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Energy Efficiency Optimization in Algorithm for RIS-Assisted UAV-Enabled MEC-IoT Networks

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Abstract—The combination of drones and smart reconfigurable surfaces (RISs) is becoming increasingly important for improving energy efficiency and wireless communication performance in Internet of Things (IoT) networks. This research focuses on developing an iterative optimization algorithm based on the fmincon algorithm in MATLAB. Sensing and transmission parameters are updated simultaneously at each iteration to achieve maximum energy efficiency. The algorithm starts with initial values. To optimize the energy efficiency of a system integrating a drone that provides mobile edge computing (MEC) services to IoT devices, the proposed system takes into account several critical factors, including drone trajectory optimization, optimal bit allocation between local and drone processing, and phase shift optimization in smart reconfigurable surfaces. The goal is to maximize overall energy efficiency by jointly optimizing these elements through a novel algorithm that alternates between optimizing the smart reconfigurable surfaces' phase shifts, the drone trajectory, and bit allocation. Simulation results demonstrate that the proposed solution significantly outperforms other measurement approaches in terms of energy efficiency, while examining the impact of variables such as the number of users, the reflectance elements of reconfigurable smart surfaces, and base station antennas on system performance. In conclusion, this research presents a novel approach to enhancing energy efficiency in RIS-enabled and drone-enabled MEC systems for IoT networks, achieving significant improvements over existing methods

Keywords: *Cognitive radio networks (CRNs), unmanned aerial vehicles (UAVs), Reconfigurable Intelligent Surfaces (RIS), Mobile Edge Computing (MEC), Energy Internet of Things (IoT)*

1. INTRODUCTION

The rapid development of the Internet of Things (IoT), data traffic will increase completely, necessitating a large amount of spectrum. Cognitive radio (CR) technology has been proposed as a solution to the spectrum scarcity problem[1] .It improves spectrum efficiency. In cognitive IoT, secondary IoT devices can coexist with nearby primary IoT devices on the same spectrum while ensuring that secondary users' interference is kept to a minimum The utilization efficiency of the licensed spectrum can be increased. Integrating ground-based and air-based networks is one of the challenges in building a six-generation (6G) communication system[2] . Unmanned aerial vehicle (UAV) assisted communication has been extensively researched in civil and military applications due to its numerous benefits, including high maneuverability [3], on-demand deployment, and so on. UAVs can be used as aerial base stations, providing wireless service to ground users Because of the bottleneck in battery technology [4], the UAV system's operating time will be reduced. Therefore, it is urgent to improve the energy efficiency (EE) of the UAV system. The UAV is deployed as an aerial base station, providing wireless services to ground users. The UAV's trajectory, bandwidth allocation, and user communication scheduling are optimized to maximize EE while meeting user quality-of-experience (QoE) requirements Consider a spectrum sharing system in which the UAV circles the PU transmitter and detects its status using spectrum sensing. When detected to be idle, UAVs can use the licensed spectrum for short packet communications [5]. Because of the UAV's high

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altitude, wireless channels between and ground nodes are assumed to be links. For micro rotary-wing UAVs that are typically powered by batteries, EE is an important performance metric to consider. First, we calculate the effective throughput of the UAV communication system by taking into account the effect of imperfect sensing and packet error rate [6]. The average energy consumption of the UAV system is then calculated, which includes hovering energy, propulsion energy, and communication energy. The EE is the ratio of average throughput to average power consumption [7]. We aim to maximize EE by designing the packet error rate, sensing duration, normalized sensing threshold, and the UAV's transmit power.

The packet error rate, sensing duration, normalized sensing threshold, and UAV transmit power are all optimized together to maximize the UAV system's EE [8].

The integration of (UAVs) and Reconfigurable Intelligent Surfaces (RIS) marks a significant step forward in the design of next-generation wireless communication networks [8]. UAVs, with their mobility and flexibility, offer a dynamic platform for improving wireless coverage and capacity, especially in challenging environments. Simultaneously, RIS technology provides a novel method of controlling the propagation environment [9], enabling intelligent manipulation of electromagnetic waves to improve signal strength and reduce interference In the context of Mobile Edge Computing (MEC) [10], which needs to bring computation and storage closer to end users, the collaboration between UAVs and RIS has the potential to significantly improve the efficiency and reliability of data processing and transmission in Internet of Things (IoT) networks. However, optimizing such a complex system presents numerous challenges [11], particularly in terms of energy efficiency, which is critical given UAVs' limited power resources and need for long-term operation without frequent battery replacements or recharges [12].

In This paper the objective: Develop a comprehensive optimization framework to enhance energy efficiency in a RIS-assisted UAV-enabled MEC system.

2. RELATED WORKS

. This study focuses on using (UAVs), Reconfigurable Intelligent Surfaces (RIS), and Multi-Access Edge Computing (MEC) to improve energy efficiency in wireless networks. Several studies have investigated these approaches separately or in combination to improve wireless network performance.

