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Quantitative and Comparative Analysis of Energy Consumption in Urban Logistics Using Unmanned Aerial Vehicles and Selected Means of Transport

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Abstract: Cities are moving towards sustainable development, which consists of tasks and challenges to improve the quality of life, and minimize energy consumption. The concept of sustainable mobility includes the choice of means of transport other than the car for all journeys, especially short distances, and for the delivery of goods. Due to the growing populations of cities, lack of free space, and high costs of building infrastructure for traditional means of transport, cities are looking for modern solutions that allow for the cheap, fast, and green transportation of people and goods. Urban air mobility is the answer to these problems, and uses eVTOL (electric vertical take-off and landing) aircraft and unmanned aerial vehicle systems (UAVs). The article's main purpose is to present an energy efficiency analysis using UAVs and electric scooters in the transport of takeaway food, which is a solution that fits into the zero-emission transport policy. The article presents the following research problem: which type of electric transport (scooters/UAVs) shows a lower demand for electric energy when delivering food from restaurants to individual customers? The analysis method was applied using the D'Andrea, Dorling, Figliozzi, Kirchstein, and Tseng energy models. The completed calculations were used to perform a comparative analysis of energy consumption for three adopted scenarios related to energy consumption by drones.

Keywords: UAVs; electric scooters; smart cities; sustainability analysis in urban context; urban logistics; urban air mobility; energy consumption

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1. Introduction

Urban logistics is an essential process for moving goods in the city. It covers all processes and activities related to the delivery of a specific product. Urban logistics aims to control the effective flow of resources in the town, and subsystems following sustainable development, and to meet users' expectations at an established level [1]. Urban logistics contributes to added convenience in cities, minimizing costs and overcoming difficulties in the context of adverse effects leading to more air pollution, noise, or traffic jams. Urban logistics focuses on the efficient and effective transport of goods in an urban area, considering the negative impact of urban logistics on congestion, safety, and the environment, which is crucial to residents' quality of life.

The distribution of goods to customers is a component of last-mile delivery. Because it represents the final stage, this phase is one of the most important for supply chains, as it is where the last customer is contacted. In addition, this phase is frequently used in urban areas, where problems with parking, travel times, and environmental pollution are particularly pressing.

Urban logistics and its operations are linked to a specific purpose. Urban logistics distinguishes the following objectives: technical, economic, and organizational, as presented in Table 1.

Table 1. The target of urban logistics.

Technical	Economical	Organizational
The selection of technical elements (the improvement and new construction of devices and means of transport) shaping spatial systems, applying control, IT, and communication techniques.	Own or third-party services controlling for the cost-optimization use of financial tools.	Creation of the process and the logistics structure. The generation, formulation, and implementation of logistics strategies.

Source: [2].

The technical objective is based on the operation of IT processes in order to record goods and their flow efficiently. It supports the company in analyzing the delivered products, and allows it to control the flow of goods. In the case of large companies, it is a goal that is necessary for achieving specific results. The economic objective focuses on the optimization of financial costs, and the use of financial tools. The last organizational goal creates the entire logistics structure, and is responsible for implementing new technologies to improve the city's goods flow [2].

In response to the problems of cities and climate change, the European Union has set trends to improve the quality of urban life, including introducing electric vehicles, or improving road surfaces. The electrification target refers to the EU climate package, which is to contribute to the growth of emission-free, sustainable transport. Some of the first significant changes that introduced electric vehicles involved restaurants introducing electric scooters for deliveries. The introduced vehicles were more advantageous than combustion vehicles regarding use, costs, and technical parameters. In response to the trend of zero-emission vehicles, and the popularization of eating out, this work presents an alternative to electric scooters, in the form of UAVs, which can be more sustainable and beneficial to introduce in the city.

Electric vehicles (EVs) are increasingly becoming a sustainable and cost-effective means of transport, taking into account their lower CO_2 emissions, air pollution, and noise, compared to combustion vehicles. The research conducted in [3] shows that China, the United States, and Great Britain are leaders in the research on electric vehicles and their large-scale applications. In addition, China is a leading country in terms of the research institutions exploring electric vehicles.

Globally, the number of electric vehicles in 2020 has increased fivefold compared to 2016. The number of electric vehicles sold worldwide has reached over 10 million, which means an increase of 43% compared to 2019 [4]. The share of electric vehicle sales worldwide increased by 70%, reaching a record high of 4.6% in 2020, despite a decrease in registrations of conventional cars, and in total new cars [5].

UAVs appear increasingly often in many areas of the economy. Among others, authorities use UAVs in geodesy, agriculture, rescue, transport, and control. With their efficiency and usefulness in urban spaces, drones arouse curiosity on many levels. Electricity is one of the main obstacles to unmanned vehicles' faster implementation in urban air mobility [6]. Many studies are being carried out concerning climate change and European requirements when planning a new form of transport, urban air mobility. Their use may contribute to replacing internal combustion vehicles in urban logistics or pollution monitoring in the city. Improvements in the technical specification of UAVs aim to popularize this form of transport. To allow the use of drones in urban logistics, quadcopters and octocopters have been developed, which, thanks to their parameters, can replace ground vehicles for deliveries. Therefore, drone model research and improvement work focuses on greater energy efficiency.

Drones, or unmanned aerial vehicles (UAVs) are aircraft whose flight operations are performed remotely, or via the onboard computer. There is neither a pilot nor passengers onboard these vehicles. UAVs can speed up delivery times, because they do not participate in traffic, and use electric motors, which are also good for the environment. However, when designing a drone-based last-mile delivery service, adverse weather conditions, complex urban scenarios, and customer identification issues must all be considered, as well as the energy aspects.

Based on the trend of smart cities, this work aims to propose an alternative means of transport for electric scooters in the city, which may be more favorable regarding energy consumption. The paper describes two models of UAV; one is a quadcopter, and the other is an octocopter; assuming scenarios and making calculations. The calculations were prepared using five energy models considered in different use cases. The models of D'Andrea, Dorling, Figliozzi, Kirchstein, and Tseng were used for calculations. Then, the energy the assumed electric scooter model would consume is compared in three scenarios related to energy consumption by drones.

The paper is organized as follows: Section 1 provides an introduction to the research question, indicating the potential for UAV application in cities. Section 2 deals with a review of the literature on the application of UAVs for cargo transportation, with a special focus on the problem of energy consumption. Section 3 characterizes urban air mobility, which is an important concept in terms of urban mobility. A description of the current status of ongoing projects and prospects for development, based on defined goals, is included. The application of electric scooters in the process of food delivery is presented, as well as the technical specifications of the adopted UAVs, and assumptions for the area of meal delivery. Adopted scenarios are presented, taking into account the weight of the UAV and the possible transport distance, as well as a description of the energy consumption models, and their application in the adopted models and scenarios. Section 4 presents a comparative analysis of the energy consumption of UAVs and electric scooters during food delivery in the city. Section 4 provides a comparative analysis of the adopted scenarios, considering delivery by UAVs and electric scooters. Finally, Section 5 summarizes the discussion of this work.

2. Literature Review

2.1. UAV Background

UAVs can fly on their own, and make decisions without the assistance of a pilot on the ground, thanks to artificial intelligence. Based on previous experience, it is demonstrated in the paper [7] that drones can achieve an increasingly targeted response, for example, to sudden wind gusts. The study [7] looks into the possibility of sending small packages to remote islands in various logistical dead zones using drones. Using a mixed-integer (0–1 linear) green routing model, the paper [8] examined CO_2 reduction and cost savings over conventional ground-based delivery methods. UAVs should additionally have the option to send correspondences to the stockroom, for instance, in a crisis. Subsequently, they require a steady association with a phone radio wire and, contingent upon the transmission strength, may have to change the association receiving wire. UAV delivery may be severely restricted by adverse weather [8].

The battery performance consists of the following central aspect of energy consumption by drones, with reference to the empirical research on the use of batteries in various situations, which shows a few basic UAV maneuvering actions: hovering, flying vertically upward, and flying vertically downward. The new and improved energy consumption model has conducted a series of studies aiming to understand the influence of several factors on UAV energy consumption. Researchers considered the effects of wind, speed, tacking, hovering, payload, communications, and ground power consumption [9]. The paper researched the use of drones compared to van delivery. The study covered deliveries in last-mile delivery systems from a sustainability point of view, concerning the CO_2 emissions and energy consumption.

The work [10,11] developed a new analytical model that identifies factors affecting UAV power consumption. The designed nanomachine energy harvester was also presented, based on plasmonic nanoantenna technology. As a result of the simulations, and for the proposed scenarios, the UAV's flight time under different conditions was obtained. The MD results for several proposed scenarios showed that different MDs were obtained under different hover conditions. The capacity of the energy storage system limits travel distances. The work focused on a novel model that identifies factors that determine the power consumption of a UAV, which negatively affects the flight time.

The problem of food delivery using UAVs was considered in a paper [12]. This research paper presented the results of data analysis conducted in Korea, which showed that UAV food delivery service innovation is highly valued. Similar research was conducted in Pakistan, and the results were presented in [13]. This study evaluated the implementation of a UAV food delivery service, using an extended technology acceptance model to assess customer behavior.

Drone energy consumption models include separate models for forces and different components of UAVs. These models are often presented in considerable detail, to obtain specific features of drone design. The paper [14] showed a nonlinear regression model for UAV power consumption, including the horizontal and vertical speed and acceleration, payload mass, and wind speed, with a detailed drone model with the power to maintain lift and overcome parasite drag, and the profile power to overcome the rotating drag caused by the propeller blades.

