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A Survey on the Design Aspects and Opportunities in Age-Aware UAV-Aided Data Collection for Sensor Networks and Internet of Things Applications

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Abstract: Due to the limitations of sensor devices, including short transmission distance and constrained energy, unmanned aerial vehicles (UAVs) have been recently deployed to assist these nodes in transmitting their data. The sensor nodes (SNs) in wireless sensor networks (WSNs) or Internet of Things (IoT) networks periodically transmit their sensed data to UAVs to be relayed to the base station (BS). UAVs have been widely deployed in time-sensitive or real-time applications, such as in disaster areas, due to their ability to transmit data to the destination within a very short time. However, timely delivery of information by UAVs in WSN/IoT networks can be very complex due to various technical challenges, such as flight and trajectory control, as well as considerations of the scheduling of UAVs and SNs. Recently, the Age of Information (AoI), a metric used to measure the degree of freshness of information collected in data-gathering applications, has gained much attention. Numerous studies have proposed solutions to overcome the above-mentioned challenges, including adopting several optimization and machine learning (ML) algorithms for diverse architectural setups to minimize the AoI. In this paper, we conduct a systematic literature review (SLR) to study past literature on age minimization in UAV-assisted data-gathering architecture to determine the most important design components. Three crucial design aspects in AoI minimization were discovered from analyzing the 26 selected articles, which focused on energy management, flight trajectory, and UAV/SN scheduling. We also investigate important issues related to these identified design aspects, for example, factors influencing energy management, including the number of visited sensors, energy levels, UAV cooperation, flight time, velocity control, and charging optimization. Issues related to flight trajectory and sensor node scheduling are also discussed. In addition, future considerations on problems such as traffic prioritization, packet delivery errors, system optimization, UAV-to-sensor node association, and physical impairments are also identified.

Keywords: Age of Information (AoI); drone; energy efficiency; information freshness; Internet of Things (IoT); scheduling; trajectory; unmanned aerial vehicle (UAV); wireless sensor networks (WSNs)

1. Introduction

Wireless sensor networks (WSNs), the Internet of Things (IoT), and unmanned aerial vehicle (UAV) technologies have many benefits and thus have been utilized in a huge variety of applications, including healthcare, disaster management, agriculture, and transportation. In WSNs, sensors are deployed for data collection and aggregation. They are also useful within the more advanced IoT networks (which help to connect different smart entities) for sensing, actuation, and computations through the Internet [1,2]. Data generated by these sensors and smart devices can be used in the aforementioned application domains [3], including smart grids [1]. Sensor nodes in WSNs and IoT are mainly characterized by limited transmission range and energy constraints; therefore, they cannot transmit sensed data over large distances efficiently. This motivates the deployment of UAVs for relaying sensed data in WSNs and IoT (i.e., UAV-assisted WSN/IoT) to their required destination. In other words, UAVs fly to collect data sensed by WSNs/IoT devices and transmit that data to the data center or base station (BS). However, one of the main challenges of UAVs' deployment in WSN/IoT networks is to effectively send the required data in real-time. Due to the numerous limitations of WSNs and IoT themselves, there have been many studies investigating the many aspects that could be enhanced to ensure the data's freshness using the Age of the Information (AoI) metric. The AoI is the amount of time that elapses after the generation of the most recent update before it is received at the destination. This study investigates a few key components of AoI optimization, including the planning and designing of the UAV's trajectory.

1.1. Applications of UAV-Aided Data Collection for WSNs/IoT

UAV-assisted WSN/IoT applications are abundant in the literature, and some are time-critical. Such applications can be categorized into monitoring, industrial, environmental, smart city, data gathering, security, health, agriculture, and disaster management. Figure 1 ((a) https://www.flickr.com/photos/mikecogh/22339765443/ accessed on 18 January 2023; (b) Picture by DFID—UK Department for International Development (see https://www.flickr.com/photos/dfid/17313224411/ accessed on 18 January 2023); (c) https://www.rawpixel.com/image/5912255 accessed on 18 January 2023; (d) Picture by Frankhöffner, https://commons.wikimedia.org/wiki/File:Md4-1000_microdrones_frank.jpg accessed on 18 January 2023; (e) https://commons.wikimedia.org/wiki/File:4X-UHJ_Agridrones_d.jpg accessed on 18 January 2023) depicts deployments of UAVs in real-world scenarios. UAV-based monitoring applications have huge prospects. For instance, ref. [1] studied the use of IoT for monitoring physical phenomena (e.g., temperature, humidity, etc.) in a geographic area. Similarly, refs. [2,3] considered an environmental monitoring application, while [4] is applicable in agriculture, health, safety, and industrial data monitoring. The work in [5] is targeted at a post-disaster early warning scenario, while environmental sensing is considered in [6,7], and the monitoring of time-stamped status updates is studied in [8,9]. The identification, exposition, and understanding of the technical design aspects and considerations for UAV-assisted IoT architecture targeted at these applications would help researchers and network designers to make informed decisions with respect to alternative architectures, trade-offs, and techniques to achieve target design objectives, thus enhancing the efficiency of data gathering in these applications.

Figure 1. Illustration of UAVs deployed in different applications.

1.2. Objectives and Contributions of This Paper

This paper primarily aims to identify the fundamental design considerations in UAV-assisted WSN/IoT networks for ensuring the information reaches its destination within the least tolerable time. The following research questions are formulated to address the research aim and objectives of this study:

- What are the pertinent architectural design considerations identified from the previous works on AoI minimization in UAV-assisted data collection for WSNs/IoT?
- What are the concerning issues related to the identified fundamental design aspects of AoI minimization in the literature on UAV-assisted WSNs/IoT?
- What are some potential study areas of AoI-aware UAV-assisted WSN/IoT network architectures?

Given the above, this paper presents three main contributions:

- A comprehensive study of previous work on age-aware UAV-assisted WSNs/IoT for data gathering applications, focusing on the technical design aspects. This includes the classification of the studied works into three major categories and 17 subcategories, presenting illustrations on some of the common architectures, and identifying limitations and significant results in these works.
- A discussion on pertinent issues related to the identified design aspects, namely energy management, flight trajectory, and UAV/SN scheduling.
- A discussion of potential research directions in this field towards motivating further research and problem-solving in this area.

1.3. Related Surveys

The study provided in this paper is unique in many aspects and thus differs from the existing review articles on UAV-based wireless communication applications. For instance, a conference paper [10] focused on distributed processing applications for UAVs, while [11] reviewed 3D wireless ad hoc and sensor networks. The authors in [12] surveyed the use of multiple UAVs for persistent surveillance and [13] studied the use of UAVs for civil applications. On a similar note, UAV applications for civil infrastructure are surveyed in [14]. The authors of [15–17] focused on UAV-assisted disaster management and [18] reviewed UAV-based intelligent transport for smart cities, while [19] studied UAV swarm and nanosat applications and architectures. The collaborative deployment of UAVs and WSNs for monitoring is reviewed in [20], while autonomous inspection via multi-UAV is studied in [21] and UAV applications in WSNs are reviewed in [22]. The authors in [23] surveyed green UAVs for public safety applications, while Okada et al. [24] reviewed the deployment of aerial wireless relays for emergencies. Generally, FANET technologies and applications have been studied in [25]. Key issues related to UAV data collection in the IoT were reviewed by Yang et al. [26], while UAV applications for precision agriculture were surveyed in [27]. The authors in [28] focused on viticulture, while UAV-based air quality monitoring was discussed in [29]. In [30], the authors reviewed mobile edge computing in UAV networks, while [31] studied air–ground integrated edge systems. For future wireless technologies, ref. [32] studied UAV softwarization applications and trends, while the use of UAVs for 5G and beyond was surveyed in [33]. Finally, the Internet of Flying Things (IoFT) was reviewed in [34]. Apart from the aforementioned, several other surveys have been published on UAVs (see Table 1). None of these studies thoroughly investigated the fundamental technical considerations in the subject of AoI minimization in UAV-assisted data gathering in WSN and IoT applications.

In relation to AoI-related studies, surveys on AoI have recently appeared in the literature with diverse focus areas. For instance, the concept of AoI and its optimization in wireless communication networks, in general, are discussed in [35] with some discussion on definitions, variants, sampling policies, packet management strategies, resource-constrained source nodes involving EH, and UAV-assisted sampling. The authors of [36] mainly focus on AoI in Ambient Intelligence (AmI) IoT networks, methods, metrics, and their queuing and scheduling policies. The authors in [37] focused on methods, metrics, and AoI optimization in low-latency cyber-physical systems and applications requiring timely status updates. In contrast to all the aforementioned surveys, this paper studies the literature on UAV-assisted data gathering in WSN/IoT applications with the goal of identifying the most fundamental design considerations/aspects, classifying them based on how they have been jointly considered, identifying critiques of some of these works based on the literature, and highlighting some of the challenges and future considerations in this area. Table 2 summarizes surveys related to AoI minimization in UAV-assisted data gathering.

On the contrary, the main focus of this paper is not on methods, algorithms, and assumptions related to this research field. Rather, this paper is meant to be an introductory survey for those planning to construct a similar network architecture or hypothesize the network performance, keeping in view different design considerations. It is worth noting, however, that we have also conducted a comprehensive study focusing on metrics, methods, assumptions, and other influencing factors on AoI minimization for UAV-assisted data gathering in WSN/IoT networks (refer to [38]).

Minimizing the AoI to facilitate the timely delivery and freshness of information involves complex design considerations of many elements, including flight (trajectory and altitude) control, scheduling of sensor nodes and UAVs, the association of sensor nodes with the UAV or with their cluster heads and selection points, UAV data collection mode selection, as well as energy-efficiency. Furthermore, issues such as network size, number of UAVs, channel conditions, and physical impairments also affect the AoI. Various architecture-specific assumptions and techniques that have been studied by researchers will also be highlighted in this paper.

Table 1. Summary of UAV-related surveys.

Ref	Year	Focus
[10]	2015	Distributed processing applications for UAVs
[11]	2014	3D wireless ad hoc and sensor networks
[12]	2014	The use of multiple UAVs for persistent surveillance
[13]	2016	UAV communication networks for civil applications
[14]	2016	UAVs for civil applications
[15]	2016	UAV-based disaster management applications and issues
[16]	2017	WSN- and multi-UAV-assisted disaster management
[17]	2017	UAV-based disaster prediction and management
[18]	2017	UAV-based intelligent transport for smart cities
[19]	2017	UAV-assisted disaster management
[20]	2019	Collaborative UAV-WSN for monitoring
[21]	2019	Autonomous inspection via multi-UAV
[22]	2020	UAV applications in WSNs
[23]	2019	Green UAV for public safety applications
[24]	2020	Aerial wireless relay for emergencies
[25]	2020	FANET technologies and applications
[26]	2020	UAV data collection in the IoT
[27]	2020	UAV applications for precision agriculture
[28]	2021	Viticulture
[30]	2020	Mobile edge computing in UAV networks
[31]	2020	Air–ground integrated edge systems
[32]	2020	UAV softwarization applications
[34]	2020	Internet of Flying Things
[33]	2021	UAV for 5G and beyond
[39]	2022	Micro UAV charging techniques
[40]	2022	Applications in disaster management
[41]	2022	Drone scheduling problems
[42]	2022	Drone-based logistics systems
[43]	2022	Farm monitoring and pesticide spraying
[44]	2022	Green UAV for 6G
[45]	2022	UAV path planning using optimization
[46]	2022	UAV for precision agriculture
[47]	2022	Computing for UAV-assisted 6G and Industry 4.0/5.0
[48]	2022	UAV-based forest health monitoring
[49]	2022	AI-enabled routing protocols for UAVs
[50]	2022	AI applied to path planning in UAV swarms
[51]	2022	Cyber security threats and solutions for UAVs
[52]	2022	Environmental monitoring
[53]	2022	UAV-assisted data collection for IoT
[54]	2022	AI-powered 3D deployment of drone BS
[55]	2022	Forest insect pests and disease monitoring

Table 1. *Cont.*

Ref	Year	Focus
[56]	2022	SDN solutions for drone detection and defense
[57]	2022	Resource optimization
[58]	2022	UAV placement optimization for 5G and beyond
[59]	2022	UAV-aided maritime communications
[60]	2022	Drone-assisted monitoring of atmospheric pollution
[61]	2022	UAV digital technologies for Construction 4.0
[62]	2022	UAV placement and trajectory optimization
[63]	2022	UAV deployment and trajectory
[64]	2022	Security threats to UAV-aided IoT applications
[65]	2022	AI meets UAVs for precision agriculture
[66]	2022	UAV placement and trajectory design optimization
[67]	2022	Physical layer security for UAVs
[68]	2023	UAV formation trajectory planning algorithms
[69]	2023	Drone routing for delivery systems

Table 2. Summary of AoI optimization surveys.

Ref	Year	Focus	Summary
[37]	2021	Low-latency cyber-physical systems	Provides an overview of the current state of the art in the design and optimization of low-latency cyber-physical systems and applications requiring timely status updates. It also describes the various methods and metrics used to evaluate the Age of Information (AoI) in a wide range of systems and explores the use of AoI optimization in cyber-physical applications.
[36]	2022	Ambient Intelligence (AmI) Internet of Things (IoT) networks	Provides a review on notations of AoI, parameters affecting AoI in IoT systems, and techniques for modeling AoI. No special attention was given to UAV-assisted IoT.
[35]	2023	Wireless communication networks in general	The paper provides a comprehensive survey of the Age of Information (AoI) in wireless networks and reviews current progress from an optimization perspective. This includes AoI definitions, optimal sampling policies, packet management strategies, scheduling policies, and potential future research directions for AoI research.
This paper	2023	Design considerations in age-aware UAV-IoT	The paper provides a comprehensive survey of the design aspects of Age of Information (AoI)-aware UAV-assisted IoT and its architectures.

1.4. Paper Organization

The rest of the paper is organized as follows: Section 2 outlines the methodology used in this study and provides a summary of the fundamental design aspects identified from the literature. Section 3 provides a brief background discussion on the concept of AoI and the typical UAV-aided WSN/IoT architectures. Section 4 thoroughly examines the fundamental design aspects of AoI minimization in UAV-assisted WSNs/IoT in the literature. Subsequently, Section 5 focuses on pertinent issues related to UAV-assisted WSNs/IoT design aspects for data-gathering applications. Particularly, Section 5.1 discusses energy efficiency and the affecting factors, Section 5.2 analyses the factors to optimize UAV trajectory, and Section 5.3 discusses the scheduling issues of IoT devices and UAVs. Section 6 discusses other challenges related to AoI minimization in UAV-assisted WSNs/IoT as well as proposes some future research directions. Finally, Section 7 concludes this paper. The complete meanings of the abbreviations and acronyms are provided in Abbreviations.