In (UAVs) The UAVs have shown to be a valuable tool for increasing energy efficiency and expanding wireless coverage. For example, Ghamari et al. (2022) conducted a review of UAV applications in civil domains, emphasizing their benefits in terms of wireless coverage and spectrum efficiency. Research has mostly focused on optimizing UAV trajectories and resource utilization to reduce energy consumption and Reconfigurable Intelligent Surfaces (RIS)

RIS is a novel breakthrough in wireless communication that provides new techniques to regulate the propagation environment. In a comprehensive analysis, Ahmed et al. (2024) underlined that RIS improves signal strength, decreases interference, and broadens wireless communication possibilities, making it a potential solution for future networks (MEC).

MEC dramatically improves wireless network performance by lowering latency and increasing data processing efficiency. Narayanan et al. (2020) examined important achievements in MEC for industrial IoT applications, noting its critical role in enhancing data transmission reliability, especially when linked with UAV and RIS technologies, and challenges and improvements in energy efficiency.

Despite tremendous advances in these fields, increasing energy efficiency remains a serious problem. Key concerns include UAVs' limited energy resources and the necessity for long-term operations without regular battery replacement. To solve these difficulties, this research provides a comprehensive system that includes UAVs, RIS, and MEC. The suggested solution uses iterative algorithms and gradient-based approaches to optimize system parameters over several time periods, with the goal of significantly improving energy efficiency.

The associated works stress the need for ongoing research to increase energy efficiency in integrated wireless systems. Building on previous contributions, this study presents a novel paradigm that may be used to real-world settings, paving the way for more sustainable and efficient wireless communication systems.

TABLE 1. Abbreviation for related works.

REF	*PAPER*	*Field*	*Main Goals and Results*
[9] 2024	*Active Reconfigurable Intelligent Surface es: Expanding the frontiers of wireless communication.*	*(RIS)*	*Comprehensive review of RIS technology and its potential to improve signal strength and reduce interference in wireless communication.*
[13] 2023	*Joint optimization of resource Allocation, phase shift, and UAV trajectory for Energy Efficient RIS-Assisted UAV-Enabled MEC.*	*EE optimization*	*Optimization resource allocation, phase shift, and UAV trajectory to maximize EE in RIS-assisted UAV-enabled MEC.*
[11] 2023	*Reconfigurable intelligent surface for physical layer security in 6G-IOT*	*physical layer security*	*Improving security in 6G-IOT networks using RIS,*
[1] 2022	*Throughput optimization of interference limited cognitive Radio Radio-based IOT Network.*	*IOT Networks*	*Enhancing spectrum efficiency by optimizing throughput in cognitive Radio Radio-based IOT Networks.*
[3] 2022	*UAV communications for civil Applications*	*UAV communications*	*Reviewing the civil applications of UAVs and their benefits in enhancing wireless coverage and spectrum efficiency.*
[10] 2020	*Key Advances in pervasive Edge computing for Industrial IOT.*	*Edge computing*	*Enhancing efficiency and reliability of data transmission in industrial IOT networks through edge computing technologies.*
[2] 2019	*IOT Enabled wireless sensor Network for physiological data Acquisition.*	*Wireless sensor networks.*	*Improving physiological data acquisition using IOT-enabled wireless sensor networks.*
This Paper 2025	*Energy Efficiency optimization in cognitive Radio Networks RIS assisted UAV Enabled MEC system.*	*Energy Efficiency In Networks.*	*Proposing a comprehensive frame work to optimize Energy Efficiency by integrating UAVs, RIS, MEC.*

3. SYSTEM MODEL

This system model describes the integration of (UAVs), Reconfigurable Intelligent Surfaces (RIS), The model encompasses the operational parameters and interactions between these components, focusing on energy efficiency optimization.

4. OPTIMIZATION OF THE ORIGINAL SYSTEM

In this section, we focus on optimizing the performance of the UAV system supported by the reconfigurable intelligent surface (RIS) in terms of energy efficiency

The goal is to maximize the (EE) by adjusting various system parameters.

4.1 Energy Efficiency Optimization

The objective function is the function we aim to r maximize (EE) of the system.

The energy efficiency of the UAV system can be calculated using the following equation:

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

x1 represents the sensing duration, x2 the sensing threshold, x3 the UAV transmit power, x4 the packet error rate, q the gaussian q-function, fs is the sampling frequency, W is the bandwidth, M is the number of symbols [14], pc circuit power, ps represents sensing power, g is the gravitational acceleration, Nu is the number of rotors, and mUAV is the UAV's mass [15] .

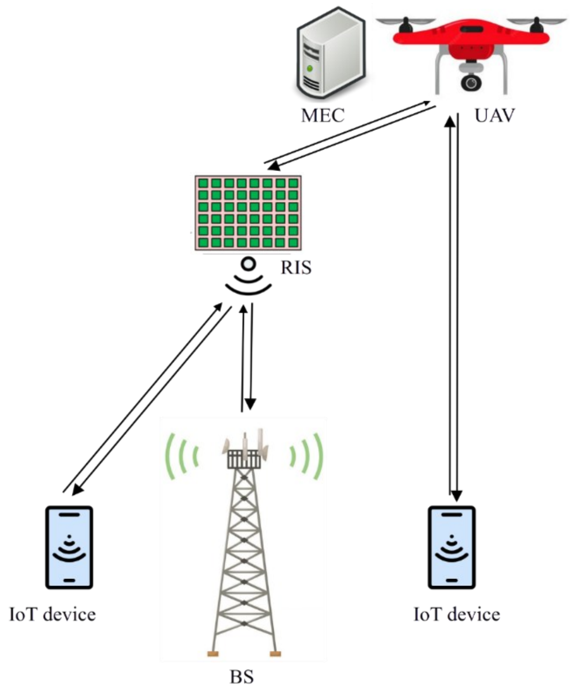

Fig 1: System Model illustrating UAV, RIS, and MEC -Assisted communication for IOT

