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Abstract

This is the final technical report of the 'Modelling the Economics of Delivery UAS in airspace Surrounding Airports' (MEDUSA) project, which was awarded funding through the Engage 2 KTN's first Call for catalyst funding.

Engage 2

MEDUSA (Modelling the Economics of Delivery UAS in airspace Surrounding Airports)

Final technical report

Engage 2 catalyst fund project

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Engage 2

THE SESAR 3 KNOWLEDGE TRANSFER NETWORK

Engage 2

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1 Introduction

1.1 Abstract

The MEDUSA (Modelling the Economics of Delivery UAS in airspace Surrounding Airports) project, supported by the SESAR 3 Joint Undertaking, aimed to predict drone delivery hotspots across Europe by assessing economic viability and market potential. The core methodology involved developing the MEDUSA Simulator (WP1) to quantify operational costs and profitability for a spoke-hub distribution model, focusing on detailed unit economics such as ground crew logistics. This was integrated with a Market Potential Model (WP2) that used a custom population clustering approach, excluding highly dense urban cores, to identify viable market reach. Key theoretical predictions (WP3) demonstrated that optimal hub locations frequently overlap with existing regulated airspaces. Profitability is highly sensitive to external USSP fees and requires a break-even market reach of a minimum of 50,000 people. Expected peak drone traffic in top airspaces could reach 400 to 500 movements per hour, underscoring the urgent need for scalable U-space solutions and sustainable cost-sharing models.

1.2 Executive summary

The MEDUSA project was conducted as an Engage 2 catalyst fund project and successfully addressed the thematic challenge of integrating new entrants (TC4) into European airspace. Recognizing the anticipated exponential growth in drone traffic, particularly within the drone delivery sector, the primary objective was to predict future traffic hotspots by thoroughly investigating the underlying economics of drone operations. This research provided crucial insights for Air Navigation Service Providers (ANSPs) regarding the identification of priority airspaces for necessary preparation and the investigation of viable U-space funding mechanisms

Project Methodology and Approach

The research was structured across three main Work Packages (WPs):

1. WP1: MEDUSA Simulator This bespoke simulator was developed to model the unit economics and profitability of a drone delivery service, based on the prevalent spoke-hub distribution model. The simulator precisely estimated ground crew personnel needs, recognising that ground handling time and salary constitute a significant portion of total costs.

2. WP2: Market Potential Model This model identified the realistic market size and relevant reach for hypothetical drone hubs across Europe, utilising 1 km² population grid data for 27 countries. A key assumption driving this model was that early drone deliveries would primarily occur outside highly dense city centres, where drones hold a competitive advantage over established traditional delivery

coverage. The model used a modified Degree of Urbanisation Methodology (DEGURBA) to identify the relevant market.

3. WP3: Theoretical Predictions Findings from the simulator and the market potential analysis were combined to predict drone hotspots under four different angles, including an attempt to predict hotspots over the next 10 years.

Key Outcomes and Economic Viability

The MEDUSA simulations demonstrated a strong potential profit incentive for drone delivery services in many regions of Europe. For the high-potential European locations analysed, the estimated annual base contribution ranged between $1 million and $2 million. The most viable deployment zones were identified as semi-dense urban and rural clusters, specifically the suburbs or outskirts of larger cities.

Economically, success requires significant scale: the break-even market reach is estimated to be approximately 50,000 people, with 100,000 people or more considered the optimal market size ("Goldilocks"). Crucially, the simulations found that profitability is highly sensitive to external costs. A per-order USSP fee, intended for U-space funding, could entirely eliminate profits for locations with lower market reach.

Implications for Airspace Integration and Improving the State of the Art

The core predictions highlight significant ramifications for air traffic management concerning the Integration of new entrants. The analysis showed that the most attractive areas for placing drone hubs frequently coincide with existing controlled traffic regions (CTRs) and traffic information zones (TIZs). This overlap occurs because airports are often situated near medium-density population clusters, which are identified as optimal market zones for drone delivery.

Based on predicted adoption rates and market reach, the top 200 airspaces in Europe are estimated to reach an average of 200,000 people. Assuming a conservative annual order frequency, this could result in 400,000 deliveries per year within that airspace, leading to peak drone traffic of 400 to 500 movements per hour, or a take-off and landing every 4 seconds. This high density of traffic highlights a critical need to update airspace management infrastructure.

Interviews with stakeholders, including NATS (UK) and LFV (Sweden), confirmed that current practices relying on manual coordination via phone and email are unsustainable for managing high-volume drone activity. Stakeholders validated the need for scalable, digital solutions, such as digital flight intent systems, to improve situational awareness and streamline permit handling.

Furthermore, the economic sensitivity analysis supported stakeholders' concerns regarding U-space funding. Both LFV and NATS noted that U-space services are not expected to be financially sustainable in the near term and will require subsidies or cost-sharing models. NATS specifically uses a cost model based on operational volume, which aligns with the need for volume-based pricing structures reflected in the MEDUSA financial framework.

In conclusion, MEDUSA provides ANSPs and regulators with essential, predictive data such as expected drone delivery traffic density within airspaces to prioritize investment and planning for U-space deployment in the most critical European airspaces. The findings validate that high-volume drone delivery is economically feasible in peri-urban areas, but only if appropriate, scalable digital oversight systems and sustainable, shared economic policies are developed and implemented to manage the resulting high-density traffic.

2 Overview of catalyst project

2.1 Operational/technical context

Drone traffic is expected to grow exponentially over the next 10 years, and the drone delivery sector is expected to be a large driver of increased UAS airspace traffic. PwC projects 808 million B2C drone deliveries worldwide by 2034.[3] While other SESAR projects have advanced the analysis and demonstration of U-space technologies, MEDUSA shifts the focus to two foundational challenges for ANSPs.

1) Airspace Categorisation

   Most ANSPs recognize the need to prepare for the growing commercial drone traffic in the airspace near airports, e.g. by rolling out UTM/U-space services and setting up C-UAS measures. However, it's not clear where to conduct the first investments, because it's not always clear where the drone traffic is expected to boom. If it was easier to predict which CTR and TIZ airspaces are expected to become drone operations hotspots, then ANSP could work early with regulators to prepare appropriate airspace categorizations.

2) Business Models, Incentives and Regulations

   While the utility of U-space service provision is generally accepted, it is still unclear to many how it will actually be funded. In order to accelerate this debate, we will use the MEDUSA model to investigate the viability of the third option. An area with conditions that allow for very profitable drone delivery will probably have more willingness to pay for U-space services than an area with lower profitability. By understanding the underlying economic incentives of UAS operations, regulators will more clearly understand which economic policies are most suitable for a healthy drone ecosystem.

2.2 Project scope and objectives

The **objective** of MEDUSA is to predict hotspots for drone delivery across Europe based on the economics and market potential of drone deliveries in a given area.

To investigate the location of the drone traffic hotspots, one needs information about which geographical locations are feasible and most likely to exist in the future. This quickly becomes a question regarding the unit economics of these drone delivery services, including funding models for

[3] https://cee.pwc.com/drone-powered-solutions/drone-deliveries-taking-retail-and-logistics-to-new-heights.html

U-space services. MEDUSA combines publicly available data with data from Aviant's home delivery operations, in order to simulate the economic viability of drone deliveries near airspaces.

The main **research question** is; *How does the operational model and input parameters affect Cost of Delivery at different Order Volumes?*

Scope and constraints

The project focuses on the UAS business case which is drone delivery. The modeling is based on Aviant's current operational model, a spoke-hub distribution model[4]. Though economics may look different with a different distribution model, the spoke-hub model is still the most common model among existing drone delivery operators such as Wing and Manna. Also, the parameters in the modeling can easily be changed to cater to other models (such as point-to-point).

The goods distributed from the hub are in practice sourced from nearby retailers or restaurants. Today, the drone hubs are typically located either at shopping malls, large retailers (such as Walmart[5]), or smaller "nests" in close proximity to a selection of restaurants and retailers.

The MEDUSA project does not look at the current regulatory environment in assessing potential areas/countries for drone deliveries.

2.3 Research carried out

The research was split into the following Work Packages:

WP0: Literature review and industry outreach. Research on delivery economics, ANSP operations economics and interviews with stakeholders. Parameters discovered in WP0 are fed into the MEDUSA simulator as parameters.

WP1: MEDUSA Simulator. The simulator quantifies operational costs and revenue potential for drone delivery services for a given set of input parameters. The simulator models the movement of drones and delivery service personnel to estimate unit economics and profitability for a base hub at various market sizes.

WP2: Market Potential Model. The Market Potential Model uses population clustering algorithm and market data to find the market size for hub locations across Europe.

[4] https://en.wikipedia.org/wiki/Spoke%E2%80%93hub_distribution_paradigm

[5] https://wing.com/news/wing-and-walmart-announce-world-s-largest-drone-delivery-expansion-ever

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WP3: Theoretical Predictions. Combining findings from MEDUSA Simulator and Market Potential Model to predict drone hotspots across Europe.

An illustration of the relationship between the different work packages are found in Figure 1.

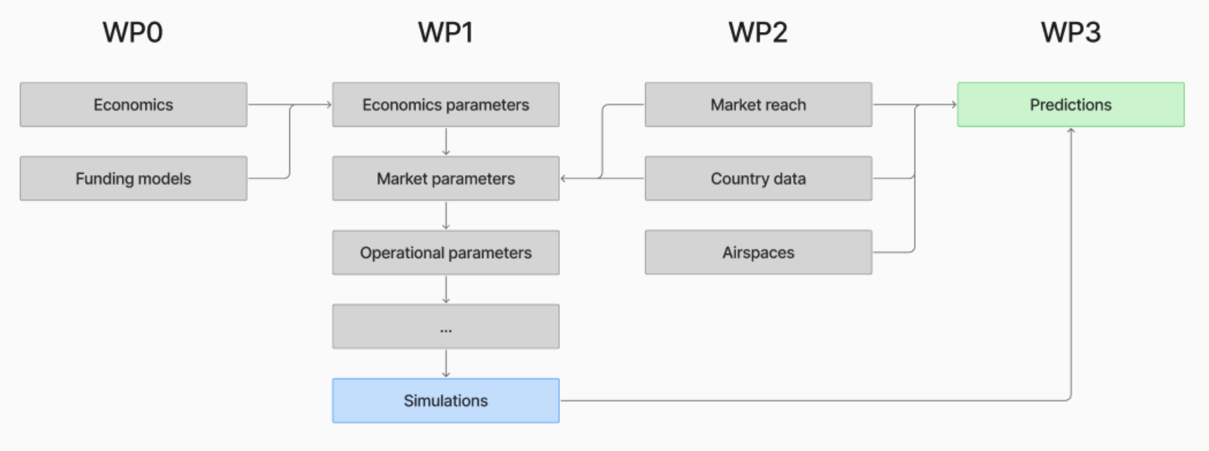

Figure 1: Relationship between work packages

WP1: MEDUSA Simulator

The MEDUSA Simulator models the profitability of a drone delivery service. This is done by creating a simulation of a drone hub with delivery crew moving orders around a graph and drones performing deliveries. The number of orders handled within a certain time frame gives an estimate of the overall expected volume of drone deliveries. For drone (home) delivery in particular, the amount of traffic is expected to fluctuate throughout the day and the week aligning with typical consumer demand behaviour.

The software gives detailed information such as:

- Optimal ground handling schedule.
- Visualisation of base logistics.
- Expected base profitability.
- Sensitivity analysis of input factors.

The MEDUSA Simulator takes more than 60 parameters, within the categories of Economics, Market, Operational, Graph, Schedule, Optimization, Simulator. The full set of these can be found in Appendix A. Each of these parameters affect the simulation to a greater or lesser extent.

