An Optimization Perspective on the Interactions Between Models in the Internet of Drones

Hazim Shakhatreh, Wa'ed Malkawi, Ala Al-Fuqaha

***Abstract*—Unlike terrestrial wireless stations, using drones as aerial wireless stations allows for improved wireless services due to their 3D mobility. Therefore, model interactions play a pivotal role in determining the locations and trajectories of drones and their performance. In this paper, we discuss the interactions between models in the Internet of drones under different real-life scenarios. These models include: the channel path loss models, intelligent reflecting surface (IRS) placement model, solar energy model, wireless power transfer (WPT) model, and power consumption model. Moreover, we discuss learned lessons and highlight future research directions relevant to these models.**

***Index Terms*—Drones, optimization techniques, trade-off models, channel path loss, solar energy, wireless power transfer, wireless networks.**

INTRODUCTION

THe use of drones is becoming increasingly popular in providing a variety of wireless services, including data collection and wireless power transfer (WPT) in Internet of Things (IoT) networks, providing wireless coverage for remote areas, remote sensing, and cooperating with terrestrial wireless networks to enhance wireless coverage. During a specific task for a drone in a wireless network, it is important to consider the trade-off models related to the service that a drone will provide. These trade-off models will play an essential role in determining the location and trajectory of a drone and its performance quality. Flight time, power consumption, resource usage, and performance are frequently trade-offs during design optimization for drone operations in the Internet of drones. To achieve the proper balance of these factors for drone operations in the Internet of drones, we need to understand the trade-off models for drones. For instance, using a drone at high altitudes will provide a high probability of line-of-sight (LoS) wireless channels with ground users, enhancing a drone's coverage. On the other hand, it will cause high power consumption for a drone, minimizing a drone's flight time.

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There are significant differences between the use of aerial and terrestrial base stations in wireless networks. First, we must choose the drone's position in the horizontal space as well as its altitude. Second, a terrestrial cell's coverage area is known in advance. Before solving the placement problem, it is unknown what a drone's coverage area is because it depends on its 3D placement. Finally, the drone's mobility enables it to move to wherever the demand is, as opposed to a terrestrial cell, which must wait for the demand to approach it. As a result, it is important to identify the coverage area of a drone that will bring in the most benefits for the Internet of drones [1].

Path loss, a key consideration in the analysis and design of wireless channels, reflects the signal's loss of power. Due to the variations in propagation conditions, wireless aerial channels have different characteristics than wireless terrestrial channels. So, compared to traditional terrestrial wireless channel path loss models, drone path loss models frequently differ from those.

The expanded requirements for data transmission of wireless communication networks call for next-generation wireless networks to support aerial communications [2]. Beyond fifth-generation (B5G) communication technology and sixth-generation (6G) cellular communication both utilize intelligent reflecting surfaces, or IRSs. To take advantage of this cutting-edge technology for 6G communications, recent research studies integrate an IRS into the Internet of drones. Improved spectral and energy efficiency, increased network coverage, and flexible deployment are some of the benefits of integrating an IRS into the Internet of drones.

The drone-based communication systems' onboard batteries have a limited amount of energy storage capacity, which limits their operational duration. To recharge their batteries, the drones must frequently return to their charging stations. As a result, these designs cannot ensure reliable and long-lasting communication services, which could slow down system performance [3]. Due to their potential to achieve perpetual flight, solar-powered drones have drawn a lot of attention as a solution to these drawbacks.

By lowering the energy use of an IoT device during data transmission, using a drone as an aerial data collector can increase the lifetime of IoT networks, which necessitates an efficient trajectory design for a drone because it also influences the effectiveness of data collection. Another potential method for increasing the lifetime of IoT networks is WPT technology, in which a drone is utilized as a source of radio frequency signals for IoT device recharging.

Utilizing a drone as an aerial base station requires considering different parameters that affect the drone's power consumption and therefore its performance. These parameters include cruising velocity, power consumption of electronics, power transfer efficiency for motor and propeller, lift-to-drag ratio, drone mass, payload mass of communication devices, and altitude of the drone.

The authors in [4] present the system trade-offs in multi-drone networks. The trade-off analysis framework that is presented in this research work involves four steps. The first step is to define the goal of the drone network by defining the requirements that must be met. The second step involves identifying alternatives by formulating several courses of action. The third step is to compare the alternatives in terms of performance measures. The fourth step is to perform a sensitivity analysis of the final solution to test the sensitivity of the assumptions and confirm them. Moreover, they discuss the design requirements and their impacts on drone components and their major influence on drone performance.

In [12], [13], the authors revisit drone-enabled wireless communication's fundamental energy, delay, and throughput trade-offs. In particular, it is shown that energy consumption, delay, and throughput can be traded off using different drone trajectory models, shedding new light on the trade-offs that exist in terrestrial communication. The authors of [14] aim to study and analyze the currently existing drones in terms of last-mile and last-yard delivery possibilities. Numerical results and linear relationships between drone energy efficiency, takeoff weight, and payload are presented. The main contribution of this study is to discuss the tradeoffs among drone last-yard delivery constraints, safety, sustainability, and logistical capabilities.

In [15], the authors present a comprehensive analysis of the trade-offs between the key drone deployment parameters: beamwidth, height, and coverage radius. They also provide a mathematical model to estimate the received signal strength at any distance from the antenna boresight as a function of altitude and antenna beamwidth. The analysis has been extended to multiple drones, and a new multi-drone packing scheme is proposed for wireless coverage, which offers several advantages over previous approaches.

However, the current research works [4], [12]–[15] do not consider the interactions between trade-off models in the Internet of drones for different real-life scenarios such as channel path loss, IRS placement, solar energy, WPT, and power consumption. In this research work, motivated by these scenarios, we discuss the interactions between models in the Internet of drones under different real-life scenarios. We also present a comparison among these models. Moreover, we discuss the lessons learned and future research directions of these models.

The remainder of this research work is organized as follows. In Section II, we discuss the methodology that is utilized in this research work. In Section III, we present the trade-off in path loss models for the air-to-ground scenario in urban environments, the air-to-ground scenario in millimeter-wave (mmWave) wireless networks, the outdoor-to-indoor scenario, and the terrestrial cellular base station-to-drone scenario in suburban environments. In Section IV, we discuss the trade-off in the IRS placement model. In Section V, we present the trade-off in the solar energy model. In Section VI, we discuss the trade-off in the WPT model. In Section VII, we present the trade-off in the power consumption model. In Section VIII, we present a comparison of trade-off models. In Section IX, we discuss the lessons learned and highlight future research directions relevant to these models. Section X concludes the study.