5. CONSTRAINTS

Constraints are important in any optimization problem because they ensure that the optimal solutions meet particular requirements or limitations. To optimize the energy efficiency of a UAV system supported by a Reconfigurable Intelligent Surface (RIS), certain restrictions must be considered to ensure that the system operates properly and efficiently.

5.1 Detection Probability

The detection probability refers to the likelihood of successfully detecting the signal. To achieve consistent performance, the detection probability must be high. We utilize the Gaussian Q-function to get the detection probability:

$$pd = Q\left(k - ys - 1)\sqrt{\frac{nfs}{w(2ys+1)}}\right) \tag{2}$$

Where:

Q is the Gaussian Q-function, which represents the likelihood that a Gaussian random variable will surpass a given value w. (SNR), fs is the sampling frequency ys, and w is the bandwidth.

We want to achieve a detection probability of at least 0.9 for effective signal detection.

False alarm likelihood pf

$$pf = Q\left((k-1)\sqrt{\frac{nfs}{w}}\right) \tag{3}$$

where κ is the normalized threshold of the energy detector, fs is the sampling frequency [13], Q(x) is the complementary distribution function of the standard Gaussian, γs is the signal-to-noise ratio (SNR) of the primary signal at the UAV [14]

$$\gamma s = \beta 0 Pp / (r\alpha\ s\ \sigma 2\ u) \tag{4}$$

where σ2 u is the noise power.

5.2 *Sensing* duration

The sensing duration is the time period during which the UAV collects information [16]. It must be within reasonable limits to ensure system efficiency:

$$Ts = (1+\gamma.\log(d)).\ (1+\alpha.\frac{pt}{pt\ max}).\ (1+\lambda.\frac{I}{pt}).\ (1+\beta.\frac{1}{1+exp\ (-\delta.d)} \tag{5}$$

γ the factor adjusts the influence of distance, while α adjusts the effect of transmit power. β represents the environmental effect, while δ represents the effect over distance.

5.3 *Sensing Threshold*

The sensing threshold is the signal level that is deemed sufficient to detect the signal. It must fall inside specified boundaries:

$$\Theta = \eta.\log\ (1+\frac{pt}{\sigma}).\ (1+\zeta.\frac{d}{R}).\ (1+\alpha.\frac{I}{pt}).\left(1+\beta.\frac{1}{1+exp\ (-\gamma.SNR)}\right).(\ 1+\delta.E) \tag{6}$$

η.log (1 + pt/σ) This section depicts the influence of transmission power pt in relation to noise. σ is heavily influenced by the signal-to-noise ratio in the communication environment. (1+ ζ.d/R) reflects the effect of distance (d) and R. The efficacy of communication diminishes.

5.4 *UAV Transmit Power*

The transmit power refers to the energy utilized by the UAV to send the signal. To avoid excessive energy use and ensure energy efficiency, it must adhere to particular constraints.

$$Pt = (\frac{\alpha}{\beta+\gamma}).\ (1+\log\ (\frac{d}{R})).\ (1+\ \delta.\ \exp\ (-\epsilon.\ d)).\ (1+\zeta.SNR).\ (1+\eta.\frac{I}{pt}).\ (1+\theta.E) \tag{7}$$

α, β, and γ are scaling parameters, while δ and ϵ are adjustment parameters.

5.5 *Packet Error Rate (PER)*

The packet error rate is the percentage of packets that do not arrive at their intended destination. To ensure the quality of communication, it must be within reasonable boundaries.

$$pe = \frac{\mu}{1+\omega.Pt}.(1+\ \zeta.\frac{pe^{inter}}{pt}).\ (1+\mathcal{E}.\log(\frac{d}{R})) \tag{8}$$

μ, ω, ζ , Ɛ constants adjusted for different effects.

6. COMMUNICATION MODEL

Tthe channel gain between the UAV and the RIS at time slot n can be given by:

$$hRu[n] = \sqrt{pdRu^{-2}[n]}\left[1, \dots, e^{-j\frac{2\pi}{\lambda}(M-1)d\varphi Ru[n]}\right] \tag{9}$$

where ρ is the path loss at the reference D0 =1 m, d is the antenna separation; λ is the carrier wavelength; RU[n] is the cosine of the AD of the signal from the RIS to the UAV at time slot n [17].

the channel gain from the IoT device to the UAV at time slot n can be expressed as:

$$Hiu[n] = \sqrt{p\ d^{-\epsilon} iu\ [n]} giu \tag{10}$$

the IoT device at timeslot n; ε is the pathloss exponent and giu represents the random scattering component [18]. For the communication links from the IoT devices to the RIS [19]. we assume that they are Rician fading channels.

the channel gain between the IoT device and the RIS at time slot n can be given by:

$$hiR\ [n] = \sqrt{\mathrm{p\ d^{-\gamma} iR[n]}} \left(\sqrt{\frac{\beta}{1+\beta}}\ \mathrm{hiR^{loS}} + \sqrt{\frac{1}{1+\beta}} \mathrm{hiR^{NLoS}} \right) \tag{11}$$

the distance between the IoT device and the RIS is dir., γ denotes the path loss exponent; β represents the Rician factor; h loss and N loss are the Loss component and N Loss component [20], respectively For h loss .