While the inputs of the models are based on publicly available data and Aviant's actual data from existing operations, the simulator has flexibility to cater to other operational models and circumstances by changing the input parameters. Since the drone delivery sector is not fully developed, there is not much available data regarding the profitability of various drone delivery concepts. The approach used to overcome this obstacle is to use known information to run simulations aiming to generate synthetic data. Then, under a given set of input parameters, it is possible to give an estimate of the profitability of the drone delivery service and the expected volume of drone activity in a given area.

The MEDUSA simulator was developed as a software application in the Julia programming language. The graphical user interface was developed using the Dash.jl library, which is a library built using Plotly to create interactive dashboards using HTML and Javascript. The simulator aims to capture more of the order economics than conventional statistical methods using averages. The simulator uses some averages as inputs, but it simulates the time spent by the ground crew personnel in a quite detailed way to find the required number of workers given a certain order volume.

The graphical interface of the MEDUSA Simulator can be seen in Figure 2. On the left of the interface, the different parameters are listed (scrollable). The configuration can be exported or imported using CSV files. More complicated graphs (supplier distribution can also be uploaded as a matrix using CSV files.

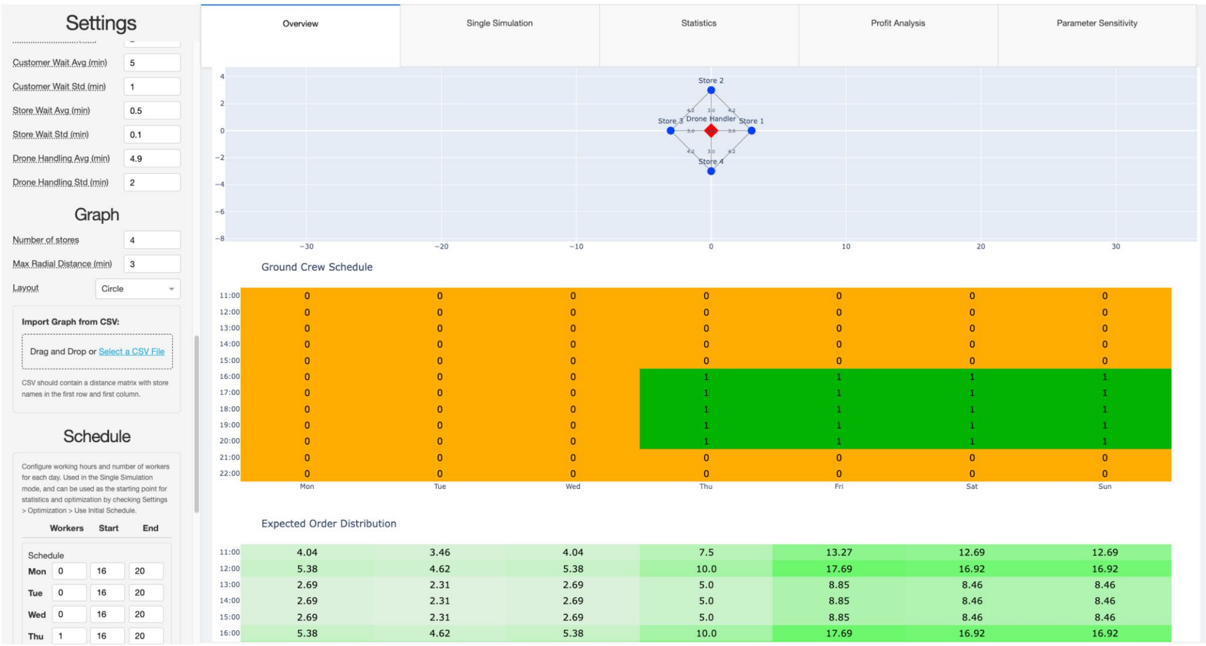

Figure 2: MEDUSA Simulator GUI

One of the primary drivers of costs in the existing delivery service is salary for employees. Even in a drone delivery service, where the last mile delivery is performed semi-autonomously, having ground crew bringing and loading the deliveries into the drones is potentially a large portion of the total costs. Due to this, the simulation is focused on finding a quite precise answer to how many people are really needed for a given drone delivery concept. This gives an indication of the location's profitability and the number of drones simultaneously in the air, which can be used to assess the likelihood and significance of a drone delivery service appearing at the location.

The physical layout of the supplying restaurants (or retailers but referred to as restaurants going forward) and drone dropoff interaction was modelled as a fully connected graph with several nodes, with the drone delivery base in the center. A visualization of the graph can be seen in Figure 3. The nodes in blue represent the restaurant locations and the red node represents the drone delivery base location. The edges of the graph is the time spent moving between the nodes. The graph to the left is generated by a circular layout, the middle graph is generated using a randomized Euclidean layout and the graph to the right made from data uploaded from a CSV-file with measured walking times.

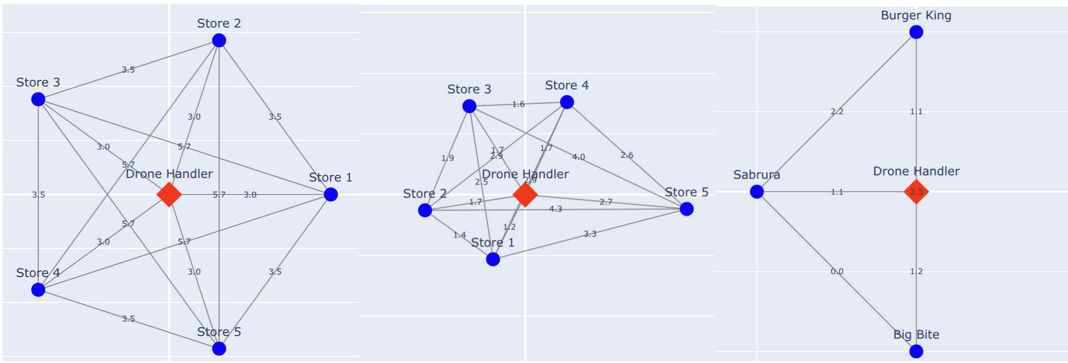

Figure 3: Graph visualisations

On the graph, the ground crew personnel will move back and forth between the nodes, picking up orders and delivering them to the drone delivery base in the middle. The advancement of time is performed using an event-based simulation approach, which consists of looking up the next event in a queue and fast-forwarding the simulation to that point in time.

The volume of orders expected throughout a week is distributed across the week according to a prior assumed distribution of orders. An example of a weekly distribution can be seen in Figure 4. Based on these distributions, a single simulation is set up by sampling the daily and hourly distribution, to create a random draw of weekly orders.

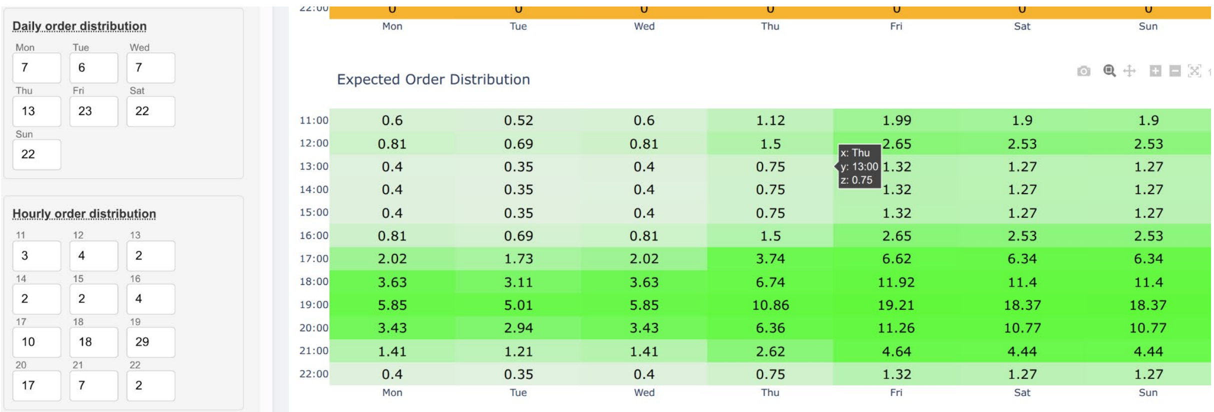

Figure 4: The order distribution

After the random order sample for a single simulation has been drawn, the ground crew walks around the graph and handles the orders. Here, time used on walking, delays from the restaurant, time spent handling the drone, and more, is simulated. After the single simulation has been completed, the process is repeated for several simulations, and results are summarized using the statistics on all the single simulations.

Since the optimal number of workers is unknown for a given set of simulation parameters, the statistical analysis involves finding the optimal shift schedule for the ground crew. This optimal schedule gives the maximum achievable profit for a given scenario, and shows the distribution of workers throughout the week. Settings regarding the minimum shift length and wages affect the optimization results.

The MEDUSA Simulator provides a Financial Summary (Figure 5), and Profit Analysis (over various order volumes.

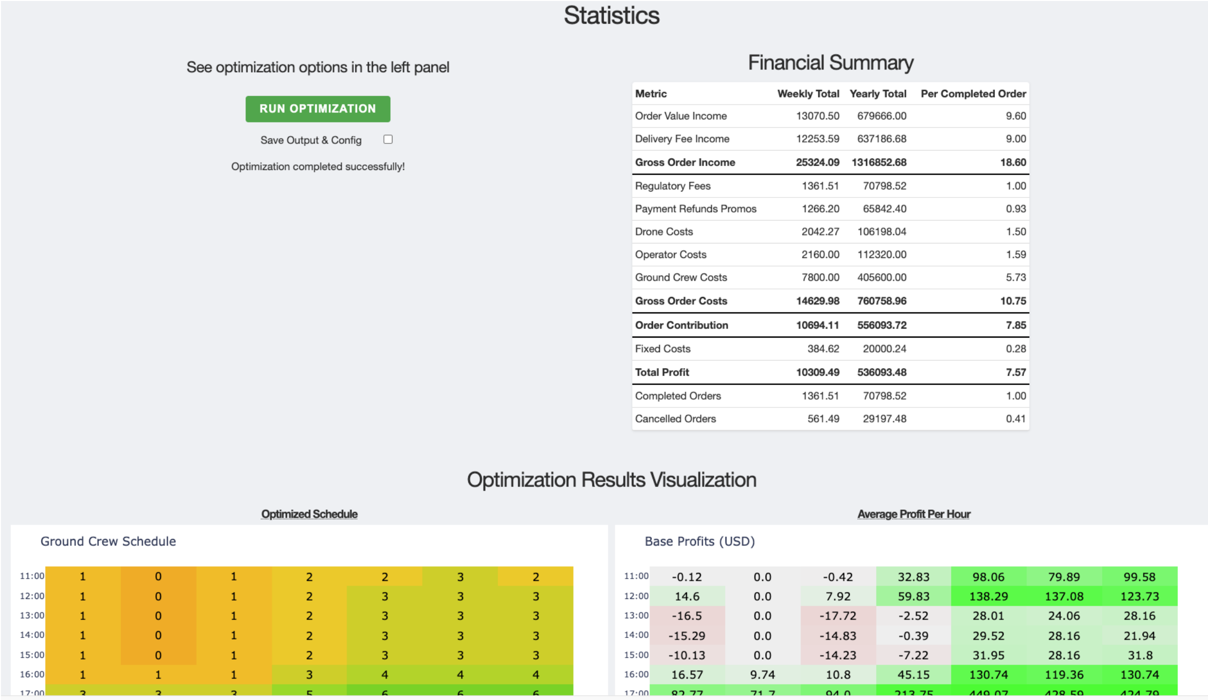

Figure 5: Financial Summary

The simulator GUI has a separate tab for Parameter Sensitivity Analysis as seen in Figure 6 below. In the Parameter Sensitivity Analysis two parameters can be analyzed at the same time to create sensitivity plots.