METHODOLOGY

In this section, we discuss the methodology that is utilized in this research work. As we mentioned before, the Internet of drones can be utilized in different real-life scenarios. The performance of each scenario can be modeled as a mathematical equation to help understand the parameters affecting the performance, and also to discover new features of the scenario.

Many research studies focus on a single trade-off model to determine a placement for a drone. For instance, the drone can be utilized to provide wireless coverage for ground wireless devices in disaster situations. At high altitudes, there is a greater chance of LoS connections, but there is also a greater path loss between a wireless device and a drone. While there is a low chance of LoS connections and the path loss decreases at low altitudes. Therefore, there is an optimal placement for a drone that balances the probability of LoS connections and path loss. How about if this aerial station is a solar-powered drone? In addition to considering the quality of providing wireless coverage, we need to consider the captured solar energy which is also affected by the placement of a drone.

In this research work, we discuss the interactions between different models in the Internet of drones under different real-life scenarios. Table 1 demonstrates the mathematical models and parameters of these models in the Internet of drones that have been utilized in this research work. We focus on how trade-offs occur among these models when the placement of a drone changes.

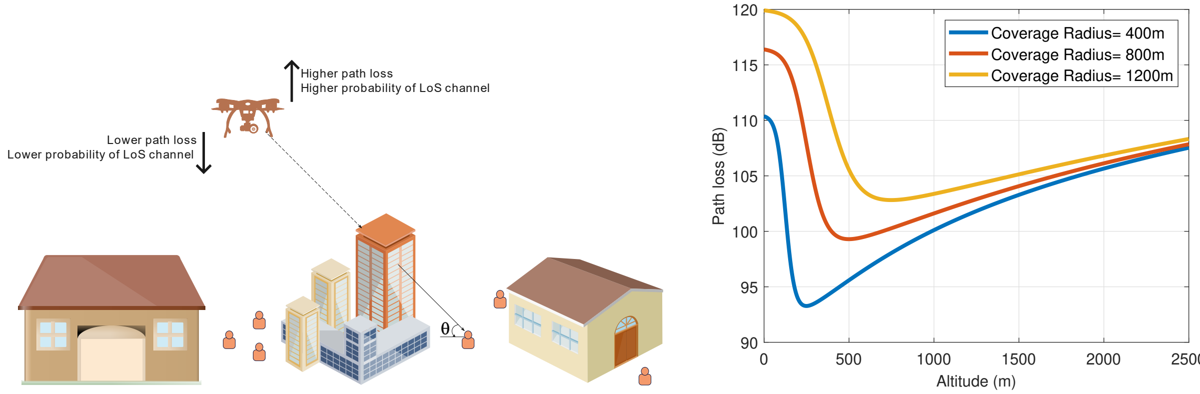
TABLE I: Mathematical models and parameters of the trade-off models in the Internet of drones.

Model type	Reference	Mathematical model	Parameters
Air-to-ground path loss model for drones in urban environments	[5], [6]	$P_{LoS} = \frac{1}{1+\alpha.exp(-\beta[\theta-\alpha])}$ $L = P_{LoS}L_{LoS} + (1-P_{LoS})L_{NLoS}$	P_{LoS}: probability of having LoS α and β: constant values which depend on the environment θ: elevation angle L: average path loss L_{LoS}: average path loss for LoS L_{NLoS}: average path loss for NLoS
Air-to-ground path loss model for drones in mmWave wireless networks	[7]	$P_{LoS} = exp(-\lambda g_B \frac{r_i(h_B-h_R)}{(h_D-h_R)})$ $L = P_{LoS}L_{LoS} + (1-P_{LoS})L_{NLoS}$	λ: density of blockers g_B: diameter of blockers r_i: 2D distance between the drone and the receiver h_D: height of the drone h_R: height of the receiver h_B: height of the blocker
Outdoor-to-indoor path loss model	[8]	$L = L_F + L_B + L_I = (wlog_{10}d_{3D} + wlog_{10}f + g_1)$ $+(g_2 + g_3(1-cos(\theta))^2) + (g_4 d_{2D})$	L: total path loss L_F: free space path loss L_B: building penetration loss L_I: indoor loss w, g_1, g_2, g_3, and g_4: constant values d_{3D}: distance between the drone and the indoor user d_{2D}: distance between the building wall and the indoor user f: carrier frequency θ: incident angle
Path loss model of terrestrial cellular base station-to-drone for suburban environments	[9]	$L = 10\alpha log(d) + A(\theta-\theta_o)exp(-\frac{\theta-\theta_o}{B}) + \eta_o$ $+N(0, a\theta + \sigma_o)$	L: total path loss α: terrestrial path-loss exponent d: terrestrial distance from the base station A: excess path-loss scaler θ: depression angle θ_o: angle offset B: angle scaler η_o: excess path-loss offset N: gaussian random variable a: drone shadowing slope σ_o: drone shadowing offset
Solar energy model	[3]	$P = \begin{cases} \eta SG, & z \geq L_u \\ \eta SGe^{-\beta(L_u - z)}, & L_l \leq z < L_u \\ \eta SGe^{-\beta(L_u - L_l)}, & z < L_l \end{cases}$	P: electrical output power of solar panels η: energy harvesting efficiency S: equivalent area of the solar panels G: average solar radiation intensity on earth z: altitude of the drone β: absorption coefficient L_u: altitude of the upper boundary of the cloud L_l: altitude of the lower boundary of the cloud
WPT model	[10]	$P_T = \frac{(m_v + m_p)v}{370\eta r} + p$ $P_H = 13.0397H + 196.8490$ $P_C = \frac{p_r}{\mu}$	P_T: traveling power consumption P_H: hovering power consumption P_C: WPT consumption m_v: drone mass in kg m_p: drone payload in kg v: speed of the drone in km/h η: efficiency of power transfer for motor and propeller r: lift-to-drag ratio p: consumed power of electronics in kW H: altitude of the drone p_r: harvested power by IoT device μ: conversion efficiency
Power consumption model	[11]	$P^H = 13.0397H + 196.8490$ $E^V = -16.9396H^2 + 216.6944H - 157.9473$ $E^S = -516V^4 + 4298V^3 - 12804V^2 + 15816V - 6251$ $P^P = 0.001L^2 + 0.0416L + 236.62$	P^H: power consumption for hovering E^V: energy consumption for flying vertically up E^S: energy consumption with speed P^P: power consumption for payload H: relative altitude in meters V: speed of a drone in meters per second L: payload in grams

