ISSN: 2321-2152

IJMECE

International Journal of modern electronics and communication engineering

E-Mail

editor.ijmece@gmail.com

editor@ijmece.com

www.ijmece.com

ISSN2321-2152 www.ijmece .com
Vol 10, Issuse.2April 2022

Offloading computations to unmanned aerial vehicles using deep reinforcement learning for catastrophe management

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ABSTRACT

Unmanned Aerial Vehicle (UAV) research and development may benefit from the rise of the Internet of Things (IoT) made possible by mobile computing. Disaster management, forest fire control, and distant operations are examples of low latency applications that are crucial to the development of mobile edge compute offloading in UAVs. In order to meet the goal demand and reduce transmission latency, the optimum offloading strategy is built on the application of deep reinforcement learning (DRL), and the task completion efficiency is enhanced utilizing an edge intelligence algorithm. Reduced execution latency and average energy usage are the results of the combined optimization. This DRL network-integrated edge intelligence technique takes use of computational operations to boost the likelihood that tracking and data transmission are both useful. The suggested combined optimization outperforms the current approaches for UAV development in terms of execution latency, offloading cost, and effective convergence. With the help of the suggested DRL, the UAV may make choices in real-time depending on the situation of the catastrophe and the availability of computer resources.

Keywords: deep reinforcement learning algorithm, edge intelligence, UAV energy consumption

1 Introduction

2 When mobile apps need to use energy and keep tabs on faraway servers, computation offloading becomes more common. Their execution time restrictions make the timing need of offloading a job a tough one [1]. In order to reduce energy consumption, it is recommended that the mobile edge server (MEC) determine when tasks should be executed and when they may be offloaded. Drones equipped with built-in cameras and sensors may help with navigation, catastrophe management, and Internet of Things (IoT)-based agricultural tasks. Between devices with limited resources and the MEC server, quality of experience (QoE) must be guaranteed [2]. By preventing congestion between sent packets and increasing the QoE UAV battery endurance, MEC drastically lowers latency. The computing burden of the featured tasks is reduced by using the water strider optimization technique, which enables deep reinforcement learning. Several strategies, including dynamic partitioning and programming, Lyapunov optimization, a game-theoretic approach, and machine learning algorithms, are involved in optimizing task offloading [3–7]. But the execution time limitation is the root of the issue. To begin, user-defined real-time offloading procedures inform the initial positioning of UAVs. Second, in order to achieve optimum throughput and minimal energy consumption, the trajectory must be meticulously plotted. With MEC, UAVs may improve their coverage area since the channel

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ISSN2321-2152 www.ijmece .com
Vol 10, Issuse.2April 2022

difficulties with line-of-sight connections to ground users are the primary concern [8–10]. Using dynamic and linear programming, the primary objective of [11–14] is to minimize energy use. In settings where data collecting is challenging, such as during forest fire monitoring or earthquake crisis management, computationally demanding UAVs equipped with MEC may find use [15]. Dealing with the challenging environment to perceive and gather data for processing is the goal of the suggested effort. Processing and analyzing data from UAVs is a computationally intensive procedure, which is beyond the capabilities of the on-site mobile terminal. Thus, to improve the efficacy and efficiency of data processing and analysis, we must implement a number of methods for data transmission and set up a high-performance data processing center. In order to extend the lifespan of the whole network, it is crucial to save the energy. In order to keep the network running in an energy-saving way, the computation for the job is either performed or offloaded. In [16], the problem of mobile cloud computing is addressed by using a semi-definite method. On the other hand, [17] suggests using fog computing and MEC in conjunction with a stochastic optimization problem to carry out the work. In [18], a stochastic game approach is suggested for lowering the energy cost function and conserving energy for the UAV. In addition, the final judgments were arrived at after a lengthy backtracking exercise. An ever-changing

