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5G Technology based Edge Computing in UAV Networks for Resource Allocation with Routing using Federated Learning Access Network and Trajectory Routing Protocol

Malkeet Singh
Researcher (PhD), IIT Ropar & Swinburne,
Orcid ID: 0000-0002-0723-6281
malkeetsingh@swin.edu.au

Dr. Mohit Angurala
Assistant Professor & Head of the Department,
Department of Computer Science and Engineering,
Khalsa College of Engineering and Technology,
Amritsar, Punjab, India
https://orcid.org/0000-0002-9506-5864

Abstract:
UAVs (Unmanned aerial vehicles) are being utilised more frequently in wireless communication networks of the Beyond Fifth Generation (B5G) that are equipped with a high-computation paradigm and intelligent applications. Due to the growing number of IoT (Internet of Things) devices in smart environments, these networks have the potential to produce a sizeable volume of heterogeneous data.This research propose novel technique in UAV based edge computing resource allocation and routing by machine learning technique. here the UAV-enabled MEC method regarding emerging IoT applications as well as role of machine learning (ML) has been analysed. In this research the UAV assisted edge computing resource allocation has been carried out using Monte Carlo federated learning based access network. Then the routing through UAV network has been carried out using trajectory based deterministic reinforcement collaborative routing protocol.We specifically conduct an experimental investigation of the tradeoff between the communication cost and the computation of the two possible methodologies.The key findings show that, despite the longer connection latency, the computation offloading strategy enables us to give a significantly greater throughput than the edge computing approach.

Keywords: UAV, Fifth Generation, Internet of Things, edge computing resource allocation, routing, machine learning

1. Introduction:

Communications of the fifth generation (5G) and beyond are primarily distinguished by (i) extremely high connectivity, (ii) ultra-reliability, and (iii) minimal latency.Fulfilling these goals in the face of the explosive expansion of IoT applications is a difficult challenge, particularly in situations with high levels of dynamicity and heterogeneity [1].Adopting unmanned aerial vehicles (UAVs) as flying BS or aerial user equipments (UEs) is a potential strategy (BSs).UAV-based communications, in particular, can boost the performance of the network in emergency situations by offering quick service recovery and offloading in densely populated environments.The standardising bodies [2] and academics are both interested in these traits.Additionally, the use of machine learning (ML) and artificial intelligence (AI) approaches in wireless networks can use intelligence to address a variety of problems.As a result, the integration of AI/ML with UAVs seems to be strongly associated across domains, applications, and network levels, offering unheard-of speed improvements and complexity reduction.In the subsections that follow, a succinct introduction to the fields of UAVs and ML is provided, and pertinent surveys are reviewed. This helps to highlight the gap in the literature that has inspired the current work [3].The Open Edge Computing (OEC) programme was introduced by Vodafone, Intel, and Huawei in collaboration with Carnegie Mellon University (CMU) in June 2015 in order to go forward.Similar to this, industry heavyweights Cisco, Microsoft, Intel, Dell, and ARM teamed together with Princeton University to form the Open Fog Consortium (OFC) in November 2015 [4].By utilising its telco cloud platform, a world leader and member of MAEC_ETSI ISG, Nokia, also suggested a solution called multi-access edge computing (MEC).This platform efficiently processes data

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right at edge of mobile network, bringing flexibility, scalability, and efficiency to a number of BS.Similar to this, Dell has created an edge computing architecture that enables edge analytics using a variety of power sources.Leading businesses including Microsoft, Sun, IBM, and Oracle have been working on development of cloudlets for latency-sensitive computing as a result of the recent shift from client/server to distributed computing methods [5].Transmission of computational resources on demand through the Internet is referred to as CC.It provides consumers with a vast array of services and practically limitless resources.All data from physical assets is moved to cloud for storage as well as in-depth analysis in classic cloud systems.Shifting computation-intensive jobs to core CC platform is an efficient method for data processing since the cloud has greater computational capacity than the devices at the network edge [6].

The contribution of this research is as follows:

1. To propose novel technique in UAV based edge computing resource allocation as well as routing by machine learning technique.
2. To develop UAV assisted edge computing resource allocation has been carried out using Monte Carlo federated learning based access network
3. To design routing through UAV network has been carried out using trajectory based deterministic reinforcement collaborative routing protocol

2. Related works:

The goal of resource management in MEC is to minimise system latency [7], energy consumption [8], and overall method latency and/or energy consumption costs [9]. In [10], the tradeoff problem is examined for computing networks with fog node cooperation with goal of reducing fog node reaction time within a specified power efficiency restriction.In order to reduce computation delay while maintaining a low overall computation energy consumption, work [11] studied joint service caching as well as task offloading problem in dense network.With goal of reducing the overall job duration while adhering to energy budget restrictions, author [12] looked into the MEC task offloading issue in software-described ultra-dense network.For minimising system latency of all mobile devices, author in [13] developed a joint communication as well as computation RAissue under collaboration of CC and EC.In order to investigate energy-delay tradeoff dilemma in a MECCmethod, work [14] developed a multiuser evaluation offloading game.In order to reduce total energy cost as well as less delay among all users, author [15] jointly optimised the offloading decisions of all users as well as resource allocation (RA).To reduce overhead of local energy consumption as well as simulation time costs, work [16] presented a distributed joint computation offloading as well as RA optimization strategy in heterogeneous networks with MEC. Particularly, case where number of MUs enhances explosively or network facilities are sparsely dispersed does not apply to the existing MEC approaches [17].Authors in [18] have been summarized journey of ML in the last thirty years and roles for the next generation wireless network as road for best optimization technique. To achieving this ambitious goal of future intelligent wireless technology and manage the complexity of heterogeneous nature of the network structures and wireless service using machine learning algorithm for intelligent decision making from edge level. The authors in [19] have been emphasized about the role of diverse ML methods in different key problems of networking across various network technologies. Works are realized on Deep Reinforcement Learning (DRL) method surveys for cellular network, next generation wireless networks, self-organization cellular network [20]. DRL is a machine learning algorithm that has recently gained popularity for managing edge computer resources and is an effective optimization method for radio access networks.DRL has recently [21] been utilised as an emerging tool to successfully address a variety of issues and challenges in contemporary networks like HetNets, Vehicle to Vehicle (V2V), Machine to Machine (M2M), Vehicle to Everything (V2I), Self-Organization Cellular Network, and UAV Network become more decentralised, ad hoc, and autonomous in nature [22].