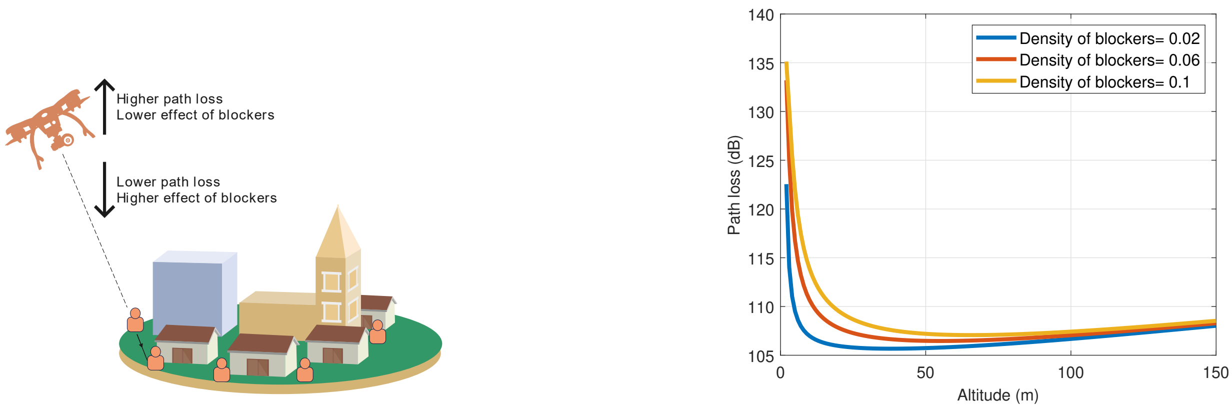
Path Loss Trade-off Model

The trade-off in the air-to-ground path loss model: The authors of [5], [6] present a model of air-to-ground path loss for drones in urban environments and discuss the optimal drone altitude for maximum wireless coverage. This model is appropriate for the following three frequencies: 0.7 GHz, 2 GHz, and 5.8 GHz. The probability of LoS between a drone and a wireless device in this model is a function of elevation angle θ and propagation condition parameters. The trade-off in this model is depicted in Figure (1.a). At high altitudes, there is a greater chance of LoS connections, but there is also a greater path loss between a wireless device and a drone. While there is a low chance of LoS connections and the path loss decreases at low altitudes.

The trade-off in the air-to-ground path loss model for drones in mmWave wireless networks: The authors of [7] present a model of air-to-ground path loss for drones in mmWave wireless networks. MmWave systems have many advantages, but they also have many technical challenges. One of these is the short wavelength for signals, wherein the LoS radio signal is obstructed by smaller objects. Therefore, it is essential to consider the obstacles when assessing the performance of the deployment of drones in mmWave



(a) The trade-off in the air-to-ground path loss model for drones in urban environments.[1]



(b) The trade-off in the air-to-ground path loss model for drones in mmWave wireless networks.[2]

Fig. 1: The trade-off in path loss models. This Figure shows that the lowest operating altitude is not the optimal altitude for a drone. Therefore, the altitude of a drone should be optimized to have optimal performance quality in the Internet of drones.

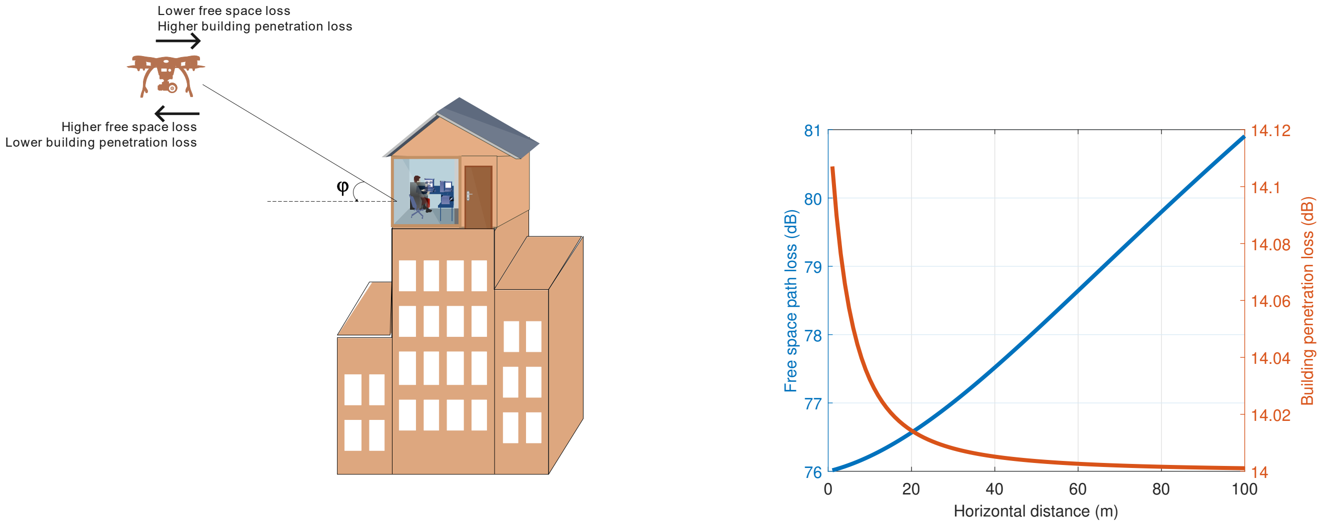
wireless networks. Compared to lower frequencies, mmWave frequencies present another challenge in that as the distance between a drone and a wireless device increases, the path loss increases noticeably. The trade-off in this model is depicted in Figure (1.b). When the density of blockers increases, the drone's altitude is increased to increase the probability of LoS connections while taking into account the growing path loss. On the other hand, an environment with a low density of blockers will allow a drone to fly at a low altitude to minimize path loss.