- Task execution and UAV coverage expansion in the face of signal fading and other barriers need aerial-ground computational collaboration, as discussed above. Firefighters were able to assess the situation and formulate a strategy with the use of aerial photographs. An effective and user-friendly multi-UAV system will allow a single person to operate the whole fleet. Rather of "steering" individual UAVs, the operator in this case assigns broad responsibilities, such monitoring certain regions or avoiding certain areas, on a digital map [20]. Both computing throughput and energy usage should be taken into account.
- To optimize the UAV edge intelligence based on DRL cooperative methodology and to allocate minimum power constraint to each UAV.
- To formulate the UAV energy minimization problemas a Markov decision process to generate the maximum reward and to design edge intelligence algorithm.
- To compute low energy operation with computational resources of UAVs, DRL enabled MEC framework is proposed in the multi-UAV system forsurveillance report.
- To compare the experimental results with prevailing methodologies refereed in previous research so as to enable the prominence of the proposed edge intelligence in UAV.

The paper is organized as the following manner. Chapter 2 details the MEC enabled UAV system, chapter3 entitles about the MDP problem with Edge intelligence algorithm, chapter 4 discusses the experimental Multi- UAV results and discussion and chapter 5 details about the conclusion of the paper.

3 Methodology

MEC-enabled UAVs leverage edge servers to process data in real-time applications. In this framework, ground mobile Users (GU) receive computing services
from many UAVs with restricted energy B for a predetermined amount of time. Using $t = 0, 1, 2, ..., T{-}1$, the

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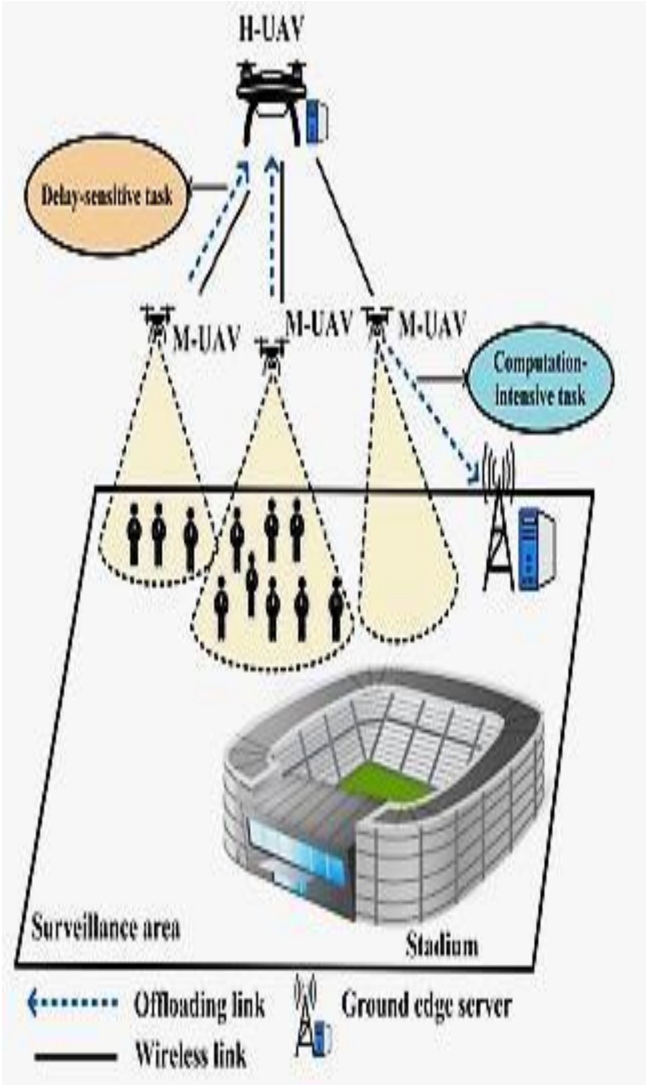

Fig. 1. UAV edge intelligence system model Communication between edge server on people,
The disaster communication architecture coordinates the movement of vehicles and embedded sensors nearby. Even though the use of UAVs for ground server deployment is not specified specifically, the vehicles may be equipped with them. Command and control can maintain situational awareness with the use of distributed and cooperative sensing.

