An Overview of Drone Energy Consumption Factors and Models

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Abstract

At present, there is a growing demand for drones with diverse capabilities that can be used in both civilian and military applications, and this topic is receiving increasing attention. When it comes to drone operations, the amount of energy they consume is a determining factor in their ability to achieve their full potential. According to this, it appears that it is necessary to identify the factors affecting the energy consumption of the unmanned air vehicle (UAV) during the mission process, as well as examine the general factors that influence the consumption of energy. This chapter aims to provide an overview of the current state of research in the area of UAV energy consumption and provide general categorizations of factors affecting UAV’s energy consumption as well as an investigation of different energy models.

\textit{Keywords:} Unmanned aerial vehicle, Energy consumption, Drone energy models

1 Introduction

Drones offer a number of advantages over trucks while they are more efficient. They eliminate the need of the drivers and can often travel with a higher speed than vehicles since they are not restricted to the road systems (Agatz et al. 2018). These advantages enable logistics companies and online retailers to deploy drones to deliver packages quickly. Humanitarian organizations are also actively considering using drones in disaster situations (Cheng et al. 2020). Also, drones have a significant environmental advantage over trucks by reducing emissions. While UAVs have a number of desirable features, the limited battery life is a major limitation for them. As most UAVs are electric devices powered by onboard batteries, this constraint significantly limits their capabilities. Many studies have been recently proposed contributing towards saving energy and increasing endurance. A major focus of these contributions is the design of an automated system for charging and replacing batteries (Yacef et al. 2017). The smaller UAVs do not entirely solve the mechanization problem since they have one major flaw, which is insufficient power (Alwateer et al. 2019). Larger drones, such as those primarily employed in military applications, have enough power...
sources, but this advantage comes at the cost of being considerably larger, less maneuverable, and rather loud. The importance of having an appropriate power source is critical since it leads to lengthy flight endurance. It would allow further flight mission planning and optimal recharging for UAVs. It is therefore essential to plan and design UAV missions in an energy-efficient manner. In order to achieve this, a reliable power consumption model is required for predicting the power consumption \( \text{(Abeywickrama et al. 2018)} \).

## 2 Factors Affecting Energy Consumption of Drones

The features and configurations of UAVs vary considerably depending on their missions. Understanding the elements of the determined energy use is critical for designing energy consumption models that are accurate and efficient. Drone activities are more energy-sensitive than conventional vehicle operations \( \text{(Cheng et al. 2020)} \). Internal and external factors can affect energy consumption. As an example, the lower power consumption was observed when flying into headwinds \( \text{(Tennekes 2009)} \), which is due to the increasing thrust generated by the translational lift as the UAV moved from hovering to forward flight. Temperature and air density are also linked to battery drain and lift capacity of aircraft. Below zero degrees Fahrenheit, UAVs fly shorter distances and experience more malfunctions. The weight and payload of UAVs also individually affect their energy consumption more than all other factors \( \text{(Thibbotuwawa et al. 2018a)} \). There is an analysis of different parameters that influence the energy consumption of the UAV Routing Problem in \( \text{(Thibbotuwawa et al. 2018b)} \). This is achieved by analyzing an example scenario of a single UAV multiple delivery mission. Based on the analysis, the relationships between UAV energy consumption and the influencing parameters are examined. Therefore, it is vital to have better knowledge and estimate of drone energy use. The four main elements that influence drone energy usage are drone design, environment, drone dynamics, and delivery operations, which will be discussed further. \( \text{(Demir et al. 2014, Zhang et al. 2021)} \).

### 2.1 Drone Design

The weight and size of the drone’s body, number and size of rotors, weight, size, and energy capacity of the battery, power transfer efficiency, maximum speed and payload, lift-to-drag ratio, delivery mechanism, and avionics are all elements to consider while designing a drone \( \text{(Zhang et al. 2021)} \). It is inherently complex to design mechatronics systems since they involve multiple domains. During the design process, the different engineering domains involved in the activity influence one another, which makes the task of designing a complex process for design engineers \( \text{(Mohbibi et al. 2014)} \). The mechatronics systems are traditionally designed sequentially, with the mechanical component coming first, followed by the electronic components, then the control strategy.

In order to achieve an optimized design, the coupling between the different components and domains must be evaluated in the early stage of the design process to avoid negative consequences associated with dependency \( \text{(Alvagout et al. 2011)} \). Several methods have been suggested in order to achieve a better design that incorporates both mechanical and control aspects of the mechatronics system. The proposed methods tend to aim an optimal aspect of
the system, for example, the control or the mechanisms in isolation. The literature has identified some approaches for the design support of drones or mechatronics systems in general. As an example, the design for control strategy applied to visually served drones is presented by [Mohebbi et al. 2015]. This process involves simplifying the dynamics model of the system in order to better understanding and improving its representation and then devising a control algorithm that will enhance the control of system. A further method for designing a structure-control system is a robust structure-control design, which uses nonlinear dynamic multi-objective optimization to design a system. It considers the interactions between the structure and the control to propose a robust design, as presented by [Alyaqout et al. 2011]. This method relies on the design of the controller to achieve the robustness of the system, which limits it to a robust approach of the control. For both of these methods, it is the control component on the focus, and little information is gleaned about the mechanisms; in addition, the interaction goes in a single direction, from control to mechanism, while the other direction can only be achieved by further simplification of the dynamics by adding extra constraints, such as stability criteria [Mohebbi et al. 2015]. [Coulombe et al. 2017] aims to develop a robust design for a quadrotor drone, with particular attention to structural parameters, such as the mass and dimensions. In definition, a robust design method is one that emphasizes the minimization of the effects of variation in design parameters on the response of the system. This paper presents a system’s response in terms of its energy consumption. Monte Carlo simulation is used to determine the most influential design parameters, and then a designer-defined objective function is minimized to determine a robust mechanical design for the quadrotor under consideration.

2.2 Environment

Air density, gravitational force, wind conditions, weather (snow, rain, etc.), ambient temperature, and operational restrictions are all environmental elements [Zhang et al. 2021]. The existing research indicates that reduced power consumption was observed when flying into headwinds [Tennekes 2009], which can be attributed to the increasing thrust caused by translational lift. In the presence of a headwind, the translational lift will increase as the relative airflow increases, resulting in reduced power consumption for hovering. If the wind speed exceeds a certain threshold, aerodynamic drag may outweigh the benefits of translational lift [Alyassi et al. 2022]. In addition, temperature and air density have a relationship, which is linked to the battery drain. The air density around a flying aircraft changes with temperature, thus affects their lift capacity. Studies have been shown that UAVs tend to fly shorter distances and experience increased malfunction rates in cold weather conditions (below zero degrees Fahrenheit). Outdoor routing for UAVs must account for the stochasticity of weather variables that affect UAV energy consumption [Kinney et al. 2005]. The majority of UAV routing studies either assume infinite fuel capacity or presume that they would never run out of fuel [Frazzoli & Bullo 2004] or do not take fuel into consideration [Thibbotuwawa et al. 2018a]. The weather’s impact on UAV routing is influenced by two primary elements, which are: i) Wind: the major environmental factor that affects the UAV is wind direction and its speed. In some circumstances, wind can reduce energy consumption while increasing resistance to movement. ii) Temperature: since temperature is connected to battery drain and capacity, it might impair the UAV’s battery performance [Dorling et al.
Ignoring the effects of the weather will not result in more realistic answers (Erfani & Tavakolanzadeh 2020), as flying with the wind can cut energy usage, and cold temperatures can harm battery performance (Dorling et al. 2016). As weather changes over time in a stochastic manner (Wu et al. 2014), one must expect that the fuel consumption of a particular route will vary at different times (Thibbotuwawa et al. 2018a). It is critical that the drone be highly mobile and unaffected by the surroundings (Tang & Shao 2015).