3. System model:

This section discusses novel technique in UAV based edge computing resource allocation and routing by machine learning technique. here the UAV-enabled MEC method regarding emerging IoT applications as well as role of ML has been analysed. In this research the UAV assisted edge computing resource allocation has been carried out using Monte Carlo federated learning based access network. Then the routing through UAV network has been carried out using trajectory based deterministic reinforcement collaborative routing protocol.

Network model:

We take into account a unidirectional route with M UAVs positioned along it, as seen in Figure 1.Each UAV has a MEC server with constrained computational power. We write M = 1,..., M to represent the ID set of UAVs.We partition the road into M segments to make it easier to

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describe, and we designate ID set of roads as L = L1, L2,..., LM.The Poisson distribution is followed by the N vehicles that arrive at the road's beginning.Or, to put it another way, vehicle I can offload a job, λi,jdi, to MEC server on UAV j and evaluate remaining task, 1 − λi,j di, locally,describexi,j as choice made by vehicle I meaning xi,j∈ {0, 1}.In particular, xi,j = 1 if vehicle I selects UAV j for job offloading and xi,j = 0 otherwise. Additionally, our model of the relevant system includes an eavesdropper named Eve who has the ability to intercept the sent data Ξi.

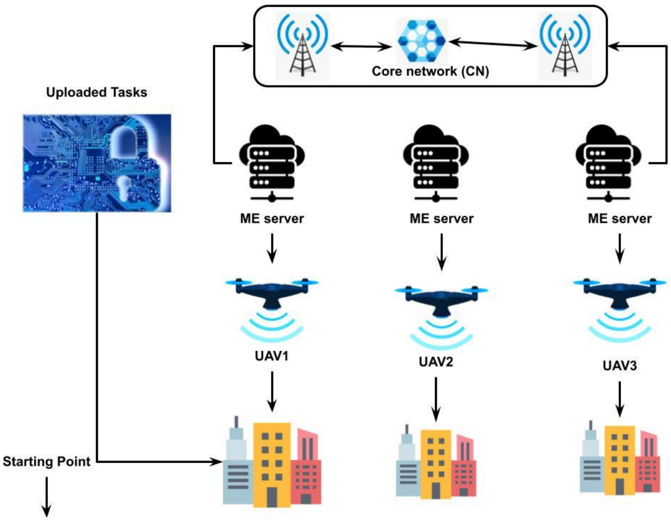

Figure-1 Network model for MEC_UAV

Communication Model: Due to high altitude of UAV, LoS links are far more prevalent in the UAV-enabled network than other channel damages like shadowing or small-scale fading.Consequently, free-space route loss model can be used to represent the uplink channel gain from MU I to UAV in eq. (1).

$$h_i^{\mathrm{UL}} \triangleq \alpha_0\left(d_i^{\mathrm{UL}}\right)^{-2} = \frac{\alpha_0}{\left\|Q_i^{\mathrm{MU}} - Q^{\mathrm{UAV}}\right\|^2} \tag{1}$$

where dUL I is distance from MU I to UAV, is Euclidean norm of a vector, and 0 is received power at reference distance of 1 m for a transmission power of 1 W. Similar to that, UAV's downlink channel gain to EC j can be expressed as eq. (2)

$$h_j^{\mathrm{DL}} \triangleq \alpha_0\left(d_j^{\mathrm{DL}}\right)^{-2} = \frac{\alpha_0}{\left\|Q^{\mathrm{UNV}} - Q_j^{\mathrm{FC}}\right\|^2} \tag{2}$$

where dDL j stands for the distance between the UAV and the EC in question. For the purpose of bandwidth sharing in MUs during task offloading, we presumptively use the FDMA protocol.The attainable uplink transmission data rate from MU I to UAV is written as follows using Shannon's capacity in eq. (3):

$$R_i^{\mathrm{UL}} = B_i^{\mathrm{UI}} \log_2\left(1 + \frac{h_i^{\mathrm{UL}} P_i^{\mathrm{MU}}}{\sigma^2}\right) \tag{3}$$

where BUL I PMU I and 2 stand for the bandwidth that has been given to MU I MU i's transmit power, and noise power at UAV.For sake of simplicity, consider both ECs and UAVs have same noise power. It can, however, be simply extended to the situation in which they are different.Similar to that, the UAV to EC j downlink transmission data rate is calculated as eq. (4)

$$R_j^{\mathrm{DU}} = B_j^{\mathrm{Dd}} \log_2\left(1 + \frac{h_j^{\mathrm{DL}} P_{\mathrm{TX}}^{\mathrm{UAV}}}{\sigma^2}\right) \tag{4}$$

where BDL j and PUAV TX stand for the transmit power of the UAV and the per-device bandwidth that has been allotted to EC j, respectively.

Monte Carlo federated learning based access network in resource allocation:

By performing four phases, Monte Carlo creates a search tree iteratively (Figure 2).The edges of the tree correspond to activities, while each node in the tree represents a single state.A child-selection policy is applied iteratively during the selection phase until a leaf node1 is reached.

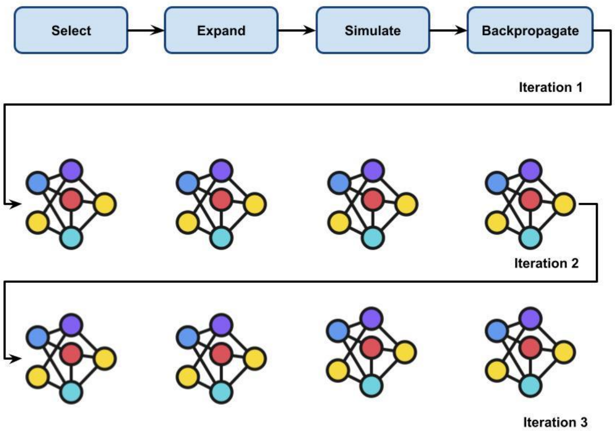

Figure 2: Stages of Monte Carlo

We take into account a FL instance made up of a number of ground devices connected to a number of parameter servers located on various UAVs in the sky.The multi-UAV enabled network, as depicted in Fig. 4, is made up of N UAVs and K single-antenna devices, represented by N = 1,..., N and K = 1,..., K.Mobile devices are dispersed over the ground, as shown in Fig. 4, and several UAVs fly in sky to give wireless services for them via FDMA.