3.1 Ground mobile user model

The distributions of GUs are deployed in random field in a circular area. The change in location are updated during the duration t=0 and $\triangle_{t,-1}$ between t and t-1 time slots.

The velocity and direction of the GU is

$(t) = k_1 u_n(t-1) + (1-k_1)\bar{u} + \sqrt{1-k^2}\phi_n,$ (1) 1

$(t) = k_2 \theta_n(t-1) + (1-k_2)\bar{\theta} + \sqrt{1-k^2}{}_n,$ (2) 2

where $0 \leq k_1$, $k_2 \leq 1$ are the adjusted state of GUs withaverage velocity $\bar{u}$ and average direction $\bar{\theta}$ of all GUs. ϕ_n and ${}_n$ are the Gaussian distributions. The locationof the UAV in the t^{th} time slot is
$l^{UAV}(t) = [x^{UAV}(t), y^{UAV}(t)]$
operational period is discretized into T times slots, having a non-uniform length. Assume that each time slot, or

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"association between the UAV and GU," can only have one GU served by the UAV. Only one of M fixed base stations (BS) may be hovered over by the UAV during each time slot in order to establish a directlink with the corresponding GU and carry out its offloaded responsibilities.
$m \in \{1,2,3 \ldots \ldots \ldots \ldots . . M\}$

3.2 Energy consumption model

There are three categories considered for the energyconsumption model of UAV.

3.2.1 Energy consumption during flying

The energy consumption during flying from one BS control to another BS control in the given time slot *t*–1 is computed as

$E_f(t) =$

3.2.2 Energy consumption during hovering

The energy consumption during hovering from the LoS channel between UAV and GU in the specified timeslot t-1 is computed as control latency and energy computing of the local phase.

2.3.2 Task offloading

The generated tasks after some period are forcedlydropped due to their characteristics and sensitive

$E_h(t) = P_h \qquad \frac{K}{\quad} + \beta \frac{K}{\quad}$

$l \quad \max E^{edge,tx}$

offloading in the given slot *t*-1 is calculated as

$(t) = \gamma_c C(f_c)^2 \mu_n(t) N_b.$ (7)

γ_c represents the effective switched capacitance and C represents the CPU cycles to complete one task, f_c is thesystem CPU frequency. (t) is the amount of offloadedtask.

3.3 Task computation model

The computational task of M-UAV is to perform which can be of local computation or of edge computation linked with ground edge server. The local computing of M-UAV is described as $\alpha^l = 0$ and

$\alpha_j^l = 1$ represents the task offloading of M-UAV.

j

3.3.1 Local computing

The task execution time duration depends on theclock frequency $f_{h,}$ and CPU cycles $L_{j,}$ to enable the computational capability of M-UAV.

The different weights are enabled to improve the energyconsumption and low latency.

4 DRL framework for edge intelligence (DRLEI)

The DRL problem is formulated to solve the issues given below.

1. The location and direction of UAV are difficult to control due to the dynamic environment. The tasks mayarrive and release dynamically so that the task specific requirements depend on when to execute and when to offload.

2. Even though the conventional algorithms such as linear and dynamic programming can give the optimal solution when the number of UAVs are limited, However, the scalability and complexity raises due to theincrease in number

of UAVs.

