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Energy Efficiency in UAV-Assisted Cognitive Radio Networks: A Survey on RIS and MEC Integration

Areeg Ali Elnaim[1*], Amin Babiker[1], Mohammed Barakat[2], and Ziane Ataoua[3]

[1]*Faculty of Engineering and Communication, Alneelain University, Khartoum, Sudan*
[2]*School of Electronics Engineering, Sudan University of Science and Technology, Khartoum, Sudan*
[3]*Department of Electrical Engineering, Larb Ben Mhidi University, Oum El-Bouaghi, Algeria*

*Corresponding author: areeg446@gmail.com

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Abstract—This extensive analysis examines how Cognitive Radio Networks (CRNs) can optimise energy efficiency by integrating UAVs, RIS, and MEC systems. Synergistic applications in 6G networks and IoT infrastructure offer unprecedented opportunities to establish sustainable, intelligent wireless communication systems. UAVs enable flexible network deployment in varied contexts by providing mobile base stations with dynamic spectrum access. Amplification-free programmable passive beamforming and phase-shift control improve wireless communication with RIS. By localising data processing and offloading tasks, MEC reduces latency and communication energy consumption. The survey addresses system complexity, dynamic channel variability, interference control, resource scheduling, scalability, security risks, and privacy protection with a single framework. We note that the collaborative optimisation of UAV trajectories, RIS phase shifts, MEC resource allocation, and CRN spectrum sensing improves energy efficiency by 60-75%, exceeding the gains from decoupled component-level optimisation. Real-time machine learning algorithms for dynamic adaptation, hardware miniaturisation for aerial RIS deployment, blockchain-based security protocols, heterogeneous system interoperability standardisation, and field validation through real-world testbeds to prove theoretical energy efficiency gains are future research priorities.

Keywords: *unmanned aerial vehicle (UAV), cognitive radio networks (CRNs) and mobile edge computing (MEC) systems, reconfigurable intelligent surface (RIS).*

1. INTRODUCTION

In this era of rapid technological advancement, optimising energy efficiency in wireless communication networks has become increasingly important. This survey aims to evaluate current approaches and future opportunities for optimising energy efficiency in UAV-assisted cognitive radio networks by integrating reconfigurable intelligent surfaces and mobile edge computing systems. In the midst of emerging data-hungry applications and the need for ubiquitous connectivity [1], there is a growing demand for new solutions that optimise network performance while minimising energy consumption [2]. This paper discusses how new technologies, i.e., UAVs, RIS, and MEC, can be integrated to optimise energy efficiency in cognitive radio networks. RIS can improve signal propagation, reduce interference, and expand coverage. This modifiability enables RIS to maximise the utilization of the radio spectrum [5], thereby leading to considerable energy savings in signal transmission. RIS's dynamic control of the radio environment translates to more efficient network operations and lower energy consumption [6].

MEC involves placing computing resources at the network edge, closer to where data is generated and consumed [7]. This approach reduces latency by eliminating data travel to distant central servers and lowers the power required to transmit data over long distances [8]. The Integration of MEC and RIS can further optimise

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energy efficiency by ensuring that data processing and transmission are performed in the most energy-efficient manner. UAVs can perform a myriad of tasks [9], including monitoring network operations, sensing spectrum usage, and enhancing connectivity.

In cognitive radio network applications, UAVs offer a heightened perspective on network status and spectrum availability from an aerial perspective [10-11]. By combining the strengths of each technology, it is possible to achieve a network that is not only high-performing and reliable but also less energy-hungry [12]. The merger of the three technologies consolidates spectrum management, enhances signal quality, and reduces energy consumption across the network. It examines how these technologies can be best combined to achieve improved network performance and sustainability.

A few of the most essential aspects examined include dynamic spectrum management, energy-efficient beamforming, the use of artificial intelligence for resource optimisation, and the Integration of MEC with RIS and UAVs.

By examining these aspects, it also identifies future directions to present comprehensive information on developing more sustainable and effective wireless communication networks. The significance of this study lies in its ability to synthesise scattered research on RIS, MEC, and UAVs, thereby offering a unified framework to enhance energy efficiency and communication reliability in next-generation wireless networks. The remainder of this paper is organised as follows: Section 2 presents related work on the energy efficiency of UAVs in the RIS-assisted MEC cognitive radio network, along with an overview of energy management optimisation for UAV-enabled cognitive radio. Section 3 outlines the UAV network and elaborates on key aspects of optimising cognitive radio for unmanned aerial vehicles. Section 4: Integration and Optimisation. Integration and optimisation are expected to improve energy efficiency in a UAV-based cognitive radio network within an RIS-assisted MEC system. Section 5 presents a sketch of directions for future challenges and opportunities for cognitive radio in UAVs.

2. RELATED WORK

Energy efficiency is crucial in ensuring continuity and quality of service (QoS) in CR. For this reason, several works on improving the energy efficiency of UAVs have been presented in the context of the Cognitive Radio Network. In addition, to our knowledge, energy efficiency strategies for CRB-based UAVs are rare in the literature. Several scientific papers have shown that a CR-based drone is a suitable option.