2. Methodology

A systematic literature review (SLR) method was adopted in this work. The SLR approach is typically utilized by researchers to perform an organized and thorough literature review. Such an approach has been widely used in the computer network and wireless communication domains as well as in [70–74]. Other forms of literature review approaches are usually devoid of rigor and tend to follow a freestyle rather than a predetermined process [75]. On the contrary, the SLR is distinct from other review methods as it adheres to certain scientific standards, and the process can be replicated [70,76]. Therefore, this study applies the SLR technique to study the past literature on AoI minimization in UAV-assisted WSN/IoT-based data-gathering applications as depicted in Figure 2. We applied a similar process to those observed in some of the previous SLR studies [70,71,77,78] to systematically report the findings on recent AoI-aware UAV-aided data collection for WSN/IoT application studies focusing on the architectural design aspects. Moreover, the approach of this study is congruent with our previous work in [38], although with different aims and objectives.

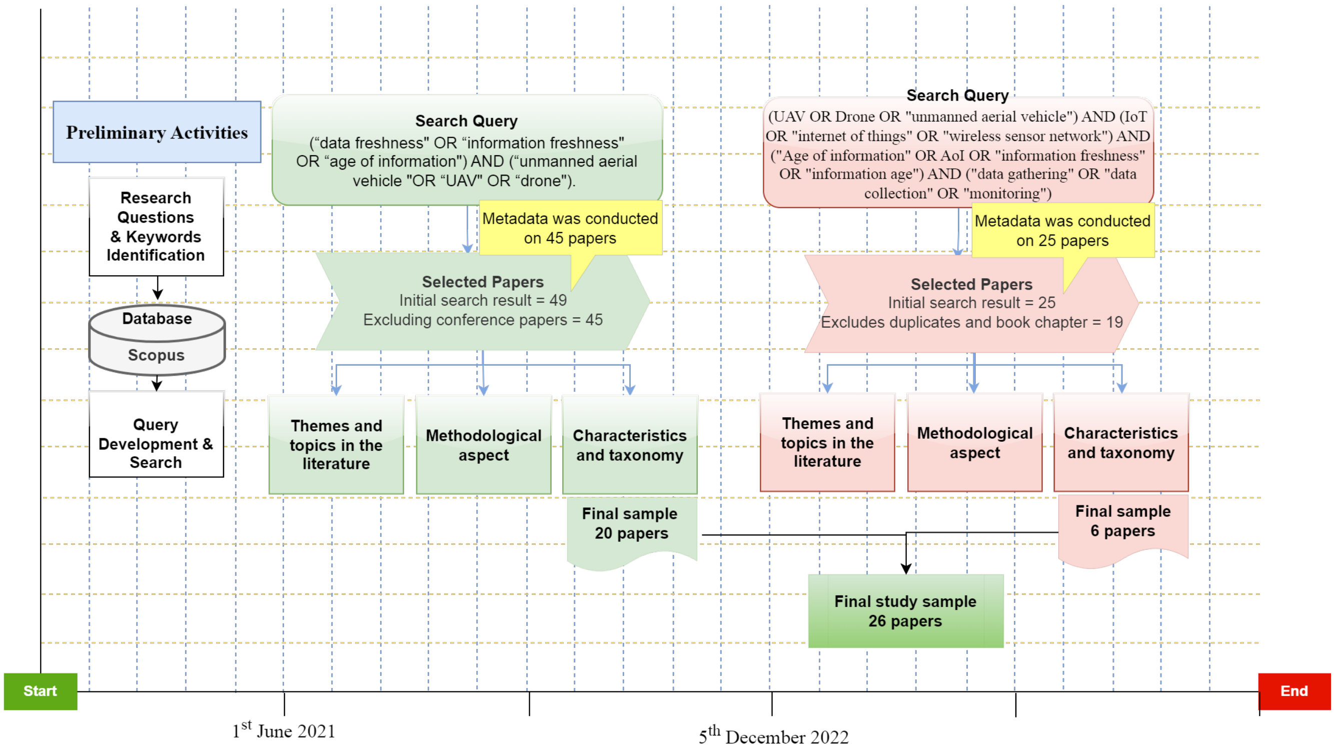

Figure 2. Literature search methodology.

In this paper, prior works on UAV-assisted data gathering [1,2,4,8,9,79–93] were studied following similar search procedure used in [38]. On the 5th of December 2022, we further investigated more recent references using the following search keywords in the Scopus database: ((UAV OR Drone OR "unmanned aerial vehicle") AND (IoT OR "internet of things" OR "wireless sensor network") AND ("Age of information" OR AoI OR "information freshness" OR "information age") AND ("data gathering" OR "data collection" OR "monitoring")) which yielded 25 results. After excluding these papers from certain criteria, another 6 articles were studied and included in this work (refer to Figure 2 for the summary of the SLR process). The exclusion criteria were as follows:

- Articles included in the initial results [1,85,93].

- Articles on UAV-IoT mobile edge computing (MEC) systems or those where UAVs have been used for computation [94–97].
- Article involving the use of UAVs for sensing [98].
- Articles in which the UAV is assumed to function as an aerial BS [99,100].
- Article in which the UAV is assumed to perform task assignment [101].
- Articles that do not assume the presence of BS [102,103].
- Article on covert communication [104].

The additional six articles of interest [3,5–7,105,106] were then also studied along with the selected 20 articles to identify the fundamental design considerations to minimize the time taken by the UAVs to collect sensed data from the sensor devices and transmit them to the data center or BS. Two fundamental design aspects have been identified: (1) UAV flight and trajectory (including altitude) [1,2,4,8,9,79–86,88–93] and (2) UAV scheduling [87]. In addition, energy management (including energy efficiency and energy consumption) is another major design consideration in AoI optimization. We refer to these three as primary design aspects. Figure 3 depicts these primary design aspects. Other important considerations have been identified in the study, albeit they are not as significant as the primary aspects. We refer to these as the secondary considerations, which include SN scheduling, mode selection, association, and sampling policies. For instance, [1,2,4,8,9,79–86,88–93] fall into the flight trajectory category (green color), while [87] falls into the scheduling category (brown color). Note that these studies are strictly based on network planning and design perspectives only. Figure 4 shows the combination of these primary and secondary design areas that have been considered in the respective models. In other words, we have classified the various works into similar research themes for further discussion. For instance, [4,81] mainly studies trajectory optimization and incorporate scheduling in the studied models, while [7,80,82,92] focus on trajectory optimization in addition to energy management and scheduling. On a similar note, trajectory optimization was only studied in [79,83], while [5,6] investigated trajectory optimization and energy efficiency. In summary, based on the conducted SLR, we have identified three primary design aspects that will be further examined in detail in the subsequent sections.

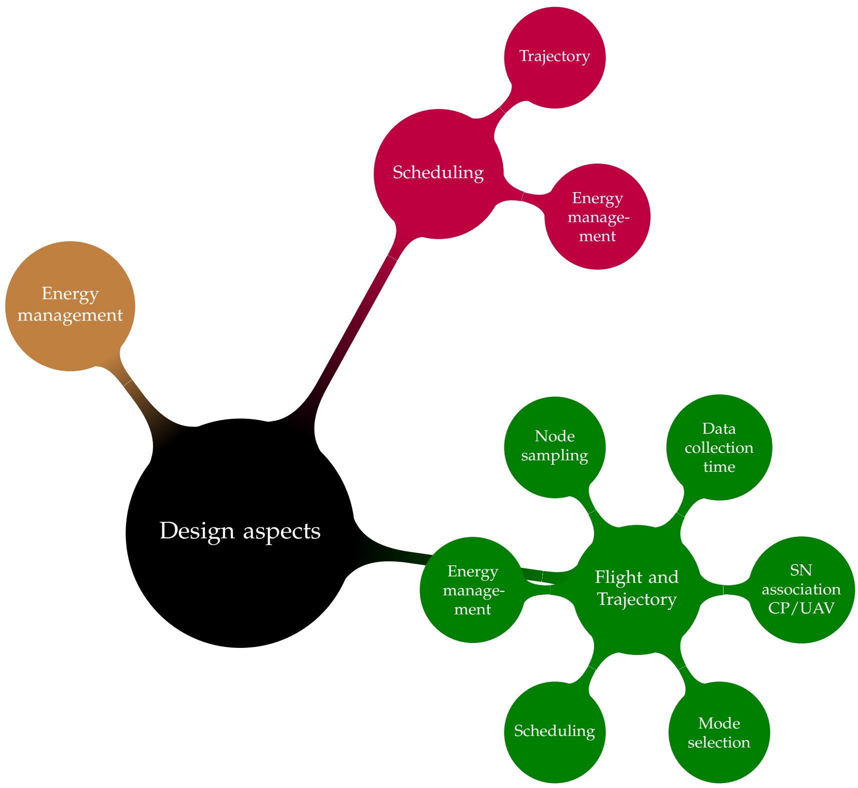

Figure 3. Primary design aspects from the literature.

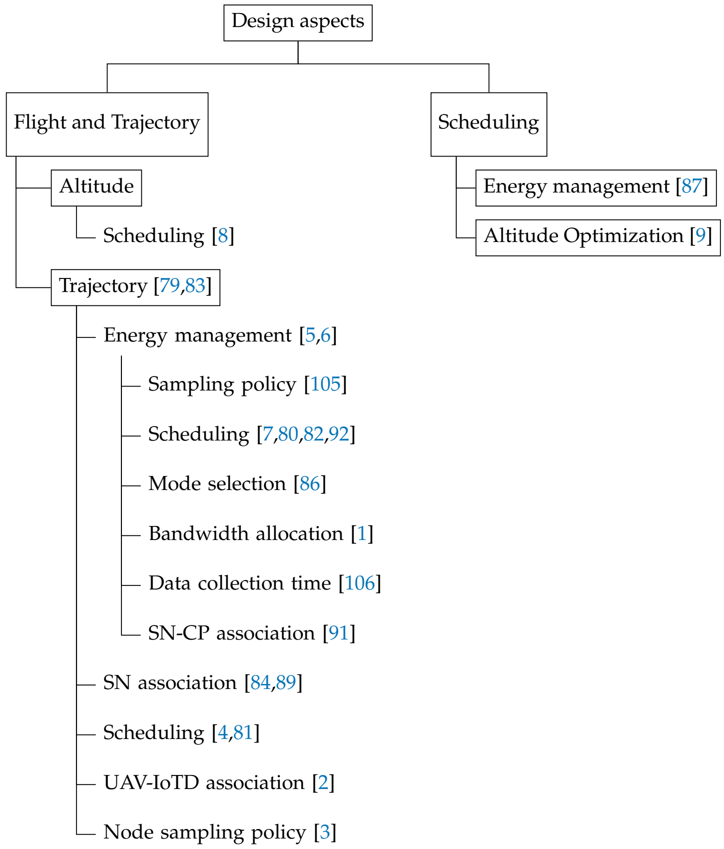

Figure 4. Categorization of design aspects of AoI minimization in UAV-assisted WSN/IoT networks based on [1–8,79–84,86,89,91,92,105,106].

3. AoI Minimization in UAV-Assisted WSN/IoT Application Architectures

3.1. AoI Minimization

The critical applications of UAV-assisted IoT emphasize the importance of timely data delivery by the UAV, especially in disaster and time-sensitive monitoring applications. This is particularly because timely sensed information can make an accurate and informed decision. Untimely updates may not correctly capture the current state of the data being sensed, which may lead to wrong decisions being made. It becomes even more concerning considering IoT devices have constraints, such as relatively short transmission range and low onboard energy, despite the need for reliable communication to the final destination. This motivates the consideration of techniques for timely information delivery [9], such as the use of UAVs for relaying data sensed by sensors and IoTDs, which led to the study of the AoI metric on the UAV-assisted WSN/IoT architecture. The first research study that introduced the concept of AoI can be traced back to the year 2012 in [107], which focused on real-time status updates.

AoI is defined as the amount of time that elapses after the generation of the most recent update before it is received at the destination. AoI characterizes the inter-delivery time arrivals and latency [8]. It differs from the delay metric, i.e., the time that was spent on data transmission from the source to the destination [2]. Applications where status information needs to be delivered to the destination quickly for online data analysis and decision-making, such as environmental monitoring, health monitoring, and safety protection, can be characterized using AoI [85]. UAVs are favorable in terms of their speed, flexibility, and dynamism, thus they attract researchers' attention, particularly in AoI-aware WSN and IoT architecture design. For UAV-based data gathering, the AoI of an arbitrary physical process is defined as the time elapsed since the most recently received update packet at the UAV was generated at the ground node [4].

Numerous researchers have studied the objective of AoI minimization using different target metrics. For example, normalized weighted sum AoI (NWAoI) was considered in [4], AoI cost in [87], maximum AoI (max. AoI) in [1,79,84,89,91], and meanwhile, average AoI was investigated in [79,85,89,92,106]. In [85], the authors specifically studied minimum average AoI. The sum of AoI was used in the work of [9,81], and this metric has been further extended to the weighted sum of AoI in [3,8,80]. The authors in [1] formulated weighted sum expected AoI. Expected sum AoI (ESA) was studied in [9], the authors of [90] evaluated peak AoI, while ave peak AoI was considered in [82]. Finally, the general AoI performance metric was investigated in [2,5–7,83,86,93,98,99,101–103,105].

3.2. Typical Architecture of UAV-Assisted WSN/IoT Applications

Figure 5 shows a generic UAV-assisted WSN/IoT network where the UAVs fly to collect data from multiple sensor nodes that sense various environmental phenomena. The sensors could be deployed based on different distributions and orderings (random or deterministic). For instance, nodes can be deployed randomly within the sensed region. These nodes could form a clustered architecture, where a cluster head collects data from other sensor nodes and the UAV flies close to these nodes from the cluster head. In other cases, there could be stopping points that the UAV hovers above to collect data from neighboring sensors. The collected data can be sent to the BS or data center for further actions.

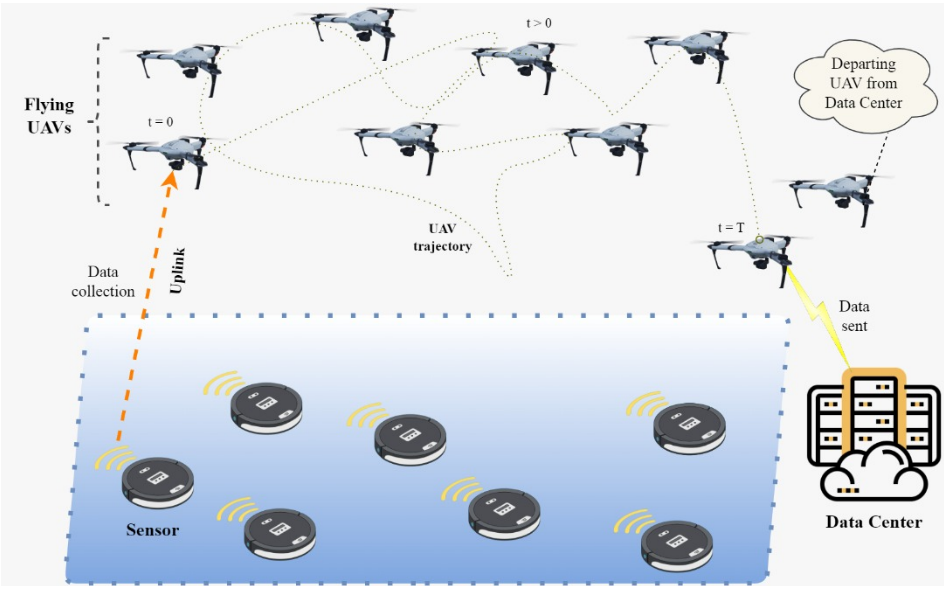

Figure 5. A typical UAV-assisted sensor architecture where UAVs follow a trajectory to deliver fresh information to the data center.