3. The traditional RL optimization depends on the actionspecific and reward specific environment. But we proposed the MDP strategy to learn the new energy efficient task offloading without prior knowledge about

$$T^{exe} = \frac{L_{j,t}}{} \quad (16)$$

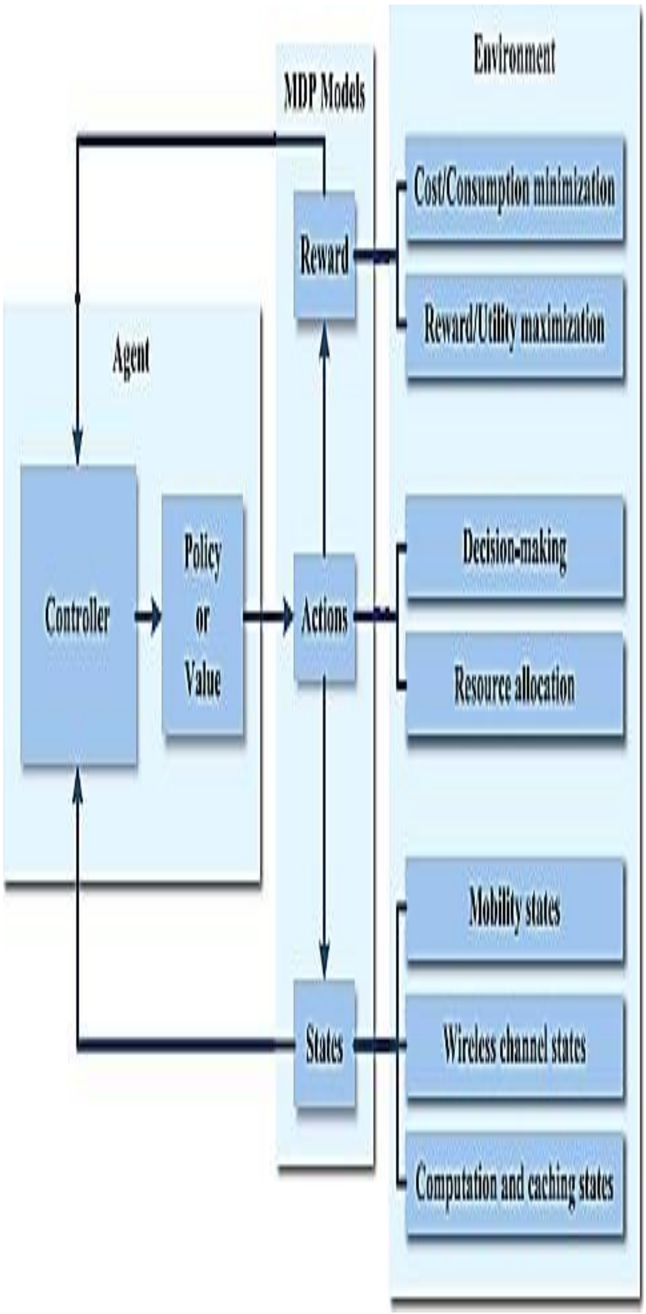

Fig. 2. DRL framework for edge intelligence

The reward function is based on the utility function and computed as

$$r_t^j = \begin{cases} p, & if\ Z_{j,} - Z_{j,-1} < 0 \\ q, & if\ Z_{j,} - Z_{j,-1} > 0 \\ 0, & otherwise \end{cases}$$

In Eqn. (17), p is the positive reward, q is the negative reward of each agent. It depends on the cumulativeutility function.

3.4 MDP problem formulation

From [16], the DRL policy pertaining to the state transition probability of selecting the optimal action a_t in conjunction with the current state s_t. The main objective of MDP is to attain the optimal policy π^* to increase the reward function achieved for each M-UAVand is given as

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DRLEI Algorithm with MDP policy		
Initialize	:	Values for D, C , f, $s_{j,t} = [0]$ $r=0$ N-Number of Episodes
Repeat	:	for j=0 to N do Let t=0, T=0 and get initial state $s_{j,t}$
Repeat	:	update action a_t to obtain optimal solution update s_t Use (18) to update reward functions
If	:	$\sum_{t=0}^{T-1} \mu_n(t) \geq Z_j$
Return 1.2	:	Z_j cumulative reward, optimal task offloading and $R_m(t)$ **End if**