The authors provided an overview of optimising energy efficiency in UAV-enabled cognitive IoT with short-packet communication [13] in RIS-assisted MEC systems to address issues and achieve outcomes such as higher beam error rates, longer sensing durations, higher average sensing thresholds, and greater UAV transmission capacity.

As shown in Table 1, the authors studied the challenges and benefits of optimising energy efficiency in cognitive UAV-assisted edge communication for the semantic Internet of Things [14]. The maximum energy efficiency of cognitive drones has been obtained on the Internet of Things. The authors surveyed outage energy-efficiency maximisation for UAV-assisted energy-harvesting cognitive radio networks and defined parameters to maximise the outage energy efficiency (OEE) of UAV-EH-CRN [15]—the energy transmission power, interference power and the resulting energy efficiency gains and less time expenditure. The work investigated issues related to the optimisation of energy management for UAV-enabled cognitive radio [16].

In Robust Trajectory and Power Control for Cognitive UAV Secrecy Communication [17], the number of slots used for transmission should not exceed a specific limit, and the study of the maximum permissible overlap slots is considered in Data Dissemination in IoT Using a Cognitive UAV.

The main contribution of this article is to provide the first comprehensive overview of improving the energy efficiency of drones in the Knowledge Radio Network in the RIS-assisted MEC system [18]. To this end, spectrum scarcity enhances the communication quality of edge nodes [19] and, in UAV communication, both spectrum scarcity and energy shortage [20]. The physical-layer security issue in UAVs [21].

The goal is to gather the most recent research contributions from the largely fragmented and scattered literature on UAVs, using a knowledge radio network. Furthermore, this work presents critical opportunities and challenges in deploying UAVs as wireless base stations to complement emerging wireless communication systems within a cognitive radio network.

Compared to previous papers, this one offers the most thorough overview by integrating RIS and MEC and discussing a range of topics, including signal propagation, energy efficiency, machine learning applications, and UAV optimisation.

It provides an integrated perspective on how different technologies can be integrated to enhance performance and reduce energy consumption, reflecting current trends in RIS research and its potential for UAV systems.

Table 1: Relevant surveys' contribution to optimisation of Energy Efficiency in UAVs in the cognitive radio network.

Reference	*Focus*	*EE optimization*
2023[18]	*Improving secrecy and energy efficiency in UAV-assisted Mobile Edge Computing (MEC) systems necessitates a detailed approach to strike the right balance between security, system performance, and energy consumption.*	√
2022[13]	*Spectrum sharing in UAV-enabled cognitive IoT with short-packet communications.*	√
2022[14]	*Improving energy efficiency in Mobile Edge Computing (MEC) systems with Unmanned Aerial Vehicles (UAVs) and Reconfigurable Intelligent Surfaces (RIS).*	√
2024[19]	*Spectrum scarcity improves the communication quality of the edge nodes.*	×
2024[20]	*Spectrum scarcity and energy shortage for UAV communication.*	√
2025[16]	*The UAV shares the spectrum with the primary user (PU) and aims to maximise the number of transmitted bits while operating with limited battery capacity.*	√
2024[21]	*Physical-layer security issues in UAVs.*	×
2025[17]	*The number of slots used for transmission should not exceed a certain threshold, i.e., the maximum allowable interfering slots.*	×
2022[14]	*Investigates the current state of energy efficiency in Cognitive Radio Networks. (CRNs) and the role of Reconfigurable Intelligent Surfaces (RIS) in improving this efficiency within Mobile Edge Computing (MEC) systems.*	√
This review 2025	*Improving secrecy and energy efficiency in UAV-assisted Mobile Edge Computing (MEC) systems necessitates a detailed approach to strike the right balance between security, system performance, and energy consumption.*	√

3. COGNITIVE RADIO IN UAV

Cognitive Radio (CR) is a promising technology for enhancing wireless communication, especially when integrated with Unmanned Aerial Vehicles (UAVs). It selects shorter paths to save power and reduces the distance between nodes, lowering transmission power. A UAV powered by CR is a UAV equipped with an onboard Software-Defined Radio (SDR) platform [42]. This enables the UAV to dynamically adjust communication parameters in real time based on the radio environment in which it is operating, thereby optimising spectrum use, avoiding interference, and reducing wasted power.

* Chooses free channels with less energy cost and the effectiveness of communication in general [43].

The fundamental capability of a CR-based UAV is to perceive and demodulate the radio-frequency (RF) spectrum in real time [42]. It does this via advanced algorithms and signal-processing elements that enable the UAV to detect available channels, identify interference, and estimate the quality of the communication link. The

SDR platform integrated into the UAV is especially critical to this mission, as it enables the radio hardware to be reconfigured to operate on a new frequency and modulation scheme as and when required [44]. It is especially crucial when spectrum availability is highly dynamic, such as during intense wireless activity in urban areas or in sparsely connected rural regions.