In Figure 5, a UAV can hover above the sensors one after the other or hover above collection/stopping points to collect data before it finally offloads them to the BS or data center. Assuming the UAV hovers above each sensor, the AoI of the base station or data center initially starts at A_0 and increases at a unit rate until it receives updates from the UAV. Data are sampled by sensors at time τ_1 and received at τ_2 when the previous data at the BS are received. Thus, the AoI is $\tau_2 - \tau_1$ and the process continues [1]. In Figure 6, the AoI of each sensor is the elapsed time from when the information is sensed to when it is delivered to the data center [79]. Whenever the destination successfully collects the newest updated data, the AoI decreases. On the other hand, the AoI increases when the sensor nodes are outside the UAV's coverage area [92], which might be due to the UAV's limited coverage radius; wider radius results in a lower AoI because the UAV could collect data quickly from more sensor nodes [80]. Similarly, whenever the UAV has a greater communication range, it may communicate directly with more sensor nodes, collecting data faster while using less energy and thus reducing AoI. Consequently, it is crucial to maximize the UAV's communication range [92]. The UAV's altitude also affects the AoI's performance because the propagation characteristics between IoT devices and the UAV, as well as the UAV and BS [8], affect the quality of communication.

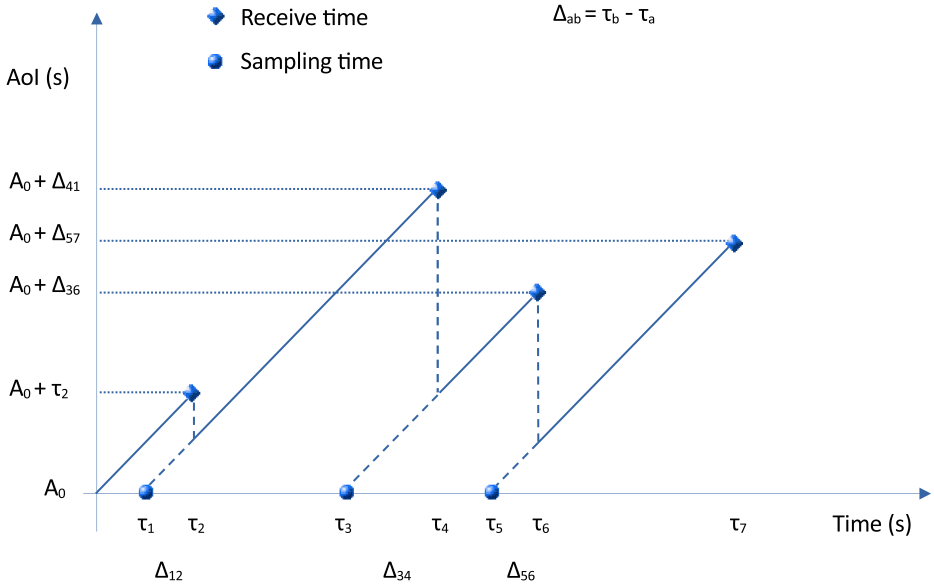

Figure 6. Illustration of AoI evolution for a typical UAV-assisted WSN architecture.

4. Classification of Multiple Design Aspects of AoI Minimization in UAV-Assisted WSN/IoT Applications in the Literature

This section provides a detailed discussion of the identified primary and secondary design aspects shown in Figure 3. Note that the flight and trajectory as well as UAV and SN scheduling are identified as the most critical aspects for an efficient design of AoI-minimal UAV-assisted data-gathering WSN/IoT applications. In fact, all the reviewed papers considered UAV trajectory as the primary design objective, except the authors in [87]. In addition, it is also established from the existing literature that energy management and UAV altitude are fundamentally important in design considerations. Hence, the following subsections examine these fundamental design aspects with a summary provided in Table 3.

Table 3. Summary of design aspects' classification for AoI minimization.

Ref	Aspect	Summary
[8]	Altitude scheduling	Joint study of dynamic UAV altitude control and scheduling policy in a UAV-assisted wireless IoT network.
[9]	Altitude optimization	Optimization of RIS configuration for AoI minimization in a network with UAV altitude constraints.
[5]	Trajectory and energy management	AoI minimization in a scenario where UAVs return to the ground control station to be recharged.

Table 3. *Cont.*

Ref	Aspect	Summary
[6]	Trajectory and energy management	AoI optimization with UAVs possessing varying energy capacities which introduces some degree of heterogeneity.
[84,89]	SN association	Design of sensor node association and trajectory planning for UAV-assisted data collection.
[4,81]	Trajectory and scheduling	Optimize the flight path of a UAV and schedule updates of the ground nodes'status.
[2]	UAV-IoTD association	The UAV trajectory planning for maintaining information freshness in IoT.
[3,105]	Node sampling policy	The UAV trajectory planning for maintaining information freshness in IoT.
[87]	Scheduling and energy management	Age-optimal UAV scheduling with battery recharging.
[105]	Sampling policy	Trajectory design of UAV was created before the UAV's flight and not in real-time.
[7,80,82,92]	Scheduling	Ground node transmissions of status update packets are scheduled
[86]	Mode selection	Framework where a battery-limited UAV flies in multiple turns.
[1]	Bandwidth allocation	UAV-assisted energy-aware data collection for a group of IoT devices.
[106]	Data collection time	Joint optimization of UAV trajectory, transmit power, and data collection time from each sensor on the backscatter IoT architecture
[91]	SN-CP association	Cooperative framework for energy-constrained multi-UAV data collection for time-sensitive WSNs.

4.1. UAV Trajectory

The optimization of UAV trajectory is important to utilize the UAV effectively in view of the limited resources [62] and constrained battery capacity of the UAV. This section discusses papers that have mainly studied trajectory in system design and optimization. Four papers best fit this category: the first [79] can be categorized as *trajectory only* as it presents the simplest case, while the other [83] mainly involves trajectory design and minimization of packet expiry. In the third [3], trajectory and sampling policies of IoT devices are considered, which adds some complexity to the system. Finally, UAV trajectory is considered with UAV-IoTD association in [2] due to the dynamic nature of the network where a different number of IoT nodes may be associated with the same UAV over time.

The authors in [79] investigate the impact of AoI on UAV-assisted data collection. In the proposed work, the age-optimal trajectory planning problem is studied in UAV-assisted WSN where the UAV visits all sensor nodes in a sequential manner and delivers the data to the data center for information processing. The authors investigate the impact of UAV trajectory on the AoI of each sensor node where the AoI of each node corresponds to the time taken for information to get from the sensing point to the data center. However, this work did not examine the joint optimization of the data acquisition method and visiting node order [93]. Similarly, ref. [95] did not investigate the use of full-duplex devices, instead, half-duplex UAV transmissions were studied, and only uplink transmissions were investigated. Additionally, before returning to the base station, the UAV visits all the sensor nodes, which might not be optimal with respect to AoI [87]. The unreliable channel conditions and the absence of knowledge of channel state information (CSI) were also not considered [8]. Furthermore, the studied architecture assumed a fixed energy supply for sensor nodes, making it difficult to deploy in dangerous (or hard-to-reach) areas where it cannot be recharged [85]. The concept of UAV recharging was not explored [90], and only one UAV was considered, which makes it unsuitable for large-scale sensor networks [91]. Finally, only a near-optimal (as opposed to an optimal) solution was derived [106], and the optimal scheduling of update packet transmissions was not considered [81].

It is important to carefully study UAV trajectory since packet transmission rate is highly dependent on the UAV's flight time between sensor nodes and its flight order over all the sensor nodes. Considering the importance of time effectiveness, the authors in [83] investigated the importance of AoI metrics in UAV-aided information sensing for environmental monitoring applications. The main objective was to study the UAV trajectory design and reduce packet expiry or dropped messages when a UAV is dispatched to collect data from a cluster of sensors. Data stored on sensor nodes are continuously generated and characterized by a finite lifetime. A reinforcement learning (RL) method was deployed to help the UAV learn how to adapt to the dynamic environmental conditions within the proposed framework to improve the time effectiveness and performance of path design. However, the waiting time of update packets [105], the scheduling policy of update packets, and queuing was not considered despite the fact that, in real applications, continuous sampling would require some packets to be queued. Although more complex, the potential of full-duplex radios was not explored despite their potential to facilitate high-bandwidth applications. Similarly, the authors assume the UAV must visit all sensor nodes before returning to the base station, which might not be optimal in large-sized networks [87]. A discrete trajectory was considered, which is prone to approximation errors as compared with real-world implementations [4].

The authors of [3] study the age-optimal data collection problem in UAV-assisted IoT (Figure 7a) by jointly considering the data sampling, queuing, and UAV-assisted relaying processes. Using a sample and replace policy, the authors considered a model involving the replacement of update packets in the sensor node buffer with those of a newly sampled packet. The UAV collects the sensor node update packets when it flies over the sensor nodes. In order to obtain the age-optimal policy, they formulate the UAV-assisted data collection problem as a finite horizon MDP intending to minimize the weighted sum AoI, packet drop rate, and energy consumption of the UAV. To overcome the curse of dimensionality, the authors propose using a deep RL algorithm for designing the UAV age-optimal trajectory while also minimizing the packet drop rate. Via simulations, they show that the proposed learning algorithm has the potential to reduce both the packet drop rate and AoI significantly using the learned topology and sensor node sampling status. However, the paper only considers a single-UAV scenario, and that of multiple UAVs has not been studied. A number of such UAVs can be investigated in the future to embark on data collection and further optimize the AoI collaboratively.

Trajectory optimization and UAV-IoTD association are important design considerations in planning UAV-assisted WSN and IoT applications for data gathering. This is especially important when the set of IoT devices within the UAV coverage area varies with time. The authors of [2] investigate the UAV trajectory planning for maintaining information freshness in the IoT with unknown traffic generation patterns (such as the AoI evolution of a fire alarm triggered when the temperature is above a specific threshold) as shown in Figure 8a. They identify and formulate the associated AoI-minimized trajectory planning problems and propose a novel online AoI-based trajectory planning algorithm using deep RL considering the time-varying and unknown traffic generation patterns of IoT devices. To prevent being trapped in a local optimum and speed up the proposed algorithm's convergence, the authors adopt a randomized policy for pre-training deep neural networks. Via extensive simulations, the results show that the proposed algorithm can reduce the AoI of collected data.

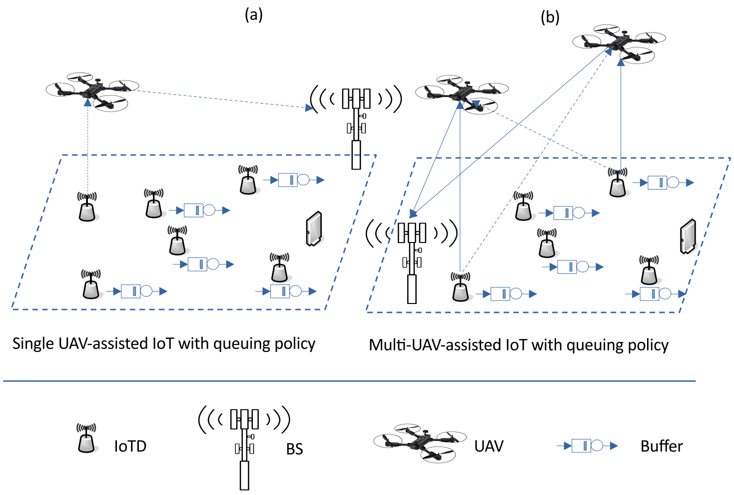

Figure 7. Illustrative architecture for single- (**a**) and multi- (**b**) UAV-assisted data collection from IoT with queuing policy based on [3,105] respectively.

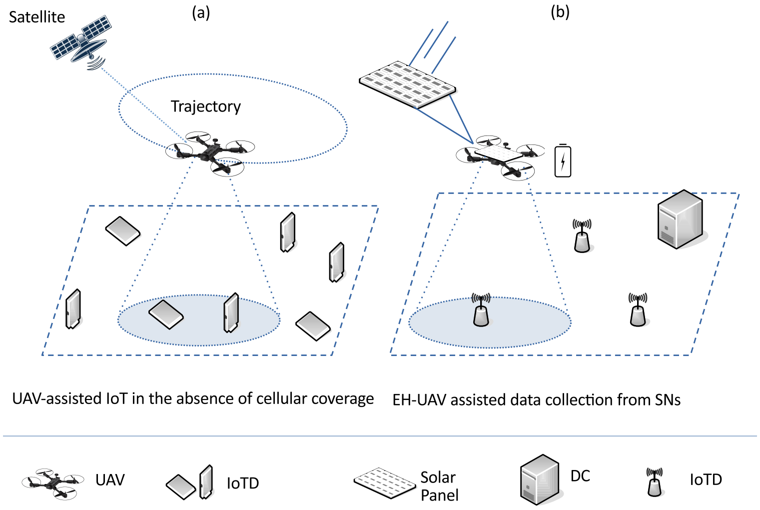

Figure 8. Illustrative architecture for UAV-assisted IoT without cellular coverage (**a**) and EH-UAV-assisted IoT (**b**) based on [2,92] respectively.

4.1.1. Trajectory and Sensor Node Association

The consideration of AoI in network design could lead to advancements in the proposal of novel transmission and scheduling policies which are essential in UAV-enabled applications. In large-sized networks with several CPs, the sensor nodes have to be associated with CPs based on a policy. Thus, new ML-based techniques have recently been deployed for network optimization. For instance, the authors in [89] focus on the design of sensor node association and trajectory planning for UAV-assisted data collection to minimize sensor node maximal AoI. In [84], the focus was on designing an AoI-aware UAV-assisted data collection strategy in a scenario where the UAV hovers above each CP to collect data from a set of sensor nodes (Figure 9a). To minimize the maximum AoI of all sensor nodes, a joint optimization of CP association and UAV flight trajectory was carried out via a joint sensor nodes association and trajectory planning policy. The location of CPs was first determined via an AP-based algorithm, which was also used to determine the association between sensor nodes and CPs. Dynamic programming was then used to obtain an age-optimal trajectory along CPs by iterating these two steps alternatively. Via simulations, the authors show the effectiveness of the proposed method above.

