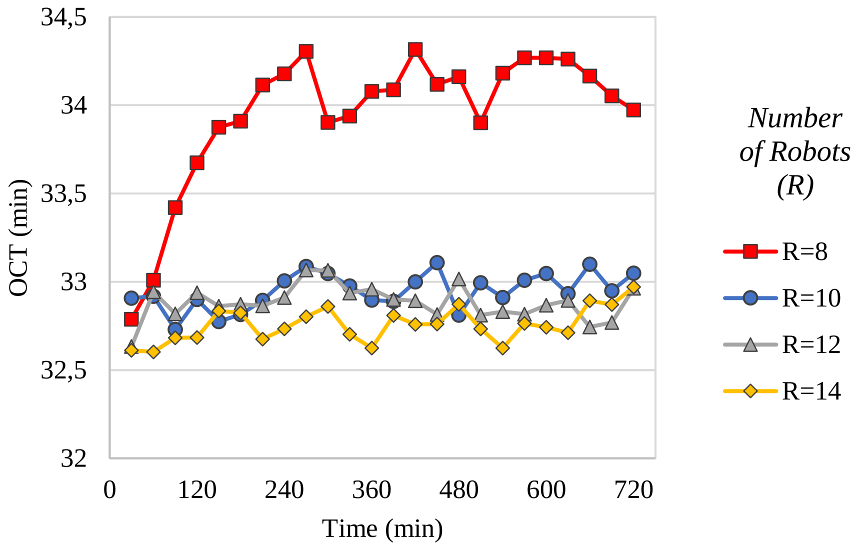


Figure 6 Average order cycle time as a function of the ordering hour in the case of UNI distribution. Sensitivity analysis conducted on the number of robots (R)

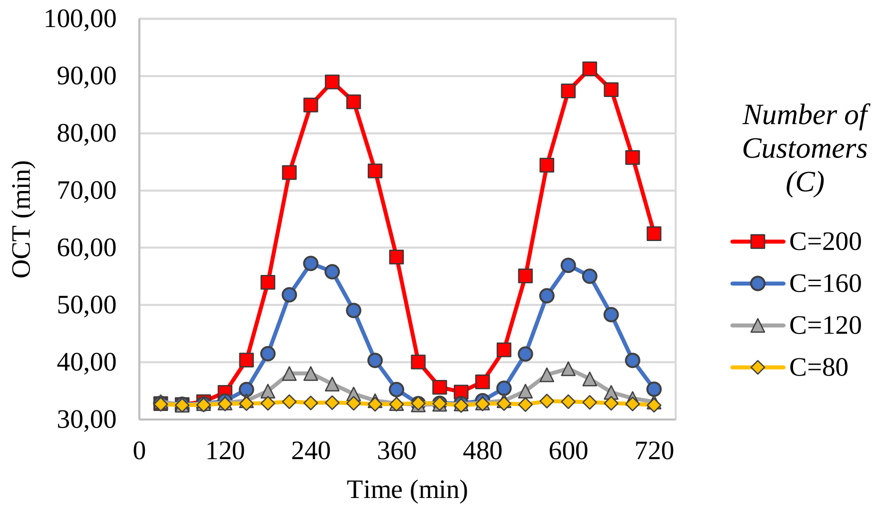


Figure 7Average OCT as a function of the ordering hour in the case od DTRI distribution. Sensitivity analysis conducted on the number of customers (C)

Range and Speed

Finally, the impact of range and speed is analyzed. Starting from the declared range of 6km (2 hours of functioning without recharge), the sensitivity analysis has shown how the reduction to range of 5km does not lead to drastically negative results in both DTRI and UNI distributions increasing to 3.55 and 0.55 respectively. Overall, in the experiments considered, the range parameter is not as influencing on OCT and Lateness as other parameters studied. Speed is one of the most important parameters analyzed. The values studied range from 2 to 6 km/h (formally set as the speed limit for autonomous robots). Higher speeds not only affect the reduction of lateness, but impact on the Travel time between restaurant and customers, progressively reducing the average order cycle time. The results show how with a speed of 2km/h only 54% of the orders are delivered before 1 hour while almost 100% of them can be delivered within 40 mins in the case of travelling speed of 6km/h. The effects of speed are seen in the simultaneous reduction OCT average and standard deviation.

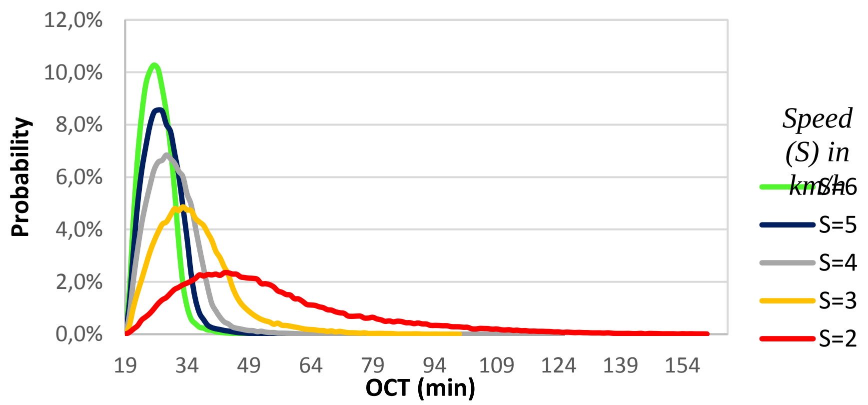


Figure 8 Effects of speed on the distribution of OCT

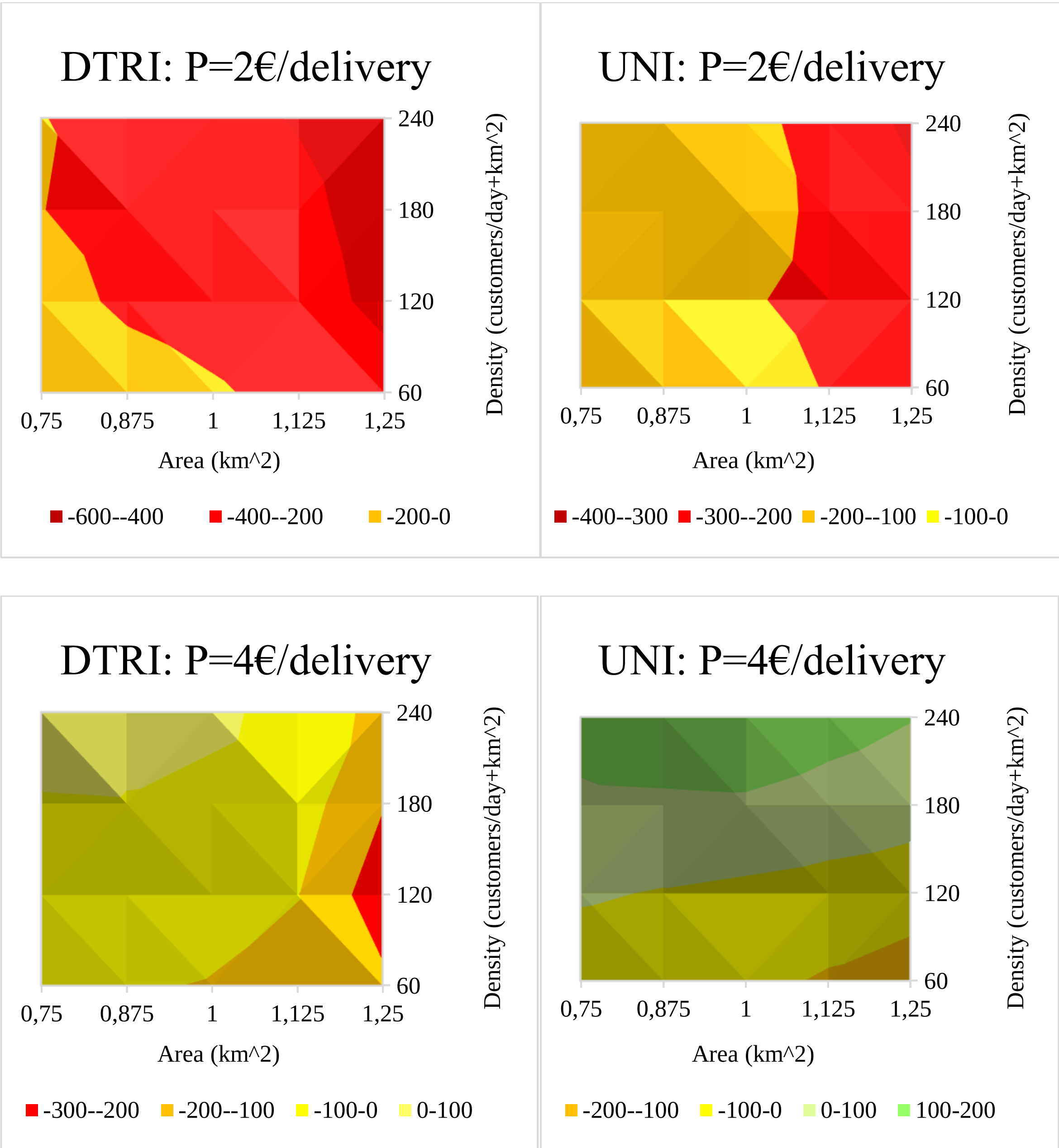
Economic Analysis

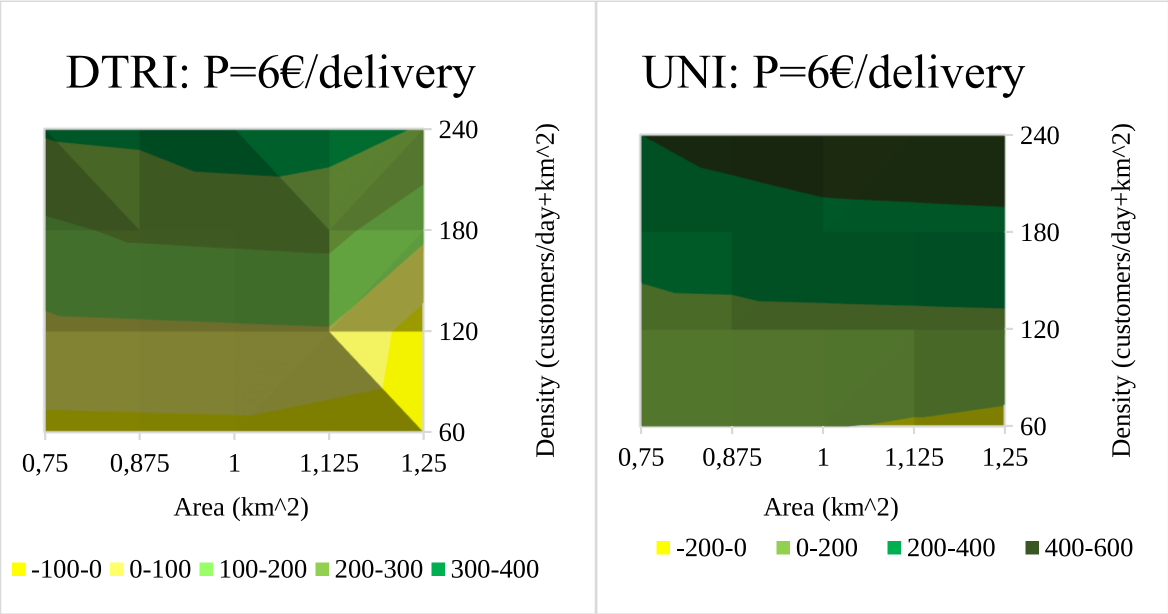
In order to study the economic return of the deployment of delivery robots, from the perspective of the owner of the technology and delivery service provider, an additional experiment is set. Four different levels of densities of orders/daykm^2 (60,120, 180, 240) and 5 different sizes of area in km^2 (0.75, 0.875, 1, 1.125, 1.25) are considered as input parameters. For each combination of density and area the minimum number of robots required to maintain an average OCT of 35 mins is studied. Larger areas on the one hand positively affect revenues due to the increase of customers but on the other negatively affect the number of robots required which grows more than linearly to compensate for the longer distances to travel. In the Economic Analysis the following have been supposed:

- Investment cost for the Robots 5500 €/unit;
- Operational costs including energy consumption and a fixed annual rent of 50,000€ for the depot/recharging area
- the personnel cost required to supervise on delivery operations (1 every 10 robots).
- Four different pricing levels (from 2 to 6€/delivery). This price can be flexibly interpreted as the sum of delivery cost payed by the customer and a percentage of order price got by the delivery service provider.
- Cost of capital equal to 8%.
- A two-year horizon of 365 working days/year to exclude from calculations additional maintenance costs related to vehicle usage

The number of Robots required to maintain an OCT of 35 mins is higher in the case of DTRI distribution. For instance, 30 units are needed in the case of a density of 240 order/daykm^2 and 1.25km^2 against 22 in the case of UNI distribution. The different prices studied range from 2 to 6 € per delivery. This price can be flexibly interpreted as the delivery return gained by the service provider as the sum of delivery fee payed by the customer and percentage of return based on the price of goods sold by the restaurants. 2 €/delivery do not make any of the scenarios studied profitable. The growth of price starts showing profitability in the case of small areas (0.75km^2) and high density (240 customers/daykm^2). For instance, for a price level of 3€, a density of 240 the areas smaller than 1.125 km^2 allow to generate profit in case of UNI distribution, with a maximum in 0.875km^2 (24.6 k€). DTRI distribution become profitable starting from 4€ per delivery in the case of smaller areas higher density. Higher prices enlarge the profitable scenarios, moving the maximum return towards large areas and high densities (maximum return for 6€, 240 customers/daykm^2 and Area of

$1.25 km^2$ $526k€$. Density of 60 customers day*km^2 is never profitable in cases of areas larger than 1 km^2 even with a price of 6 €/delivery for both distributions.





1.6 Discussion of Results

The sensitivity analysis has shown how each of the crucial parameters in the scenario considered affect the relevant performance of Lateness and OCT. The study on the different distributions has proven the negative effects generated by high peaks during the day which if not properly met lead to high order cycle times, resulting in a higher number of robots to maintain satisfying performance.

It has been shown how increasing the number of Points of Origin contributes not only from a commercial but also under the logistic operations perspective due to an increase of density reducing the average distance to pick up points. This suggests strong efforts should be made by companies to include many Shops/restaurants in the Platform possibly enlarging the current scope of the deliveries. Including pharmacies, supermarkets and more could both act on smoothing distribution of requests increasing pick up density and enlarging the commercial offer.

The study on robots and customers has shown the risks of unbalanced systems the benefits of increase of delivery points density. Many requests per day, if met by proper fleet dimensioning, positively affect revenues and operational performance.

The sensitivity analysis on Area and speed has confirmed the relevance of the application sites for the success of the implementation. The effects on order cycle time are not only related to the increase/decrease in lateness, but also on the average travel time between customer and restaurant. For the role the network of routes has on influencing travel time, selecting proper location for the deployment of the technology is the most crucial factor. Limited traffic and road crossings as well as flexibility in routes are great characteristics to look for when selecting the deployment Area. University campuses are perfect examples for the application due to the restricted area, high density of potential customers and traffic restricted routes. Great is and will be the role of regulations and infrastructures which act as moderating or enhancing factors on speed to witness a much wider application of the technology.

The economic analysis has shown potential reference values for profitably deploying delivery robots. Improvements in economic returns will be reached when and if lower investment cost will be reached thanks to economies of scale related to robots' production, and regulations might enable truly autonomous delivery removing the highly impacting cost of personnel. Finally, considering the profile of demand and the reduced advantages of persistent delivery which might lead to additional fixed costs, opportunistic on-site delivery might be a viable option technology.

The main limitations of the present work mainly concern the network related elements of the model, the technological factors in modelling the robot and the input data for the profit analysis. Future research might start studying larger areas with higher number of depots/recharging areas to evaluate the possible advantages both under the operational and economic perspective. Starting from this study, a comparison with alternative solutions such as drones and riders might provide useful insights on the validity of the technology as well as including mixed fleet modelling to investigate their potential utilization.

2. Introduction

E-commerce retail has seen a continuous growth in the recent years. In countries such as USA, China and UK the percentage of goods purchased online has grown rapidly generating success for companies such as Amazon, JD.com and TaoBao. Among the different key success factors which led these companies to success, operational excellence in Logistics has played a fundamental role to reach effective and efficient service (Cho, Ozment, & Sink, 2008). On the other hand, Logistics has been the bottleneck of e-commerce growth with related costs which can reach up to 40% of the price payed by customers (Huang, Chen, & Pan, 2015). Due to the complexity of the Logistics activities many are the potential inefficiencies which can be generated: slow and/or wrong deliveries, lost packages, damaged goods and incorrect packing are some examples. Among all, last mile delivery, i.e the last leg of transportation to the final customer is characterized not only by operational complexity but it also inserts in a context where a growing emerging awareness of a need of improvement of urban mobility is forcing companies to think to smarter and greener ways to complete deliveries (Perboli & Mariangela, 2019), (Guerrazi, 2020).

One possible way to solve these complexities is through the implementation of automated systems, technologies by which a process or procedure operates under its own self-direction with minimum human assistance (Groover, 2010), (Nils Boysen, 2018), (Moon, 2019) . At the same the complexity embedded with the tasks to accomplish is high. The environment automation would be introduced in is different from the traditional in-door applications, where the possible interactions with interfering agents are limited and under control. During delivery the technology should be capable of autonomously moving around the streets/pavements, avoiding obstacles such as pedestrians and recognizing traffic lights and signs (Skeete, 2018).

Thanks to the recent improvements in the field of AI, some solutions for last mile deliveries have been developed and are being tested. These include Autonomous vehicles, UAV (more commonly called drones) and the most recent autonomous robots.

Delivery Robots are outdoor versions of Automated guided vehicles (AGVs) (Shihua Li, 2018). Currently some companies are experimenting this technology to understand the technological hurdles, potential applications and benefits (Xia & Yang, 2018). For instance, Amazon has recently announced its version of fully electric six wheeled delivery robot in charge of completing the last mile of transportation delivering packages to the final customer. In January 2019, these devices have begun delivering packages to customers in a neighbourhood in Snohomish County, Washington USA (AmazonScout, 2019). These robots are being experimented also in other industries: it is the example of Starship technology a Estonia-based company testing their technology since 2016 in university campuses and neighbourhoods with the aim of delivering food and grocery to customers ordering through their platform (StarshipTechnologies, s.d.). The vehicle presents the following characteristics

- dimensions 678 (L) x 569 (W) x 1248 (H) mm
- weight without freight of 23 kg.
- Battery lasts for 2 hours, the equivalent of 6 km of driving
- The maximum speed which can be reached is 6 km/h with an Average effective service speed of about 3 km/h
- the cargo space is limited in dimensions (402 x 344 x 330 mm) and weight: 10 kg.
- 9 cameras (3 front, 4 sides, 2 rear) together with 8 ultrasonic obstacle detectors (front) and radar enable obstacle recognition and path detection for the unit safely move around avoiding collisions.
- The Robot proceeds around thanaks to brushless electric motors powered by 8000mAh Lithium Polymer battery of 18.5V.
- The battery requires 45min to fully charge absorbing up to 250W.
- The torque is transferred to 6 driving wheels symmetrically disposed in lines of three at the sides of the vehicle (SwissPost, 2019).

Figure 9: Starship Delivery Robot

Various question marks are raised concerning the benefits of the technology from economical to operational perspective. Therefore, the objective of the thesis is to investigate its potentialities in a scenario where pickup and delivery occur in a restricted area served. Together with a deep study of the existing literature, a discussion with a manager of Deliveroo been conducted, to understand and validate the fundamental hypothesis and parameters of the model.

In section 1 the literature review on the topic of automation in last mile delivery is presented describing the methodology of research and of systematization.

3. Literature Review

3.1 Scope of analysis

In the review, the scientific literature relating to autonomous solutions and their applications in last Mile delivery is examined assuming the joint perspective of the logistic management researchers and practitioners. For the purpose of the review, only parcel/product carrier vehicles have been included excluding ICT-only applications, and people transportation systems from the research. The scope is concurrently including the conceptual theorization, technological development, performance analysis and industry of application of the proposed solutions. Considering last mile delivery, all automation discussed in other logistics processes and activities is excluded (for instance Factory Logistics, Primary transportation, Sorting).

3.2 Selection Process

A search by keyword has been conducted through library databases (e.g Scopus, e.g Science Direct, e.g Google Scholar) using keywords and strings that have been sought in both in the Title, abstract and the article main body (e.g "Last Mile Delivery and Automation", e.g "Last Mile delivery and Robots", e.g "Autonomous Delivery"). This method led to analyse the Major Logistics and transportation, Industrial engineering, and Operations Research Journals as well as Conference Papers on Autonomous and Intelligent solutions and Logistics (*e.g Journal of Advanced Transportation, Transportation Research part C, European Transport research Review, Journal of Industrial Engineering and Management, Computers and Industrial Engineering, European Journal of Operational Research, Computers and Operations research, International Conference on Intelligent Transport System, international Conference on Service Operations and Logistics etc.*). From the initial search, only the articles dealing with Autonomous solutions in last Mile delivery have been analysed excluding articles which involved military or disaster relief application of technologies for delivery of goods, concentrating on traditional goods distribution. From this base, only those focusing on vehicle characteristics, applications, system optimization have been kept excluding from the analysis the articles that included them as collateral topics. This sub-set of 24 articles published in the last 5 years has been examined in depth and used for the systematic Literature Review. In general, all the articles discussing the application of automated solutions for freight/order delivery have been considered adding to the more common system optimization articles, some discussing the technology under the hardware perspective, and others with a more general view over the application or development of the technologies.

3.3 Review Method

The literature has been systematized following what has been done by Perego Perotti and Mangiaracina ((Perego, Perotti, & Mangiaracina, 2011). After analysing all the articles found dealing with Automation in the Area of Last mile delivery, they have been clustered around five main axes.

1. Research Methodology
2. Type of carrier considered;
3. Industry of Application;
4. Environment of Application; and
5. Impact or focus of the application.

Within these topics the most common and relevant topics have been highlighted to understand and visualize the existing gaps in the scientific literature. For the sake of readability, the first table reports article general information, while in the second the most important information and the axis of classification.

3.3.1 Research Methodology

Scientific literature has addressed the topic of autonomous solutions for Last Mile delivery under three main perspectives: Conceptual, technical, and system performance analysis/optimization. These three main aspects show the different streams of active research existing on automation in last mile delivery: from the conceptualization and suggestion of a new type of delivery method, to the study of the technological requirements and finally the evaluation of the operational results.

In conceptual papers the aim is to describe a technology and its potential applications highlighting its strengths or possible limiting factors (Yoo & Chankov, 2018). Li Tan and Li analyse automated guided Vehicles and their applications in Logistics (from warehousing to Distribution) showing the prospective of growth in the Chinese market (Li, Yan, & Li, 2018). In (Hoffmann & Prause, 2018) the case of Starship Technologies has been used as case study to investigate the regulatory barriers for Robots in last mile delivery. The authors analysed where the current application conflicts with these regulations and advises on what should be done to prevent violations. For instance, relating the Delivery robot to an electric wheelchair, they underline some existing constraints in vehicle design, concerning its mass and speed. Technical papers deal with technology prototypes focusing on the hardware and/or software characteristics of the discussed technology. In (Brunner, Szebedy, Tanner, & Watternhofer, 2019) the authors address the problem of last mile with a drone capable of flying autonomously towards the drop-off location to complete the delivery. The researchers design a suite of software including autonomous control Logic, trajectory planner mode, visual marker tracker, visual odometry algorithm and simulation environment. The prototype evaluation has been conducted through empirical experiments validating the effectiveness of the module in obstacles recognition and target identification and highlighting the risks connected to GPS-based flying as well as the computational power required.

The majority of scientific literature concentrates on the optimization autonomous delivery systems, considering the optimal routing and/or scheduling of vehicles (Kim & Moon, 2019), (Ham, 2018), (Yu, 2019) or the network design (Shavarani, Nejad, Rismanchian, & Izbirak, 2018). For instance, Yu tackles the scheduling problem of Autonomous Vehicles in Logistic Systems (AVLS): the characterization of the problem adds to the traditional VRP constraints (order allocation and vehicle routing), battery dynamics with the presence of recharging stations and renewable Distributed Generators. Given the computational complexity of the Formulated Mixed integer linear programming model, a two-stage algorithm is proposed separating order allocation and battery charging from vehicle routing. Experimental results conducted through simulation both in dynamic or static scenarios show the impact of instance size on the optimality and computational time required. Murray and Chu propose the Flying sideckick Traveling salesman problem (FSTSP) and parallel drone Scheduling Problem (PDSTSP) for drone assisted parcel delivery. The combined used of truck and drones is analysed under the mathematical perspective. Delivery drones are used to support trucks for last mile delivery and are launched from the truck to serve part of the customers in case of destinations far from the depot in the FSTSP. On the other hand, the parallel scheduling of deliveries of the two vehicles is considered in case of customers close to the distribution centre. The two alternatives are compared in terms of computational time and operational results (C. Murray & . Chu, 2015).

3.3.2 Type of freight carrier

In the scientific literature a variety of automated solution are explored to assess their performance and most optimal scenarios of application. The typology of system studied highly influences the optimal working conditions. To the knowledge of the author three main vehicles/freight carriers have been explored so far by researchers: Autonomous Vehicles (AV), UAVs or more commonly called Drones, AGV or Delivery Robots.

Autonomous vehicles are vehicles “capable of driving without human intervention, sensing capability and full-fledged controllability” (Yu, 2019). Their importance for transportation both of people and freight is expected to grow and to play a key role in smart cities (Beirigo, Schulte, & Negenborn, 2018) . As an example, (Zhang, Shi, Chen, & Li, 2017) formulate the Automated Vehicle Routing

Problem with Time Windows. As sustained by the authors in the initial stage of introduction AV will be subject to route opening and limitations to allow a safe integration with traditional mobility. In the study, additional constraints modelling route availability are added to the traditional VRP.

As claimed in (Dorling, Heinrichs, Messier, & Magierowsky) UAV or drones are an innovative solution to relieve from part of the problems connected with traditional delivery. In their research the relation between drone flight autonomy and battery weight is analysed and implemented first in mixed integer programming (MIP) model and then in Simulated Annealing. The study underlines the relevance of battery weight and drone's reutilization on the results. Similarly, Songa and others (Songa, Parkb, & Kimc, 2018) evaluate the possibility of persistent delivery with UAVs leveraging on multiple recharging stations. Both exact solution through mixed integer linear programming and heuristic algorithm are provided.

In general, smaller vehicles such as drones are characterized by a slower travelling speed, limited range of operations and limitations in terms of number and weight of the parcels to deliver compared to a traditional truck delivery (Kim & Moon, 2019). To make up for the negative aspects of UAV technology scientific literature the combination of drones and traditional trucks/urban mobility has been proposed (C. Murray & . Chu, 2015), (Yoo & Chankov, 2018), (Ham, 2018). The idea of these studies is to take advantage of traditional mobility to cover longer distances and opportunistically utilize UAVs for part of the deliveries of the last mile. Ham examines the combined delivery with trucks and drones in a standalone and multi depot scenarios where pickup and deliveries requests can be processed by both vehicles. Trucks and drones are used in tandem to fulfil requests, with the objective of minimizing the time at which both vehicles return to the depot. It is shown how a vehicle that travels near the boundary of the coverage area of a depot might be more effective to serve customers that belong to the neighbouring depot and how the truck usage increases with an increase of jobs.

AGV are another ground alternative to solve last mile delivery complexity. These autonomous Robots are capable of safely moving around serving customers proceeding on pavements and zebra crossings. Boysen, Schwerdfeger, and Weidinger evaluate the newly designed delivery alternative in a scenario where they are launched from truck to serve final the customer. In the article the impact of robot speed, truck capacity, and depot network density on late deliveries is studied through mathematical formulation, heuristic algorithm and simulation study (Boysen, Schwerdfeger, & Weidinger, 2018).

No.	Authors (year)	Journal	Title	Country	Type of Journal: Journal	Type of Journal: Conference
1	Haque et al. (2014)	*International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*	Autonomous Quadcopter for Product Home Delivery	Bangladesh		•
2	Murray and Chu (2015)	*Transportation Research Part C*	The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery	USA	•	
3	Ferrandez et al. (2016)	*Journal of Industrial Engineering and Management*	Optimization of a Truck-drone in Tandem Delivery Network Using K-means and Genetic Algorithm	USA	•	
4	Zhang et al. (2017)	*Journal of Advanced Transportation*	Analysis of an automated vehicle Routing Problem in Logistics considering path interruption	China	•	
5	Shavarani et al. (2017)	*The International Journal of Advanced Manufacturing Technology*	Application of hierarchical facility location problem for optimization of a drone delivery system: a case study of Amazon prime air in the city of San Francisco	Cyprus/ South Korea	•	
6	Kevin Dorling et al. (2017)	*IEEE Transactions on Systems, Man, and Cybernetics Systems*	Vehicle Routing Problem for Drone Delivery	Canada		•
7	Songa et al. (2018)	*Computers and Industrial Engineering*	Persistent UAV Delivery Logistics: MILP formulation and efficient Heuristic	Usa/ Republic of Korea	•	
8	Shihua Li et al. (2018)	*Proceedings of the 2018 IEEE International Conference on Service Operations and Logistics, and Informatics*	Automated Guided Vehicle: the Direction of Intelligent logistics	China		•
9	Boysen et al. (2018)	*European Journal of Operational Research*	Scheduling last-mile deliveries with Truck-based Autonomous Robots	Germany	•	
10	Ranieri et al. (2018)	*Sustainability*	A review of Last Mile Logistics Innovations in an Externalities Cost Reduction Vision	Italy	•	

No.	Title	Industry			Environment		Research Methodology			Vehicle considered			Main Focus		
		General E-commerce	Food Delivery	Others/ not Specified	Urban	Rural	Conceptua	Technology	Optimization	AV	UAV	DR	Economic	Time	Feasibility
1	Autonomous Quadcopter for Product Home Delivery	•			•			•			•				
2	The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery	•			•				•		•			•	
3	Optimization of a Truck-drone in Tandem Delivery Network Using K-means and Genetic Algorithm			•					•		•				
4	Analysis of an automated vehicle Routing Problem in Logistics considering path interruption			•	•				•	•			•		
5	Application of hierarchical facility location problem for optimization of a drone delivery system: a case study of Amazon prime air in the city of San Francisco	•			•				•		•		•		
6	Vehicle Routing Problem for Drone Delivery			•					•		•		•		
7	Persistent UAV Delivery Logistics: MILP formulation and efficient Heuristic			•		•			•		•				
8	Automated Guided Vehicle: the Direction of Intelligent logistics			•			•					•			
9	Scheduling last-mile deliveries with Truck-based Autonomous Robots	•			•				•			•		•	
10	A review of Last Mile Logistics Innovations in an Externalities Cost Reduction Vision			•			•			•	•				

No.	Authors (year)	Journal	Title	Country	Type of Journal: Journal	Type of Journal: Conference
11	Andy Ham (2018)	*Transportation Research part C*	Integrated scheduling of m-truck, m-drone, and m-depot constrained by time-window, drop-pickup, and m-visit using constraint programming	USA	•	
12	Buchegger et al. (2018)	*21st International Conference on Intelligent Transportation Systems (ITSC)*	An Autonomous vehicle for Parcel delivery in Urban Areas	USA		•
13	Beirigo et al. (2018)	*FAC PapersOnLine*	Inttegrating people and freight Transportation using shared autonomous vehicles with compartments	Nederlands		•
14	Hoffmann and Prause (2018)	*Machines*	On the Regulatory Framework for Last-Mile Delivery Robots	Estonia	•	
15	H. D. Yoo and S. M. Chankov (2018)	*Proceedings of the 2018 IEEE*	Drone-delivery Using Autonomous Mobility: An Innovative Approach to Future Last-mile Delivery Problems	Germany		•
16	Haa et al. (2018)	*Transportation Research Part C*	On the min-cost Traveling Salesman Problem with Drone	Vietnam	•	
17	Kim and Moon (2019)	*IEEE Transactions On Systems, Man and Cybernetics Systems*	Traveling Salesman Problem with a Drone Station	Republic of Korea		•
18	James J. Q. Yu (2019)	*IEEE Transactions on Intelligent Transportaation Systems*	Two stage request scheduling for autonomous vehicles systmes	Hong kong		•
19	Aurambout et al (2019)	*European Transport Research Review*	Last Mile delivery by drones: an estimation of the Viable Market potential and access to citizens across European Cities	Italy	•	
20	Ulmer and Streng (2019)	*Computers and Operations Research*	Same Day delivery with pick up stations and autonomous vehicles	Germany	•	
21	Gino Brunner et al. (2019)	*International Conference on Unmanned Aircraft Systems (ICUAS)*	The Urban Last Mile Problem: Autonomous Drone Delivery to Your Balcony	Switzerland		•

No.	Title	Industry			Environment		Research Methodology			Vehicle considered			Main Focus		
		General E-commerce	Food Delivery	Others/ not Specified	Urban	Rural	Conceptua	Technology	Optimization	AV	UAV	DR	Economic	Time	Feasibility
11	Integrated scheduling of m-truck, m-drone, and m-depot constrained by time-window, drop-pickup, and m-visit using constraint programming	•							•		•			•	
12	An Autonomous vehicle for Parcel delivery in Urban Areas	•			•			•				•			
13	Inttegrating people and freight Transportation using shared autonomous vehicles with compartments			•	•				•	•			•		
14	On the Regulatory Framework for Last-Mile Delivery Robots	•			•		•					•			•
15	Drone-delivery Using Autonomous Mobility: An Innovative Approach to Future Last-mile Delivery Problems			•	•		•			•	•				
16	On the min-cost Traveling Salesman Problem with Drone	•							•		•		•		
17	Traveling Salesman Problem with a Drone Station	•			•				•		•			•	
18	Two stage request scheduling for autonomous vehicles systmes			•	•				•	•					
19	Last Mile delivery by drones: an estimation of the Viable Market potential and access to citizens across European Cities	•			•	•	•		•		•		•		
20	Same Day delivery with pick up stations and autonomous vehicles	•			•				•	•				•	
21	The Urban Last Mile Problem: Autonomous Drone Delivery to Your Balcony			•	•			•			•				

No.	Authors (year)	Journal	Title	Country	Type of Journal	
					Journal	Conference
22	Yanchao Liu (2019)	*Computers and Operations Research*	An optimization-driven dynamic vehicle routing algorithm for on-demand meal delivery using drones	USA	•	
23	Jinsoo Hwanga et al. (2019)	*International Journal of Hospitality Management*	Perceived Innovation of Perceived innovativeness of drone food delivery services and its impacts on attitude and behavioral intentions: The moderating role of gender and age	South Korea/ Hong Kong	•	
24	S. Watkins et al. (2020)	*Building and Environment*	Ten questions concerning the use of drones in urban environments	Australia	•	

No.	Title	Industry			Environment		Research Methodology			Vehicle considered			Main Focus		
		General E-commerce	Food Delivery	Others/ not Specified	Urban	Rural	Conceptua	Technology	Optimization	AV	UAV	DR	Economic	Time	Feasibility
22	An optimization-driven dynamic vehicle routing algorithm for on-demand meal delivery using drones		•		•				•		•			•	
23	Perceived Innovation of Perceived innovativeness of drone food delivery services and its impacts on attitude and behavioral intentions: The moderating role of gender and age		•				•				•		•		
24	Ten questions concerning the use of drones in urban environments			•	•		•				•				•

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3.3.3 Industry of Application

Every industry presents relevant characteristics which make some applications more suitable than others. In the scientific literature often parcel delivery in the general e-commerce industry is considered as in (Boysen, Schwerdfeger, & Weidinger, 2018) (C. Murray & . Chu, 2015) (Dorling, Heinrichs, Messier, & Magierowsky) (Ham, 2018) (Hoffmann & Prause, 2018) (Kim & Moon, 2019). For instance, the case of Amazon prime Air is used for the network design including distribution depots and recharging stations (Shavarani, Nejad, Rismanchian, & Izbirak, 2018). (Ulmer & Streng, 2019) Ulmer and Streng investigate the use of autonomous vehicles for same day delivery to pick-up stations. Dynamic dispatching policies are benchmarked showing the trade-off between fast delivery dispatches (faster arrival to the customer, faster arrival to the depot but less consolidation) slow dispatches (later arrival to the current customer, higher consolidation) and a proposed method. The model of (Yu, 2019) on the other hand considers the characteristics of a network of the retail industry with a central Distribution Center and limited points of delivery represented by supermarkets. Despite being expressively related to a Supermarket chain the model can be extended to any type of network with similar characteristics. Growing importance is being received by the food delivery industry. Liu studies the utilization of UAVs in the scenario of on demand meal delivery (Liu, 2019). In the article together with drones with various payload capacity the distinction between hot order and cold orders are characterizing elements of the industry added in the formulation of the dynamic VRP. In (Hwanga, Leeb, & Kimc, 2019) the impact of drone delivery in the food industry under its marketing perspective. The study reveals how the perceived innovativeness, the word of mouth effect and use intentions are moderated by the effect of gender and age of the customers, thus highlighting the relevance of concentrating on the right market segment to maximize companies' profit.