7. SYSTEM OPTIMIZATION AFTER INTEGRATING WITH RIS AND MEC

In this section, we will optimize the system following its integration with Reconfigurable Intelligent Surface (RIS) and (MEC) [21]. The goal is to increase the system's energy efficiency (EE) by adding these technologies and modifying the necessary system parameters.

7.1 Formulating the Optimization Problem after Integration

Objective Function

As stated in the first section, the goal is to maximize (EE). The integration of RIS and MEC increases the system's complexity [22], but the goal function can be stated similarly, accounting for the additional impacts.

Modified Objective Function

Following the integration of RIS and MEC, the goal function is adjusted to take into account the additional features, such as increased signal quality from RIS and reduced latency from MEC. The modified objective function may be stated as:

$$EE(X) = \frac{R(x) - p(x)}{p(x)} \tag{12}$$

Rx: Data rate (throughput) after optimization, and P(x): System power consumption after optimization.

8. MODIFIED CONSTRAINTS

In current UAV systems, integrating technologies such as Reconfigurable Intelligent Surface (RIS) and (MEC) has the potential to significantly improve overall system performance [22]. However, in order to properly utilize new technologies, traditional system limits must be revised. These updated limitations provide an ideal mix of performance, efficiency, and sustainability while adhering to legal and operational standards.

Modified constraints are important because they can increase energy efficiency, signal quality, and reaction time, which includes:

8.1. Accurate Signal Detection: Increasing the detection probability to achieve improved signal recognition accuracy[23] and reduce interference mistakes.

8.2. Improving Response Time: Using MEC capabilities to reduce data processing response time and enhance system performance in time-sensitive applications.

8.3 .Improving Signal Quality: Using the RIS system's reflection angles to manage signal direction and quality.

8.4. Compliance with Legal restrictions: Ensuring that UAV transmission power is within legal and operational restrictions [23].

1 .Detection Probability Constraint:

The detection probability of a system relates to its capacity to detect signals accurately in the face of noise. A high detection probability is required to avoid missing key signals or misidentifying them as noise. This limitation ensures that the system's signal detection remains highly efficient.

$$Pd = Q\left(\frac{\gamma - Tth}{\sqrt{\frac{N0}{2T}}}\right) \tag{13}$$

Sensing Duration (T): The time required for the system to detect a signal. Longer sensing times can improve detection accuracy but may cause delays.

Sensing Threshold: The threshold value used to assess whether a detected signal is meaningful or not. Increasing this amount may result in fewer false detections.

Signal-to-Noise Ratio (SNR, γ) is the ratio of signal strength to background noise. High SNR ratios suggest clearer signals and consequently better detection, while N0 denotes the power density of noise in the signal.

2 .MEC Constraints

(MEC) systems process data at the network edge, close to users, to minimize latency and boost efficiency. This restriction ensures that the latency caused by data processing in MEC does not exceed a predetermined level, hence maintaining service quality.

$$D\ total\ = \frac{L}{R}.\left(1 + \sum_{i=1}^{M} \frac{p\ useri}{R\ network\ i}\ .\delta i\right) + \sum_{k=1}^{N} \left(\frac{Lk}{Ck}\ .(1 + \frac{Ntasks\ k}{\mu k}\right)) \tag{14}$$

L is the magnitude of the data being communicated, and R is the network's transmission rate. M represents the number of users in the system. δ Interference between users represents the number of edge servers.

9. ANALYSIS AND PROBLEM FORMULATION

In this research, we seek to maximize the energy efficiency of an integrated system that includes a drone-enabled MEC and a reconfigurable smart surface (RIS) to increase connectivity to a variety of Internet of Things (IoT) devices. Improving energy economy and lowering overall system power consumption to ensure fast and reliable communications strikes a balance between performance and uptime.

Initialized parameters are bandwidth, sampling frequency, SNR of the primary signal at the UAV, transmit power, path loss exponent, noise power at the UAV and SGR, UAV mass, and so on. These parameters are important in defining the physical characteristics of the UAV, channel models, and the energy consumption model.

System Parameters for RIS-Assisted UAV-Enabled MEC System: The number of RIS elements, the number of IoT devices, the mission period, the UAV height, the maximum UAV speed, and the CPU frequency for IoT and UAV are all defined. These parameters are necessary for the MEC system's operation.

Initial Positions and Channel Models: The UAV, RIS, and IoT devices' initial positions have been set. Channel models between UAV-RIS, IoT-UAV, and IoT-RIS are

Defined using these positions.