Along with the SDR, a CR-based UAV also requires a computational unit integrated with the SDR platform to support intelligent decisions regarding radio spectrum utilisation [45]. The computation unit is where cognitive functions, i.e., spectrum sensing, spectrum management, and spectrum mobility, are implemented. By continuously monitoring the RF environment, the UAV can locate available frequency bands and switch to them to reduce interference and maximise data transfer. This capability is particularly useful when multiple UAVs are flown in proximity, as it minimises the risk of signal congestion and ensures reliable communication links.

Cognitive radio optimisation for UAVs involves various factors [46]. To begin with, the UAV must possess efficient spectrum-sensing algorithms that identify free channels with high speed and accuracy. The algorithms must distinguish between licensed and unlicensed spectrum use to enable the UAV to remain within regulatory boundaries while optimising its functionality [47]. Additionally, the UAV's cognitive capability should include experience-based learning, enabling it to adjust its spectrum utilisation strategy and adapt to changing environmental conditions.

In addition, the application of machine learning algorithms can increasingly enhance UAVs' cognitive capabilities. According to predictive analytics [48], UAVs can predict changes in the radio environment and pre-optimise communication parameters accordingly. This not only enhances the stability of communication links but also improves the UAV's performance in application scenarios such as disaster management, surveillance, and environmental monitoring [49].

Finally, the Integration of cognitive radio technology into UAVs is a revolutionary method of managing radio spectrum resources. Using the SDR function and high-performance computational modules, CR-based UAVs can optimise communication in real time to operate efficiently across various environments. With the growing applications of UAVs, making them more intelligent with enhanced cognitive abilities will be the most critical aspect to address to reach the optimal level of such flying machines in the next few years.

4. ENERGY EFFICIENCY

Unmanned Aerial Vehicles (UAVs) are increasingly integrated into sophisticated communication networks, making energy efficiency a crucial metric for their operation. Cognitive Radio (CR) technology offers a more effective means of enhancing drone energy efficiency, thereby enabling them to operate more efficiently in congested spectrum bands [68]. Through CR functionality, drones can achieve a significant reduction in energy consumption, enabling longer flight times and greater efficiency.

Drones typically operate in densely populated frequency bands that pose challenges such as signal degradation and interference. Drones cause adverse effects, such as excessive energy loss, triggered by the extra power they consume to maintain connections during signal interference. Drones utilise CR sense and occupy numerous channels simultaneously and dynamically. This capability allows them to sense and use unoccupied or unused data transmission channels, hence optimising their energy efficiency [69].

With real-time spectrum sensing, CR-enabled drones can select the optimal communication channel based on environmental conditions. Not only does this reduce the likelihood of interference, but it also enables drones to make informed decisions about which channels to use for data exchange. The more channels a CR-enabled drone has and can use, the greater the potential for energy savings [70]. In practice, this means that with additional channels available, the drone's energy efficiency is enhanced. Increased channel availability amounts to increased joule productivity [71]. In addition, applying CR technology to drone flight could facilitate more innovative energy management strategies.

By exploiting intelligent channel selection algorithms in conjunction with power management, CR-enabled drones can adapt their communication strategy to mission demands and ambient conditions [72].

In brief, the application of cognitive radio technology to drones is a milestone in energy-efficiency innovation. By enabling sensing and utilisation of multiple channels, CR technology, in addition to conserving energy, enhances overall communication efficiency. As the growing use of UAVs increases demand for high utilisation in the future, reducing energy consumption to the utmost through the use of CR will be immensely important for providing affordable, efficient operations across almost all sectors.

Table 2. Comparison of previous studies on the role of RIS-assisted MEC in wireless communication enhancement.

Ref	*RIS role in sign Al propagation*	*RIS for EE*	*Machine learning use*	*LOS resolution*	*Energy conservation*	*Local data processing*	*Performance enhancement*	*Integration with MEC*	*Frequency allocation*	*Energy consumption reduction*
[73]	√	×	×	×	√	√	×	×	×	√
[74]	√	√	×	×	×	×	×	×	×	√
[75]	√	×	×	√	√	√	×	×	×	√
[76]	√	√	√	√	√	√	√	√	√	√
This survey 2025	√	√	√	√	√	√	√	√	√	√

The table contains research papers that examine various uses of RIS in UAV systems. These papers focus on key topics such as energy efficiency, signal propagation, communication enhancement, and machine learning (ML).