Table 1. Simulation parameters

Parameter	Value
UAV environment	100×100 m²
Number of GU	25
Base station radius	200 m
Velocity	20 m/s
UAV transmitted power	0.1 W
UAV flying power	110 W
UAV hovering power	80 W
Packet interval	0.1 sec
CPU frequency	2 GHz
Number of bits per task	100 Mb
Effective switched capacitance	10^{-27} F
Number of CPU cycles	1000

5 Results and discussion

5.1 Simulation environment used

In this section, Table 1 details the list of simulation parameters. The fundamental parameters for UAV are frequency, CPU cycles, UAV transmitted power, flyingpower and hovering power etc. The evaluated parameters are simulated through MATLAB software using Laptop core i3 with 16 GB RAM and 1 TB ROM.

5.2 Discussion

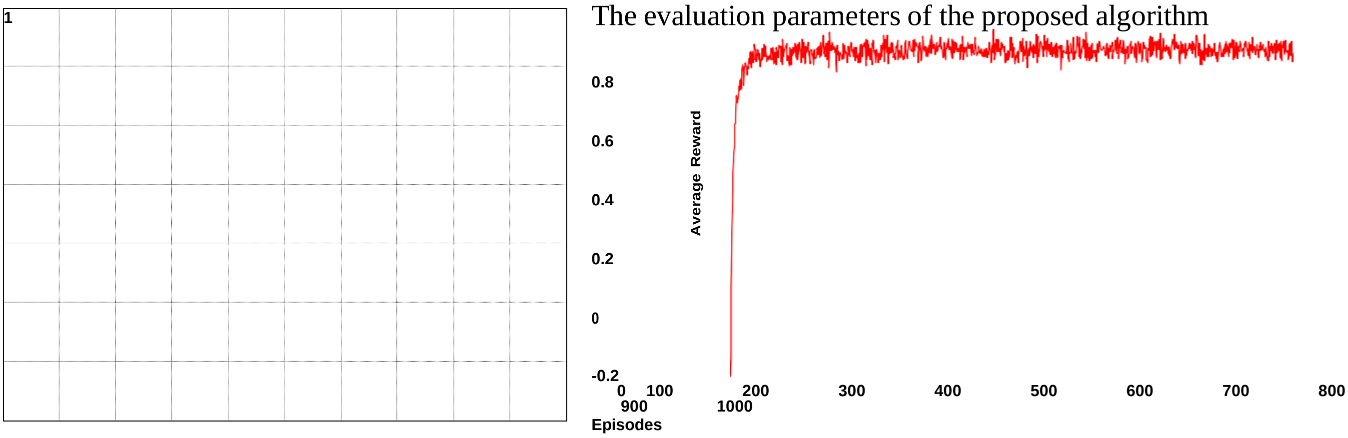

Fig. 3. Average reward of UAV

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are speed, average UAV battery energy, and average throughput and calculation system latency. These factors are evaluated in comparison to pre-existing algorithms, such the widely-used Q-Learning approach in this MEC-enabled UAV, All of the UAVs' characteristics, settings, and simulation implementation were done in the same environment with the same parameters. For optimal computational complexity, the number of UAVs in the simulation environment may range from 2 to 12.
With an increase in the number of UAVs, the suggested technique (DRL+MDP) achieves a bigger cumulative reward and a somewhat greater convergence rate, as shown in Figure 3, compared to the standard Q-Learning methods.