In the case of UAV deliveries, the energy requirements determine the performance metrics, which include the range, cost, and emissions. An accurate estimation of the UAV's power consumption is important to the operator and control systems, as wireless communication, safety, and efficiency are involved. A paper [15] attempted to locate urban distribution centers along the city's perimeter, by optimizing the drone route in response to energy constraints. According to [16], a series of charging stations to be installed throughout the city could address the issue of drone autonomy. There have been several publications taking into account energy consumption in terms of UAV endurance (flight time limit) or range (flight distance limit) [17]. In addition, in this paper aimed to determine the optimal fleet size and energy consumption for drone battery charging in urban areas. In the work, two optimization solutions were suggested: (i) the first involved arranging missions by shortening their distances; (ii) the second found a compromise between the number of drones and the distance. The work of [18] addressed the issue of extending the range of drones, again referring to the problem of the range of possibility of using strategically placed recharging stations to power drones as they traveled to their final destinations.

UAV energy consumption models vary in complexity, from simple models containing only a few parameters, to very complex models with many interdependent components [19–21].

Factors that affect UAV power consumption include the UAV design, the environment, the drone dynamics, and the delivery operations. The design aspects of UAVs are related to, among others, the weight and size of the UAV, the number and size of rotors, the size and energy capacity of the battery, and the maximum speed and payload. Many researchers have studied UAV routing and scheduling [22–24] and location issues [25,26], including charging station location [27].

The partitioning of delivery points within a cluster has been studied, in which researchers evaluated how to carry out an effective partitioning, taking into account two scenarios:

- a single cluster node, which is then served by the ground vehicle;
- multiple cluster delivery points, which assume parallel drone use.

2.2. Research Areas Using UAVs

A literature review on UAV path optimization examines the type of autonomous drone delivery from a city distribution center to end users. Due to the fact that each drone has a maximum flight range, the main restriction is that the route is time-dependent. The flight season of the robot is, likewise, an element of the heaviness of the heap (i.e., of the bundles):

the time decreases as the weight increases. In [28], the model describes the purpose of designing the UAV trajectory to check the time to complete the mission in multicasting systems using UAVs.

Some papers present the models necessary for optimal path planning for drones [29,30]. The papers [31,32] described a genetic algorithm for a trajectory that uses the least energy to reach all base stations and return to the home of the UAVs. The path-following control involves the tracking of the time reference position. A path-following approach eliminates the time dependence on the power, performance, and design range, and minimizes energy consumption. The paper [33] examined the relationship between the navigation speed and energy consumption in quadrotor helicopters, and proposed a dynamic speed profile that varies with geometric requirements, based on the results.

The new routing model that considers van–drone synchronization to arrive at end-clients, and return to the van to re-energize or recover different bundles to be conveyed, was presented in [34]. Using a heuristic approach, [35] demonstrated that the delivery time and the number of drones carried by the van are inversely proportional, because more tasks can be performed simultaneously with more drones, and delivery times dramatically decrease. Today, there are two potential choices for the UAV conveyance of products:

(i) autonomous, in which the drone leaves the depot, makes deliveries, and then returns to the starting point;
(ii) paired with a van that serves as the UAV's depot and charging station.

The last arrangement includes changing the mobile sales rep issue (TSP) to the bunched general mobile sales rep issue (CGTSP). While the CGTSP only requires the van to touch one point per cluster into which the served area is divided, and the drones meet each node contained in the cluster, the TSP requires the ground vehicle (the van) to reach each customer point by taking the shortest route.

Finding the shortest route that satisfies two requirements is what the CGTSP is all about. This way, it visits precisely one hub for each sub-bunch; inside each bunch, every hub is visited. As a result, the van only needs to reach one node in each sub-cluster before the drones can visit all of the nodes in that cluster [35].

In the paper [36], the analysis also looks into the advantages of using drones for last-mile deliveries in Europe. According to the analysis, drone-based last-mile delivery services could be available to up to 7% of European citizens in the most technologically feasible scenario, a percentage that, under conditions of rapid technological advancement, would rise to 30%. Drone deliveries could serve 20% of the population in Italy. End-users prefer drone deliveries primarily due to the product's increased value and the delivery's urgency [37].

Several businesses have recently begun developing and designing drones for package delivery in various industries, including e-commerce and medicine. Through real-world tests, companies such as Amazon, UPS, DHL, and others are evaluating solutions for safely and effectively delivering packages. In addition, many medical researchers are investigating the use of drones in mountainous regions, where response times can be longer, in their research. In this instance, the use of AED-equipped drones that can intervene in the event of a sudden cardiac arrest is being evaluated.

2.3. Urban Air Mobility

Wasting time in traffic jams is a serious problem in modern cities. As a result, there is an interest in searching for a new form of transport that will relieve cities of noise, pollution, and traffic jams. Urban air mobility is the concept of connecting several points, such as airports, railway lines, and roofs of buildings, using air traffic in the city via UAVs that can use the existing infrastructure [38].

Paper [39] described UAM as a new means of transport that allows change in the traffic volume in the city, contributes to safety on the streets, and reduces air pollution. NASA defines UAM as a set of advanced air mobility technologies. Urban air mobility is expected to be used in, among others, emergency patient transport, cargo transport, and passenger transport. As a concept, UAM was defined in [40], which is based mainly on the on-demand approach. It refers to a new generation that expects vertical take-off and landing vehicles, autonomously operated flights, and adapted infrastructure.

The introduction of UAM is a long-term decision. Drones influence high-level decision-making, including legal regulations, urban planning, digitalizing, and infrastructure. In addition, there are the issues of UAM control systems, network design, ground support, the so-called landing sites in cities (vertiports), and the integration of aircraft into the already-existing airspace. Meteorological conditions may be a barrier to the full use of the UAM concept. Weather constraints are a critical and complex element that characterizes the UAM market. Weather can affect many aspects of UAM, including operations, service delivery, passenger comfort, community acceptance, infrastructure, and traffic management. The research in [41] identified factors that occurred in the winter and spring in urban areas of northeastern Texas and Denver. The occurrence of thunderstorms, high temperatures, and a high frequency of strong winds for most of the operating day can greatly limit the use of UAM.

Urban air mobility will introduce many changes in the city and industry [42]. Aircraft manufacturing companies are vying for leadership in urban aviation. This sector also includes design and certification bodies, as obtaining a document from the regulatory authorities is often challenging. Regarding the development of intelligent, sustainable, and safe vehicles, the main objectives are [43]:

- to create an aircraft with non-existent operational carbon dioxide emissions,
- to achieve low operating costs, to be beneficial, reasonable for customers, and profitable for companies,
- to produce a low noise level, so as not to disturb the environment.

2.4. *Problems in Road Transport*

The choice of means of transport in logistics depends on the type of transport in terms of the city's capabilities and profitability. When the transport infrastructure capacity exceeds the limit, pedestrians and vehicles experience congestion. Such an effect can be seen when the number of vehicles is close to the road network's maximum capacity, which prevents smooth movement. Urban logistics transport is divided into the transport of people and of goods. The planning process creates a communication system that connects the whole into a communication line.

Road transport is the basis of the communication line for transporting people in the city. Road transport uses means such as cars, buses, and micromobility [44]. Passenger cars are the most common form of transport. Due to the use of road infrastructure, they have almost no restrictions [45]. For the achievement of zero-emission transport, the European Union is considering the USER-CHI project related to the electric vehicle sector. The acceleration of actions toward electromobility requires several tasks. To this end, the European Union aims to support electromobility's large-scale introduction in Europe financially. The project will use novel models, new regulatory frameworks, and intelligent solutions. It will use the synergy between electromobility and the greening and smartification stages of the network. In connection with the project's assumptions, the objectives pursued, such as business models and regulatory measures, will be tested and implemented in five EU cities (Barcelona, Rome, Berlin, Budapest, and Turku). Research in the area of minimizing the total cost of all truck types was presented in [46]. The results showed that measures are needed to reduce emissions of harmful substances into the environment, e.g., the purchasing of electric vehicles.

Regarding urban logistics for people, their usage of cars can be attributed to the activities of service companies that offer rides in the city. The transport of people with high throughput on the road is carried out by city buses. They form the basis, in most cities, for the transportation of people. Micromobility in urban logistics is a means of transport including scooters and bikes. They are light, emission-free vehicles that cover short distances, usually the first or last section of the route. Micromobility is based on shared mobility, and is made available by the city via the possibility of renting a vehicle for a time period. It is a complementary means of transport [47].

The flow of goods via road transport in the city involves movement between the city and the suburbs. It takes place mainly through the use of a fleet of cars. Goods logistics includes the use of trucks and delivery vehicles. The large dimensions of these vehicles cause competition between passenger cars and delivery vans for infrastructure elements. In addition, the small area to move around in within the city, and the lack of designated delivery zones cause many difficulties in the work of suppliers. Road transport also uses micro vehicles to transport goods; these are a popular form of low-emission vehicles (electric scooters) based on food delivery from restaurants in the city.

2.5. UE Challenges

Changes gradually introduced by the European Union allow the country's economy to develop, and the freedom to live, study, and work. Additionally, the European Union strives to develop cities sustainably, by promoting an active lifestyle, and providing access conditions to mobility for residents and commuters. Therefore, the European Union sets trends and supports projects that affect the cities in development. European projects in the field of transport and infrastructure play a significant role, due to their importance in creating a coherent EU transport network for the future. Transportation policy is one of the pillars of economic development in EU countries. A key element influencing the functioning of the single market is the flow of people and goods [48]. The overriding objective of transport policy is to improve accessibility, and mitigate the negative effects of private vehicle use [49,50]. Improved accessibility can significantly contribute to sustainable urban development and quality of life.