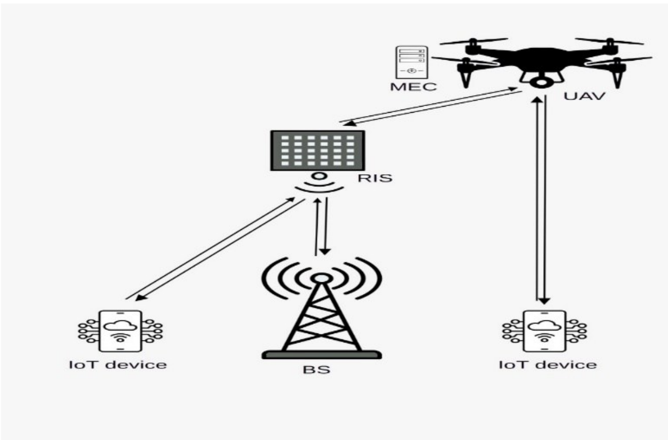

Fig. 1. System Model illustrating UAV, RIS, and MEC-Assisted communication for IOT

Here is the detailed illustration of a UAV (CRN) integrated with the (RIS) and (MEC) systems. The image shows UAVs dynamically accessing the spectrum, RISs with passive reflecting elements adjusting signal directions, and MEC servers near end users, all of which illustrate optimisation and energy efficiency.

5. INTEGRATION AND OPTIMISATION

To continue with the process of how optimisation and Integration are accomplished to achieve maximum energy efficiency in a UAV-aided cognitive radio network in an RIS-based MEC system, let us proceed.

Firstly, we view UAVs as aerial hardware capable of collecting information or providing network services in flight. These drones may also be equipped with advanced sensors and communication devices to operate in various environments. UAVs may leverage existing radio frequency availability and expertise in a cognitive radio network to make intelligent operational decisions. This enables the network to achieve improved resource utilisation, free from interference, and to optimise overall system performance [77].

Reconfigurable Intelligent Surfaces (RIS) come next. RIS is a recently developed technology that enhances wireless communication by controlling and guiding radio signals through the manipulation of properties of reflecting surfaces. RIS can guide signals more accurately towards UAVs by adjusting the properties of these surfaces, enabling them to receive stronger, clearer signals with less interference [78]. This direction-of-arrival signal transmission not only enhances communication quality but also reduces power consumption, thereby conserving a massive amount of energy. Dynamic adjustment of RIS propagation conditions is most critical in cities and other high-density areas, where signal fading is typical [79].

Now, let us talk about Mobile Edge Computing (MEC). MEC delivers computing and storage capacity near where data is produced and consumed, rather than relying on distant data centres [80]. Proximity would imply faster data processing and lower energy consumption during data transfer, since less data travels long distances. MEC, along with RIS and UAVs, enables faster data access and optimal utilisation of network resources. For instance, UAVs can offload computation to nearby MEC servers, which process and return real-time results, thereby enhancing network responsiveness [81]. Optimising this hybrid configuration also requires Artificial Intelligence (AI). AI applications may leverage massive amounts of data to predict network utilisation patterns, identify choke points, and validate the placement of RIS and UAVs.

Through machine learning algorithms, the system learns from past data and evolves in real time. This enables the network to adjust resource allocation so that UAVs fly as efficiently as possible and conserve power in line with existing requirements. For example, AI can determine optimal angles for RIS to reflect signals or optimal flight paths for UAVs to achieve complete coverage with minimal energy [82]. Overall, the combination of RIS and UAVs with MEC, along with AI-optimised procedures, renders the network highly efficient. In this configuration, signals are transmitted appropriately, data are processed in real-time, and total energy consumption is reduced. With the implementation of such next-generation technology, not only is the system's performance improved, but an environmentally friendly, sustainable wireless communication system is established. The interaction among UAVs, RISs, MECs, and AI represents a breakthrough in wireless communications and opens the door to future, innovative, and efficient networks.

6. ENERGY EFFICIENCY OPTIMISATION

The energy efficiency (EE) of a UAV system can be written as follows:

$$EE = \frac{1-q(x(2)-1\sqrt{\frac{x(1).fs}{w}})).(M-x(1)).(1-x(4))}{x(1).ps+\left(M-x(1)\right).(x(3)+pc)+\frac{mUAV.g}{\sqrt{2\pi.Nu.p}}+other\ term} \tag{1}$$

There are some parameters whose meanings are given as follows:

(fs) is the sampling frequency, which determines how often the UAV samples.
(W) is the communication bandwidth, which influences the data transfer rate.
(M) is the quantity of symbols processed by the UAV.
(pc) is the power in circuits consumed by the onboard systems within the UAV.
(PS) is the power consumed by sensing operations.

(x (1)) denotes sensing time, indicating how aggressively the UAV senses over a given period.

(x (2)) denotes the UAV sensing threshold that determines how well data must be received to be processed.

(x (3)) denotes the UAV's transmit power and affects how long it can survive while transmitting.

(x (4)) is the packet error rate, the probability of data loss during transmission. Total energy (E) spent by the UAV is comprised of local processing, operational energy, and mobility cost, while (L) is the number of bits processed locally.