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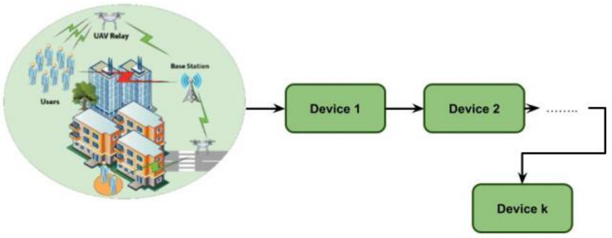

Figure. 3. Federated learning-based UAV-enabled wireless networks.

Let wk signify local methodspecifications of k-th device, Dk is set of training dataset utilised at k-th device, and wn denote model specifications associated to global method of n-th UAV server.Sum loss function on k-th device's training dataset Dk can be written as eq. (5)

$$F_k(\mathbf{w}_n) = \frac{1}{|\mathcal{D}_k|}\sum_{i\in\mathcal{D}_k} f\left(\mathbf{w}_n; \mathbf{s}_{k,i}, z_{k,i}\right), \quad \forall k \in K_1 \tag{5}$$

where |Dk| denotes set's cardinality. Average global loss function using dispersed local datasets of all chosen devices is thus described at n-th UAV server as eq. (6)

$$F(\mathbf{w}_n) \triangleq \sum_{k\in\mathcal{K}_n} \frac{|\mathcal{D}_k| F_k(\mathbf{w}_n)}{|\mathcal{D}_n|} = \frac{1}{|\mathcal{D}_n|}\sum_{k\in\mathcal{K}_n}\sum_{i\in\mathcal{D}_k} f\left(\mathbf{w}_{n;}\mathbf{s}_{k,i}, z_{k,i}\right) \tag{6}$$

where Kn is collection of devices connected to nth UAV server, and Kn = |Kn| is total number of choosed devices, and Dn| = P k∈Kn |Dk| is sum of data samples from all choosed devices at nth UAV-enabled cell.Finding ideal model specifications at n-th UAV server that minimises overall loss function is goal of FL job by eq. (7).

$$\mathbf{w}_n^* = \arg\min F(\mathbf{w}_n), \forall n \in \mathcal{N} \tag{7}$$

For uplink channel access, consider that OFDMA approach is employed, with every UAV-enabled cell having M orthogonal uplink subchannels that are shared by all cells.Each UAV server in this scenario will experience inter-cell interference (ICI) from neighbouring gadgets connected to other cells using the same frequency band. The received SINR over designated subchannel m at nth UAV server in uplink is therefore described as when k-th device is connected to n-th UAV server by eq. (8).

$$SINR_{n,k,m}^{\mathrm{U}} = \frac{P_{k,m}^{\mathrm{U}} 10^{-t_{m,k}/10}}{\sum_{k'\in R', k'\neq k} P_{k',m}^{\mathrm{U}} 10^{-t_{m,k}/10} + \sigma^2} \tag{8}$$

where σ 2 stands for power of Gaussian noise and P U k,m is transmit power of k-th device assigned to m-th subchannel.ICI received at UAV server n across m-th subchannel, which is produced by adjacent devices connected by other cells, is also known as $\sum_{k'\in K', k'\neq k} P_{k',m}^{\mathrm{U}} 10^{-l_{m,i}/10}$.As a result, the uplink data rates that can be achieved for k-th device over designated subchannels are stated as eq. (9)

$$R_k^{\mathrm{U}} = B_{\mathrm{sub}}\sum_{m=1}^{M}\left(\chi_{n,k,m}\log_2\left(1 + SINR_{n,k,m}^{\mathrm{U}}\right)\right) \tag{9}$$

The amount of CPU cycles utilized to train the method on a single sample of data at kth device and the nth UAV server, are denoted by the abbreviations Ck and Cn.Let's say that fk and fn stand for the computing capabilities of device k and UAV server n, and that $f_k \in \left(f_k^{\min}, f_k^{\max}\right)$ with $f_k^{\min}$ and $f_k^{\max}$denotes the corresponding lowest and high CPU computation.As a result, during t-th time slot, local methodevaluation latency of device k as well as global method aggregation latency of UAV server n are given by eq. (10)

$$T_k^{\mathrm{Loc},\,,t} = |\mathcal{D}_k| C_k / f_k, \forall k$$
$$T_n^{Glo,t} = |\mathcal{D}_n| C_n / f_n, \forall n \tag{10}$$

To broadcast global methodspecifications to connected devices, each UAV server needs to broadcast Ln bits, where Ln is the number of bits. The global model parameters broadcast latency for n-th UAV server is written as$T_n^{\mathrm{D},t} = L_n / R_n^{\mathrm{D},t}, \forall n$.

In order to reduce the FL methodsimulation time as well as learning accuracy loss, we design UAV placements, control subchannel, and transmit power resources. We specify execution time cost in nth UAV-enabled cell as eq. (11)

$$c_n^{\mathrm{Time}}(t) = \frac{1}{K_n}\sum_{k=1}^{K_n} T_{k,}^{t} \tag{11}$$

where Kn is number of devices chosen for federated model aggregation by n-th UAV server. Additionally, definition of the learning accuracy loss is given by eq. (12)

$$c_n^{\mathrm{L}es}(t) = \frac{1}{|\mathcal{D}_n|}\sum_{k\in\mathcal{K}_n}\sum_{i\in\mathcal{D}_k} f\left(\mathbf{w}_{ni}\mathbf{s}_{k,i}, z_{k,i}\right), \quad \forall n \tag{12}$$

To increase speed and significance of learning, it is preferable to choose a subset of devices with high processing capacity, locate UAVs in areas with the best channel quality, and manage subchannel as well as power resources. Consequently, optimization issue may be expressed as eq. (13).

$$\begin{aligned} &\min_{\Theta_{n,p,\mathcal{X},p_n^{\mathrm{D}}}} \left(\lambda c_n^{\mathrm{Time}}(t) + (1-\lambda) c_n^{\mathrm{Los}}(t)\right), \forall n \\ &\text{s.t. a) } \rho_{n,k} \in \{0,1\}, \chi_{n,k,m} \in \{0,1\}, \forall k, m, \\ &\text{b) } \sum_{n\in\mathcal{N}} \rho_{n,k} \le 1, \forall k, \\ &\text{c) } \sum_{k\in K}\sum_{m\in M} \chi_{n,k,m} \le M, \\ &\text{d) } 0 \le P_n^{\mathrm{D}} \le P_n^{\max}. \\ &\text{e) } 0 \le f_k \le f_k^{\max}, \forall k; \end{aligned} \tag{13}$$

Thus, according to the formulas ∀w, w0 ∈ R d, Fn(·) is L-smooth and -strongly convexin eq. (14).