Optimization Variables:

Variables used for optimization: Variables like the local computation bits, UAV computation bits, and phase shifts (theta) are all initialized, and Objective function

The objective function seeks to maximize energy efficiency (EE). The function takes into consideration many variables, such as sensing duration; furthermore, sensing threshold, UAV transmit power, and packet error rate. The function is defined by utilizing system parameters and optimization variables; moreover, the constraint (Pd) ensures that the probability of detection exceeds or equals 0.9. This is modeled as a nonlinear constraint.

The energy efficiency is calculated after integrating the system with the assisting system using the following iteration:

$$EE = \frac{\sum_{n=1}^{N} L[n]}{\sum_{n=1}^{N} E[n]} \tag{15 a}$$

L is the total number of bits processed locally and, on the UAV,E is the total energy consumed, including local processing, UAV operation, and its movement [24] .

$$\text{s.t.}|\theta m[n]| = 1 \ ,\forall m \in M, n \in N \ , \tag{15b}$$

$$q\,[1] = q0, q[N+1] = qF, \tag{15c}$$

$$\|\upsilon[n]\| \leq \ \ V\,Max, \forall n \in N, \tag{15d }$$

$$\frac{l\ i^{loc}\,[n]c\ i}{t} \leq \ F\ i\,, \forall i \in I\,, n \in N, \tag{15e}$$

$$\frac{\sum_{i=1}^{I} li^{UAV}\ [n]ci}{t} \leq \ \ F\ UAV, \forall n \in N \tag{15f}$$

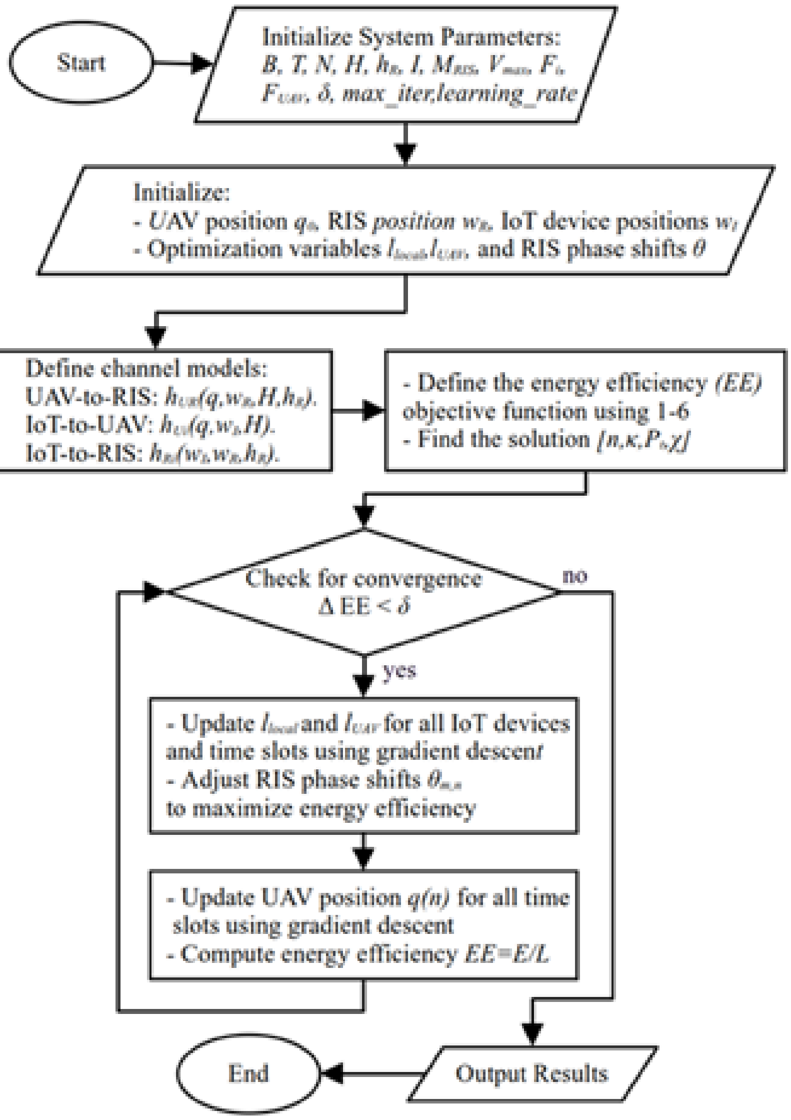

Fig 2: Flowchart for Energy Efficiency optimization in UAV-RIS IOT Systems

Constraint (15b) represents the viable set of RIS phase shifts. Constraint (15c) refers to the UAV's starting and ultimate horizontal locations. Constraint (15d) specifies that the speed of the UAV must be less than its maximum speed. Fi and FUAV represent the maximum CPU frequencies of IoT device i and the UAV, respectively. Constraints (15e) and (15f) require that the workloads of IoT devices and UAVs not exceed their maximum CPU frequency.

10. SOLUTIONS OF THE FORMULATED PROBLEMS

The Iteration Index is a fundamental aspect of any iterative optimization algorithm. It plays a crucial role in tracking and guiding the optimization process toward reaching the best possible solutions. the Iteration Index is used to enhance the energy efficiency of a UAV system supported by RIS in a (MEC) environment and iterative algorithm is used to optimize the UAV trajectory, bit allocation, and RIS phase shifts. The algorithm consists of three steps, and it is repeated until convergence or until the maximum number of iterations is reached.