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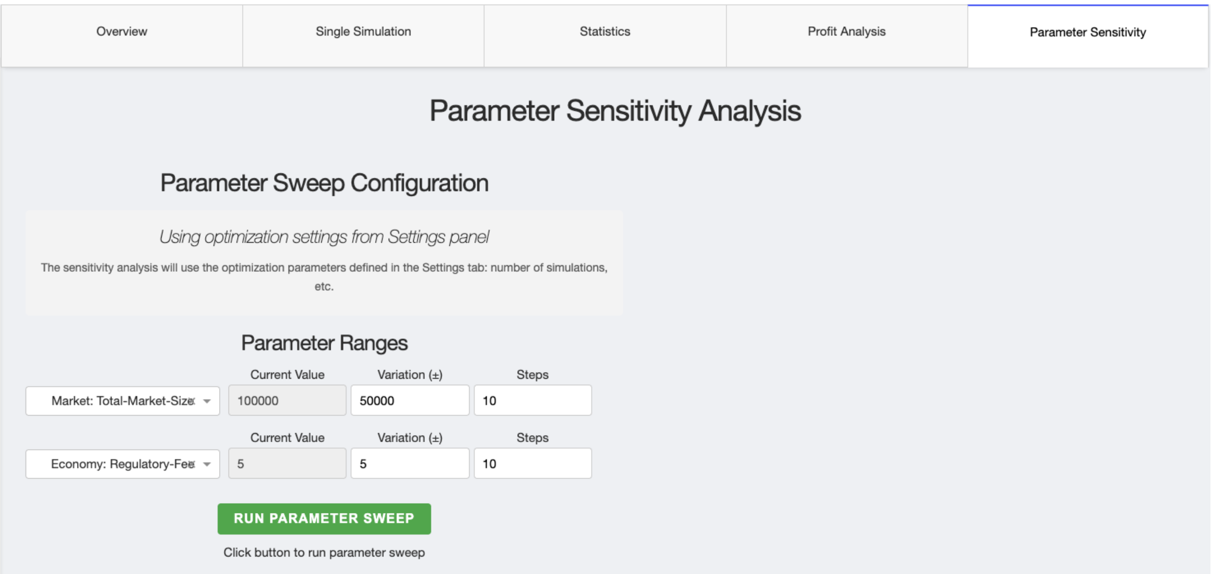

Figure 6: Parameter Sensitivity Analysis

WP2: Market Potential Model

The Market Potential Model uses population clustering algorithm and market data to find the market size for hub locations across Europe. The main input to the model is the population and its distribution/density, while also other factors such as existing adoption rates of delivery services were added and explored in WP3.

The population analysis was based on 1 km² population grid data for the EU population[6]. In total 27 countries were analyzed. The full list available in Appendix B.

A drone with a certain radius will in theory reach the entire population within this radius. If purely looking at population on 1 km² grids, all hubs for drone deliveries would mostly be placed in the city centres. Instead a key assumption is that the majority of drone deliveries in the next 10 years will happen outside cities and the most densely populated areas. This is due to both the regulatory restrictions and safety concerns in densely populated areas. Another related assumption is that drones will start off by being more competitive outside of areas with excellent coverage by traditional delivery methods such as bicycles or cars. As of now, the competitive advantage of drones scales with distance and the marginal cost per km favors drones over traditional delivery methods such as cars.

[6] https://ec.europa.eu/eurostat/web/gisco/geodata/population-distribution/population-grids

To account for the two assumptions above we applied a Degree of Urbanisation Methodology (DEGURBA[7]) to the market reach analysis, initially using DEGURBA L2.[8] However, the thresholds for settlement size and population density did not match the data from our Competition Mapping Model[9], based on real world data on existing delivery platforms. To improve the accuracy we created a new clustering algorithm that tweaked Settlement (cluster) Size and Population Density thresholds, using a modified version of the schematic overview[10] of such classification is seen in Figure 7.

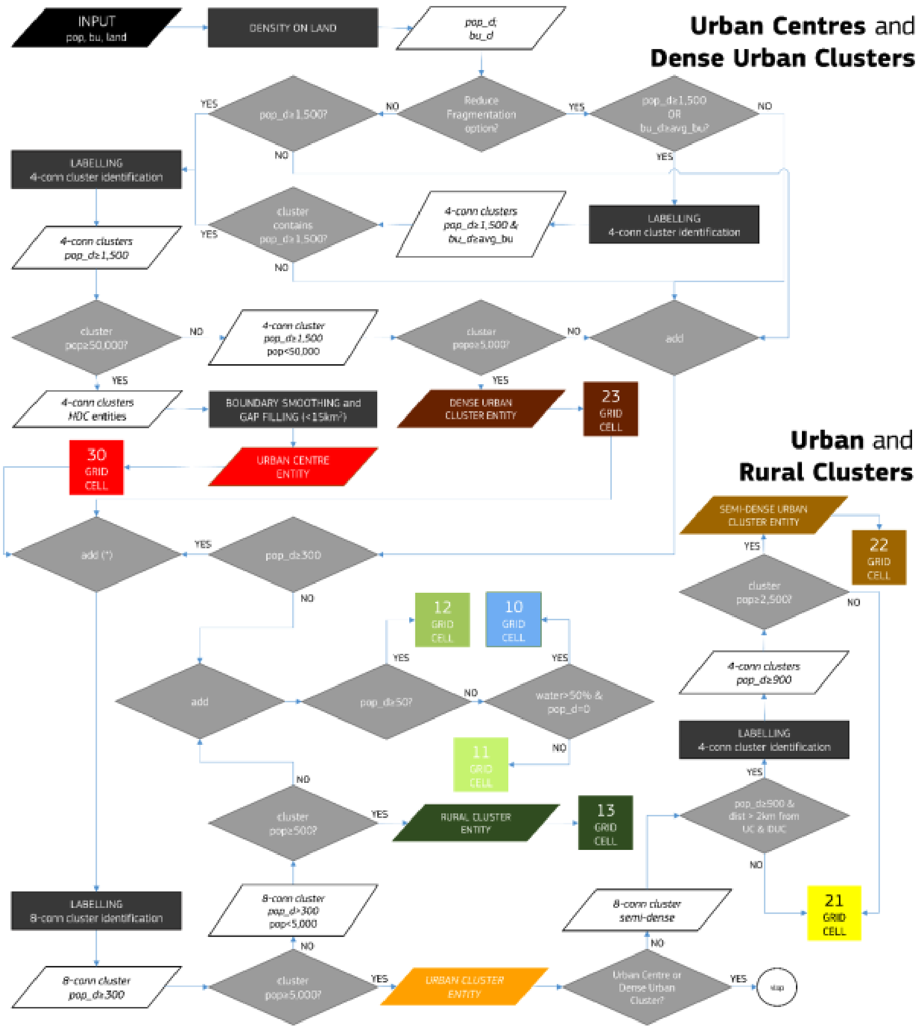

Figure 7: Schematic Overview from Degree of Urbanisation Grid

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7 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Degree_of_urbanisation

8 https://ec.europa.eu/assets/estat/E/E4/gisco/website/stat_expl/population_grid/grid_maps/degurba.html#

9 Internal Model developed by Aviant to find areas in which traditional delivery methods work well.

10 https://human-settlement.emergency.copernicus.eu/tools/GHS-DUG_User_Guide.pdf

After calibrating our model against our Competition Model we generated a dataset of 1 km x 1 km grid cells for Europe with the (1.8 million) grid cells population and a custom urbanization level, mirroring our competitive model and excluding cells of population density above 4096 per square kilometer.

The next step was to calculate the market potential, i.e. how many (relevant) people that could be reached from a hypothetical base location, with a drone range up to 20km. We used another custom software tool to calculate the reach from all the grid cells in Europe.

Hence, the output of the Work Package was two datasets;

1) Market Potential in Europe (grids)
2) Drone Hub Market Reach

In practice, the first data set provides an overview of areas in which we predict drone deliveries could happen. The second dataset provides optimal base locations to maximize (relevant reach).

An overview of Work Package 2 can be seen in Figure 8 below.

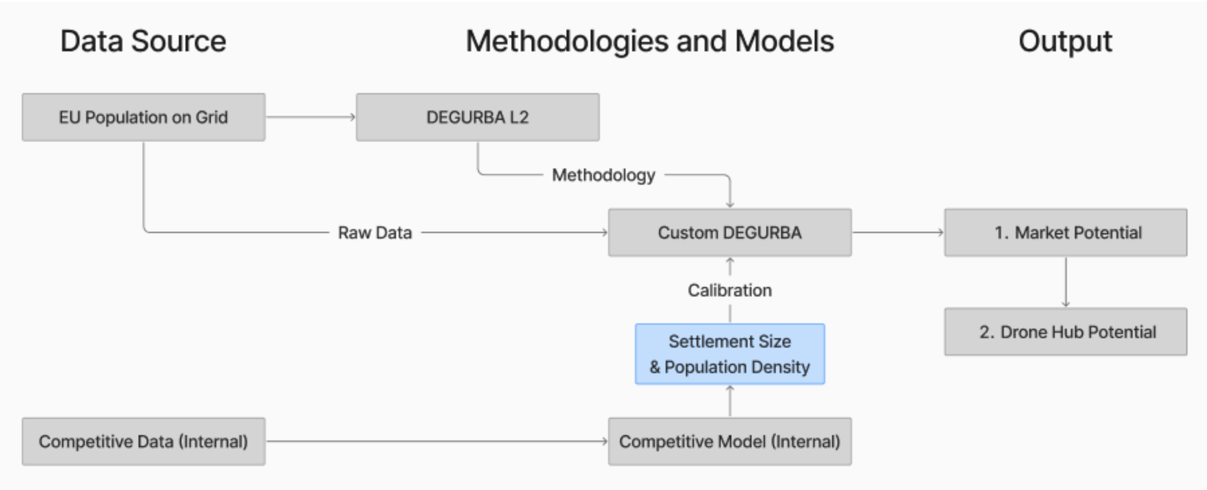

Figure 8: Process of finding Market Potential

WP3: Theoretical Predictions

In this Work Package, the results from the MEDUSA Simulator and the Market Potential Model (including country data and airspaces) were combined to create theoretical predictions of drone hotspots across Europe. Our approach was to look at this from four different angles;

1) Hotspots for drone hubs, disregarding airspaces

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2) Hotspots drone hubs within airspaces
3) Airspaces only analysis
4) Hotspots next 10 years

1.Hotspots for drone hubs, disregarding airspaces

The methodology is to view each grid cell as a potential drone hub location. The total market reach for each location is from the Drone Hub Market Reach dataset generated in WP2. The threshold for a relevant base location was set based on the break-even points for market reach from WP1. Based on the dataset and the established threshold, a heat map showing the most attractive areas for placing a drone hub was created. This analysis disregards country specific attractiveness such as general adoption rates, purchase power and the regulatory environment.

2.Hotspots for drone hubs within airspaces

Assuming that drone hubs are placed within an airspace, every movement (take-off and landing) will happen within that airspace. Potentially also the delivery if the destination is within the airspace. To find hotspots within airspaces, we combine the analysis above, but filter on airspaces.

Airspaces (CTR and TIZ) in Europe were obtained from OpenAIP[11]. The number of airspaces per country can be found in Appendix B.

3.Airspaces only analysis

The two analyses above assume that an operator would like to place a drone hub in the most attractive locations, regardless of whether this is within an airspace or not. Various U-space funding models may influence that decision, and instead operators may want to consider placing the drone hubs outside of the airspace, but still deliver within that specific airspace. In other words, instead of looking at the drone hub potential *from* the airspace, this analysis looks at market reach *within* the airspace itself.

We look at each airspace polygon and find the relevant market reach within that airspace using the Market Potential Dataset from WP2. Hence, the relevant reach is in this case also based on the custom DEGURBA approach previously outlined.