Infrastructure development also refers to the development of cities and communes. The obtained funds contribute to improving traffic safety, urban and suburban areas, and bicycle traffic, and introduce innovative technology. The Ultimo (Advancing Sustainable User-centric Mobility with Automated Vehicles) project contributes to a more extraordinary revolution in urban transport. Based on the tests and preparations carried out by the European Union, the project assumes the implementation of vehicles (autonomous vehicles) in the urban public transport network in three cities [51].

One of the most critical challenges the European Union has set itself is to reach climate neutrality by 2050. It appointed goals to guide European environmental policy, including zero net greenhouse gas emissions. The "Fit for 55" program is to help approximate the target. It consists of revising and updating EU legalization proposals, and introducing new initiatives, ensuring the implementation of the climate target. Providing a just and socially fair transition strengthens the EU industry's innovation and competitiveness [52]. The Sustainable and Smart Mobility Strategy assumes the new plan for mobility appointed by the European Union. The strategy marks the beginning of a way for the transport system to become more digital, environmentally friendly, and resilient to crises. The goal leading up to 2050 is a 90 percent reduction in emissions, which outlines the European Green Deal [53]. The Strategy defined the initiative in the following areas:

- Improvements in intercity and urban mobility, implementation in a sustainable direction via doubling high-speed railway traffic and expanding railway infrastructure within ten years;
- Increasing ecological freight transport, doubling rail traffic by 2050;
- Setting carbon prices, ensuring fair and efficient prices for each mode of transport;
- The development of zero-emission vehicles, ships, aircraft, renewable and low-emission fuels, and creation of related infrastructure;
- Zero-emission airports and ports.

The research conducted [54] concerned the introduced solutions, such as bicycles, e-bikes, and car-sharing, to achieve a sustainable city transport system. The study's results revealed that general characteristics, such as the travel time, waiting time, and cost of travel significantly impact city transport preferences.

3. Material and Methods

The food delivery process in urban logistics involves different stages of implementation to the transport of people or products. In delivering meals, the time and the quality of the received product count. Meal delivery includes the determination of delivery services, especially meal delivery and grocery delivery. Meal delivery consists of ready meals and food ordered directly online for use. Grocery delivery includes unprepared food, beverages, household items, and personal care products. The delivery process includes food delivery directly from the restaurant, and online delivery services that provide customers with meals from partner restaurants (the platform provider). Grocery delivery includes the process of delivering fresh, unprepared produce from supermarkets or retailers (retail delivery). Figure 1 presents an upward trend in ordered meals and groceries.

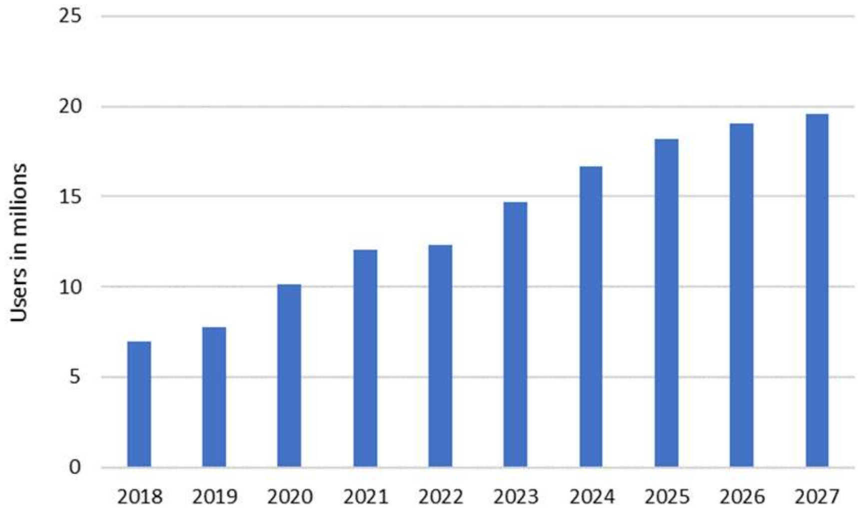

Figure 1. The number of online food delivery users in Poland from 2018 to 2027 (in millions). Source: own elaboration.

3.1. Electric Scooters in the Process of Delivery

Micromobility in the city's transport system includes the use of small and light means of transport to cover short distances. Due to their small size and ease of movement around the city, these means of transport have gained tremendous popularity. Electric scooters are gaining particular popularity. The Statista report shows how the growth of electric scooters is taking place, and describes the forecast for the coming years.

Figure 2 describes the number of electric scooters in Poland. Based on data from the Statista platform, there is, and will be, an upward trend of almost twofold over two years.

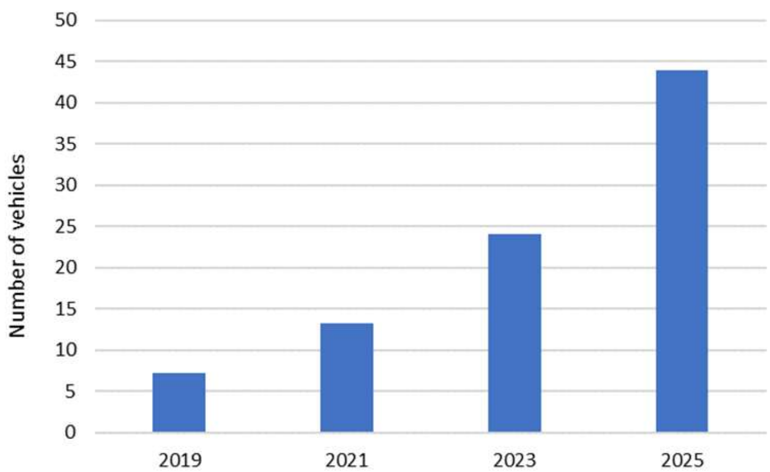

Figure 2. The projected number of electric scooters in Poland from 2019 to 2025. Source: own elaboration.

Analyzing the available data on food delivery platforms led to the selection of a company that uses electric scooters. The data show Poland's leading apps with free food delivery in February 2023. The most popular are Glovo, Pyszne.pl, Wolt Delivery, and Bolt Food.

Figure 3 shows that Pyszne.pl and Glovo are at the forefront of the most popular applications in Poland. Due to this result, we have used the technical parameters of an electric scooter from Pyszne.pl, which has four models of scooters in its fleet, including two models of electric scooters, and two models of diesel scooters. One model of the Robo SC electric scooter is used for the calculations. Based on the information in Figure 3, an electric scooter from Pyszne.pl will be used for the comparative analysis of energy consumption by UAVs and selected means of transport.

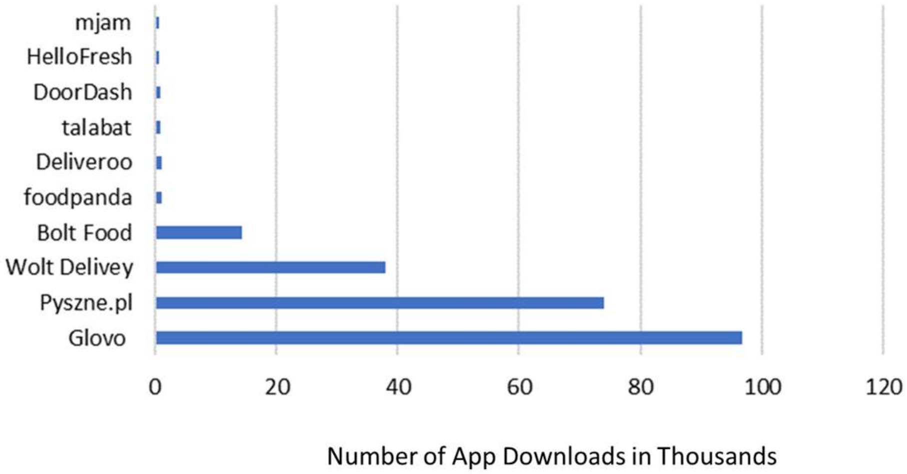

Figure 3. The leading mobile apps with free food delivery in Poland in February 2023 by the number of downloads in thousands. Source: own elaboration.

Table 2 shows the technical parameters of the scooter. The technical specification, visual effects, and adaptation to use in logistics determined the choice of this model.

Table 2. Scooter specifications.

Model of Electric Scooter	
Model	**Robo SC Delivery**
Propulsion	3000 W
Max speed	80 km/h
Battery	2 × 72 V 20 Ah Li-lon
Maximum range	135 km
Time to load	4 h
Battery life	2 × 1000 cycles

Source: own elaboration.

3.2. Unmanned Aerial Vehicles

Unmanned aerial vehicles (UAVs) comprise an innovative technology commonly used in various professional sectors. From the design point of view, drones can be divided into the following groups: military, industrial (entrepreneurship), and commercial.

In most cases, drone flights are unregulated, and flying is only allowed over selected areas. UAVs are a wide topic in terms of legal regulations. They require adaptation on many levels, for example, of infrastructure, urban planning, and the environment. Regarding the popularization and increasing use of drones, the legal issues involve constant analysis and fine-tuning.

The quadcopter, otherwise known as a classic UAV, is the most popular and versatile drone, due to its specifications and simplicity. Quadcopters have become widespread and used for a variety of purposes. The quadcopter is a heavier-than-air aircraft capable of vertical take-off and landing (VTOL), propelled by four rotors parallel to the ground.

Due to the basic model and smaller dimensions, this type of drone is described as smaller in the calculations. Based on the technical specifications, Table 3 shows the assumed parameters.