10.1 Bit Allocation Optimization:

$$\mathrm{MaX}_{\mathrm{L\,loci}}[\mathrm{n}], \mathrm{LUAVi}[\mathrm{n}] \sum_{\mathrm{n}=1}^{\mathrm{N}} \mathrm{L}[\mathrm{n}] - \alpha \sum_{\mathrm{n}=1}^{\mathrm{N}} \mathrm{E}[\mathrm{n}] \tag{16a}$$

$$\text{s.t. (7e)} - \text{(7g)} \tag{16b}$$

This step adjusts the local and UAV computation bits l and l UAV to minimize the energy consumption for processing [13]. The gradients represent the partial derivatives of the energy consumption with respect to the computation bits.

10.2 Phase Shift Optimization:

$$Max\ \theta m[n]\ \sum_{n=1}^{N} \sum_{i=1}^{1} BtR_{0ff\pi i}\,[n] \tag{17}$$

Optimizing the phase shifts of the RIS (Reconfigurable Intelligent Surface) improves signal reception and system efficiency [25].

Then, the channel gain between IoTdevice πi[n] and the UAV can be expressed as:

$$\left|\ \mathrm{h}_{\mathrm{U\pi i}}\ [\mathrm{n}] + \ (\mathrm{h}_{\mathrm{R\pi i)}}\ [\mathrm{n}])^{\mathrm{H}} + \mathrm{dig}(\ \Phi\ [\mathrm{n}])\mathrm{h}_{\mathrm{UR}}\ [\mathrm{n}]\ \right|^2 = |h\pi i[n]|\text{^}2 \tag{18}$$

10.3 UAV Trajectory Optimization:

$$Max\ q[n]\ \sum_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{I}} \mathrm{BtR}_{\mathrm{0ff\pi i}}\ [\mathrm{n}] - \mathrm{t}\alpha \sum_{\mathrm{n}=1}^{\mathrm{N}} \left(\mathrm{T1}\ \upsilon^3\ [\mathrm{n}] + \frac{\mathrm{T2}}{\upsilon[\mathrm{n}]}\right) \tag{19}$$

This step optimizes the UAV's trajectory to ensure it does not exceed the maximum allowable speed (υ). The gradient represents the change in trajectory required to minimize energy consumption [26] , and packet error rate.

10.4 Algorithm

Algorithm 1 : Energy-Efficient UAV-Assisted IoT Optimization

1. Input: System parameters, initial UAV trajectory, RIS and IoT device positions, phase shifts, and bit allocation.

2. Output: Optimized energy efficiency, bit allocation, phase shifts, and UAV trajectory.

// Initialization

3. Set system parameters.

4. Initialize UAV trajectory, RIS and IoT device positions, phase shifts, bit allocation.

// Solve Optimization Problem

5. Define the objective function and constraints.

6. Calculate the initial values for sensing duration, sensing threshold, UAV transmit power, and packet error rate.

7. While (Energy efficiency change < threshold)

8. Solve Bit Allocation using Gradient Descent: Update local and UAV computation bits using 8.

9. Solve Phase Shift Optimization using Gradient Descent: Update phase shifts of RIS elements using 9.

10. Solve UAV Trajectory Optimization using Gradient Descent: Update UAV trajectory using 11.

11. Update Energy Efficiency based on the updated bit allocation, phase shifts, and UAV trajectory.

12. End

TABLE 2: Simulation Parameters

parameters	*values*
B	*30e6HZ*
Li	*200e6 bits*
M UAV	*0.4kg*
fs	*50e3*
Pt max	*5w*
Pt min	*0.4w*
Ps	*0.2w*
Pc	*0.1w*
I	*6*
H	*40m*
N	*25*
g	*9.8 m/s2*

11. SIMULATION RESULTS

Fig .3 depicts the exact of n on the EE when ps =0.2 w and pt=5w at small n=10 Energy Efficiency is low for rs, moderate increases in improve EE [27] , but excessive increases lead to stabilization without further improvements, affected by distance and time 2%.

Fig. 4 presents the effect of each individual optimization parameter on EE,EE decreases as n increases past a certain point due to excessive Energy consumption for sensing and EE improves with increasing Pt from 0.4 to 5 w initially,but starts to decline after a peak value is reached,increasing packet error rate X drastically reduces EE,highlighting the importance of minimizing data loss.