2.3 Drone Dynamics

Drone dynamics factors include drone travel speed, drone motion (i.e., takeoff/landing, hover, horizontal flight), acceleration/deceleration, angle of attack, and flight altitude. The idea of drones being transported for part of their journey on other vehicles also should be considered, such as trucks or public transportation (Zhang et al. 2021). Different cargo weights can have a major influence on energy consumption models; thus they should be taken into account (Alyassi et al. 2017, Dorling et al. 2016). Fuel/energy usage is recognized to be dependent on various aspects in the airline industry. Take-off gross weight, empty weight, and thrust to weight ratio might limit the maximum flying distance or time of a UAV (Shetty et al. 2008), fuel weight, and payload (Zhang et al. 2015). Wind speed and direction are related to flying speed since the direction of the wind can affect the UAV’s flying status either positively or adversely. A UAV’s flight status might be one i) hovering; ii) horizontal moving or cruising or level flight; iii) vertical moving: vertical take-off/landing/altitude change. As a result, while calculating energy consumption, the UAV’s flying state, as well as its speed, should be taken into account (Alyassi et al. 2017). During a drone delivery journey, many of these variables are interrelated and dynamic.

All of these elements, notably drone design, drone dynamics, and delivery procedures, might cause uncertainty in calculating drone energy usage.

2.4 Delivery Operations

Delivery operations factors may only apply to drone delivery missions, whereas other missions require consideration of other factors, which is not mentioned here. Weight and size of the payload, ”empty returns” (i.e., the return trip after delivery is without the payload, implying a successful delivery), fleet size and mix, number of deliveries per trip, delivery mode, and service region area are all crucial factors in a delivery operation. Some of these elements are specified or limited by the drone design (e.g., maximum payload, the projected area of the drone, etc.), while others are operational parameters (Moeinifard et al. 2022, Aghakhani et al. 2022) that can vary for a given drone design (e.g., payload, speed, etc), and still others are external factors (e.g., weather) (Zhang et al. 2021). As drone delivery continues to develop, many literature have been considered the use of drones in transportation problems. Dorling et al. (2016) investigated vehicle routing problems for drone delivery (VRPDD). Based on an energy consumption model for drones, the authors investigated the implications of payload and battery weight on energy consumption. Dukkanci et al. (2021) describes the Energy Minimizing and Range Constrained Drone Delivery Problem (ERDDP),
where drones are used to deliver products to a number of customers, and the drones themselves are transported by traditional vehicles. As part of the ERDDP, (i) launch points will be selected among a possible set of sites from where drones will take off to serve a number of customers, (ii) customers will be assigned to the launch points, and (iii) the speed at which drones will travel between the launch points and the customers will be determined. It proposes a nonlinear model for ERDDP that minimizes the total operational cost, including an explicit calculation of the drone’s energy consumption in relation to its speed. The results demonstrated the effect of various factors on location, assignment, and speed decisions. As a result of two problems related to drone-assisted cargo delivery (flying sidekick traveling salesman problem (FSTSP), parallel drone scheduling to travel salesmen (PDSTSP)) based on Murray & Chu (2015), the researchers concluded that the speed of a drone has a significant effect on drone delivery operations due to range alternation. Even if the drone range is reduced, it is preferable to have higher speeds. Other studies used the FSTSP setup have examined coordination between trucks and drones (e.g., Wang et al. (2017), Poikonen et al. (2017), Carlsson & Song (2018)) with some extending the problem to minimize operational costs.

3 Modeling of Drone Energy Consumption

Due to the limited energy provided by the lithium polymer (LiPo) batteries, which are typically installed on mini drones, the energy consumption of each drone plays a critical role in determining its figure of merit (Famili et al. 2022). To account for the drone’s limited battery capacity, numerous algorithms have been proposed in the literature to assist in optimizing the different aspects of the energy considerations. Nevertheless, the most studies do not analyze the battery according to its actual performance (Chen et al. 2018). The most drone travel models impose time and/or distance limits. Some of the studies assume that the energy consumption is constant per unit of time or traveled distance; hence the drone energy consumption is modeled as a linear function of time or traveled distance (e.g., Ferrandez et al. (2016), Ha et al. (2018), Huang et al. (2020b), Moore (2019)). Also many models assumes the motor draining power at a 1:1 ratio to the battery. However, this is not correct since a battery supplies power with different efficiency values depending upon its state of charge (SOC).

Many models have been proposed in the literature with respect to the energy consumption; they consider a variety of parameters, aspects and missions such as optimal path planning, path following control, battery-aware and battery performance, target tracking, UAV-enabled mobile edge computing, UAV-enabled multicasting and drone’s component models. The following subsections provide a review of these models.

3.1 Optimal Path Planning

In order to use UAVs in an optimal manner, path planning is one of the most important factors that can be realized in autonomous control. Path planning is a challenging process due to the increased number of parameters, such as control points, radar coverage areas, physical obstacles, etc., (Sonmez et al. 2015). There are many methods that have been used to solve
NP-hard optimal path planning problems, including heuristic methods (e.g., Christofides, Concorde) and meta-heuristic methods (e.g., genetic algorithms or discrete particle swarm optimization) (Wai & Prasetia 2019).