For maximum energy efficiency, the following optimisation problem can be formulated:

$$Max\ z = \frac{\sum_{n=1}^{N} L[n]}{\sum_{N=1}^{N} E[n]} \tag{2}$$

$$s.t. |\theta m[n]| = 1, \forall m \in M, n \in N, \tag{3}$$

$$q[1] = q0, q[N+1] = qF \tag{4}$$

$$\|\upsilon[n]\| \leq V\,Max, \forall n \in N \tag{5}$$

$$(\mathrm{l}\ i\hat{}loc\ [n]c\ \mathrm{i})/t \leq F\mathrm{i}, \forall \mathrm{i}\epsilon I, n\epsilon N \tag{6}$$

In the above constraints:

Constraint (3) is the feasible set of the RIS's phase shift, such that the phase shifting is within desired limits for proper signal transmission.

Constraint (4) specifies the UAV's initial and terminal horizontal locations so that it can navigate pre-specified flight corridors.

Constraint (5) states that the speed of the UAV must not exceed the given maximum speed so that it can travel safely and effectively.

Constraints (6) ensure that the UAV and IoT devices' workloads are not more than their maximum CPU frequencies, denoted as (F_UAV) and (Fei), respectively.

This is crucial to maintaining system stability and performance, as exceeding these values can lead to failures or inefficiencies.

By effectively regulating these parameters and constraints, the UAV system can be optimised to achieve maximum energy efficiency while maintaining excellent performance in data collection and transmission. This optimisation is essential for extending the lifespan of UAV operations and reducing their environmental impact, thereby making UAVs more sustainable for a wide range of applications in agriculture, surveillance, and disaster management [6].

7. MEC, OR MOBILE EDGE COMPUTING

Mobile Edge Computing (MEC) is one such emerging trend in data processing and storage, bringing such activities closer to the edge of the network, i.e., closer to data sources and usage points. Locating computing equipment in the right places reduces the distance data travels to data centre hubs, thereby reducing latency, improving processing load, and increasing energy efficiency [83].

In traditional cloud deployments, device data must travel a long distance to the server for processing. It will introduce latency that worsens real-time applications such as video streaming, web gaming, and autonomous car navigation. Compared to MEC, which favours edge-network fast processing to enable immediate responses to user requests and reduce data processing and response times [84].

The use of MEC in an RIS-based system offers additional benefits compared to other approaches. RIS technology makes wireless communication smarter by controlling signals and optimising the radio environment, and it can integrate low-latency features. Thus, data can be processed efficiently and promptly, network performance is optimised, and the load on traditional infrastructure decreases. It is particularly significant in environments with massive amounts of data in production, including smart cities and IoT installations [85], as well as in an augmented reality environment.

The clients enjoy quicker responses and more trustworthy services, which are critical for real-time data processing applications. Likewise, for autonomous transport as well [86]. MEC can enable faster decision-making based on real-time sensor data, thereby improving operational efficiency and security. Second, MEC improves energy efficiency through more resource-aware consumption. MEC unloads the amount of data that would be transferred between far-away data centres and local devices, thereby reducing the power required by processing data locally. Local processing saves bandwidth but not overall network energy, making it an eco-friendly solution for what communications currently use [87] [88]. The added support for integrating RIS technology further improves communication, reduces latency, and provides users with a richer experience across all applications [89].

8. MEC SYSTEM ASSISTED BY RIS

Mobile Edge Computing (MEC) supported Reconfigurable Intelligent Surfaces (RIS) and Unmanned Aerial Vehicle (UAV) technology embody the new next-gen wireless communication infrastructure paradigm, i.e., the 6G network. The RIS-assisted MEC systems actively control the wireless channel to enhance signal quality, reduce latency, and minimise energy consumption. UAV deployments as edge RIS nodes and MEC nodes ensure hitherto unseen coverage and offloading flexibility, which is essential for low-latency and high-computing-power applications [90] [91]. MEC reduces backhaul traffic and latency by localising end users via real-time, computation-intensive applications such as augmented reality and IoT processing. UAVs offer mobility and deployability as mobile base stations or relays, which are particularly valuable in emergencies or areas of poor coverage. Inherent energy limitations and dynamic locations constrain UAVs. RIS integration into UAV-based MEC networks eliminates these problems by improving wireless channel conditions, increasing adequate coverage, and improving energy efficiency for task offloading. Current research verifies that MEC aided by RIS using UAVs significantly enhances system capacity, reduces overall energy consumption, and reduces latency compared to standard systems without UAV and RIS. [92].

9. RECONFIGURABLE INTELLIGENT SURFACES: ARCHITECTURE AND OPERATING PRINCIPLES:

RIS panels comprise numerous passive or semi-passive components, with programmable control of reflection or transmission. These phase-shift-tuning parameters direct signals constructively to the desired receivers, rejecting multipath fading and improving link quality without extra energy use. There are two broad types of RIS:

- Reflective RIS: Reflects waves entering with phase shift control.