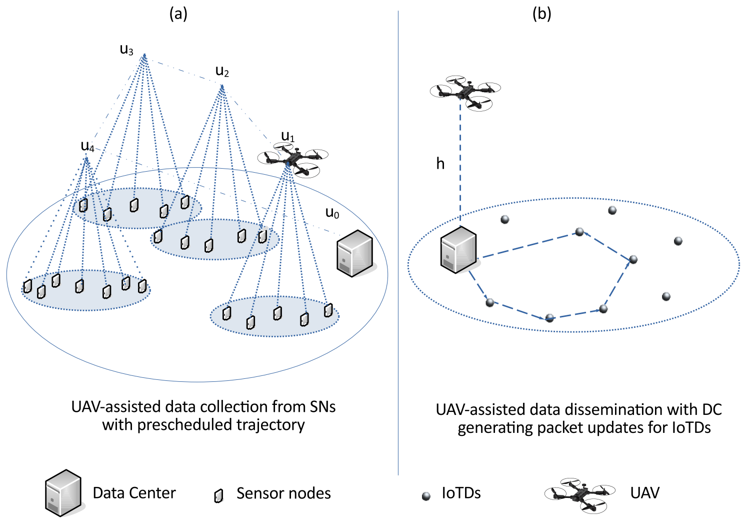

Figure 9. Illustrative architecture for UAV-assisted WSN with pre-scheduled trajectory (**a**) and UAV-assisted data dissemination (**b**) based on [84,86] respectively.

The age-optimal UAV-assisted data collection problem is extended and generalized in [89]. In this case, the rotary wing UAV is dispatched from the data center to collect data from ground sensor nodes, which are grouped into (non-overlapping) clusters. A data collection point is associated with each cluster. The UAV flies from one CP to the next to collect data from the associated sensor nodes following a trajectory. In this framework, the focus was to jointly optimize the locations of the CPs, sensor node–CP association, sensor nodes' uploading sequence, and the trajectory of the UAV along the CPs for minimizing the sensor node maximum and average AoI values. Using two iterative steps involving an affinity-propagation-based association algorithm with clustering weight, the authors found the locations of CPs and the association between the sensor node and CP. The authors show the effectiveness of the proposed strategy via simulations, particularly the proposed algorithm, which can balance sensor nodes' uploading time and UAV flight time to minimize the sensor node maximum or average AoI in various scenarios. However, the online decision-making paradigm where the UAV learns its next move on the fly was not considered. In other words, UAV flight is designed before the UAV leaves to collect data, which does not facilitate the real-time decision-making of the UAV [105]. Similarly, the impact of the energy limitation of low-power IoT devices and the dynamic nature of the time-varying channel was not studied even though channel attenuation impacts transmission efficiency [102].

4.1.2. Trajectory and Mode Selection

UAV data collection can occur while the UAV is hovering over the sensor nodes or CPs. Similarly, data can be transmitted to the UAV while it is flying as long as it is within the transmission range of the sensor nodes. Considering the significance of optimizing data collection time for reducing the age of collected information by the UAV, authors in [93] aimed to find the optimal flight path via a joint consideration of the node's visiting order and the data acquisition mode at each node. The authors consider three different data acquisition modes while assuming LOS links: (1) hovering mode, where the UAV hovers above the node to collect packets; (2) flying mode, where the UAV begins to collect packets, then flies to the next node at maximum speed; and (3) hybrid mode, where the UAV begins to collect data by hovering above the node and keeps collecting data while flying. They show that the age-optimal adaptive strategy outperforms that of the flight-time-optimal strategy with respect to the average age of delivered information. The flight-time age-optimal strategy offers a competitive solution compared with the flight-time-optimal strategy. Additionally, the age-optimal strategy's performance can be further improved by adapting a data acquisition strategy for each node. However, the impact of unreliable channel conditions, an absence of knowledge of CSI [8], and obstacles were not considered. Moreover, it was assumed that sensor nodes are of equal importance and heterogeneity with respect to the function or importance was not considered [87].

4.1.3. Trajectory and Scheduling

This category mainly consists of two papers. In the first paper, the authors consider joint trajectory and scheduling policy design in UAV-assisted sensor-based networks for age minimization. In the second, the authors investigate the UAV trajectory planning for maintaining information freshness in the IoT with unknown traffic generation patterns (such as the AoI evolution of a fire alarm triggered when the temperature is above a threshold), which differs from a regular periodic pattern. Further details on these works are provided below.

The authors of [4] present a novel technique combining convex optimization and ML tools for optimizing the UAV flight trajectory and scheduling ground nodes' status updates. The aim was to minimize the UAV's normalized weighted sum AoI values. A UAV moves to ground nodes to collect status update packets about the processes observed by the sensor nodes. The problem for this setting is formulated as an NWAoI minimization problem, in which the UAV flight trajectory and packet update scheduling are jointly optimized. The authors draw many key insights from their analysis and analytically obtain a lower bound on the NWAoI, which is useful for determining nodes' weights. They show that the lower bound on NWAoI is independent of the number of nodes, but is rather a function of node weights and status updates. The authors show from the derived analytical expression that to make each node have a similar effect on NWAoI, the nodes' weights should be proportional to the total number of updates transmitted by the nodes. However, the authors only considered opportunistic transmission, thus, the scenario, where some packets might have to be buffered, was not considered. Consequently, the waiting time of update packets was not captured [105]. Moreover, the potential of backscatter communications was not studied [106]. However, the paper only accounts for one trip for the UAV, and a non-linear AoI function cannot be accommodated [87].

The authors of [81] consider a wireless network where several ground nodes are deployed for observing different physical processes for a geographic region. The UAV comes to collect status update packets while it seeks to maintain the freshness of its information status about the processes observed during its time of operation. They propose a novel RL framework to optimize the UAV trajectory and schedule status update packets to minimize the weighted sum AoI. A weighted sum AoI minimization problem is formulated where the joint optimization of UAV flight trajectory and scheduling of update packet transmission is considered. The problem is modeled as a finite-horizon MDP having finite state and action spaces, and the age-optimal policy was derived. However, the extreme curse of dimensionality in the state space makes it impractical to use a finite-horizon dynamic programming algorithm and rather a deep RL algorithm is proposed to tackle this problem. The authors prove the convergence of the proposed algorithm and numerically show its superiority over distance-based and random walk policies with respect to the achievable sum AoI per process. The authors were the first to apply deep RL tools to characterize the age-optimal policy. To avoid local optimum and speed up the convergence of the proposed algorithm, the authors adopted the randomized policy for pre-training deep neural networks. They show that the proposed algorithm can reduce the AoI of collected data via extensive simulations. However, the waiting time for update packets was not considered, since the authors studied a generate-at-will policy [105]. The paper also considered UAV trajectory with a single trip and not multiple trips [87]. Furthermore, discrete trajectory and time instants were studied, which might not fully capture the implementation in field environments due to approximation errors [4]. The UAV energy consumption was also not captured as discussed in [80], and the proposed solution was only near-optimal [106].

This category consists mainly of four works with different notions of energy management, as opposed to several other works that have considered both (but not strictly) energy management and trajectory optimization as will be observed later. The first of the four [5] requires the UAV to return to the ground control station to be recharged if at any time it has insufficient energy to complete its mission. In the latter [6], UAVs are considered to have different energy capabilities resulting in some heterogeneity. Similar to the first case, UAVs may either choose to perform the data acquisition task or return to the data center. They should ensure sufficient energy is available to return to the data center; however, they are not recharged. In [90], the authors were motivated by the necessity to charge UAVs while aiming at minimal information age. In [85], the authors consider a wireless-powered IoT network with radio frequency energy harvesting (RF-EH) where the UAVs transfer energy to sensor nodes and also collect data from them. These works are discussed in much more detail below.

UAV trajectory optimization is crucial for data collection in energy-constrained IoT devices. Prior works to [5] have not considered the potential of UAV recharging despite the limited energy of the UAV. Thus, the authors incorporate UAV recharging in a post-disaster early warning UAV-assisted data collection scenario. In the studied model (Figure 10a), the authors assume that UAVs perform data collection in teams in a scenario with changing AoI requirements and UAV power levels. As opposed to prior works using MDP, the authors did not divide the environment into discrete areas with separate action spaces. The UAV moves toward ground nodes for collecting data and is also recharged. To ensure the charge of the UAV is sufficient and the data remain fresh, the authors formulate the path planning as a semi-MDP and use a proposed hierarchical DQN to handle this problem. This way, the agent can select options at a high level, which dictates its actions.

Optimizing the AoI with heterogeneous UAVs using deep RL is studied in [6]. Particularly, this is motivated by the fact that the UAV has limitations in the service it can provide due to its small-sized antenna, low transmit power, and initial battery capacity. Prior works (see refs. in [6]) study single UAV scenarios and do not study the heterogeneous UAV swarm setting needed to meet the target requirements in delay-sensitive applications and for better service of timely data collection. In such cases, planning their trajectory becomes a great challenge. Thus, the authors study AoI optimization in the scenario with a heterogeneous UAV swarm where path planning is the main objective. Additionally, they propose using an encoder–decoder model using an attention-based RL algorithm designed for UAV swarm path planning. Simulation results show that the proposed algorithm converges quickly and is characterized by a high reliability and efficient optimization capability to solve the AoI-based heterogeneous UAV cooperative swarm optimization problem effectively. Although the authors consider free space path fading and additional losses due to obstruction, it would be interesting to study this proposal with data obtained from real measurements in future works.

In [90], the authors consider a UAV constrained in mobility (modeled by a graph G) which gathers information from several ground terminals having lower power transmitters. The UAV moves close to the nodes when it collects information. Due to the short transmit–receive distance and static nature of the network, the authors assume that interference and path loss in such a system can be ignored. They also consider constraints involving charging rate and battery capacity (i.e., energy constraints). They first formulate the lower bound of peak age for the graph under energy constraints and the results prove that the low bound is highly influenced by the charging rate, while the battery capacity's influence on the low bound is limited (much lower). In this regard, the authors design a semi-randomized peak age-optimal trajectory based on the Metropolis–Hastings algorithm and the proposed charging strategy. The agent moves randomly around ground terminals and the power state largely determines when it visits and leaves the charging station. A heuristic trajectory is further proposed to determine the visit of each ground terminal.

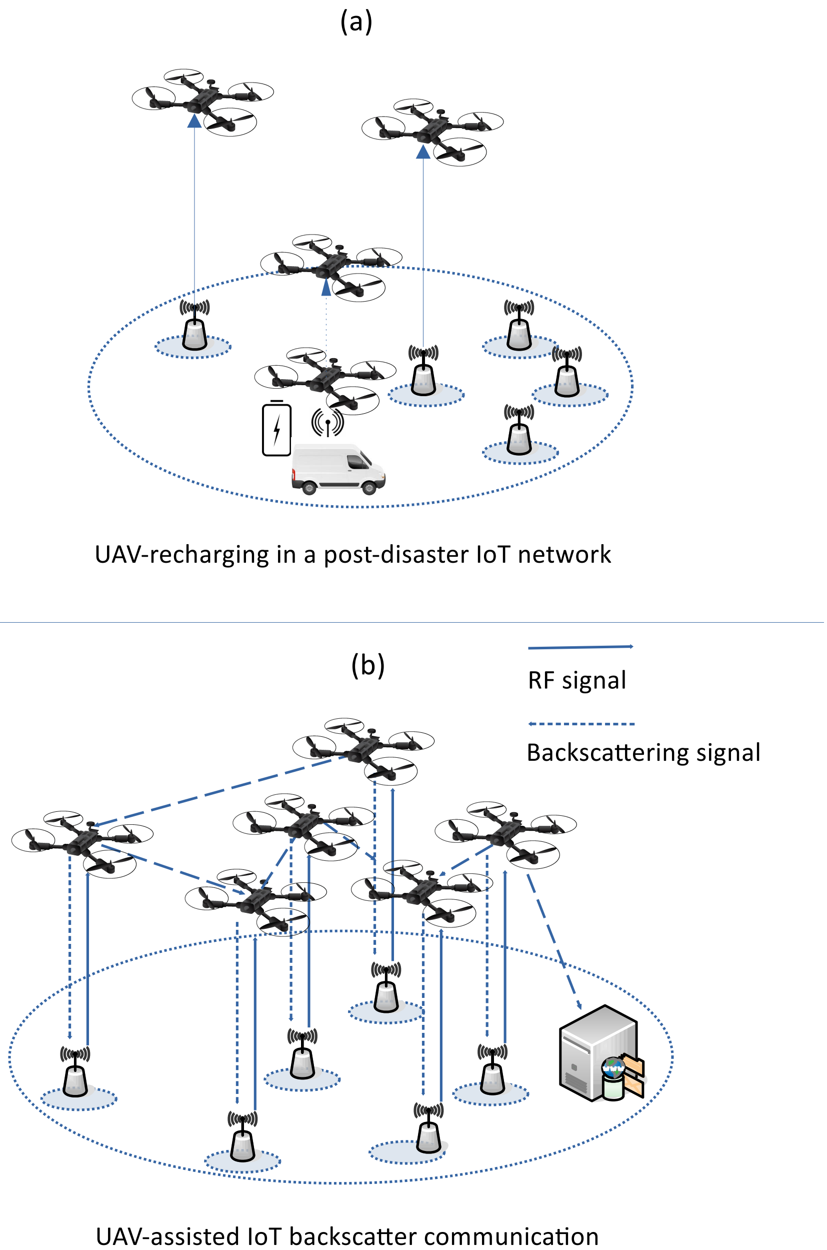

Figure 10. Illustrative architecture for UAV recharging in post-disaster IoT- (**a**) and UAV-assisted IoT backscatter communications (**b**) based on [5,106] respectively.

To fill the gap in the study of AoI-based UAV-aided wireless networks with RF-EH, ref. [85] investigated the joint optimization of UAV trajectory and task assignment in AoI-aware UAV-aided wireless-powered IoT (Figure 11a). In this case, the UAV leaves the data center and flies to each sensor node one after the other to transfer energy to them. It then collects data from the sensor nodes and returns to the data center. The objective, in this case, is to minimize the systems' average AoI. The UAV functions as a mobile energy source that charges low-power ground IoT nodes and performs data collection. The authors consider a nonlinear EH model based on real data measurements. In the aforementioned architecture, they formulate an optimization problem to minimize the average AoI of data collected from the ground sensor nodes by optimizing UAV trajectory, the time required for EH, and the time needed for data collection at each sensor node. The authors show that as

UAV altitude increases, the AoI increases, and the gap between the nonlinear model and linear EH with respect to AoI is increased. However, the trajectory design of the UAV was created before the UAV's flight and not in real-time [105]. Furthermore, only data collection was studied while data transmission has recently been incorporated with data collection (see [98]). Similarly, the unreliable nature of channel conditions was not captured, unlike in [8]. Moreover, the proposed scheme does not yield optimal solutions but near-optimal results [106].