Cheng et al. (2020) investigated a multi-trip drone routing problem (MTDRP) with time windows, where drones’ energy consumption is modeled as a nonlinear function of payload and travel distance. Instead of using a linear approximation, they added logical cuts and subgradient cuts to the solution process in order to handle the more complex nonlinear (convex) energy function. A Branch-and-Cut algorithm is developed using a 2-index formulation. Wai & Prasetia (2019) examined an optimal path planning and disturbance rejection control for a UAV surveillance system. A K-agglomerative clustering method is used to create a clustered 3D real pilot flight pattern and is then processed using A-star and set-based particle swarm optimization (S-PSO) algorithms to generate an optimal path planning scheme. The online adaptive neural network (ANN) controller combines a variety of learning rates with a fast disturbance rejection response to ensure control stability. The traveling salesmen problem (TSP) is used in (Zeng et al. 2018) in order to design the trajectory of an UAV so as to minimize the time taken to complete the mission in UAV-enabled multi-casting systems. Sambo et al. (2019) applied a genetic algorithm to design a trajectory that consumes the least energy to visit all base stations and return to the UAV station. Van Huynh et al. (2021) proposed optimal path planning approaches for UAVs to minimize their completion time and total energy consumption during data collection. A real-time optimization algorithm provides low computational complexity with fast deployment and low processing time for tracking and collecting sensor data. Deng et al. (2022) aimed to develop a new vehicle-assisted UAV delivery solution that the energy consumption takes into account. It allows UAVs to serve multiple customers on a single take-off. In order to allocate tasks among UAVs and to plan the path of a vehicle, a multi-UAV task allocation model and a vehicle path planning model were developed. The model also considered the impact of changing the payload of the UAV on energy consumption, bringing the results closer to reality. To solve the problem, a hybrid heuristic algorithm based on an improved K-means algorithm and ant colony optimization (ACO) was proposed. Thibbotuwawa et al. (2019) developed an off-line solution to the problem of UAV mission planning, taking energy consumption constraints and collision avoidance into account based on historical data. A predictive strategy is employed to avoid collisions between UAVs over the time horizon to create collision-free routing and schedules. Morbidi et al. (2016) discussed the problem of the minimum energy path through a model for the brushless DC motors and solved it with regard to the angular acceleration of the propellers of a quadrotor. Dorling et al. (2016) analyzed the routing optimization for drone delivery services; however, the power model included only the weight of the battery in addition to the payload. The authors of (Di Franco & Buttazzo 2015) presented an algorithm that minimizes the total energy consumed by the IRIS quadrotor, through a power model that describes the drone’s energy consumption in different operating conditions. In (Abdilla et al. 2015), the authors studied the performance of different LiPo batteries and the models considered for battery runtime are based on the capacity rate effect, as well as Peukert’s law (Di Franco & Buttazzo 2015).
3.2 Path Following Control

The trajectory control problem, defined as making a vehicle follow a pre-established path in space, can be solved by means of trajectory tracking or path following. The trajectory tracking problem involves the tracking of a timed reference position. A path-following approach eliminates any time dependency of the problem, which has many advantages for controlling performance and design (Sallouha et al. 2018). Considering path following control with minimum energy consumption, in (Gandolfo et al. 2016), the authors examined the relationship between navigation speed and energy consumption in a miniature quadrotor helicopter, which travels over the desired path in an experimental study. Then a path-following controller proposed with a dynamic speed profile that varies with the geometric requirements of the path. The stability of the control law is proved using the Lyapunov theory.

3.3 Battery-Aware & Battery Performance

It is not realistic to assume that the power drawn by a motor is in a 1:1 correspondence to the power drawn by the battery, since the battery supplies power with different efficiency values depending on its state-of-charge (SOC), and this efficiency is also non-linearly dependent on the amount of the power requested (Di Franco & Buttazzo 2015, Chen & Rincon-Mora 2006). Thus, omitting the battery performance analysis may result in inaccurate estimates of the real flight time of the drone (Aleksandrov & Penkov 2012), and integrating battery awareness into the drone power model is essential to avoid significant errors (Chen et al. 2018).

On the basis of empirical studies of battery usage for various UAV activities, Abeywickrama et al. (2018) presented a consistent model of power consumption for UAVs. In (Ahmed et al. 2016), the experimental results were presented for a few basic UAV manoeuvring actions: hovering, flying vertically upward and flying vertically downward. In (Tseng et al. 2017), the authors have investigated the impact of movement (hovering, vertical and horizontal movements), payload, and wind on the power consumption of an unmanned aerial vehicle. Abeywickrama et al. (2018a) proposed an enhanced energy consumption model and conducted a series of studies aimed at understanding the impact of several factors on UAV power consumption. A number of factors have been taken into consideration, including impact of wind, speed, tacking-off, hovering, payload, communication, and on-ground power consumption. Chen et al. (2018) described a battery-aware model for assessing drone energy consumption, which is then applied to a scenario of drone delivery. According to the results, failing to account for battery performance leads to considerable inaccuracy in estimating the amount of available energy and, consequently, the duration of flight.

Poikonen et al. (2017) presented a model for solving a problem of minimizing the delivery time for a certain number of packages. Battery performance was considered in this case solely from the viewpoint of service time. Chen et al. (2018) described a battery-aware model for an accurate analysis of the drone energy consumption. This model was then applied to a scenario of drone delivery, and the results showed an accuracy more than about 16% with respect to the traditional estimation model. Baek et al. (2018) demonstrated that the proposed battery-aware delivery scheduling algorithm can carry more packages than the traditional delivery model with the same battery capacity. For the same delivery scheme, the
battery-aware delivery model was 17% more accurate than the traditional delivery model, which eliminates the possibility of a drone landing unexpectedly. As a result, the authors demonstrated how a model that incorporates SOC-dependent battery efficiency can be useful for modeling drone power. Using a battery-powered state-of-charge (SOC), a controller was described in (Podhradský et al. 2014), which can be used for both fixed wings and multirotor UAVs. In this scenario, the battery model was based on the equivalent electrical circuit of (Chen & Rincon-Mora 2006) applied to LiPo batteries, as well as the relationship between nominal thrust and battery SOC.

3.4 Target Tracking

There are many situations in which visual tracking is used, such as search and rescue missions and the monitoring of vehicular traffic by tracking cars (Apvrille et al. 2014, Heintz et al. 2007). A challenge of such a mission is the transmission of target images in real time, tracking the target accurately, and preserving the UAV’s energy (Elloumi et al. 2017). There are two phases in the tracking process. The transient phase of this process begins with the UAV taking off and localizing the mobile target. The second phase is known as the steady phase, which the UAV performs adjustments in order to maintain the target in its field of view. A fixed-wing UAV is tracking a target by making circular movements in (He et al. 2014). When tracking a stationary target or when the target velocity is lower than the UAV’s minimum velocity, the objective is to generate an optimal path for the UAV.

Zorbas et al. (2013) illustrated a tracking of several targets by several unmanned aerial vehicles. The objective was to save energy while ensuring continuous coverage while only the altitude was adjusted and kept as low as possible during tracking. Elloumi et al. (2017) proposed three zones single UAV tracking algorithm, and according to the target placement in those zones, the UAV will do a specific type of actions. In additional zone called the authorized zone, the UAV keeps a fixed velocity and a fixed altitude, and this contributes to the limitation of the energy consumption. The energy consumption was also evaluated using an adapted criterion, which takes into account the velocity, altitude, and acceleration changes. Limiting the UAV adjustments will reduce energy consumption while maintaining the target in sight. Siam et al. (2012) introduced a method for multi-target detection and tracking based on fast corner detection and Kalman filtering, but the clustering algorithm was not able to identify the target. Teuliere et al. (2011) combined a particle filter algorithm with a color tracker based on multi-part representations in order to account for target occlusion and deformation.