3.3.4 Environment of Application

Another relevant element defining the boundaries of application of automated solutions in last mile delivery is the area served. Considering e-commerce, application of these technologies might enable Rural areas to be served more efficiently, but on the other hand high density and limited ranges of operations seem to be preferred scenarios for the battery constraints.

In many of the articles analysed the context of application of the technology is urban. For instance, specific networks of the city of San Francisco, Cologne are used to analyse the effectiveness of the proposed solution (Shavarani, Nejad, Rismanchian, & Izbirak, 2018) (Yu, 2019). In the design of their prototype the authors explicitly refer to the application in a city centre. (Brunner, Szebedy, Tanner, & Watternhofer, 2019). During on field experiments the characteristics of the test environment, create difficulties for the successful completion of the tasks assigned due to the collision of the vehicles with the surrounding buildings. In the test conducted on the prototype of vehicle developed for urban delivery the Buchegger and colleagues selected a university campus and the city center of Graz (Austria). These areas were selected because of the limited accessibility for other vehicles and legal reasons connected to semi-autonomous driving in Austria (Buchegger, Lassnig, Loigge, M¨uhlbacher, & Steinbauer, 2018). The numerous operational and technical challenges which are inhibiting the use of drones in Urban environments are addressed in (Burry, et al., 2020). The authors underline that the variety throughout the globe of urban environments is wide ranging from isolated single buildings to high-rise buildings with a high population density. In mature cities the obstacles include vegetation, fences, cars, power and communication poles and others. In (C. Murray & . Chu, 2015) the authors point out how the distribution centers supporting truck-drone combined delivery will be located near densely populated urban areas to benefit from economies of scale, despite the characteristics of building create the difficulties in receiving deliveries via UAV.

Rural or remote areas are often costly and hard to reach for deliveries. In (Aurambout, Gkoumas, & Ciuffo, 2019) the authors aim at evaluating the potential returns of installation of drones beehives depot in UK and other European Countries based on customers density and potential returns. The area available for the installation considered are to commercial/industrial and abandoned commercial/industrial sites (often located near major roads). Finally, Songa et al. (Songa, Parkb, & Kimc, 2018) test the MILP developed with an island-Area where recharging stations are located to guarantee persistent delivery service.

3.3.5 Focus of the application

The introduction of autonomous intelligent transportation systems offers a wide variety of topics of discussion which are reflected on the focus of the study. The relevance of time and economic factors in last mile delivery is shown by the focus of the objective functions on related dimensions.

In the optimization articles the objective functions span from considering economical aspects such as cost and profit to time of completion of deliveries. The studies of Boysen et al., Liu, Ulmer and Streng put time and customers at the centre of the optimization (Boysen, Schwerdfeger, & Weidinger, 2018) (Liu, 2019), (Ulmer & Streng, 2019). The first aims at minimizing the weighted sum of late deliveries, i.e the orders which are delivered with a delay compared to announced delivery date; the second aims at serving the customers with meal delivery as soon as possible minimizing the value of Lateness, identified as the difference between drone arrival time at pickup point and the earliest pick up time. Ulmer and Streng’s model aims at minimizing the expected sum of delivery times, which is directly connected to the average serving time for all customers. In drone and Truck combined delivery the focus of the objective function is minimizing the time to serve all customers by either the vehicles both (Ham, 2018) and (C. Murray & . Chu, 2015) (Kim & Moon, 2019). The work of Ham expands what studied by Murray and Chu considering multiple depot and pickup option for drones, while the work of Kim and Moon evaluates a different type of scenario where the drone station is not located in a distribution centre but needs to be visited and activated to allow the utilization of drones.

Most of the literature concentrates on economic aspects such as the cost of the system, operational costs or profit. Cost function are often introducing real costs such as operative costs and fictional costs related to the waiting time of customers. Zhang et al. consider the minimization of the sum of fixed, transport and penalty costs for an area served by AV. Penalty costs are defined in accordance with the concept of hybrid time windows: if the vehicle arrives before the earliest time the penalty cost and waiting time have a linear relationship, if the robot arrives after the latest time the penalty cost is set as infinite (Zhang, Shi, Chen, & Li, 2017). Haa et al. consider drone and truck operating costs as well as the waiting costs at customer location (Haa, Devillea, Phamb, & Hàc, 2018).

Finally, in (Shavarani, Nejad, Rismanchian, & Izbirak, 2018) the total cost of a system for supporting drone delivery is studied including launching and recharging stations opening, drones acquisition and usage.

Profit is another very important aspect considered in some of the articles analysed. Breno and others maximize the profit including the delivery revenue and operating cost of the autonomous vehicle (Breno, Schulte, & Negenborn, 2018). Also non optimization studies such as (Aurambout, Gkoumas, & Ciuffo, 2019) consider the return of installation of drone beehives across Europe. The cost included the warehouse installation, operative costs, and drone costs both for the working and backup fleets while revenues are calculated from reachable population and rate of use of the drone delivery service.

Another part of the scientific literature concentrates on feasibility, constraints and limitations of the proposed/ analysed solutions. Yoo and Chankov evaluate strengths and weaknesses of drone delivery combined with autonomous mobility through a SWOT matrix created and validated through interviews and discussions with experts in the field of automation.

Among the limiting factors of the proposed solution technical feasibility and legal issues make the proposed one an alternative method for delivery in high-demand seasons, instead of a major delivery method (Yoo & Chankov, 2018). Hoffman and Prause understand the legal restrictions currently existing for delivery robots(Hoffmann & Prause, 2018) while Burry et al. (Burry, et al., 2020) understand the hurdles in drone utilization in urban environment addressing legal, battery, sound and other issues.

3.4 Literature Gaps

The current body of literature concerning autonomous solutions in last mile delivery offers a variety of possible streams of future research which have not been addressed. Despite the fact Agv technology in industrial environments has started with FMS more than 30 years ago (Li, Yan, & Li, 2018) the literature about these vehicles in last mile delivery is considerably lower compared to the more modern Drones. There are several articles addressing drone and truck-drone combined delivery both under operational perspective and under the network design perspective (C. Murray & . Chu, 2015) (Dorling, Heinrichs, Messier, & Magierowsky) (Ham, 2018). On the other hand, only few studies deal with delivery Robots (or AGV) both under operational, network and prototype design perspectives.

In the quantitative analysis of the systems mathematical modelling is the preferred methodology. Given the computational complexity of the VRP formulations often heuristic algorithms are provided to reach good solutions in reasonable times. Few papers introduce a simulation study to furtherly understand the system analysed. No extensive experiments are dedicated to understanding the changes in performance for high instances of the modelled systems which often consider few delivery drones/robots.

Research which aims at at evaluating examining a system often selects one between economical and service level dimensions. Scientific literature has not addressed the relation between service level and economic impact on costs and/or profits of the systems studied. With bigger areas to serve a higher number of customers can be reached thus leading to higher revenues, at the same leading to longer travelling time which impact on the number of vehicles and costs. As an example for drone technology, (Aurambout, Gkoumas, & Ciuffo, 2019) evaluates the return of drone beehives with simplistic hypothesis concerning number of drones required possible radius to serve and related performance to evaluate potential locations for the distribution depot.

The industry considered is often the general e-commerce one. Amazon case is explicitly taken as a case study with its service of prime air in (Aurambout, Gkoumas, & Ciuffo, 2019) (Shavarani, Nejad, Rismanchian, & Izbirak, 2018). The amount of work addressing the application in other industries is limited. To the knowledge of the author only two articles investigate the potential of such technologies in the food delivery industry (Hwanga, Leeb, & Kimc, 2019) (Liu, 2019).

3.5 Research questions

To fill the existing gap in the scientific literature on delivery Robots the thesis aims at studying the application of the new technology thoroughly highlighting how modifications in design parameters and exogenous factors affect order cycle time and profit. Since the technology utilization for the general e-commerce industry has already been studied by Boysen and colleagues (Boysen, Schwerdfeger, & Weidinger, 2018), the work aims at doing the same for the food industry, parallelly to what done by Liu (Liu, 2019) in which drone technology's application has already been studied. The main differences between AGVs and drones relate to the battery utilization, available routes and working speeds. The thesis aims at extending the current knowledge on the application of these systems by understanding which are and how do the most relevant factors affect the Order Cycle Time.

RQ1: Which are the most relevant factors and how do they impact on Order Cycle Time?

RQ2: What are the most meaningful conditions of deployment for the technology and what is the potential economic return.

3.6 Additional review

To understand the major features and criticalities of the food delivery industry additional articles have been searched following the previously listed steps using as key words "food delivery" "riders and food delivery", "crowdsourcing of deliveries" etc. To the knowledge of the author the articles focusing on this specific industry are few (Yildiza & Savelsberghb, 2019). For example, combining the search of AGV and food delivery, articles dealing with the deployment of robots inside restaurants and hospitals have been found (Jeon, Lee, & Kim, 2017). For example, Jeon and colleagues discuss task allocation for AGV in a hospital where food, drugs and other items need to be picked up and delivered. In the study two single task assignment and then multiple combinatorial approach are tested. Results show the benefits of the multiple allocation shown by lower waiting time by people requesting the delivery service. Considering food delivery in outdoor scenarios, in (Tonga, Dai, Xiao, & Yan, 2020) the application of dynamic pricing on economic results of Chinese food delivery companies are analyzed. The authors underline some of the factors affecting the industry concerning for instance the high differences in orders between weekend and the rest of the week, demand profile during the day, changes in prices based on distance and weather condition. In food delivery no results have been found which could give information on operational performance of riders in the context of food delivery Li, Zhang and Wang consider crowdsourcing of deliveries for Food Delivery Industry (Li, Zhang, & Wang, 2018). Task selection and allocation is done with a Game Theoretical approach: a non-cooperative game among riders is set, where each rider aims at maximizing his own utility. The positive results generated in terms of average utility and percentage of task assigned justify the validity of the model.

4. Methodology

The systematic and additional literature reviews have shown how food delivery is seldom at the centre of scientific publications. In this section, both the technology and the context will be described to highlight why delivery robots are a relevant solution for the considered industry and at the same time which elements might be considered as influential for the operational performance. As done in the previous work concentrating on food delivery and automation, the order cycle time is at the center of the study.

4.1 Technology and Context of Application

Among the factors which could be included in the analysis of performance, technology related factors are for sure playing a big role. The aim of application of this new type of technology is to avoid the problems characterizing the traditional delivery (such as traffic congestions, high manpower cost). In order to so, delivery robots are acting like pedestrians: pavements and zebra crossing are the streets these vehicles proceed on. Starting from this idea, in order to maintain a high level of safety for people walking around and nearby the robot route, limited speeds have to be maintained (maximum speed is around 6 km/h (Hoffmann & Prause, 2018).

Following the idea of green economy and environmental sustainability it is possible to say that all these types of vehicles, as the first developed, will be electric. One of the weaknesses of current electric vehicles is the duration of batteries. As shown with other types of technologies such as drones, the relation among speed/acceleration, payload and range concepts have to be properly set in order to find a chance of meaningful application for the robots. Currently, despite the big improvements brought by the innovation in EV, the duration of lithium batteries (as an example) does not allow to compare the performances of traditional means of transportations with delivery Robots in terms autonomy and range. The limited battery duration highly limits the total distance that can be travelled. Vehicle's dimension is another relevant characteristic which influences the chances of application: Delivery robots will have to be reasonably small to proceed on pavements (still with the idea of not harming people), and to increase the total distance which can be travelled limiting the weight of the vehicle itself. The vehicle dimension and electric motors, being on the one hand one of the keys to access the pedestrian world, are on the other hand, highly limiting the amount of payload, in terms of volume and weight, which can be carried around. Small both in dimensions and in number, are the products the little robot will able to deliver to the final customer.

All these characteristics in terms of payload, speed and distance, fit the scenario of a last mile delivery of a single customer e-commerce order delivery. Given all the previously explained characteristics the vehicles seem to fit the specific scenario of product pick-up and delivery with a relevance of the industry here considered justified by the growth of the market of grocery and food e-commerce purchases, and the increase number of people living in urban areas.

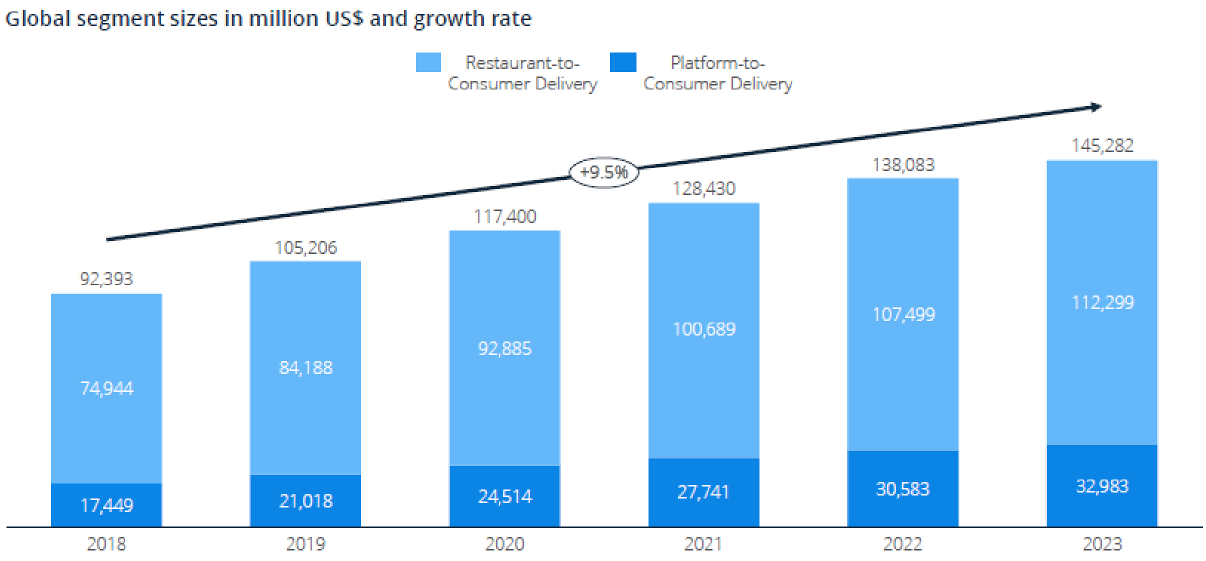

Figure 10 market growth source Statista: https://statistacloudfront.s3.amazonaws.com/download/pdf/OnlineFoodDelivery_Preview.pdf

The typical scenario of food delivery includes a three-sided Platform which matches demand and supply of food, leveraging on a crowdsourcing for the delivery. In this context, customers select the restaurants partnering with the Platform to have the food prepared. The advantages are leading Restaurants to have additional orders and outsourcing the home delivery service while for customers the possibility of avoiding preparing food and reaching the restaurant location to pick it up. Also in case of Robots, the problem faced by the company relates to a pickup and delivery task allocation, for which vehicles have to be scheduled. Demand typically presents during mealtimes, creating high peaks in the order profile.

4.2 Parameters of study

For what stated in the previous section, the characterizing elements subject of the study which play a relevant role in the scenario considered are:

1) Size of the Area: given the limitations in terms of range and speed together with the considerations done for the importance of Order cycle time, the size of the area served plays an important role.
2) Speed: this parameter is key to evaluate the time required to move between to points in the Area, affecting the order cycle time.
3) Range: Represents the battery constraint affecting the number of possible deliveries without recharging which could be done by the robot

4) Points of Delivery (customers): The number of customers ordering is one of the major elements of stress on the system
5) Points of Origin :(pickup points/restaurants/shops) number of pickup points in the area
6) Number of Robots: the most important design parameter defined by the service provider/technology owner.
7) Order Profile: high peaks of demand characterizing the industry might create additional stress to the system.

This list of parameters includes technological and network related factors which might be or not be under direct control of the company. A sensitivity analysis from starting base cases could allow to identify the relevance of each of these factors on the operational performance. For this reason, and to fill the existing gap concerning the quantitative approaches chosen to deal with automation in last mile delivery, a simulation model is designed.

4.3 Modelling metodology

Agent-based modelling (ABM) is a technique which aims at recreating the dynamics of complex systems starting from its fundamental autonomous entities (Bonabeau, 2002). When interactions between agents are complex discontinuous or discrete, their position in space is crucial and not fixed, ABM offers the possibility of modelling with flexibility and ease capturing the evolution of the states of a system based on the definition of the behavior of its constitutive elements. ABM is for this reason popular in modelling areas such as Flows of people and vehicles, Stock market and others. AB simulation is a valid technology for the evaluation of automation approaches (Henesey, Davidsson, & Persson, 2008).

Numerous scientific publications have used ABM for AGVs in various applications. (Teruaki & Abad, 2002) proposes an agent-based model for a warehouse system. Under the subsystems considered, seven kinds of basic agents are defined, including customer, supplier, order, inventory, product, supplier-order, and AGVs agents with the objective achieving efficiency in the warehouse operations. (Mes, van der Heijden, & van Hillegersberg, 2008) considers a multi-agent system for the logistics control of AGV, to construct robust schedules for transportation jobs inside a dough producing facility. Mes and colleagues consider the real time scheduling of full-truck load transportation orders in (Mes, van der Heijden, & van Harten, 2007). For all the afore mentioned reasons, Agent Based simulation is the methodology selected to model Delivery Robots' operations. According to Wooldridge and Jennings (1995), an agent is a hardware or software-based computer system with key properties such as autonomy, social ability, reactivity and pro-activeness. When designing AB simulations models is crucial to identify which elements need to be represented as agents.

In the scenario under analysis, the model aims at evaluating the performances of a new technology in last-mile delivery. With this objective, it has been decided to model as agents the following actors: Platform, Robots, Customers, Orders, Restaurants. Each of these agents has a specific role in the system: customers create orders which are prepared by restaurants; the platform schedules the missions allocating deliveries to robots responsible for the transportation of the goods. Each agent and its characteristics will be described in detail in the following paragraphs.

The simulation model has been developed with Anylogic (The AnyLogic Company (former XJ Technologies). The Java nature of AnyLogic lends itself to custom model extensions via Java Coding which have been fundamental for the characterization of the design. As an example, closely related to the object of study Merkuryeva and Bolshakovs modelled vehicle scheduling problem with Anylogic (Merkuryeva & Bolshakovs, 2010). In the next paragraph a quick view of the simulation environment must be given to let the reader understand the links between the conceptual model and its representation in the simulation software. The book of Andrei Borschev (Borschev) has been used as learning tool and reference for the explanation of the main elements of the software.

4.3.1 Fundamentals of Agent-Based Modelling in Anylogic

As explained by Macal and North (Macal & North, 2010) usually an AB model presents three elements:

1. A set of agents, their attributes and behaviours.
2. A set of agent relationships and interactions: An underlying topology of connectedness defines how and with whom agents interact.
3. The agents' environment: Agents interact with their environment in addition to other agents.

Agents behavior and interaction with other agents in the population is regulated by statecharts. Statecharts are composed by a number of blocks representing possible states the agent could be in during simulation. The change from one state to another is caused by transitions. Figure 4 shows the main types of transition and their visual representation. A brief explanation is provided:

- Timeout: agents change state after a specified time period.
- Condition based: the agent is allowed to move to another state only if one or more conditions are met.
- Message: agents can communicate among them with messages. The transition could be fired with a specific message for example "message!". Only if the content of the message corresponds to the triggering key the transition is fired.

- Agents arrival: as soon as a moving agent arrives to the specified location the transition enables the agent to enter in the following state.

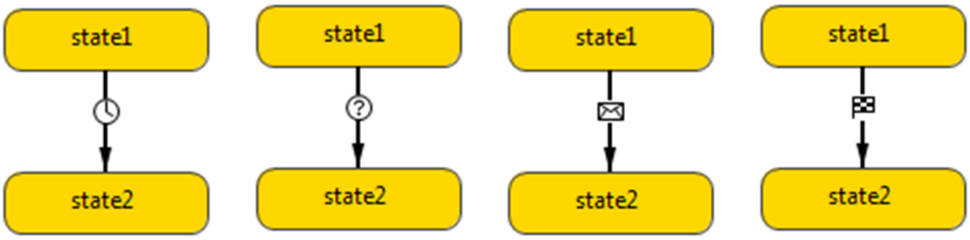

Figure 11Different types of transitions in Anylogic

Crucial to distinguish among agents is the role of parameters and variables. Parameters of an agent are fixed characteristics which identify its peculiarities. For instance, the preference of a restaurant as well as their position might be a distinguishing factor among different customers. Parameters can also be subject of study in the analysis of different experiments in which different values of the same parameter are given to understand the impact on the final performance. Parameters can be of different types, the most used for the model are: double (real numbers), integer, Boolean (true or false), Agent. A parameter of type Agent is a pointer to an agent of a population. Thinking to the previous example of customer preferences about restaurants, the parameter *restaurant* defined for each customer is a pointer to its favorite restaurant in the population.

Variables defined for an agent can change during simulation run and cannot be subject of study in a sensitivity analysis. For example, an important variable for a Robot Agent might be its battery level, which is changing from mission to mission.

Finally, the environment is where agents live and is itself modelled as an agent called Main.

5.Model

In this section the characteristics of the scenario to model are described. The model is a representation of reality aimed at capturing the main characteristics of the processes in Food delivery with a level of detail sufficient to recreate the most important working mechanisms useful to obtain reliable results. In food delivery customers issue orders through a platform they can select their favorite restaurant from. In this process customers can specify order characteristics: products to be delivered, location of delivery and time of delivery. In the modelling scenario customers are free to choose from any of the restaurants in the area without any limitation. Restaurants or points of origin (POO) are uniformly randomly distributed in the area. The ordering time and position of delivery are not known in advance by the platform and the objective of customers is to have the products delivered as soon as possible as usually happens in this industry. Restaurants and orders are all equal to one another, meaning that all the preparation times for orders do not change based on the restaurant. With the objective of delivering orders as soon as possible, a crucial role is played by order allocation and vehicles scheduling. The platform has to select the best Robots which can complete delivery. The limitation in payload make the robot capable of serving only one customer at a time: before starting a new mission, the previous order has to be delivered.

Robots are based in a depot located in the central area. This depot models the place of recharging activity, where robot can swap their battery with a fully charged one. In current applications these depots are either represented by facilities or autonomous charging pods.

Robots which are free from other orders immediately start their mission: the first step consists of moving from their current location towards the pickup point. If the order is ready, the loading activity is completed by POO personnel and the robot starts moving towards the point of delivery. If in the meanwhile, a new order has been assigned, the robot starts the new mission, following the steps previously defined. otherwise it immediately returns to the depot where it can be recharged. In the case an order arrives while travelling back to depot, the robot starts the mission from its position. Robots are constrained by battery: if a robot has enough level of battery to complete delivery it starts the mission, otherwise it is forced to return to the depot before beginning the new mission. Both order allocation processes consider the battery constraint in the evaluation of the best robots.

To model the scenario of application each of the relevant actors previously described has been modelled as an Agent. All the elements which have been considered as fundamental for capturing the relevant aspects of the scenario have been included to find an optimal compromise between level of detail and computational time. In the next sections a detailed description of each Agent and the mechanisms of interaction with the others is explained.

For each agent presented, after a short introduction on what the modelling includes and does not include, all parameters and variables are described, followed by the statechart modelling its behavior in the environment during simulation. In robot agent section, a recap on all the interaction among agents is provide the reader with a comprehensive view of the system.

5.1 Main Agent

The Main agent (or Main) in agent-based simulation is the top-level Agent and environment where all other agents live. In the Main the most relevant functions as well as the parameters of the simulation are defined and have been made accessible by any of the agents living in the environment. The environment where all the agents live is a squared area of 400x400 pixels. The shape of the simulation environment has been kept squared similarly to what has been done in (Mes, van der Heijden, & van Harten, 2007) and (Liu, 2019) to consider a general neighborhood.

In Anylogic it is possible to define the conversion from pixels to a length of unit of measure such as meters, kms, inches and others. Instead of increasing the number of pixels of the environment, a scaling factor has been used to simulate larger environments of operations. This parameter called *conversion (pixels/km),* plays a fundamental role in all distance and time related functions since gives the possibility to express the Area as a parameter of the experiments without the need of modifying the simulation code or the number of pixels of the simulation environment. Defining l as the length of the side of the square in kilometers:

$$1)\quad l = 400\, pixels/conversion$$

The Area considered is a flat plane, with no network. The distance between two any points which will be expressed as $d_{a,b}$ includes a correction factor cf used to increase the otherwise Euclidean distance between two points. The Area considered is served by a central depot called *home* located in the center of the square, with x and y coordinates set at pixels (200,200). At the beginning of the simulation, the Robot agents will start their missions from this node, to emulate the beginning of a working day. The depot is not modelled as an agent but as a point Node (defined simply with x and y coordinates) since the activities done inside the depot are either out of the scope of the model or have been included in the modelling of other agents.

Every simulation run replicates a working day which starts at time 0 and ends as soon as all orders are served (finite horizon simulation). No information about customers' orders is known at the beginning of the day, making the degree of dynamicity equal to 1. This hypothesis is based on the current characteristics of online food delivery, where most orders are not planned by consumers.

In Main all the most important functions are defined. Instead of modelling the platform as an agent, the agent-nature of the environment has been used to simplify the definition of functions and the topology of the model. Conceptually all the agents “live” in the platform. Customers’ position and preferences, restaurants’ location and preparation time, robots’ status are all information which are known by the platform. For these reasons instead of creating an additional agent representing the platform, the Main agent has been used.

5.1.1 Parameters and Variables

In the Main agent the parameters which are subject to a sensitivity analysis are defined. These parameters include the size of the agents’ population as well as the area served reconducted to the parameter *conversion*. In the analysis of results different combinations of parameters will be tested to understand the impact on the performance under analysis. Each agent’s population (except orders) has a fixed number of agents defined at the beginning of the simulation through the following parameters:

- *nRobots:* number of robots employed for delivery.
- *nRestaurants:* number of points of supply in the area.
- *nCustomers:* number of customers ordering in a day in the area.

Each agent is indexed from *0* to the population-size parameter -1. For example, if *nCustomers* is set equal to 80, in a simulation run reproducing a day of operations 80 customers will order and their identification indexes will go from 0 to 79.

As mentioned before the Main agent models the Platform and the mechanisms of order allocation. Every new order received is added as last to the list *serviceRequests* and removed as soon as it has been assigned.

5.2 Restaurant agent

The restaurant Agent models the presence of Points of Origin (POO) for customers in the Area. Despite not having any activity which models its behavior in the environment, it has been useful to treat these points of supply as agents and not as point Nodes (like *home*) to have a higher flexibility in the parameters variation process, communication with other agents and a simplicity in writing the main parts of the code which involved them.

The number of Points of Origin is defined in the Main by the parameter *nRestaurants*. The location of each agent is random. The coordinates x and y are taken randomly from a uniform distribution *uniform (a,b)* where the minimum (*a)* and maximum (*b)* value are the edges of the Area in pixels (0,400). Keeping the location of Points of origin random in each experiment allows to study a generic rather than a specific network configuration.

The model supposes the presence of *nRestaurant* identical agents. Considering general and identical POO instead of differentiating among them has been preferred to maintain a higher generality.

5.3 Customer Agent

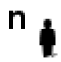

Figure 12 Icon used for the visualization of customers in the simulation. The letter n changes from customer to customer and refers to the index of the customer in the population going from 0 to nCustomers-1

These agents have the objective of modelling customers activities in the process of food ordering. As supposed for Restaurant agents the x and y coordinates on the plane are taken randomly from a uniform distribution *uniform (a,b)* where the minimum and maximum value are the edges of the Area in pixels (0,400) and stay the same throughout the whole run.

Customers are supposed to be in the location of delivery as soon as the robot arrives. For this reason, agents position in the environment represents the delivery and order point. Ordering and delivery point might differ in real life but simulating such scenarios is not objective of the simulation. Order time and selected restaurant might change from customer to customer.

5.3.1 Parameters and Variables

The two parameters defined in the customer agent have the objective of linking each customer agent specifically to other agents in the restaurants and orders populations. The *restaurant* parameter (type R*estaurant*) is a pointer to the restaurant the customer will be ordering from. This restaurant is randomly selected among all the restaurants in the area with no restrictions on the distance. It is supposed the integrity and characteristics of the products are maintained no matter the distance from the restaurant. The *order* parameter is a pointer to the order agent the customer creates when issuing the order (more in the statechart paragraph). This parameter is fundamental to link the order agent to its issuer.

In the customer agent a variable of type double called *orderTime* (set null at the beginning of the simulation run and changed to the simulation time as soon as the agent enters the hungry state) and a variable called *deliveryTime (*set null at the beginning of the simulation run and changed to the simulation time as soon as the agent comes out from the hungry state) allow to set the value of the variable OCT as follows:

$$1)\quad OCT = deliveryTime - orderTime$$

This variable is then written on a text file and used for the analysis conducted with Microsoft excel.

Two variables called t_f and t_m are used to store the information concerning the beginning of the delivery mission by the robot and the moment of assignment of the customer to the delivery robot responsible for the delivery.

5.3.2 Statechart

Figure 3 represents the statechart modelling the behavior of Customer agents. In the design phase there were two main possibilities: the first was to dynamically create and delete Customer agents from the population when the issuing and being delivered the order; the second one was to keep a fixed number of agents in the population and modelling the state previous to ordering and the one after being served. The latter has been preferred to the former both to have a one-to-one correspondence between the agent and each numerical index in the population throughout the whole run and because of the low impact on performance of higher number of agents in the simulation for the size of the experiments.

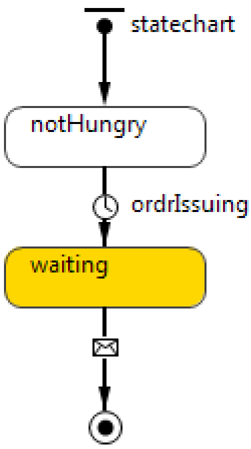

Figure 13 Customer Agent statechart

Each agent begins the simulation entering the *notHungry* State. In this state the agent is not visible by the system since no order has been issued and not visible in the animation being the color set to white.

With a timeout transition, for which an agent moves from one state to the other at the end of the specified time, the agent enters the *waiting* state (in yellow). The specified time for the *orderIssuing* transition is taken from a custom probability distribution which has the aim of replicating the order profile of the food industry capturing the high peaks during lunch and dinner time and the fewer orders in between. The distribution returns the number of minutes the customer remains in the *notHungry* state to identify the moment in time when he/she issues the order. The order with which customers move from *notHungry* to waiting, does not depend on their index in the simulation model: for example, customer 13 does not necessarily order as the 14th of the population. When issuing the order, the customer is added to the list in the Main agent *serviceRequests* and calls the function/s required to find (if possible) the robot which will be served by (more on order allocation in paragraph). Moreover, issuing the order triggers the creation of an order agent whose position is set equal to the coordinates of the selected restaurant. The customer stays in the *waiting* state until a robot comes to deliver the order. When the agent receives the message "DELIVERED!" (more on this message in the Robot Agent chapter), it moves out from the *hungry* state to the final state *served.* This statechart models the hypothesis that each customer can order only once during each simulation run.