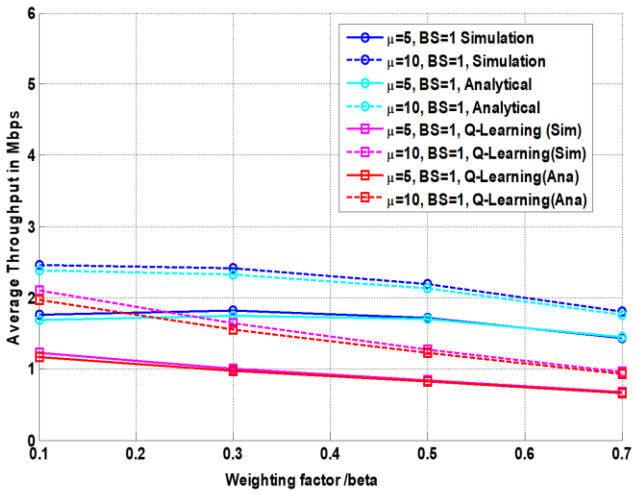

Fig. 4. Average throughput of UAV

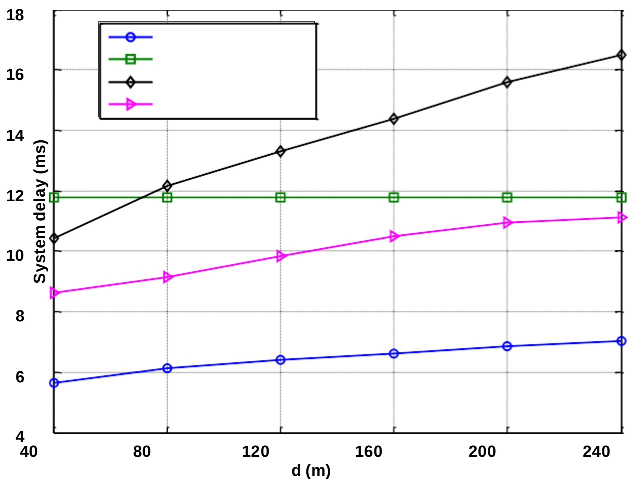

Fig. 6. System delay with UAV distance

As shown in Figure 6, the computational delay is plotted against the UAV distance from the place where the M-UAV is located to the MEC GU. As the distance tends to expand, it reveals that the system latency increases as well. The device's distance is related to the server latency in the MEC system. With the performance of the computation delay varied in proportion to the number of UAVs, Figure 7 compares the edge computing, local computing, and channel matching policies. Without a doubt, the method outperforms the three compute offloading rules when the mobile device is in close proximity to the MEC server.