3.5 UAV-Enabled Mobile Edge Computing

The UAV-assisted mobile edge computing (MEC) networks provide on-demand computation services to mobile terminals (MTs) through their high mobility and ease of deployment. There is a reduction in latency in this network, but energy efficiency remains a major concern, as both the UAVs and MTs have limited battery storage capacity (Budhiraja et al. 2021). It is difficult for user devices (UDs) to execute these applications on their own computing resources due to the limited battery power and low computational capacity (Hu & Qian 2014). As a solution, MEC offers UDs at the edge of wireless networks access to cloud
computing services with a low transmission delay (Othman et al. 2013). Zhang et al. (2018) studied an energy minimization scheme for MEC networks based on UAVs to maximize computation rates. To accomplish this, the authors divided the primary problem into three subproblems: user scheduling, offloading ratio, and trajectory of the UAV.

Sardellitti et al. (2015) examined a multicell MEC system where computation and radio resources were optimized together in order to minimize the total energy consumption. You et al. (2016) proposed an offloading policy aimed at reducing the energy consumption under the constraints of a data processing delay. Zhou et al. (2018) investigated an MEC system with UAV assistance, in which the sum energy consumption at the UAV was minimized by optimizing the CPU frequency and trajectory of the UAV. Hua et al. (2018) investigated the method for minimizing the energy consumption of a computation with a fixed trajectory for UAVs. Ji et al. (2020) aimed to formulate new optimization problems for non-orthogonal and orthogonal multiple access modes that minimize the weighted-sum energy consumption for the UAV and UDs by optimizing the UAV trajectory jointly with the allocation of computation resources, under the constraint of the number of computation bits. Budhiraja et al. (2021) evaluated how to minimize the energy consumption of NOMA-based MEC networks that support UAVs based on time, computation capacity, and trajectory. As a nonlinear programming problem, the formulated model is subdivided into two subproblems: joint time allocation and task computation capacity, and optimization of UAV trajectory.

3.6 UAV-Enabled Multicasting

It is possible to use UAVs as aerial base stations to improve the coverage and performance of communication networks in various scenarios, such as emergency communications and network access in remote locations (Liu et al. 2018).

Mozaffari et al. (2016b) optimized the UAV stop points by using the disk covering theory. Kalantari et al. (2016) utilized a heuristic algorithm to optimize the 3D placement of multiple UAVs in order to serve all users. An optimal placement algorithm for UAV-BSs was proposed by Shakhatreh et al. (2017), which maximizes the number of users covered with the least amount of transmission power possible. Mozaffari et al. (2016a) developed a framework for determining the optimal location of UAVs based on circle packing theory in order to maximize the downlink coverage performance with minimal transmission power. Song et al. (2019) proposed a fly-and-communicate protocol in which the UAV follows a zigzag trajectory rather than a spiral pattern trajectory optimization scheme and disseminates some common information to the ground units. In order to minimize the completion time, the optimal altitude is set as the maximum value, while the optimal beamwidth can be obtained through a one-dimensional search. The optimal altitude and beamwidth can be determined iteratively so as to minimize the energy consumption. Yang et al. (2019) aims to maximize the energy-efficient communication coverage of drone-cell networks while preserving the network connectivity with 3D continuous movement control of multiple drone cells. The E2CMC algorithm is based on an emerging deep reinforcement learning method to mitigate this problem. An energy efficiency reward function considering energy consumption, quality-of-service (QoS) requirements of users, and coverage fairness is first designed in E2CMC. As a result of interacting with an environment, E2CMC adjusts drone cells’ locations continuously. If the networks are disconnected, E2CMC will reduce the reward dras-
tically. Liu et al. (2018) proposed leveraging emerging deep reinforcement learning (DRL) for UAV control, and present a novel, highly energy-efficient DRL-based method, entitled DRL-based energy efficient control for coverage and connectivity (DRL-EC3). The proposed method maximizes energy efficiency by taking into consideration communications coverage, fairness, energy consumption, and connectivity while learning the environment and its dynamics under the guidance of two deep neural networks. Deng et al. (2019) investigated a novel UAV-enabled multicast system in which a UAV transmits CI to several GTs. To minimize the total energy consumption of the UAV, including mechanical and transmission energy, the objective is to minimize the total energy consumption of the UAV. An ML-based joint optimization framework for UAV-enabled multicasting is presented.

### 3.7 Drone’s Component Models

An alternative approach for modeling drone energy consumption relies on a component model derived from helicopter operations, under the assumption that the power consumed during level flight, takeoff, or landing is approximately equivalent to the power consumed while hovering. Components can be modeled based on fundamental forces of flight, including the weight force of the aircraft (due to gravity) and drag force. Models for drone energy consumption include separate models for the forces and the different components of a drone flight (takeoff, landing, cruising, hovering), and are often quite detailed in order to capture particular characteristics of the drone design.

Liu et al. (2017) provided a detailed three-part drone energy model that includes the power to maintain lift and overcome parasite drag, along with profile power to overcome rotating drag caused by propeller blades. Field tests in (Liu et al. 2017, Di Franco & Buttazzo 2015) showed that ascending takes 9.8% more power than hovering, and descending takes 8.5% less power than hovering. Dorling et al. (2016) provided an equation for the power required by a multirotor helicopter in the hover mode as a function of battery capacity and payload weight. In (Kirschstein 2020), a component model was used in an idealized delivery process with separate calculations for takeoff, ascent, level flight, descent, hovering, and landing. Stolaroff et al. (2018) used a required thrust to balance the drone weight and the parasitic drag force; the authors developed a two-component model; an assessment of the energy use and greenhouse gas (GHG) emissions for small drones with short ranges performing deliveries. Many articles have been developed the component drone power and energy models similar to those above for problems involving drones in wireless communication networks. (e.g., Zeng & Zhang (2017), Zeng et al. (2019), Wu et al. (2019)) There is also a modeling of drone energy consumption that involves regression based on field experiments. Tseng et al. (2017) and Alvassi et al. (2017) presented a nine-term nonlinear regression model for the drone power consumption, which includes horizontal and vertical speed and acceleration, as well as payload mass and wind speed. A standard energy efficiency data set provided by manufacturers from an independent or governmental source would be ideal such as the energy efficiency measures for automobiles or appliances (Zhang et al. 2021).
3.8 Joined Models

There are multiple uses for drones today, including emergency services for humanitarian operations (e.g., search and rescue) (Mudivanselage et al. 2021, Shakerian et al. 2022), traffic surveillance, package delivery, and telemetry and mapping. A number of studies have been conducted that cover different aspects of the use of drones for modeling. Yacef et al. (2017) presented an energetic model for quadrotor UAVs, which contains the vehicle dynamic, actuator dynamic and battery dynamic with an efficiency function. The objective is to minimize the energy consumed by a quadrotor at the end of its mission while satisfying the boundary conditions and feasibility constraints on the states of the system and control inputs. Yang et al. (2022) proposed an energy consumption model for UAV swarm topology shaping that takes into account the energy consumption for UAVs flying vertically upward, vertically downward, and horizontally. Van Huynh et al. (2021) proposed a scheduling strategy by considering the UAV’s characteristics in terms of energy consumption and reputation. For the scheduling strategy rules of UAVs, authors proposed an energy-efficient strategy and a reputation-based mechanism separately. Furthermore, they built a game-theoretic model to examine how working UAVs schedule new tasks. Finally, they calculated the Nash equilibrium for UAV scheduling based on the balance between energy minimization and reputation maximization. In (Tran et al. 2020), the UAV trajectory was designed to minimize the total energy consumption while meeting the requested timeout (RT) requirement and energy budget, which is achieved by optimizing the path and UAV’s velocity along subsequent hops. Firstly, the authors proposed two algorithms, namely, heuristic search and dynamic programming (DP), to obtain a feasible set of paths without violating the GU’s RT requirements based on the traveling salesman problem with time window (TSPTW). As a reference method, exhaustive search and traveling salesman problem (TSP) were compared. The results showed that the DP-based algorithm approaches the exhaustive search’s performance with significantly reduced complexity.