The trade-off in the outdoor-to-indoor path loss mode: According to the 5G infrastructure public-private partnership (5G PPP) technology board report about data consumption statistics, the vast majority of data usage occurs indoors [16]. The authors of [8] make use of an ITU-approved outdoor-to-indoor path loss model to provide wireless coverage from outdoor drones to indoor wireless devices. This model considers three types of losses, an indoor loss, a building penetration loss, and a free space path loss. The indoor loss is a function of the indoor distance between an indoor wireless device and a wall of a building. The building penetration loss is a function of an incident angle ϕ between a drone and an indoor wireless device. The free space path loss is a function of the distance between a drone and a wall of the building and the frequency. The trade-off in this model is depicted in Figure (2.a). A building penetration loss decreases while a free space path loss increases as the horizontal distance between a drone and a building wall increases. Similarly, as the horizontal distance between a building wall and a drone decreases, the free space path loss decreases and the building penetration loss increases.

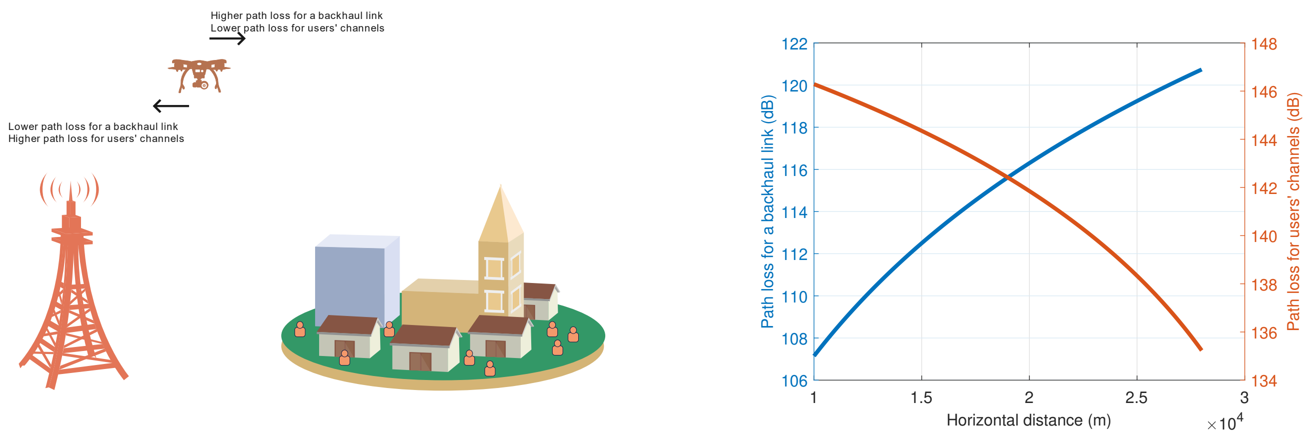
The trade-off in the path loss model of terrestrial cellular base station-to-drone for suburban environments:

[1]The parameters in numerical analysis are: the carrier frequency is 2 GHz, the average additional loss to the free space propagation loss for LoS and NLoS links are 1 dB and 20 dB respectively, and the parameter values α and β which depend on the environment are 9.6 and 0.28 respectively.

[2]The parameters in numerical analysis are: the carrier frequency is 28 GHz, the path loss model parameters for LoS are ($\alpha_L = 61.4$ and $\beta_L = 2$), the path loss model parameters for NLoS are ($\alpha_N = 72$ and $\beta_N = 2.92$), the height of a receiver is 1.3 meters, the height of a blocker is 1.7 meters, and the diameter of a blocker is 0.5 meters.



(a) The trade-off in the outdoor-to-indoor path loss model.[3]



(b) The trade-off in the path loss model of terrestrial cellular base station-to-drone for suburban environments.[4]

Fig. 2: The trade-off in path loss models. This Figure shows that the horizontal placement of a drone should be optimized to have optimal performance quality in the Internet of drones.

One possibility for providing the necessary backhaul links for drones is the terrestrial cellular networks. Therefore, extending traditional terrestrial cellular services to drones in future wireless networks is of great interest to the telecommunications sector and standardization organizations. The authors of [9] present a model of terrestrial cellular base station-to-drone path loss for suburban environments. The trade-off in this model is depicted in Figure (2.b). When the horizontal distance between a drone and a terrestrial base station increases, the path loss of a backhaul link from a terrestrial base station to a drone increases, while the path loss of channels between a drone and wireless devices decreases. Similarly, as the horizontal distance between a drone and a terrestrial base station decreases, the path loss of a backhaul link from a terrestrial base station to a drone decreases, while the path loss of channels between a drone and wireless devices increases.

IRS Placement Trade-off Model

In the field of wireless communications research, a new IRS concept has recently been introduced. The IRS is a 2D electromagnetic material surface that has been artificially created by humans, called a metasurface. It is made up of a vast number of passive scattering elements that have been given a unique physical structure. The electromagnetic characteristics

[3]The parameters in numerical analysis are: the carrier frequency is 2 GHz, the parameter values for the path loss model are ($w = 20$, $g_1 = 32.4$, $g_2 = 14$, $g_3 = 15$, and $g_4 = 0.5$), and the distance between the indoor user and the building wall is 10 meters.

[4]The parameters in numerical analysis are: the carrier frequency is 2 GHz, the terrestrial path-loss exponent is 3.04, the excess path-loss scaler is -23.29, the angle offset is -3.61, the angle scaler is 4.14, the excess path-loss offset is 20.7, the drone shadowing slope is -0.41, the drone shadowing offset is 5.86, the drone height is 150 meters, the average additional loss to the free space propagation loss for LoS and NLoS links are 1 dB and 20 dB respectively, and the parameter values α and β which depend on the environment are 9.6 and 0.28 respectively.

of how the incident radio frequency signals reflect off of each scattering component are changeable in a software-defined way. It is possible to freely control the radio frequency signals' reflecting phases and angles to synchronize phase control of all scattering components to achieve the desired multipath effect. In particular, to increase the received signal power or decrease interference, the reflected radio frequency signals can be added coherently or destructively. The range of user needs that can be supported by wireless systems with IRS will be greater, including more secure data transmissions, reduced power consumption, expanded coverage, and increased data rate [17].