Table 3. The technical specifications of the quadcopter.

Term	Symbol	Quadcopter
Number of rotors [unitless]	N	4
Spinning area of one rotor [m^2]	ς	0.2
Mass of drone body [kg]	m_1	2.27
Mass of battery [kg]	m_2	1.11
Mass of payload [kg]	m_3	(max 0.68)
Projected area of drone body [m^2]	A_1	0.0599
Projected area of battery [m^2]	A_2	0.0037
Projected area of payload [m^2]	A_3	0.0135
Drag coefficient of drone body [unitless]	C_{D1}	1.49
Drag coefficient of battery [unitless]	C_{D2}	1
Drag coefficient of payload [unitless]	C_{D3}	2.2
Lift-to-drag ratio [unitless]	r	3
Power required for avionics [Watt = J/s]	P_{avio}	0
Factor for induced power [unitless]	K	1
Factor for profile power (m/kg)1/2	K2	0.502
	K3	0.118
Battery and motor power transfer efficiency [unitless]	η	0.5

Source: own elaboration.

An octocopter is a model of a drone with eight engines. Given the extensive form of octocopters, they enable complete control over the system and maximum performance. In terms of quality and functionality, it is unrivaled. Due to the necessity of comparing the two models, this type of drone shows as the larger one, with better technical specifications. Table 4 presents the assumed parameters for the octocopter. Due to the larger dimensions and different batteries, the data present different values for the number of rotors, batteries, and surfaces.

Table 4. The technical specification of the octocopter.

Term	Symbol	Octocopter
Number of rotors [unitless]	N	8
Spinning area of one rotor [m^2]	ς	0.2
Mass of drone body [kg]	m_1	4
Mass of battery [kg]	m_2	6
Mass of payload [kg]	m_3	(max 7)
Projected area of drone body [m^2]	A_1	0.224
Projected area of battery [m^2]	A_2	0.015
Projected area of payload [m^2]	A_3	0.0929
Drag coefficient of drone body [unitless]	C_{D1}	1.49
Drag coefficient of battery [unitless]	C_{D2}	1
Drag coefficient of payload [unitless]	C_{D3}	2.2
Lift-to-drag ratio [unitless]	r	3
Power required for avionics [Watt = J/s]	P_{avio}	0
Factor for induced power [unitless]	K	1
Factor for profile power (m/kg)1/2	K2	0.502
	K3	0.118
Battery and motor power transfer efficiency [unitless]	η	0.5

Source: own elaboration.

3.3. Study Area of Delivery

Deliveries in downtown areas are a very complex process due to the diverse and contradictory nature of the demand, the area's structure, and the delivery point's density. The significant number of vehicle-kilometers that freight vehicles travel between logistics centers in suburban areas to consignees in the city center, in addition to often having to drive around to find parking, result in additional fuel consumption and traffic congestion.

Determining the delivery area involves many necessary factors. Due to the high importance of the delivery time, the meal delivery area cannot consider a remote area. According to the Pyszne.pl guide, the average distance should be 4 km. As a result of other variables, such as expanding housing estates and emerging office buildings, the range may increase slightly. In addition, the guide from Pyszne.pl justifies its maximum distance of 4km to the customer via the high importance of residents near the restaurant. By focusing on remote areas, the supplier would not be able to return quickly, which might be at the expense of people living near the restaurant [55].

The delivery area for electric scooters refers to the above-mentioned 4 km. Concerning cities, there are no restrictions, and they are only excluded from traffic-free zones, usually found in the city center. The delivery area for electric scooters has no prohibitions that restrict the delivery process in the city.

The delivery process regarding drones includes the take-off from the base, the flight to the customer, sending the package, and the return to the warehouse. Various cases should be defined to determine the delivery area, including the energy consumption, breakdowns, and repair points. Currently, cities are not adopting the delivery of parcels or food via drones. The urban infrastructure does not have vertiports that will allow free landing. In addition, the lack of legal regulations still does not allow the designation of the supply area.

Additionally, due to their size and technical parameters, UAVs move at much lower heights, which can affect parks, reserves, and farms [56]. Scenarios form the basis of data, right after the technical parameters of UAVs used in the calculations. Using scenarios allows for better specifications of energy models in various cases. Using two models of UAVs and three scenarios improves the assessment of energy models and final results.

Determining the parameters of a small quadcopter and a large octocopter, they differ in some values that will be useful to determining the scenarios. The total payload of the drone is the basis for determining the data in three scenarios; because the meal is delivered, it is the main element, and its weight is essential.

Due to its small dimensions and worse technical specifications compared to a large octocopter, a small quadcopter is used only in scenario no. 1. The payload of the quadcopter is 0.68 kg. Therefore, the weight of the meal included in scenario no. 1 is 0.5 kg. In addition, the maximum delivery area is described in the Pyszne.pl guide as 4 km. Therefore, scenario no. 1 assumes the shortest distance, of 1.5 km, out of all the scenarios.

Scenario no. 2 contains parameters that differ significantly in weight from scenario no. 1. The assumed weight is 5 kg, the highest payload of all three scales defined in the three scenarios. Specifying a greater weight of food delivered would not reflect accurate deliveries. A weight over 5 kg is probably relatively rare for people delivering food. The distance specified in scenario 2 is 2.7 km, the second-longest distance out of the three scenarios considered. The second scenario only assumes a large octocopter with a maximum payload of 7 kg. Scenario 3 defines a more significant distance to cover than in the two previously described scenarios, 4 km. Scenario 3 uses only the octocopter model for calculations. The assumed weight that the UAV transports for food delivery is 4 kg.

Table 5 shows, in a table, all the scenarios described above. The assumptions consider the type of drone, the distance to be covered, and the weight.

Table 5. Accepted scenarios for calculations.

Assumed Scenarios			
Scenario [No.]	1	2	3
Distance [km]	1.5	2.7	3.9
Weight [kg]	0.5	5	2

Source: own elaboration.

Each model of calculation requires a mass of components. It consists of the mass of the drone body, the battery, and the payload.

$$m_k = m_1 + m_2 + m_3 \tag{1}$$

Due to the quadcopter's maximum payload of 0.68 kg, this drone was used only in scenario no. 1. Considering the assumed scenarios, the following component weights were calculated for the quadcopter and octocopter, which are presented in Table 6. Based on the calculated component weights, the smallest quadcopter has the lowest weight, due to its technical parameters. Then, the weights of the octocopter vary according to specific scenarios. In scenario no. 1, the weight of the goods was the lowest, which meant that the weight of the octocopter component was the lowest of all the scenarios, at 10.5 kg. Then, in scenario no. 2, it was 15 kg, and in scenario 3, it was 12 kg.

Table 6. The mass of the component.

Mass of the Component			
Term	Type of drone	Number of scenario	m_k [kg]
Mass of the component—m_k	Small quadcopter	1	3.88
	Large octocopter	1	10.5
		2	15
		3	12

Source: own elaboration.

3.4. Energy Models

The following subsection shows the energy requirements described in several models. It describes the course of calculations, and presents the results. All models use the assumed scenarios, and consider the energy consumption in three specific cases. Five energy consumption models in different use cases were used for the calculations.

Various energy models for UAVs are available online. Juan Zhang developed some of these models, by assuming his data using selected formulas [57]. The formulas study energy consumption based on different types of drones, and then compare models. Most of the models used have a similar calculation scheme and use similar values. The D'Andrea model describes a model that combines aerodynamic and design aspects into one parameter that takes into account the ratio of lift to drag, including in the energy model an element of constant power supply to the avionics [58]. Figliozzi extends the model described by D'Andrea to include empty turns without avionics, to include a parameter for the battery charging efficiency, and to model the lift-to-drag ratio as a function of the speed. Dorling provides the power consumed in a hover as a function of the battery, payload, and weight. The energy consumption model uses elemental forces based on the force of gravity (due to gravity) and the drag force. Kirchstein uses an energy model that is more elaborate than other models [59], separating the energy for the take-off, climb, steady flight, descent, hover, and landing for delivery. The last approach to modeling drone power consumption is the Tseng model, which uses the battery mass and speed. Tseng only considers drones moving up to 5 m/s.

Considering several models, it is possible to notice the calculation process leading to the final calculation of the energy. Some calculations use the thrust model and power, and some do not extend their models and give the final formula for energy. Table 7 shows the relationships between the models in calculating the energy needed to fly the drone.

Table 7. Units used to calculate the energy.

	T [N]	P [J/s]	Epm [J/m]	Epm [J/m] + Headwind
D'Andrea	x	x	x	x
Figliozzi			x	
Dorling	x	x	x	
Kirchstein	x		x	
Tseng			x	

Source: own elaboration.

Some models that provide the final formula for energy do not break down the acquired data in stages. Table 8 presents the components and factors considered by individual models in the calculations.

Table 8. The units used to calculate the energy.

Reference	Travel Components			Wind	Avionics	Empty Return
	Horizontal	Hover	Vertical			
D'Andrea [58]	x			x	x	
Figliozzi [9]	x					x
Dorling [24]	x	x	x			
Kirchstein [59]	x	x	x	x	x	x
Tseng [56]	x	x	x	x	x	

Source: own elaboration.

3.4.1. D'Andrea Model

The D'Andrea model considers the thrust, the energy needed to cover a certain distance, the energy required from the battery for stable flight, the energy necessary for avionics, the power consumption, the energy required for level flight, and the energy for the headwind.