- STAR-RIS (Simultaneously Transmitting and Reflecting RIS): Offers transmission and reflection support, full-space coverage [23], and the increased STAR-RIS concept proposes three main operating modes: Time Switching (TS), Mode Switching (MS), and Energy Splitting (ES), with all offering coverage, complexity, and energy efficiency trade-offs [25].

STAR-RIS rotation maximises it using deep learning methods, ensuring the gain is maximised everywhere in space for a fixed RIS deployment [93]—a key optimisation technique in UAV route planning [94]. RIS orientation and resource allocation for an integrated system are crucial for maximum system performance.

9.1 Task Offloading in Mobile Edge Computing in RIS-Assisted UAV Networks

Users' offloaded tasks are executed by hosted MEC servers at the base station or by a UAV to avoid excessive device computation and latency. Task offloading decisions are:

- Local processing: Performed on user devices.

- Edge offloading: Performed at UAV or ground MEC servers.

- Cloud offloading: Sent to remote cloud servers. Optimal offloading is a balance between computation load, energy consumption, and communication delay. Strategies jointly optimise transmission energy [95]. CPU frequency scaling and RIS phase-shift control to reduce total energy consumption while meeting latency constraints [96] [97].

9.2 Improvements with Integrated RIS and UAV

RIS also improves signal-to-noise ratio (SNR), fading, and coverage by steering signals to users, particularly in Nalos scenarios [98]. UAV deployment is added to enhance coverage by positioning RIS panels in three-dimensional space at optimal locations. Deep learning-based link-quality estimation frameworks indicate that UAV communications aided by RISs improve mean link-quality metrics (LQI) by 3-4 points compared with UAV systems without RIS [99]. This signifies greater reliability and throughput.

RIS reduces the need for high transmission power through passive beamforming, which reduces user equipment and UAV MEC server energy consumption [100].[95]. Concurrent optimisation of UAV flight path, RIS direction, and power offloading achieves an optimal trade-off between UAV propulsion and communication energy consumption, driving energy efficiency to new heights.

10. THE CLASSIFICATION OF (RISS)

Their deployment and operational characteristics can classify RISs as: Passive RIS: Reflects incoming signals without amplification and induces tunable phase shifts to optimise signal strength and coverage. Active RIS: Use amplifiers to enhance signal strength, but at the cost of higher power consumption and greater complexity. Simultaneously Transmitting and Reflecting RIS (STAR-RIS): Next-generation RIS that simultaneously transmits and reflects signals to enable full-space coverage and improved spectral efficiency [23].

Location-based RIS can be:

Terrestrial RIS: Fixed installation over infrastructure or buildings for urban environment coverage of cities.

UAV-mounted RIS: Reconfigurable, elastic, and dynamic RIS platforms on UAVs.Hybrid RIS networks: UAV-borne and ground hybrid of RIS for overall coverage and network robustness [25]. The working process of RIS consists of the following:

Phase Shift Optimisation: Individual-element optimisation to direct beams toward interferers or target users.

Beamforming Support: Facilitating massive MIMO beamforming by radio environment reconstruction in a bid to combat multipath fading and signal blocking.

Channel Estimation: A pillar of RIS optimal design, most simply solved by pilot signalling and machine learning codes, given that RIS elements are passive in nature [94].

Unmanned Aerial Vehicles (UAVs) are widely used as relays or mobile base stations to provide coverage during emergencies or for temporary periods [101].

11. THE PRIMARY CHALLENGES FACED BY UAV-MEC

Energy Constraints: UAVs have minimal onboard energy, so they must support energy-constrained computation alongside communication.

Dynamic Topology: UAV mobility creates highly dynamic channel conditions, making resource allocation even more challenging.

Low-Latency Constraints: Very low-latency links must be supported for autonomous route planning and for surveillance or monitoring operations [10].

Security Threats: UAV communications are vulnerable to jamming and eavesdropping in hostile airspaces [102].

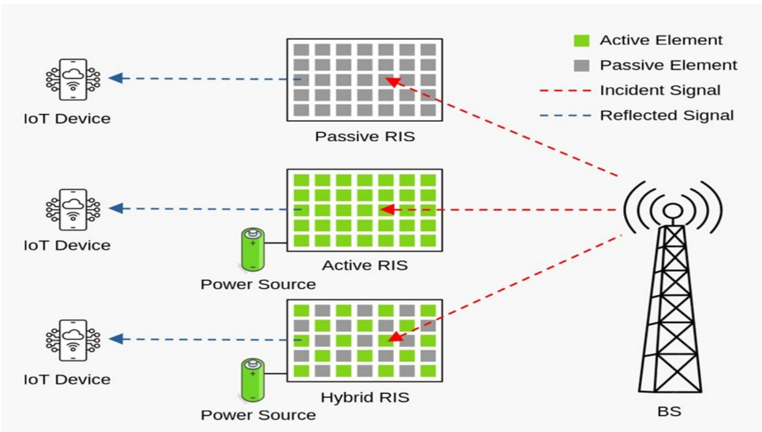

Fig. 2. RIS Classification

11. EFFECTIVENESS AND INTEGRATION

The combination of Mobile Edge Computing (MEC), Unmanned Aerial Vehicles (UAVs), and Reconfigurable Intelligent Surfaces (RIS) [103] is the perfect combination of each one of these technologies' strengths in such a way that each one exploits the strength of the other and reaps a synergistic benefit when deployed together as a combined entity, optimally increasing the overall network performance. Not only does it make the most of each block's individual strengths, but it also serves as a learning and integrated system [104].