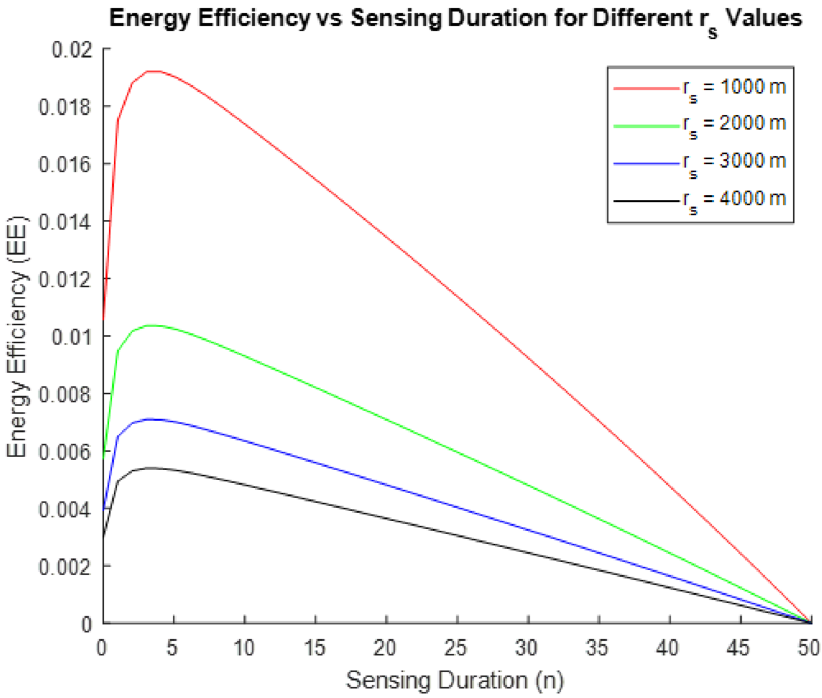

Fig. 3. Energy Efficiency versus the Sensing Duration used (rs=1000,2000,3000 and 4000 m), mUAV=0.4 kg, Nu=4, ru=0.2 m.

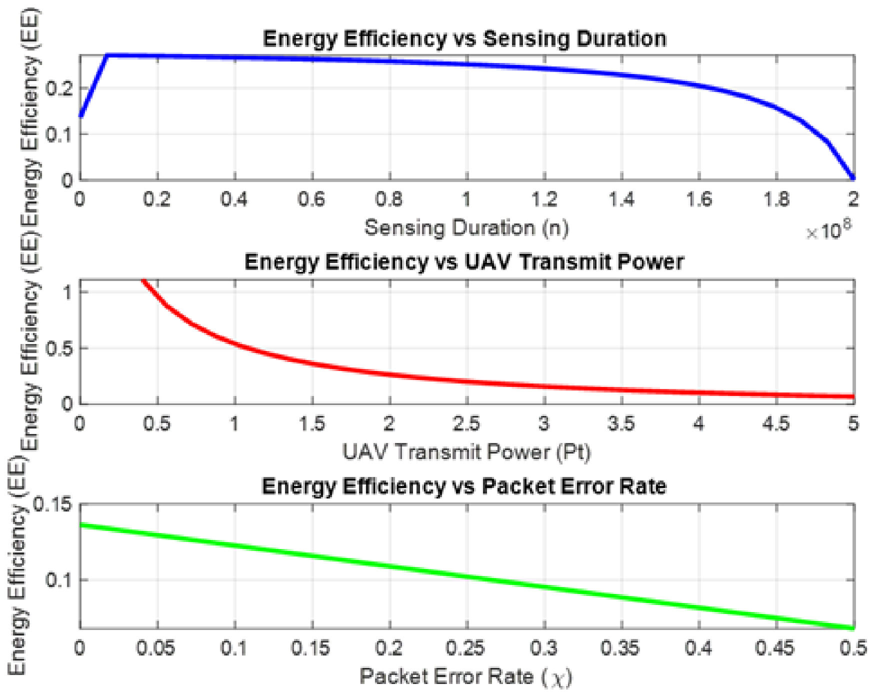

Fig. 4. Energy Efficiency Vs.Each optimization Parameter n=200,fs=50 x103, pc=0.1 ,ps=0.2.

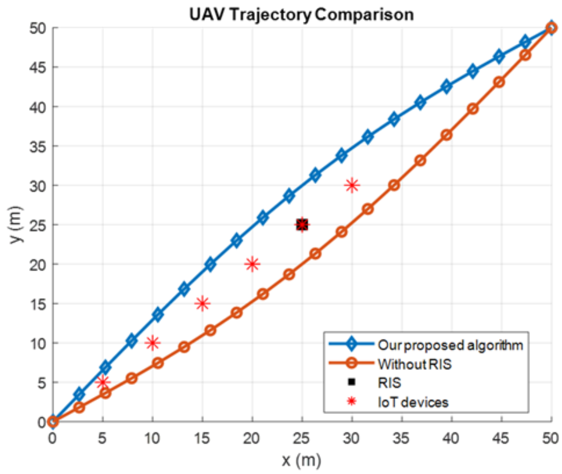

Fig. 5. UAV Trajectories Comparison when H=40m,hR=20m,Vmax=10m/s,N=20.

Fig. 5 depicts the without RIS,the UAV follows a less efficient path,leading to higher power consumption and paths of the UAV 50m and Q0=(0,0),qf=(50,50),wR=(25,25), the RIS position acts as a reflection point, improving communication between the UAV and IOT . IOT Device positions ω1fixed at (5,5),(10,10),(15,15),(20,20),(25,25),(30,30).