However, the majority of studies focus on drone delivery. In the context of delivery services, i) meeting deadlines in terms of quality of service; ii) the number of packages delivered as measured by throughput per charge cycle; iii) improving battery health by reducing the number of charge cycles per time interval should be considered (Chen et al. 2018). Bongermino et al. (2017) presented a complete Simulink model and a control strategy for a parallel hybrid electric UAV powertrain. Model components include an internal combustion engine, a gearbox, an electric motor, an electric drive, and a lithium-ion battery. This control strategy employed a near real-time, iterative algorithm based on dynamic programming to solve an optimization problem involving optimal power management and torque-split for the powertrain with final state constraints.

The majority of studies on drone-only delivery systems assumed that there are several drones and each drone can serve one or more consumers every trip. Dorling et al. (2016) proposed two variations of the vehicle routing problem (VRP) for drone delivery. The first reduces overall operational costs while adhering to a delivery time limitation, whereas the second optimizes delivery time while adhering to a budget constraint. The prices include the costs of operating the drone fleet and the consumption of energy. To reduce costs, each drone may make several journeys and visit multiple consumers on each trip. The authors used a linear approximation function that fluctuates linearly with the weight of the payload and
battery rather than dealing directly with the original nonlinear form of the power function and solve the models with the simulated annealing (SA) heuristic. Troudi et al. (2018) analyzed an example of a drone delivery challenge with time constraints and a trip duration limit. Efforts are being made to reduce the number of drones used, the distance traveled, and the number of batteries required. Batteries are set aside as buffers for exceptional circumstances when applied linear energy limits.

Delivery can also be accomplished with a truck and one or more drones. There are several optimization models for drone or truck-drone routes or drone delivery systems that only indirectly consider energy consumption as a set constraint on drone endurance (flight time) or range (flight distance). (e.g., Murray & Raj (2020), Chiang et al. (2019), Kitjacharoenchai et al. (2020). Others have used an energy consumption model based on the underlying physical forces involved in flight or field measurements in their drone delivery research (e.g., Kirschstein (2020), Murray & Raj (2020), Poikonen & Golden (2020), Stolaroff et al. (2018), Figliogetti (2017), Dorling et al. (2016)). Murray & Raj (2020) design truck-drone tandem delivery routes using a three-phase heuristic that considers multiple drone energy models, such as the model for fuel efficiency of (Liu et al. 2017), the simple regression model that is linear in payload, and other models that operate with a fixed distance or time limit (basically, modeling energy consumption as a linear function of drone travel time or distance). The findings from Zhang et al. (2021) indicated that (i) different energy models can produce very different routes, with several energy models resulting in energy infeasible drone routes, and (ii) it is critical to include the energy consumed during steady level flight portions of a delivery trip (for example, for launch, retrieval, and delivery), especially for any hovering required to communicate with a truck or other drones prior to landing (Zhang et al. 2021).

Drone energy consumption models can consist of only a few parameters or multiple interdependent components the provide accurate representations of flight forces and drone design. Since the seminal work of Murray & Chu (2015), researchers have studied the possibilities of designing and optimizing drone delivery, in which drones are launched from a depot or other vehicle, which is usually a truck. This research includes drone routing and scheduling (e.g., Dorling et al. (2016), Agatz et al. (2018), Schermer et al. (2018), Liu (2019), Murray & Raj (2020), Kitjacharoenchai et al. (2020)), facility location problems, including charging stations (Chauhan et al. 2019, Hong et al. 2018, Ferrandez et al. 2016), and fleet sizing (Troudi et al. 2018). Recently conducted surveys of drone modeling specifically focus on truck-drone operations, in which drones can be transported by trucks to extend their useful range (or in delivery settings where trucks function as resupply points for drone deliveries (e.g., Otto et al. (2018), Chung et al. 2020)). Several other methods have been developed that enable drones to use public transportation in order to extend their useful delivery range (Huang et al. 2020b, Choudhury et al. 2021). In general, drone travel models impose time and/or distance limits as a result of their limited battery capacity.

The majority of the research assumes that the drone energy consumption is linear as a function of time or traveled distance, so drones are modeled as linear functions. However, there is considerable variance in the assumed consumption values. Drone energy consumption models have been incorporated explicitly into some optimization models, with one key difference being the assumption regarding thrust when flying horizontally. It is possible to assume (i) that the thrust force equals the drag force and that the weight force equals the lift force. Various assumptions are reflected by different perspectives on drone operations,
for instance, whether they operate more like fixed-wing aircraft or helicopters. Based on these three approaches, there has been a continuous stream of literature on drone energy modeling. D’Andrea (2014) aimed to model drone energy consumption by translating the fundamental flight principles of manned aircraft into a model for unmanned aerial drones rather than manned aircraft. Using an integrated approach, this article presented a model that incorporates aerodynamics and drone design aspects into a single key parameter: the lift-to-drag ratio. Additionally, the energy model includes a fixed component for avionics power. Troudi et al. (2018) employ the same model to analyze drone fleet sizes; however they ignore the power of the avionics. Figliozzi (2017) adopted a same modeling approach to derive drone emissions based on a continuous approximation travel distance model. D’Andrea (2014) integrated a model that is also used in a series of reports from the RAND Corporation. The authors explored energy consumption for city-scale drone delivery systems (Lohn 2017, Xu 2017, Gulden 2017). Lohn (2017) used this model to analyze truck and drone delivery in cities of various sizes, and Gulden (2017) provided a GIS-based analysis of shifting truck deliveries to drones in Minneapolis. Xu (2017) discussed aspects of drone design related to drone energy consumption and suggested that fixed-wing VTOL (vertical takeoff and landing) or hybrid multicopter configurations that combine VTOL capabilities with lifting surfaces (wing-like structures) would be more suitable for many drone delivery purposes.

References

Abdilla, A., Richards, A. & Burrow, S. (2015), Power and endurance modelling of battery-powered rotorcraft, in ‘2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)’, IEEE, pp. 675–680.

Abeywickrama, H. V., Jayawickrama, B. A., He, Y. & Dutkiewicz, E. (2018a), ‘Comprehensive energy consumption model for unmanned aerial vehicles, based on empirical studies of battery performance’, IEEE access 6, 58383–58394.