5.4 Order Agent

Figure 14 Order Agent Icon

5.4.1 Parameters and Variables

As explained in the section Customer Statechart, the Order agent is created and visualized as soon as the customer enters the waiting state after the issuing of the order to the specific restaurant. Graphically the agent is at the same coordinates of the restaurant where it has to be prepared.

The *customer* parameter of type Customer is initialized in the order creation process by the customer agent, referring the pointer to the Customer responsible for its issuing to create a one to one correspondence.

The *preparationTime* (*pt)* parameter (type Time:minutes) identifies the amount of time required to complete the preparation of the order: it has the objective of including all the activities carried out inside the Point of Origin which allow to transform inputs to the final product ordered by the customer with the specific packaging required for the delivery. The value of the parameter is determined and does not change from order to order and from restaurant to restaurant. In reality, the preparation time is highly affected by the type and size of the order as well as the type of restaurant and other factors not under the direct control of the delivery service provider. For example, the preparation time might change based on the number of orders already demanded to the restaurants (both through the platform and not). In the model, this type of complexity is not included being highly affected by the characteristics of the Point of origin under analysis. Order are always started as soon as they are created.

The *earliestTime* et_c for an order is a parameter of type Time which identifies the simulation time when the order is ready for pickup by the robot. It is initialized as soon as the order is created and is set equal to the time of simulation (*time (…)*) of order creation plus the preparation time:

$$2) \quad et_c = time(\dots) + pt$$

The robot parameter (type Robot) identifies the robot responsible for the delivery mission which will come and pick up the order, defined after the order allocation process has been completed with the objective of linking the carrier to the product.

The variable *ready* (type: Boolean) models the status of the order: true if the order is in the state completed, false otherwise.

5.4.2 Statechart

The Order Agent statechart consists of two consequent states. As soon as the order is created enters the preparation state in which stays for the time expressed by *pt*. The timeout transition *preparationCompleted* makes the agent enter in the waiting*ForPickup* state from which the agent comes out only triggered by the message "LOADED!" sent by the robot responsible for the mission (more in Robot Agent section). When entering the final state, the order is removed from the population and disappears from the simulation model.

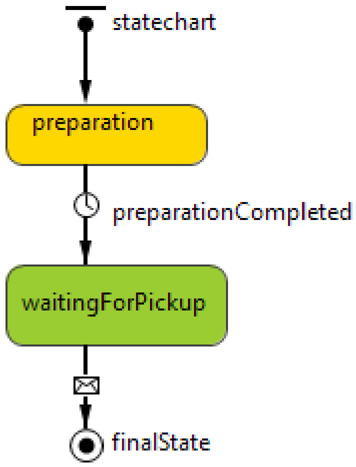

Figure 15 Order Statechart

The order agent was not a fundamental element of modelling of the system. It would have been possible to capture the most relevant functionalities and states described in this section including them in the customer agent. It has been added to keep an intuitive design to the model for a greater understandability in the design phase and in the debugging process.

5.5 Robot agent

Figure 16 Icon used to represent the Agent in the presentation. The center circle can be red (occupied), green (free) or yellow (recharging).

Robot agents are the vehicles responsible for pick up and delivery. These agents freely move in environment following the steps of the missions they are required to complete. The fleet includes identical robots.

5.5.1 Parameters and variables

The speed of the vehicle in any trip from point to point has been set as deterministic and constant defined by the parameter *s* (type Speed: km/h).

The travel time for a robot to move from point *a* to *b* will be then:

$$tt_{a,b} = \frac{d_{a,b}}{s}$$

The indexes used are *c* for customers, *o* for restaurant, *r* for robots and *h* for the depot.
batteryCapacity (BC), consumptionRate (CR), and swappingTime (sw) are the parameters affecting the Battery consumption and recharging dynamics. In order to make the battery Level easy to calculate battery related parameters (*BC* and *CR*) have been converted to Km with the following hypothesis:

1. The Battery Level is expressed as a distance which can be travelled by the robot with one charge. For instance, batteryCapacity is set to 6 km. Battery is expressed as the maximum range for the electric vehicle.
2. The battery consumption is not affected by the condition of the robot (loaded or empty).
3. The robot consumes battery only when moving and not when staying still (for example during loading or unloading)

*consumptionRat*e (meters) is the portion of battery consumed every battery update when the robot is moving. When possible, the battery of the robot is substituted with a new battery in *home* with a swapping time regulated by the homonym parameter.

loadingTime (*lt)* identifies the time required for the loading of the vehicle in the point of origin. Identifies the time after the completion of the order required by the personnel to complete all other activities enabling the start of the trip towards the customer (coming out of the store, linking the order with the robot and loading the vehicle). On the other hand, *unloadingTime (ut)* identifies the time required for the customers to reach the Robot and complete the operations of unlocking the robot through the smartphone application and removing the order from the Robot case.

To keep track of the changes of the battery level, crucial to define the feasibility of assignment of a mission to a robot, the variable *batteryLevel* and *actualBatteryLevel* are used. The first one is used as input for the calculation of the effectiveness of an order allocation, while the second identifies the instantaneous condition of Robot’s battery.These variable (type double) are initialized as *batteryCapacity* at the beginning of the simulation and updated progressively based on the policy of order assignment and the missions the robot completes (more on this in Battery).

The other relevant variables are pointers to the customer the robot is currently serving and the restaurant it has to visit to pick up the order, which are set to null when the robot is free from tasks. Available Time (type Time: minutes) identifies the simulation time at which the robot is free to start a new mission. This parameter is fundamental in the phase of order allocation since allows the system to have control on when the agent could start serving a new customer.

Recharging is a Boolean variable which, if true, indicates the need for the robot to complete a swapping battery activity.

The list of customers assigned to the robot by the system is called *ordersList.* Customers are added as last whenever the Robot is selected as the best candidate to serve a specific customer.

5.5.2 Battery

The hypothesis regarding the battery and its meaning in the model have been discussed in the previous section. The battery Level is a crucial factor for the assignment of orders to robots. For this reason, before discussing the statechart and allocation methods considered in the model a deeper explanation on the dynamics of consumption must be provided.

As already mentioned, at the beginning of a mission and after a battery swap the battery is at the maximum of its capacity defined by the *BC*. Batteries are not a scarce resource in the depot: when needed, a new fully charged battery can be found and plugged into the robot to guarantee smooth operations. In the model the charge left in the battery is identified by the variable *actualBatteryLevel*. The information contained in this variable is crucial to understand if a robot has enough charge left to complete a specific mission. For each customer *c*, the robot must have sufficient battery to complete the 3 legs of mission which allow it to satisfy the customer and safely return home:

1. moving towards the restaurant of *c*
2. moving from the restaurant to the customer
3. moving from the customer position to *home*

The objective of this policy has the aim of simulating autonomous operations in the area served, avoiding the need of specific personnel to reach the robots in random points of the Area where they could run out of battery. It has been defined the concept of worst-case trip distance (WCTD), which is the distance including the previously listed 3 legs of mission which the robot has to be able to complete.

In order for a mission to be defined feasible without the need of returning to the depot for a battery swap, the following relation has to be true:

$$WCTD_{r,c} < ABL_r$$

The worst-case trip distance is a function of the robot *r* and the customer *c*. When a mission is being processed, i.e the robot has started moving towards the POO, cannot be reassigned to another Robot agent. Therefore, it is possible to calculate and subtract the part of the battery including the first 2 legs of the WCTD from ABL_r. On the other hand, the last part of WCTD is influenced by the possibility for a new order to be assigned to the robot. For the last part, the battery consumption is updated continuously with an internal timeout transition, which subtracts *CR* parameter every *t* time units. An internal timeout transition is a transition which fires every *t* time units but does not change the state of an agent, therefore continuously repeats until the agent is out from the state. The smaller *t*, the higher the number of events the simulation will have to complete but the greater the accuracy leading to an almost instantaneous battery update. *CR* is defined as follows:

$$4)\quad CR = \frac{s}{t}$$

Being the battery expressed as a distance, this parameter is the distance travelled at speed *s* in *t* time units. This method used for updating battery consumption has been used to reduce the number of events during each run, maintaining a high level of accuracy. The following graph has the objective of exemplifying the process explained. At the beginning of the simulation the Robot starts with a battery Level set to the battery capacity (BC). At moment *t1,* an order is assigned and the battery referring to the first 2 legs is subtracted (b1-b2). The battery level remains unchanged until the end of the mission (t2), when it starts decreasing constantly with a slope determined by CR. At moment t3 a new order is assigned to the Robot and the procedure repeats again. At *t4*, the Robot arrives home and the battery is swapped and its level brought to BC again.

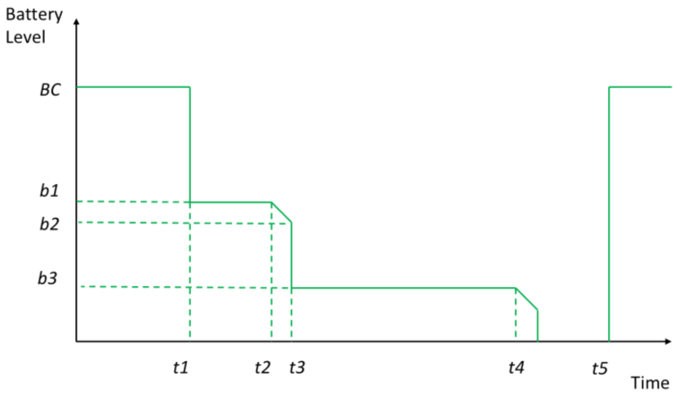

Figure 17 Exemplification of battery profile during a mission for a single Robot

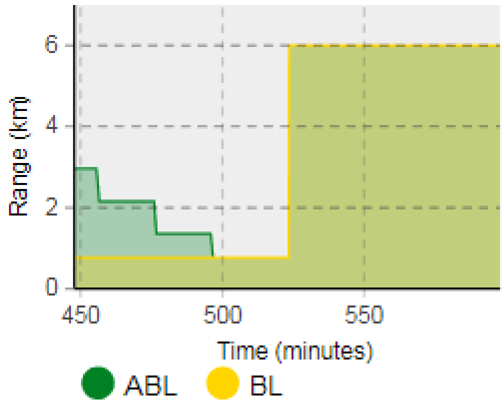

Figure 18 Battery Level and Actual battery Level snapshot from the simulation model.

5.5.3 Statechart

Robot agents start in the state available and in the sub-state idle, located in the point Node *home* in the center of the Area. When in the *available* state, the transition T1 starts the new mission. This transition is a message-based transition which triggers the change in state when the robot receives the message "START THE MISSION!" and the variable *recharging* is false. An internal transition (T11) is responsible for a continuous check on the presence of orders to process: if the *orderList* is not empty the Robot sends itself the message to start the mission; the message allows to enter the next state if recharging variable is false. When fired, the robot starts processing the first customer in the list, the restaurant variable is changed from null to the pointer to the restaurant the customer has ordered from and the ABL_r is updated to subtract the amount related to the new mission as shown in figure 9.

In the *drivingToRestaurant* state the robot moves from its position to the location of the restaurant with a speed defined by the parameter *s*.

The next state is triggered by the agent arrival at the predetermined location T2. As soon as the robot reaches the restaurant enters the state *waitingForLoading*. During simulation two scenarios can occur:

1. the robot arrives at the restaurant before the order is ready: $time(\dots) < et_c$
2. the robot arrives at the restaurant and the order is ready: $time(\dots) \geq et_c$

In the first case the robot cannot exit the *waitingForLoading* state since the order is still being prepared. The condition-based transition is guarding the possibility of entering the following state by checking the value of the variable *ready* of the Order agent. The robot can access to the new state when receiving the message" READY!" sent from the order agent.
In the second case, the message has already been sent but has not triggered any transition since the robot was not in the right state to convert that message into an action; on the other hand the condition-based transition is enabling in this scenario to enter the next state.
The following states include the loading of the vehicle, whose duration is defined by the parameter *loading,* the movement of the robot from the restaurant to the final customer, and the unloading activity(*unloading)*. Since all these states are deterministic and are not influenced by any other agent in the environment, they are conceptually grouped together referring to the total time required to complete them as *JobTime.*

$$5)\ \ JobTime = loadingTime + unloadingTime + tt_{o,c}$$

After unloading the vehicle, the message "DELIVERED!" is sent to the customer forcing it to move to the final state; in T7 the variables *customer* and *restaurant* are set to null again to avoid being visited again and the customer is removed from the list *ordersList.*
At the end of each mission, the robot can either continue its tour serving another customer or returning home (T8, T9). The policy of immediate return to home has been preferred over other policies (such as waiting at customers location) since there have not been defined places where robots can safely wait for new orders. In case a new mission is started, the activities and states are the same as described so far. In the other scenario, the Robot enters the *drivingHome* state moving towards the depot: each iteration of T11 updates the level of the battery and the Available time of the robot as follows:

$$6)\ \ AT_r = time(\dots)$$

$$7)\ \ ABL_r = ABL_r - CR$$

The robot than reaches home and the battery swapping activity is carried out. At the beginning of this state available time is updated again while at the end *BL* is brought back to full capacity.

$$8) AT_r = AT_r + sw$$

$$9)\ BL_r = BC$$

The *batterySwapping* activity is done regardless the battery level of the Robot, and its completion time is constant and defined by the parameter *sw.*

As shown by the statechart, only one order at a time can be collected by Robots: this hypothesis has been formulated to model the current limitations in payload and the actual pickup and delivery process of the food industry.

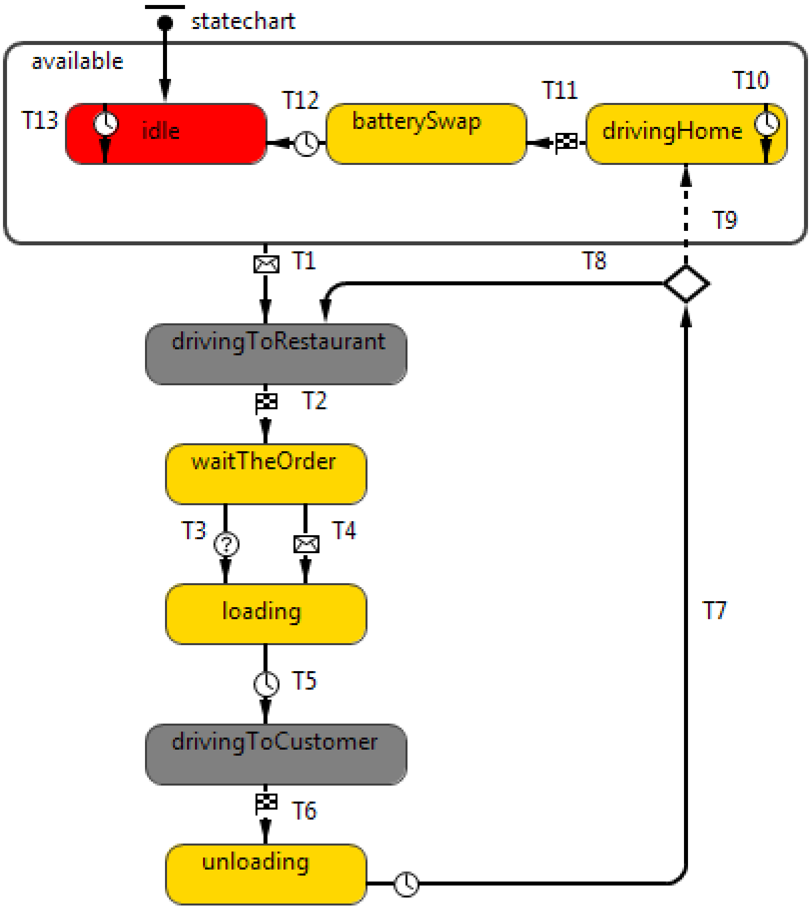

Figure 19 Robot Agent statechart

:

The following message sequence diagram aims at providing a complete view of the system and activities of the agents highlighting the communication among them. Each Agent name is reported in the top of the image. The vertical axis is used to represent time, while horizontal axis to show their interaction. Continuous blue axes are used to show the robot and the agent just reached; black bold lines are representing the interactions through messages; finally, blue dotted lines indicate interactions based on other functions. For customer and order agents the change from one state to another has been highlighted with circles on the respective axis. For Robot Agent the activities requiring movement have been represented in black while all other activities and beginning is delimited by brackets. In the first example the Robot arrives to the restaurant before the order completion and the switch to the next activity is enabled by the message delivered by the order agent. In the second example on the other hand the robot arrives after the order completion and it is possible to see how the message received does not trigger any change in state in the robot which continues its trip towards the restaurant. The Order agent axis begins and ends when the order is created and removed from simulation.

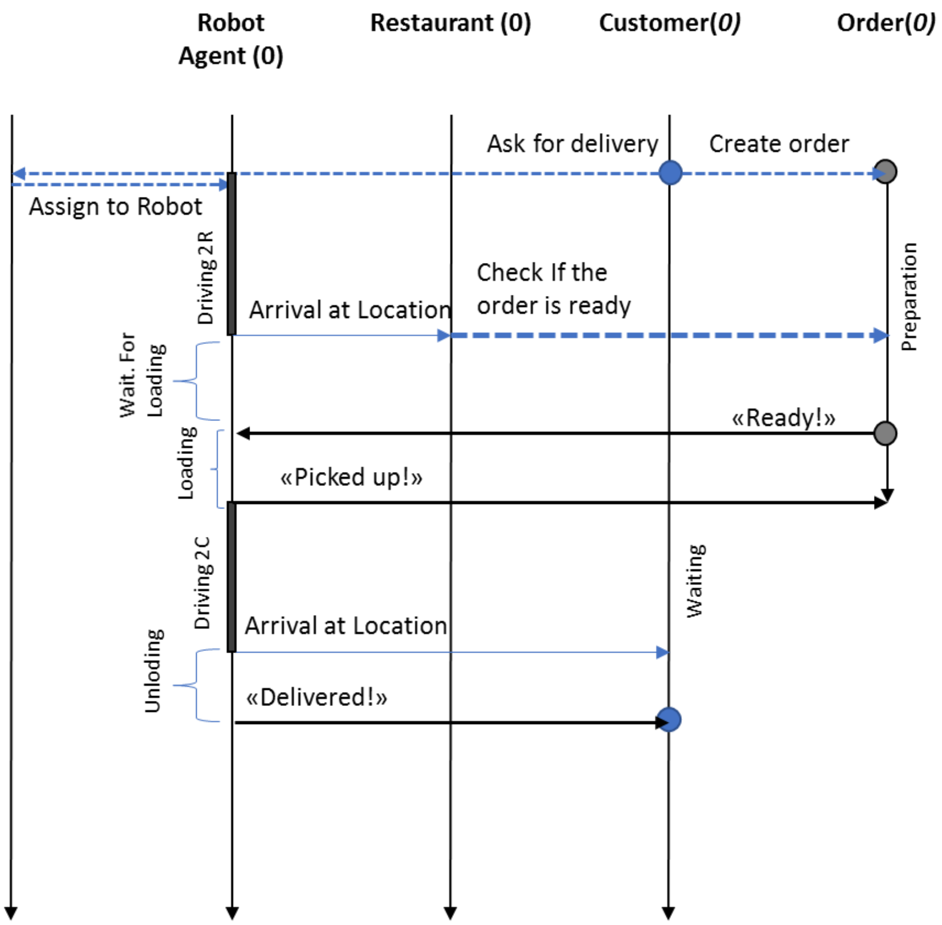

Figure 20 Interaction Diagram In scenario 1

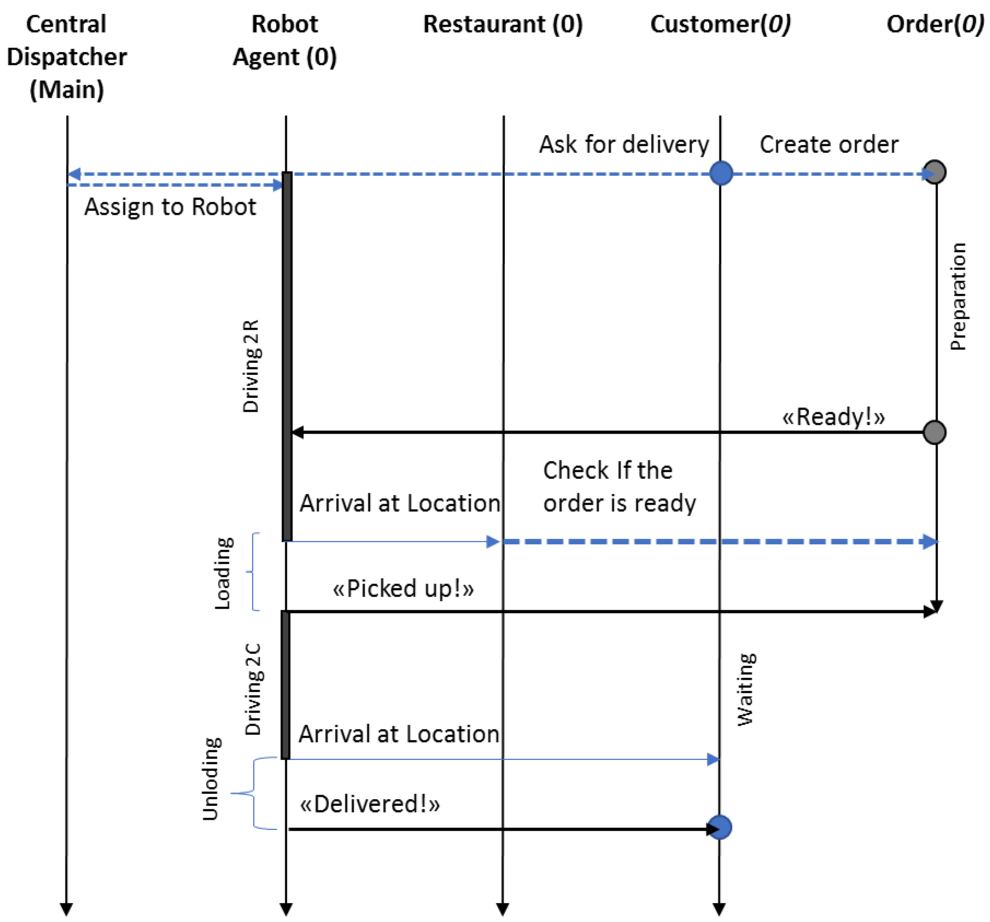

Figure 21 Interaction Diagram in Scenario 2

5.6 Order allocation Policies

In the Discussion with a Manager Deliveroo, one of the European company leaders in the food delivery industry, the importance of the respect of delivery time provided to the customers to allow an effective synchronization in the final stage of delivery have been underlined.

In this regard, two seem to be the relevant factors which can be extended to the delivery with Robots: order cycle time duration and order traceability. The first identifies the time period between the placing and the receiving of the order, while the second expresses the possibility for the customer to follow the stages of the delivery following the routing of the courier and the time left to reach the him/her. All delivery platforms nowadays provide one or both these information to the customer. As an example, a customer ordering through Glovo application can follow the steps of the delivery and the position on the map of the rider in charge of the mission.

An essential role in this regard is played by the order allocation method. This process can be reported to vehicle scheduling problems where vehicles are assigned to one/more tasks to maximize the results expressed through an objective function (Jaeyeon & Seohyun , 2017).

In the model presented, order allocation is Centralized: requests are assigned to Robots by a Central Server (the Platform) with a complete view of the system, including the position of the actors and their Status. This section has the objective of addressing two possible mechanisms for order allocation: the first one considers immediate allocation of an order without the possibility of reassignment. In this case the customer knows immediately which will be the robot completing the delivery and the time required to be served which will not change during the simulation. In this case traceability is prioritized with respect to OCT since no changes in the robot responsible for the delivery will take place. The second considers the possibility of a wider optimization including a group of orders already assigned but not processed. Reassigning orders based on more information leads to better solutions in terms of OCT but on the other hand does not permit to have precise information on the delivery time which might increase or decrease based on the following different allocations which will be done.

5.6.1 Traceability vs Lateness

As already mentioned, traceability plays an important role for the synchronization of the delivery between the customer and the transporter. The other factor which will be used as focus of the optimization and performance analysis is Lateness. In the case under analysis, where the fleet is composed by homogenous vehicles, and no variability exists in the travelling times between two points, OCT for a customer *c* ordering to restaurant *o* and assigned to a free robot *r* can be calculated through the following:

$$OCT_{c,r} = \max(pt, tt_{r,o}) + lt + tt_{o,c} + ut$$

As previously defined, the last three terms defined for simplicity *jobTime* are not function of robot assignment process. Moreover, since it has been supposed customers can freely order from any restaurant in the area, $tt_{o,c}$ is a component the customer is virtually aware of when ordering, being the fleet homogeneous and the distance from the restaurant known. This last component of the OCT will be a function of the area analyzed and will be the time required to move at speed *s* between two random points taken inside a square. Therefore, it has been decided to concentrate on the portion of the OCT for which the assignment process has influence on. The first component is defined as the maximum between the preparation time and the travel time between the position of a robot *r* and the POO *o*. For this purpose, Lateness is defined as follows:

Given a Robot r, restaurant o and customer c Lateness is the delay of arrival of robot r compared to the earliest pickup time for the order of customer c in o.

Alternatively, it can be conceptually seen as:

Lateness identifies the time order preparation has to be postponed compared to the earliest preparation time to allow the order to be ready at the arrival of the robot.

In the model the restaurant starts preparing the order as soon as the customer issues it. The order preparation might be postponed in case no Robots can be at location before the earliest pickup time. Modelling postponement is not fundamental in this case being the pickup time window constrained only by the earliest time. As soon as the order is processed by r, it starts moving towards o, possibly reaching it before the earliest pickup time. In this case Lateness is considered equal to 0. Considering negative values of lateness does not generate any additional advantage to the system. It is important to point out that lower values of lateness do not necessarily mean shorter travel distances to reach the restaurant.

In order to quantify the differences in traceability the following Traceability Index has been used and analyzed.

$$TI = 1 - \frac{(t_f - t_o)}{(t_m - t_o)}$$

Where t_f is the time at which the order is assigned to the robot which will be responsible for the mission, t_o is the time at which the customer issued the order and t_m is the time at which the mission begins. A value of T equal to 100% means the order is assigned right away to a robot which will be responsible for the mission.   In the simulation model t_f is assigned as soon as T=0% identifies the cases in which the moment of assignment coincides with the beginning of the mission by the robot. In case the mission starts at the moment of the issuing the indicator is considered equal to 100%. The higher the level of traceability the sooner the customer can know when and by which robot the order will be delivered. The value is expressed in percentage to put together all the different results from simulation and express it with a reference average value. This indicator can be lower than 100% for different reasons: in case a policy of order delay before immediate assignment exists (for example to optimize vehicle dispatching process) as in the case of one of the proposed allocation methods. In this specific example, the elements impacting on the traceability index can be relate to 2 main effects:

1. The impossibility to assign the order due to full queue
2. The changes in delivery robots related to permutations

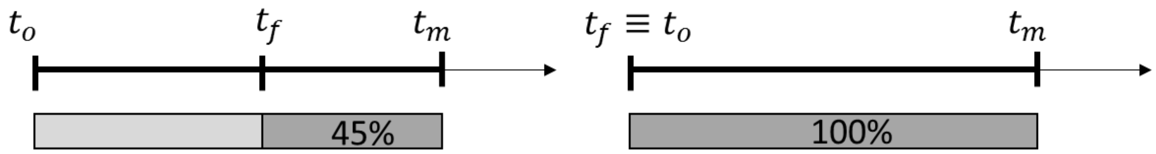

Figure 22 Graphical representation of Traceability index: in the first case the final assignment is between the ordering time and the start of the mission, while in the second case the final assignment coincides with the ordering time allowing the customers to follow the robot since the issuing of the order

5.6.2 Look Ahead Immediate and Permanent Assignment (LAIPA)

Under this policy orders are assigned to Robots to favour traceability over optimization of lateness and then of OCT. When issuing the order, the centralized system immediately assigns *c* to the best robot *r*, with the objective of evaluating lateness and the battery required to complete the mission:

$$11) \quad \min_r \; w_1 L_{r,c} + \; w_2 WCTD_{r,c}$$

The smaller the value of lateness the sooner the customer will be served by the Robot; on the other hand, the smaller the worst-case trip distance the smaller the amount of battery required to complete the mission. Since a solution which requires less energy is to pursue because potentially allows a greater number of missions by the fleet without recharging. The weighting factors are used to prioritize lateness over battery consumption so that in case of equal values of lateness for more than one robot the assignment which allows to use the least battery is selected. For instance, considering $w_1 = 1,\ w_2 = 10^{-8},$ and two solutions where:

$$L_{1,c} < L_{2,c} \text{ and } WCTD_{1,c} > WCTD_{2,c}$$

With the weights used the worst solution in terms of lateness is selected if:

$$(L_{1,c} - L_{2,c}) > (WCTD_{2,c} - WCTD_{1,c})10^{-8}$$

Usually the values of lateness are around 1 to 10 while the worst-case trip distances are in thousands of meters. As it is possible to see in the unlikely scenario in which a worse solution in terms of lateness is chosen the difference is negligible.
With LAIPA each of the robots in the fleet has a subset of Customers which is processed with a FIFO policy. It is important to point out that with this method is optimizing locally using all the previous assigned orders (processed and queueing) as starting points for calculating Lateness and Worst-Case Trip distance. In order to calculate lateness, the system must be able to know in advance the following information:

- The position from which *r* can start the mission
- The time at which *r* can start the mission.
- The feasibility of direct delivery, influenced by the battery level and WCTD

This information can be computed progressively while assigning orders to robots. The variable called Available Time (*AT)*, is used to update the moment in which a robot can start processing a new order, while Battery level (BL) keeps track of the charge left for the robot after completing all the deliveries queued. Four scenarios distinguish the way in which Lateness is calculated. Defining C_r as the subset of C already assigned to *r* and $C_{r,k}$ the element in position k and *K* as its last element, b_r as battery level of *r*, t_c as the ordering time for customer *c*.

A) $C_r = \emptyset \ \cup \ b_r > WCTD_{r,c}$

$$L_{r,c} = \max\left(0, AT_r + tt_{r,o} - et_c\right) \quad (12)$$

In case A the robot is free and could either be waiting or driving back home, in both cases with enough Battery to move immediately towards *o*. $L_{r,c}$ takes into account the travel time between the robot position in the moment of the allocation and the restaurant together with the earliest time for pickup.

B) $C_r \neq \emptyset \ \cup \ b_r > WCTD_{r,c}$

$$L_{r,c} = \max\left(0, AT_r + tt_{C_{r,K},o} - et_c\right) \quad (13)$$

In case B the robot has to complete another task before being able to start the new one. Through these formulas, lateness is calculated including the travel time between the last customer in C_r $(C_{r,K})$ and the position of the new restaurant o

C) $C_r \neq \emptyset \cup b_r < WCTD_{r,c}$

$$14)\ L_{r,c} = \max(0, AT_r + tt_{C_{r,K},h} + sw + tt_{h,o} - et_c)$$

In case C lateness has to include the stop at the depot for swapping the battery thus including the travel time to and from home and the swapping time.

D) $C_r = \emptyset, b_r < WCTD_{r,c}$

$$15)\ L_{r,c} = \max(0, AT_r + tt_{r,h} + sw + tt_{h,o} - et_c)$$

Similarly to case A) and B), the difference between D) and C) is to look in the travel time and distance which are considering the position of the robot instead of the one of its last customer on the list in the moment of the order allocation.

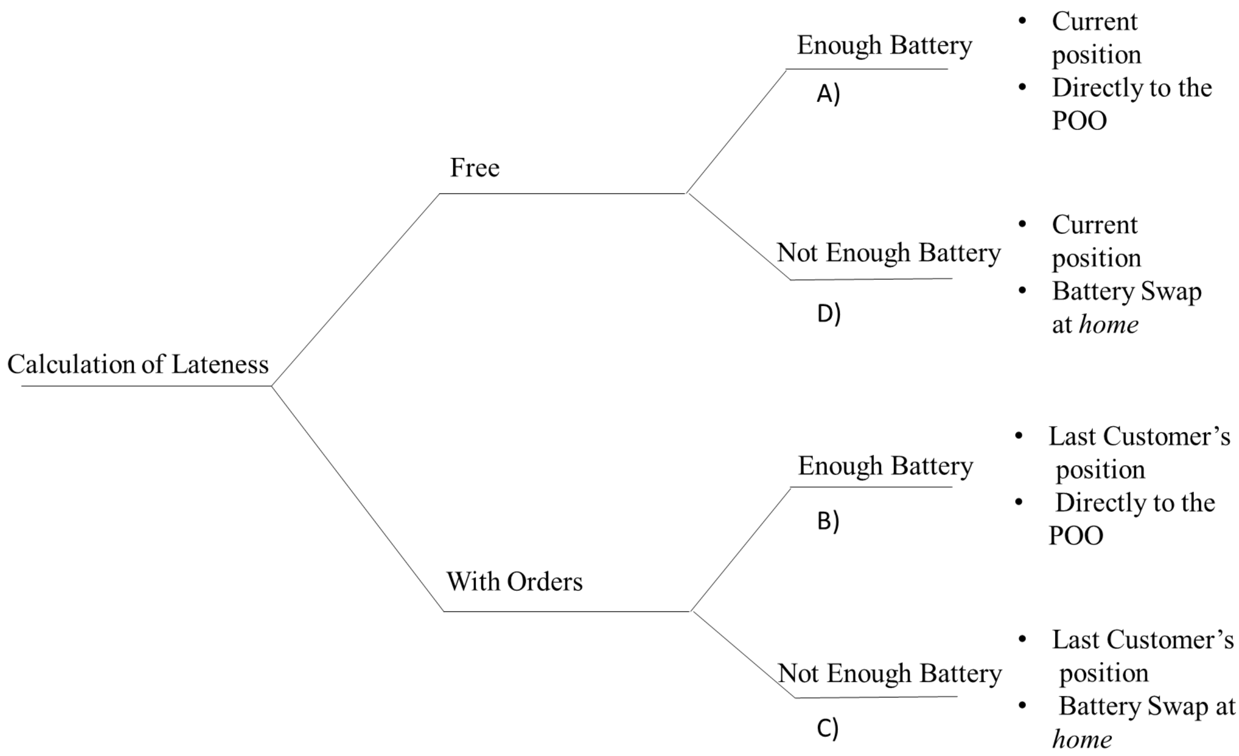

Figure 23 Diagram of the different scenarios for calculation of Lateness

5.6.3 LAIPA in the Simulation Model

This section explains how the policy has been implemented in the simulation model. The order is issued when the transition *orderIssuing* allows the Customer agent to change state from *notHungry* to *waiting.* As discussed in the previous paragraph the aim is to minimize the objective function 1) looking for the best Robot. The iterative algorithm is simple: two help variables called *bestRobot* and *bestLateness* are used to keep track of the best candidate found and the results for the objective function; while analyzing all robots in the population another help variable is used to avoid multiple assignment. Once a robot has been selected, the order is added as last to the queue of orders of *r* and the important variables AT_r and BL_r are updated. These variables guarantee the system has the information about the robot after the mission, since it will be used to evaluate its viability for the next customers ordering.