Three scenarios were used for the calculations, taking into account different weights of goods and distances to be covered. The thrust force is based on the mass (mk), gravity ($g = 10\ \mathrm{m/s^2}$), and lift/drag ratio (r = 3). Based on the above data, the formula for the thrust is described as:

$$T = drag = \frac{lift}{r} = \frac{weight}{r} = \frac{mas \times g}{r} \quad (2)$$

Using the formula for the thrust force in the D'Andrea model, we obtain the results presented in Table 9.

Table 9. The thrust force based on the D'Andrea model.

Type of Drone	Number of Scenario	T [N]
Small quadcopter	1	12.67
Large octocopter	1	34.3
	2	49
	3	39.2

Source: own elaboration.

The calculation of the power consumption necessary to maintain a stable flight, including the electronics operation regarding the weight of the drone, takes into account the mass of components (mk), the force of gravity ($g = 9.8\ \mathrm{m/s^2}$), the power consumed by the avionics ($Pavio = 0.1\ \mathrm{J/s}$), the ratio of lift to drag ($r = 3$), and the efficiency ($n = 0.5$). The resulting formula, based on D'Andrea's calculations, is:

$$P = \frac{\left(\sum_{k=1}^{3} m_k\right) g v_a}{r\eta} + P_{avio} \quad (3)$$

Based on the D'Andrea formula concerning the power, Table 10 shows the results obtained. Considering the obtained results, the small quadcopter requires significantly less power, due to its specification.

Table 10. The power consumption required for stable flight.

Type of Drone	Number of Scenario	P [J/s]
Small quadcopter	1	104.03
Large octocopter	1	3704.50
	2	5292.10
	3	4233.70

Source: own elaboration.

Based on the results obtained, the energy formula consists of the power (P) obtained in Table 11 divided by the speed (v):

$$Epm = \frac{P}{v_a} \tag{4}$$

Table 11. The results of the obtained energy from the D'Andrea model.

Type of Drone	Number of Scenario	Epm [J/m]
Small quadcopter	1	25.37
Large octocopter	1	205.81
	2	294.01
	3	235.21

Source: own elaboration.

Table 11 shows the results obtained via the basic D'Andrea energy model.

The D'Andrea model also describes the formula for the energy, with the inclusion of headwinds. For this reason, the ratio of the headwind (v_{head} = 8.33 m/s) to the speed of the drone (v) is calculated by:

$$\varphi = \frac{headwindspeed}{droneairspeed} \tag{5}$$

After calculating the headwind coefficient, the quadcopter eliminates the negative value caused by the headwind speed being more significant than the maximum speed of the drone. The coefficient indicating the headwind for the octocopter is 0.46. On this basis, the calculation of the energy taking into account the headwind can be calculated using the formula:

$$Epm = \frac{1}{1-\varphi}\left(\frac{g\sum_{k=1}^{3} m_k}{r\eta} + \frac{P_{avio}}{v_a}\right) \tag{6}$$

Table 12 presents the results obtained after taking into account the headwind. Analyzing the obtained results, the energy, including the headwind, is much higher, which, in the case of the large octocopter in scenario 1, is as much as 94% more energy than in the D'Andrea energy model without the headwind.

Table 12. The energy obtained taking into account the headwind.

Type of Drone	Number of Scenario	Epm [J/m]
Large octocopter	1	3382.46
	2	3396.17
	3	3387.05

Source: own elaboration.

3.4.2. Figliozzi Model

Figliozzi, in his energy model, describes an equation considering empty returns in a UAV after delivering a meal to a customer. He does not take into account the power consumed by the avionics ($Pavio$ = 0), models the ratio of lift to drag depending on the speed (with $r(v)$), and provides a unitless parameter for the battery-charging efficiency (ηr).

$$Epm = \frac{1}{2}\left(\frac{g\sum_{k=1}^{3} m_k}{r(v)\eta\eta_r} + \frac{g\sum_{k=1}^{2} m_k}{r(v)\eta\eta_r}\right) \tag{7}$$

The results using the Figliozzi model are given in Table 13. The obtained results are close to those of the D'Andrea energy model.

Table 13. The results for the energy obtained via the Figliozzi model.

Type of Drone	Number of Scenario	Epm [J/m]
Small quadcopter	1	22.46
	1	63.42
Large octocopter	2	77.34
	3	68.06

Source: own elaboration.

3.4.3. Dorling Model

The Dorling model provides a hovering power that depends on the battery. It uses forces based on gravity as well as sag, so the airspeed is zero, and the thrust balances the force.

$$T = g\sum_{k=1}^{3} m_k \tag{8}$$

The force thrust in the final formula consists of the acceleration due to gravity and the weight of the components. Table 14 describes the results where the thrust of a large octocopter is slightly superior. Based on helicopter theory, Dorling developed a formula for the required power.

$$P = \frac{T^{\frac{3}{2}}}{\sqrt{2n\rho\varsigma}} \quad \frac{\left(g\sum_{k=1}^{3} m_k\right)^{3/2}}{\sqrt{2n\rho\varsigma}} \tag{9}$$

Table 14. The thrust via the Dorling model.

Type of Drone	Number of Scenario	T [N]
Small quadcopter	1	38.02
	1	102.90
Large octocopter	2	147.00
	3	117.60

Source: own elaboration.

Table 15 describes the result of the power required by drones, where n is the number of rotors, and ς is the area of the spinning blade disc of one rotor. In the calculation, the parameter ς is assumed to be the same value for the octocopter and quadcopter.

Table 15. The power required to fly.

Type of Drone	Number of Scenario	P [J/s]
Small quadcopter	1	167.48
	1	527.21
Large octocopter	2	900.19
	3	644.12

Source: own elaboration.

The energy formula is the same as for the D'Andrea model, consisting of the power [P] and the UAV speed [v_a]. After taking into account all parameters, the formula looks like this:

$$Epm = \frac{P}{v_a} \frac{\left(g\sum_{k=1}^{3} m_k\right)^{3/2}}{v_a\sqrt{2n\rho\varsigma}} \tag{10}$$

Table 16 shows the final energy required by drones via the Dorling model.

Table 16. The results of the obtained energy via the Dorling model.

Type of Drone	Number of Scenario	Epm [J/m]
Small quadcopter	1	40.85
	1	29.29
Large octocopter	2	50.01
	3	35.78

Source: own elaboration.

Based on the results obtained, in Table 16, the energy in the Dorling model resulted significantly lower than in the D'Andrea model. This is due to the significantly different formula for power, which considers the number of rotors and the surface of the propeller.

3.4.4. Kirchstein Model

A Kirchstein model considers an idealized delivery process, with the take-off, climb to cruising speed, level flight, descent, hover, landing, and delivery. The return takes place without a load. It takes into account the energy used for the induced power, parasite power, and profile power. In addition, it includes the power for climbing, avionics, and corrections related to power loss to the electric motor, transmission efficiency, and charging.

$$T = \sqrt{\left(g\sum_{k=1}^{3} m_k\right)^2 + \left(\frac{1}{2}\rho\left(\sum_{\mathrm{k}=1}^{3} C_{D_k}\mathrm{A_k}\right)v_a^2\right)^2 + \rho\left(\sum_{\mathrm{k}=1}^{3} C_{D_k}\mathrm{A_k}\right)v_a^2\,\mathrm{mg}\sin\theta} \tag{11}$$

After transformation, where $v_a = 0$, we are left with the following formula:

$$T = g\sum_{k=1}^{3} m_k \tag{12}$$

Table 17 shows the results of the force thrust via the Kirchstein model. Considering other models, the obtained results are the same as those obtained via the Dorling model. Both models use the same dependence.

Table 17. The thrust required via the Kirchstein model.

Type of Drone	Number of Scenario	T [N]
Small quadcopter	1	38.02
	1	102.9
Large octocopter	2	147
	3	117.6

Source: own elaboration.

The Kirchstein model presenting the required energy consists of several parts. The first term takes into account the induced power, including the factor "K" (the lifting power) and "w" (the downwash coefficient). The "w" factor can be determined using the formula for thrust contained in the D'Andrea model.

The next part contains the air density, the drag coefficient of the drone component k [unitless], the projected area of the drone component k $[\mathrm{m}^2]$, and the speed of the drone. Based on Kirchstein's article, the CDk and Ak coefficients were calculated based on assumptions for small and large drones. The third and fourth parts deal with the power of the profile, where the constants κ2 and κ3 reflect the details of the rotors and the environment. The last term in the equation reference refers to avionics.

$$Epm = \frac{1}{\eta}\left(\frac{KTw}{v_a} + \frac{1}{2}\rho\left(\sum_{k=1}^{3} C_{D_k}A_k\right)v_a^2 + \frac{K_2\left(g\sum_{k=1}^{3} m_k\right)^{1.5}}{v_a} + K_3\left(g\sum_{k=1}^{3} m_k\right)^{0.5} v_a\right) + \frac{P_{avio}}{\eta_c v_a} \quad (13)$$

Table 18 presents the results of the Kirchstein model. Due to the similar assumptions of the coefficients, the results for the large drone do not differ much.

Table 18. The required energy via the Kirchstein model.

Type of Drone	Number of Scenario	Epm [J/m]
Small quadcopter	1	43.42
Large octocopter	1	121.58
	2	127.75
	3	123.61

Source: own elaboration.

3.4.5. Tseng Model

Tseng presents his model as a nine-period non-linear regression model. It considers the horizontal and vertical speeds, acceleration, load weight, and wind speed. After reduction, the formula is as follows:

$$Epm = -2.595 + \frac{0.197m_2 + 251.7}{v_a} \quad (14)$$

The Tseng model takes into account the energy consumption equation at speeds of up to 5 m/s, which is why we only classify the small quadcopter. The result for the small quadcopter is presented Table 19.