This analysis disregards cases in which the flight path crosses the airspace (but take-off, landings and deliveries are outside). A note here is that the sizes of the airspaces vary greatly, which correlates with the reachable population. Hence, we will rather rank the attractiveness per km^2 of airspace.

4. Hotspots next 10 years

In the initial scope of the project one objective was to predict the significance of drone deliveries in airspaces in the next 10 years. As the uncertainty of adoption rates is already high, predicting this 10

[11] https://www.openaip.net/data/airspaces

years into the future is subject to even greater uncertainty. Regardless, we have attempted to make some predictions.

There is currently not a lot of data in regards to expected adoption rates of drone deliveries. Manna claims a 46% adoption rate within 12 months of launch for their service in Dublin[12]. Many factors are at play here, the newsworthiness & publicity and pricing.

We approach the question with the core assumptions that some countries will be more attractive to drone deliveries from a consumer perspective, or demand, perspective.

To establish a baseline adoption for each country, we use Eurostat's e-commerce adoption rates[13]. A key assumption here is that countries lagging behind on e-commerce adoption also will be slower to embrace drone delivery services than countries with a high adoption rate of general ecommerce. More specifically, we consider the adoption rate of *Online purchases: deliveries from restaurants, fast-food chains, catering services* for *Individuals living in Cities* as the best proxy for possible adoption rates for drone deliveries. This is because 1) *deliveries from restaurants* (food) is something that works well with the benefits and constraints of drones, such as urgency/speed and limited pooling capacity, and 2) *Individuals living in Cities* is the segment that in most cases also have access to such a service today. Whereas individuals living in towns and suburbs or in rural areas, in many cases currently do not have such access. This is one of the promises of drone deliveries, enabling deliveries in areas that currently does not make sense. Further, we assume that a country's future E-commerce adoption rates will follow the typical adoption rate curve from the EU.

To predict the adoption rate of deliveries within the next 10 years, we use the following formula:

$$AD_{C,Y} = R_C \ x \ A_{C,Y}$$

- ***C*** - Country
- ***Y*** - Year
- ***R_C*** - Ratio of *Individuals living in Cities* that has *deliveries from restaurants, fast-food chains, catering services* vs. *any online purchases of physical goods* for country (C)
- ***$A_{C,Y}$*** - *Estimated online purchase* adoption rate for country (C) in year (Y) for *Individuals living in Towns or Suburbs*, based on typical e-commerce growth rates in the EU
- ***$AD_{C,Y}$*** - Estimated adoption rate for deliveries for country (C) in year (Y)

[12] https://www.linkedin.com/posts/bhealy_manna-drone-delivery-is-seeing-a-46-adoption-activity-7295183051662180354-h12a

[13] https://ec.europa.eu/eurostat/databrowser/explore/all/science?lang=en&subtheme=isoc.isoc_i.isoc_iec&display=list&sort=category&extractionId=isoc_ec_ibgs

Comment: Italy has one of the lowest e-commerce adoption rates ($A_{Italy,,2024}$) in the EU for people living in towns and suburbs. Using the formula above we expect this adoption rate to increase (following the typical adoption rate in the EU) over the next 10 years. However, Italy also has one of the lower ratios of individuals living in cities that have ordered from food delivery vs. any physical delivery (R_C). This ratio on the other hand, we expect to be more constant.

With the general adoption rate of food delivery, or what we believe is a good proxy for drone deliveries, what remains is order frequency and share of these deliveries being delivered by drones. Here, the uncertainty obviously becomes even larger. To simplify, we assume that the share of deliveries being delivered by drones grows linearly from 1% in 2026 to 80% in 2035. In terms of annual order frequencies, existing estimates (within food delivery) range from less than 10 per year to more than 50 per year[14]. Based on Aviant's internal data and the anecdotal evidence from Manna[15], we use an annual Order Frequency of 10 as what we believe to be a conservative baseline.

Hence, the formula for estimating drone deliveries per capita for a country (within medium density):

$$DD_{C,Y} = AD_C \ x \ SH_{C,Y} \times OF$$

- ***OF*** - Annual Order Frequency
- ***$SH_{C,Y}$*** - Share of Deliveries being delivered by drones
- ***$DD_{C,Y}$*** - Estimated Drone Deliveries per capita for country (C) in year (Y)

We believe the approach above sufficiently takes into account the overall attractiveness of the market (e.g. purchase power). However, there are most certainly other factors such as the demographic differences between cities and towns/suburbs that are very different between countries. Nor does it take into account population growth/decline. Keep in mind that the analysis does not take into account the drone specific regulatory environment. In practice, the analysis will likely do a better job of indicating the relative attractiveness of different countries and airspaces, than to actually predict the absolute volume of drone traffic.

2.4 Results

The results from the MEDUSA simulator show that there is a potentially large profit incentive for drone delivery services in many areas across Europe, with an annual base contribution between $1 million

[14] https://www.yipitdata.com/resources/blog/3p-shifting-market-dynamics

[15] https://www.linkedin.com/posts/bhealy_manna-drone-delivery-is-seeing-a-46-adoption-activity-7295183051662180354-h12a

and $2 million. (Obviously very sensitive to the input parameters). Though this potential profit comes from a lot of flights and up to 500 drone movements per hour. The best locations in Europe have a relevant reach of more than 250,000 people. These locations have the potential to be profitable even with a smaller USSP fee. However, for locations with a lower market reach, a USSP fee will likely eat up the profit.

Two of the more interesting parameters to look at are Market Reach and USSP fee (for U-space funding models). In almost all likely scenarios, the profitability is very sensitive to a per order USSP fee. This is not surprising given the slim margins and the unit economics of delivery in general). As an example, a USSP fee of $1 per flight would in most simulations reduce the profitability of a base significantly.

In terms of Market Reach, a minimum of 50,000 people seems to be a break-even point in most of the simulations completed (but again very sensitive to input parameters). This is the same minimum reach Manna mentioned "could work" in the Vertical Space Podcast[16]. Though reaching 100,000 people and up would be the "Goldilocks". These estimates likely do not include a significant U-space fee. The theoretical predictions below are based on a minimum (relevant) market reach of 50,000 people. Note that these are people living outside of very densely populated areas.

Theoretical Predictions

1. Hotspots for drone hubs

The following heatmap (Figure 9) highlights the areas predicted to be the most attractive to drone deliveries, and hence will see most drone traffic. The darker, the more attractive. At a high level this map does seem to correlate with population density in Europe. With Belgium, Netherlands, northern Italy, western Germany and parts of Switzerland having the largest population densities. It is important to note that the heatmap does exclude the most densely populated areas and areas in which traditional delivery methods work well. This is evident when zooming in on the map as seen in Figure 10, showing Milan, Italy. Nevertheless, the areas we predict will see the most drone deliveries are usually areas with medium population density, which often happens to be the suburbs or outskirts of larger cities.

[16] https://theverticalspace.net/episode/70-bobby-healy-manna-unveiling-the-unit-economics-behind-profitable-drone-delivery