It is challenging to support drones with high transmission power while reducing inter-cell interference. Inter-cell interference in the aerial region is a problem that IRSs effectively address and provide the wireless environment with a high degree of design freedom. The elevation angle of a drone, or the angle formed by the base station-drone link and the horizontal plane, determines the level of interference in the adjacent cells. A base station main beam spreads horizontally when the elevation angle is small. As a result, drones in the neighboring cell experience greater interference power. To prevent this, IRSs are placed inside each cell to control how signals are reflected and prevent them from penetrating adjacent cells, as depicted in Figure 3. To offer precise directivity in the base station-IRS-drone link and reduce the transmission power used in the drone's direct connection to a base station, the base stations and IRSs work together to perform beamforming. Drones that are close to or in its line of sight are subject to severe interference because of the base station-drone link's powerful transmission power. Instead of lowering the base station-drone link gain to prevent interference in the neighboring cells, the base station-IRS-drone link's high gain transmission will prevent the spread of transmitted signals over a wide area [18].

The trade-off in the IRS placement model: There is a key trade-off in the IRS placement model. Base station-drone direct links can cover a larger area when a cell boundary and an IRS are close to one another, which causes the drone that a base station serves to have a small elevation angle. Consequently, the base station-drone link's interference with a different drone in the adjacent cell gets high. The IRS must serve a drone at a smaller elevation angle when there is a greater distance between it and the cell boundary, which results in more interference from the base station-IRS-drone link.

Solar Energy Trade-off Model

Fixed-wing drones can carry solar cells and utilize solar energy. Utilizing a solar storage system can significantly increase drones' endurance while reducing fuel consumption.

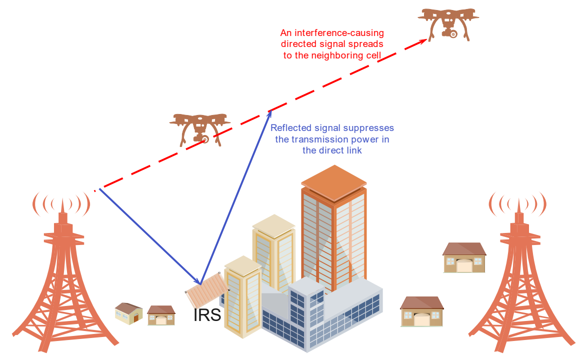


Fig. 3: Interference mitigation using IRS in the Internet of drones.

Therefore, it appears that the hybridization of the power supply system, which combines multiple power sources, is the best option to ensure a high level of drone endurance. The use of photovoltaic (PV) generation systems in unmanned vehicles, such as drones, is getting a lot of attention. If a battery is set up as a form of energy storage to power a drone during the night or in the event of sun availability, then a drone equipped with PV arrays can fly indefinitely. Drones that run on solar power are frequently used for high-altitude, long-endurance (HALE) applications. For solar-powered drones to receive the most light energy, their wings must be large [19].

The trade-off in the solar energy model: The drone's flight altitude affects how much solar energy is captured. A reduced flux of solar energy is received at the solar cell due to the solar energy's intensity significantly decreasing when light passes through clouds. As a result, drones that are above clouds typically have a higher capacity to capture solar energy than drones that are below clouds. Since more energy could be collected, a drone always prefers to fly at a higher altitude. On the other hand, more path loss for wireless communication channels is caused by higher flight altitudes for drones. The trade-off in this model is depicted in Figure 4.

WPT Trade-off Model

Recently, IoT networks have gained popularity because they can significantly enhance the quality of human life in different applications, such as environmental surveillance, smart healthcare, and smart cities. By 2025, it is estimated that there will be 25 billion IoT devices deployed for a wide variety of applications. Due to the limited radio resources, such a large number of devices with wireless connectivity will put more strain on the current communications infrastructure. Additionally, since IoT devices are typically randomly distributed, it is difficult to gather the data they generate for further processing. Using drones as data collectors in IoT

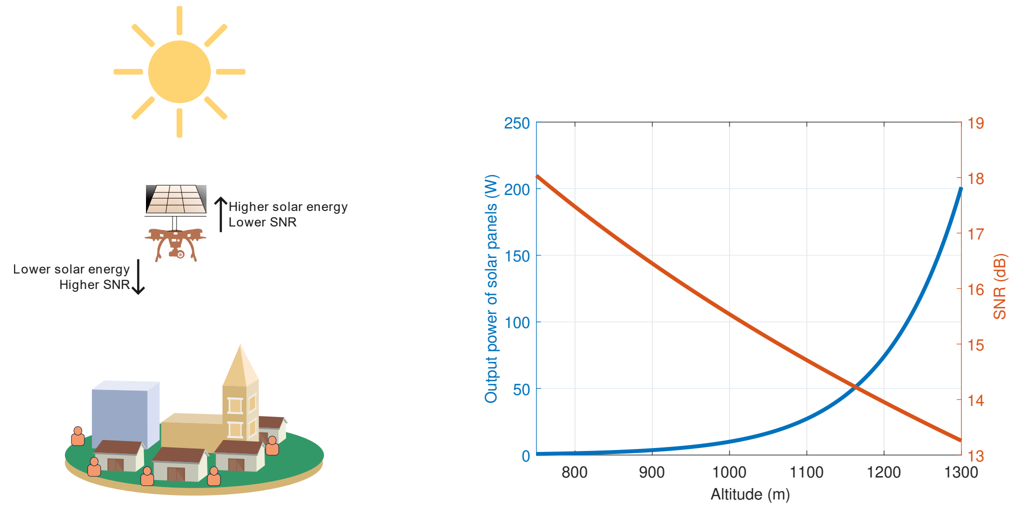


Fig. 4: The trade-off in the solar energy model. This Figure shows that the altitude of a drone should be optimized to have a balance between the captured solar energy and the SNR.[5]

networks can significantly improve the performance of data collection due to the advancement of drone technology and the equipments used for communication has become smaller.

When designing a reliable and robust drone-enabled IoT network, the energy problem poses a significant challenge because IoT devices are usually deployed in locations with unstable power sources or difficult access. Radio-frequency WPT technology has been suggested as a solution to offer low-power IoT devices a dependable energy supply to overcome this challenge. WPT uses electromagnetic waves to transmit radiation-based energy from a drone to an IoT device. The channel between a drone and an IoT device, however, can have a significant impact on WPT efficiency. Therefore, we need to minimize the distance between a drone and an IoT device and/or create LoS links to ensure WPT's performance [20].