Table 19. The data for the first scenarior.

Type of Drone	Number of Scenario	Epm [J/m]
Small quadcopter	1	59.01

Source: own elaboration.

4. Results

4.1. Energy Needs for Drones

Based on the selected models, two drone models are used in the calculation of the energy required by drones: one model quadcopter and one octocopter. The selection of specific models focuses on technical specifications; significant differences in speed, the load capacity, the body weight, or battery-related parameters allow for different results.

Table 20 summarizes the results of the models used to calculate the energy needed for drones. Next to each model name is the type of drone, the scenario involved, and the thrust, power, energy, and headwind energy. Because not all models had the same calculation schemes, some of them, such as the Figliozzi and Tseng models, did not consider the thrust and power. The Kirchstein model does not account for the power. Only the D'Andrea model calculates a headwind.

Table 20. The results for the Epm.

Computational Model	Type of Drone	Number of Scenario	T (N)	P [J/s]	Epm [J/m]	Epm [J/s] + Headwind
D'Andrea model	Small quadcopter	1	12.67	104.03	25.37	-
	Large octocopter	1	34.30	3704.50	205.81	3382.49
		2	49.00	5292.10	294.01	3396.17
		3	39.20	4233.70	235.21	3387.05
Figliozzi model	Small quadcopter	1	-	-	22.46	-
	Large octocopter	1	-	-	63.42	-
		2	-	-	77.34	-
		3	-	-	68.06	-
Dorling model	Small quadcopter	1	38.020	167.48	40.85	-
	Large octocopter	1	102.90	527.21	29.29	-
		2	147.00	900.19	50.01	-
		3	117.60	644.12	35.78	-
Kirchstein model	Small quadcopter	1	38.02	-	43.42	-
	Large octocopter	1	102.90	-	121.58	-
		2	147.00	-	127.75	-
		3	117.60	-	123.61	-
Tseng model	Small quadcopter	1	-	-	59.01	-
	Large octocopter	1	-	-	-	-
		2	-	-	-	-
		3	-	-	-	-

Source: own elaboration.

Figure 4 presents the thrust force results obtained graphically in different models. Dorling and Kirchstein's models take into account the thrust. Based on the results, the large octocopter in scenario no. 2 requires the most significant thrust force. Additionally, the Dorling and Kirchstein models describe the same formula. Therefore, the results obtained are the same. Thus, they outweigh the required thrust over the D'Andrea model. The Figliozzi model and the Tseng model do not take the thrust into account.

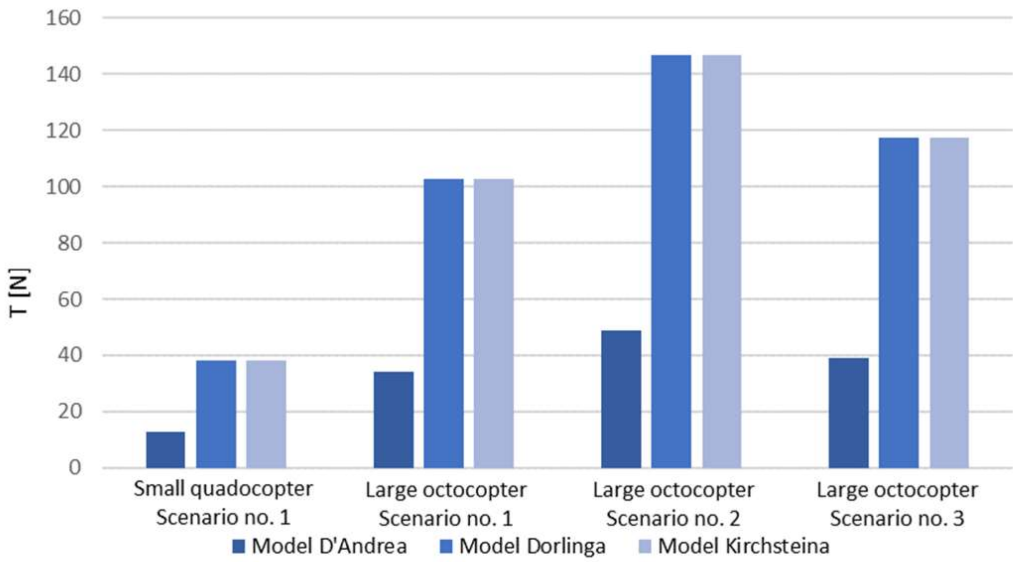

Figure 4. The required thrust force for each model. Source: own elaboration.

The power required for the drone takes into account the D'Andrea model and the Dorling model. Figure 5 shows the obtained results. Based on the data presented, the Dorling model outperforms the power requirement compared to the Dorling model. The lift-to-drag ratio, battery and motor power transfer efficiency, and power of avionics contribute to the higher required power in the D'Andrea model.

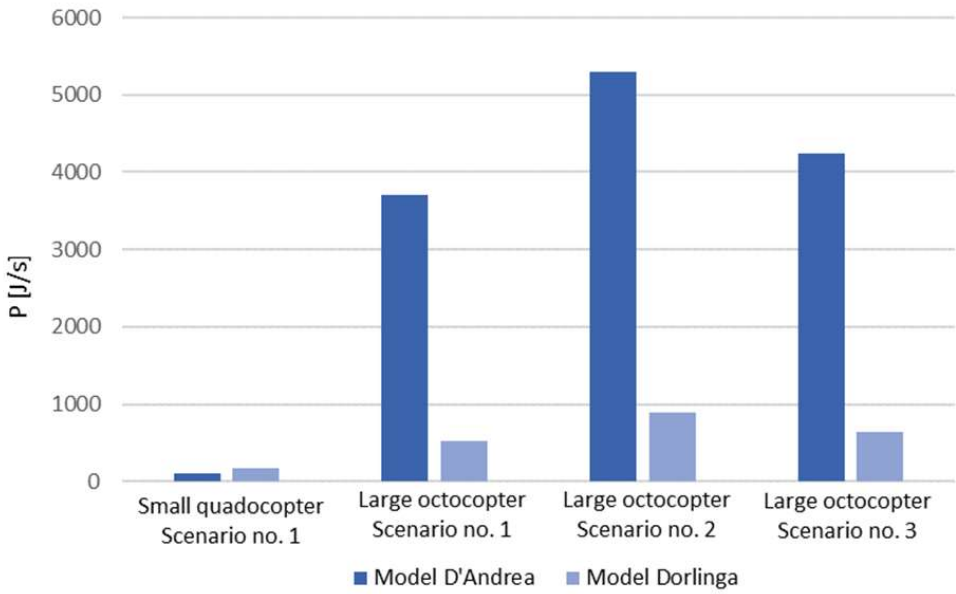

Figure 5. The key models of power for the drones. Source: own elaboration.

The key drone energy models are presented in Figure 6. Due to the required speed of up to 5 m/s, the Tseng model is only included for the small quadcopter. Compared to other Tseng models in a small quadcopter, it requires the most energy. The minor demand in a quadcopter requires the Figliozzi model. This is due to the inclusion of empty returns in the computational model.

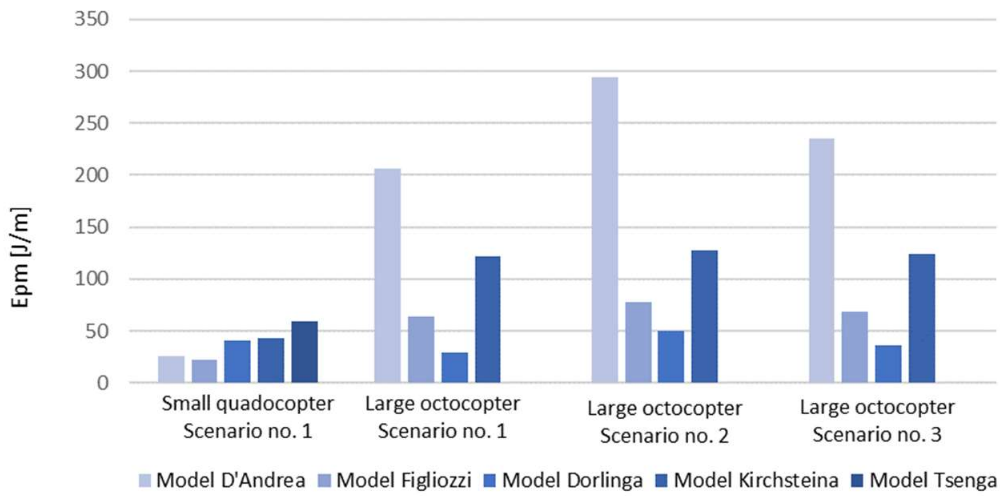

Figure 6. Key drone energy models. Source: own elaboration.

In Scenario 1 with the small quadcopter, the Tseng model achieves a value 58% higher than the D'Andrea model, which requires the most energy in other analyses. Analyzing the remaining bars in the case of the octocopter, all models in the three scenarios look the same. The D'Andrea model needs the most energy, followed by Kirchstein, Figliozzi, and Dorling.

4.2. Comparative Analysis of Energy Consumption

The final stage of this paper is an analysis of the comparative study of energy consumption by UAVs and electric scooters while delivering food in the city. This chapter uses the technical parameters of the electric scooter, and calculations based on various energy models for UAVs from Figure 6. Then, using statistical tables and charts, we present the obtained data.