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$$F_w(w) \leq F_n(w') + \langle \nabla F_n(w'), w - w' \rangle + \frac{L}{2}\|w - w'\|^2$$
$$F_w(w) \geq F_w(w') + \langle \nabla F_n(w'), w - w' \rangle + \frac{\beta}{2}\|w - w'\|^2 \quad (14)$$

In this essay, the terms hw, w0 I and kk refer to the Euclidean norm and the inner product of the vectors w and w 0, respectively.We point out that Assumption 1's strong convexity and smoothness may be observed in a variety of applications, including the l2-regularized logistic regression $f_i(w) = \frac{1}{2}(\langle x_i, w \rangle - y_i)^2 + \frac{\beta}{2} \| w \|^2, y \in \mathbb{R}$and the l2-regularized linear regression models with the formulas $f_i(w) = \log\left(1 + \exp\left(-y_i \langle x_i, w \rangle\right)\right) + \frac{3}{2} \| w \|^2, y_i \in \{-1, 1\}$.The Hessian matrix's condition number ρ := L β, is also denoted. The edge server aggregates local method w t n and gradient $\nabla F_n(w_n^t)$, ∀n after receiving them by eq. (15).

$$w^t := \sum_{n=1}^{N} p_n w_n^t$$
$$\nabla F^t := \sum_{n=1}^{N} p_n \nabla F_n(w_n^t) \quad (16)$$

in order for contributing UEs to minimise their surrogate J t+1 n in following global round t+1, broadcast w t and ∇F¯tto all UEs by eq. (17).

$$F(w^t) - F(w^*) \leq \epsilon, \forall t \geq K_{9t} \quad (17)$$

where w ∗is the ideal response to (1). We'll then give the FEDL convergence analysis after that. Due to the fact that $J_n^t(w)$ and Fn(·) share same Hessian matrix, we can observe that both of them are β -strongly convex and L-smooth. We can utilise GD to solve (18) using these J t n (w) attributes.

$$z^{k+1} = z^k - h_k \nabla J_n^t(z^k) \quad (18)$$

where hk is a predetermined learning rate at iteration k and zk is local model update, it is demonstrated to produce a convergent sequence (zk)k≥0 fulfilling a linear convergence rate as eq. (19).

$$J_n^t(z_k) - J_n^t(z^*) \leq c(1-\gamma)^k \left(J_n^t(z_0) - J_n^t(z^*)\right) \quad (19)$$

where c and (0, 1) are constants that rely on and z ∗is the local problem's ideal solution (2). The best course of action for each m ∈ M ⊆ N taking part in the game (i.exm∈ (0, dn)) Proof, According to Eqn. (19), for any $m \in \mathcal{M}$, we have

$$\sum_{n=1}^{M} x_n^* = \sqrt{\frac{\tau \sum \quad sM(m) x_m^*}{\sum_m^* + c_m^{*m}}}. \quad (19)$$

By setting $\varepsilon = \sum_{n=1}^{M} x_m^*$, we can derive that, Therefore by eq. (20),

$$\xi = M\xi - \frac{\xi^2 \sum_{n=1}^{M} (c_m^{0m} + c_{nmp})}{\tau}. \quad (20)$$

Based on Eqn. (21), we have

$$\xi = \frac{(Mf-1)\tau}{\sum_{n=1}^{M} (c_m^m + c_n^{cmp})} \quad (21)$$

Algorithm of MC-FLAN:

1. The cloud server initializes w_{cs}
2. Each system k initializes w_k and w_k^{prev} $as w_{cs}$
3. For $t\epsilon\{0,1,\ldots\} do$
4. For each system k do
5. Observe s_k^t and translate it as $s_k^{-t} \leftarrow d_k^s(s_k^t)$
6. choose $a_k^{-t} \leftarrow \pi(s_k^{-t}; w_k)$ and translate it as $a_k^{-t} \leftarrow d_k^s(a_k^t)$
7. do action a_k^t and observe u_k^t and s_k^{t+1}
8. translate s_k^{t+1} as $s_k^{-t+1} \leftarrow d_k^s s_k^{t+1}$
9. store experience $(s_k^{-t}, a_k^{-t}, u_k^t, s_k^{-t+1})$
10. update w_k using its experiences by a DQN algorithm
11. end for
12. if mod (t,T_{FL})==0 then
13. all systems calculate their local gradients f_k's from their previous DNN w_k^{prev} to the current DNN w_k
14. The cloud server updates w_{cs} by aggregating the local gradients from all systems
15. All system replace their DNNs w_k's and w_k^{prev} to w_{cs}
16. End if
17. End for

Trajectory based deterministic reinforcement collaborative routing protocol:

Suppose vm = [xm, ym] The 2D coordinates of UE m are T, m ∈ M, where xm and ym are UE m's respective coordinates.Following equation describes the horizontal separation between UE m as well as UAV I at time t by eq. (23):

$$L_{i,m}(t) = \sqrt{[x_i(t) - x_m]^2 + [y(t) - y_m]^2}. \quad (23)$$

Distance between UAV I and UE m at time t is therefore determined to be as eq. (24)

$$d_{i,m}(t) = \sqrt{z_i^2(t) + l_{i,m}(t)^2} \quad (24)$$

Every UAV may have a maximum flight distance based onimperfect flying speed of UAVs, which is specified as by eq. (25)

$$\|v_i(t+1) - v(t)\| \leq V_H T$$
$$\|z_i(t+1) - z(t)\| \leq V_A T \quad (25)$$

where VH and VA stand for respective horizontal as well as vertical flight speeds of UAVs throughout every time slot T. In order to prevent UAVs from colliding, collision avoiding restrictions of UAVs are considered, which are provided by eq. (26)