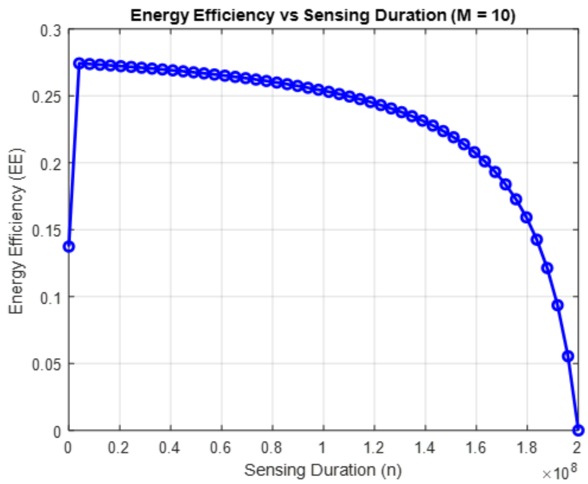

Fig. 6. Energy Efficiency versus.Sensing Duration (M=10)

Fig. 6 However, the EE increased by up to 27% after integration compared to fig 4 before integration of RIS and MEC technologies, which shows a clear effect in increasing EE.n starts from small values and extends to approximately 2x 10^{-8}.

Fig. 7 displays the Due to increased power consumption and computational effort, EE decreases as the number of users increases.

When U=10 to 100, PRIS=10 mW, employing methods such as STAR-RIS increases EE by improving signal quality and lowering power loss. [28]. The most recent research outperforms Studies 1 and 2, improving resource allocation by 5%.

Maximizing EE requires choosing the ideal transmission power [29].Signal enhancement methods, such as RIS, can increase efficiency and lower the requirement for high transmission power.

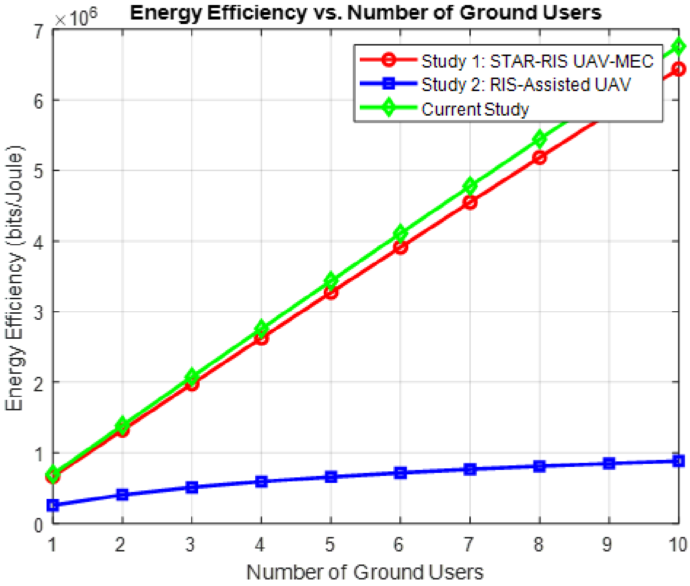

Fig. 7. Energy Efficiency vs. Number of Ground Users S=50Mbps,Pu= o.2 W, N=128, pn=0.01.

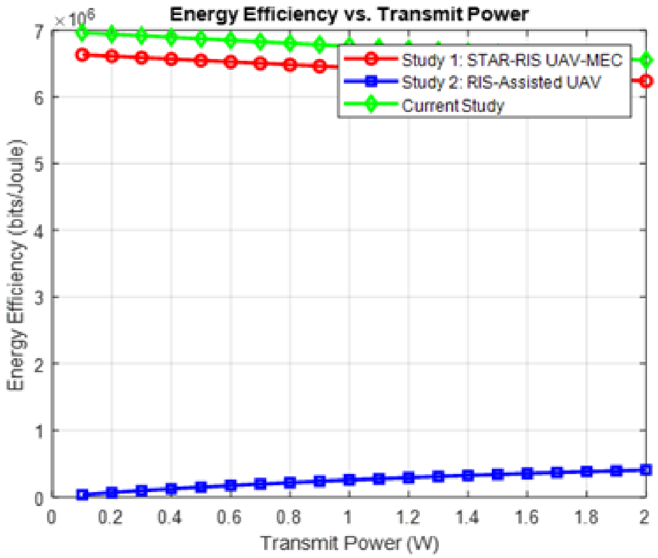

FIGURE 8. Energy Efficiency vs. Transmission Power pRIS =10mW,pt=0.1 to 2 W,PUAV=2 W.

Fig . 8 display the EE is first improved by raising because of increased transmission rates.

12. CONCLUSION

Field tests can check the UAV and RIS system's performance in real-world scenarios, taking into account varied surroundings and UAV models to evaluate parameters such as size and battery capacity. Machine learning can maximize energy efficiency while also supporting multi-objective goals such as increased throughput and reduced latency. Furthermore, scalability can be examined by testing with more IoT devices and researching dynamic network topologies to effectively adapt to changing situations and conditions.

In this study, an integrated system combining UAVs and RIS was created to improve energy efficiency in IoT systems. Significant performance improvements were achieved over conventional systems using an optimization algorithm and gradient descent techniques. The findings indicate that this approach could be extremely useful in future applications where UAVs and RIS are integrated into complex wireless communication systems. These systems can provide broader coverage and higher energy efficiency, making them suitable for a variety of applications such as remote monitoring and communication in remote locations.

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