Comparative analysis requires the transformation of the obtained data, and the presentation of the results in the kWh unit; therefore, the following formula is used to obtain the energy the scooter consumes in kWh.

$$\frac{batterycapacity \times voltage}{1,000,000} \quad (15)$$

Through the calculation of the battery capacity, amounting to 20.000 mAh, multiplied by the voltage, and divided by 1,000,000, the electric scooter's energy consumption in kWh was determined to be 1.44 kWh (Table 21).

Table 21. The required energy via the Tseng model.

	Electric Scooter	
Battery capacity	20.000	mAh
Tension	72	V
Result	1.44	kWh

Source: own elaboration.

Table 22 shows the energy conversion from Epm [J/s] to W. This calculation required the multiplication of Epm by the average flight speed, then division by 3.6. Based on the input data, the result is obtained in watts. The last necessary conversion of the unit for comparison is the conversion of watts to kWh. For this purpose, the energy [W] is multiplied by the time expressed in hours, and divided by 1000. On this basis, we can reach the results given in Table 22. The power expressed in kWh shows the lowest result in the small Figliozzi model quadcopter, which is 0.09; the highest value, 98.11% higher, is obtained with the large D'Andrea model octocopter.

Table 22. Table showing the conversion from [J/m] to [kWh].

Computational Model	Type of Drone	No. Scenario	T (N)	P [J/s]	Epm [J/m]	P [W]	W on kWh (t = 1)
D'Andrea model	Small quadcopter	1	12.67	104.03	25.37	104.017	0.10
	Large octocopter	1	34.30	3704.50	205.81	3704.58	3.70
		2	49.00	5292.10	294.01	5292.18	5.29
		3	39.20	4233.70	235.21	4233.78	4.23
Dorling model	Small quadcopter	1	38.02	167.48	40.85	167.485	0.17
	Large octocopter	1	102.90	527.21	29.29	527.22	0.53
		2	147.00	900.19	50.01	900.18	0.90
		3	117.60	644.12	35.78	644.04	0.64
Figliozzi model	Small quadcopter	1	-	-	22.46	92.086	0.09
	Large octocopter	1	-	-	63.42	1141.56	1.14
		2	-	-	77.34	1392.12	1.39
		3	-	-	68.06	1225.08	1.23
Tseng model	Small quadcopter	1	-	-	59.01	241.96	0.24
	Large octocopter	1	-	-	-	-	-
		2	-	-	-	-	-
		3	-	-	-	-	-
Kirchstein model	Small quadcopter	1	38.02	-	43.42	178.022	0.18
	Large octocopter	1	102.90	-	121.58	498.478	0.50
		2	147.00	-	127.75	523.775	0.52
		3	117.60	-	123.61	506.801	0.51

Source: own elaboration.

Table 23 introduces the results obtained via the same calculation as the energy with a headwind in the D'Andrea model. Only the large octocopter is involved in the transformation.

Table 23. Table showing the conversion from [J/m] to [kWh] for the Epm with a headwind.

Type of Drone	No. Scenario	T (N)	P [J/s]	Epm [J/s] + headwind	P [W] + headwind	W on kWh (t = 1)
Small quadcopter	1	12.67	104.03	-	-	-
Large octocopter	1	34.30	3704.50	3382.49	13,640.86	13.64
	2	49.00	5292.10	3396.17	13,696.03	13.70
	3	39.20	4233.70	3387.05	13,659.25	13.66

Source: own elaboration.

In the transformation obtained, the results are as follows: in scenario no. 1, 13.64 kWh; then in scenario no. 2, 13.70 kWh; and then, in scenario 3, the result is 13.66 kWh. The difference between the lowest and highest A W per kWh conversion is 0.43%.

Table 22 describes significantly lower values P [W] than Table 23 based on the obtained results. The results obtained from the transformations of energy obtained without a headwind are 61.39% lower than those described in Table 23 with a headwind.

4.3. Energy Consumption in the Delivery Process

The paper aims to justify the theory that drones may be more efficient in terms of energy consumption. Therefore, based on the assumed scenarios, the necessary parameters were defined. To conduct a comparative analysis, we specify how many hours it would take to overcome a particular scenario. Tables 24 and 25 show the fraction of an hour.

Table 24. The time taken to cover a certain distance—drone.

Type of Drone	No. Scenario	Average Speed [km/h]	Distance in Scenario [km]	Time [min]	Part of an Hour [h]
Small quadcopter	1	14.76	1.5	6.10	0.10
Large octocopter	1	64.80	1.5	1.39	0.02
	2	64.80	2.7	2.50	0.04
	3	64.80	3.9	3.61	0.06

Source: own elaboration.

Table 25. The time taken to cover a certain distance—electric scooters.

Model of Scooter	No. Scenario	Average Speed [km/h]	Distance in Scenario [km]	Time [min]	Part of an Hour [h]
ROBO—S.C.	1	45	1.5	2	0.03
	2	45	2.7	3.6	0.06
	3	45	3.9	5.2	0.09

Source: own elaboration.

Based on the calculated part of the hour and kWh, we have all the data to calculate the energy consumption of specific drone and electric scooter models in the adopted scenarios. As a result, the kWh energy necessary to cover the distance given in the scenarios is calculated. Table 26 shows the converted W units to kWh. On this basis, a large octocopter has the highest energy requirement relative to other types of drones in each scenario. The large octocopter does not consider the conversion of the unit, because of the relevance of the energy model only to the small quadcopter.

Table 27 describes the conversion of W to kWh via the D'Andrea model, using an octocopter with a headwind. Due to its low speed the small quadcopter was excluded from the D'Andrea energy model. The large octocopter has the highest energy in scenario no. 1. Tables 27 and 28 show the results of the final consumption.

Table 26. The energy required to cover the distance description in the chosen scenario in [kWh].

Computational Model	Type of Drone	No. Scenario	W on kWh (t = 1)	Energy [kWh]
D'Andrea model	Small quadcopter	1	0.10	0.011
		1	3.70	0.086
	Large octocopter	2	5.29	0.221
		3	4.23	0.255
Dorling model	Small quadcopter	1	0.17	0.017
		1	0.53	0.012
	Large octocopter	2	0.90	0.038
		3	0.64	0.039
Figliozzi model	Small quadcopter	1	0.09	0.009
		1	1.14	0.026
	Large octocopter	2	1.39	0.058
		3	1.23	0.074
Tseng Model	Small quadcopter	1	0.24	0.025
		1	-	-
	Large octocopter	2	-	-
		3	-	-
Kirchstein model	Small quadcopter	1	0.18	0.018
		1	0.50	0.012
	Large octocopter	2	0.52	0.022
		3	0.51	0.031

Source: own elaboration.

Table 27. The energy required to cover the distance described for the drones with a headwind in each chosen scenario in [kWh].

Computational Model	Type of Drone	No. Scenario	W na kWh (t = 1)	W on kWh (t = 1) Headwind	Energy [kWh]
D'Andrea model	Small quadcopter	1	0.10	-	-
		1	3.70	13.64	0.316
	Large octocopter	2	5.29	13.70	0.221
		3	4.23	13.66	0.255

Source: own elaboration.

Table 28. The energy required to cover the distance description for scooters in each chosen scenario in [kWh].

No. Scenario	Energy [kWh]
1	0.048
2	0.086
3	0.125

Source: own elaboration.

The energy the electric scooter requires in individual scenarios is detailed in Table 28. The highest consumption occurs in scenario no. 3, with a value of 0.125 kWh.

Figure 7 presents the energy consumption results of drones compared to the electric scooter in scenario no. 1. In this case, drones have a significant advantage over electric scooters, reaching twice as much minor energy consumption. The balance of calculations in drone models appears similar. Only the Tseng model slightly exceeds the average energy.

Due to its technical parameters and much greater requirements, a large octocopter exceeds the energy demand of an electric scooter. Figure 8 shows that the D'Andrea model requires twice as much energy as a scooter.

Figures 9 and 10 are significantly different from Figure 8, with values 60% higher than the D'Andrea model in Figure 8. Due to differences in the weight of the transported product, there is no large discrepancy in the data described in the charts. Still, the D'Andrea model requires the most energy, followed by the electric scooter and drones described via the Dorling, Figliozzi, and Kirchstein models.

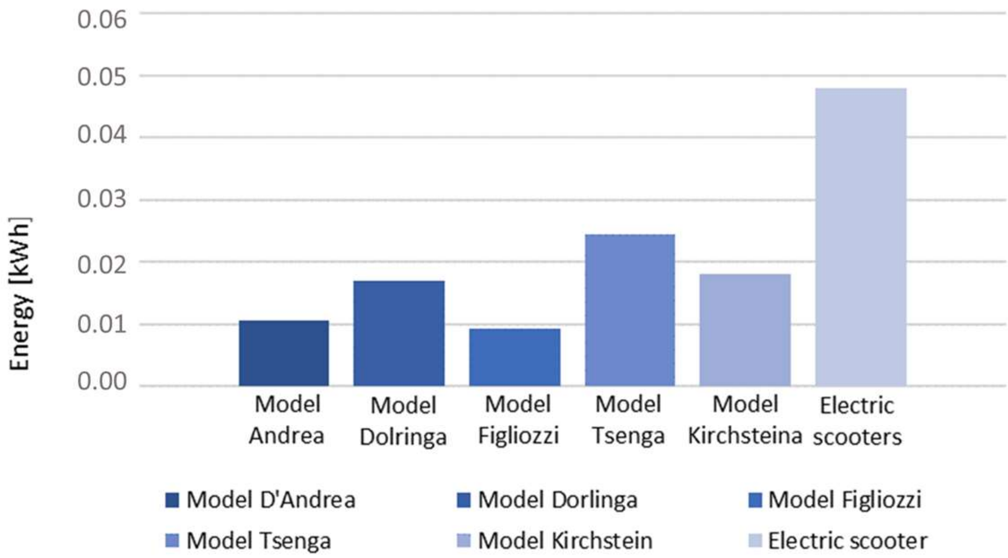

Figure 7. The energy consumption of small quadcopters (various models) and electric scooters in scenario no. 1. Source: own elaboration.