The trade-off in the WPT model: The trade-off in the WPT model is illustrated in Figure 5. When the hovering time of a drone over an IoT device increases, more data is collected from an IoT device, and more energy is transferred to an IoT device, while the flight time of a drone decreases to cover the other IoT devices. Similarly, when the hovering time of a drone over an IoT device decreases, less data is collected from an IoT and less energy is transferred to an IoT, while the flight time of the drone increases to cover the other IoT devices.

Power consumption trade-off model

Automation research must address three key issues to make drone tasks feasible in the Internet of drones. These key issues are drone coordination, localization and navigation, and drone design. Robust coordination will be needed to manage thousands of drone agents in the air, sharing resources like charging stations. Because so many platforms already exist that support GPS, localization and navigation may seem like problems that have been solved. However, using drones in various operating environments, in changing and unstructured environments, will necessitate the integration of sensors and positioning systems still in development. Drone design entails developing machines that are reliable, capable of operating in a variety of environments, efficient, can hover, and can operate in a wide range of conditions. This is a significant undertaking that will require creativity and contributions from scientists in various fields [10].

Despite growing popularity, a number of obstacles prevent drone applications from reaching their full potential. A significant disadvantage of drones is their short battery life. The typical drones are electric motorized vehicles with finite-life onboard batteries. Most drone applications can't take advantage of their full potential as a result. Planning drone missions so that there is minimal power consumption will help to overcome the limited flight time that drones have due to their short battery lives. Energy-efficient drone trajectory planning is required for drone applications. Identifying and reducing actions that use a lot of power is crucial for achieving

[5]The parameters in numerical analysis are: the energy harvesting efficiency is 0.4, the equivalent area of the solar panels is 1 m^2, the average solar radiation intensity on earth is 1367 W/m^2, the altitudes of the upper and lower boundaries of the cloud are 700 meters and 1400 meters respectively, the absorption coefficient modeling the optical characteristics of the cloud is 0.01, the carrier frequency is 2 GHz, the average additional loss to the free space propagation loss for LoS and NLoS links are 1 dB and 20 dB respectively, the parameter values α and β which depend on the environment are 9.6 and 0.28 respectively, the noise power is -120 dBm.

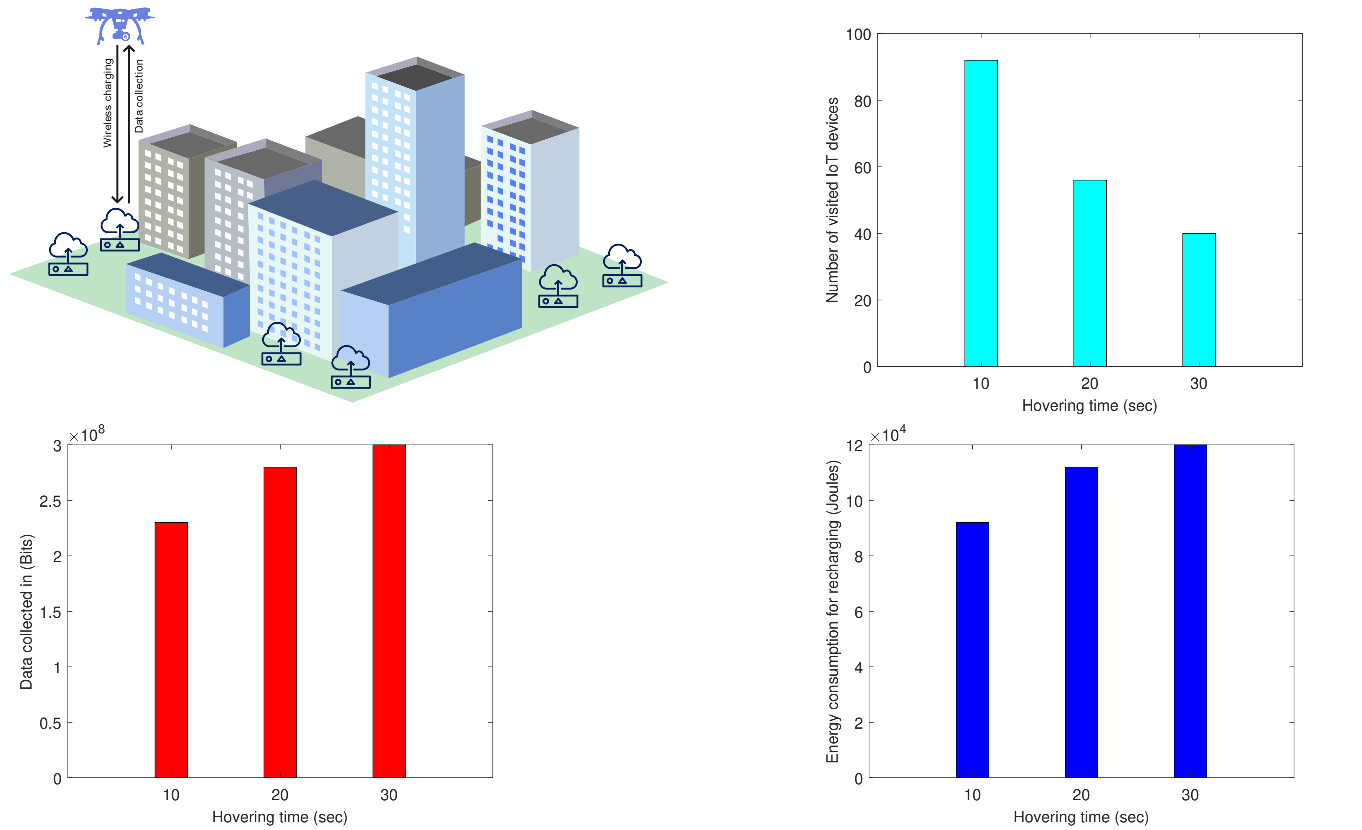


Fig. 5: The trade-off in the WPT model. This Figure shows that the hovering time of a drone over an IoT device should be optimized to have an efficient trajectory for data collection and WPT operations in IoT networks.[6]

energy-efficient drone missions. Following an accurate and thorough model of drone power consumption is crucial for this. It would be possible to plan drone flight missions and recharge batteries more effectively with the help of a precise model of battery performance in various scenarios [11].