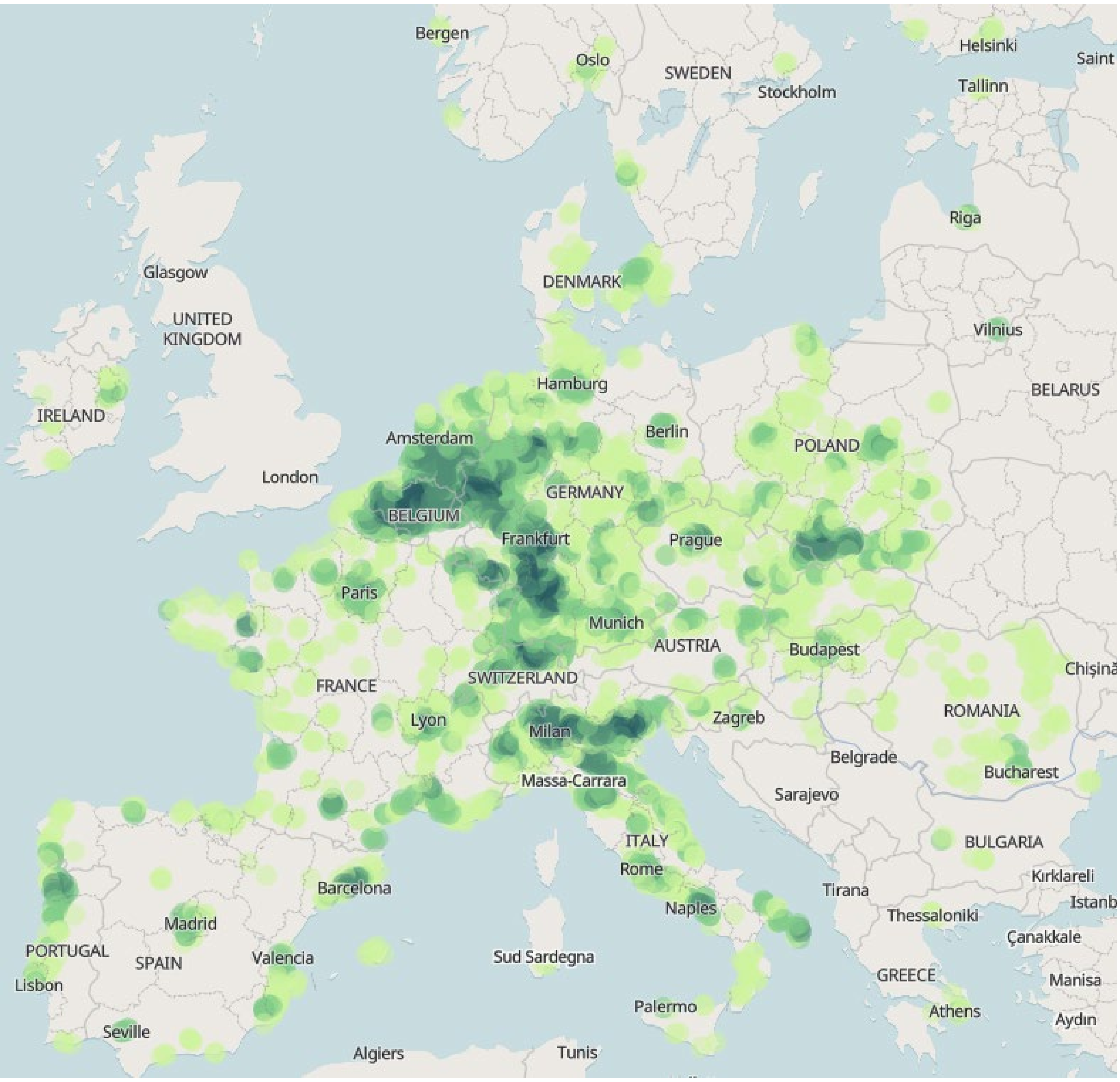

Figure 9: Drone hotspots across Europe

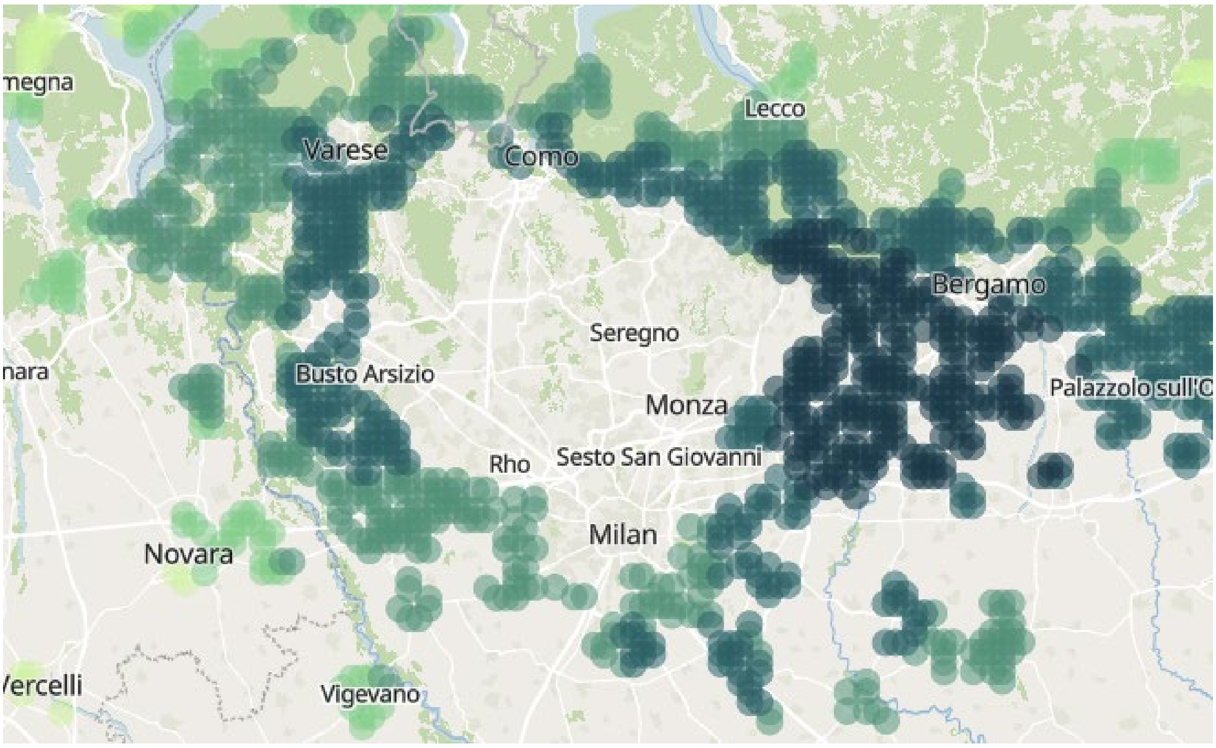

Figure 10: Heatmap around Milan, Italy

2.Hotspots for drone hubs within airspaces

By overlaying the airspaces of Europe on the same map (figure 11), we can clearly see that many of the airspaces happen to be in the areas attractive for drone delivery operations. Similar to the reasoning above, this is also not very surprising as airspaces are often located outside of larger cities, which is exactly the areas we predict are often a good fit for drone deliveries.

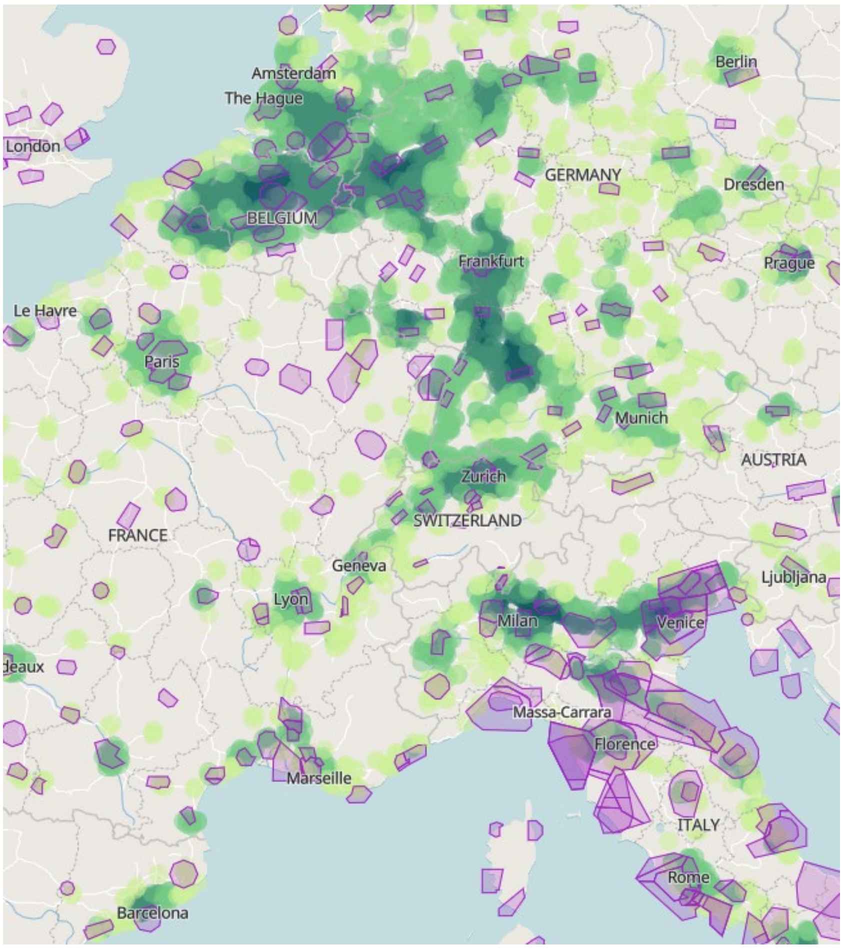

Figure 11: Drone hotspots and airspaces

A ranked list of the 200 airspaces we predict would be most attractive for placing a drone hub is found in Appendix C.

3.Airspaces only

When looking at market reach *within* the airspace itself, the list of attractive airspaces look different. One key factor here is obviously that the airspaces are of very different sizes. As a result many of the top airspaces are in Italy, which tend to have larger airspaces. If we instead look at attractiveness per km^2 of airspace size, the list looks quite different.

A list of the top airspaces can be found in Appendix D.

4.Hotspots next 10 years

Following the methodology outlined, the predicted drone deliveries per capita over the next 10 years are seen in Table 1 below. Due to the very large uncertainty, it is more meaningful to look at the relative size between the countries, more than the absolute volume.

		2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Bulgaria	BG	0.0	0.2	0.3	0.6	0.8	1.1	1.4	1.7	2.1	2.4
Romania	RO	0.0	0.3	0.5	0.8	1.2	1.6	2.0	2.4	2.8	3.3
Italy	IT	0.0	0.1	0.3	0.4	0.6	0.8	1.0	1.3	1.5	1.7
Latvia	LV	0.0	0.2	0.4	0.7	1.0	1.3	1.6	1.9	2.2	2.5
Portugal	PT	0.0	0.3	0.6	0.9	1.2	1.6	2.0	2.4	2.8	3.2
Lithuania	LT	0.0	0.2	0.4	0.7	1.0	1.2	1.5	1.8	2.1	2.5
Greece	GR	0.0	0.4	0.8	1.3	1.8	2.4	2.9	3.5	4.1	4.7
Slovenia	SI	0.0	0.3	0.5	0.8	1.1	1.4	1.8	2.1	2.5	2.8
Croatia	HR	0.0	0.2	0.4	0.6	0.9	1.1	1.4	1.6	1.9	2.2
Spain	ES	0.0	0.3	0.7	1.1	1.4	1.8	2.3	2.7	3.1	3.6
Poland	PL	0.0	0.2	0.4	0.6	0.9	1.1	1.4	1.6	1.9	2.2
Finland	FI	0.0	0.4	0.8	1.2	1.6	2.1	2.5	3.0	3.4	3.9
Hungary	HU	0.0	0.4	0.8	1.2	1.7	2.1	2.6	3.0	3.5	4.0
Estonia	EE	0.0	0.3	0.7	1.0	1.4	1.7	2.1	2.5	2.9	3.3
Cyprus	CY	0.1	0.6	1.2	1.9	2.6	3.3	4.0	4.7	5.5	6.2
Luxembou	LU	0.0	0.3	0.7	1.0	1.4	1.8	2.2	2.6	3.0	3.4
Germany	DE	0.0	0.3	0.7	1.0	1.4	1.7	2.1	2.5	2.9	3.3
Malta	MT	0.1	0.6	1.2	1.8	2.4	3.0	3.7	4.4	5.1	5.7
Austria	AT	0.0	0.4	0.8	1.2	1.6	2.0	2.5	2.9	3.4	3.8
Slovakia	SK	0.0	0.3	0.6	0.9	1.2	1.6	1.9	2.2	2.6	2.9
France	FR	0.0	0.2	0.5	0.7	1.0	1.2	1.5	1.7	2.0	2.3
Belgium	BE	0.0	0.3	0.5	0.8	1.1	1.4	1.7	2.0	2.3	2.6
Czechia	CZ	0.0	0.4	0.7	1.1	1.5	1.9	2.3	2.7	3.1	3.5
Sweden	SE	0.0	0.3	0.6	0.9	1.2	1.5	1.8	2.1	2.4	2.7
Norway	NO	0.1	0.5	1.0	1.5	2.1	2.6	3.1	3.6	4.2	4.7
Ireland	IE	0.1	0.5	1.0	1.4	1.9	2.4	2.8	3.3	3.8	4.2
Denmark	DK	0.1	0.5	1.0	1.5	2.0	2.5	3.0	3.6	4.1	4.6
Netherlan	NL	0.1	0.5	1.0	1.5	2.0	2.5	2.9	3.4	3.9	4.4

Table 1: Predicted annual drone deliveries per capita

When combining these predictions with the analysis of reachable population within airspaces (#3 above), we get an estimate of drone traffic per airspace. As the airspace sizes still influence the overall volume, we look at predicted drone traffic density within airspaces instead. In other words, the expected drone delivery traffic per square kilometer of airspace. As seen in Figure 12 below, the

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airspaces we predict will have the highest traffic densities are mostly located in the Germany, Belgium and Netherlands.

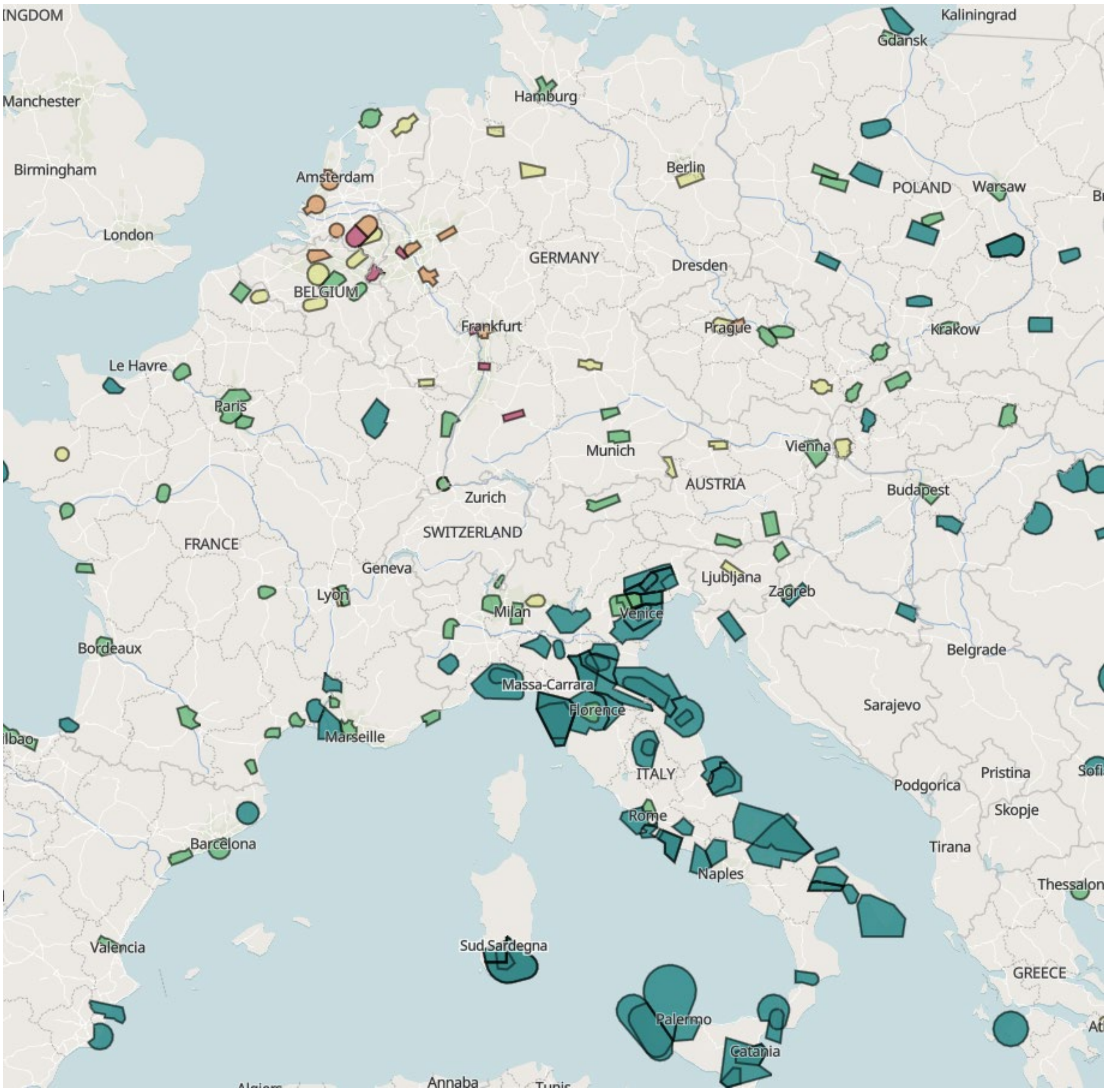

Figure 12: Predicted drone delivery traffic density within airspaces

And finally, we look at what this means in terms of actual traffic within the airspace.