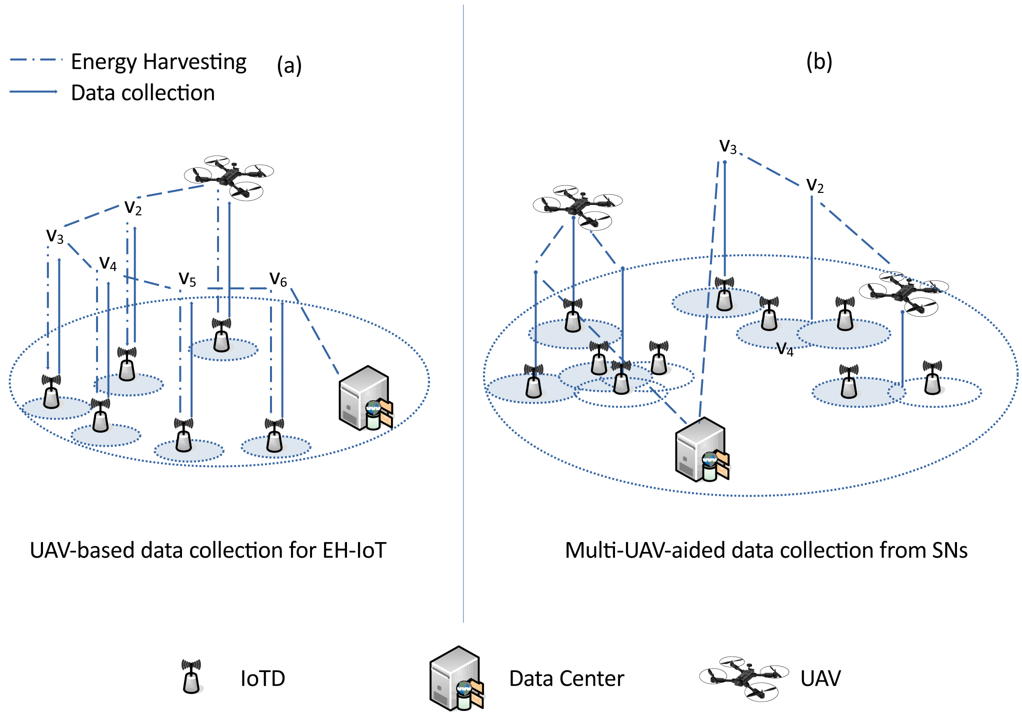

Figure 11. Illustrative architecture for UAV-assisted data collection for EH-IoT (**a**) and multi-UAV-aided data collection (**b**) based on [85,91] respectively.

4.2. Trajectory and Energy Management (TE)

4.2.1. TE with Node Sampling Policy

In practice, sensor nodes can sample data using different policies. For instance, it is not in all cases that sensor nodes generate packets at will. In many situations, autonomous sensing is applicable where the data sensed and generated may follow a unique pattern. For example, environmental sensors can monitor humidity, wind, and temperature after regular time intervals. In other words, sensor node transmissions might follow a regular pattern rather than transmit whenever they find the opportunity. This motivates the authors in [105] to study AoI-aware data collection using a learning-based approach. In the considered multi-UAV model (see Figure 7b), sensor nodes sample the environment at fixed or random intervals based on their sampling mode. The update packet containing the latest sampled information is stored in a buffer. The SNs' update packets are delivered via multiple energy-constrained UAVs. In the first scenario, the base station gathers real-time information (globally) about the network and decides on the UAV flight direction and data collection schedule using its collected information. In the second case, each UAV acts as an agent that (autonomously) make decisions based on what they locally observe. Additionally, flight directions are chosen based on the system state in each time slot in accordance with the optimal strategy. Using Sarsa and a multi-agent VDN-based learning algorithm with partial and full observation, the AoI-optimal trajectory of the UAV was found.

4.2.2. TE with Node Selection

The paper in this category is unique because it considers the use of UAVs to disseminate data for IoT devices apart from the data acquisition task. In many cases, it is also essential to select a few devices from a larger set within a flight round to save energy. Selecting these devices from the AoI perspective constitutes another challenge. Since multiple devices would have to be selected in each flight turn and there is a large number of visiting sequences for selected devices, trajectory planning algorithms are required. Thus, ref. [86] considered a framework where a battery-limited UAV flies in multiple turns towards selected IoT devices to collect and disseminate data provided by the data center to the base station (Figure 9b). The authors focus on the optimal selection of the tasks carried out by the UAV. Particularly, the UAV may not be able to visit several nodes in a flight turn due to its energy limitations, which motivates the consideration of efficient node selection and visiting order (one way of maximizing energy).

4.2.3. TE with Data Collection Time

Backscatter communication systems have been rarely studied in the prior literature on AoI-aware UAV-assisted IoT applications despite their prospect for the efficient utilization of energy in such scenarios. Moreover, notions of AoI that differ based on the initial calculation time have appeared in the literature. Motivated by these, ref. [106] considered a backscatter IoT communication architecture and calculated AoI from the latest data updating time. The studied scenario is more appropriate when sensors periodically update data. Particularly, the sensor nodes transmit data to the UAV via passive backscatter communications (Figure 10b). In the considered architecture, the UAV leaves the data center, collects data from sensor equipment one after the other, and returns to the data center for data processing. The authors aimed to find the optimal average AoI by jointly considering UAV trajectory, UAV transmit power and data collection time from each piece of sensor equipment to increase the sensor equipment's lifetime. To achieve this, they formulated a new AoI minimization problem including discrete (collection sequence of sensors) and continuous (transmission power and data collection time) variables. The problem is difficult to solve directly, so it was divided into two subproblems. The problems required the optimization of continuous (using KKT conditions) and discrete variables, while the backtracking method for trajectory design was proposed.

4.2.4. TE with SN-CP Association

In many of the proposed works, researchers consider a single UAV for data gathering, which might be very challenging in large-scale WSNs, especially considering the limited energy storage of the UAV. In such large-scale networks, it is expedient to have nodes clustered to facilitate easier network coordination, thus emphasizing the need for sensor nodes to be associated with the most appropriate CPs. As opposed to these works using a single UAV, the authors in [91] consider a multi-UAV-assisted WSN with a data center and multiple sensor nodes as shown in Figure 11b. The UAV flies at a fixed velocity and altitude. Particularly, the authors propose a cooperative framework for energy-constrained multi-UAV data collection for time-sensitive WSNs. Because of the UAV's limited energy supply, its flight trajectory is designed to reduce the max AoI of the ground sensor nodes. Each UAV is expected to collect data from the sensor nodes inside of its coverage area. As a result, the UAV's flight path is reduced to a series of ordered CPs, where it hovers to collect the data. The authors decomposed the formulated problems into three different parts. For the first, a graph-theory-based approximation was used to determine a set of CPs and to establish the SN-CP association. Afterwards, the kernel K-means clustering method was used to establish CP-UAV association. Finally, the planning of AoI-optimal trajectory for each UAV was performed subject to the UAV's energy constraint. The simulation results show that the proposed scheme outperforms the traditional ones with respect to AoI performance. Future work can explore other more efficient clustering algorithms for CP-UAV association.

4.2.5. TE and Scheduling

This section will discuss several works that have considered UAV trajectory design, energy management, and scheduling. Depending on the architectural setup and underlying assumptions, scheduling can take several forms. In [1], the authors consider bandwidth allocation and scheduling of IoT devices for transmission in an unequal time-slotted system where the UAV hovers above them. In the second work, the service time is allocated for IoT devices in the uplink and UAV in the downlink, respectively. In [80], the authors assume that UAVs fly toward the sensors to collect data within a particular duration and optimize the scheduling of sensor nodes to minimize the weighted average AoI of all sensor nodes. In [7], the authors emphasize the importance of hovering points and the visiting order of sensor nodes on AoI as they greatly influence the UAV flight time. The authors in [92] focus on handling the sensor node transmission opportunities in a time-slotted system where sensor nodes sample data packets using a sampling strategy and the sampled data are stored in a buffer. The joint optimization of power consumption and age performance is important to improve UAV-assisted data collection efficiency and quality in such scenarios. Optimizing the transmission energy of IoT devices and proper bandwidth allocation saves more energy which can significantly prolong the sensor lifetime.

The authors in [1] investigated UAV-assisted energy-aware data collection for a group of IoT devices deployed in a geographical area to minimize the weighted sum of expected AoI, propulsion energy consumption, and transmission energy consumption of IoT devices. In the considered architecture (illustrated in Figure 12), IoT devices are assumed to upload data continually and a UAV helps to transfer the data to the base station. Scheduled IoT devices upload the sensed data to the UAV while it is hovering and the UAV relays these data to the base station before it flies to the next hovering location. The proposed scheme can decrease the expected AoI and energy consumption, thus motivating the need to jointly optimize the UAV trajectory, IoT device scheduling, and channel allocation for enhancing UAV-assisted data collection performance.

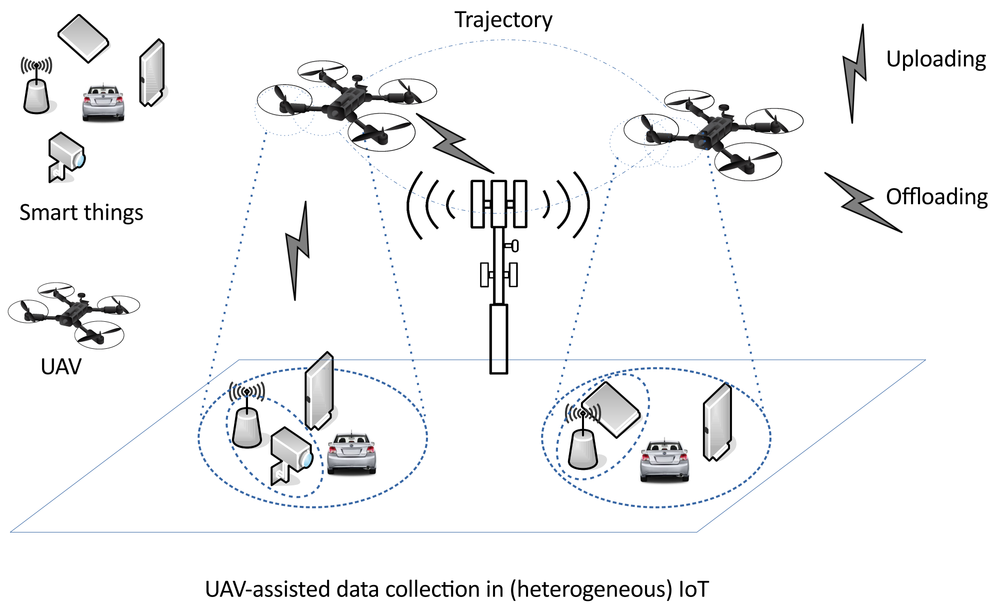

Figure 12. Illustrative architecture for UAV-based data gathering in heterogeneous IoT based on [1].

The authors of [82] consider an IoT-based setup with a source–destination pair where the UAV acts as a relay. In this setup, the source node sends its measurements (status updates) to the destination node. The source node could be an IoT gateway close to IoT devices that transmits measurements to the destination (e.g., base station) via the UAV. They formulated the average peak AoI minimization problem to jointly optimize the UAV flight trajectory, energy allocation, and service time duration for the transmission of update packets at the source node and UAV. The formulated problem is non-convex, thus an efficient iterative algorithm is proposed to solve the problem, and the algorithm's convergence is analytically established. In order to achieve this for a given UAV flight trajectory, the authors characterized the optimal energy and the service time allocation for packet transmission. This subproblem is particularly interesting when the UAV's trajectory cannot be altered considering its energy and other mission-critical constraints. These results derived show several insights and closed-form characterization of some of the subproblems captured. For instance, the results emphasize the importance of optimizing the UAV's flight trajectory to ensure the freshness of collected status updates at the destination, particularly when the source node's available energy is limited, or update packets are large in size. However, the UAV cannot make real-time decisions when its trajectory is designed before its flight [105]. Additionally, the joint optimization of the visiting order of the node and the mode of data acquisition (as studied in [93]) was not considered. The authors did not explore the potential of full duplex communication [95], and the limited onboard energy of UAVs, which affects AoI, was not considered as a constraint during optimization [98]. Similarly, the unreliable channel conditions and the absence of knowledge of CSI were not considered [8]. Sensor nodes were also assumed to have equal importance, which might not reflect the reality of sensor heterogeneity in applications with sensor-specific AoI costs [87]. Similarly battery recharging for sensor nodes [85] and UAVs were not captured within the studied framework and one source–destination pair was investigated [2]. The energy consumption of UAVs was not considered in the age-optimal trajectory design [91]. Finally, the analysis did not consider the optimal scheduling of update packet transmission from different nodes while optimizing the UAV trajectory [81].

Prior to [80], many studies did not consider the energy consumption of the UAV in age-optimal trajectory optimization. This motivates the authors to consider UAV energy constraints by studying age-optimal data collection in UAV-assisted IoT using deep RL. A UAV leaves a depot, flies towards the sensor nodes to collect status update packets, and reaches the destination within a given time frame. While the weighted sum of the AoI of sensors is minimized during UAV flight, the UAV must maintain non-negative residual energy. The problem is formulated into a finite-horizon MDP to obtain optimal flight trajectory and sensor node transmission scheduling. Solving the MDP using dynamic programming is computationally prohibitive due to the high-dimensional state space. Thus, the authors propose a deep-RL-based UAV-assisted data collection algorithm where the UAV decides on which direction to fly and which sensor node it should connect to at each step. Extensive simulations show that the algorithm can reduce the weighted sum AoI compared to other policies. However, the authors did not consider the potential of backscatter communications for improving the energy management in the network [106]. They did not also consider the recharging of the UAVs [90].

In [7], a UAV collects data from a group of clusters by interacting with the cluster heads alone. In this scenario, the authors jointly optimize UAV hovering points and trajectory for minimal AoI data collection. The optimization problem is formulated as a traveling salesman problem with neighborhoods, which is quite challenging due to the continuous (optimization of hovering points) and combinatorial (optimization of visiting order) aspects. To reduce the computational complexity involved in the joint optimization of UAV hovering points and trajectory for minimal AoI data collection, the authors transform the continuous optimization traveling salesman problem with neighborhoods into the Generalized Traveling Salesman Problem (GTSP) using a sampling-based concept. The transformed GTSP is combinatorial in nature and can be solved using exact algorithms, approximate algorithms, or heuristics. However, they cannot balance optimality and complexity effectively. Thus, the authors use ML-based algorithms to solve the GTSP (i.e., UAV trajectory design problem) to achieve this balance. However, this work does not study the use of multiple UAVs for data gathering; it is considered for future work. Although using multiple UAVs adds some complexity to the model, it can potentially reduce the AoI further. Note that a generate-at-will policy was used and thus other policies can be considered in the future.

Zhang et al. [92] deployed deep RL for trajectory optimization in an energy-harvesting UAV-aided data collection in WSN setup as illustrated in Figure 8b. The main motivation was to extend the operation time of the UAV. The problem is formulated using MDP, and deep-RL-based methods were deployed to optimize the UAV flight trajectory and sensor node transmission opportunities to minimize AoI and energy consumption. EH was adopted to acquire renewable energy from the environment to ensure the UAV enjoys a longer operation time. Additionally, to avoid the crashing of the UAV due to a fall (because of insufficient energy), the UAV was permitted to descend to the ground and resume its data collection after harvesting sufficient energy. Finally, the Asynchronous Advantage Actor Critic (A3C)-based algorithm was chosen to collect real-time data, and decisions were taken. Results show that an increase in the harvesting rate of the UAV results in a significant decrease in AoI at the expense of an increase in energy consumption. However, as the harvesting rate increases, the total cost decreases in a monotonic fashion with more weight on AoI. This is because the UAV remains in working mode for a longer period since it has more energy for data collection.

4.3. UAV Altitude and Scheduling

Two papers by Samir et al. [8,9] fit into this category. For the first paper, its motivation lies in the fact that environmental conditions (e.g., height and density of buildings), which affect UAV-based communication quality, vary at different locations. The second considers an environment with obstacles, which motivates the optimization of UAV altitude and the deployment of re-configurable intelligent surfaces.