The trade-off in the power consumption model: The trade-off in the power consumption model is illustrated in Figure 6. The movement type, speed, and payload parameters will be crucial in this model, while the power requirement for communication can be regarded as insignificant. The total power consumed by onboard sensors and communication hardware is fixed and low.

A Comparison of Trade-off Models

To utilize drones as aerial base stations, we need to model the path loss for drone wireless channels for different frequency bands, different environments, and different scenarios. The altitude of a drone should be optimized to have optimal performance quality in the Internet of drones when wireless devices are outdoors. On the other hand, the horizontal placement of a drone should be optimized to have optimal performance quality in the Internet of drones when wireless devices are indoors or when considering the performance of a backhaul link with a ground base station.

In IRS-aided Internet of drones, the IRS placement should be optimized inside each cell to control how signals are reflected and prevent them from penetrating adjacent cells. For solar-powered drones, the altitude of a drone should be optimized to have a balance between the captured solar energy and the SNR.

In drone-enabled IoT networks, the hovering time of a drone over an IoT device should be optimized to have an efficient trajectory for data collection and WPT operations. On the other hand, the movement type, speed, and payload parameters will

[6] The parameters in numerical analysis are: the dimensions of the geographic area are $250m\ x\ 250m$, the number of IoT devices is 100, the energy capacity of the drone is 80 W.h, the drone payload is 2 k.g, the drone mass is 8 k.g, the speed of the drone is 1.8 km/h, the efficiency of power transfer for motor and propeller is 0.8, the lift-to-drag ratio is 3, the consumed power of electronics is 0.25 kW, the altitude of the drone is 5 meters, the power consumption of the drone during the recharging is 0.1 kW, the conversion efficiency is 0.5, and the data rate of each IoT device is 250 kbps.

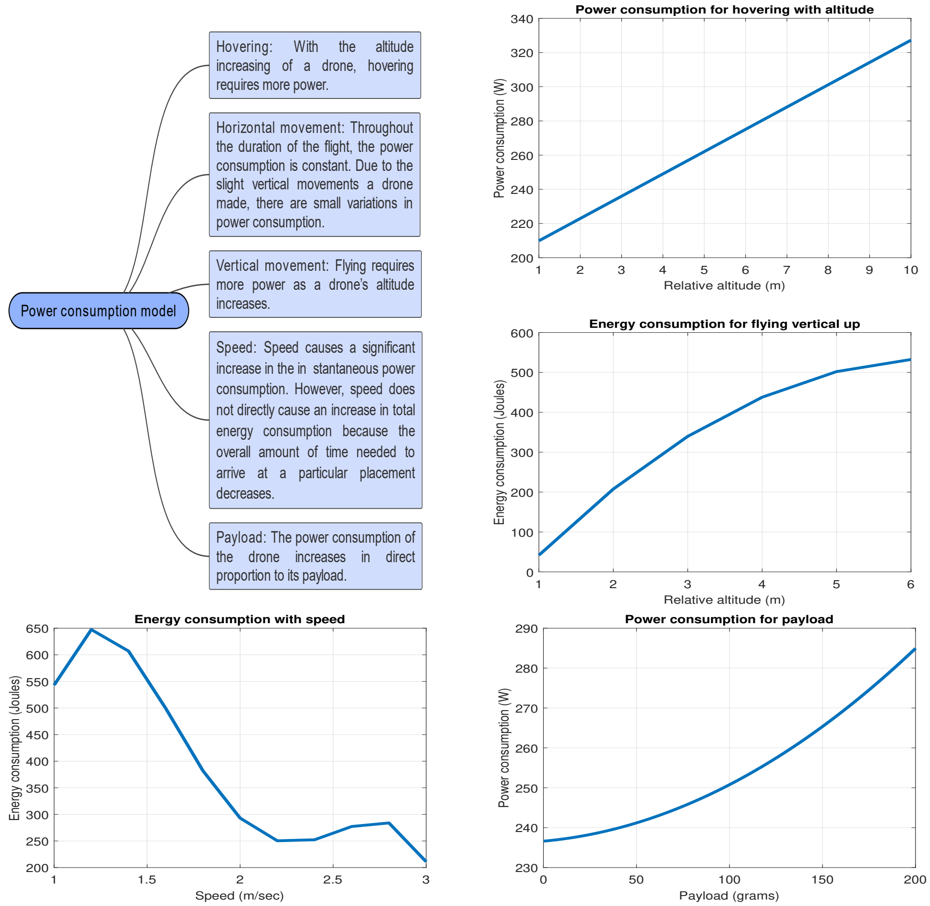


Fig. 6: The trade-off in the power consumption model. This Figure shows that the movement type, speed, and payload parameters are crucial to achieving energy-efficient drone missions.[7]

be crucial to achieving energy-efficient drone missions. Figure 7 summarizes the comparison among these models.

In Figure 8, we demonstrate how the vertical and horizontal movements of a drone affect the trade-off model in the Internet of drones. The models that are affected by the vertical movement are the air-to-ground path loss model, the air-to-ground path loss model for mmWave, the solar energy model, and the WPT Model. On the other hand, the outdoor-to-indoor path loss model and the path loss model of a terrestrial cellular base station are affected by horizontal movement. The models that are affected by the vertical and horizontal movements of a drone are the IRS placement model and the power consumption model.

Lessons Learned and Future Research Directions

In the following paragraphs, we summarize the learned lessons from our study and highlight future research directions that are relevant to the drone models:

- **Path Loss Trade-off Model:** Most of the proposed path loss models for drones are performed using simulation software. To make use of drones as aerial base stations, we need to conduct actual experiments to model the drones' path loss. These experiments should include different frequency bands, different environments, and different scenarios. These realistic path loss models will help telecommunications companies to appropriately use drones in future wireless networks. Moreover, additional experiments in various flight scenarios will aid in elaborating the stationary characteristics of the drone channels.
- **IRS Placement Trade-off Model:** A problem involving aesthetics is one of the real challenges in commercializing IRS-aided systems. The roofs or walls of buildings are typically where IRSs are installed. Consequently, an unannounced IRS deployment could ruin the appearance

[7] The parameters in numerical analysis are: the power consumption model for hovering with altitude is ($P = 13.0397H + 196.8490$), the energy consumption model for flying vertical up is ($E = -16.9396H^2 + 216.6944H - 157.9473$), the energy consumption model with speed is ($E = -516V^4 + 4298V^3 - 12804V^2 + 15816V - 6251$), and the power consumption model for payload is ($P = 0.001L^2 + 0.0416L + 236.62$) where H is a relative altitude in meters, V is the speed of a drone in meters per second, and L is a payload in grams.