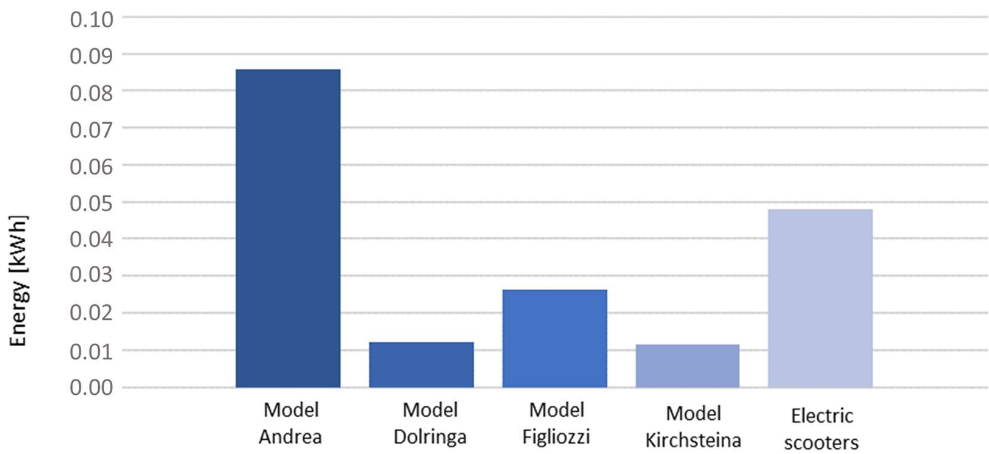

Figure 8. The energy consumption of large octocopters (various models) and electric scooters in scenario no. 1. Source: own elaboration.

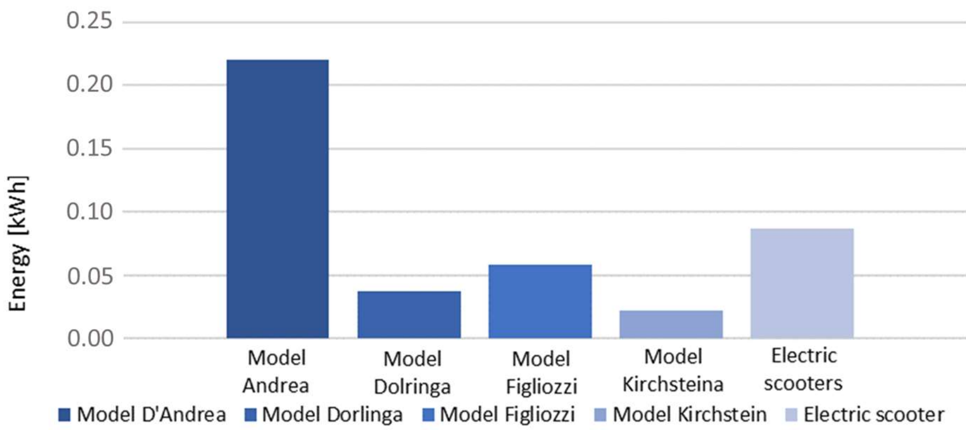

Figure 9. The energy consumption of large octocopters (various models) and electric scooters in scenario no. 2. Source: own elaboration.

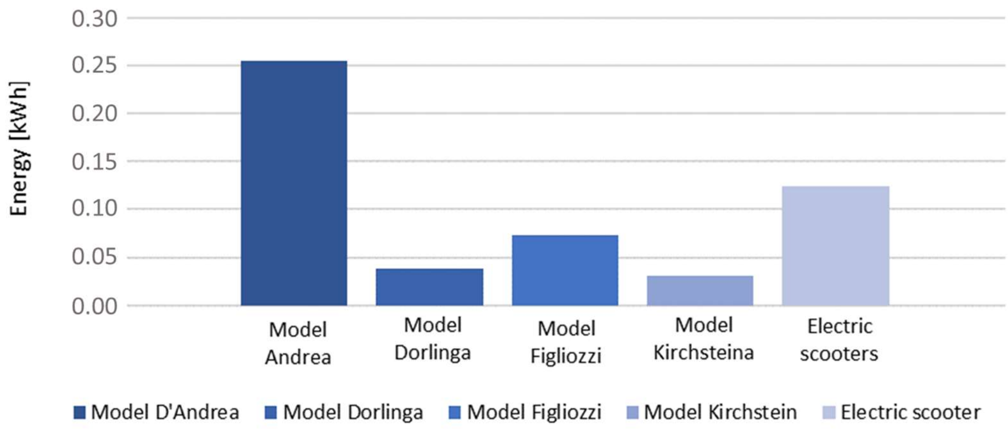

Figure 10. The energy consumption of large octocopters (various models) and electric scooters in scenario no. 3. Source: own elaboration.

5. Discussion and Conclusions

Cities are implementing changes towards sustainability, and implementing the concept of sustainable mobility. Urban air mobility is a concept that uses eVTOL and UAVs. The article indicates a research problem concerning the type of electric transport (scooters/UAVs), and demonstrates which has a lower electricity demand when delivering food from restaurants to individual customers. For this purpose, an energy efficiency analysis using unmanned aerial vehicles and electric scooters to transport takeaway food was carried out, which is a solution that fits into the zero-emission transport policy. Calculations were used to carry out a comparative analysis of energy consumption for three adopted scenarios related to the energy consumption by drones. The analysis method used the energy models of D'Andrea, Dorling, Figliozzi, Kirchstein, and Tseng. This paper compares the energy consumption of UAVs and electric scooters in urban logistics. The research problem justifies the theory that drones can be more beneficial than electric scooters in delivering food. We assumed the technical parameters based on the technical specification data, and adopted some data based on the size of the drones. Calculations of energy consumption were made, considering energy models. We created scenarios that allowed us to determine whether the variability of weight or distance significantly affected the final result. The final analysis of drones compared with electric scooters shows the dependencies in the energy models. The paper shows how energy models differ from each other. The equation for the D'Andrea and Dorling energy models is the same, but the upstream calculation is significantly different, due to previous calculations, such as the power and force thrust. Determining the lift-to-drag ratio r, and the power transfer efficiency η, without making measurements, may be crucial to determining unmanned aerial vehicles' energy consumption. The developed results show how the lack of taking into account of one factor, e.g., a headwind, can affect the final result. The results obtained via the models determined how many parameters are still needed to unify a specific energy model. Nevertheless, preliminary formulas and attempts to determine energy use show results favoring urban air mobility. Investment in specialized control systems and navigation and control systems in the future may help control energy consumption. In addition, adapted infrastructure in the form of vertiports and better adaptation batteries are also necessary elements in air traffic.

The conducted analyses and research in the implementation of UAVs are important from the point of view of the accessibility of this type of transport for the population. Public transportation is heavily crowded during peak hours, and UAV implementation for food delivery can cover a wide range of delivery options. UAV deployment is the future in the suburbs because, as described in [55], people do not always want to use services, due to limited transportation availability. The solution of food delivery with a UAV to the suburbs of the city could be extremely important for the population. It is worth mentioning that the methodology adopted in this study can only be applied if relevant data are available for UAVs and electric scooters. The results of this study may be helpful to policymakers and stakeholders in evaluating the implementation of food transport UAVs for individual customers.

Future work should extend the models described in the paper with additional information that will be investigated or determined. More significant development of UAVs and infrastructure for urban air mobility can significantly change the existing ambiguities, and introduce changes in the perception of some aspects. Important analyses should be carried out in the development of smart, sustainable, and safe vehicles, in terms of creating an aircraft with low operating costs (which will be beneficial, justifiable for customers, and profitable for companies), and producing low noise levels. Proper technical support and serviceability are required for the smooth operation of unmanned aerial vehicles. An important aspect is air traffic management, which must take into account the infrastructure, legal regulations, and planning of airspace available for UAVs.

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Abbreviations

	List of symbols and markings:
ρ	air density [kg/m^3] (e.g., 1.225 kg/m^3 at 15 °C at sea level)
g	acceleration of gravity [m/s^2]
v_a	airspeed [m/s] (speed of the drone relative to the air)
φ	ratio of the headwind to the airspeed [unitless]
v	drone ground speed [m/s], so v = (1 − φ)v_a
v_{head}	headwind speed [m/s]
d	drone one-way travel distance for a single delivery trip [m]
r	lift-to-drag ratio [unitless]
η	battery and motor power transfer efficiency (from the battery to the propeller) [unitless]
η_a	battery-charging efficiency [unitless]
k	index of the drone components: drone body = 1; drone battery = 2; payload (package) = 3
C_{Dk}	drag coefficient of drone component k [unitless]
A_k	the projected area of drone component k [m^2]
m_k	mass of drone component k [kg]
P	power required to maintain a steady drone flight [watt = J/s]
$Pavio$	power required for all avionics on the drone (independent of drone motion) [watt = J/s]
n	number of rotors for a rotocopter drone [rotors]
c_d	blade drag coefficient [unitless]
ς	area of the spinning blade disc of one rotor [m^2]
Epm	the energy required for steady drone flight per unit distance [J/m]

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