We estimate that the top 200 airspaces in Europe will reach more than 100,000 people (following the methodology from WP2), with an average reach of 200,000 people. (This includes large airspaces that

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would need multiple drone hubs to be served). With an annual order per capita of 2 (example from Table 1 above), this means 400,000 deliveries per year within the airspace.

In comparison, the busiest airports in Europe typically have around 500,000 aircraft movements per year. At the same time, activity at major airports is usually more distributed throughout the week compared to what we expect drone deliveries will be. With 400,000 deliveries for a year, one can assume 400-500 deliveries happening at the peaks.

Discussions with stakeholders

In the area of airspace management, both LFV and NATS described how current methods of managing drone flights, particularly in controlled traffic regions (CTRs) and traffic information zones (TIZs), are largely manual and not suited for high-volume drone activity. LFV noted that most coordination today is handled via phone and email, while NATS has implemented a digital flight intent system that allows operators to register planned drone operations in advance. This system supports faster permit handling and improves situational awareness for air traffic controllers.

With respect to economics and funding, LFV highlighted that current business models for U-space services are not financially sustainable. They projected that U-space will remain unprofitable in the near term and will require subsidies or government support. NATS described their cost model based on operational volume, where operators pay a fixed fee for defined levels of activity. Both stakeholders emphasized the need for cost-sharing models involving drone operators, ANSPs, and U-space service providers. During informal talks with participants during the Airspace World 2025 conference, several stakeholders mentioned the huge uncertainties if drone delivery will ever take off due to the low profit margin, especially if a USSP fee is introduced.

The discussion on operational considerations focused on constraints and enabling factors for safely integrating drones into shared airspace. LFV pointed to longstanding aviation rules, such as minimum separation distances, as potential barriers. NATS detailed how their system provides digital oversight, automatic alerts in case of airspace non-conformance, and streamlined communication between operators and ATCs.

In terms of future perspectives, both LFV and NATS saw significant potential for drones in both rural and urban environments. NATS expected high drone densities around cities for last-mile logistics, as well as in industrial and offshore applications. Both stakeholders emphasized that public acceptance would depend on managing noise levels and ensuring operational safety.

Avinor (in Norway) are, as with many other Air Navigation Services, investing in systems for detection and traffic management for UA. However, our results indicate that smaller airports may see more drone traffic (as they reach more relevant people). The larger airports built in the last two decades are often placed further away from the major cities.

The topic of suitable locations for drone operations were discussed with Manna. Manna's strategy is to locate their hubs inside of airspaces, and in Dublin Manna operates within the CTR of the airport with their own geozone where they operate. The benefit of this approach is that airspaces tend to have the correct population density and reach (as the results from MEDUSA supports). Another argument mentioned by Manna is that the location of the hub within an airspace removes the need for a separate airspace risk analysis. However, Manna is forced to fly at 65m AGL at all times and is only allowed to go below 65m AGL at delivery sites and at FATO/base. If other drone operators would like to fly within the area, they need to be cleared by Manna and not the ATC. If there is an emergency (Police and HEMS), the drone operations must be stopped. Though the lack of separate restricted area simplifies things, the downside is that it could take 1.5 to 2 years to get approval to operate within the airspace.

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3 Conclusions, next steps and lessons learned

3.1 Conclusions

The MEDUSA simulator results confirm that a potentially large profit incentive exists for drone delivery services across many European regions, specifically in medium-density areas like the outskirts of larger cities. However, this profitability is extremely sensitive to input factors and the operational model; the introduction of a substantial USSP fee can quickly render drone delivery unprofitable. The prediction models clearly indicate that many optimal drone delivery base locations frequently overlap significantly with existing controlled airspaces. This coincidence suggests that many airspaces in Europe will be attractive to drone operators, potentially leading to substantial traffic volumes estimated at up to 400,000 deliveries per year and peaking at 500 deliveries during peak hours within these airspaces.

In parallel with the simulation work, stakeholder interviews offered critical insights into the current state and challenges. Manual airspace management practices (relying on phone and email) are ill-suited for handling the anticipated high-frequency drone traffic. This analysis demonstrates the acute necessity for industry stakeholders to invest in scalable digital oversight systems to replace manual coordination and establish sustainable shared economic policies to manage high-density traffic. An adoption of a digital flight intent platform highlights the importance of scalable, integrated systems. ANPS's needs to be able to identify drones, and differentiate between drones that are approved. MEDUSA's modelling of peak drone density provides useful input for identifying where such digital oversight systems will be most urgently needed. The largest airports (in terms of regular passenger traffic) are not necessarily the airports we expect will be the most attractive for drone deliveries.

The interviews reinforced the finding that U-space services are not expected to be financially sustainable in the short term, consistent with MEDUSA's simulations suggesting limited profitability without sufficient operational scale. Hence, cost sharing mechanism and volume-based pricing should be considered, while acknowledging that a substantial USSP fee potentially can make many areas unattractive for drone operators.

The MEDUSA project has significantly helped to increase the maturity towards applied and industrial research by moving foundational economic and operational theories into quantifiable predictions grounded in real-world data constraints.

The project delivered detailed analytical models, synthetic data generation capabilities, and predictive tools designed specifically to inform infrastructure investment and prioritization decisions for ANSPs. By combining Aviant's operational data with publicly available European population and airspace data, MEDUSA provided realistic constraints such as the break-even market size, and peak traffic density which are essential for developing system requirements. The simulation outputs and hotspot predictions provide the necessary input to define the performance and functionality requirements for future U-space systems needed in specific, high-priority airspaces across Europe.

The MEDUSA project functioned as a strong TRL 3-4 enabling activity.

- It successfully moved from the analytical proof of concept (TRL 3, demonstrating feasibility through the MEDUSA Simulator and Market Potential Model) towards the system requirements definition phase (TRL 4), based on realistic market and operational constraints derived from the simulation and stakeholder input.
- The project generated synthetic data and predictive maps which serve as the foundation for the eventual development and testing of U-space solutions.

3.2 Next steps

Aviant will continue to discuss our findings in more detail with ANSPs and other drone operators to contribute to a sustainable drone delivery industry, starting with presenting the findings at SID 2025 (Safe Integration of Drones). A possible next step would be to create an updated simulator for the use of other drone operators and ANSPs. Another potential next step is to share the results even more widespread, ensuring both ANSPs and USSPs understand how the drone delivery business case works.

3.3 Lessons learned

The light touch catalyst funding approach worked well, and we are satisfied with the overall execution of the project. The few challenges were related to (internal) changes in the project members throughout the project.

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4 Dissemination

Aviant attended the SESAR Innovation Days 2024 with a stand and poster. Aviant's Flight Operation Manager presented MEDUSA at Airspace World 2025 providing a background, goals and methodology and preliminary findings. Aviant is also presenting the findings from MEDUSA at SID (Safe Integration of Drones) hosted by the Norwegian CAA on Nov 14th, 2025.

5 References

5.1 Project outputs

[1] Presentation at Airspace World, 04.05.2025 (link).

[2] Publicly shared map of drone delivery densities within airspaces (link).

[3] Presentation at SID, 14.11.2025 (forthcoming).

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6 List of acronyms

Acronym	Description
AGL	Above Ground Level
ANSP(s)	Air Navigation Service Provider(s)
ATC(s)	Air Traffic Controller(s)
B2C	Business-to-Consumer
CTR(s)	Controlled Traffic Region(s)
C-UAS	Counter-Unmanned Aircraft Systems
DEGURBA	Degree of Urbanisation
FATO	Final Approach and Take-Off
HEMS	Helicopter Emergency Medical Service
LFV	Luftfarsverket (Sweden)
NATS	National Air Traffic Services (UK)
SESAR	Single European Sky ATM Research Programme
TIZ	Traffic Information Zone
UAS	Unmanned Aircraft Systems
U-space/UTM	Unmanned Traffic Management/U-space services
USSP	U-space Service Provider

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Appendix A - WP1 Simulation Model Parameters

A.1 Market Parameters

Total market size

The total number of potential customers in a given market.

Order Frequency per year

How many orders each active customer puts in per year.

Adoption Rate (%)

The percentage of the total market population that adopts the service and are active customers.

Weekly Order Volume

The weekly order volume based on the formula
Total market size x *Order frequency per year* x *Adoption rate (%)* / 52.

Yearly Order Volume

The yearly order volume based on the formula
Total market size x *Order frequency per year* x *Adoption rate (%)*

Daily Order Distribution

The relative number of orders for each corresponding weekday, each weight gets normalized according to the sum of all weights, that is

$$w_i = n_i \ / \ (n_1 + n_2 + \ldots + n_7),$$

where w_i is the weight for day number i (1 = Monday, et cetera). This, in turn, is used to create a categorical probability density function (PDF) for sampling orders during a single realization of a week.

Hourly Order Distribution

Similar to the *Daily Order Distribution*, but for each hour within a day. After the number of orders for a given day has been sampled according to the *Daily Order Distribution* PDF, this number of orders are again distributed throughout the day. The weights here are normalized in the same fashion as the *Daily Order Distribution*, and are used to create a mixed model PDF, where each hour is a categorical variable and the orders are uniformly distributed within the respective hour.

A.2 Economics Parameters

Ground Crew Wage

The hourly wage for the ground crew. This multiplies the weekly shift schedule to get the hourly GC wages throughout the week. The shift schedule is an input parameter defined under Schedule Parameters.

Operator Wage

The hourly wage for the drone operator, used similarly to the ground crew wage.

Operator Simultaneous Drones

The drone operator can pilot this many drones simultaneously. This parameter affects the number of operators required, especially during peak hours when there are many drones flying simultaneously.

Operator Number of Bases

How many bases a drone operator has access to simultaneously. When order volume is low, there will be fewer drones flying per operating base, so it is synergistic to have fewer operators piloting drones on several base locations. During peak hours, this will usually have a minimal effect on operator costs, as each base will have enough orders to fill up the *Operator Simultaneous Drones* quota.

Delivery Fee

The fee charged to the customer for delivering the order. This is a source of revenue which comes on top of the take rate from the restaurant defined below.