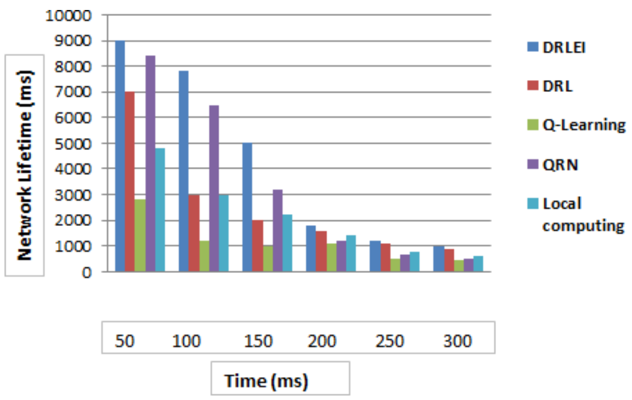

Fig. 10. Comparative network lifetime

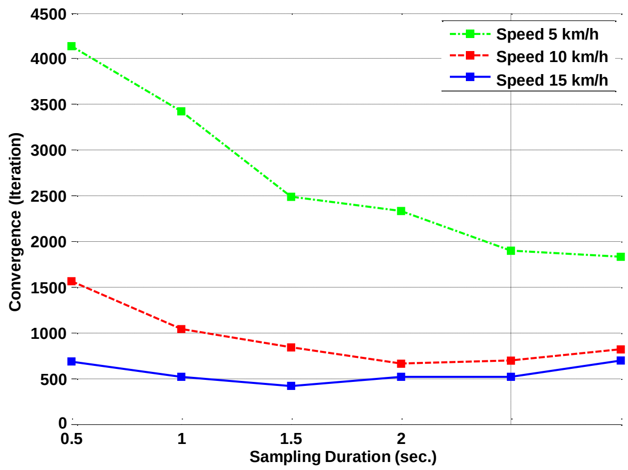

Fig. 9. Convergence rate *versus* sampling duration

The analyzed result demonstrates how processor power and job size affect battery consumption and task execution delay. During testing, DRLEI achieved a 4% and 10% performance improvement over the standard techniques, respectively. Fig. 10 displays the M-UAV network lifespan calculated using the following algorithms: local computing, edge computing, Q-learning, DRL, and the proposed DRLEI. Several parameters are assigned to the suggested DRLEI approach at the end. 1) the organizational structure for carrying out tasks. 2) A reinforcement learning framework that uses a new reward function to offload tasks. 3) To address the overestimation issue, DRLEI should be implemented with minimal processing latency and decreased complexity.

No matter how many times you play, the battery life will remain constant. When looking at the battery life of UAV networks, Figure 8 shows the results of the simulations and comparisons of the aforementioned methods.

Figure 9 displays the suggested algorithm's convergence analysis as the sample time increases. To minimize execution cost, the DRL algorithm often avoids discarding jobs by increasing the average completion time.

The average energy consumption of the UAV while utilizing the DRLEI algorithm is shown in Table 2. The factors that have been compared in previous research include the average execution cost, which varies with processing capability and the offloading job. It was found that the overall cost of computing power and energy usage is enough to prove that the suggested RL-based edge computing method is successful. The suggested DRLEI cut down on computational cost, tasksize, and decrease by 52.13%, 43.5 %, and 28.7 %, respectively, on offloading and average execution costs. In Table 2, the impact of the suggested DRLEI was compared to that of DQN, local, and edge computing.

8

6 Conclusion

7 After successfully offloading computing, the suggested DRLEI approach is put into action. When it comes to computation-intensive jobs, the ground edge server is there to aid with offloading, ensuring that all execution and offloading are completed successfully according to energy consumption and task execution delay metrics. As a weighted sum average, the DRLEI framework aids in optimizing both computing power and costs. By completing the demanding training phase, selecting the optimal offloading technique, and acting in accordance with the unique reward functions of the suggested DRLEI scheme, an agent may achieve optimal optimization. Finally, DRLEI convergence is verified by means of simulation. Compared to DLQ, edge, and local execution plans. Impressive and exceeded are the comparison outcomes. The suggested study integrating networked and collaborative UAVs might overcome the problems caused by single-use UAVs, such as reduced operating ranges, smaller payloads, and shorter flying times. During a large-scale fire drill, the system setup took less than five minutes, and providing aircraft surveillance of the whole area took just a few more minutes.

Table 2. Results of energy consumption (EC) performance of the proposed DRLEI with existing algorithms

Refs.	Algorithm	Avg EC (Joules)	Avg EC with computational capacity	Avg EC varying with offloading task size
[11]	Local	28.54	48.18	49.55
[11]	Edge	22.58	43.5	45.87
[16]	DQN	19.18	39.35	41.84
[4]	DRL	19.78	38.75	41.48
Proposed method	DRLEI	18.17	37.65	38.24

References

"Learning to optimize: Training deep neural networks for interference management" was published in the IEEE Transactions on Signal Processing in October 2018 and can be accessed online at doi:10.1109/TSP.2018.2866382. The authors of the article are H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiro-poulos. "Design of Biped Robot Using Reinforcement Learning and Asynchronous Actor-Critical Agent (A3C) Algorithm," by M. Navaneethakrishnan et al. The article "Reinforcement Learning-Empowered Mobile Edge Computing for 6G Edge Intelligence" was published in 2022 in the IEEE Access journal and was presented at the 2023 2nd IEEE International Conference on Vision Towards Emerging Trends. The article can be accessed online at doi: 10.1109/ACCESS.2022.3183647.

In their paper titled "AI-based resource provisioning of IoE services in 6G: A deep reinforcement learning approach," the authors take a thorough dive into the topic. doi:10.1109/TNSM.2021.3066625 published in 2021 in the IEEE Transactions on Network and Service Management, volume 18, issue 3, pages 3527-3540.