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$$\left|v_i(t) - v_j(t)\right|^2 + \|z_i(t) - z_j(t)\|^2 \geq D_{\min}^2, \quad \forall i,j \in \mathcal{K}, i \neq j \qquad (26)$$

where Dmin represents the shortest distance between any two UAVs. Keep in mind that time frame T needs to be brief sufficient to treat channel as a rough constant.The time slot T then needs to adhere to the following restriction in order to prevent an accidental collision between two UAVs eq. (27):

$$T \leq T_{\max} = \frac{D_{\min}}{2\sqrt{V_L^2 + V_A^2}} \qquad (27)$$

where Tmax is a time slot's maximum value. Maximum vertical distance L v max and horizontal distance L h max is represented as eq. (28),

$$L_{\max}^h = V_H T_{\max}$$
$$L_{\max}^* = V_A T_{\max} \qquad (28)$$

Next, taking into account whether the radio signals sent by UAVs are LoS or NLoS. Likelihood that UE m and UAV I will establish a LoS connection at time t is given by eq. (29)

$$P_{i,m}^{Las}(t) = \frac{1}{1 + a\exp\left(-b\left(\frac{1N!}{\pi}\tan^{-1}\left(\alpha_{i,m}(t)\right) - a\right)\right.} \qquad (29)$$

where αi,m(t) represents angle of UAV I and a and b are environment-related factors. Likelihood of the NLoS can therefore be calculated as eq. (30)

$$P_{i,m}^{NLas}(t) = 1 - P_{i,m}^{ILS}(t) \qquad (30)$$

Path loss methods of LoS and NLoS in dB is given as follows at time t by eq. (31).

$$L_{i,m}^{LaS}(t) = 20\log\left(\frac{4\pi f_c d_{i,m}(t)}{c}\right) + \eta L_{LoS}$$
$$L_{i,m}^{NLLS}(t) = 20\log\left(\frac{4\pi f_c d_{i,m}(t)}{c}\right) + \eta_{NLoS} \qquad (31)$$

where fc stands for the carrier frequency, ηLoS and ηNLoS, respectively, are mean additional losses. Next, it is possible to determine the estimated mean path loss1 as eq. (32)

$$L_{i,m}(t) = L_{i,m}^{LLS}(t) \times P_{i,m}^{L\sin}(t) + L_{i,m}^{\text{NLos}}(t) \times P_{i,m}^{\text{NLos}}(t) \qquad (32)$$

Assume that each UE receives an equal share of the bandwidth B. The bandwidth of UE m at hotspots I can therefore be calculated using the information provided by eq. (33)

$$B_{i,m} = B/M(i) \qquad (33)$$

Additionally, every UAV's transmission power is distributed evenly to all Ues in hotspot I, which is denoted by the following eq. (34):

$$p_{i,m}(t) = p_i(t)/M(i) \qquad (34)$$

where Pmax is highest transmission power and UAV I's transmission power is 0 ≤ pi(t) ≤ Pmax. Next, the received SINR of UE m from UAV I is given by depending on transmission power of UAV pi(t) by eq. (35).

$$\varphi_{i,m}(t) = \frac{p_{i,m}(t) g_{i,m}(t)}{B_{i,m} N_0 + \sum_{j \neq i} p_{j,m}(t) g_{j,m}(t)}, \quad \forall i,j \in \mathcal{K} \qquad (35)$$

Rate of UE m served by UAV I is then equal to eq. (36)

$$\phi_{i,m}(t) = B_{i,m}\log_2\left(1 + \varphi_{i,m}(t)\right) \qquad (36)$$

Total rate of UAV iis given as eq. (37)

$$\phi_i(t) = \sum_{m=1}^{M(i)} \phi_{i,m}(t) = \sum_{m=1}^{M(i)} B_{i,m}\log_2\left(1 + \varphi_{i,m}(t)\right) \qquad (37)$$

The utility of a UAV is then defined as difference between its profit and its transmission cost, or, in other words by eq. (38),

$$w_i(t) = \rho_i \phi_i(t) - \lambda_p p_i(t) = \sum_{m=1}^{M(\rho)} \left[\rho_i \phi_{i,m}(t) - \lambda_p p_{i,m}(t)\right] \qquad (38)$$

where λp is the cost of the transmit power used by the UAV and ρi is the profit per rate.A ground-based user requesting task routing to dN under coverage of sN (source) initiates the routing path discovery (destination).Path discovery is finished, and sN also selects the routing path.The path discovery as well as selection operations are once more started by new source after altering sN.Since the UAVs in our example use a Wi-Fi network, physical time for the exchange of path discovery data is in ms, making it reliant on the wireless radio's available bandwidth.

Each UAV serves as a node in undirected graph G that we take to be the created network.Thus, in this undirected graph, an edge only exists between two nodes if and only if the UAVs that make up those nodes in G are direct one-hop neighbours in grid.The group of nodes (UAVs) is designated as V when every node contains an adjacency list that identifies its edges.Final set of pathways connecting sN and dN is designated by the symbol pL. Algorithm 2 is used to determine all paths between sN and dN. It is based on a network flooding-based methodology.Every UAV adds its method information to packet when it approaches dN and then broadcasts it to all of its other neighbours.pL = p1, p2, p3, p4, ,px, Unlike conventional network discovery methods, which take hop-based metrics into account, every node in our suggested methodology updates all of its relevant data, including its current energy level (Ei(t), task completion time (T), and hop distance (cN) from sN.Each path's collected data from all the UAVs is updated at sN.Because a node can be visited more than once when using this flooding-based method to find all potential routes between sN and dN, the number of identified paths can become prohibitively large, especially for larger grid sizes N ×N.