USSP Fee

The fees charged to use the airspace. It is taken on a per order basis, and is subtracted from the *Delivery Fee*.

Value per Order

The estimated value per processed order, used with the *Take Rate* to calculate the revenue.

Take Rate (%)

The percentage of the value per order that is taken by the delivery service provider.

Payment Refunds, Promos (%)

The percentage of gross order value which is refunded or discounted due to unforeseen events or promotions and so on.

Drone Parts per order

The cost of drone parts per processed order.

Drone Maintenance per order

The cost of drone maintenance per processed order.

Drone Other per order

Other miscellaneous drone costs per processed order.

Fixed Annual Costs

This cost parameter is not directly used in the simulation, but is presented as a comparison value on the profitability plots and financial summary table.

A.3 Operational Parameters

Walking Strategy

There are 3 implemented strategies for ground crew walking the graph; *Simple*, *Roundtrip*, and *Dynamic*:

- The *Simple* strategy involves the ground crew simply walking to the restaurant that has the next available order, picking this up when it is ready, and returning to the dropoff point for drone delivery.

- The *Roundtrip* strategy involves the ground crew running a predetermined round based on the travelling salesman solution between each restaurant. At each restaurant the GC will pick up orders until at a *Max Carry* capacity, then they will return to the drone dropoff point.

- The *Dynamic* strategy is similar to the *Simple* strategy, but the GC will take the order that is closest in both travel time and waiting time, up to a certain point in the future, called the *Pooling Window*. It will also obey the *Max Carry* constraint when scheduling order pickup.

Max Carry

Defines the maximum number of orders a single GC member can carry simultaneously, before needing to return to the dropoff location for drone delivery.

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Max Wait (min)

The maximum time a customer will wait for an order, before they will cancel, demand a refund, or otherwise stop using the service causing a revenue loss. In the simulation, this will simply mark the order as cancelled if it is outside of this window, and the GC carrying packages has several criteria to try to avoid this happening.

Pooling Window (min)

In the case the *Dynamic* walking strategy is chosen, the *Pooling Window* defines how long the GC will postpone returning to the dropoff for drone delivery in anticipation of new orders which can be picked up synergistically.

Drone Travel (min)

The *Drone Travel* time is split into an average (Avg) and standard deviation (Std), and it defines the time the drone will spend traveling to the customer.

Customer Wait (min)

The time the drone will have to wait at the customer dropoff location before the customer picks up the delivery package. This is also split into an average and a standard deviation input.

Store Wait (min)

The time the GC will have to wait at each restaurant due to unforeseen circumstances or time required to pick up the order. This is also split up into an average and a standard deviation. This greatly affects the number of orders the ground crew are able to process within a certain amount of time.

Drone Handling (min)

The time used by the GC to handle the drone for each order, this is similar to the store wait time, in that each GC member has to spend a certain period of time for each order handled. This also has a large impact on the number of orders a GC member can handle.

A.4 Graph Parameters

The *Graph* is an object defining the physical layout of the stores or restaurants involved in the delivery service. The ground crew members walk between each node of the graph, picking up orders which are randomly placed around the graph. The *Graph* can be supplied using a CSV with a symmetric distance matrix or generated using the representative parameters below. The dropoff point for drone delivery is defined as the origin in all graph layouts.

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Number of Stores

The number of stores or restaurants that the graph will be generated from. The different walking strategies are affected differently by this parameter. The *Roundtrip* walking strategy will be most affected by the number of stores due to the roundtrip time being scaled, while the *Simple* and *Dynamic* walking strategies will be affected slightly less, due to spread of orders.

Max Radial Distance (min)

The maximum distance a store will be located away from the dropoff location for drone delivery, used for generating a *Graph* based on a few inputs.

Layout

The layout method for generating the *Graph* object, where the options are *Circle* and *Random*:

- The *Random* layout creates random (x,y)-coordinates for each store, up to the *Max Radial Distance* and then calculates the Euclidean distance between all the stores.

- The *Circle* layout creates a graph where each store lies on a circle with the radius defined in *Max Radial Distance*.

A.5 Schedule Parameters

The ground crew shift schedule is a parameter that has been partly automated in many of the simulations, and it defines when the ground crew members are assigned to work during the workweek. This parameter input is primarily used for the “Single Simulation”-mode, when one wants to see what happens for a randomly drawn sample for a single week.

The generated ground crew schedule here can also be used as an initial input to the schedule optimization algorithm, used with statistics to find the optimal schedule for ground crew, given a set of parameters. The option to use the initial schedule as an input is defined below, under *Use Initial Schedule*.

A.6 Optimization Parameters

Number of Simulations

The number of ensemble iterations that are used to find the statistical properties for a given scenario. Since the customer orders are distributed randomly throughout the week based on a given order volume and a statistical distribution of orders, individual variations are combined into statistical results.

Maximum Iterations

The maximum allowed number of iterations during the optimization process for the shift schedule. This should usually be set quite high, and is primarily a safety for the optimization algorithm.

Minimum Shift Length (hours)

The *Minimum Shift Length* is the number of hours that a single ground crew member must be allocated to work as a unit. For example, if the minimum shift length is 4 hours, then the optimization algorithm will use 4 hour blocks as a base unit, so that each iteration allocates 4 hours or more to a single ground crew member.

Number of Threads

The number of processor threads to use when running statistical simulations and optimizations. The default value for the number of threads that Julia has been launched with, which must be increased before it has any effect on the performance of the simulations.

Use Initial Schedule

As mentioned under the *Schedule Parameters* section, this is a checkbox option that enables or disables the use of the user defined schedule for the optimization algorithm.

Minimum Coverage (%)

The optimization algorithm will attempt to meet the *Minimum Coverage* target after finishing optimizing for maximum profitability. The *Minimum Coverage* is the percentage of completed orders relative to the total number of orders.

Appendix B - Countries analyzed

Country	Country Code	Airspaces
Austria	AT	11
Belgium	BE	11
Bulgaria	BG	5
Croatia	HR	11
Cyprus	CY	5
Czechia	CZ	10
Denmark	DK	8
Estonia	EE	3
Finland	FI	22
France	FR	91
Germany	DE	64
Greece	GR	35
Hungary	HU	6
Ireland	IE	11
Italy	IT	125
Latvia	LV	1
Lithuania	LT	4
Netherlands	NL	17
Norway	NO	54
Poland	PL	31
Portugal	PT	12
Romania	RO	19
Slovakia	SK	5
Slovenia	SI	4
Spain	ES	46
Sweden	SE	51
Switzerland	CH	16

Appendix C - Most attractive airspaces for placing a drone hub

Rank	Airspace	Rank	Airspace	Rank	Airspace	Rank	Airspace
1	BERGAMO CTR Z1 (IT)	51	TORINO CTR (IT)	101	CTR PROVENCE (FR)	151	CTR SAINT ETIENNE 2 (FR)
2	BERGAMO CTR Z2 (IT)	52	PRATICA DI MARE CTR Z1 (IT)	102	CTR OBERPFAFFENHOFEN (DE)	152	CTR CAEN (FR)
3	LINATE CTR (IT)	53	ROMA CTR Z3 (IT)	103	CTR HAMBURG (DE)	153	ROSKILDE CTR (DK)
4	CTR STUTTGART (DE)	54	CTR NUERNBERG (DE)	104	CTR TURANY (CZ)	154	CTR SAINT ETIENNE 1 (FR)
5	TREVISO CTR Z4 (IT)	55	BOLOGNA CTR Z5 (IT)	105	CTR BORDEAUX (FR)	155	CTR ZAGREB (HR)
6	TREVISO CTR Z1 (IT)	56	FIRENZE CTR Z2 (IT)	106	CTR EPPO (PL)	156	SÃVE CTR (SE)
7	TREVISO CTR Z3 (IT)	57	CTR BLAGNAC (FR)	107	CTR LOWL (AT)	157	CTR KUNOVICE (CZ)
8	BRUSSELS CTR (BE)	58	LIEGE CTR (BE)	108	CTR EPKS (PL)	158	ANCONA CTR Z1 (IT)
9	MALPENSA CTR Z1 (IT)	59	CTR EHDL (NL)	109	SEVILLA CTR (ES)	159	CTR BREST (FR)
10	ANTWERP CTR (BE)	60	CTR EHGR (NL)	110	CTR EHDP (NL)	160	PERUGIA CTR Z2 (IT)
11	CTR MANNHEIM (DE)	61	AVIANO CTR Z1 (IT)	111	CTR PERPIGNAN (FR)	161	PERUGIA CTR Z1 (IT)
12	VENEZIA CTR Z2 (IT)	62	FIRENZE CTR Z1 (IT)	112	CTR LJLJ (SI)	162	CTR VILNIUS (LT)
13	TREVISO CTR Z2 (IT)	63	CTR GENEVA (CH)	113	CTR MELUN (FR)	163	CTR BERLIN (DE)
14	CTR DUESSELDORF (DE)	64	CTR EMMEN 2 (HX) (CH)	114	AVIANO CTR Z5 (IT)	164	EIDW (IE)
15	VENEZIA CTR Z3 (IT)	65	CTR RENNES (FR)	115	CTR MUENSTER (DE)	165	LPPT CTR (PT)
16	CTR MOENCHENGLADBACH (DE)	66	CTR EHRD (NL)	116	CTR DRESDEN (DE)	166	CTR EPOK (PL)
17	VENEZIA CTR Z4 (IT)	67	LECCE CTR Z1 (IT)	117	LATINA CTR Z1 (IT)	167	BILBAO CTR (ES)
18	CTR ZURICH (CH)	68	CTR BERN (HX) (CH)	118	ANCONA CTR Z2 (IT)	168	GRAZZANISE CTR Z1 (IT)
19	CTR DUEBENDORF (HX) (CH)	69	CTR EPWA (PL)	119	CTR ROUEN (FR)	169	PALERMO CTR Z3 (IT)
20	VERONA CTR (IT)	70	CTR EPKK (PL)	120	BOLOGNA CTR Z4 (IT)	170	CTR LBSF (BG)
21	CTR DORTMUND (DE)	71	ROMA CTR Z2 (IT)	121	OOSTENDE CTR (BE)	171	CTR ATHINAI (GR)
22	CTR SAARBRUECKEN (DE)	72	CTR AVIGNON 1 (FR)	122	CTR FRIEDRICHSHAFEN (DE)	172	CTR THESSALONIKI (GR)
23	CTR FRANKFURT (DE)	73	CTR AVIGNON 2 (HX) (FR)	123	CTR LAHR (DE)	173	CTR ANNECY (FR)
24	CTR WIESBADEN (DE)	74	CTR TEMPO ORANGE 2 (FR)	124	ALICANTE CTR (ES)	174	CTR RIGA (LV)
25	VENEZIA CTR Z1 (IT)	75	PISA CTR Z2 HIGH (IT)	125	CTR GARONS (FR)	175	EFHK CTR NORTH (FI)
26	CTR EHEH (NL)	76	PISA CTR Z2 LOW (IT)	126	BANEASA CTR (RO)	176	ZILINA CTR (SK)
27	CTR LILLE (FR)	77	CTR VODOCHODY (CZ)	127	VIGO CTR (ES)	177	CTR SAINT NAZAIRE 2 (FR)
28	CTR EHBK (NL)	78	CTR BALE (FR)	128	CTR LEIPZIG (DE)	178	CTR SAINT NAZAIRE 1 (FR)
29	CTR NOERVENICH (DE)	79	BALE-MULHOUSE (DE)	129	CTR TEMPO ORANGE 1 (FR)	179	MALAGA CTR (ES)
30	CTR EHVK (NL)	80	CTR NANTES (FR)	130	CTR LOWW (AT)	180	CTR TOURS VAL DE LOIRE (FR)
31	CTR KOELN/BONN (DE)	81	PARMA CTR Z1 (IT)	131	BOLOGNA CTR Z8 (IT)	181	CTR EPLB (PL)
32	CTR GEILENKIRCHEN (DE)	82	CTR MOSNOV (CZ)	132	BOLOGNA CTR Z2 (IT)	182	CTR ISTRES 1.1 (FR)
33	MCTR KBELY (CZ)	83	ROMA CTR Z4 (IT)	133	CTR LUCKO (HR)	183	REUS CTR (ES)
34	BEAUVECHAIN CTR (BE)	84	CTR HANNOVER (DE)	134	CTR INGOLSTADT (DE)	184	CTR BEZIERS 1 (FR)
35	CTR1 EHAM (NL)	85	CTR EPKT (PL)	135	CTR AUGSBURG (DE)	185	BRASOV (RO)
36	KLEINE BROGEL CTR-1 (BE)	86	CTR STRASBOURG 1 (FR)	136	CTR EHGG (NL)	186	RONCHI CTR (IT)
37	LPPR CTR (PT)	87	CTR SAINT EXUPERY (FR)	137	CTR BREMEN (DE)	187	CTR LORRAINE (FR)