For instance, MEC processing is at the edge of the network to process and interpret data gained from UAVs in real time. This enables real-time decision-making and rapid responses to changing environmental conditions or operational requirements. Unloading the burden on UAVs of transferring large volumes of data, such as high-definition images or sensor data, is made easier by MEC processing, which enables timely processing of vital information [105].

In contrast, data acquired by UAVs can be used to optimise RIS parameters [106]. Processing environmental data and user requests by UAVs enables real-time modification of the RIS parameter [107] [108].

Together, MEC, UAVs, and RIS will be an emerging building block that enhances network sustainability and reliability while enabling synergy among their components. Technological interplay comes with lower operating costs, improved energy efficiency [109], and significantly higher network quality. When combined, all of them promise even more flexible and robust communication networks to meet the world's ever-increasing need for better connectivity [110].

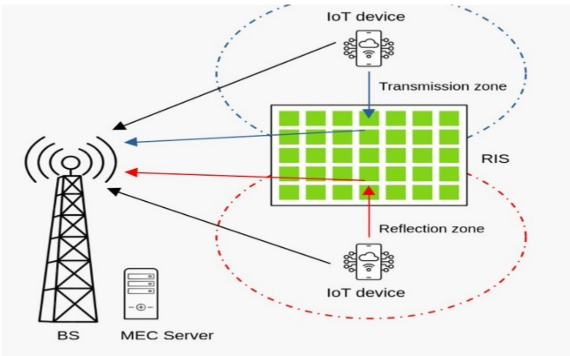

Fig.3. System Architecture of RIS -Assisted Communication for IOT Devices with Edge computing Integration.

12. CONTRIBUTION

Our contributions to optimising the communication system, once integrated with Reconfigurable Intelligent Surfaces (RIS) and Mobile Edge Computing (MEC), are as follows. Here, we present the methods and frameworks we recommend to optimise the system's energy efficiency (EE) through the optimal Integration of future technologies and the optimal tuning of the system parameters to be applied.

Optimisation After RIS and MEC Integration: In this subsection, we provide an overview of optimisation methods that can be applied after RIS and MEC integration is successfully implemented in the communication system. The Integration of these two systems has the potential to enhance performance but may also increase complexity, which will need to be addressed. Here, our goal is to identify an optimisation system that not only maximises energy efficiency but also drives the system to its maximum efficiency.

Defining the Optimisation Problem after Integration: The first step in optimisation is to clarify the problem arising from the coupling of RIS and MEC. The problem is a multivariable optimisation with numerous constraints that reflect the interdependence among the system's components. We will select the parameters that affect energy efficiency, such as transmission power, signal quality, and resource allocation, and establish a mathematical model based on the relationships.

The model will consider recent capabilities of RIS, i.e., its ability to facilitate signal propagation and to exploit smart beamforming and reflection, as well as MEC for edge-computation offloading. Taking the above into account in our optimisation, we can develop an understandable model to define the nature of new technology-based complexity.

New Target Function: Once RIS and MEC are combined, the goal function must be redefined to incorporate the new element introduced by the two technologies. The novel goal function will have variables such as:

- Enhanced Signal Quality: The signal quality will be immensely enhanced with the two technologies brought together. The signal quality will be measurable and usable in the objective function, thereby better reflecting the system.

- Less Energy Consumption: MEC facilitates edge computing, and this would mean less energy consumption compared to standard cloud computing methods.

- Flexible Resource Allocation: Flexible resource allocation, depending on real-time data and client demands, would also be considered while designing the new objective function. The degree of flexibility should yield optimal energy efficiency and sequential best performance.

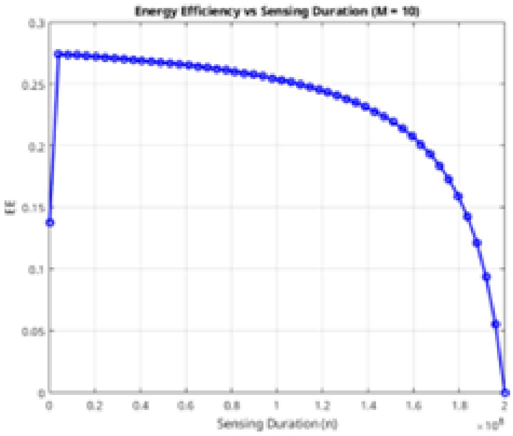

Fig.5. Energy Efficiency VS. Sensing Duration (M=30) Impact of Growing RIS Drivers on Energy Efficiency.