Abeywickrama, H. V., Jayawickrama, B. A., He, Y. & Dutkiewicz, E. (2018b), Empirical power consumption model for uavs, in ‘2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)’, IEEE, pp. 1–5.

Agatz, N., Bouman, P. & Schmidt, M. (2018), ‘Optimization approaches for the traveling salesman problem with drone’, Transportation Science 52(4), 965–981.

Aghakhani, S., Mohammadi, B. & Rajabi, M. S. (2022), ‘A new hybrid multi-objective scheduling model for hierarchical hub and flexible flow shop problems’, arXiv preprint arXiv:2205.06465.

Ahmed, S., Mohamed, A., Harras, K., Kholief, M. & Mesbah, S. (2016), Energy efficient path planning techniques for uav-based systems with space discretization, in ‘2016 IEEE wireless communications and networking conference’, IEEE, pp. 1–6.

Aleksandrov, D. & Penkov, I. (2012), Energy consumption of mini uav helicopters with different number of rotors, in ‘11th International Symposium” Topical Problems in the Field of Electrical and Power Engineering’, pp. 259–262.
Alwateer, M., Loke, S. W. & Fernando, N. (2019), ‘Enabling drone services: drone crowdsourcing and drone scripting’, IEEE access 7, 110035–110049.

Alyaqout, S. F., Papalambros, P. Y. & Ulsoy, A. G. (2011), ‘Combined robust design and robust control of an electric dc motor’, IEEE/ASME Transactions on Mechatronics 16(3), 574–582.

Alyassi, R., Khonji, M., Chau, S. C.-K., Elbassioni, K., Tseng, C.-M. & Karapetyan, A. (2017), ‘Autonomous recharging and flight mission planning for battery-operated autonomous drones’, arXiv preprint arXiv:1703.10049.

Alyassi, R., Khonji, M., Karapetyan, A., Chau, S. C.-K., Elbassioni, K. & Tseng, C.-M. (2022), ‘Autonomous recharging and flight mission planning for battery-operated autonomous drones’, IEEE Transactions on Automation Science and Engineering.

Apvrille, L., Tanzi, T. & Dugelay, J.-L. (2014), Autonomous drones for assisting rescue services within the context of natural disasters, in ‘2014 XXXIth URSI General Assembly and Scientific Symposium (URSI GASS)’, IEEE, pp. 1–4.

Baek, D., Chen, Y., Bocca, A., Macii, A., Macii, E. & Poncino, M. (2018), Battery-aware energy model of drone delivery tasks, in ‘Proceedings of the International Symposium on Low Power Electronics and Design’, pp. 1–6.

Bongermino, E., Mastrorocco, F., Tomaselli, M., Monopoli, V. G. & Naso, D. (2017), Model and energy management system for a parallel hybrid electric unmanned aerial vehicle, in ‘2017 IEEE 26th International Symposium on Industrial Electronics (ISIE)’, IEEE, pp. 1868–1873.

Budhiraja, I., Kumar, N., Tyagi, S. & Tanwar, S. (2021), ‘Energy consumption minimization scheme for noma-based mobile edge computation networks underlaying uav’, IEEE Systems Journal 15(4), 5724–5733.

Carlsson, J. G. & Song, S. (2018), ‘Coordinated logistics with a truck and a drone’, Management Science 64(9), 4052–4069.

Chauhan, D., Unnikrishnan, A. & Figliozzi, M. (2019), ‘Maximum coverage capacitated facility location problem with range constrained drones’, Transportation Research Part C: Emerging Technologies 99, 1–18.

Chen, M. & Rincon-Mora, G. A. (2006), ‘Accurate electrical battery model capable of predicting runtime and iv performance’, IEEE transactions on energy conversion 21(2), 504–511.

Chen, Y., Baek, D., Bocca, A., Macii, A., Macii, E. & Poncino, M. (2018), A case for a battery-aware model of drone energy consumption, in ‘2018 IEEE International Telecommunications Energy Conference (INTELEC)’, IEEE, pp. 1–8.
Cheng, C., Adulyasak, Y. & Rousseau, L.-M. (2020), ‘Drone routing with energy function: Formulation and exact algorithm’, *Transportation Research Part B: Methodological* **139**, 364–387.

Chiang, W.-C., Li, Y., Shang, J. & Urban, T. L. (2019), ‘Impact of drone delivery on sustainability and cost: Realizing the uav potential through vehicle routing optimization’, *Applied energy* **242**, 1164–1175.

Choudhury, S., Solovey, K., Kochenderfer, M. J. & Pavone, M. (2021), ‘Efficient large-scale multi-drone delivery using transit networks’, *Journal of Artificial Intelligence Research* **70**, 757–788.

Chung, S. H., Sah, B. & Lee, J. (2020), ‘Optimization for drone and drone-truck combined operations: A review of the state of the art and future directions’, *Computers & Operations Research* **123**, 105004.

Coulombe, C., Gamache, J.-F., Mohebbi, A., Chouinard, U., Achiche, S. et al. (2017), Applying robust design methodology to a quadrotor drone, in ‘DS 87-4 Proceedings of the 21st International Conference on Engineering Design (ICED 17) Vol 4: Design Methods and Tools, Vancouver, Canada, 21-25.08. 2017’, pp. 395–404.

D’Andrea, R. (2014), ‘Guest editorial can drones deliver?’, *IEEE Transactions on Automation Science and Engineering* **11**(3), 647–648.

Demir, E., Bektaş, T. & Laporte, G. (2014), ‘A review of recent research on green road freight transportation’, *European journal of operational research* **237**(3), 775–793.

Deng, C., Xu, W., Lee, C.-H., Gao, H., Xu, W. & Feng, Z. (2019), Energy efficient uav-enabled multicast systems: Joint grouping and trajectory optimization, in ‘2019 IEEE Global Communications Conference (GLOBECOM)’, IEEE, pp. 1–7.

Deng, X., Guan, M., Ma, Y., Yang, X. & Xiang, T. (2022), ‘Vehicle-assisted uav delivery scheme considering energy consumption for instant delivery’, *Sensors* **22**(5), 2045.

Di Franco, C. & Buttazzo, G. (2015), Energy-aware coverage path planning of uavs, in ‘2015 IEEE international conference on autonomous robot systems and competitions’, IEEE, pp. 111–117.

Dorling, K., Heinrichs, J., Messier, G. G. & Magierowski, S. (2016), ‘Vehicle routing problems for drone delivery’, *IEEE Transactions on Systems, Man, and Cybernetics: Systems* **47**(1), 70–85.

Dukkanci, O., Kara, B. Y. & Bektaş, T. (2021), ‘Minimizing energy and cost in range-limited drone deliveries with speed optimization’, *Transportation Research Part C: Emerging Technologies* **125**, 102985.

Elloumi, M., Escrig, B., Dhaou, R., Idoudi, H. & Saidane, L. A. (2017), Designing an energy efficient uav tracking algorithm, in ‘2017 13th international wireless communications and mobile computing conference (IWCNC)’, IEEE, pp. 127–132.
Huang, H., Savkin, A. V. & Huang, C. (2020a), ‘A new parcel delivery system with drones and a public train’, *Journal of Intelligent & Robotic Systems* **100**(3), 1341–1354.