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38	ROMA CTR Z1 (IT)	88	CTR ST. GALLEN (HX) (CH)	138	CTR EPLL (PL)	188	MCTR PARDUBICE (CZ)
39	LUGANO CTR (IT)	89	PISA CTR Z1 (IT)	139	CTR LOWG (AT)	189	PESCARA CTR Z5 (IT)
40	CTR LUGANO (HX) (CH)	90	CTR PARIS (FR)	140	FROSINONE CTR Z1 (IT)	190	CTR LORIENT (FR)
41	BOLOGNA CTR Z6 (IT)	91	STEFANIK CTR (SK)	141	CTR EPGD (PL)	191	SAN JAVIER CTR (ES)
42	BOLOGNA CTR Z3 (IT)	92	VALENCIA CTR (ES)	142	LATINA CTR Z2 (IT)	192	CTR LJMB (SI)
43	CTR BRON (FR)	93	CTR BUECKEBURG (DE)	143	CTR LOWS (AT)	193	CTR RAMSTEIN (DE)
44	AVIANO CTR Z4 (IT)	94	MADRID CTR (ES)	144	CTR EPRZ (PL)	194	GRANADA CTR (ES)
45	AVIANO CTR Z3 (IT)	95	CTR MUENCHEN (DE)	145	CTR CLERMONT (FR)	195	SUCEAVA CTR (RO)
46	BOLOGNA CTR Z1 (IT)	96	BUDAPEST CTR (HU)	146	PESCARA CTR Z2 (IT)	196	CTR EPPR (PL)
47	CTR MERVILLE (FR)	97	PRATICA DI MARE CTR Z2 (IT)	147	PESCARA CTR Z1 (IT)	197	A CORUNA CTR (ES)
48	CHARLEROI CTR (BE)	98	CTR BRAUNSCHWEIG (DE)	148	OTOPENI CTR (RO)	198	KOSICE CTR (SK)
49	BARCELONA CTR (ES)	99	CTR EHWO (NL)	149	CTR EPWR (PL)	199	FLESLAND CTR (NO)
50	CTR RUZYNE (CZ)	100	CTR MONTPELLIER (FR)	150	GROTTAGLIE CTR Z1 (IT)	200	CAGLIARI CTR Z1 (IT)

Appendix D - Most attractive airspaces (per km2)

Rank	Airspace	Rank	Airspace	Rank	Airspace	Rank	Airspace
1	CTR MANNHEIM (DE)	51	TORINO CTR (IT)	101	AVIANO CTR Z4 (IT)	151	GENOVA CTR Z1 (IT)
2	BERGAMO CTR Z1 (IT)	52	CTR EPPO (PL)	102	CTR LJMB (SI)	152	GRAZZANISE CTR Z1 (IT)
3	CTR MOENCHENGLADBACH (DE)	53	CTR MONTPELLIER (FR)	103	BOLOGNA CTR Z6 (IT)	153	BRASOV (RO)
4	CTR STUTTGART (DE)	54	LIEGE CTR (BE)	104	TALLINN CTR (EE)	154	GIRONA CTR (ES)
5	CTR DUEBENDORF (HX) (CH)	55	CTR EHGR (NL)	105	CTR TOURS VAL DE LOIRE (FR)	155	EIDW (IE)
6	ANTWERP CTR (BE)	56	CTR1 EHAM (NL)	106	ANCONA CTR Z1 (IT)	156	LATINA CTR Z2 (IT)
7	CTR WIESBADEN (DE)	57	CTR SAINT EXUPERY (FR)	107	CTR PROVENCE (FR)	157	EFTP CTR (FI)
8	CTR DUESSELDORF (DE)	58	CTR EPKK (PL)	108	CTR EPLB (PL)	158	PERUGIA CTR Z2 (IT)
9	BRUSSELS CTR (BE)	59	CTR BREMEN (DE)	109	CTR NICE (FR)	159	CTR OSIJEK (HR)
10	CTR GENEVA (CH)	60	BEAUVECHAIN CTR (BE)	110	CTR MUENCHEN (DE)	160	CTR ATHINAI (GR)
11	LINATE CTR (IT)	61	CTR ROUEN (FR)	111	CTR EPRZ (PL)	161	CTR LBSF (BG)
12	CTR EHBK (NL)	62	CTR EPLL (PL)	112	FLESLAND CTR (NO)	162	VENEZIA CTR Z3 (IT)
13	TREVISO CTR Z1 (IT)	63	CTR MERVILLE (FR)	113	MADRID CTR (ES)	163	TENERIFE SUR CTR (ES)
14	MCTR KBELY (CZ)	64	CTR EHDP (NL)	114	PRATICA DI MARE CTR Z1 (IT)	164	PALERMO CTR Z3 (IT)
15	CTR KOELN/BONN (DE)	65	CTR STRASBOURG 1 (FR)	115	CTR LOWG (AT)	165	CTR EPRA (PL)
16	ROMA CTR Z4 (IT)	66	BOLOGNA CTR Z1 (IT)	116	CTR MOSNOV (CZ)	166	CAGLIARI CTR Z1 (IT)
17	CTR LUGANO (HX) (CH)	67	CTR EHVK (NL)	117	BILBAO CTR (ES)	167	AVIANO CTR Z5 (IT)
18	LUGANO CTR (IT)	68	VERONA CTR (IT)	118	CTR EPWR (PL)	168	PISA CTR Z2 HIGH (IT)
19	CTR BRON (FR)	69	CTR BERLIN (DE)	119	CTR EPKT (PL)	169	PISA CTR Z2 LOW (IT)
20	TREVISO CTR Z4 (IT)	70	CTR LOWS (AT)	120	BUDAPEST CTR (HU)	170	PESCARA CTR Z1 (IT)
21	CHARLEROI CTR (BE)	71	VIGO CTR (ES)	121	KOSICE CTR (SK)	171	SUCEAVA CTR (RO)
22	CTR LILLE (FR)	72	SANTANDER CTR (ES)	122	CTR EHGG (NL)	172	IASI CTR (RO)
23	CTR ZURICH (CH)	73	TREVISO CTR Z2 (IT)	123	FIRENZE CTR Z2 (IT)	173	ALICANTE CTR (ES)
24	CTR EHEH (NL)	74	CTR LUCKO (HR)	124	CTR LOWI (AT)	174	ANCONA CTR Z2 (IT)
25	CTR BERN (HX) (CH)	75	AVIANO CTR Z1 (IT)	125	CTR CAEN (FR)	175	SAN JAVIER CTR (ES)
26	CTR FRANKFURT (DE)	76	CTR MELUN (FR)	126	SOLA CTR (NO)	176	GRAN CANARIA CTR (ES)
27	CTR RENNES (FR)	77	LPPR CTR (PT)	127	CTR RIGA (LV)	177	CTR EPLK (PL)
28	CTR DORTMUND (DE)	78	PERUGIA CTR Z1 (IT)	128	VENEZIA CTR Z2 (IT)	178	CTR RIJEKA (HR)
29	CTR AVIGNON 1 (FR)	79	CTR PARIS (FR)	129	CTR GARONS (FR)	179	PISA CTR Z1 (IT)
30	CTR RUZYNE (CZ)	80	BOLOGNA CTR Z3 (IT)	130	CTR TEMPO ORANGE 1 (FR)	180	PIACENZA CTR Z3 (IT)
31	CTR SAARBRUECKEN (DE)	81	CTR EPKS (PL)	131	BOLOGNA CTR Z4 (IT)	181	CTR EPPW (PL)
32	CTR NUERNBERG (DE)	82	CTR INGOLSTADT (DE)	132	MCTR PARDUBICE (CZ)	182	REGGIO CTR Z3 (IT)
33	STEFANIK CTR (SK)	83	REUS CTR (ES)	133	ZILINA CTR (SK)	183	REGGIO CTR Z1 (IT)
34	TREVISO CTR Z3 (IT)	84	CTR BREST (FR)	134	GROTTAGLIE CTR Z1 (IT)	184	EICK (IE)
35	CTR LOWL (AT)	85	CTR EPGD (PL)	135	CTR BARI (IT)	185	BOLOGNA CTR Z5 (IT)
36	KLEINE BROGEL CTR-1 (BE)	86	FROSINONE CTR Z1 (IT)	136	CTR LOWW (AT)	186	CATANIA CTR Z2 (IT)
37	CTR LJLJ (SI)	87	CTR BEZIERS 1 (FR)	137	CTR EPOK (PL)	187	BACAU CTR (RO)
38	EFHK CTR NORTH (FI)	88	MCTR ELEFSIS (GR)	138	CTR LOWK (AT)	188	GIOIA DEL COLLE CTR Z1 (IT)
39	BALE-MULHOUSE (DE)	89	PARMA CTR Z1 (IT)	139	CTR BIARRITZ (FR)	189	PESCARA CTR Z5 (IT)
40	CTR BALE (FR)	90	A CORUNA CTR (ES)	140	EFTU CTR (FI)	190	CTR LBBG (BG)
41	FIRENZE CTR Z1 (IT)	91	CTR KUNOVICE (CZ)	141	LAMEZIA CTR (IT)	191	BAIA MARE CTR (RO)

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42	CTR EHRD (NL)	92	CTR VILNIUS (LT)	142	CTR THESSALONIKI (GR)	192	CATANIA CTR Z1 (IT)
43	CTR EPWA (PL)	93	AVIANO CTR Z3 (IT)	143	OTOPENI CTR (RO)	193	CTR LORIENT (FR)
44	CTR CLERMONT (FR)	94	VALENCIA CTR (ES)	144	LATINA CTR Z1 (IT)	194	CTR LBPD (BG)
45	CTR TURANY (CZ)	95	CTR HAMBURG (DE)	145	CTR EPBY (PL)	195	PESCARA CTR Z2 (IT)
46	SEVILLA CTR (ES)	96	CTR ZAGREB (HR)	146	ROMA CTR Z1 (IT)	196	LECCE CTR Z1 (IT)
47	CTR NANTES (FR)	97	CTR LAROCHELLE ILE DE RE (FR)	147	BARCELONA CTR (ES)	197	GRAZZANISE CTR Z2 (IT)
48	MALPENSA CTR Z1 (IT)	98	SÃVE CTR (SE)	148	CLUJ-NAPOCA CTR (RO)	198	CAGLIARI CTR Z3 HIGH (IT)
49	CTR BLAGNAC (FR)	99	CTR BORDEAUX (FR)	149	CTR EHLW (NL)	199	CAGLIARI CTR Z3 LOW (IT)
50	CTR HANNOVER (DE)	100	BOLOGNA CTR Z2 (IT)	150	BOLOGNA CTR Z8 (IT)	200	ORADEA CTR (RO)