In [8], the authors explored a joint study of dynamic UAV altitude control and scheduling policy in a UAV-assisted wireless IoT network. IoTs with limited transmission capabilities are visited by UAVs that relay their data to the base station (in a clustered scenario with blockages shown in Figure 13a). The main objective of the stochastic scheduling and altitude control in the paper was to minimize the expected weighted sum AoI of sampled data, which largely depends on the wireless channel conditions and UAV altitude, to facilitate effective communication. The sampled data of stochastic processes by IoT devices are uploaded to UAVs via unreliable channels. The data are relayed to the base station that processes the packets. UAVs are assumed to have virtual queues to re-transmit undelivered data, thereby improving the efficiency of transmission. The propagation characteristics of the channel between IoT devices and UAVs are affected by the UAV altitude. Particularly, the received signal power is lower due to the long-distance path loss at higher altitudes.

In a similar architecture characterized by blockages (Figure 13b), the authors in [9] focused on the optimization of RIS configuration for AoI minimization. A wireless network with IoT devices with limited transmission capabilities was used to sample stochastic processes to be processed by the base station. A single UAV enriched with RIS was used as a passive relay for forwarding data to the base station considering different IoT device activation patterns. A successful transfer of sampled data occurs when the signal-to-noise ratio exceeds a predefined threshold, at which the AoI decreases. An optimization problem was used to capture this framework with the objective of minimizing the expected sum AoI considering the signal-to-noise ratio constraints, UAV altitude constraints, and IoT device scheduling constraints.

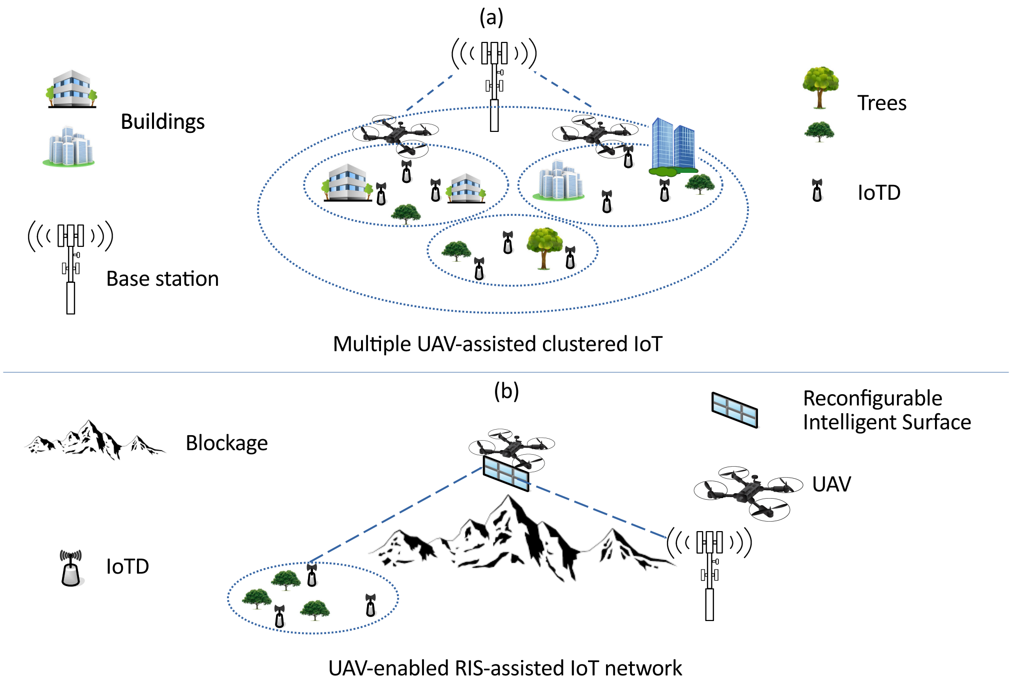

Figure 13. Illustrative architecture for multiple-UAV-assisted clustered IoT (**a**) and UAV-RIS-assisted IoT (**b**) based on [8,9], respectively.

4.4. Scheduling and Energy Consumption

Only one paper fits this category, where the UAV trajectory is fixed since the UAV repeatedly leaves the base station and visits a subset of sensor nodes (with different priorities) to collect data from them. Particularly, ref. [87] considers age-optimal UAV scheduling with battery recharging. In addition to the consideration of capacity, the advantage here is that it is possible for the UAV to embark on multiple trips. In the considered system model involving a base station, a limited-battery-capacity UAV, and a set of sensor nodes, the authors studied optimal scheduling with a sensor-node-specific AoI cost function. They provided a system complexity analysis and proved that the problem is NP-hard in its general form. However, the uniform scenario problem was proven to be tractable. To solve the problem, the authors deployed the graph labeling concept to develop a polynomial-time algorithm that can be used to tune the trade-off between computational effort and solution optimality using a simple control parameter. Via simulations, the authors evaluate the performance of the algorithm by comparing it with greedy-scheduling-based solutions. The results show that the proposed algorithm outperforms the greedy scheduling approach.

5. Issues Relating to the Fundamental Design Aspects

A thorough investigation into the literature of AoI-aware UAV-assisted data gathering applications [1,2,4,8,9,79–92] provides insights into three significant issues that affect the timely dissemination of data in these applications. These include the energy consumption of the UAV and sensor nodes, the UAV trajectory, and the scheduling of both the sensor or IoT devices and the UAV. These issues are discussed in this section with a summary provided in Figure 14. Similarly, associated issues related to UAV energy efficiency, trajectory, and scheduling, as well as some of their influencing factors are summarized in Table 4. Features related to design considerations and constraints of associated optimization problems as well as trade-offs and their relevant references are provided in Figure 15. In addition, the existing optimization frameworks in the literature have been summarized in Figure 16.

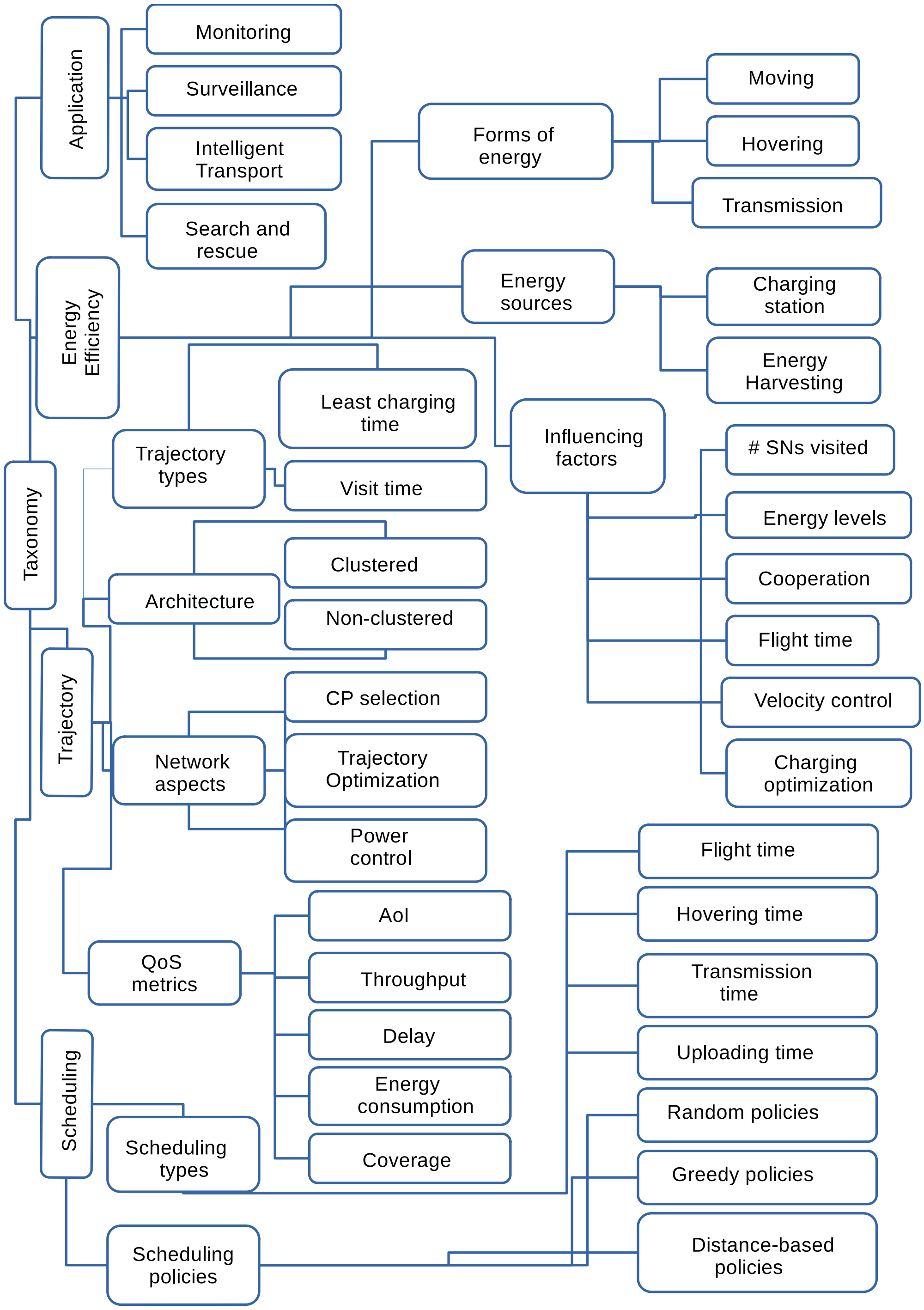

Figure 14. Taxonomy of identified issues.

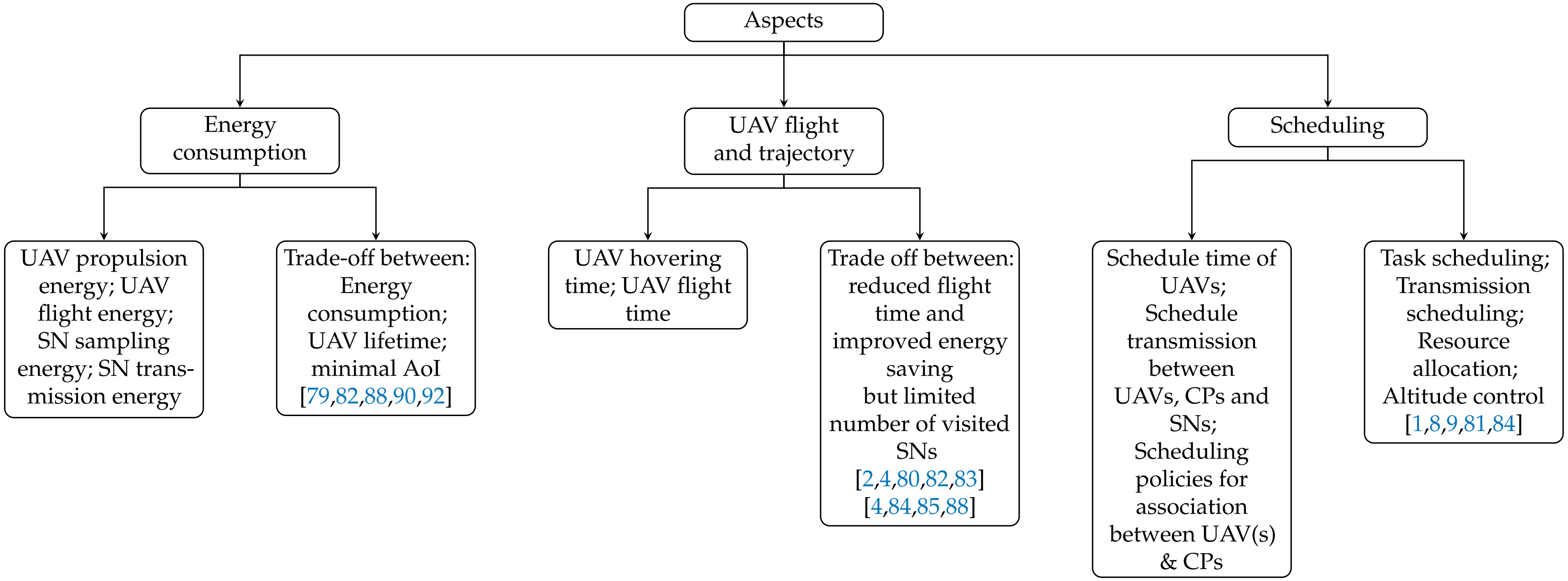

Figure 15. Summary of major considerations as well as trade-offs based on the aspects discussed and the associated literature [1,2,4,8,9,79–85,88,90,92].

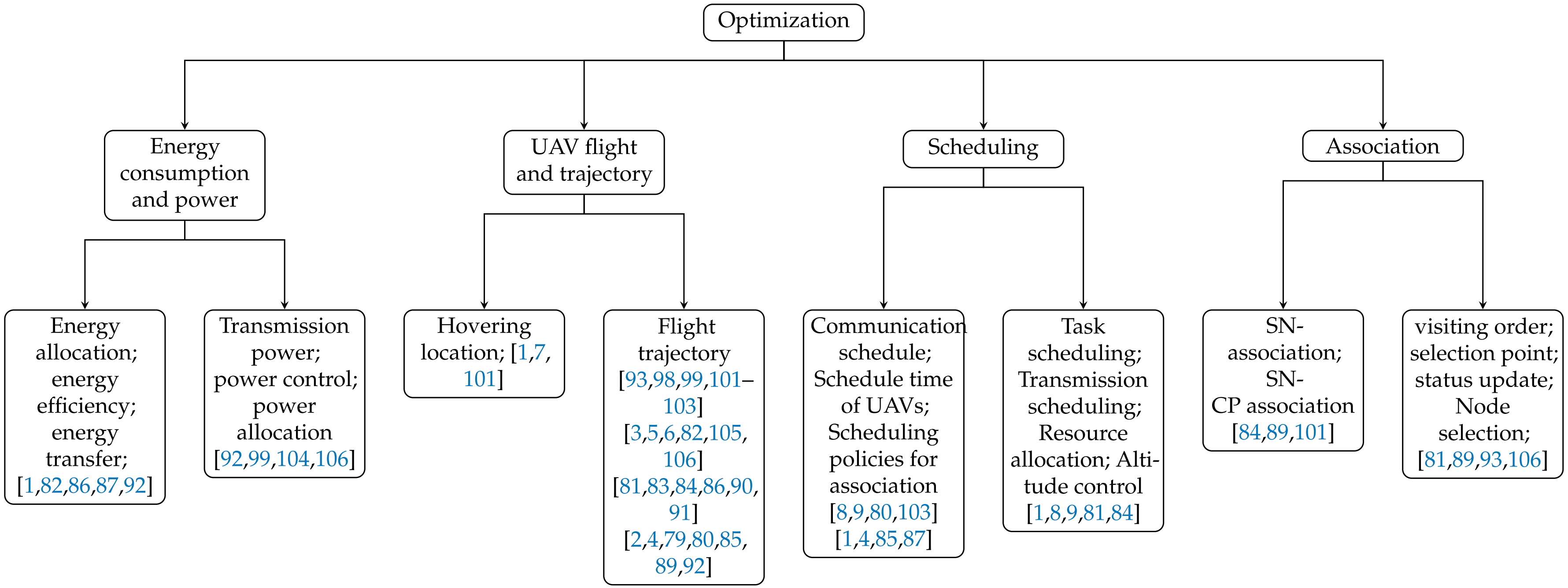

Figure 16. Optimization design framework based on the literature [1–8,8,9,79–87,89–93,98,99,101–106] on some of the aspects discussed.