These variables are updated based on the case A), B), C) and D) previously listed for calculating lateness.

A) $C_r = \emptyset \cup b_r > WCTD_{r,c}$

$$AT_r = et_c + L_{r,c} + JT_c$$
$$BL_r = BL_r - (d_{r,o} + d_{o,c})$$

Available time and Battery Level are updated to identify the moment of time and charge of end of left at the end of the mission. They are considering the travel time and the distance from the robot current position and the restaurant

B) $C_r \neq \emptyset \cup b_r > WCTD_{r,c}$

$$AT_r = et_c + L_{r,c} + JT_c$$

$$BL_r = BL_r - (d_{C_{r,K},o} + d_{o,c})$$

AT_r and BL_r are updated with the same logic as case A but considering the position of $C_{r,K}$ instead of *r* current position.

C) $C_r \neq \emptyset \cup b_r < WCTD_{r,c}$

$$AT_r = et_c + L_{r,c} + JT_c$$
$$BL_r = BC - (d_{h,o} + d_{o,c})$$

In case C, *AT* has to include the stop at the depot for swapping the battery thus adding the travel time from and to *home* and the swapping time. The distance between *home* and *o*, and the distance between *c* and *o*, are subtracted to the battery Capacity to compute the battery level at the end of the mission. It is important to point out that the distance $d_{C_{r,K},h}$ is not considered since it will be "deleted" by the battery swap restoring the full charge of the unit.

D) $C_r = \emptyset \cup b_r < WCTD_{r,c}$

$$AT_r = et_c + L_{r,c} + JT_c$$

$$BL_r = BC - (d_{h,o} + d_{o,c})$$

Similarly to case A) and B), the difference between D) and C) is to look in the travel time and distance which are considering the position of the robot instead of the one of its last customer on the list in the moment of the order allocation.

As it is described so far, the centralized system can efficiently assign orders to robots. On the other hand, robots are not aware which is the first not feasible customer in the list of orders which have been assigned. To solve this problem the variable called actual battery level $ABL_r$is tracking the battery level influenced only by the customers which have already been processed and not by the ones assigned in advance. The variable *recharging* (type: Boolean) set true if the robot has to come home for recharging, false otherwise is used as conditioning factor to force the robot to return home. The value of this variable is changed to false if the robot's actual battery is not sufficient to complete the new mission, forcing it to return to the depot. This check is done in T8/9 of the robot agent. In the cases in which the robot is forced to return home to recharge, since the battery consumption has already been planned equations 6) and 7) are not valid for BL_r but only of ABL_r

5.6.4 Single order Queue Permutation (SQP)

In dynamic scenarios where the degree of dynamicity is close to 1, an order assignment which has been done could be suboptimal when other orders arrive. To exploit the additional information, the optimization with the new policy is not done on the single customer but considers all orders which have been received but not processed yet. Similarlyto what has been done before, a queue of orders for each robot is created. Recalling C_r as the subset of orders which have already been issued, the optimization process will be done on its subset C_* which includes only the orders which have not been completed and processed. Supposing a queue of one customer per robot, $\#C_* \in \{$ 0, *nRobots-1*$\}$. This limitation on the number of orders to optimize on has been done with the following considering the following:

1. Find a good compromise between optimization and respect of the FIFS logic, for which orders which have been issued before are considered (and possibly served) before by the system.
2. Computational complexity increases as *n!* with the increase of orders considered in the optimization.
3. A System where many orders are waiting and are not processed immediately might be unbalanced and for this reason not interesting to analyze.

Each of these factors will be furtherly discussed in the next paragraphs when looking at the experiment results.

With this policy, orders might not be assigned in case all robots' queues are full and wait for a queue to get free to be considered by the system. The following example has the objective of showing this policy in practice.

Defining:

- r : robot in the population. $r = 0,1,2,3 \ldots n$
- c : the customers in the population. $c = 1,2,3 \ldots m$
- q_r: the customer assigned to the queue of robot *r*. if no customer is assigned $q_r = -1$.
- x_r: binary variable equal to 1 if $q_r \neq -1, 0$ otherwise.
- p_r: the customer currently served by the robot *r*. if no customer is assigned $p_r = -1$;
- $\boldsymbol{Q}$ $=\{q_0, q_1, q_2 \ldots\ q_n\}$: vector whose i^th element is the customer assigned to the ith robot in the population.

For instance, with a population of 3 robots $\boldsymbol{Q}$ $=\{2,-1,3\}$ identifies that robot 0 has customer 2 in queue, robot 1 has no customers in queue, robot 2 has customer 3 in queue.

- $P_w(Q)$: a permutation of the values of $\boldsymbol{Q}$
- $P^* = \{P_1(Q), P_2(Q), P_3(Q) \ldots P_W(Q)\}$ the set of all possible *W* permutations of the values of vector $\boldsymbol{Q}$
- $F(P_w(Q))$: the value of objective function for the permutation $P_w(Q)$.

Whenever a new order *c* is issued, if there is at least one empty queue ($\sum_{r=1}^{n} (x_r) \neq n$) the best permutation $P_w^*(Q)$ if found so that:

$$F(P_w^*(Q)) = \min(\{F(P_1(Q)), F(P_2(Q)), F(P_3(Q)) \ldots F(P_W(Q))\})$$

The function in this case considers not only the information related to the new order *c*, but all q_r, calculating the average penalty for that specific permutation.

$$F(P_w(Q) = \frac{\sum_{r=1}^{n} (w_1 L_{r,q_r} + w_2 WCTD_{r,q_r})(x_r)}{\sum_{r=1}^{n} (x_r)}$$

The value of $L_{r,q_r}$and $WCTD_{r,q_r}$ are calculated following 12), 13),14), 15).

In case all queues are full ($\sum_{r=1}^{n} (x_r) = n$ previous to the assignment of *c*), the order waits for the first robot which completes the order, is added to its queue and the procedure explained is repeated.

The method considers permutations and not combinations since the order with which Q is arranged influences the assignment to a different Robot. The number of calculations that need to be done are increasing as *n!* with the number of robots and are repeated for every new customer *c* leading to longer and longer simulations with the higher values of these two parameters.

5.6.5 SQP in the Simulation Model

In this section is explained how the methodology has been implemented in the simulation model. To model q_r a variable type customer called *nextCustomer* is added to the Robot agent. This variable is the equivalent of *orderList* in the LA (Heap, 1963) (Heap, 1963)IPA policy. Q is represented by an array *a[ ]* of size *n.* As done for the other policy, two variables are used to store the best permutation and the value of the objective function while evaluating the elements of P^*. The best permutation is saved in *c[ ]* of size n, while the average value of the objective function is saved in *bestPenalty.* The following procedure steps follow the arrival of the order.

1. If possible, the order is added to the first empty queue of any of the Robots.
2. *a[ ]* is updated to include the new customer.
3. All possible permutations of the array are computed, saving in *c[ ]* the best permutation and in *bestPenalty* the value of the permutation.
4. The variables next customers are updated taking as reference the values of *c[ ]*
5. For all the robots not processing any order, the order in queue becomes the actual order.
6. *a[ ]* is updated to include the changes in the queues.
7. Values of *c[ ]* and *bestPenalty* are reset.

A numerical example is here presented. Setting $p_0 = 13, p_1 = 7, p_2 = -1$ and $q_0 = 9, q_1 = -1, q_2 = -1$, the three robots are in different conditions: robot 0 is currently occupied in a delivery and has an order already waiting to be processed, robot 1 is processing an order but with no immediate other task after completion, while robot 2 is free and available. Supposing a new customer *c=10* issues an order with the system in the defined condition. Since there is at least one empty spot in the queues of the robot, the order can be added for evaluation and the variable *nextCustomer* of the first empty robot is changed in this example making $q_1 = 10$. The array is updated becoming *a[9, 10, -1].* All the possible permutations of the array are computed:

[10, -1, 9], [10, 9, -1], [9, -1, 10], [9, 10, -1], [-1, 9, 10] [-1, 10, 9].

All possible permutations of the array are generated through Heap's algorithm (Heap, 1963). Whenever a new permutation is computed the objective function value is compared to the best result found up to that permutation: if the value is better is saved in the variable *bestPenalty* and the permutation is saved in *c[ ].* After all possible permutations have been generated, *c[ ]* contains the optimal allocation of the orders to the robots. The information has now to be translated to the local

Robot's variable *nextCustomer*. Supposing the permutation *[-1, 10,2]* is the best now: $q_0 = -1, q_1 = 10, q_2 = 2$. It is important to mention that the objective function despite operating on the queues of the robot takes as inputs parameters *AT* and *BL* which identify the moment the condition of the robot at the end of a mission, which, in case of no current mission (so $p_r = -1$), consider the actual condition of the robot for the immediate start of the delivery (see case B and C of the Lateness calculation). At this point, if the order has been assigned to queue but no order is currently processed by the robot, $p_r = q_r$ for all robots. In the example since $p_3 = -1$, it is possible to process the order 2 immediately so that $p_2 = q_2 = 2$ resetting $q_2 = -1$. All this information is translated in the local variables *customer* and *nextCustomer* at the Robot agent level.

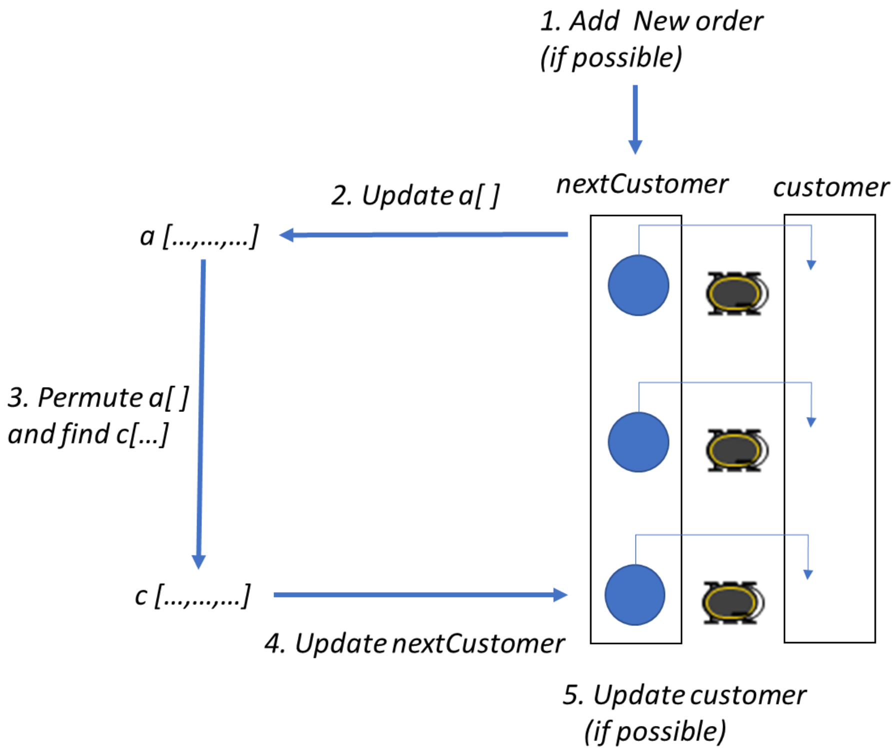

Figure 24 Mechanism of update of next customers variables in case of a new order and empty queue.

In case two or more robots at the moment of the permutation do not have orders in queue, the permutations in P^* are not unique. This characteristic does not impact on the optimality of the solution found but on the other hand leads to useless calculations which increase the computational time.

In case all the robots have orders in queue, the order waits until one of them is free and the process is restarted from point 1). All these functions are introduced in two transitions in the simulation model: the first one is in the *orderIssuing* transition which triggers adds the order to the service Requests seen by the system; the second one is transition 8 in the Robot agent where the aim is pulling the first element of the list adding it to its queue right after starting the mission as exemplified by image. Figure 17 shows how after the delivery to customer *0*, the first robot immediately starts serving the customer in queue. The empty spot in queue is filled by the first customer in the service Requests queue. In the service requests list order are then processed following the FIFO logic. Despite not being optimal limiting the optimization on a restricted number of orders at a time, the negative effect is partially limited by the hypothesis that all orders have the same preparation time. moreover, accumulating orders in queue might not be in general a scenario to prefer over immediate processing, due to the negative impact of long waiting times on the order cycle time.

Compared to the LAIPA policy SQP is expected to lead to better results in terms of Lateness and order cycle time since it is considering a wider number of cases. The two solutions are the same in case only one robot is Considered.

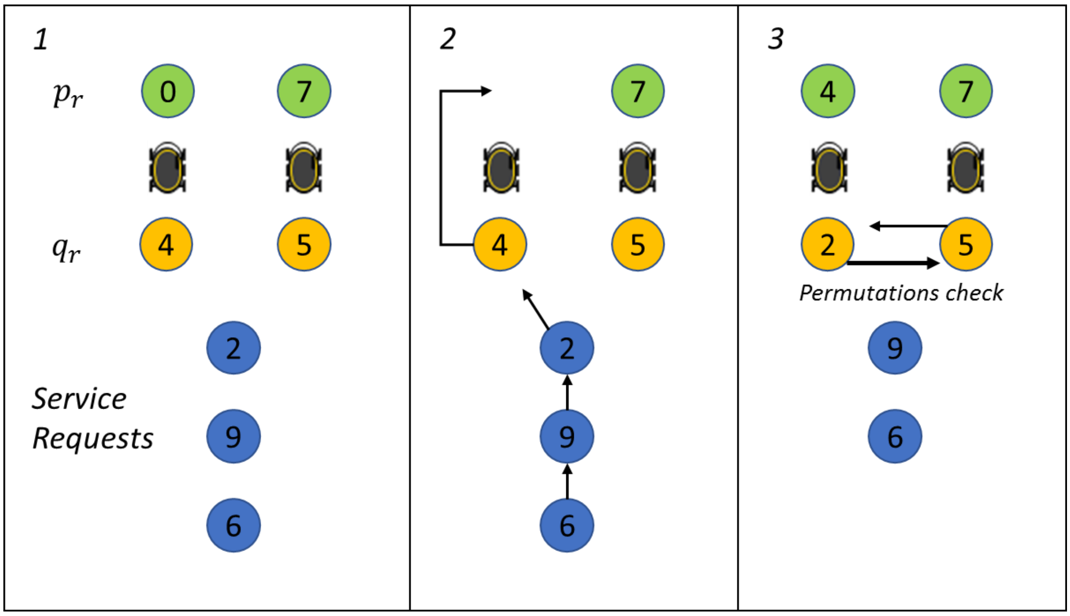

Figure 25 Representation of a full system

The following two images show the animation of the simulation environment which has played a crucial role in the design and debugging phase to evaluate the code written to control vehicles movement and agents actions.

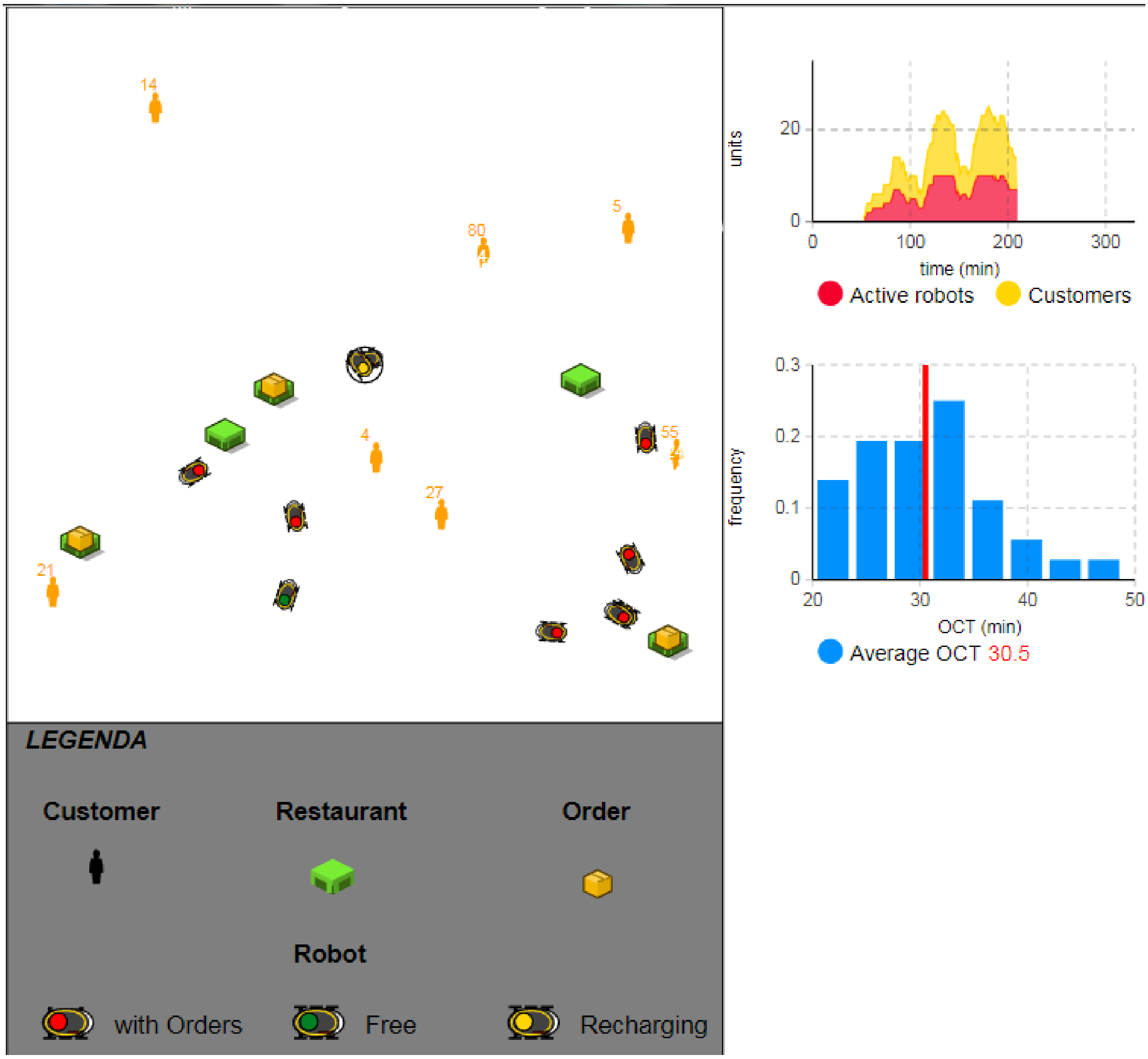

Figure 26 Screenshot of the simulation environment animation during deliveries. The two graphs have been used to check the average conditions of the systems in terms of requests, active robots and delivery times.

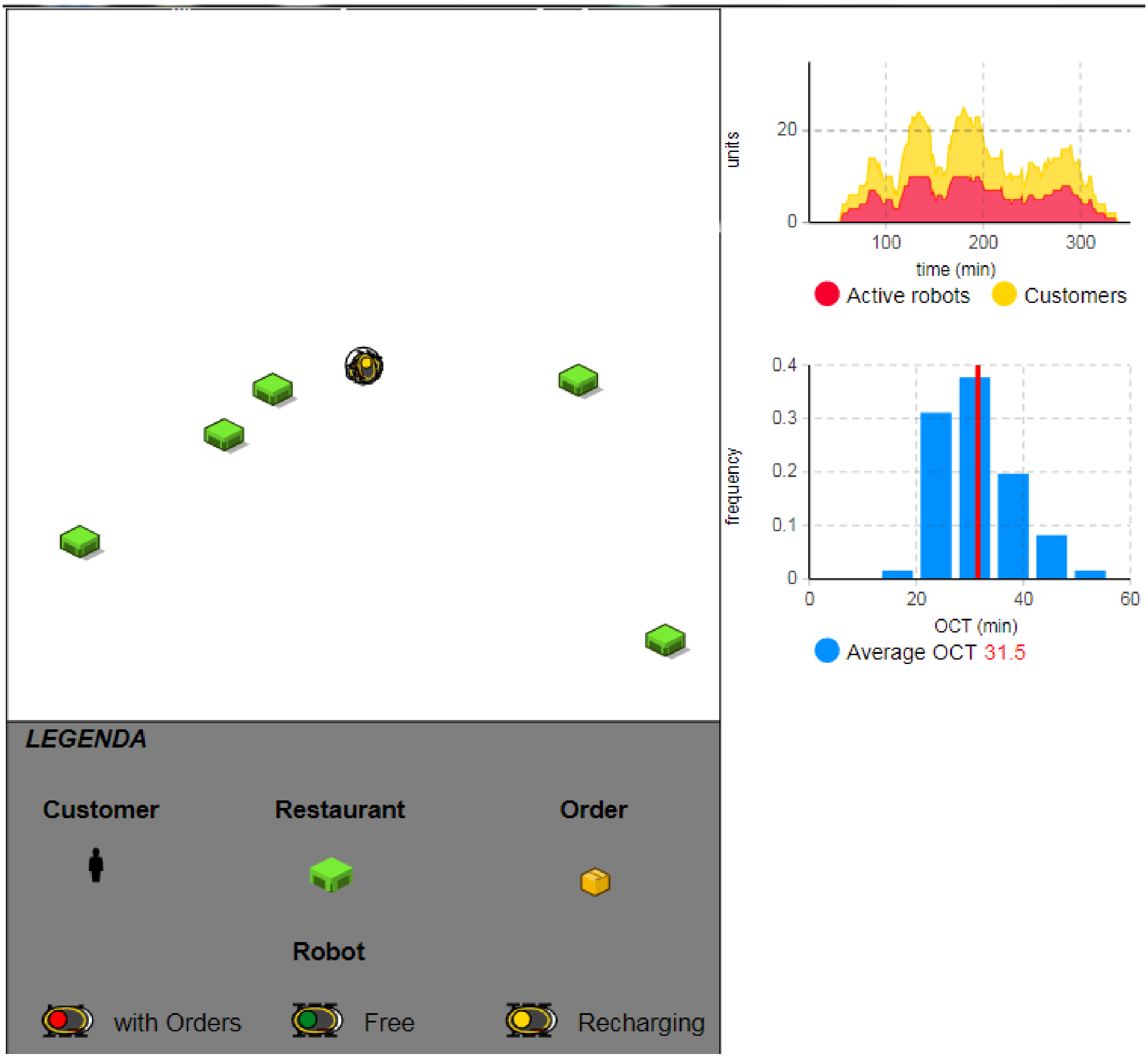

Figure 27 Screenshot of the simulation environment animation with no requests from customers. The two graphs have been used to check the average conditions of the systems in terms of requests, active robots and delivery times

6.Simulation Results

6.1 Comparison of order allocation methodologies

The advantages and disadvantages of both methodologies which affect the trade-off between order traceability and low delivery times are reported and briefly discussed in this section. The two order allocation methodologies are compared on a small-scale experiment similar for order distribution, methodologies used for calculation of number of runs and parameter levels to the ones which will be conducted to answer the research questions (provided in section).

The objective of this initial comparison has the aim of understanding which of the two presented methodologies can be used for large scale experiments. The two methodologies are compared on two hours ordering window with order profile as a triangular distribution with minimum, maximum and mode equal to 0,120 and 60 minutes. The comparison is done considering 4 different sizes of experiments keeping constant the ratio between Customers and Robots to maintain a structure to the comparisons. Battery Level, number of customers, area, speed and circuit factor as well as other parameters are the same discussed in the base case of larger scales experiments presented in the next section. Simulations are run on Intel Core i5-520 processor 2GB Ram.

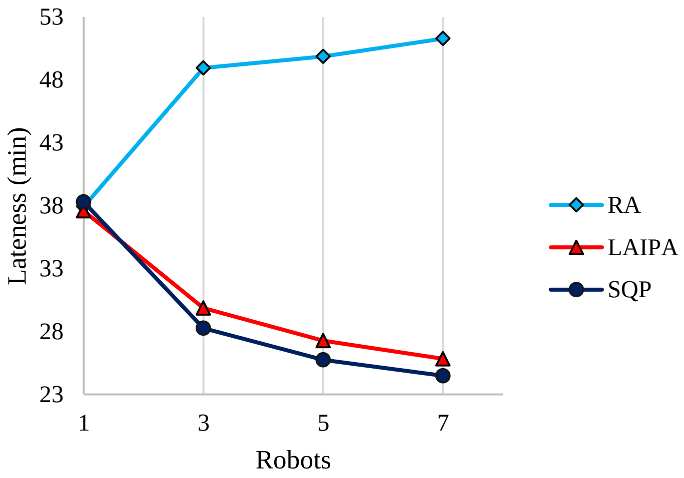

Figure 28 Lateness results for the 3 allocation methods tested

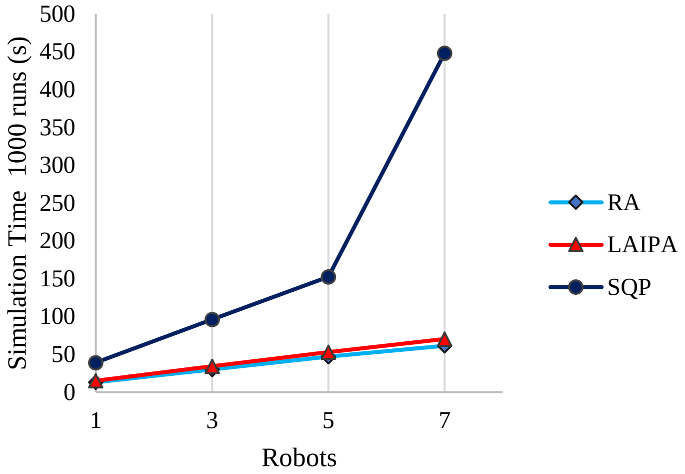

Figure 29 Computational Time for 1000 runs with the 3 considered allocation methods

The relevant performances taken into account are on the one hand Lateness and the computational time required for 1000 experiments. The two methodologies are compared with random allocation (RA) for which at order issuing, the system assigns a random robot for the fulfillment of the order. As it is possible to see, in case of single Robot, no difference exists among order allocation policies, since the choice of robot is forced for all customers. For larger systems both methodologies outperform the random allocation, proving effectiveness in reaching objectives of lower lateness they have been defined for. The performance of RA is progressively worse becoming the probability of selecting the best robot smaller with the increase of potential candidates. The SQP outperforms LAIPA for Lateness as supposed, due to the inclusion of a wider number of scenarios to optimize with no constraint on immediate and permanent allocation.

On the other hand, it is possible to see how the computational time grows for larger instances in graph. The time required for 1000 runs for 7 robots reaches 447,5 seconds. Calculating all possible permutations, the number of calculations grows as the factorial of the number of robots: n factorials calculations are done for every customer order. Scaling up the experiment has led to the computer stalling. The simple yet effective Look ahead immediate permanent assignment algorithm has led to satisfying results both in terms of lateness and computational time. No differences exist between the trends of results of SQP and LAIPA, proving both methods can let emerge existing relation between changes in parameters and performance. For these reasons, LAIPA has been considered as the allocation method for answering the research questions on delivery robots.

The second factor considered is Traceability. Traceability for LAIPA in all cases is equal to 100% being the assignment immediate and permanent. In SQP allocation method traceability is influenced by two factors: the limitations in assignment queue and the reassignment of orders in queue. In the

case of SQP allocation method for example, the system does not assign the order if all robots queue are full resulting in a value of TI lower than 100% also in the case of single robot delivering.
With the increase of the system the second effect plays an important role on reduction of Oct and lateness but at the same time reduction of the traceability. With a higher number of robots and customers the possibility of optimization grows, with higher chances for new orders to lead to changes of the previous allocation.
In the case of a single robot in theory traceability could be considered as 100% since no other possible allocation candidates exist. Since the same code is used for experiments with more robots, rules exist on the number of orders which could be allocated to the single robot, delaying the final assignment. As is shown in figure 30, the effects are shown in a traceability index equal to 80%. In practical terms by looking at the average time which elapses between order issuing and beginning of the mission $(t_m - t_o)$ it is possible to give an absolute average measure of how soon customers can know about the delivery time and robot responsible for the delivery. Table reports traceability index and the traceability time for customers. Traceability time identifies the minutes before the starting of the mission for which on average customers have been assigned to the robot responsible for the delivery of their orders.

$$T\ time = TI \times (t_m - t_o)$$

It is shown how if on average orders are processed in shorter times for larger systems (reflected also by lower lateness levels), the traceability time reduces due to the effect of permutations which update robots assignments.

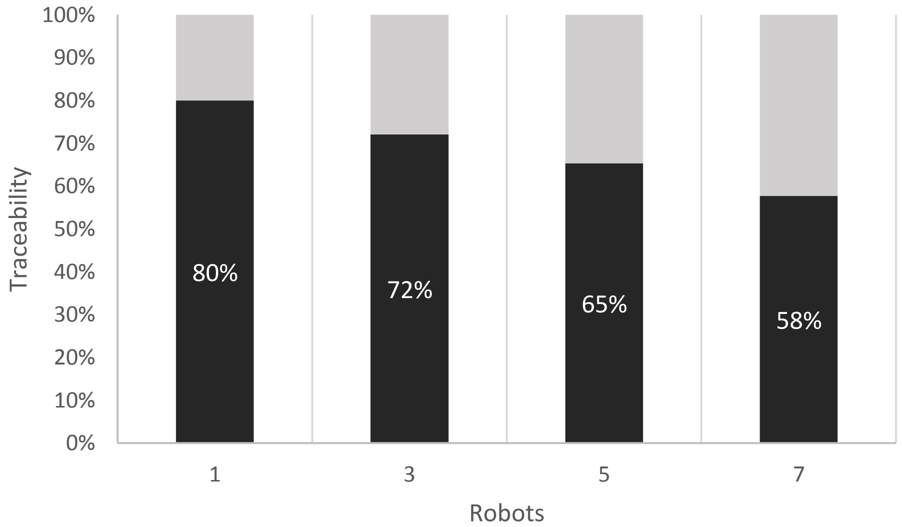

Figure 30 Traceability index results in the different experiments of comparison among order allocation methodologies

R	C	AM	time (s)	OCT (min)	Lateness (min)	TI
1	5	SQP	39,06	70,90	38,29	80%
3	15	SQP	95,85	60,91	28,27	72%
5	25	SQP	152,4	58,37	25,74	65%
7	35	SQP	447,93	57,03	24,48	58%
1	5	LAIPA	15,04	70,03	37,58	100%
3	15	LAIPA	34,12	62,38	29,86	100%
5	25	LAIPA	52,93	59,94	27,26	100%
7	35	LAIPA	70,19	58,39	25,83	100%
1	5	RA	13,02	70,57	37,93	100%
3	15	RA	30,01	81,52	48,93	100%
5	25	RA	46,76	82,36	49,85	100%
7	35	RA	61,23	83,77	51,28	100%

Figure 31 Results of the experiments conducted for comparing order allocation. R idetifies the number of Robots, C the number of customers, AM the allocation Method, time is the simulation time required to complete 1000 runs.

R	C	TI	To-Tm	T time
1	5	80%	39,98	31,98
3	15	72%	31,47	22,67
5	25	65%	29,40	19,21
7	35	58%	28,39	16,38

Table 1Traceability index and Traceability time for customers in the experiments conducted.

6.2 Sensitivity Analysis

With the objective of understanding the performance of the system in the scenario previously described, an extensive number of experiments has been conducted. Each of the different factors has been investigated through experiments which could give meaningful and generalizable results for the parameter/s studied. This has been done first through understanding meaningful parameters levels for each experiment combining the information provided by Deliveroo with the outcome of the model. Second, by selecting a sufficiently high number of runs for each experiment to guarantee the validity under statistical perspective. The method for establishing the number of runs is the MSPE (calculated on Lateness) a graphical statistical method which allows the decision maker to consider a poll of meaningful and representative scenarios and comparing the evolution of the statistical indicator with the increase of the number of runs (Giribone, Mosca, & Mosca, 2010). The objective is understanding for which number of runs MPSE of Lateness converges to stable results.

The number of parameters considered in the simulation study is high and is including technological, system design, and exogenous factors. A reference scenario has been set as a starting point for the analysis of the results. In the study (Liu, 2019) the simulation time is set equal to 6 hours of working activity in food delivery. In order to capture the possible utilization of this system for persistent delivery a 12 hours simulation time is set. As shown by Tonga and colleagues (Tonga, Dai, Xiao, & Yan, 2020), in food delivery order profile is characterized by high peaks during meals. From their study it is possible to see how a triangular distribution approximates the order profile of customers for the first working hours.