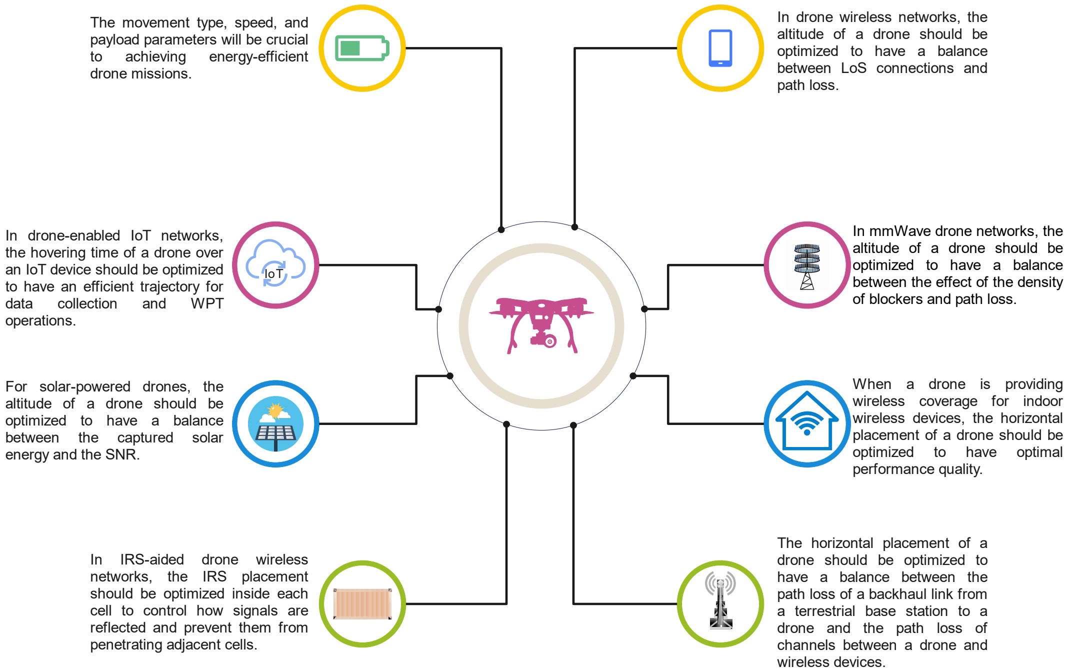


Fig. 7: A comparison of trade-off models. This Figure shows the crucial parameters for trade-off models in the Internet of drones.

of a location. To increase the signal's strength as it travels along a reflecting path before reaching users, IRS should also have a good propagation path free of obstacles. Therefore, the installation location constraints should be added to the problem of optimal placement for an IRS. Additionally, there is still much to be learned about how many IRSs are required to accommodate users' high levels of mobility. MmWave and sub-terahertz (THz) frequencies, reflection efficiency of IRSs, and security vulnerabilities of IRSs are possible research opportunities for IRS-aided drone applications in the future.

- **Solar Energy Trade-off Model:** The performance of a single source-based power supply system for a drone will be severely constrained due to its poor performance in a variety of real-life scenarios. As a result, when designing a drone's electric power system, power sources with different properties are increasingly being hybridization. Choosing a hybrid power source is highly influenced by the weight/duration requirements of the drone tasks. Possible research opportunities to enhance energy harvesting for drones include mechanical energy harvesting using flapping wing motion and wind-induced vibration.
- **WPT Trade-off Model:** Using a drone as a flying data collector and an aerial charger using WPT technology can prolong IoT networks' lifetime by reducing the consumption of IoT devices' energy, which necessitates route planning for drones. Drones' flight times can be prolonged, which will improve their performance in IoT networks, by utilizing the WPT technology in their interaction with other energy storage systems, such as the power transfer among drones and electric vehicle-drone charging systems. To help autonomously update drone trajectories online, reinforcement learning tools may present research opportunities.
- **Power Consumption Trade-off Model:** The weight and size of the equipment that drones can carry are constrained. Most power loggers that are available commercially are either too heavy or too big to be carried by a drone. The GPS signal strength is essential for controlling a drone to achieve the desired trajectory. For a drone, a 3D GPS with a sufficient number of satellites visible is required. On the availability and strength of GPS signals, environmental factors have a significant impact. The external payloads on a drone must be perfectly balanced when conducting experiments with payloads. The flight and a secure landing depend on this. It's crucial to have good wind conditions. The drone needs to have favorable wind conditions because it struggles to do missions in windy conditions. This has a significant impact on the drone's power usage as well. Investigating the similarities and differences between the power consumption models of various drone types would be a possible future research

Fig. 8: A comparison of trade-off models based on vertical and horizontal movements of a drone. This Figure shows how the type of drone's movement affects the trade-off model in the Internet of drones.

direction.

- **The Joint Trade-off of Drone Models:** Many research studies focus on a single trade-off model to determine a 3D placement for a drone. Considering the joint trade-off models for drones in wireless networks will enhance the performance quality of these vehicles. To clarify the joint trade-off of these models, the benefits and drawbacks are presented when the vertical and horizontal placements of a drone are changed. When a drone's altitude increases, the probability of LoS channels increases, the effect of blockers decreases, and the capture of solar energy increases. On the other hand, when a drone's altitude decreases, the path loss decreases, the SNR increases, the quality of WPT and data collection increases, and the lifetime of a drone increases. When a drone's horizontal placement changes, the operators of wireless networks should consider many issues such as the quality of service for indoor wireless devices, the proper balance between the path loss for a backhaul link and the path loss for wireless devices, and the IRS placement.

CONCLUSION

The interactions between trade-off models in the Internet of drones for different real-life scenarios are discussed in this article. These models are the channel path loss model, IRS placement model, solar energy model, WPT model, and power consumption model. We also present a comparison among these models. Furthermore, the lessons learned and future research directions of these models are discussed. Utilizing these models with machine learning and artificial intelligence techniques is a promising future direction for research.

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