Table 4. UAV issues and their influencing factors.

Aspect	Considered Factors	References														
		[1]	[91]	[92]	[90]	[87]	[85]	[81]	[2]	[80]	[83]	[84]	[86]	[89]	[9]	[4]
Energy consumption	Number of SNs visited	✓	✓	●	●	●	●	●	●	●	●	●	●	●	●	●
	Nature of application	✓	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	UAV cooperation	●	✓	●	●	●	●	●	●	●	●	●	●	●	●	●
	Energy level	✓	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	Flight time	●	✓	●	●	●	●	●	●	●	●	●	●	●	●	●
	Velocity control	●	●	✓	●	●	●	●	●	●	●	●	●	●	●	●
	Charging optimization	●	●	✓	✓	✓	✓	●	●	●	●	●	●	●	●	●
	Choice and order of visited nodes	✓	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	Scheduling policy of UAV	✓	●	●	●	●	●	●	●	●	●	●	●	●	●	●
UAV trajectory	UAV flight trajectory	●	✓	●	●	●	●	●	●	●	●	●	●	●	●	✓
	UAV flight time	✓	●	●	●	●	●	●	●	●	✓	✓	●	●	●	●
	Scheduling of ground nodes	●	●	●	●	●	●	✓	●	●	●	✓	●	●	●	●
	Flight trajectory types	✓	●	●	✓	●	●	●	●	●	✓	●	●	●	●	●
	QoS metrics	✓	●	●	●	●	●	●	✓	✓	●	●	●	●	●	●
	Flight trajectory model	●	●	●	●	●	●	●	●	●	●	✓	✓	●	●	●
	Service time allocation	●	●	●	●	●	✓	●	●	●	●	●	✓	●	●	●
	UAV connection methods	✓	✓	●	●	●	●	●	✓	●	●	✓	●	●	●	●
Scheduling	Scheduling policies (random, greedy, distance-based)	✓	✓	●	●	●	●	●	●	●	●	●	✓	●	●	✓
	Scheduling of IoTDs	✓	●	●	●	●	●	●	●	●	●	✓	●	●	✓	●
	Scheduling using machine learning	✓	●	●	●	●	●	●	●	●	●	●	●	●	✓	●
	Scheduling packets	✓	●	●	●	●	●	●	●	●	●	●	✓	●	●	●

5.1. Energy Management

Constraints in the energy supply of IoT devices pose technical challenges, making it important to design reliable power supply and data communication mechanisms to achieve efficient IoT device communication. UAVs have been promising in addressing this challenge [104]. Additionally, UAVs have energy constraints that affect scheduling and flight time. From Section 4, it was observed that energy consumption plays a significant role in the planning, deployment, and operation of UAV-assisted data gathering [1], since proper network energy management helps to prolong the operation of both UAVs and sensor nodes. As observed in Section 4, not all papers consider UAV energy consumption in the design of UAV age-optimal trajectories, despite power and energy have a significant impact on AoI [86]. Considering that the energy consumed by both UAVs and sensor nodes is vital, this section is dedicated to discussing this subject.

5.1.1. Importance of Energy Consumption in UAV-Assisted Data Gathering

More energy is dissipated when UAVs accelerate or move at speed to collect new data in the least possible time, which helps to reduce AoI; however, higher energy consumption reduces the lifetime of the UAV. The nature of energy consumed is also architecture- and application-dependent. For instance, applications requiring continuous data collection by the UAV increase the amount of energy consumed by the UAV; thus, energy optimization in these scenarios is very important (see [1]). Another factor that significantly affects the amount of energy consumed by the UAV is the scheduling policy of the UAV, the choice of a node to visit, and the order of visits. In such situations, the UAV service time duration should be optimized. Scenarios where energy consumption is more sensitive are cases when the UAV embarks on special missions or an urgent need for update packets, such as military applications. Information freshness should be achieved in such scenarios while optimizing UAV energy consumption. The proper allocation of energy for each sensor node or CP visited is also important as it can help to optimize the overall energy consumed by the UAV.

The energy consumed by the UAV can be a result of several factors, such as its propulsion, movement, hovering, as well as transmission. Usually, the energy for hovering and flying can be very significant and much higher than the energy required for communication with the sensor nodes or the ambient RF-EH delivered by the UAV. Sensor nodes have limited onboard energy, which makes it challenging to maintain highly reliable communication [92]. A solution for providing a reasonably stable energy supply is via energy harvesting. In this case, sensor nodes can harvest energy from the environment and also be charged via wireless energy transfer from UAVs. In other words, UAVs can transfer energy to sensor nodes, which can be used to upload data to the UAV.

5.1.2. Factors That Affect Energy Consumption in AoI-Aware UAV-Assisted Data Gathering

Proper consideration of the factors that affect energy consumption in UAV-assisted data gathering would significantly help to optimize energy efficiency, thereby reducing AoI. These factors are discussed below.

Number of Sensor Nodes Visited

The number of IoT devices a UAV visits in a time round affects the AoI and should thus be planned appropriately and well-optimized. In large-scale networks, using CPs has proven to be an efficient alternative to optimize the UAV trajectory since the UAVs would not need to visit all the sensor nodes individually, but rather the CPs. Another energy-saving technique could involve timing the data collection task for each sensor or CP. For instance, in [1], IoT devices monitor UAV signals to determine the presence of UAVs for data collection. If the signals are received, and the UAV switches to a hovering status, the sensors then upload data to the UAV.

Energy Levels

In specific applications where data are collected continually, energy consumption might have to be traded off for minimal AoI. In such cases, optimizing energy use as much as possible is still very important. For instance, a UAV continually collects data from sensor nodes in [1], and thus an optimization problem is formulated to minimize energy consumption and the weighted sum expected AoI while incorporating UAV distance, flight speed, direction, and IoT device scheduling. The most important issue here is ensuring that UAVs have sufficient energy levels to sustain their missions effectively within the least possible time.

UAV Cooperation

A cooperative deployment of UAVs is advantageous when UAVs are assigned the task of collaboratively collecting data. In large-scale IoT networks, a single battery-constrained UAV will usually be unable to efficiently cater to the entire network, especially given the strict time and performance constraints of AoI-sensitive applications. In this respect, ref. [91] considers a multi-UAV cooperative data collection framework for time-sensitive dense WSNs. The aim is to find the AoI-optimal trajectory for each energy-constrained UAV.

Flight Time

An optimal design of UAV flight time and visiting sequence can also help reduce the energy consumed in AoI-sensitive applications. The trajectory of a UAV can be optimized when several parameters relating to the UAV's flight and sensor node deployment are well planned. Particularly, the flight time of UAVs plays a significant role in determining which sensor nodes or IoT devices are visited. If the flight time is not optimized, some IoT devices would have to wait longer, which might conflict with the purpose of AoI minimization in UAV-based data gathering. The trade-off between UAV flight time and speed is a prime design consideration in optimizing energy consumption. Similarly, UAV acceleration, altitude, and coverage radius should all be factored in. The choice of hovering spots and the impact of physical characteristics, such as interference and path loss, must also be considered.

Velocity Control

The UAV's velocity can be dynamically controlled when needed to meet the target deadlines of data-gathering applications. At the same time, altitude control is fundamental, especially since the UAV should be able to effectively avoid obstacles while establishing reliable LOS communication with ground sensor nodes and IoT devices. The aim should be to effectively reduce the energy expended due to mobility, transmission, and reception. To minimize energy waste, the UAV can be made to remain in a waiting mode when no horizontal flight takes place [92]. Similarly, in an EH setup, an energy threshold can be set such that when the UAV's energy is lower than the set threshold, the UAV takes no action and rather harvests energy. Only after harvesting sufficient energy does it switch to working mode to continue collecting data.

Charging Optimization

Determining the most efficient methods for charging UAVs is important, given the criticality of many data-gathering applications. Energy waste can occur due to the UAV's movement to the charging station [90]; therefore, the UAV's visit to the charging station should be properly planned. This was explored in [90], where the UAV gets charged via a charging station. The authors aimed to reduce the visit times to the charging station to minimize the energy waste incurred.

The UAV's energy can be constrained, and ground sensors or IoT nodes are usually energy-constrained. To address the energy problem in ground nodes, some researchers consider a different dimension to energy harvesting, particularly where ground nodes can harvest RF energy from UAVs for transmission [85]. For instance, in [85], the UAV performs wireless energy transfer for powering sensor nodes while collecting data from the devices. The UAV takes off from the data center and then flies to sensor nodes to transfer energy. The harvested energy is used to upload data to the UAV.

5.1.3. Issues Pertaining to Energy Efficiency

UAV energy is mainly dissipated during flight and transmission. Hence, including an energy supplement is a promising idea for achieving a stable and sustainable data collection procedure. As discussed earlier, energy can be obtained from charging stations or by designing energy-efficient schemes to improve or extend UAV service time [92]. This is particularly important in applications involving large-sized update packets as more energy is required to send each data packet from the source to the destination. The uplink transmit power of IoT devices is impacted by the location of hovering spots [1], especially since those locations determine the transmit distance of sensor nodes. Thus, UAVs can be made to hover above nodes [88] (or carefully optimized spots) to collect sensed data (via air-to-ground communication links of low altitude) in order to reduce the sensor nodes' energy consumption and improve the network lifetime.

One major challenge is maintaining highly reliable and stable communication among sensor nodes due to their onboard energy constraints [92]. As such, UAV-assisted WSN data gathering needs to factor in energy efficiency on the part of the UAV, which traverses the sensor nodes and finally relays the data to the destination, and the sensor nodes that observe the environment. It is interesting to note that the sensor network lifetime highly depends on implementing energy-efficient routing and MAC protocols. A popular technique used in this regard is scheduling sensor nodes to remain in sleep mode when no major activity is performed. Thus, techniques such as wakeup radio can be used in WSN or IoT applications to wake sleeping nodes when it is time to transmit to the UAV to save their energy. Additionally, sensor nodes can form clusters and send sensed data to the cluster heads that upload data to the UAV. Such cluster heads' roles can be rotated and even some nodes with higher initial energy can either be randomly deployed or strategically positioned to function as advanced nodes to reduce the energy burden on the other regular nodes in the network.

5.2. UAV Flight and Trajectory

In this section, issues pertaining to UAV flight and trajectory are discussed. To guarantee data freshness, it is very important to ensure efficient UAV trajectory optimization [2], especially for UAVs that can cover a larger area (having higher coverage radius) as they would generally require a shorter time for data collection [80]. Particularly, the packet expiration rate in such applications is connected to the flight time between the sensor nodes, and the flight order of the UAV. In this case, the UAV flight time constitutes the upper bound of the AoI for expired packets [83].

Guaranteeing data freshness in UAV-assisted IoT can be quite challenging because UAVs have to fly from one location to another while meeting the requirements of an overall network-wide objective. Applications such as environmental and health monitoring, as well as safety protection, thus require thorough trajectory planning and AoI characterization as outdated information may lead to erroneous decisions or catastrophic disasters. This makes it very important to properly design the trajectory of UAVs for time-sensitive applications [2]. Practically, traveling latency is greater than offloading latency, hence, UAVs should be made to fly close to IoT devices to achieve a higher data transmission rate. However, this implies that only a few can be served simultaneously, thus motivating the need to select hovering spots for UAVs. Similarly, in this case, the energy required for IoT devices to transmit in the uplink increases, and the same for the uploading latency.

Several approaches can be used to reduce flight time while also saving energy. UAVs can stop at specific points within the network where sensor nodes can upload data before the UAV flies to another location. These locations (stopping points) provide performance gains with respect to UAV flight time reduction. Similar to this is the use of CPs, whose positions constitute the UAV's stopping or hovering points that largely determine the flight time and trajectory. Sensor nodes can transfer sensed information to another sensor node functioning as cluster heads (or CP). The information is then transmitted to the UAV (when the UAV hovers above it) based on a schedule. Using CPs has other advantages, for instance, whenever there is an overlap in the coverage area of ground nodes, the UAVs can collect data from those nodes when they fly or hover above or across the area.

The rationale for using CPs is to save energy and reduce flight time. In network architectures with many CPs, optimizing the total number of CPs or reducing them is important to achieve an age-optimal UAV trajectory (see [91]). Architectures involving CPs are sometimes challenging to optimize, especially when the number of CPs could change in every round (see [84]). As mentioned earlier, using CPs can significantly help improve the age-optimal trajectory, thereby reducing flight time. Sensor nodes functioning as CPs or heads of clusters would contribute to evident performance trade-offs. In many cases, the distance between the sensor nodes and the CP is large, significantly increasing the uploading time. Sensor nodes functioning as CPs or heads of clusters would contribute to evident performance trade-offs. In many cases, the distance between the sensor nodes and the CP is large, which significantly increases the uploading time (see [84]), thus affecting the information age. Flight trajectory can be viewed as a permutation of the number of CPs to be visited and the data center. It is also possible that multiple devices can be selected in each flight turn, which necessitates proper trajectory planning [86].

Many papers have considered a clustered or CP-based architecture. For instance, a UAV takes off from the data center and flies above each CP until data gathering is over. It returns to the data center for data analysis to be carried out [84]. Whenever there is a large set of potential devices or CPs to be visited, the devices to be visited are selected first before determining the order of visits. An example of such can be found in [86]. In some cases, trajectory optimization is performed after finishing the first subtask. For instance, an affinity-propagation-based algorithm and UAV-CP association were deployed to find CP locations [84]. The authors deployed a dynamic programming technique to find the age-optimal trajectory along the CPs. Ref. [88] also optimized three major network aspects: CP selection, trajectory optimization, and power control.

The authors in [89] studied an age-optimal data collection problem for a UAV-based WSN in which the AoI of sensors were derived as the weighted sum of sensor uploading time and UAV flight time. An iterative SN association and trajectory planning policy was proposed to minimize both sensor node maximal and average AoI in a unified manner. Whenever the number of CPs, flight trajectory, and uploading sequence of sensor nodes are optimized iteratively, all sensors' maximum and average AoI reduce gradually.

5.3. UAV and Sensor Node Scheduling

When a UAV visits nodes in an area, it requires a schedule to determine which nodes to receive data from and in what order. In other cases, UAVs might need to schedule their arrival at stopping points so that sensor nodes within that range can upload their data to the UAV. Similarly, flight, hovering, transmission times, and sensor node uplink transmissions to the UAV should be properly scheduled. In networks with CPs, sensor nodes may also need to schedule their transmissions to CPs, while CPs schedule theirs to UAVs. These scheduling processes could affect the age of information of the data sensed and sampled by sensors or IoT nodes. Many UAV and sensor node scheduling methods have been proposed in the literature and scheduling could be performed concerning association with CPs or even UAVs. ML has recently gained popularity for scheduling in UAV-assisted data collection for WSN/IoT applications. Schedule policies could vary significantly, for instance, in random, greedy, and distance-based policies or exploring heuristics to ensure IoT nodes have a higher AoI chosen to transmit status updates [9].