To consider general scenario the order profile presents two equal peaks in the middle of each of the two 6 hours sections of the day. The order profile follows a custom probability distribution function made of two consecutive triangular distribution, whose parameter have been adapted to respect the original characteristics of a triangular distribution (called DTRI). The random value from the distribution is the number of minutes a customer agent stays in the *notHungry* state. It is important to point out that simulating two consecutives equal distributions cannot always be represented by simulating two times one distribution: the effects of late deliveries and battery constraints as well as recharging activities might influence the results in the second part of the day.

Additionally, a uniform distribution of orders is used to compare the impact of peaks of demand on the relevant performance. In the base case the area served is 1 km^2 (*conversion*=400) with 10 robots serving 120 customers, who can order from 4 local restaurants. The design parameters of the vehicle are the ones found on Starship Robots factsheet in (SwissPost, 2019) with a range of 6km and an average speed of 3km/h. The circuit factor is set equal to 1,3 since a good approximation factor for urban environments (Gonçalvesa, Gonçalves, de Assis, & da Silva). Loading, Unloading and Preparation time for the orders are respectively set equal to 2, 2 and 15 minutes (For what stated concerning job time, the outcome is representative of every couple of loading and unloading time whose sum is equal to 4 minutes).

The battery swapping time in the depot has been set equal to 5 mins (Vidović & Ratković, 2015). Results for each experimental setting show the changes of lateness with respect to the parameter studied and the average order cycle time based on the Order Time of customers.

The number of runs for each experiment has been set equal to 1000 being a significant value for both starting scenarios as shown in the figures 33 and 34.

To keep under control the variability the travel time between restaurants and customers are reported in the table of results. This value can be reconducted to the distance between two random points taken inside a square divided by the travelling speed. For example in case of a side of length 1 the average distance between two random points is 0,52. (Philipp, 1991) Considering a Circuit factor of 1,3 and a travel speed of 3 km/h the average travel time will be about 13,52 mins as in most of the results analysed. The variation related to the distance between customers and restaurants is one of the main drivers of variability in the evaluation of lateness.

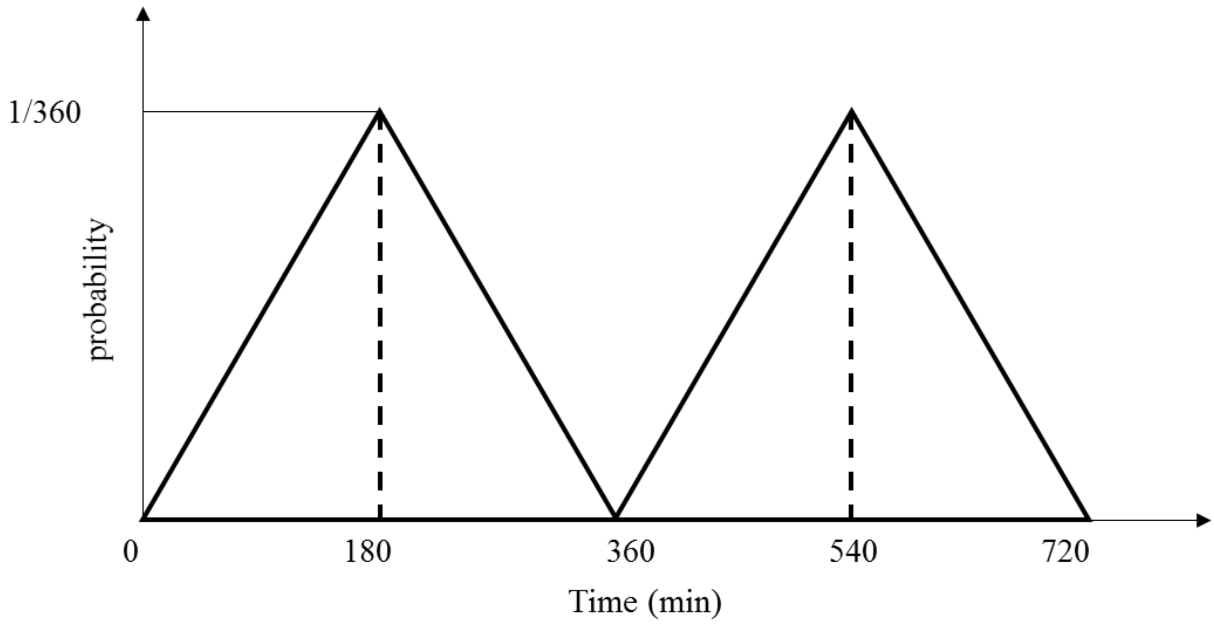

Figure 32 DTRI distribution used to simulate order profile

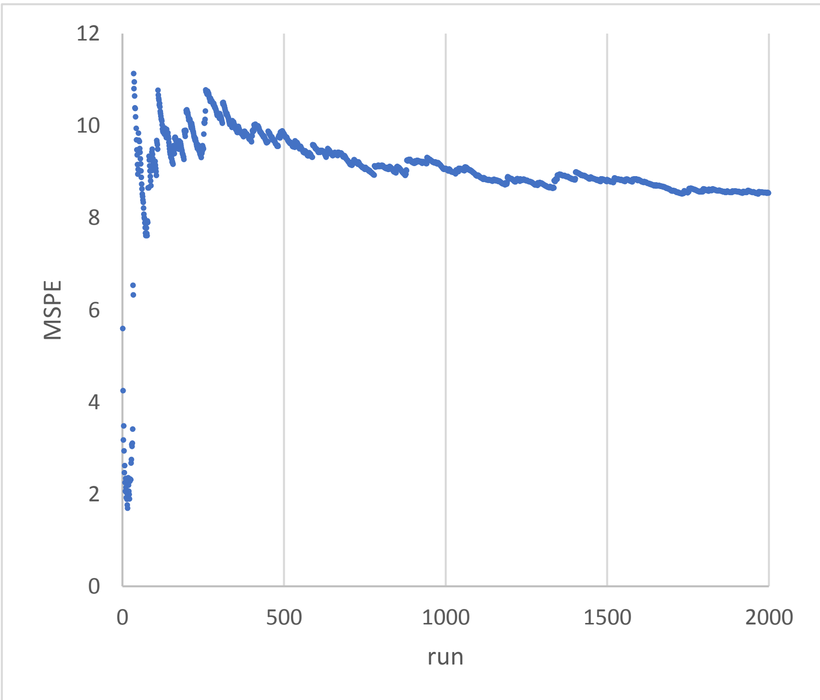

Figure 33:Converence of MSPE for DTRI distribution

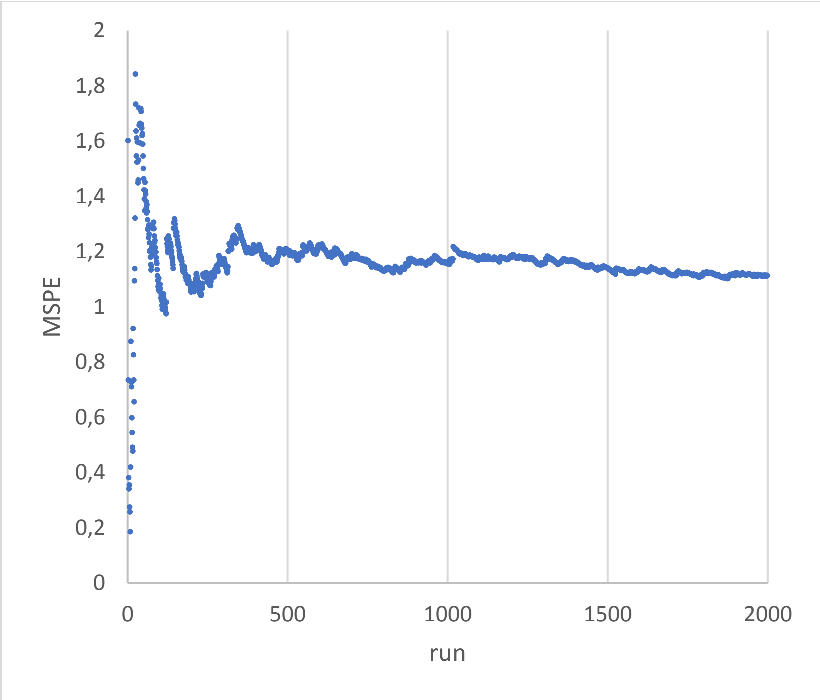

Figure 34: Convergence of MSPE for UNI distribution

For the 2000 runs the time required have been 350,4 and 367,2 seconds respectively for the uniform and DTRI distribution,

6.2.1 Base Case

The following graphs show the results for the base case with the UNI and DTRI distributions. The average lateness in case of DTRI distribution is equal to 2,63 minutes. In graph 3 the results of average OCT are clustered to calculate the average OCT in different hours of the day: for instance, for the x value "30" the average OCT for customers ordering from 0 to 30 mins is calculated. For DTRI distribution, the peaks follow the order profile, shifted by about 30 mins. Delivery time in peak hours reaches up to 39 minutes, a fair result for the industry. Graph 38 shows the distribution of OCT from 19 minutes to 107 minutes (the maximum result obtained). 96,7% of the orders are delivered before hour since their issuing time.

On the other hand, uniform distribution of orders leads to better results considering the same initial parameters. The average value of lateness decreases to 0,37 mins. As it is possible to see from a pairwise comparison Uniform distribution allows to reach lower values of lateness in all the scenarios studied: 95,6 % of orders are delivered within 45 mins and 99,85% within 1 hour. The average Oct fluctuates between 33,1 and 32,73 mins showing a slight increasing trend from the beginning hours during simulation run.

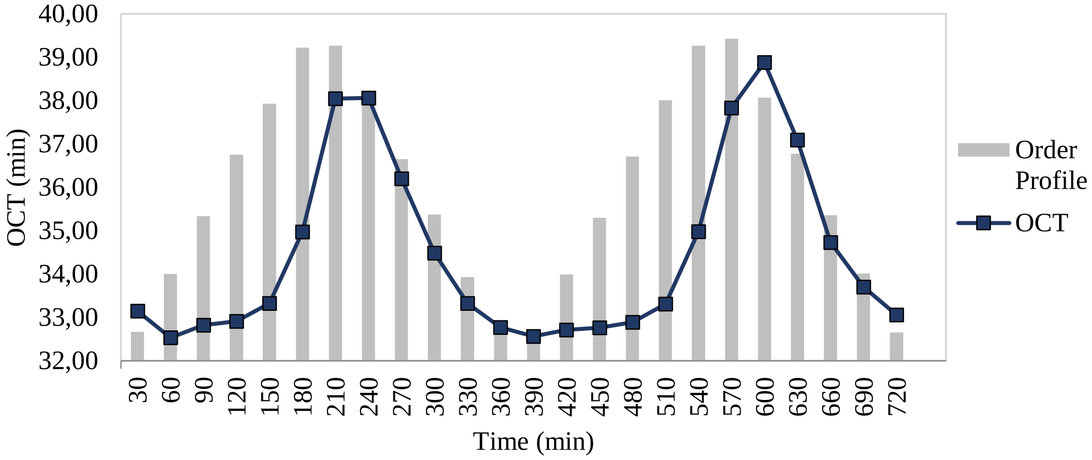

Figure 35 DTRI Average OCT for customers ordering in different hours for the base case.

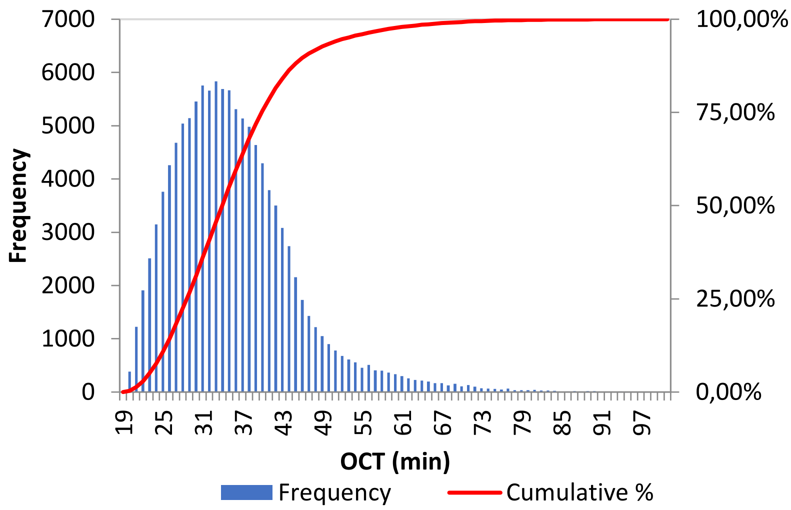

Figure 36Distribution of OCT in the Case of DTRI distribution

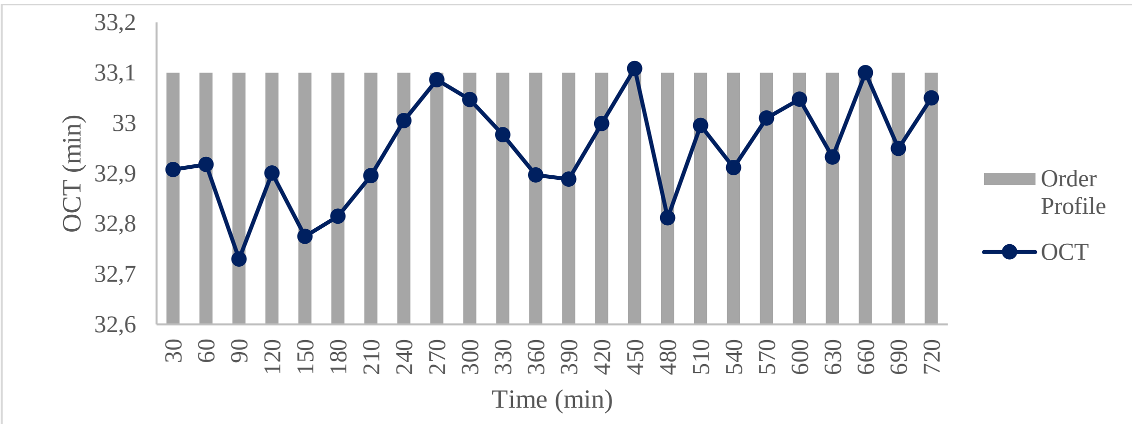

Figure 37 OCT for different ordering times during simulation

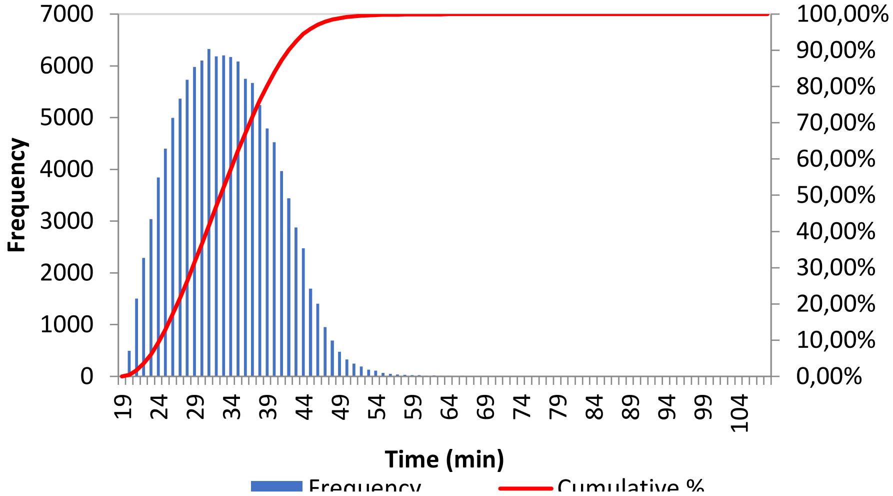

Figure 38: Distribution of OCT with UNI distribution

No.	POO	Robots	POD (Orders/day)	Area (km^2)	BC (km)	Speed (km/h)	OCT DTRI (min)	SD OCT DTRI (min)	TT DTRI (min)	L DTRI (min)	OCT UNI (min)	SD OCT UNI (min)	TT UNI (min)	L UNI (min)
1	4	10	120	1	6	3	35,23	9,44	13,60	2,63	32,95	6,79	13,58	0,37
2	***1***	10	120	1	6	3	36,94	12,50	13,47	4,47	32,93	6,94	13,4	0,50
3	***8***	10	120	1	6	3	34,81	8,94	13,55	2,27	32,90	6,75	13,55	0,35
4	***16***	10	120	1	6	3	34,68	8,74	13,53	2,15	32,86	6,77	13,52	0,34
5	4	***8***	120	1	6	3	42,04	16,15	13,55	9,49	32,95	7,98	13,55	1,41
6	4	***12***	120	1	6	3	33,34	7,22	13,58	0,76	33,96	6,68	13,64	0,24
7	4	***14***	120	1	6	3	32,89	6,77	13,56	0,33	32,88	6,60	13,55	0,20
8	4	10	***80***	1	6	3	32,86	6,76	13,53	0,34	32,76	6,63	13,60	0,18
9	4	10	***160***	1	6	3	44,06	17,65	13,55	11,51	32,95	8,25	13,61	1,60
10	4	10	***200***	1	6	3	62,06	30,53	13,54	29,52	32,78	14,64	13,54	7,45
11	4	10	200	***0,50***	6	3	28,94	4,97	9,55	0,40	28,66	4,65	9,56	0,10
12	4	10	200	***0,75***	6	3	31,88	6,91	11,77	1,11	30,90	5,75	11,74	0,16
13	4	10	200	***1,25***	6	3	39,01	13,08	15,13	4,88	34,97	7,88	15,23	0,74
14	4	10	200	***1,50***	6	3	43,76	16,89	16,62	8,14	36,95	9,24	16,57	1,38
	4	10	200	1	***5***	3	35,81	10,568	13,57	3,23	33,12	7,10	13,57	0,55
15	4	10	120	1	***7***	3	34,74	8,81	13,58	2,17	34,20	6,73	13,52	0,33
16	4	10	120	1	***8***	3	34,40	8,31	13,56	1,84	40,00	6,71	13,57	0,32
17	4	10	120	1	***9***	3	34,30	8,04	13,61	1,68	32,95	6,69	13,56	0,30
18	4	10	120	1	6	***2***	54,33	22,90	20,26	15,07	32,86	12,83	20,27	3,79
19	4	10	120	1	6	***4***	29,91	5,76	10,13	0,78	32,89	5,02	10,22	0,17
20	4	10	120	1	6	***5***	27,58	4,39	8,13	0,46	32,86	4,09	8,12	0,20
21	4	10	120	1	6	***6***	26,15	3,66	6,80	0,35	32,95	3,44	6,73	0,20

Table 2 results of simulation for average and std dev of OCT, TT and L for DTRI and UNI distributions

6.2.2: The Impact of Points of Origin on Lateness and OCT

The different levels for the experiments are set after are set starting with the information provided by Deliveroo on average density of restaurants (set at around 3/4 per squared km) simulation. Very low density is set at the minimum of 1 POO per km^2. While high and very high densities are set at 8 and 16 restaurants.

In the case of DTRI distribution with 1 POO in the Area, Lateness is equal to 4,47 mins reaching its peak. It progressively decreases to smaller values reaching 2,15 mins with 16 POO. By looking at the average OCT in the different ordering hours it is possible to see how it follows the order profile of the customers with peaks reached in time 240 and 600, identifiable as lunch and dinner time (180min, 540min). OCT varies consistently ranging from 32 minutes to more than 40 minutes in correspondence of the peaks. The second peak is higher compared to the first one in all cases, but especially stressed with POO=1. The reduction in lateness is affecting OCT especially during these hours.

Considering a scenario where demand is smooth and does not present any peak, the system is still positively having benefits from the increase of the number of restaurants. In all results a uniform distribution has lower values of lateness and OCT. For instance, in correspondence of POO=1, lateness is equal to 0,5 minutes: the increase still generates benefits which are smaller compared to the ones observable in the case of DTRI distribution. Moreover, all data are included in the interval 32,34-33,3, making hard to read any relevant trend in figure 42.

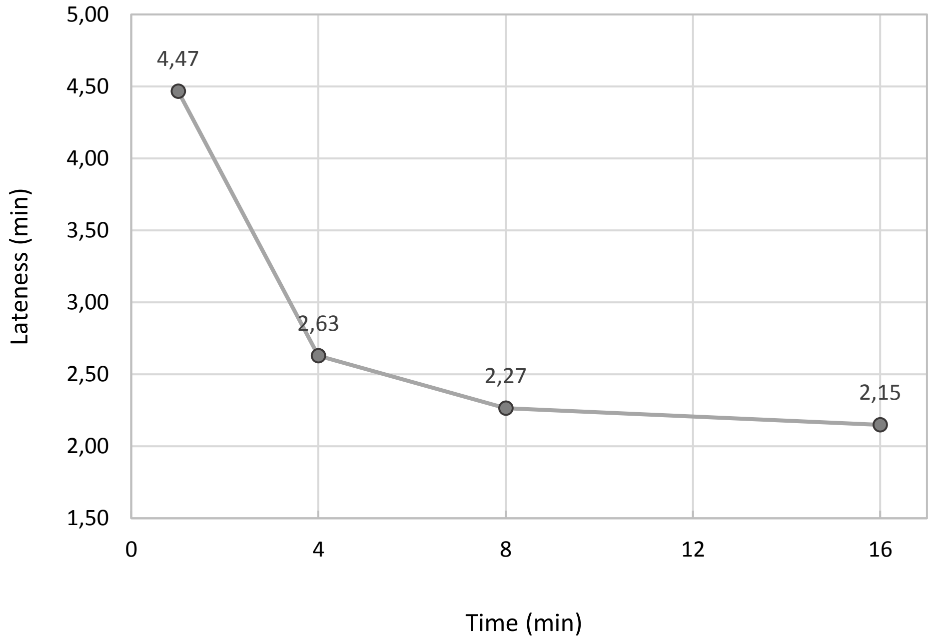

Figure 39 DTRI Impact of different levels of POO on Lateness

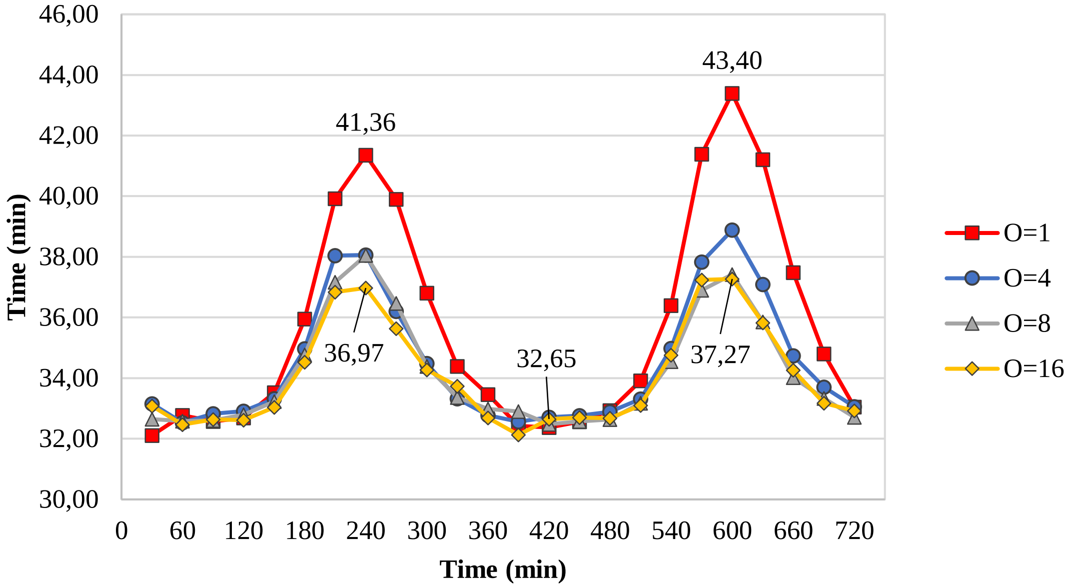

Figure 40 DTRI. Impact of POO OCT for customers ordering during the time period

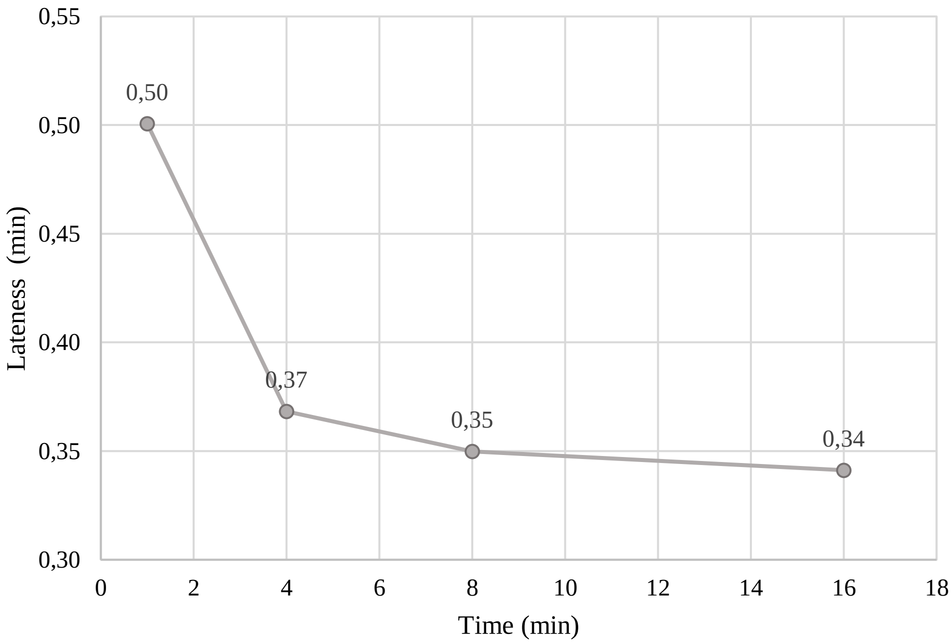

Figure 41 UNI: Impact of different levels of POO on Lateness

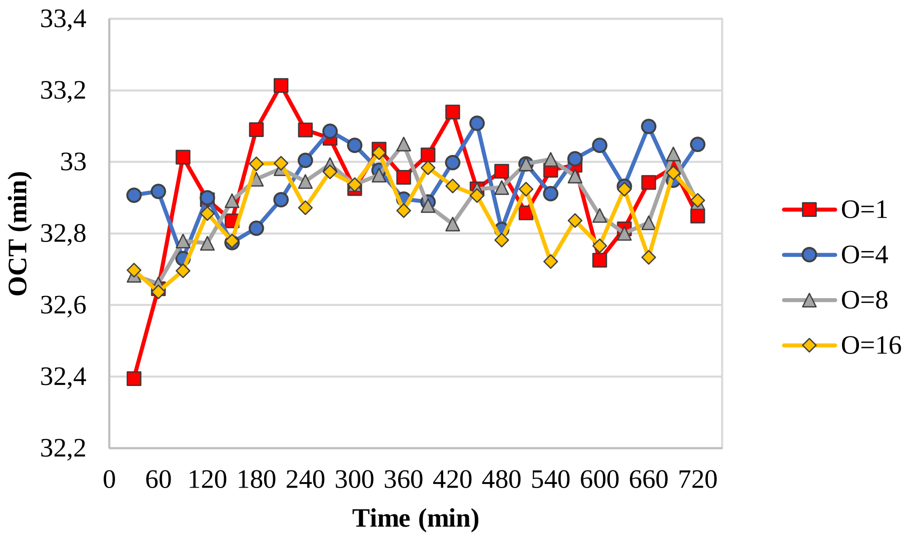

Figure 42 UNI: Impact of POO OCT for customers ordering during the time period

6.2.3 The Impact of Points of Destination on Lateness and OCT

A higher number of customers allows to generate higher revenues, but at the same time puts more stress on the system with more requests to be fulfilled. The starting level for the experiment has been set starting from the information provided by Deliveroo on the orders received in the city of Milan (10000 per day in an area of the city of around 180 km^2 , the area served by the company is smaller than the total one). With an increase of customers in the Area Lateness increases exponentially reaching almost 30 mins for 200 customers/day in the case of a DTRI distribution. By looking at the average OCT, it is possible to see how the increase of lateness especially affects peak hours. The peak of OCT is shifting along the time horizon with the increase of customers in the area: considering for example the first 360 mins the peak in OCT moves from 240 to 360 from 80 to 200 customers/day. This can be also be easily read by seeing how the second bell doesn't close (reaching lower values of OCT) at the end of the ordering period. Moreover, the values of OCT resulting from the experiment with 200 customers present OCT in the peak hours of around 90 minutes, a result which does not match the more traditional delivery time of 30mins-1h.

Also with the uniform distribution Lateness increases progressively with the increase of Customers. From 160 to 200 customers/day reaches the value of 7,45 minutes. By looking at figure 45, it is visible how the OCT progressively increases with the increase of Customers orders progressively moving towards higher and higher values for all customers ordering. Considering the uniform distribution, the results for C=160 and C=200 show an interesting increase of average OCT which stabilizes after minute 200. Despite the sensible increase, the ranges of OCT still are acceptable for the industry setting at around 42 minutes even in the worst cases considered.

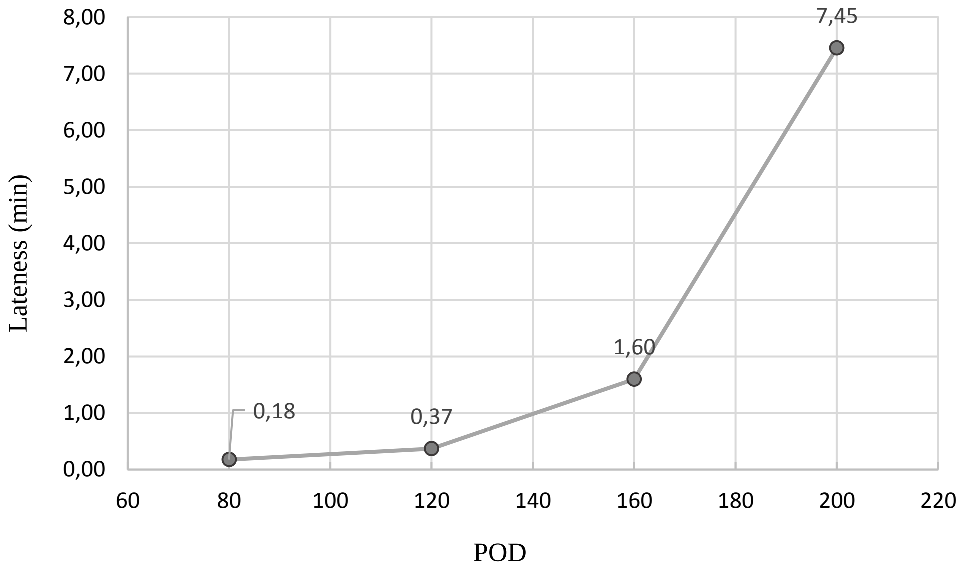

Figure 43: DTRI Impact of different levels of POO on Lateness

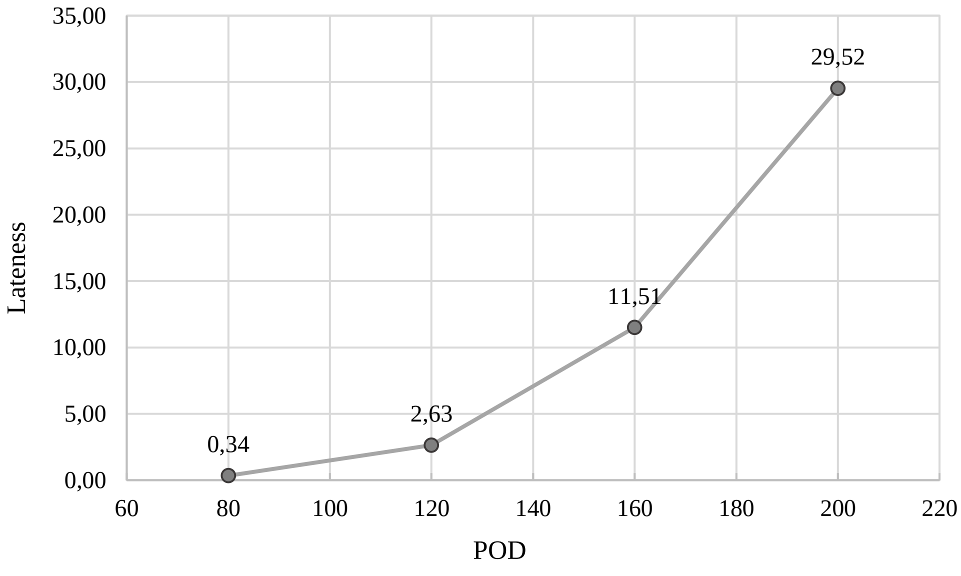

Figure 44: UNI Impact of different levels of POO on Lateness

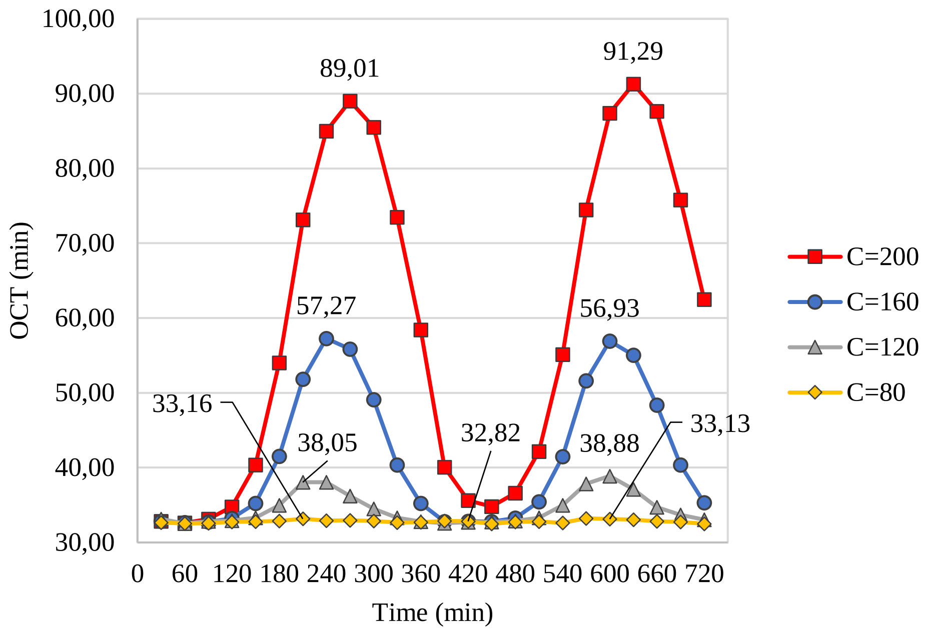

Figure 45: DTRI Impact of POD on OCT in different ordering hours

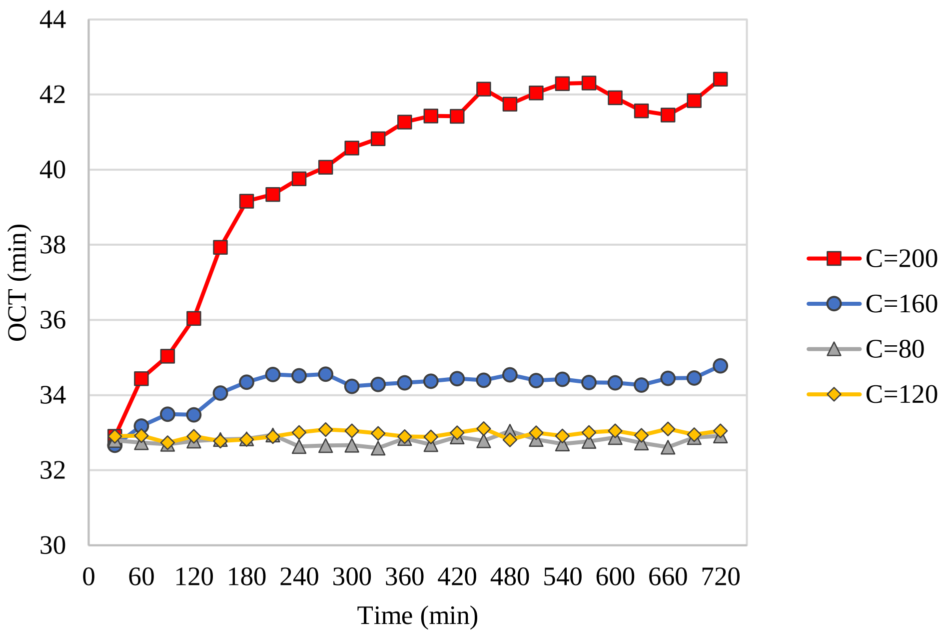

Figure 46 UNI Impact of POD on OCT in different ordering hours

6.2.4 The Impact of Area on Lateness and OCT

Larger areas of operations lead to longer trips and travel times potentially increasing the value of lateness and impacting on OCT. In figure 49 and 50 the components of OCT are reported to highlight the relative contribution. The constant part related to the preparation loading and unloading does not change being fixed (19 minutes). If usually in other experiments the parameters do not impact on the travel time and so the variation in order cycle time is only related to the changes in Lateness, in this case it is possible to see how for larger areas the strong contribution of changes in travel time from restaurant to customer highly affects OCT.