The article "Quality of Experience Aware 3D Video Streaming via Deep Reinforcement Learning in Software Defined Network Enabled Mobile Edge Computing" was written by P. Zhou and colleagues. Article published in the IEEE Transactions on Network Science and Engineering, volume 8, issue 1, pages 419-433, 2021. DOI: 10.1109/TNSE.2020.3038998.

In their paper titled "Reinforcement learning-based mobile edge computing and transmission scheduling for video surveillance," Y. Kunpeng and colleagues [5] 2021, IEEE Transactions on Emerging Topics in Computer Science, volume 10, issue 2, pages 1142-1156, doi: 10.1109/TETC.2021.3073744.

"Deep Q-Learning based resource allocation and load balancing in a mobile edge system serving different types of user requests," published in the Journal of Electrical Engineering in 2023, with the DOI 10.2478/jee-2023-0005, was written by O. Yildiz and R. Sokullu.

[7] In a 2023 article published in the Journal of Electrical Engineering, M. Rouissat et al. present "Implementing and evaluating a new silent rank attack in RPL-contiki based IoT networks." The article can be found on pages 454-462 and has the DOI 10.2478/jee-2023-0053.

[8]A. Khan, S. Gupta, and S. K. Gupta published an article titled "Multi-UAV integrated HetNet for

maximum coverage in disaster management" in the Journal of Electrical Engineering in 2022. The article can be found on pages 116-123 of the journal. Journal Article: "JEE 2022 0015"
[9]"Joint trajectory and communication design for multi-UAV enabled wireless networks" was published in the 2018 edition of the IEEE Transactions on Wireless Communications by Q. Wu, Y. Zeng, and R. Zhang. The article is located in volume 17, issue 3, and spans pages 2109-2121. Publication date: 2017-07-28
[10]Subject: S. Amalorpava An artificial intelligence method for overcoming blockage effects in next-generation heterogeneous networks, by Mary Rajee and A. Merline Journal of Radioengineering, volume 29, issue 3, 2020. publishable at 10.13164/re.2020.0555

"Multi-Agent Reinforcement Learning for resource allocation in container based cloud environment," Expert Systems, volume 1, issue 22, 2023, written by S. Nagarajan et al. Visit https://doi.org/10.1111/exsy.13362 for more information.
Vol. 27,90, no. 1, Aug. 2023, doi: 10.1063/5.0152781, "Survey on data communication for UAV and flight control system in MM wave communications," by V. T. M. Babu et al.
[13] ViTECoN, 2023, pp. 1–6, in: Communication and Networking Technologies. IEEE Communications Survey Tutorial, 2017, vol. 19, no. 4, pp. 2392-2431, P. V. Klaine, M. A. Imran, O. Onireti, and R. D. Souza, "A survey of machine learning techniques applied to self-organizing cellular networks" (doi:10.1109/COMST.2017.2727878).
The article "Intelligent 5G: When cellular networks meet artificial intelligence" was published in 2017 in the IEEE Wirel. Commun. journal and can be accessed online at doi: 10.1109/MWC.2017.1600304WC. *[15] R. Li et al.
The authors of the article "Online learning based computation offloading in MEC systems with communication and computation dynamics" (Volume 69, Issue 2, Pages 1147–1162) are K. Guo, R. Gao, W. Xia, and T. Q. S. Quek. (doi: 10.1109/TCOMM.2020.3038875) 2021.
[17]Theoretical model for power optimization in next-generation heterogeneous networks, by S. A. M. Rajee, A. Merline, and M. M. Yamuna Devi, published in SIViP, volume 17, pages 3721–3729, 2023, doi:10.1007/s11760-023-02599-8.
[18] inSensors, volume 22, issue 16, page 6286, "A Survey on UAV Computing Platforms: A Hardware Reliability Perspective" (F. Ahmed and M. Jenihhin). 10.3390/s22166286. 2022.