Huang, H., Savkin, A. V. & Huang, C. (2020b), ‘Reliable path planning for drone delivery using a stochastic time-dependent public transportation network’, *IEEE Transactions on Intelligent Transportation Systems* **22**(8), 4941–4950.

Ji, J., Zhu, K., Yi, C. & Niyato, D. (2020), ‘Energy consumption minimization in uav-assisted mobile-edge computing systems: Joint resource allocation and trajectory design’, *IEEE Internet of Things Journal* **8**(10), 8570–8584.

Kalantari, E., Yanikomeroglu, H. & Yongacoglu, A. (2016), On the number and 3d placement of drone base stations in wireless cellular networks, in ‘2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)’, pp. 1–6.

Kinney, G. W., Hill, R. R. & Moore, J. T. (2005), ‘Devising a quick-running heuristic for an unmanned aerial vehicle (uav) routing system’, *Journal of the Operational Research Society* **56**(7), 776–786.

Kirschstein, T. (2020), ‘Comparison of energy demands of drone-based and ground-based parcel delivery services’, *Transportation Research Part D: Transport and Environment* **78**, 102209.

Kitjacharoenchai, P., Min, B.-C. & Lee, S. (2020), ‘Two echelon vehicle routing problem with drones in last mile delivery’, *International Journal of Production Economics* **225**, 107598.

Liu, C. H., Chen, Z., Tang, J., Xu, J. & Piao, C. (2018), ‘Energy-efficient uav control for effective and fair communication coverage: A deep reinforcement learning approach’, *IEEE Journal on Selected Areas in Communications* **36**(9), 2059–2070.

Liu, Y. (2019), ‘An optimization-driven dynamic vehicle routing algorithm for on-demand meal delivery using drones’, *Computers & Operations Research* **111**, 1–20.

Liu, Z., Sengupta, R. & Kurzhanskiy, A. (2017), A power consumption model for multi-rotor small unmanned aircraft systems, in ‘2017 International Conference on Unmanned Aircraft Systems (ICUAS)’, IEEE, pp. 310–315.

Lohn, A. J. (2017), What’s the buzz? the city-scale impacts of drone delivery, Technical report.

Moeinifard, P., Rajabi, M. S. & Bitaraf, M. (2022), ‘Lost vibration test data recovery using convolutional neural network: A case study’, *arXiv preprint arXiv:2204.05440*.

Mohebbi, A., Achiche, S. & Baron, L. (2015), Integrated design of a vision-guided quadrotor uav: A mechatronics approach, in ‘Proceedings of the 2015 CCToMM Symposium on Mechanisms, Machines, and Mechatronics’.
Mohebbi, A., Baron, L., Achiche, S. & Birglen, L. (2014), Trends in concurrent, multi-criteria and optimal design of mechatronic systems: A review, in ‘Proceedings of the 2014 International Conference on Innovative Design and Manufacturing (ICIDM)’, IEEE, pp. 88–93.

Moore, A. M. (2019), ‘Innovative scenarios for modeling intra-city freight delivery’, Transportation Research Interdisciplinary Perspectives 3, 100024.

Morbidi, F., Cano, R. & Lara, D. (2016), Minimum-energy path generation for a quadrotor uav, in ‘2016 IEEE International Conference on Robotics and Automation (ICRA)’, IEEE, pp. 1492–1498.

Mozaffari, M., Saad, W., Bennis, M. & Debbah, M. (2016a), ‘Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage’, IEEE Communications Letters 20(8), 1647–1650.

Mozaffari, M., Saad, W., Bennis, M. & Debbah, M. (2016b), ‘Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs’, IEEE Transactions on Wireless Communications 15(6), 3949–3963.

Mudiyanselage, S. E., Nguyen, P. H. D., Rajabi, M. S. & Akhavian, R. (2021), ‘Automated workers’ ergonomic risk assessment in manual material handling using seng wearable sensors and machine learning’, Electronics 10(20), 2558.

Murray, C. C. & Chu, A. G. (2015), ‘The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery’, Transportation Research Part C: Emerging Technologies 54, 86–109.

Murray, C. C. & Raj, R. (2020), ‘The multiple flying sidekicks traveling salesman problem: Parcel delivery with multiple drones’, Transportation Research Part C: Emerging Technologies 110, 368–398.

Othman, M., Madani, S. A., Khan, S. U. et al. (2013), ‘A survey of mobile cloud computing application models’, IEEE communications surveys & tutorials 16(1), 393–413.

Otto, A., Agatz, N., Campbell, J., Golden, B. & Pesch, E. (2018), ‘Optimization approaches for civil applications of unmanned aerial vehicles (uavs) or aerial drones: A survey’, Networks 72(4), 411–458.

Podhradský, M., Coopmans, C. & Jensen, A. (2014), ‘Battery state-of-charge based altitude controller for small, low cost multirotor unmanned aerial vehicles’, Journal of Intelligent & Robotic Systems 74(1), 193–207.

Poikonen, S. & Golden, B. (2020), ‘Multi-visit drone routing problem’, Computers & Operations Research 113, 104802.

Poikonen, S., Wang, X. & Golden, B. (2017), ‘The vehicle routing problem with drones: Extended models and connections’, Networks 70(1), 34–43.
Sallouha, H., Azari, M. M. & Pollin, S. (2018), Energy-constrained uav trajectory design for ground node localization, in ‘2018 IEEE Global Communications Conference (GLOBECOM)’, IEEE, pp. 1–7.

Sambo, Y. A., Klaine, P. V., Nadas, J. P. B. & Imran, M. A. (2019), Energy minimization uav trajectory design for delay-tolerant emergency communication, in ‘2019 IEEE International Conference on Communications Workshops (ICC Workshops)’, IEEE, pp. 1–6.

Sardellitti, S., Scutari, G. & Barbarossa, S. (2015), ‘Joint optimization of radio and computational resources for multicell mobile-edge computing’, *IEEE Transactions on Signal and Information Processing over Networks* 1(2), 89–103.

Schäffer, D., Moeini, M. & Wendt, O. (2019), ‘A hybrid vns/tabu search algorithm for solving the vehicle routing problem with drones and en route operations’, *Computers & Operations Research* 109, 134–158.

Shakerian, M., Rajabi, M. S., Tajik, M. & Taghaddos, H. (2022), ‘Hybrid simulation-based resource planning and constructability analysis of rcc pavement projects’, *arXiv preprint arXiv:2204.05659*.

Shakhatreh, H., Khreishah, A., Alsarhan, A., Khalil, I., Sawalneh, A. & Othman, N. S. (2017), Efficient 3d placement of a uav using particle swarm optimization, in ‘2017 8th International Conference on Information and Communication Systems (ICICS)’, IEEE, pp. 258–263.

Shetty, V. K., Sudit, M. & Nagi, R. (2008), ‘Priority-based assignment and routing of a fleet of unmanned combat aerial vehicles’, *Computers & Operations Research* 35(6), 1813–1828.