Travel time between restaurant and customer ranges from 9,6 to 16,62 mins. These values, as already mentioned refer to the travel time between two points taken randomly inside a square scaled by the circuit factor.

Graph 47 and 48, show the usual exponential trend of growth of lateness which remains around acceptable results in the case of UNI distribution while severely impacts on OCT in case of DTRI distribution. It is possible to see how in the case of DTRI huge problems are caused to the system by the increase of the area with a Lateness which reaches 8,14 mins a result similar to the one obtained by the same system serving 80 more customers in an area of 1 km^2.

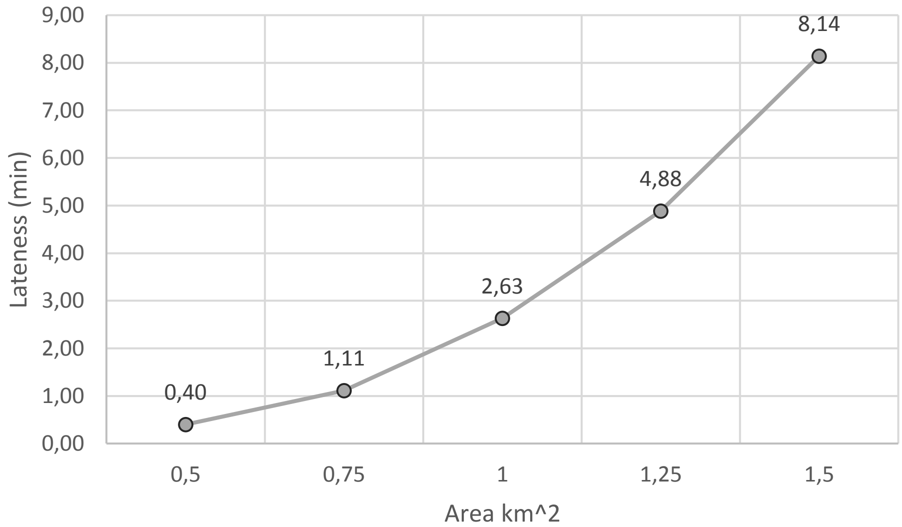

Figure 47 DTRI: Impact of Area on Lateness

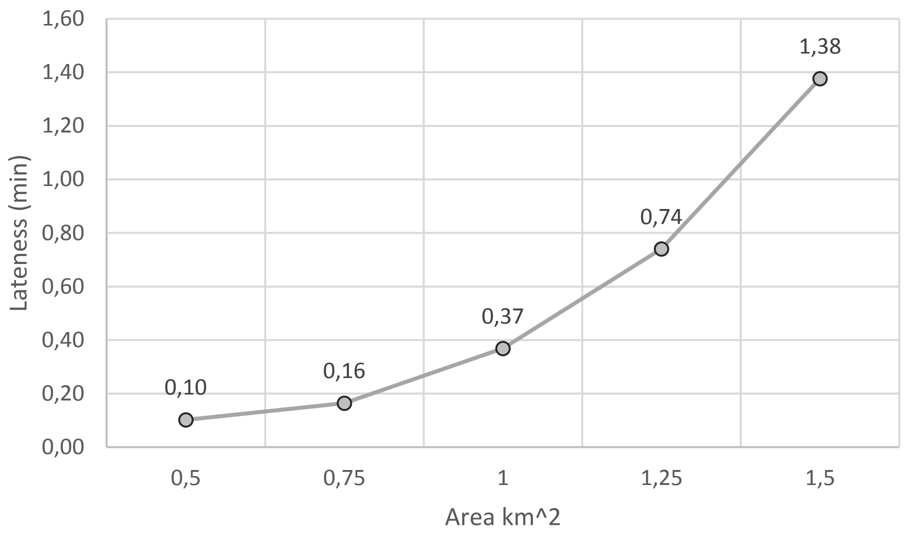

Figure 48 UNI: Impact of Area on Lateness

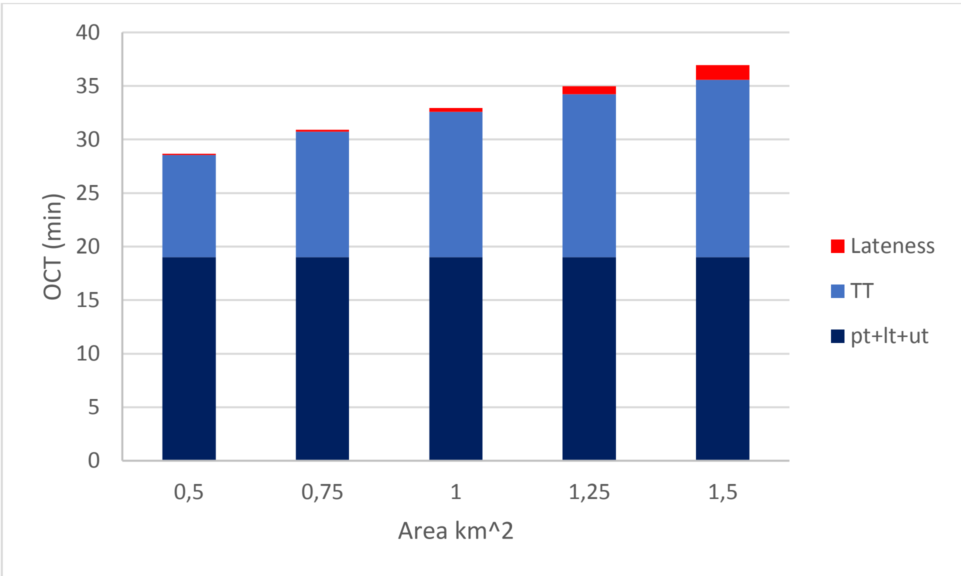

Figure 49 UNI: Different components of OCT

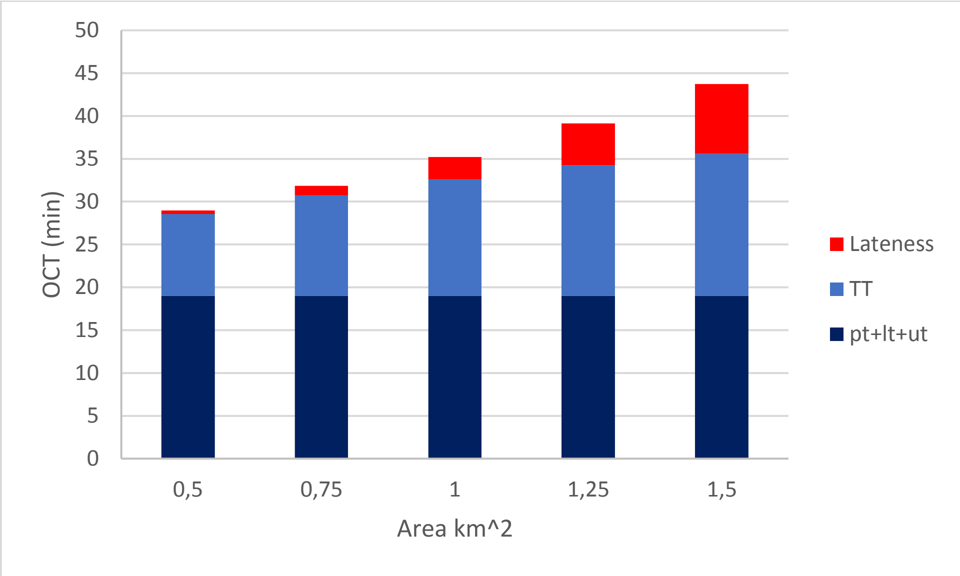

Figure 50 DTRI: Impact of different Areas on the components of the OCT

6.2.5: Vehicles parameters: speed and Range

Improvements in Electric vehicles duration is highly dependent on the improvements in batteries. It is not easy to forecast the time and magnitude of improvements in this field: in the experiment the values are supposed to reach up to 9km of range 50% more than what currently offered by the technology. The value of 5 km per charge has been included to simulate scenarios where environmental conditions negatively affect the total battery available.

Lateness and Oct steadily decrease in both DTRI and UNI distributions as shown by figure 51 and 52reaching values of 1,68 and 0,30 minutes with a range of 9 km. Greater values of range decrease the higher OCT in the peaks of demand: highlighted in figure 53 the difference between BC=69 and BC=6 of about 4 minutes. The lower range available leads to an increase of 0,6 mins and 0,18 mins from the base case. Starting values of lateness in the case of UNI distribution makes hard to read any particular trend from graph in figure 54 given the small starting values and small changes shown by figure 52.

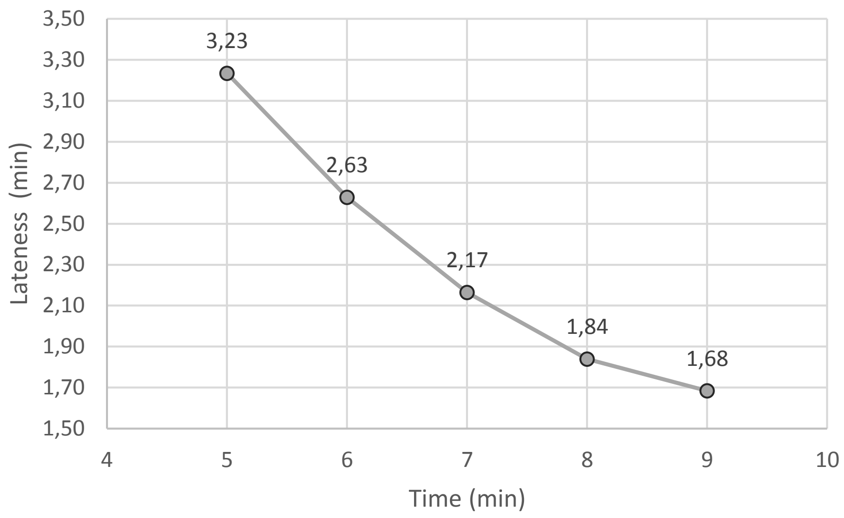

Figure 51 DTRI impact of battery capacity on Lateness

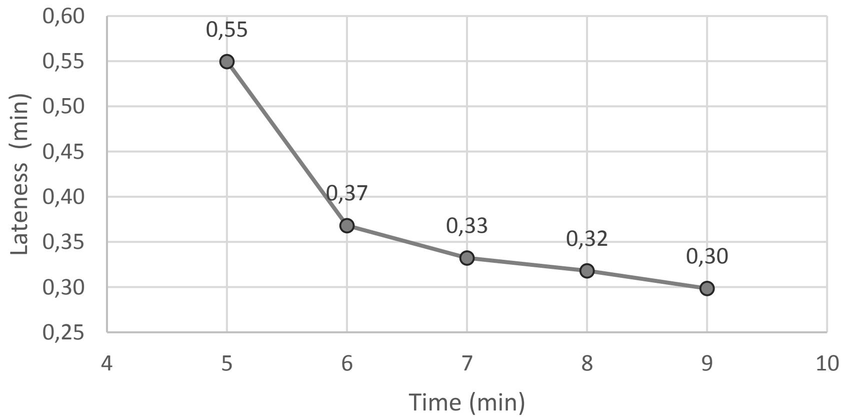

Figure 52 UNI, Impact of battery capacity on Lateness

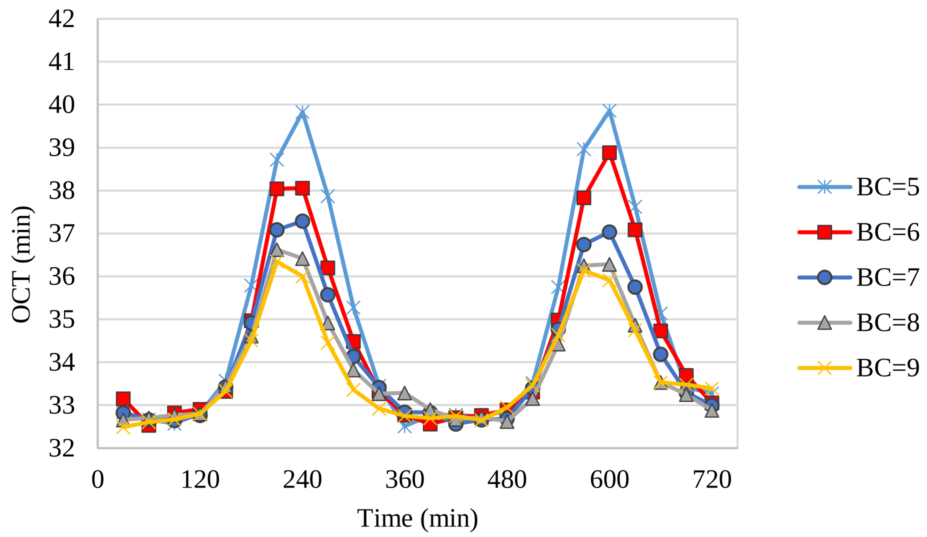

Figure 53 DTRI impact on BC on average OCT in different ordering hours

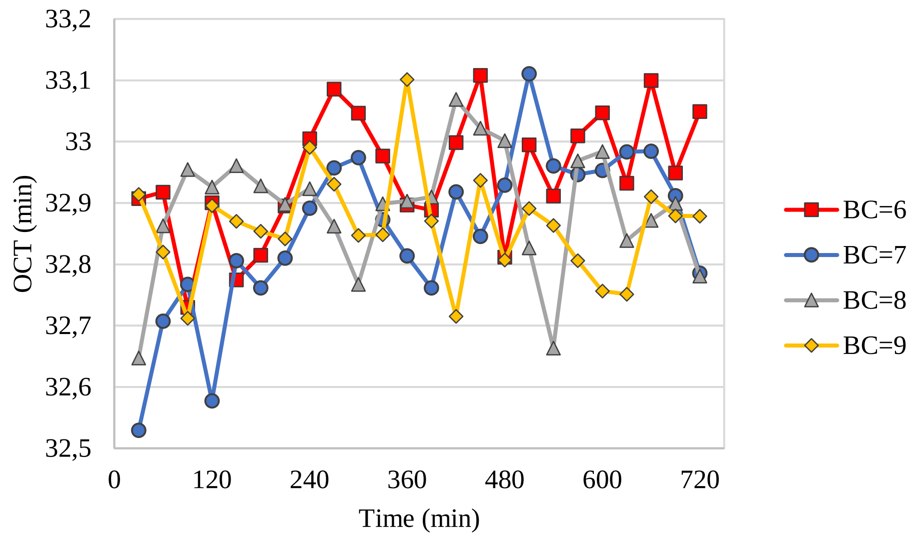

Figure 54: UNI impact of battery capacity on Average OCT in different ordering hours

Speed is affected by a series of elements: vehicle design, type of routes and its conditions and exogenous factors such as regulations are examples. From graph 55 and 56, the obvious advantages of higher speeds are reflected in the reduction of OCT and Lateness. In figure 57 is shown how the effect of higher speeds do not change the general trend of UNI distribution, but progressively lower the value of OCT. Also in graph 58, the shifting effects is shown reducing OCT for ordering times. With a speed of 6km/h formally set as the limit by law for autonomous vehicles (Hoffmann & Prause, 2018), the average OCT approaches 25 minutes in the case of UNI and 26 minutes in the case of

DTRI distribution. The value of Lateness reaches almost 0 in the case of speeds higher than 3 km/h. The positive effects of higher speeds are not only characterized by a lower average OCT but in substantial reduction of variance. Figure 61 shows how both mean and std deviation decrease for higher values of speed leading to lower and more stable OCT results. Almost 100% of the orders are delivered within 1 hour in the case of base speed of 3 km/h, reaching almost 40 mins in the case of 6km/h.

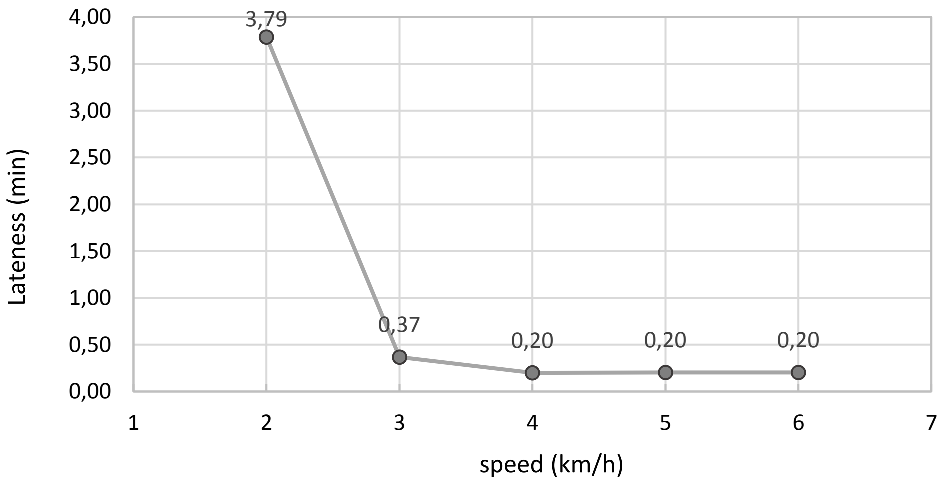

Figure 55 UNI: Impact of speed on Lateness

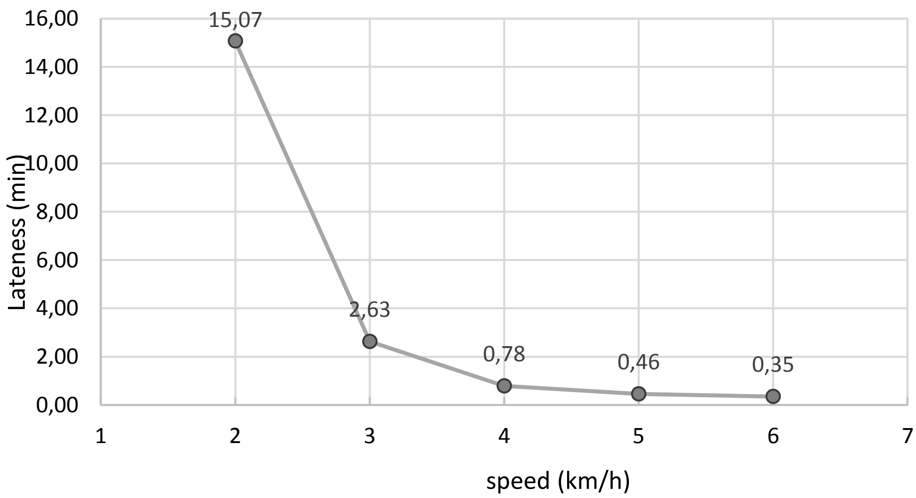

Figure 56 DTRI: impact of speed on Lateness

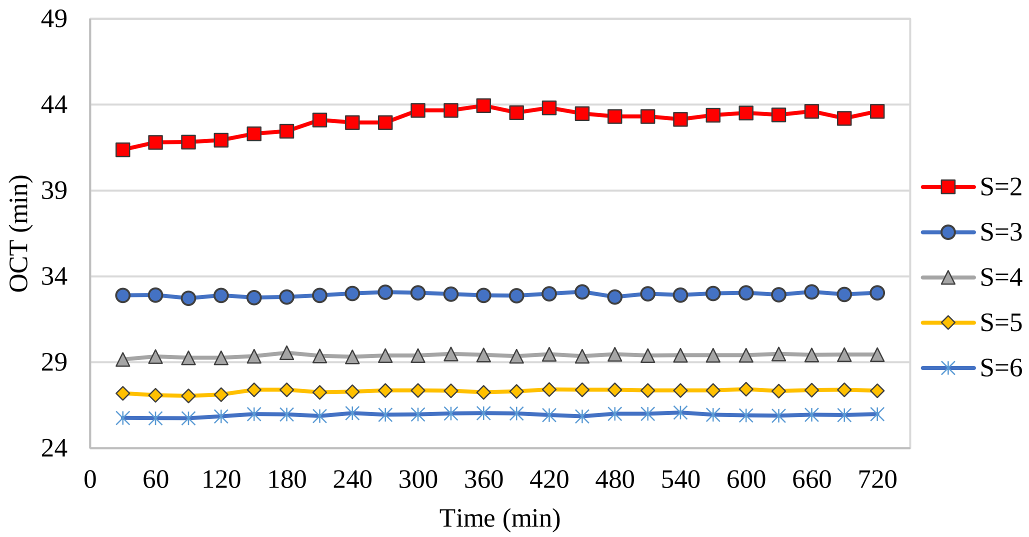

Figure 57UNI Impact of speed in km/h on OCT for different ordering hours

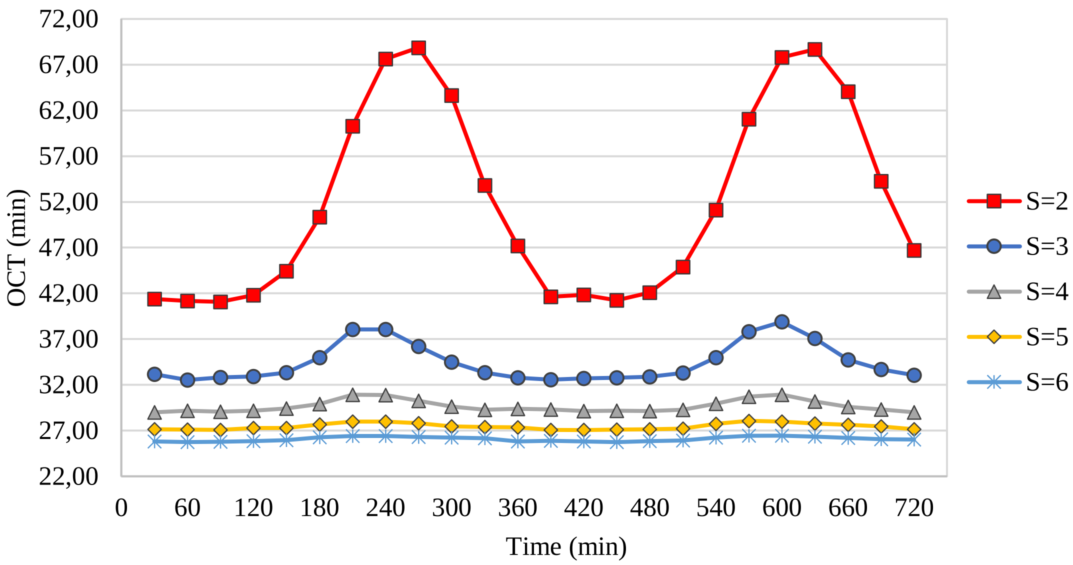

Figure 58 DTRI Impact of speed in km/h on OCT for different ordering hours

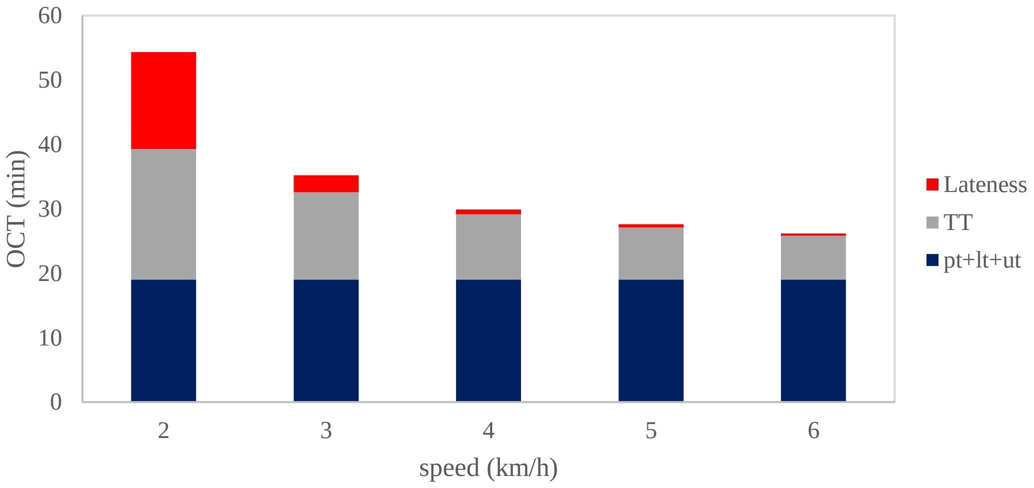

Figure 59 DTRI: impact of speed on the different components of OCT

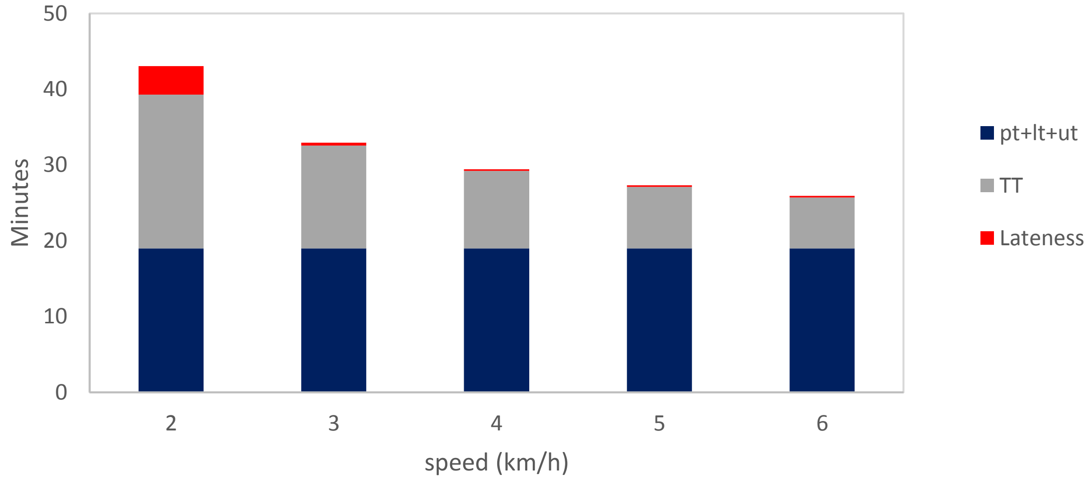

Figure 60 Impact of speed on the different components of the OCT

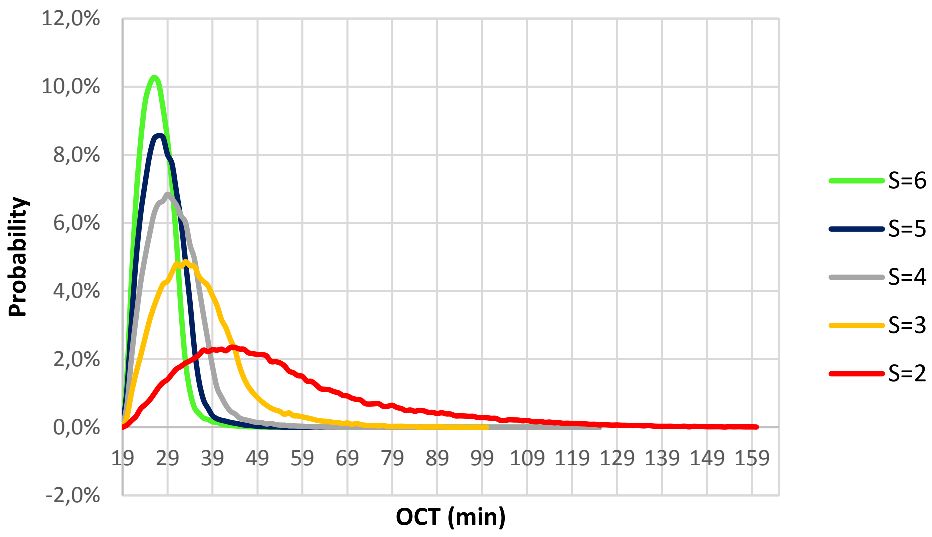

Figure 61 DTRI: influence of speed on OCT distribution

OCT <	2km/h	3 km/h	4 km/h	5 km/h	6 km/h
25 mins	1,13%	5,03%	10,19%	15,46%	21,12%
30 mins	4,74%	18,24%	33,68%	47,62%	61,08%
35 mins	10,74%	36,07%	60,38%	78,78%	91,42%
40 mins	18,39%	55,11%	82,90%	95,63%	98,41%
45 mins	27,29%	71,84%	94,61%	98,69%	99,47%
50 mins	36,44%	84,07%	97,78%	99,47%	99,84%
55 mins	45,56%	90,78%	98,88%	99,81%	99,96%
60 mins	54,09%	94,07%	99,42%	99,94%	100,00%
>60 mins	45,91%	5,93%	0,58%	0,06%	0,00%

Table 3 DTRI Probability of serving customers with different speeds

6.2.6 Impact of number of robots

One of the most important decisional parameters for the company is the number of Robots to deploy in the area. Fixing all other parameters, the increase of number of Robots reduces the values of lateness and OCT. 8 robots lead to a lateness of 9,49 mins with DTRI distribution while 1,41 mins with UNI. Values of lateness are similar for the two distributions in the scenario where 14 Robots are deployed differing by only 0,13 mins. As for the other parameters positively affecting lateness, the reduction is reflected on the peak hours in the case of DTRI. For R=8 the increase of OCT stabilizes after minute 200, reaching a steady state ranging around 34 minutes.