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Collaborative Path discovery algorithm:
Inputs: (G, V, sN, dN)
Output: (pL)
1: procedure GETPATHS (G, V, sN, dN)
2: Initialize vis to {}
4: Set vis[node]toFalse
5: end for
6: StartpL to {}
7: Start path to {}
8: Start current Node to SN
9: Call pathUtil $(G, sN, dN, pL,$ path, current Node, vis)
10: Call Path Management Score
return pL
11: end process

Based on creation of an energy-based path score function, best route between sN and dN is chosen (t).The score function takes into account the task lists Ji(t) of every UAV in the chosen path, number of UAVs in path n, and residual energy REi(t) of every UAV in path under review.Goal of choosing a less score communication path between source as well as destination UAVs is to increase communication path lifetime, maximise the collective residual energies of UAVs in the chosen path, and minimise processing costs associated with finding new paths in event that a UAV member on chosen path is lost due to energy depletion.

A UAV node's energy, Ei(t), is made up of the combined energy needed to execute assigned tasks, Ei(J), and energy needed to keep UAV's controls in good working order, Ei(Nx) by eq. (39).

$$E_i(t) = E_i(J) + E(N_x) \tag{39}$$

The designed Up(t) must ensure that none of the UAVs along the path perish while a transmission is in progress. We define the routing path selection score function as a function of REi(t), number of UAVs in path n, and Ji for a path p = 1, 2, 3,..., n. (t).The score function is kept directly proportional to residual energy because it is what we want to optimise.However, n or Ji(t) of the path increases tend to decrease REi(t), therefore it is evaluated to be inversely proportional to developed score function.The reduction of Up is achieved by accommodating a continuous increase in all three of these factors (t).To designate a point as a local minima, place t3 T between t1 and t2, so that t1 t3 t2. Assuming that t1 > t2 results in t3 = t1 + (1)t2 (from equation 5). The scoring function for t1, t2, and t3 for 1 I n is expressed as tm for m = 1, 2, and 3 such that by eq. (40)

$$U_p(t_m) = \begin{cases} \frac{\sum_{i=1}^{m} R_{E_u}(t_m)}{n^2 \times \left(1+\sum_{i=1}^{n} J_i(t_m)\right)}, & \forall i E_i(t_m) > T \times e_d \\ 0, & \exists i E_i(t_m) \le T \times e_d \end{cases} \tag{40}$$

where REi(tj) ≤ 0 ⇒ Up(tj) = 0, then ∀m ∈ T, m ≥ j by eq. (41),

$$R_{Ei}(t_m) = 0 \Rightarrow U_p(t_m) = 0 \tag{41}$$

To designate a point as a local minima, place t3 T between t1 and t2, so that t1 t3 t2. Assuming that t1 > t2 results in t3 = t1 + (1)t2 (from equation 5). The scoring function for t1, t2, and t3 for 1 I n is expressed as tm for m = 1, 2, and 3 such that by eq. (42)

$$\lambda\left(\sum_1^n\left(E_i(t_1) - (T \times e_d)\right) - \sum_1^n\left(E_i(t_2) - (T \times e_d)\right)\right) + \sum_1^n\left(E_i(t_2) - (T \times \epsilon_d)\right) \ge \sum_1^n\left(E_i(t_3) - (T \times \epsilon_d)\right) \tag{42}$$

As a result, relation in equation 5 is satisfied since the total residual energies at time t1 will always be greater than total residual energies at any point in time after t1.Equation 5 can be stated in relation to equation 3 as follows for the cumulative task list T J(t) and sum of residual energy T E(t) along a path by eq. (43):

$$\frac{TE_i(t_2)}{n^2 \times \left(1 + TJ_i(t_2)\right)} + \lambda\left(\frac{TE_i(t_1)}{n^2 \times \left(1 + TJ_i(t_1)\right)} - \frac{TE_i(t_2)}{n^2 \times (1 + TJ_i(t_2))}\right) \ge \frac{TE_i(t_3)}{n^2 \times (1 + TJ_i(t_3))} \tag{43}$$

The relationship in equation 5 is satisfied by this. The decrease in T E(t) on right hand side of equation 9 is also much greater than the total fall in T J(t), as the job list decreases by one unit with each task completed, and the energy decreases by multiple units, resulting in the change ΔREi> ΔJLi .Since the convexity of Up(t) is satisfied under all circumstances for a given t1, t2, and λ all local minima of this function must be global minima of method. Defined score depends on t, and t is always less than zero.As a result, we demonstrate that U ′ exists at all t ∈ R +in order to demonstrate that U is differentiable at all t ∈ R +. If given an infinitesimally tiny interval $h, \lim_{h\to 0^+}\left(U_p(t+h) - U_p(t)\right)h^{-1}$ exists, then U is differentiable at t. Using formula (44)

$$U'(t) = \lim_{h\to 0^+} \frac{U_p(t+h) - U_p(t)}{h} = \frac{1}{n^2\left(1+\sum_{i=1}^{n} J_i(t)\right)'} \tag{44}$$

Consequently, we may write this relationship as REi(h) = h, ∀ h → 0 +. The expression REi(t+h) can also be written as REi(t)+REi (h). You may rewrite equation 10 to read as by eq. (45),

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$$U'(t) = \lim_{h \to 0^+} \frac{U_p(t+h) - U_p(t)}{h} = \frac{1}{n^2\left(1+\sum_{i=1}^{n} J_i(t)\right)} \quad (45)$$

We may say that scoring function U is differentiable at all t ∈ R +. using equation 45.

4. Performance analysis:

In this section, we conduct comprehensive numerical experiments to verify efficacy of our suggested method.On a desktop with an Intel Core i7-4790 3.60 GHz CPU and 16 GB RAM, all experiments are carried out in MATLAB R2018a using CVX.We take into consideration a MEC system with a UAV that has 4 ground ECs situated at every vertex and 10 ground MUs scattered around a 2-D region of 1000 × 1000 m2.The UAV is deployed as well as controlled to aid in supply of MEC services, and our suggested technique can be used to determine the UAV's ideal 3-D location. Table 1 displays the primary simulation variables.