Siam, M., ElSayed, R. & ElHelw, M. (2012), On-board multiple target detection and tracking on camera-equipped aerial vehicles, in ‘2012 IEEE International Conference on Robotics and Biomimetics (ROBIO)’, IEEE, pp. 2399–2405.

Song, Q., Jin, S. & Zheng, F.-C. (2019), ‘Completion time and energy consumption minimization for uav-enabled multicasting’, *IEEE Wireless Communications Letters* 8(3), 821–824.

Sonmez, A., Kocyigit, E. & Kugu, E. (2015), Optimal path planning for uav’s using genetic algorithm, in ‘2015 International Conference on Unmanned Aircraft Systems (ICUAS)’, IEEE, pp. 50–55.

Stolaroff, J. K., Samaras, C., O’Neill, E. R., Lubers, A., Mitchell, A. S. & Ceperley, D. (2018), ‘Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery’, *Nature communications* 9(1), 1–13.

Tang, L. & Shao, G. (2015), ‘Drone remote sensing for forestry research and practices’, *Journal of Forestry Research* 26(4), 791–797.

Tennekes, H. (2009), *The Simple Science of Flight, Revised and Expanded Edition: From Insects to Jumbo Jets*, MIT press.
Teuliere, C., Eck, L. & Marchand, E. (2011), Chasing a moving target from a flying uav, in ‘2011 IEEE/RSJ International Conference on Intelligent Robots and Systems’, IEEE, pp. 4929–4934.

Thibbotuwawa, A., Bocewicz, G., Nielsen, P. & Zbigniew, B. (2019), ‘Planning deliveries with uav routing under weather forecast and energy consumption constraints’, IFAC-PapersOnLine 52(13), 820–825.

Thibbotuwawa, A., Nielsen, P., Zbigniew, B. & Bocewicz, G. (2018a), Energy consumption in unmanned aerial vehicles: A review of energy consumption models and their relation to the uav routing, in ‘International Conference on Information Systems Architecture and Technology’, Springer, pp. 173–184.

Thibbotuwawa, A., Nielsen, P., Zbigniew, B. & Bocewicz, G. (2018b), Factors affecting energy consumption of unmanned aerial vehicles: an analysis of how energy consumption changes in relation to uav routing, in ‘International Conference on Information Systems Architecture and Technology’, Springer, pp. 228–238.

Tran, D.-H., Vu, T. X., Chatzinotas, S., ShahbazPanahi, S. & Ottersten, B. (2020), ‘Coarse trajectory design for energy minimization in uav-enabled’, IEEE Transactions on Vehicular Technology 69(9), 9483–9496.

Troudi, A., Addouche, S.-A., Dellagi, S. & Mhamedi, A. E. (2018), ‘Sizing of the drone delivery fleet considering energy autonomy’, Sustainability 10(9), 3344.

Tseng, C.-M., Chau, C.-K., Elbassioni, K. M. & Khonji, M. (2017), ‘Flight tour planning with recharging optimization for battery-operated autonomous drones’, CoRR, abs/1703.10049.

Van Huynh, D., Do-Duy, T., Nguyen, L. D., Le, M.-T., Vo, N.-S. & Duong, T. Q. (2021), ‘Real-time optimised path planning and energy consumption for data collection in uav-aided intelligent wireless sensing’, IEEE Transactions on Industrial Informatics.

Wai, R.-J. & Prasetya, A. S. (2019), ‘Adaptive neural network control and optimal path planning of uav surveillance system with energy consumption prediction’, IEEE Access 7, 126137–126153.

Wang, X., Poikonen, S. & Golden, B. (2017), ‘The vehicle routing problem with drones: several worst-case results’, Optimization Letters 11(4), 679–697.

Wu, F., Yang, D., Xiao, L. & Cuthbert, L. (2019), ‘Energy consumption and completion time tradeoff in rotary-wing uav enabled wpcn’, IEEE Access 7, 79617–79635.

Wu, J., Zhang, D. & Pei, D. (2014), Autonomous route planning for uav when threats are uncertain, in ‘Proceedings of 2014 IEEE Chinese Guidance, Navigation and Control Conference’, IEEE, pp. 19–22.

Xu, J. (2017), Design perspectives on delivery drones, RAND London.
Yacef, F., Rizoug, N., Bouhali, O. & Hamerlain, M. (2017), Optimization of energy consumption for quadrotor uav, in ‘Proceedings of the International Micro Air Vehicle Conference and Flight Competition (IMAV), Toulouse, France’, pp. 18–21.

Yang, P., Cao, X., Xi, X., Du, W., Xiao, Z. & Wu, D. (2019), ‘Three-dimensional continuous movement control of drone cells for energy-efficient communication coverage’, *IEEE Transactions on Vehicular Technology* **68**(7), 6535–6546.

Yang, Y., Zhang, X., Zhou, J., Li, B. & Qim, K. (2022), ‘Global energy consumption optimization for uav swarm topology shaping’, *Energies* **15**(7), 2416.

You, C., Huang, K. & Chae, H. (2016), ‘Energy efficient mobile cloud computing powered by wireless energy transfer’, *IEEE Journal on Selected Areas in Communications* **34**(5), 1757–1771.

Zeng, Y., Xu, J. & Zhang, R. (2019), ‘Energy minimization for wireless communication with rotary-wing uav’, *IEEE Transactions on Wireless Communications* **18**(4), 2329–2345.

Zeng, Y., Xu, X. & Zhang, R. (2018), ‘Trajectory design for completion time minimization in uav-enabled multicasting’, *IEEE Transactions on Wireless Communications* **17**(4), 2233–2246.

Zeng, Y. & Zhang, R. (2017), ‘Energy-efficient uav communication with trajectory optimization’, *IEEE Transactions on Wireless Communications* **16**(6), 3747–3760.

Zhang, J., Campbell, J. F., Sweeney II, D. C. & Hupman, A. C. (2021), ‘Energy consumption models for delivery drones: A comparison and assessment’, *Transportation Research Part D: Transport and Environment* **90**, 102668.

Zhang, J., Jia, L., Niu, S., Zhang, F., Tong, L. & Zhou, X. (2015), ‘A space-time network-based modeling framework for dynamic unmanned aerial vehicle routing in traffic incident monitoring applications’, *Sensors* **15**(6), 13874–13898.

Zhang, J., Zhou, L., Tang, Q., Ngai, E. C.-H., Hu, X., Zhao, H. & Wei, J. (2018), ‘Stochastic computation offloading and trajectory scheduling for uav-assisted mobile edge computing’, *IEEE Internet of Things Journal* **6**(2), 3688–3699.

Zhou, F., Wu, Y., Sun, H. & Chu, Z. (2018), Uav-enabled mobile edge computing: Offloading optimization and trajectory design, in ‘2018 IEEE International Conference on Communications (ICC)’, IEEE, pp. 1–6.

Zorbas, D., Razafindralambo, T., Guerriero, F. et al. (2013), ‘Energy efficient mobile target tracking using flying drones’, *Procedia Computer Science* **19**, 80–87.