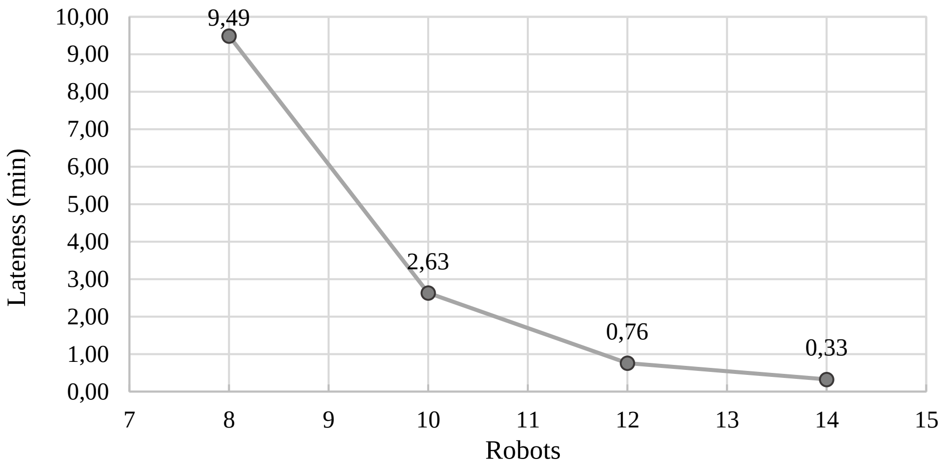

Figure 62: DTRI Impact of the number of Robots on Lateness

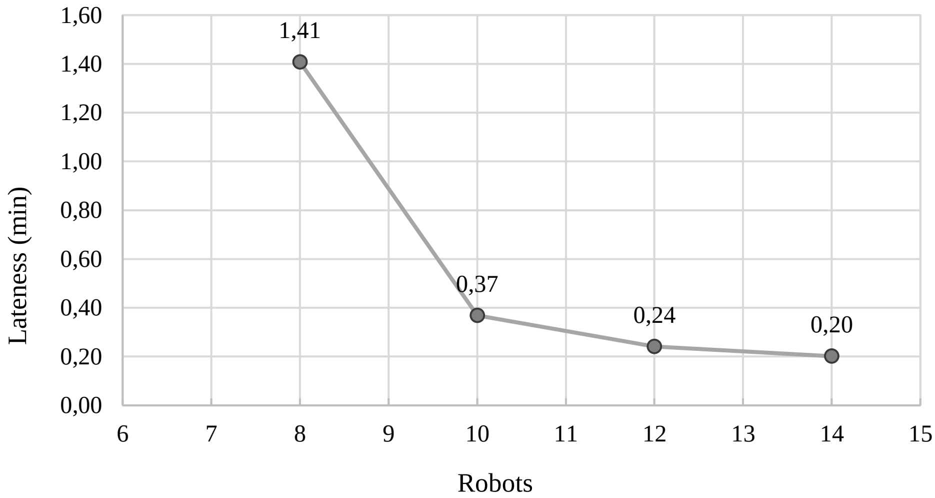

Figure 63 UNI impact of number of robots on Lateness

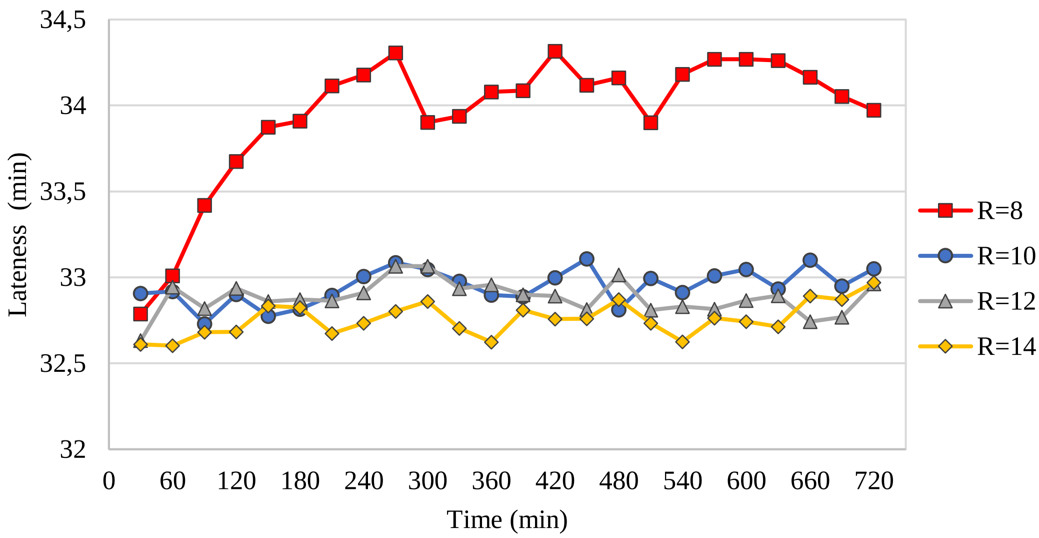

Figure 64: Impact of number of Robots on OCT in different ordering hours

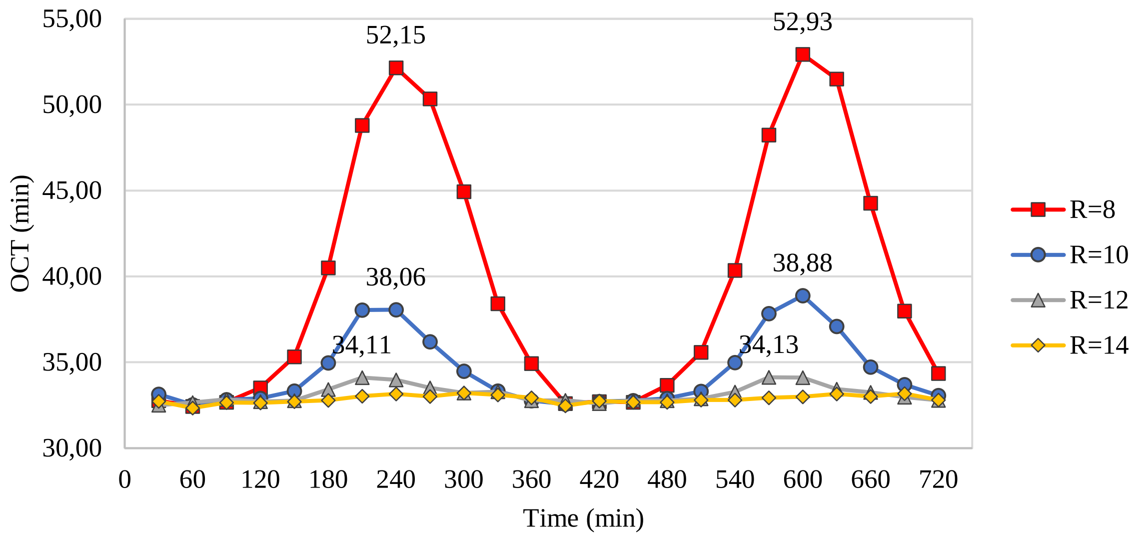

Figure 65: Impact of number of robots on average OCT in different ordering hou

6.3 Economic Analysis

In a scenario as the one considered with only one central depot, it is important to understand how different values of Area impact on Revenues, Cost and Profit. As already seen in P2, Larger Areas negatively affect Lateness. In real world scenarios, covering a Larger area allow on the other hand to fulfill a higher number of requests by customers, leading to higher revenues.

In this trade-off situation, it is important to understand what the optimal area under a profit perspective is. Starting by the information provided by Deliveroo concerning the number of orders per day in the city of Milan (10000 orders/day), four values of density (60 120,180 and 240 customers/day*km^2) representing medium-low, medium, medium-high and high density of customers, 5 different areas served are analysed. The value of 35 mins seems reasonable for this industry and at the same time not a too stringent constraint allowing to evaluate areas larger than $1km^2$. A constant density of 4 restaurants km^2 has been used for all experiments.

The minimum number of robots required to reach an average OCT of 35 mins is studied with an extensive number of simulation experiments, whose results are summarized in table 3 and 4. The different Areas analysed range from 0,75 to 1,25km^2. Due to the delivery time constraint, larger values cannot be reached by any system with the current speed of 3 km/h, while smaller areas are evaluated as too small for the application of the technology. Graph 66 and 67 show the trend in number of robots for all different values of density as a function of the Area suggesting the number of robots that need to be deployed increases more than linearly for larger areas, requiring additional units to maintain the OCT constraint for both distributions. For instance, considering a density of 240 customers and an Area of 1,25km^2 the difference between the two distribution is at its maximum

requiring 30 units for DTRI distribution and 22 units for UNI. For smaller densities and areas the values are closer but still in favour of Uni distribution: a density of 60 for an area of 0,75 requires 4 delivery robots in case of DTRI and 3 in case of Uni.
Profit analysis has been carried out supposing the following:

- Fixed costs for depot: 50000 euros/year. This value is an educated best guess averaging the considerations of Boysen and colleagues on depots of Delivery Robots (Boysen, Schwerdfeger, & Weidinger, 2018), and the depot costs stated by Aurambout and collegues on drones beehives (Aurambout, Gkoumas, & Ciuffo, 2019).
- Variable Cost of personnel: 1 person is required every 10 robots as stated by (Sifted.com, 2019) with a cost of 28 euros/h averaging the cost of personnel in Italy.
- Robots cost: 5500 euros/unit (Condliff, 2019).
- Energy cost: calculated considering the average daily recharge required for each experiment, the cost of energy (0,3€/kWh) and energy absorption by the robot (SwissPost, 2019).
- Cost of capital of 8%

Costs and values of personnel have been taken from an interview with Starship CEO with Sifted.com.

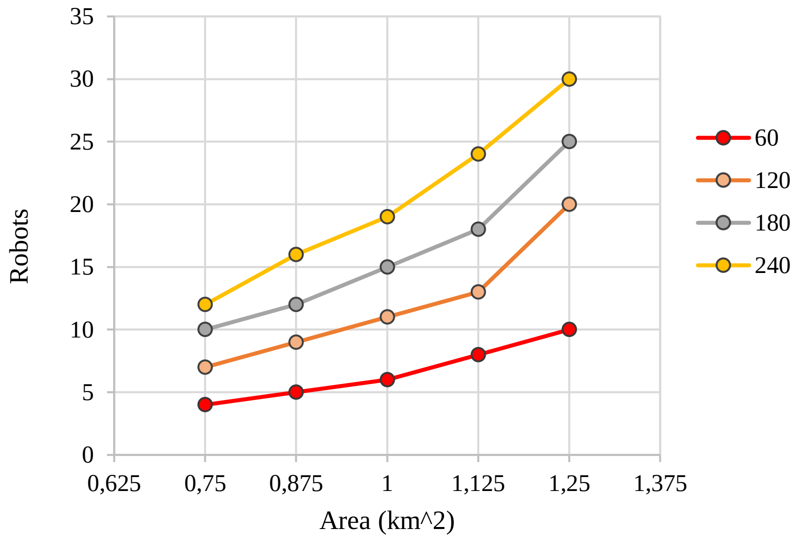

Figure 66 DTRI:Minimum number of robots for each density level as a function of the area served

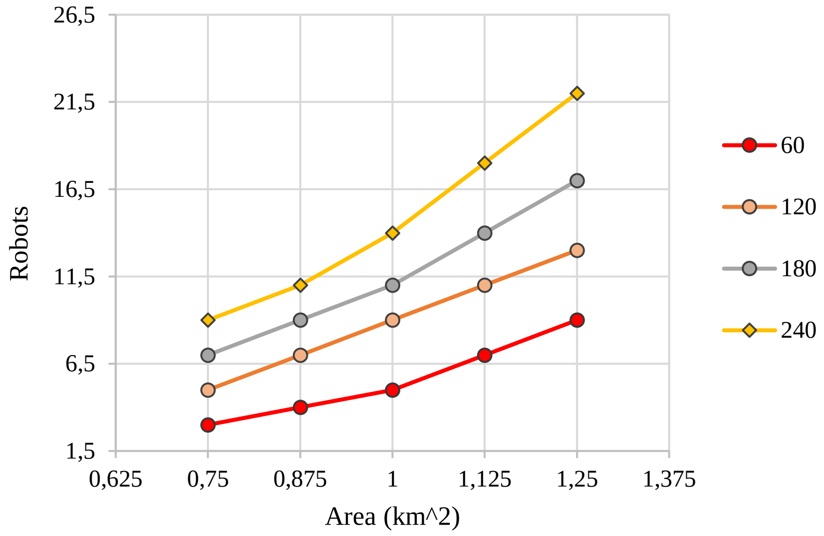

Figure 67 UNI: Minimum Number of robots for each density level as afunction of the area served

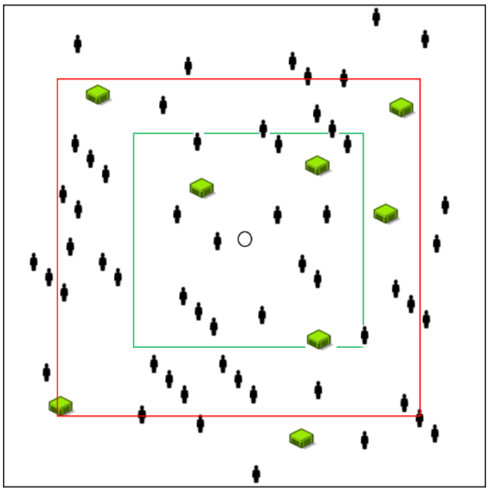

Figure 68: The idea behind the economic Experiment. Increasing the area served enables to serve higher number of customers and restaurants to partner with.

Exp No.	Area (km^2)	Density C/(day*km^2)	Customers C/day	POO	Robots	OCT (min)	TT (min)	L (min)	Energy (km)
1	0,75	60	45	3	4	33,41	11,68	2,73	45,45
2	0,75	120	90	3	7	33,34	11,76	2,58	79,88
3	0,75	180	135	3	10	33,34	11,78	2,56	133,89
4	0,75	240	180	3	12	34,72	11,80	3,92	188,45
5	0,875	60	53	3	5	34,35	12,89	2,46	54,12
6	0,875	120	105	3	9	33,79	12,83	1,95	133,23
7	0,875	180	158	3	12	34,90	12,86	3,04	235,66
8	0,875	240	210	3	16	34,28	12,81	2,47	240,18
9	1	60	60	4	6	34,35	13,56	1,79	76,13
10	1	120	120	4	11	34,22	13,54	1,68	137,88
11	1	180	180	4	15	34,38	13,52	1,86	222,72
12	1	240	240	4	19	34,80	13,55	2,25	301,23
13	1,125	60	68	4	8	34,19	14,37	0,83	93,87
14	1,125	120	135	4	13	34,54	14,30	1,24	179,88
15	1,125	180	203	4	18	34,92	14,30	1,63	231,20
16	1,125	240	270	4	24	34,85	14,36	1,49	296,66
17	1,25	60	75	5	10	34,74	15,17	0,57	115,67
18	1,25	120	150	5	20	34,68	15,18	0,50	189,68
19	1,25	180	225	5	25	34,99	15,22	0,77	255,90
20	1,25	240	300	5	30	34,83	15,22	0,61	338,24

Table 4 DTRI Minimum number of Robots for each combination of area and density to maintain an average OCT of 35 minutes

Contour plots in figure graphically show the results listed in table. The intermediate values between the combinations of density and areas studied consider a linear increase. All results are reported in Appendix part B.

The differences underlined in the previous experiments concerning the performance with the two distributions is reflected here on the minimum number of robots required to maintain an OCT of 35 mins. For all combinations of Areas and densities the UNI distribution requires less robots than DTRI distribution. For this reason, being all other elements considered in the profit calculation equal or similar, as it is for battery consumption, profit results are higher for UNI distribution in all scenarios. to calculate revenues 5 different prices levels are studied from 2 to 6 euros per delivery. This price can be flexibly interpreted as the sum of delivery cost payed by the customer and a percentage of order price got by the delivery service provider.

Graphs 69, 70 and 71 show the evolution of profit for the different densities with 3 price levels of 2, 4 and 6 euros per delivery.

Almost all densities start from the same results in case of 0,75 km^2 of area (around -120k euros). Higher densities though, generate a faster decrease of profit for larger areas reaching its minimum in the case of 240 and 1,25 km^2 (-317k€). 4 euros per delivery are sufficient to make profitable densities of 180 and 240 customers/daykm^2. The best area to serve is 1km^2 for180 customers (88k€) while 0,875 leads to the highest profit for 240 customers/day$km^2$with 172k€. The highest price considered of 6 euros makes all combinations of areas and densities but 240 and 1,25 km^2 still slightly negative. The highest weight of revenues in the calculations make the higher areas which increase the total customers to serve more and more profitable leading 1,25 km^2 the most profitable area to serve in case of 120,180 and 240 customers with 186k, 356k and 526k € of profit.

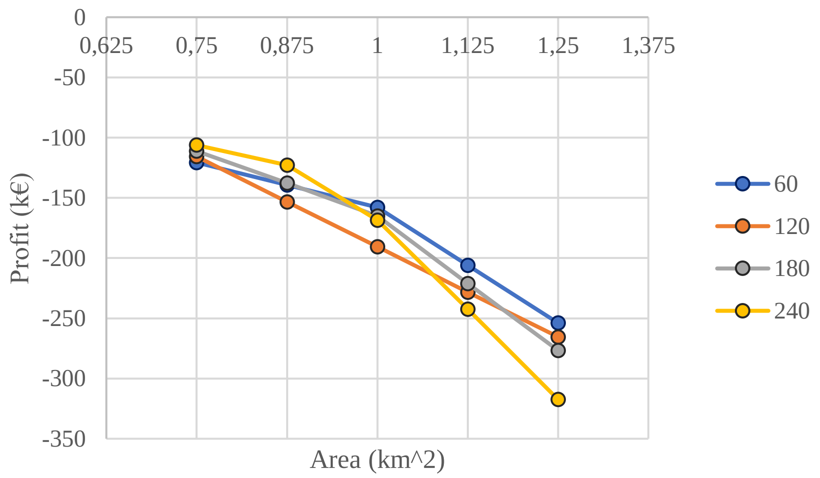

Figure 69 UNI: Profit as a function of the area for different levels of densities of customers with a price of 2 euros per delivery

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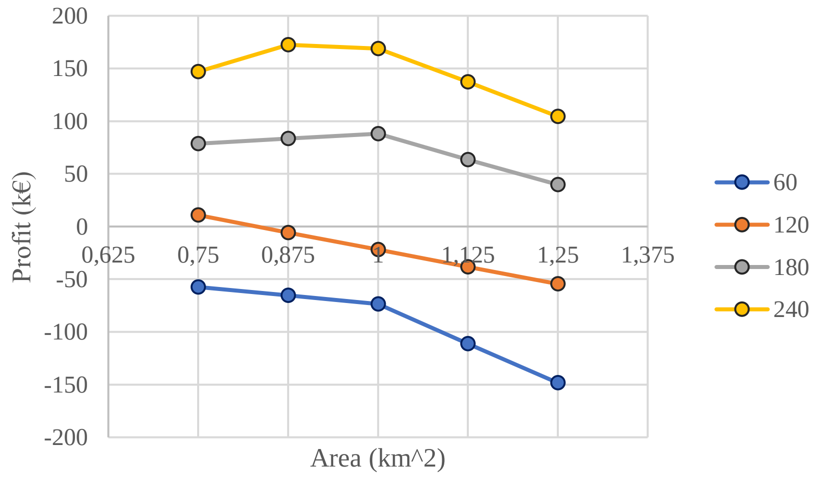


Figure 70 UNI: Profit as a function of the area for different levels of densities of customers with a price of 4 euros per delivery

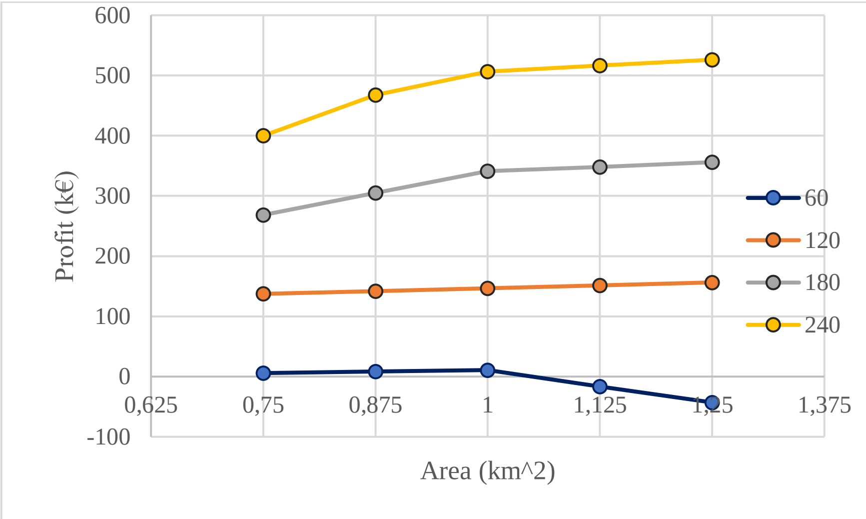


Figure 71 UNI: Profit as a function of the area for different levels of densities of customers with a price of 6 euros per delivery

Graph from 72 to 74 show the evolution of the expected profit in case of DTRI distribution in the case of prices of 2, 4 and 6 euros. It is possible to see how the growing impact of profit moves all curves towards positive results. In case of a price equal to 2, the lower density allows to obtain the best results due to the lower weight of investment and operational costs connected to the smaller number of customers to serve. The maximum for all densities is reached in the smaller area of 0,75 km^2. As the price moves to 4 euros, all results improve but are all negative except the density of 240 and areas smaller than $1km^2$. Density of 240 has its maximum with an area of 0,75 km^2 with a total of 59 k€. Finally, the result with a price of 6 euros per delivery lead almost all densities and areas to profitability. Density of 240 has its maximum with an area of $1km^2$ (356k€) while both 180 and 120 have it in 1,125 km^2 (230k and 90 k€ respectively). In appendix B all results are reported also for the intermediate prices considered, highlighting the maximum for each density.

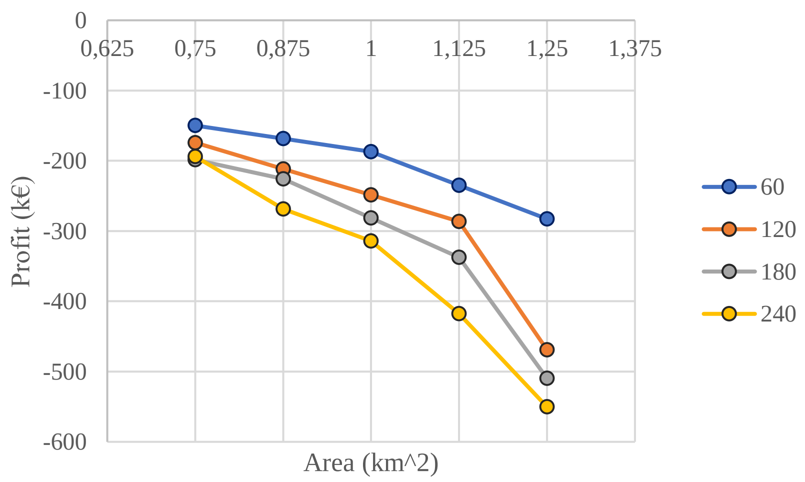


Figure 72 DTRI: profit as a fucntion of Area for a Price of 2 €

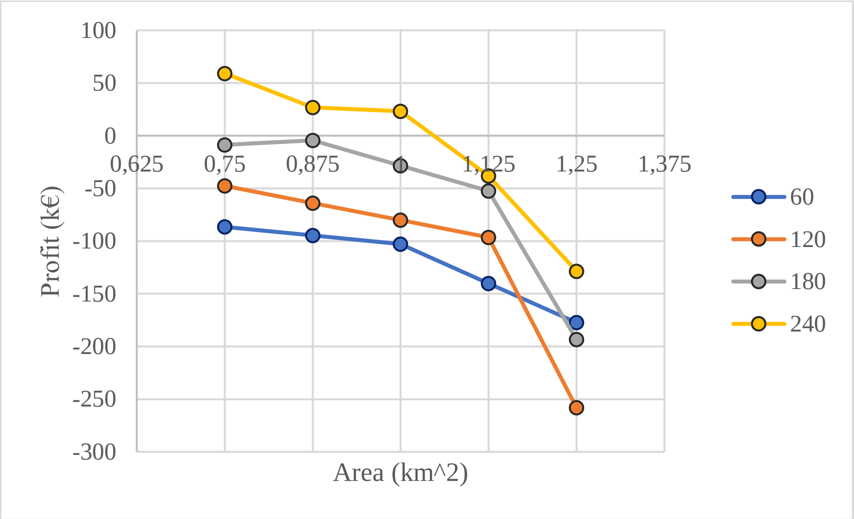


Figure 73DTRI: profit as a function of the Area for a price equal to 4 €

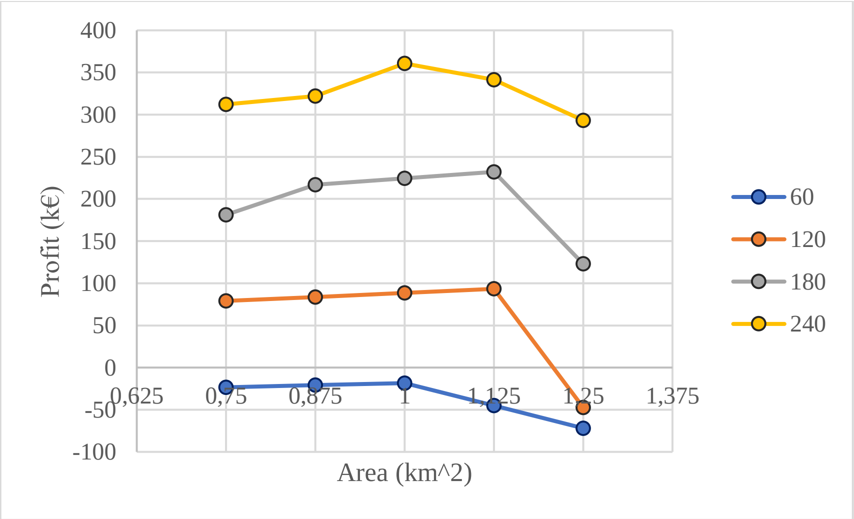
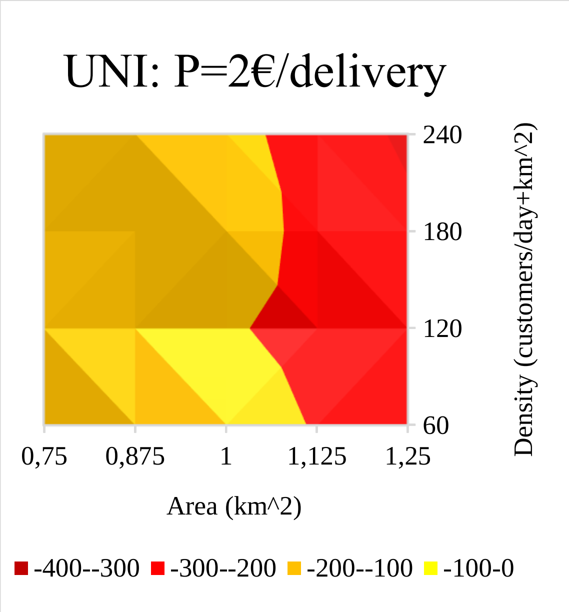
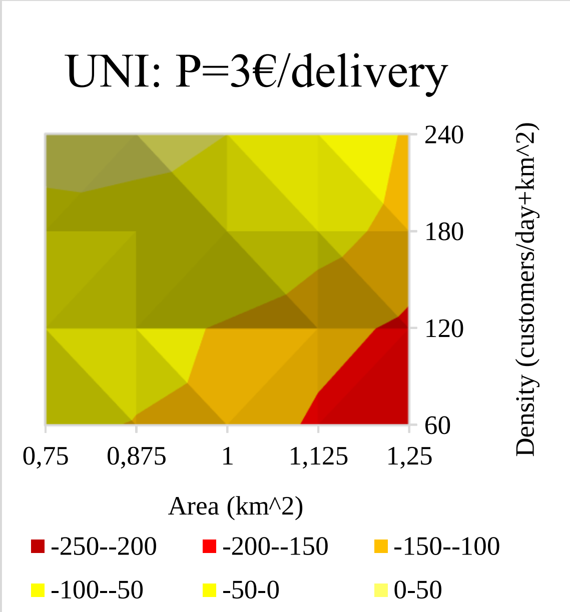
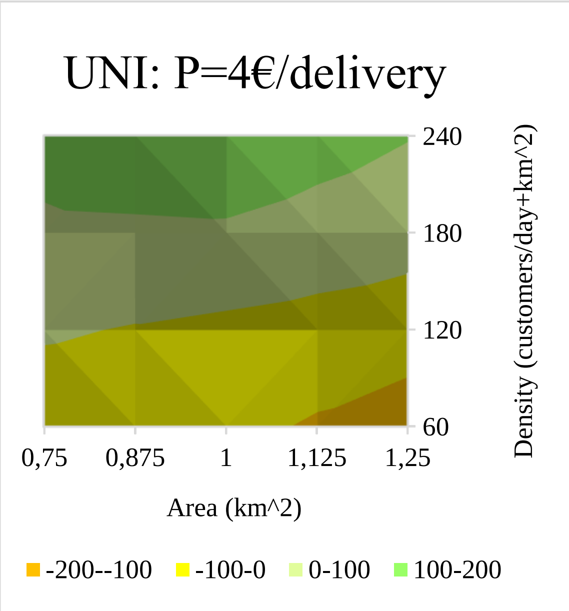
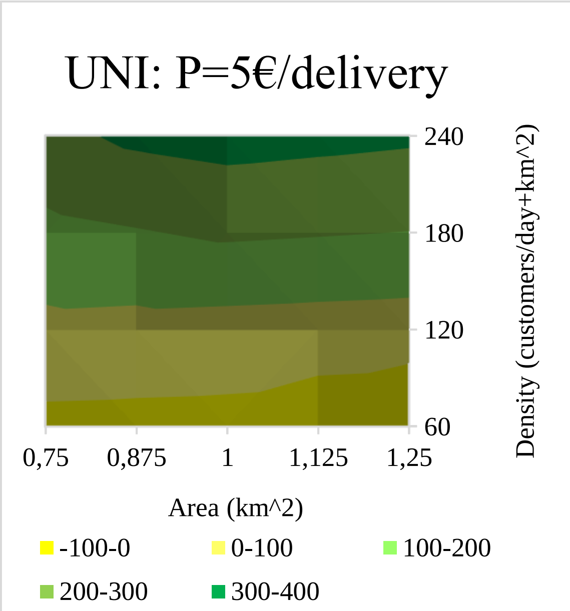


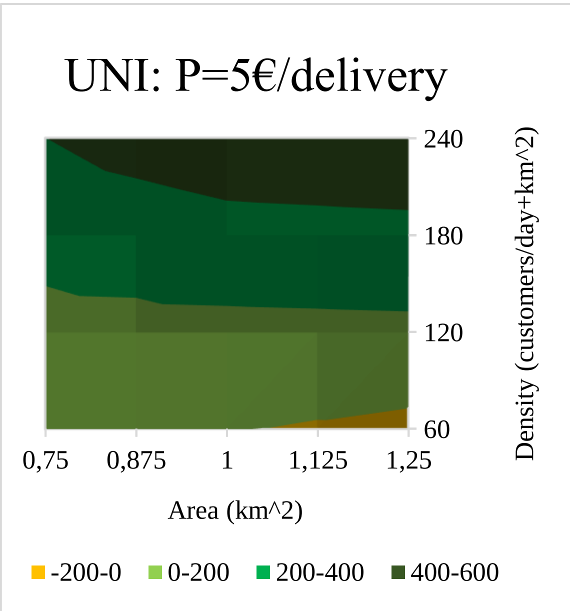
Figure 74 DTRI profit as a function of Area for price equal to 6 €

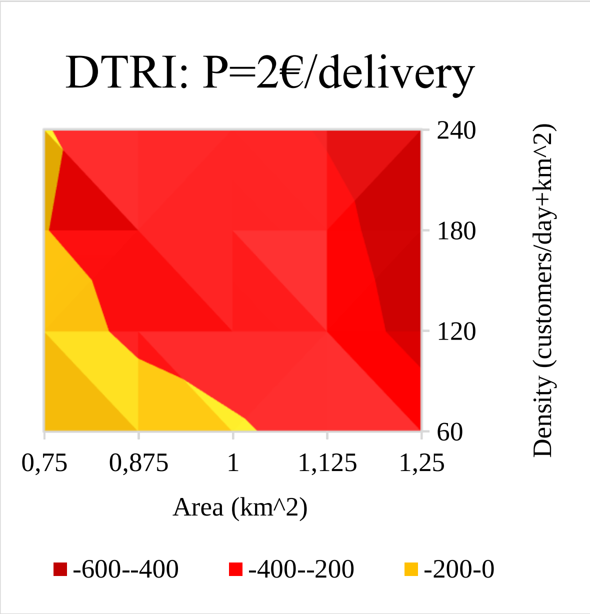

UNI: P=2€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Density (customers/day+km^2)
Area (km^2)
-400--300
-300--200
-200--100
-100-0

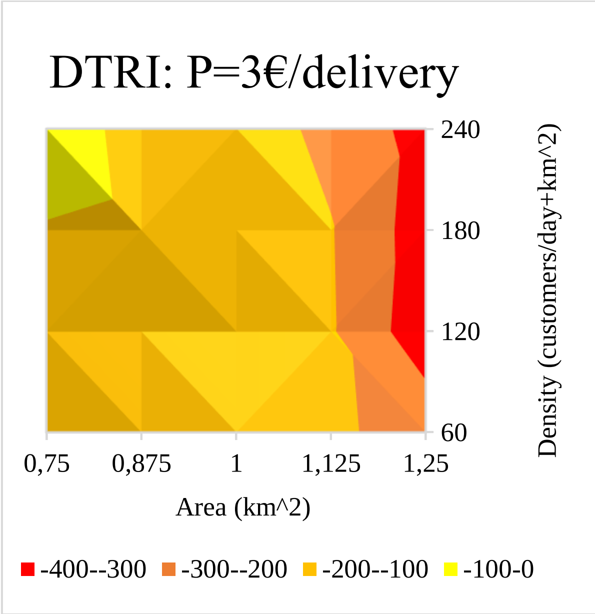

UNI: P=3€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Density (customers/day+km^2)
Area (km^2)
-250--200
-200--150
-150--100
-100--50
-50-0
0-50

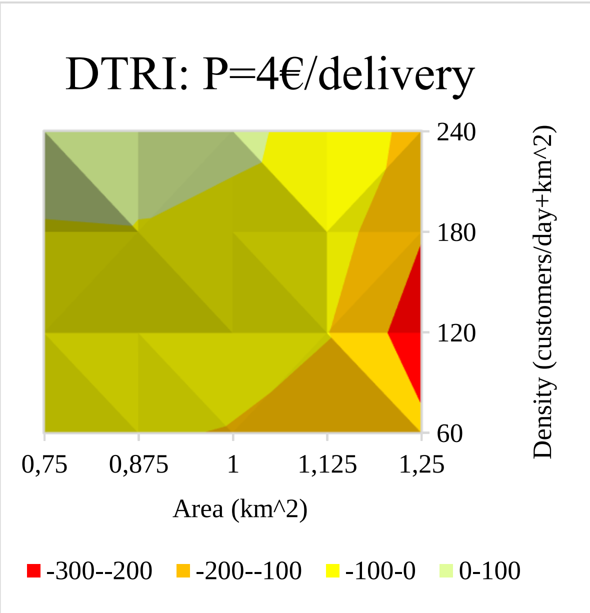

UNI: P=4€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Density (customers/day+km^2)
Area (km^2)
-200--100
-100-0
0-100
100-200

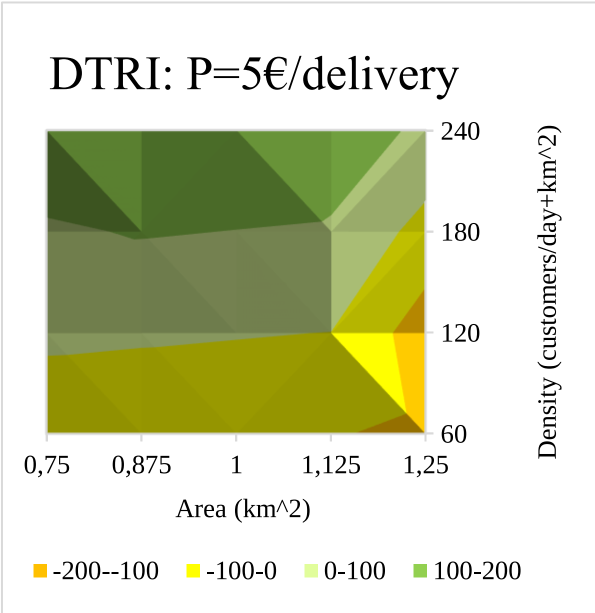

UNI: P=5€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Density (customers/day+km^2)
Area (km^2)
-100-0
0-100
100-200
200-300
300-400

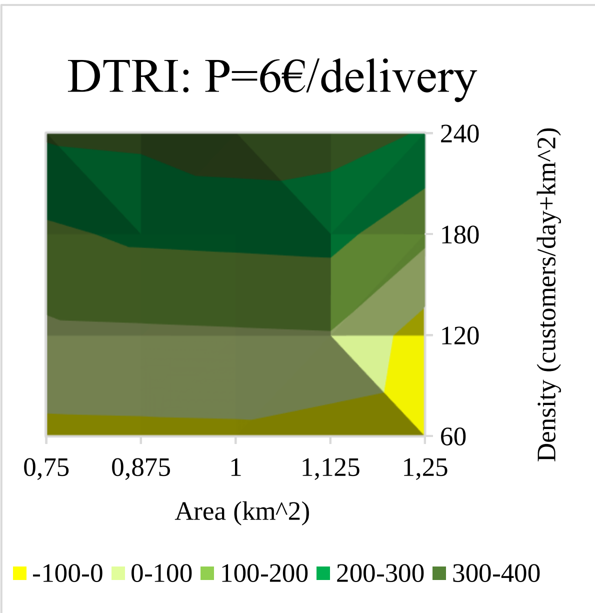

UNI: P=5€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Density (customers/day+km^2)
Area (km^2)
-200-0
0-200
200-400
400-600


DTRI: P=2€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Area (km^2)
Density (customers/day+km^2)
-600--400
-400--200
-200-0


DTRI: P=3€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Area (km^2)
Density (customers/day+km^2)
-400--300
-300--200
-200--100
-100-0


DTRI: P=4€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Area (km^2)
Density (customers/day+km^2)
-300--200
-200--100
-100-0
0-100


DTRI: P=5€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Area (km^2)
Density (customers/day+km^2)
-200--100
-100-0
0-100
100-200


DTRI: P=6€/delivery
240
180
120
60
0,75
0,875
1
1,125
1,25
Area (km^2)
Density (customers/day+km^2)
-100-0
0-100
100-200
200-300
300-400

7.Discussion of the results

7.1 Number of POO

A higher number of restaurants/shops which customer can select from offers higher choice under the commercial perspective, potentially increasing sales thanks to the greater variety offered. In this first research question the importance of increasing the number of restaurants/shops in the area is investigated under the logistic operations perspective. Set the number of customers which will order in the time period considered, the greater the number of POO the more demand will be uniformly spread in the area. Increasing the number of points of origin in the area decreases Lateness and OCT. This phenomenon is common in pickup delivery scenarios: a greater number of potential pickup locations allows a more efficient order assignment. The decrease is significant from 1 to 4 restaurants while slowly decreases with higher levels of the parameter. The advantage slowly reduces because the average distance among restaurants becomes smaller making less significant the choice of a customer for one restaurant or the other. Moreover, in dynamic scenarios, with a policy which imposes robots to come back to the depot, only concurrent orders make possible for the system to optimize allocation. Given the number of customers ordering in the time period, it is possible that not all restaurants have active orders, making the active point of origin smaller than the value of the parameter.