Table 1: Network environment parameters

Parameters	Value
Channel bandwidth B	1MHz
Minimum height of UAVs	100m
Maximum transmit power of UAVs	30dBm
Maximum height of UAVs	300m
Downlink carrier frequency fc	1950 MHz
Noise power density	-174 dBm
Minimum QoS requirement	2dB
Mean excessive pathloss for LoS	1dB
Punishment coefficient of UEs	120
coverage	
Punishment of UAVs collision	20
Unit price per transmit power	2
Mean excessive pathloss for NLoS	20dB
Elevation angle	42.44
Level flight speed	20m/s
Vertical flight speed	5m/s
Minimum distance of UAVs	50m

The combined three-dimensional trajectory and power allocation technique is depicted in Figure 4.Considered are the performances of the suggested (blue star) and existing (red star) approaches.One such combined strategy is shown in Figures 4(a) and 4(b), respectively, for single-UAV and two-UAV scenarios.Each UAV begins each episode from same location to offer UEs wireless service.In two instances, two techniques show how UAV should fly in the same general direction to cover all UEs.Additionally, utilising two optimization techniques, two UAVs in the two-UAV scenario may cover all UEs in every hotpot without overlapping.Additionally, current technique takes interference into account in addition to spectrum efficiency, unlike the suggested strategy with constant power allocation.Thus, the proposed technique consistently yields better network utility than the proposed method.

Figure 4. Positions of UEs and UAVs with trajectory design and power allocation strategy

Table-2 Comparative analysis between proposed and existing technique

Cases	Techniques	Smoothing training reward	Computational complexity	Throughput	Delay	Network optimization
Number of UE	**MEC_MU**	77	65	88	69	71
	DRL_CN	81	61	92	65	73
	5G_UAV_RA_FLAN_TRP	85	58	95	63	75
Number of UAV	**MEC_MU**	83	55	91	61	79
	DRL_CN	86	43	93	58	81
	5G_UAV_RA_FLAN_TRP	89	42	95	55	83

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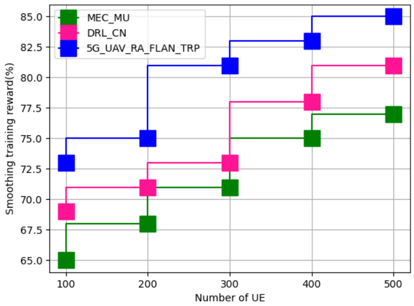
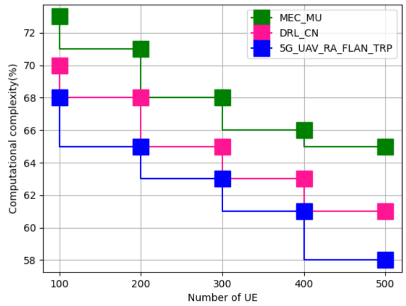
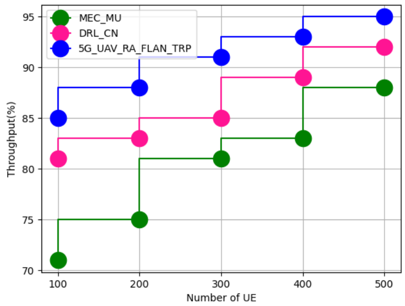
The above table-1 shows comparative analysis between proposed and existing technique based on number of UAV and number of UE. Here the parameters analysed are smoothing training reward, computational complexity, throughput, delay, network optimization.The amount of computing power required for specific tasks is the subject of the computer science notion of computational complexity.The computational complexity of some algorithms can be determined by the amount of time the CPU takes to perform them, whereas the difficulty of other methods are expressed as O(x), where x is number of nested loops in each run.It describes time it takes for a piece of data to go from one communication endpoint to another across the network.It is often expressed in fractions or multiples of seconds. A variety of networks and devices that are at or close to the user are referred to as edge computing, an emerging computing paradigm.Edge is about processing data more quickly and in larger volume near to the point of generation, providing action-driven solutions in real time.Technology called network optimization is used to enhance network performance in a certain setting.It is regarded as being a crucial element of efficient information systems management.



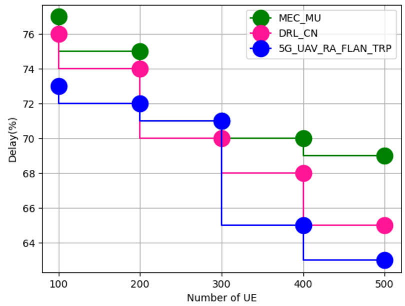
(a) smoothing training reward



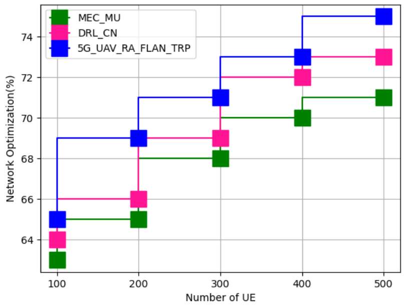
(b) computational complexity



(c) throughput



(d) delay



(e) network optimization

Figure- 5 comparative analysis between proposed and existing technique based on number of UE (a) smoothing training reward,(b) computational complexity,(c) throughput,(d) delay,(e) network optimization

The above figure-5 (a)- (e) shows comparative analysis between proposed and existing technique. here the proposed technique has been analysed based on number of UE. The techniques compared are MEC_MU and DRL_CN with proposed 5G_UAV_RA_FLAN_TRP. The proposed technique obtained smoothing training reward of 85%, computational complexity of 58%, throughput of 95%, delay of 63% and network optimization of 75%; while existing

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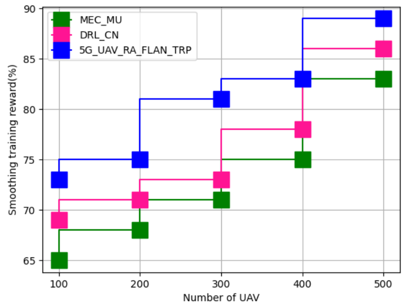
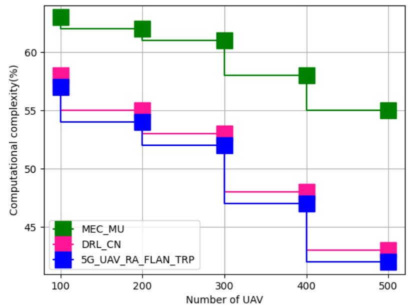
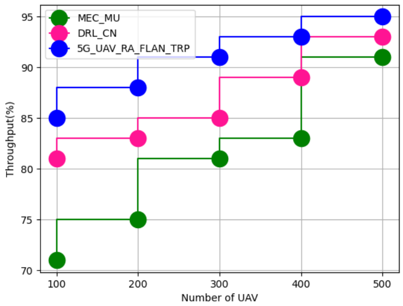
MEC_MU attained smoothing training reward of 77%, computational complexity of 65%, throughput of 88%, delay of 69% and network optimization of 71%and DRL_CN attained smoothing training reward of 81%, computational complexity of 61%, throughput of 92%, delay of 65% and network optimization of 73%.