Packet allocation is another form of scheduling considered in UAV-aided data-gathering architectures. Optimal packet allocation and scheduling should be prioritized in such applications. In many cases, nodes should have a relatively uniform packet size allocated to them, while in other cases application requirements might necessitate that some nodes have special functions and thus larger packet size allocation. This is especially important if the number of visits of the UAV for a particular node depends on the packet allocation, as nodes with large packet sizes may be rarely visited, which can significantly impact the AoI. An example is investigated in [86].

In a broader sense, besides packet allocation, scheduling can take several other forms, for instance, ref. [1] considered bandwidth allocation in their problem formulation. The UAV can also deploy scheduling-based medium access protocols, such as TDMA, to effectively control the number of IoT devices scheduled to transmit status updates. UAVs can schedule IoT devices at the beginning of each time slot or remain idle [8]. ML can also be used to determine the sensor node transmit schedule (see [80]) in addition to trajectory optimization (see [81]). The UAV could autonomously manage the scheduling process, while in other cases, it does not have control over the scheduling process [4]. AoI evolution differs on a per-policy basis [8]. Thus, to preserve UAV information freshness, in addition to flight trajectory, the scheduling of ground nodes is required [81]. The number of nodes deployed for sensing also influences both scheduling and the evolution of AoI as it affects the interval between the UAV's visit to each sensor and invariably the scheduling frequency.

Scheduling IoT Devices

Scheduling in this case has to be performed in good time, bearing in mind that if an IoT node is not scheduled in a particular time round, it has to wait longer to transmit its data, leading to higher accumulated AoI. Modeling network architectures involving sensor node-CP association can be constructed in various ways, for instance, using a binary indicator to specify whether a sensor node is uploading to a UAV or not [84]. Each SN could be scheduled to connect to a single CP. The sensor node-CP association influences the AoI. Similarly, uploading the sequence of sensor nodes to UAVs could significantly impact the AoI. Thus, it is highly important to strike an optimal balance between sensor node uploading time and UAV flight time. To achieve this, the optimal set of CPs has to be found as well as the best-choice trajectory through the CPs.

The scheduling of UAVs and sensor nodes involves many considerations, making it quite challenging due to other associated factors: architecture, application, number of UAVs, UAV height, optimization algorithm, and many more. The UAV altitude could either decrease or increase the AoI because it impacts the propagation characteristics between IoT devices and UAVs, as well as UAVs and the base station [8].

6. Discussion and Future Considerations

In this section, some of the other challenges associated with UAV-assisted data gathering for WSNs and IoT are explored with a number of future considerations. In addition to AoI minimization, other metrics can also be studied, such as coverage enhancement and throughput, thus the joint optimization of these objectives would be required.

6.1. Network Architecture and Size

Minimizing AoI in large-sized networks with a large set of nodes to visit in each round can be pretty challenging. At some point, when the number of sensors increases significantly, it becomes difficult for some heuristic algorithms to deliver high-quality results. In this case, computation-intensive algorithms may also not be the best option as high computation time negatively impacts the quality of obtained solutions [87]. In such cases, the best option might be to resort to algorithms that could produce near-optimal solutions. Artificial-intelligence-enabled IoT can improve system performance and optimize energy consumption using different training models [108]; however, this architecture is yet to be studied for AoI minimization in UAV-assisted IoT.

6.2. Traffic Prioritization

Proposed trajectory optimization and scheduling algorithms should consider node prioritization, especially in applications with node heterogeneity, where some nodes hold more critical or larger-sized packets. For instance, mechanisms must be put in place to factor in the priority of sensor node traffic for dynamic trajectory scheduling. In other words, the UAV might need to determine its trajectory to serve higher priority nodes dynamically. Related work in this area includes [84], whereby sensor nodes can be divided into frames and assigned different priorities for transmission to manage or reduce the packet loss rate. Such prioritization can be considered in other different architectural setups.

6.3. Association

Architectures involving a CP [84,89] involve the association of sensor nodes to the CP, which can be modeled via an association parameter. However, the changes in the AoI optimal trajectory depend on the changes in the number of CPs, which makes it challenging to determine the AoI-optimal solution. In other words, there exists a very large number of CP candidates (see [84]). Other parameters could also affect the system's dynamics, making it more complex, e.g., node mobility, dynamic evolution of special nodes and CPs, and association parameters. Optimizing AoI in a multi-UAV setting is also very challenging due to the varying dimensions regarding UAVs' 3D position. Similarly, the AoI of the entire network depends on the trajectory of the swarm of UAVs, the number of UAVs, network topology, sensor node communication range, and UAV energy capacity. Generally, (see [89] for instance), it is imperative to consider both AoI-aware sensor node-CP association and UAV trajectory planning to obtain minimal AoI.

6.4. Optimization

Obtaining an optimal AoI solution can sometimes be very complex, especially when dynamically changing parameters are involved [84]. Particularly, many works only arrive at near-optimal solutions without absolute optimal. Optimal solutions should be sought during trajectory optimization even if that is at the cost of reasonable complexity. Different parameters are involved in UAV trajectory optimization. For this reason, several optimization and ML techniques are being used to optimize UAV trajectories. One of the main concerns with respect to the performance of optimization algorithms is convergence, especially for neural networks, which are difficult to study analytically. In this case, the choice of algorithm for optimization highly determines the convergence speed. The proper selection of hyper-parameters is required for ML-based solutions, as emphasized in [8]. Another challenge is characterizing a globally optimal solution for non-convex objective functions [82]. This can be tackled by breaking down the problem or developing efficient algorithms for solving such problems. However, it is important to consider that the proposed algorithms should be able to solve the problem within the shortest possible time. Similarly, the issue of high dimensional state variables is commonly reported in the literature and should be solved by choosing efficient algorithms. Another important consideration is 3D trajectory optimization using 3D obstacle data as it would improve the applicability of the studied models for real-life use cases. Additionally, if UAVs can obtain data by observing the ground in real-time, a priori knowledge of obstacle information is not required [62].

6.5. Packet Delivery Errors

It is common to assume that update packets are always delivered to the destination successfully; however, in reality, packet delivery errors may occur [82]. Numerous factors related to the physical surroundings and the communication route may cause this. In this case, it would be beneficial to study the impact of different communication impairments on transmission and AoI. For instance, pathloss, obstacles, fading, etc., are some factors that can impair communication among the sensor nodes themselves and the A2G channel between the UAV and ground sensor nodes. It is also important to note that there are other reasons that could impair the quality and AoI due to transmission failures. For example, if the actions of the mobile agent (UAV) in a time slot are not properly learned using efficient ML techniques, this could lead to erroneous decisions with respect to UAV movement [8]. Hence, effective learning techniques are required to ensure that the UAV can accurately adjust its altitude and speed to reduce transmission failures.

6.6. Physical Impairments

With regards to the physical layer, in some cases, it is assumed that the IoT device should have a LOS view towards a UAV. This probability is assumed to depend on several factors, such as device location, environment, UAV location, and elevation angle. Both NLOS and LOS should be considered in practice since the presence of obstacles cannot be entirely avoided [62]. An arbitrary A2G link can be determined to be LOS or NLOS based on a 3D map containing environmental information. Since these maps are sophisticated, they can be used to obtain accurate information [62]. ML approaches with low complexity can be used to provide an efficient prediction of LOS probability for a pair of UAVs and ground user locations [95]. Additionally, it is assumed that the UAV does not necessarily have additional information about the exact location, height, and the number of obstacles as well as the channel conditions. For this reason, the randomness associated with LOS and NLOS should be considered in designing the system [1].

Deploying a UAV with a free space channel model is inaccurate in practice and may lead to a degradation in performance due to blockage [8]. Many studies have not considered the impact of blockages on AoI performance. In urban environments with high-rise buildings and dense settings, the signal propagation between the UAV and IoT nodes could be severely affected by blockages. This makes it difficult for UAVs to collect data in a timely fashion, thus resulting in high AoI due to the low transmission rate. Mitigating the effect of blockage is, therefore essential to improve wireless channel quality between the UAV and ground IoT nodes [103].

A Re-configurable Intelligent Surface (RIS) can potentially improve the transmission quality between transmitter and receiver devices. It consists of a controller and several low-cost passive elements. Each element has the potential to reflect incident signal by controlling the phase shift, thus changing the reflected signal propagation collaboratively. UAV and RIS (based on the amount of published research in this area) play a significant role in improving IoT data transmission to the cloud or base station [108]. Several factors affect the channel link between UAVs and sensor nodes. These include the number of elements in the RIS, the position of the RIS, and meta-surface material. These impact the channel link performance in UAV-assisted RIS channel modeling [108], and hence all these could be considered in future works. Optimization of UAV trajectory placement, RIS phase shift, mobility, and base station power allocation contribute to improving the system's performance [108]. Similarly, robust models should be proposed so that the UAV does not need to be re-trained once it is deployed in a different environment (building distribution, RIS location, IoT device location). Therefore, generalized approaches with more generalized policies are desired [103].

6.7. Multi-UAVs

Most of the works studied in this article assume only a single operating UAV, which is not practical or efficient for large-scale WSNs. The network becomes unstable if a single UAV experiences link failure [63]. On the contrary, multiple UAVs can reconstruct the network and find routes to deliver information to the destination should any link failure occur. Multiple UAVs could have a better completion time and can be used to cover large spaces than single UAVs [109]. Although multi-UAVs are more power-constrained [109], using multiple UAVs has the potential to improve the network performance and reduce AoI compared to a single-UAV implementation. Considering all the key features involved, optimizing UAV performance is more challenging for deploying multiple UAVs [63]. Mission planning for multiple cooperating UAVs visiting clusters of sensor nodes with a variable number of visits per cluster [104] can also be considered in the future. Multi-UAVs are capable of flying safely via collision avoidance [109]. Ensuring UAVs follow a particular formation while traversing a trajectory (not necessarily linear and avoiding collision) [109] is another potential research direction for future studies. However, if the trajectory is fixed, more attention should be given to sensor node scheduling.

6.8. Channel Models

Modeling an A2G wireless channel is important in trajectory optimization since performance degradation may be observed with inappropriate channel models compared to actual environments [62]. Obtaining realistic and reliable results for AoI minimization in UAV-assisted WSNs/IoT requires using accurate channel models. In this case, a thorough evaluation of existing channel models is important for identifying and understanding the effect of channel parameters in several use cases [108], especially those targeted at time-sensitive applications. Additionally, a map-based LOS channel model can be used to capture the actual environmental characteristics [62]. The aforementioned recommendations have the potential to reduce power consumption and properly evaluate the network performance. Therefore, realistic channel models are essential.

6.9. Flight Control

Estimation of the UAV traveling distance to accomplish a task [109] is an important aspect of measuring the efficiency of the UAV's trajectory, which impacts energy consumption; however, this has not been considered in existing works in the context of AoI minimization. Similarly, there is a need to improve existing algorithms for efficient autonomous flight control for different environmental conditions and accomplishing different missions. This makes learning-based methods for UAV control popular. They can learn from real-world experience to provide adaptive control. For instance, deep learning allows UAVs to effectively learn a pattern from navigation [109].

6.10. Energy Minimization

Optimal path planning helps to minimize the aerial mechanical energy needed for navigation, which is dissipated while the UAV flies through obstacle-free zones. Designing accurate models for estimating the aggregate energy consumption due to actions such as flying up or down or horizontal flight [109] is of prime importance in predicting UAV performance and AoI reduction. For instance, mechanical movement takes about 90–95% of drone energy. Particularly, during data gathering, the estimation and modeling of the energy required to collect data should be based on experimental results [109]. In addition to AoI, accurate energy models must be considered for estimating drone energy for throughput maximization and coverage extension. The incorporation of wireless power transfer is a promising form of energy source. However, the aggregate time needed for wireless power transfer and AoI minimization has trade-offs. This should be studied since WPT requires a notable amount of time for energy harvesting. Moreover, timeliness is important, especially in some real-time applications [104].

7. Conclusions

This paper examined critical components and important issues for an efficient design of AoI-minimal UAV-assisted data-gathering WSN/IoT applications. Our SLR study identified three critical components or primary design aspects from the selected articles, which include energy consumption, UAV flight, and trajectory control, and UAV and sensor node scheduling.

One of the interesting findings from this study is that UAV trajectory has been considered the most important element in AoI optimization by the majority of researchers. In addition, minimizing the overall UAV flight distance by proper trajectory planning and scheduling could significantly reduce the energy consumption of the UAV. The speed of the UAV also needs to be controlled to ensure a balance between energy dissipation due to acceleration and the Age of Information.

This paper also examines important issues related to each of the aforementioned components. For example, concerning UAV trajectory, the issues include UAV flight time, scheduling of ground nodes, QoS metrics, and service time allocation. In scheduling, the discussed issues include scheduling policies which involves scheduling packets, and scheduling IoTDs. In addition, UAV cooperation, energy level, flight time, velocity control, and charging optimization are some of the issues addressed in regard to energy consumption.

Similarly, major contributions made by researchers include, the study of UAV trajectory while incorporating the waiting time of (update) packets, node visiting order, backscatter communication, UAV battery recharge, energy harvesting, full duplex communication, various channel conditions, UAV heterogeneity, IoTD device selection and joint data transmission, and packet allocation.

In summary, planning for efficient UAV- aided data collection for WSN/IoT networks with minimal AoI must consider various factors, including adopting suitable optimization algorithms. This study also addressed the numerous challenges in AoI minimization and recommended a few future research directions. Finally, other topics, such as security, covert communication problems, and routing protocols, were considered out of this work's scope and thus shall be considered in future work.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Ant colony
AoI	Age of Information
AP	Affinity Propagation
A2G	Air-to-ground
BS	Base station
CH	Cluster head
CP	Clustering point
CSI	Channel state information
DC	Data center
DDPG	Deep Deterministic Policy Gradient
DP	Dynamic programming
DQN	Deep Q network
DRL	Deep reinforcement learning
EH	Energy harvesting
ESA	Expected sum AoI
FANETs	Flying Ad hoc Networks
GA	Genetic algorithm
GTSP	Generalized Traveling Salesman Problem

IoFT	Internet of Flying Things
IoT	Internet of Things
IoTD	Internet of Things Devices
KKT	Karush–Kuhn–Tucker
LoRA	Long Range
LOS	Line-of-sight
MAC	Medium Access Control
MDP	Markov Decision Process
ML	Machine learning
NWAoI	Normalized Weighted sum of Age of Information
QoS	Quality of Service
RF	Radio frequency
RIS	Re-configurable Intelligent Surface
RL	Reinforcement learning
SMDP	Semi-Markov Decision Process
SNR	Signal-to-noise ratio
UAV	Unmanned aerial vehicle
VDN	Value Decomposition Networks
WPT	Wireless power transfer
WSN	Wireless sensor networks

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