The evolution of OCT during the horizon considered follows the shape of order profile. The effect of the concurrent orders benefits is shown on the peak of oct: a higher number of restaurants is exploited more during peak hours, where a greater number of concurrent orders are seen by the system.

As far as the uniform distribution is concerned, the lower levels of Lateness can be reconducted to the lower number of concurrent orders in every interval considered. This allows for orders not to accumulate, with potential chances of being processed immediately. No specific trend can be seen in the graph 3, because of the variability affecting the simulation and the already small starting value of lateness of the base case. By looking at the general behaviour of the system in the other scenarios it is possible to state that similar behaviors may affect the changes in POO by considering a starting case where the value of Lateness is higher. Considering the results obtained with 16 POO where lateness seems to approach its minimum at around 2,15 mins, the positive effect of this parameter on the results is limited compared to other parameters discussed.

7.2 Number of customers and robots

Demand forecast is a crucial activity for capacity planning. Despite leading to better overall performance in terms of OCT, low demand might lead to not utilized vehicles creating difficulties under a profit perspective. As seen in the previous case, uniform distribution simplifies meeting reasonable OCT compared to DTRI. Even with similar trends, the values shown in the different experiments favour the uniform distribution in all cases. In unbalanced systems, i.e systems which cannot keep up with the level of demand, orders accumulate generating longer waiting times which in the end impact on OCT. Moreover, the effects of battery recharging put more stress on the delivery capacity of robots. This can be seen by looking at how the curve is shifted in the case of DTRI especially in correspondence of C=200. The case of C=200 in UNI shows how after a transitory phase during initial hours when no/limited service requests are issued, the accumulation of orders leads to a fast increase of the average OCT, which settles around OCT values of 42 minutes (still slightly growing). In all the other scenarios the system reaches a steady state where robots can keep up with requests, despite not being able of maintaining the performance shown at the beginning of the working day. Higher levels of customers per day/robot put the stress on the system in different ways in the DTRI distribution. The additional customers added to the system have higher chances of issuing the order during peak hours worsening the performance of the vehicles even more. This reflects on the increase of OCT and Lateness in all the experiments, but severely impacting the system in the last case.

At the same time deciding the optimal number of Robots to serve an Area is crucial to achieve OCT satisfactory for customers. The higher the number of Robots in the Area the higher the chances of finding a Robot in a good position to satisfy customer request quickly. The difference between the two distributions is stressed in the case of smaller number of robots. The higher number of robots the less relevant becomes orders profile. Taking as an example 14 robots, the demand during peak hour is not perceived as stressful by the system given the sufficiently high number of units. The lower the number of robots, the less this condition occurs, and the more orders accumulate generating worse and worse OCT. The effect of orders accumulation is shown in the case of R=8 for UNI distribution. As shown in the case of unbalanced system with C=200, the OCT rapidly grows due to the difference between the system receiving the first requests (with idle robots) and the later requests accumulating. In understanding whether a system is unbalanced a consideration on the number of customers per robots is taken into account. Both the analysis on Robots and Customers have shown that for the system it is difficult to keep up with the requests when too many customers per robot issue the order.. To understand whether bigger systems lead to worse results an additional comparison is done understanding the variation of the parameter C/R in 2 different levels of Robots fixing all the other parameters to the values of the base case.

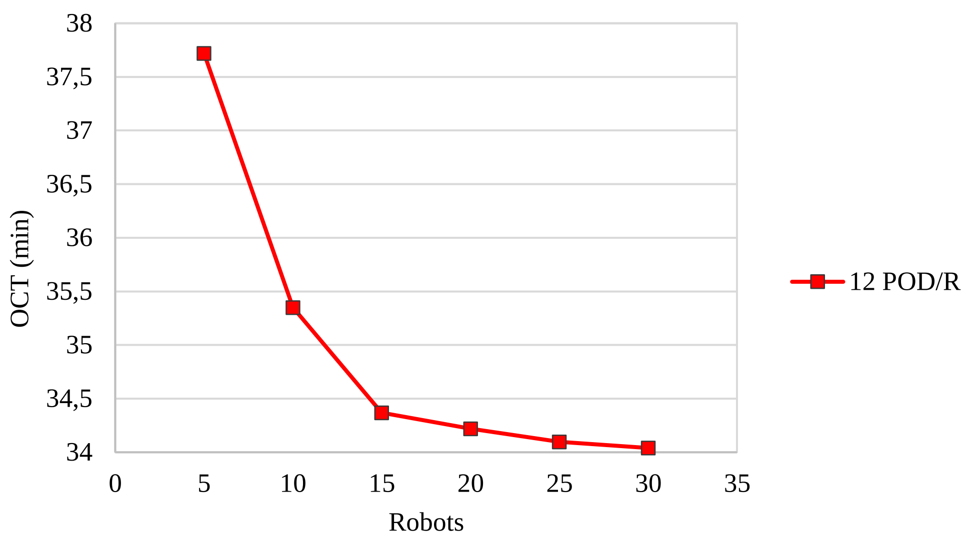


Figure 75:Comparison of different systems where the number of customers per robot is kept constant

Figure 25 show how scaling the problem keeping constant the ration between customers and robots decreases values of OCT. This means the system, by scaling up can maintain the same performance with a smaller number of robots. The reason behind the improvements can be reconducted to the increase of density of POD which generate improvements as already mentioned for the case of POO. The same consideration can be done by looking at the ratio between robots and customers in the experiment conducted to evaluate the profitability of areas and densities. It is possible to see how the ratio between customers and robots increases despite maintaining the same OCT performance.

7.3 Size of the Area

The impact of area on lateness and OCT has been understood starting from the base case. It has been shown how the area not only impacts actively directly on Lateness causing an exponential increase, but also acts on the travel time which does not depend on design levers. The increase of lateness has to be related to the longer distances robots have to travel to reach restaurants causing relevant delays in visible in the differences of results from the base case to the area of 1,5 km^2.

These experiments let understand how some useful information on relevant performance can be obtained before considering the deployment of robots in an area, by simply looking at average preparation time, loading and unloading time, as well as the average distance of potential customers from the restaurants responsible for order preparation. Deploying the correct number of robots enables the OCT to be as close as possible to this starting point. Larger areas of the one selected represent a limit for the established hypothesis of autonomous return home. The results shown prove how fundamental the role of the area served by a single depot is for customer satisfaction. With the stated hypothesis it is hard to think about possible application of the technology in areas larger than

1,25 km^2 reaching OCT in line with the ones of the industry (30-35 mins). With an area of 1,5 km^2 the sum of travel time, preparation loading and unloading times reaches the value of 35,6 mins in the case of Lateness equal to 0. The number of robots required to reach this level might not justify the investment. Multiple depots/ recharging areas might on the other hand expand the coverable area by each of the depots: guaranteeing robots the possibility to freely recharge in any of these, could highly benefit the results in terms of lateness. The reason behind this potential result which has not been verified in this study but has been shown in the case examined by Boysen and colleagues, might relate also to the context analysed. The order allocation method and Lateness calculations are based on the important parameter called worst case trip distance, which in case of higher density of depots might decrease improving the allocation process. At the same time, depots/recharge areas might require permission by the local authorities. Multiple locations might not be granted despite the small space occupied by recharge pods, or at the same time might lead to high costs.

7.4 Robot's Speed and Range

Better batteries reflect on Robots capability of serving customers for longer times delaying the need of recharging. Recharging time might be partially or fully influencing the resulting OCT. Especially in these scenarios of persistent delivery, the vehicles are forced to recharge if the level of demand is high enough to keep them occupied. For these reasons Higher values of battery positively benefit the system in a similar way done by the increase of POO: also in this case the vehicles are capable of completing an increasingly high number of requests before being constrained by their battery.

Battery capacity increase can then be seen as a complementary improvement to the one explained in the RQ1 where Robots do not travel smaller distances to reach points of origin or delivery but can operate for longer times before being affected by the recharging process, potentially fulfilling a higher number of requests.

The improvements in terms of Lateness generated by increasing range from 6 to 7 are similar to the ones generated by the increase from 4 to 8 points of origin. At the same time seeing an increase in range for these vehicles is hard to foresee with certainty. The true potentialities of higher ranges are not fully expressed in this study due to the constraints on OCT, limitations in the area covered and the policy of return to depot. Higher ranges not only enable robots to serve more customers before recharging, but at the same time increase the total area which could be covered by a depot.

Speed is a fundamental operational parameter constrained in influenced by different factors concerning regulations, type of routes, weather conditions, pedestrian traffic and more. Higher speeds allow the vehicles to move faster around the area, reaching customers and restaurants quickly. This parameter has a positive effect on Lateness reduction as some of the parameters discussed so far. Higher speeds allow the robot to travel faster towards the pickup point, thus reducing the potential risk to have a delay compared to the earliest pickup time. The effect on the average OCT per ordering time show another meaningful impact of faster vehicles. Higher speed not only leads to a reduction of Lateness but acts also on the travel time between restaurant and customer which does not depend on the order allocation process, so it is not included in lateness calculation, but actively influences the value of OCT.

Seeing the substantial impact this parameter has on performance it must be underlined that choosing the right area of application is one of the most important decisions companies applying this type of technology have to make. Considerations on routes availability, circuiting factor and higher speeds guaranteed by low pedestrian traffic are fundamental drivers of the decision. Perfect application sites for this technology are for this reason traffic restricted areas where no crossroads can slow down vehicles missions and Euclidean distances are reliable approximations. At the same time, efforts should be done on the regulatory side to evaluate the potential risks this type of technology might cause, increasing or decreasing the speed limit in pedestrian Areas. In the future a big component for autonomous delivery might be played by the infrastructures enabling preferential routes or lines on the pavements for delivery robots (as what is done for bicycle lanes).

7.5 Economic analysis

For standalone depots it is crucial to understand the range of operations allowed for robots and the area covered by the delivery service. With the hypothesis stated following the information which could be found about Starship and previous examples in literature, the Impact on costs on Revenues has been calculated for different levels of densities and areas served.

The current big limitations of this type of technology under an economical perspective still rely on the regulatory rules concerning autonomous vehicles which oblige the presence of supervisors on robots' operations.

At the same time, fixed costs related to any physical facility highly impact on profitability. In the scenario studied, a DTRI distribution has been supposed to model the order profile of customers in food delivery industry. From what has been understood studying the parameters of simulation, the first cycle of deliveries does not impact severely on the OCT of the second cycle in cases of balanced systems. From this combined information it is possible to say that a much smarter application of this technology in this type of industry might not lead to persistent delivery but more realistically to shift/ on spot delivery in which robots are physically brought to the potential delivery area at the beginning of the day and removed after the first cycle to avoid incurring in fixed costs. The trade of between operational costs for vehicles transportation and fixed costs has to be addressed in future research. In the experiment conducted the impact of fixed ad personnel cost plays the bigger role in negative affecting profitability Large areas of operations are not an interesting application for this technology:

to maintain a OCT in line with the values of the industry the number of robots required grow due to the on average longer trip per delivery.

From the outcome of the simulation experiments, prices lower than 3 euros are not sustainable in the long term due to the high cost of the technology and human supervision. In the future flat 2 euros/delivery pricing strategy can be profitable with the following needed changes:

- Regulations concerning vehicles speed and autonomous decisions might enable faster and cheaper deliveries, leading to a smaller number of robots required.
- Increase in volumes of demand might lead to the reduction of the cost of the technology already foreseen at 2250 dollars by Starship CEO.
- Increase in volumes with same area lead to less than proportional number of robots required, creating benefits in terms of costs keeping similar OCT results.

The average density of customers has to be high (at least 120 orders/day km^2) to guarantee efficient and effective deliveries.

In case of persistent delivery, the advantages of uniform demand are shown in the study. In order to alleviate some of the existing pressure on peaks, allowing to exploit vehicles also during other hours of the day, companies might consider enlarging the types of products which can be ordered through the platform: school supply, grocery, drugs are just some examples of the typology of products which might enable to saturate vehicles also in non-peak hours.

Contour plots have allowed to make general considerations on the ranges of operations and densities which lead to profitable results for the companies deploying the technology. The higher the price the larger areas and high densities become profitable. It is possible to see how the most profitable areas rotate from the bottom left (small density small area) to the top right (high density large area).

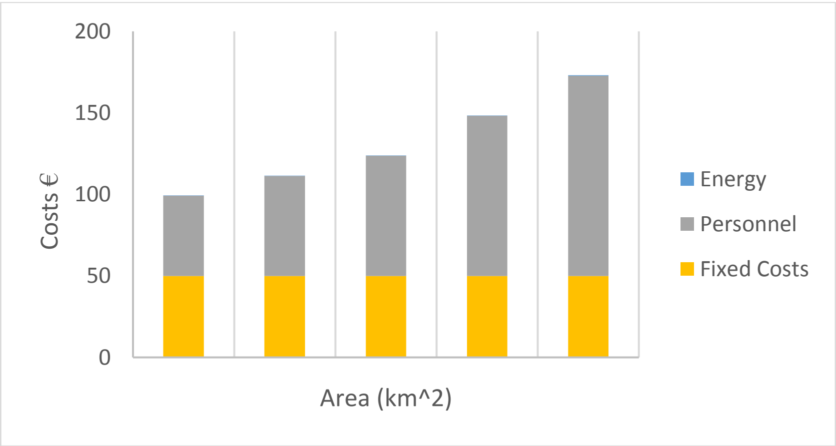


Figure 76 DTRI:Operational Costs in case of density equal to 60 customers/daykm^2. Larger densities and areas increase the weight of the cost of personnel

8.Limitations and future research

The study is affected by some limitations which restrict the utilization of results. The first series of limitations are network related.

1. The study had the aim of studying the technology in a general scenario with rather small characterization and variability. No variability has been introduced being all processes, from travel time to order preparation, deterministic.
2. The study has concentrated on the application in an Area with no network nor pedestrian traffic. In real life scenarios these factors are influencing the results of vehicles performance as shown by the effects speed has on OCT and Lateness.
3. In real applications more than one “depot” or rechanging pod can be exploited for serving a specific area. In the study of Boysen and colleagues the positive effect of a higher density of depots has been shown, while in this thesis the recharging area considered has been limited to one.
4. With the objectives of characterizing order profile with elements of the food industry a DTRI distribution has been used to simulate order arrivals. The results obtained by a uniform distribution have also been presented to show the differences between two opposite order profiles. Depending on the type of POO in the network, the peaks of demand might be different from those considered in this study.
5. In some cases, restaurant and customers are not randomly distributed but rather clustered in specific sub-areas of the area served, leading to less advantageous results connected to the increase in density.
6. Results in terms of OCT are affected by the values of parameters chosen in design phase. Depending on the typology of restaurant, customers and area, these values might highly change are and differ from the ones obtained in this study. For instance the value chosen as circuit factor might be higher or lower than the one considered based on the network distance between two points.
7. Customer preferences in restaurants might limit the advantages of higher densities of POO in the area served. Moreover, in traditional food delivery constraints exist in the maximum coverable area by a restaurant. In the thesis this factor is neglected, supposing the only customers served belong to a specific area. And the distance

The second type of limitation is connected to the building hypothesis formulated on the technology and order allocation.

8. What stated for battery consumption and range is not reliable in case of long stops, high accelerations and high variability in the travel time of the technology.
9. The policy of immediate beginning of the mission and immediate return to the depot, employed in the study for simplicity, can lead to suboptimal results.
10. Despite the good results achieved by the order allocation methodologies proposed, the results are far from optimal. The base hypothesis used for the two allocation methodologies can be reformulated to guarantee a higher degree of optimization and freedom to the allocation process. Consequently, with better order allocation methodologies, the results obtained in the simulation analysis can be highly improved reaching better results in terms of OCT and number of vehicles required.

Third limitation is connected to the analysis of relevant parameters. In the study the impact of single parameters on the relevant performance have been studied separately, thus not considering the possible interactions related to simultaneous changes in parameters.

11. The relevance of the impact of the variation of more than 1 parameter has been shown in the example of simultaneous variation of customers and robots where for larger systems the OCT performance reduces thanks to the exploitation of a higher density of POD.
12. The economic analysis has been characterized by hypothesis which might highly differ from reality: estimating operational and fixed costs of a new technology can be done with approximation which if on the one hand allow to have a general idea of the profitability, on the other are far from being precise and reliable measures of potential returns. The objective of the economic analysis has been to identify the most optimal condition of application instead of precisely calculating the return of the technology deployment since few actual data could be found.
13. The hypothesis of 365 working days might not be valid due to existing seasonality in food delivery. This leads to a delay in the return time related to the inclusion of mantainance cost and the additional weight of cash discount effect during the years.

Future research can start from this study and evaluate the application of this technology in a case study with defined network of roads and restaurants. Considering a real Area of operations such as a university Campus or city centre might more concretely affirm the potentialities of Delivery Robots. In such case studies, elements concerning customer preferences, preparation times and network distances might provide a stronger and more precise characterization of the Area and customers considered. An economical and operational comparison of the existing alternatives in last mile delivery might be of fundamental usefulness to understand the suitability of application. Mixed fleets might reveal optimal utilization of the existing delivery methodology aimed at effectively and efficiently serving customers. As far as the order allocation is concerned, state of the art heuristic algorithms such as Genetic Algorithm might be used to find good solutions in reasonable times as a compromise between LAIPA and SQL proposed methodologies. GA could increase the maximum number of orders considered in the optimization procedure achieving better results while simultaneously requiring less computations.

9.Conclusions

The new technology of autonomous delivery robots has been studied in the Thesis. Autonomous delivery robots are an innovative solution introduced to solve the existing complexity in last mile delivery. From a literature review including all automated solutions in last mile delivery the author has understood the main streams of existing research and has shown an existing gap existing for this type of technology. Most of the articles concentrate on Drone delivery often combined with trucks to compensate for the low range available to the flying unit. The industry of food delivery has been in general received less attention compared to the traditional e-commerce industry despite its growth. Highlighting both elements as gaps in the literature the research question has been understanding which parameters are influencing the performance of the vehicle and assessing their impact from an operational and economic perspective.

To understand which parameters are important in this type of industry an additional literature review on AGV and food delivery has been conducted, together with a discussion with a manager of Deliveroo. The elements identified have been the Area of coverage, the speed and range available to the vehicle, the number of customers (density), the number of robots, and the demand profile. To assess each of the listed factors a simulation model has been developed, to flexibly conduct a sensibility analysis on each of them.

The scenario modelled reproduces the daily operations of delivery service providers. Customer issue orders selecting from a restaurant partner of the company, and the Platform oversees the delivery process including vehicle scheduling and order allocation. For the type of complexity in the scenario to model, including dynamic requests, discrete interactions, and cruciality of actors position in space, agent-based simulation has been selected as the modelling methodology to achieve simplicity in the design phase and to address the current gap existing in literature in the study of large systems. The different agents represent the relevant actors in the system: customers, orders, robots, restaurants and the Platform. The crucial part to guarantee system optimization is the order allocation methodology. In this study two alternative order allocation policies are presented and analysed. The two fundamental performance considered are lateness and order traceability. The first one identifies the time elapsed at the moment of delivery since order issuing, while the second identifies the possibility for the customer to receive information of vehicles position and delivery time. The first methodology presented called Look Ahead Immediate Permanent Assignment heuristic allocation, consists in assigning the order immediately to the robot which can serve it the sooner, considering past information about orders and robots' status in the moment of allocation. The second methodology named Single order leverages on combinatorial optimization restricted to the first *n* orders in queue to reconsider order assigned based on the new information available. LAIPA has been preferred for the possibility of studying larger systems with low computational times despite the better results achieved by SQP. The main characteristics of order profile in food ordering have been included to stress the characterizing elements of this industry.

A set of experiments aimed at understanding the impact of different parameters on the system have been conducted. The results have proven the positive effects of higher density of restaurants, speed and battery capacity. The crucial balance between number of robots and number of customers has been shown by results of the experiments conducted demonstrating the importance of capacity planning for the companies deploying this technology. Moreover, the positive effects of uniform distribution of demand on order cycle time, suggest a wider utilization of this systems to maximize economical and operational results. The cruciality of the speed parameter has proven its relevance due to its impact on lateness and Travel time between customer and restaurant highlighting how the deployment area plays the most important role for this type of technology. An economic analysis in the as-is situation has been conducted considering the adoption of this technology in Italy. The analysis of profit has included investment cost for the technology, operating costs concerning battery consumption and the revenues generated by deliveries. In this experiment progressively larger areas allow more customers to order to the Platform, increasing the generated revenues but on the other hand requiring larger fleets to maintain the OCT below the constraint chosen of 35 mins. The analysis has shown how high densities of customers are fundamental to achieve profitability, possibly considering restricted areas of operations to limit the increase in minimum number of robots required generated by the longer travel distances between point in the areas. The impact of human cost and fixed costs, on profit strongly suggests that positive impact on the profitability of these solutions relies in the regulatory and infrastructural constraint currently existing. Huge economic benefits can be achieved with high bot-human ratios.

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Appendix A: Minimum number of Robots results experiments

UNI distribution

Exp No.	Area (km^2)	Density C/(day*km^2)	Customers C/day	POO	Robots	OCT (min)	TT (min)	L (min)
1	0,75	60	45	3	**3**	34,67	11,75	3,92
2	0,75	60	45	3	2	58,66	11,68	27,98
3	0,75	120	90	3	**5**	34,75	11,80	3,95
4	0,75	120	90	3	4	47,46	11,78	16,68
5	0,75	180	135	3	**7**	34,23	11,79	3,44
6	0,75	180	135	3	6	42,67	11,77	11,90
7	0,75	240	180	3	**9**	34,08	11,71	3,37
8	0,75	240	180	3	8	40,33	11,78	9,55
9	0,875	60	53	3	**4**	33,67	12,66	2,01
10	0,875	60	53	3	3	41,48	12,65	9,83
11	0,875	120	105	3	6	35,35	12,63	3,72
12	0,875	120	105	3	**7**	32,87	12,64	1,23
13	0,875	180	158	3	**9**	34,01	12,72	2,29
14	0,875	180	158	3	8	41,96	12,63	10,33
15	0,875	240	210	3	**11**	34,99	12,62	3,40
16	0,875	240	210	4	10	39,50	12,68	7,83
17	1	60	60	4	**5**	33,78	13,60	1,18
18	1	60	60	4	4	37,14	13,59	4,55
19	1	120	120	4	**9**	33,21	13,55	0,66
20	1	120	120	4	8	36,57	13,60	3,97
21	1	180	180	4	10	35,92	13,48	3,44
22	1	180	180	4	**11**	34,18	13,52	1,66
23	1	240	240	4	13	35,85	13,51	3,34
24	1	240	240	4	**14**	34,78	13,49	2,29
25	1,125	60	68	4	**7**	34,20	14,35	0,86
26	1,125	60	68	4	6	35,42	14,38	2,04
27	1,125	120	135	4	10	35,27	14,40	1,87
28	1,125	120	135	4	**11**	34,16	14,30	0,86
29	1,125	180	203	4	**14**	34,56	14,35	1,21
30	1,125	180	203	4	13	35,23	14,33	1,90
31	1,125	240	270	4	**18**	34,78	15,26	0,52
32	1,125	240	270	4	17	35,42	15,24	1,18
33	1,25	60	75	5	**9**	34,74	15,23	0,51
34	1,25	60	75	5	8	35,34	15,17	0,80
35	1,25	120	150	5	**13**	34,93	15,21	0,72
36	1,25	120	150	5	12	35,28	15,16	1,12
37	1,25	180	225	5	16	35,18	15,18	1,00
38	1,25	180	225	5	**17**	34,98	15,22	0,81
39	1,25	240	300	5	**22**	34,99	15,23	0,76
40	1,25	240	300	5	21	35,65	15,23	1,42

Dtri distribution

Exp No.	Area (km^2)	Density C/(day*km^2)	Customers C/day	POO	Robots	OCT (min)	TT (min)	L (min)
1	0,75	60	45	3	**3**	42,24	11,75	11,48
2	0,75	60	45	3	4	33,41	11,68	2,73
3	0,75	120	90	3	**7**	33,34	11,76	2,58
4	0,75	120	90	3	6	37,15	11,73	6,41
5	0,75	180	135	3	**10**	33,34	11,78	2,56
6	0,75	180	135	3	9	35,80	11,83	4,98
7	0,75	240	180	3	**12**	34,72	11,80	3,92
8	0,75	240	180	3	11	37,35	11,76	6,60
9	0,875	60	53	3	**5**	34,35	12,89	2,46
10	0,875	60	53	3	4	39,28	12,72	7,56
11	0,875	120	105	3	8	36,10	12,88	4,22
12	0,875	120	105	3	**9**	33,79	12,83	1,95
13	0,875	180	158	3	**12**	34,90	12,86	3,04
14	0,875	180	158	3	11	37,08	12,80	5,29
15	0,875	240	210	3	**15**	35,59	12,82	3,77
16	0,875	240	210	3	16	34,28	12,81	2,47
17	1	60	60	4	**5**	37,72	13,55	5,17
18	1	60	60	4	6	34,35	13,56	1,79
19	1	120	120	4	**11**	34,22	13,54	1,68
20	1	120	120	4	10	35,22	13,60	2,62
21	1	180	180	4	15	34,38	13,52	1,86
22	1	180	180	4	**14**	35,48	13,55	2,93
23	1	240	240	4	19	34,80	13,55	2,25
24	1	240	240	4	**18**	35,75	13,55	3,21
25	1,125	60	68	4	**8**	34,19	14,37	0,83
26	1,125	60	68	4	7	35,14	14,36	1,79
27	1,125	120	135	4	13	34,54	14,30	1,24
28	1,125	120	135	4	**12**	35,78	14,45	2,33
29	1,125	180	203	4	**17**	35,93	14,44	2,49
30	1,125	240	270	4	18	34,92	14,30	1,63
31	1,125	240	270	4	**24**	34,85	14,36	1,49
32	1,125	240	270	4	23	35,33	14,39	1,94
33	1,25	60	75	5	**10**	34,74	15,17	0,57
34	1,25	60	75	5	9	35,05	15,15	0,90
35	1,25	120	150	5	**19**	35,20	15,25	0,96
36	1,25	120	150	5	20	34,68	15,18	0,50
37	180	1,25	225	5	25	34,99	15,22	0,77
38	1,25	180	225	5	**24**	35,34	15,23	1,11
39	1,25	240	300	5	**30**	34,83	15,22	0,61
40	1,25	240	300	5	29	35,15	15,22	0,77

Appendix B: Returns for different combinations of Areas and densities

Results expressed in thousands of euros.

UNI distribution

P=2€ / delivery

D\A	0,75	0,875	1	1,125	1,25
60	-120,68	-139,30	-158,03	-205,87	-253,65
120	-115,87	-153,39	-190,56	-227,98	-265,20
180	-111,21	-138,48	-164,99	-220,79	-276,60
240	-106,54	-122,96	-168,52	-242,80	-317,36

P=5€ / delivery

D\A	0,75	0,875	1	1,125	1,25
60	-25,78	-28,58	-31,50	-63,52	-95,49
120	73,93	68,04	62,50	56,72	51,13
180	173,49	193,67	214,61	206,26	197,90
240	273,06	319,91	337,61	326,60	315,30

P=3€ /delivery

D\A	0,75	0,875	1	1,125	1,25
60	-89,04	-102,39	-115,85	-158,42	-200,93
120	-52,61	-79,58	-106,21	-133,08	-159,76
180	-16,31	-27,76	-38,45	-78,44	-118,44
240	20,00	24,66	0,19	-53,00	-106,48

P=6€ /delivery

D\A	0,75	0,875	1	1,125	1,25
60	5,86	8,32	10,68	-16,07	-42,76
120	137,19	141,85	146,86	151,62	156,58
180	268,39	304,39	341,15	348,61	356,06
240	399,60	467,53	506,32	516,40	526,19

P=4€ /delivery

D\A	0,75	0,875	1	1,125	1,25
60	-57,41	-65,49	-73,68	-110,97	-148,21
120	10,66	-5,77	-21,85	-38,18	-54,31
180	78,59	82,95	88,08	63,91	39,73
240	146,53	172,29	168,90	136,80	104,41

DTRI Distribution

P=2€ / delivery

D\A	0,75	0,875	1	1,125	1,25
60	-149,81	-168,44	-187,16	-234,97	-282,81
120	-174,13	-211,63	-248,81	-286,24	-469,05
180	-198,57	-225,85	-281,49	-337,27	-509,64
240	-193,91	-268,55	-314,13	-417,68	-550,33

P=5€ / delivery

D\A	0,75	0,875	1	1,125	1,25
60	-54,91	-57,72	-60,63	-92,62	-124,64
120	15,67	9,81	4,26	-1,54	-152,72
180	86,13	106,30	98,11	89,78	-35,14
240	185,69	174,32	192,00	151,72	82,33

P=3€ /delivery

D\A	0,75	0,875	1	1,125	1,25
60	-118,17	-131,53	-144,98	-187,52	-230,09
120	-110,86	-137,82	-164,45	-191,34	-363,60
180	-103,67	-115,13	-154,96	-194,92	-351,47
240	-67,37	-120,93	-145,42	-227,88	-339,45

P=6€ /delivery

D\A	0,75	0,875	1	1,125	1,25
60	-23,27	-20,82	-18,45	-45,17	-71,92
120	78,94	83,62	88,61	93,36	-47,27
180	181,03	217,02	224,64	232,13	123,03
240	312,23	321,94	360,71	341,52	293,22

P=4€ /delivery

D\A	0,75	0,875	1	1,125	1,25
60	-86,54	-94,63	-102,80	-140,07	-177,37
120	-47,59	-64,01	-80,10	-96,44	-258,16
180	-8,77	-4,42	-28,42	-52,57	-193,30
240	59,16	26,70	23,29	-38,08	-128,56