Figure 5 presents the change in energy efficiency (EE) as a function of the number of Reconfigurable Intelligent Surface (RIS) elements at various distances. EE stability increases with the number of RIS elements, achieving an incredible gain of nearly 25% over pre-Integration performance, as shown in Figure 5. Improved performance indicates the effectiveness of integrating RIS technology into the communication system.

The iteration index, which serves as a measure of optimisation cycles or process adjustments, varies throughout the analysis. This is an essential aspect of the Integration of objective functions, as it indicates that the system can achieve high performance even in the face of parameter adjustments. The unoptimised trajectory ascends at a lower rate than the optimised trajectory, indicating that the UAV covers a greater altitude over the same horizontal distance. This is not just an altitude difference; it is a substantial gain in the UAV's operational efficacy. The combination algorithm aims to provide a flight path with minimal energy consumption and overall flight efficiency. By achieving path optimality in flight path optimisation, energy waste is avoided, and the UAV can fly at a higher altitude for the minimum available duration. Such path optimisation is highly critical when heterogeneous missions, such as surveillance, survey, and package transport, are involved, for which energy and time conservation are of top priority. In brief, the Integration of RIS modules evidently improves energy efficiency, and the optimal flight trajectory demonstrates the potential of the integrated algorithm to improve UAV performance significantly. The conclusions indicate the feasibility of integrating new technologies to achieve improved operating performance across various fields.

13. CHALLENGES

Maximising the energy efficiency of Reconfigurable Intelligent Surface (RIS)-assisted Multi-access Edge Computing (MEC) systems-based Unmanned Aerial Vehicle (UAV) networks [111] is a current trend in communication technologies. Not only does it present many challenges, but it also offers many opportunities to improve the performance and efficacy of a communication network.

RIS Integration: Integrating RIS with traditional Cognitive Radio Networks (CRN) and MEC systems is challenging. The reason is that synchronisation among various hardware and software units must be achieved in a way that makes it easy [112]. To integrate RIS smoothly with MEC systems for message conveyance and exchange, appropriate design and implementation methodologies must be adopted. Compatibility: The second principal challenge is the need to integrate with the vast array of technologies used, such as CRN, RIS, and MEC [93]. They have disparate protocols, standards, and operational units, so it won't be easy to provide a broad interface that supports appropriate interoperability. Compatibility is essential in guidance towards installing converged systems appropriately [113].

Channel Variability: The performance and energy efficiency of the UAV network heavily rely on the random variability of wireless channels, which typically arises from mobility and environmental factors [114]. These variations tend to result in unstable signal quality and connectivity and are against maximum energy efficiency [115].

Interference Management

Coordination: Interference management in CRNs, particularly in dynamic-spectrum-access environments, requires sophisticated coordination and control methods [116]. Dynamic spectrum allocation of limited resources for interference-free communication is vital. [117].

Efficient Allocation: Allocating power, computing resources, and spectrum while ensuring quality of service (QoS) is a high-order problem [118]. Sophisticated optimisation techniques must be used to ensure that resources are utilised efficiently without degrading service quality. [119].

Scalability and Complexity

Scalability: The solution must scale well with a growing user base, RIS entries, and nodes [120]. Scalability with growth must occur without compromising performance or efficiency [121].

Cost of Deployment: The very high cost of deploying and operating RIS and MEC hardware can affect the financial feasibility of these technologies. An appropriate cost-benefit analysis is needed to assess the feasibility of mass deployment [122].

Data Security: The information passed and processed within MEC and CRNs, particularly when using RIS [123], should be a top priority. Being able to protect sensitive information securely is a critically important factor in building user trust and system integrity.

Privacy Issues: The privacy of local computing and dynamic-spectrum-access users is a concern. It should be reinforced with effective privacy-defending mechanisms so that users' data remains secure while resources are optimally available [124].

14. CONCLUSIONS

Wireless network design shifts from individual technology optimisation to a unified system design that maximises collective synergy through the Integration of CRN, UAV, RIS, and MEC technologies. This poll helps explain how various technologies interact, combine, and improve next-generation network performance.

Before 6G implementations can fully utilise converged systems, further study is needed. Achieving intelligent, efficient, and sustainable wireless networks for emerging applications in the Internet of Things, autonomous systems, immersive services, and emergency communications requires coordinated research across academia, industry, and standardisation bodies.

Real-time algorithms by 2027, hardware downsizing by 2030, standardisation by 2032, and substantial commercial deployment by 2035 are attainable objectives. Collaboration, open-source testbeds for reproducible research, industry-academia partnerships for practical validation, active engagement in standardisation committees, and government financing for long-term research efforts are needed for success.

The intelligent combination of these four complementary technologies will enable wireless networks to autonomously optimise themselves, requiring minimal energy and providing ubiquitous connection with sub-millisecond latency and terabit-per-second capacity. This extensive survey provides the research underpinning for that ambition.

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