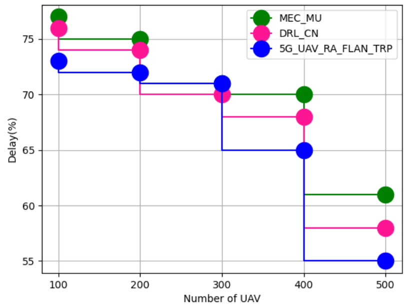
(a) smoothing training reward



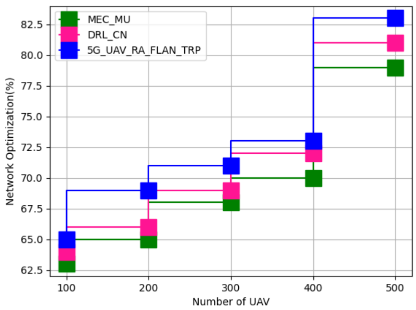
(b) computational complexity



(c) throughput



(d) delay



(e) network optimization

Figure- 6 comparative analysis between proposed and existing technique based on number of UAV (a) smoothing training reward,(b) computational complexity,(c) throughput,(d) delay,(e) network optimization

From above figure-6 (a)- (e) shows comparative analysis of proposed technique with existing technique based on number of UAV in the network. The proposed technique attainedsmoothing training reward of 89%, computational complexity of 42%, throughput of 95%, delay of 55% and network optimization of 83%; while the existing technique MEC_MU attained smoothing training reward of 83%, computational complexity of 55%, throughput of 91%, delay of 61% and network optimization of 79%and DRL_CN attained smoothing training reward of 86%, computational complexity of 43%, throughput of 93%, delay of 58% and network optimization of 81%.

5. Conclusion:

The proposed framework of this research gives novel technique inin UAV based edge computing resource allocation and routing by machine learning technique. the aim here to develop UAV assisted edge computing resource allocation has been carried out using Monte Carlo federated learning based access network. Here routing is carried out using trajectory based deterministic reinforcement collaborative routing protocol.The experimental analysis has been carried out based on number of UAV and number of UE in terms of smoothing training reward, computational complexity, throughput, delay, network optimization. The proposed technique attainedsmoothing training reward of 89%, computational complexity of 42%, throughput of 95%, delay of 55% and network optimization of 83% based onnumber of UE and based on number of UAVproposed technique attainedsmoothing training reward of 89%, computational complexity of 42%, throughput of 95%, delay of 55% and network optimization of 83%.

Reference:

[1]. Dinh, C. T., Tran, N. H., Nguyen, M. N., Hong, C. S., Bao, W., Zomaya, A. Y., &Gramoli, V. (2020). Federated learning over wireless networks: Convergence analysis and resource allocation. *IEEE/ACM Transactions on Networking*, *29*(1), 398-409.

[2]. Mukherjee, A., Misra, S., Chandra, V. S. P., &Raghuwanshi, N. S. (2020). ECoR: energy-aware collaborative routing for task offload in sustainable UAV swarms. *IEEE Transactions on Sustainable Computing*, *5*(4), 514-525.

[3]. Zhan, Y., Li, P., Qu, Z., Zeng, D., & Guo, S. (2020). A learning-based incentive mechanism for federated learning. *IEEE Internet of Things Journal*, *7*(7), 6360-6368.

[4]. Yang, H., Zhao, J., Xiong, Z., Lam, K. Y., Sun, S., & Xiao, L. (2021). Privacy-preserving federated learning for UAV-enabled networks: Learning-based joint scheduling and resource management. *IEEE Journal on Selected Areas in Communications*, *39*(10), 3144-3159.

[5]. Zhao, N., Liu, Z., & Cheng, Y. (2020). Multi-agent deep reinforcement learning for trajectory design and power allocation in multi-UAV networks. *IEEE Access*, *8*, 139670-139679.

[6]. He, Y., Zhai, D., Huang, F., Wang, D., Tang, X., & Zhang, R. (2021). Joint task offloading, resource allocation, and security assurance for mobile edge computing-enabled UAV-assisted VANETs. *Remote Sensing*, *13*(8), 1547.

[7]. Yu, Z., Gong, Y., Gong, S., & Guo, Y. (2020). Joint task offloading and resource allocation in UAV-enabled mobile edge computing. *IEEE Internet of Things Journal*, *7*(4), 3147-3159.

[8]. Liu, X., Yu, J., Wang, J., & Gao, Y. (2020). Resource allocation with edge computing in IoT networks via machine learning. *IEEE Internet of Things Journal*, *7*(4), 3415-3426.

[9]. He, Y., Zhai, D., Huang, F., Wang, D., Tang, X., & Zhang, R. (2021). Joint task offloading, resource allocation, and security assurance for mobile edge computing-enabled UAV-assisted VANETs. *Remote Sensing*, *13*(8), 1547.

[10]. Hu, J., Chen, C., Cai, L., Khosravi, M. R., Pei, Q., & Wan, S. (2021). UAV-assisted vehicular edge computing for the 6G internet of vehicles: architecture, intelligence, and challenges. *IEEE Communications Standards Magazine*, *5*(2), 12-18.

[11]. Chen, X., Liao, Y., Ai, Q., & Zhang, K. (2021, December). Joint Task Offloading and Resource Allocation for MEC Networks Considering UAV Trajectory. In *2021 17th International Conference on Mobility, Sensing and Networking (MSN)* (pp. 296-302). IEEE.

[12]. Wu, W., Zhou, F., Wang, B., Wu, Q., Dong, C., & Hu, R. Q. (2022). Unmanned Aerial Vehicle Swarm-Enabled Edge Computing: Potentials, Promising Technologies, and Challenges. *IEEE Wireless Communications*.

[13]. Wang, K., Wang, L., Pan, C., & Ren, H. (2022). Deep Reinforcement Learning-Based Resource Management for Flexible Mobile Edge Computing: Architectures, Applications, and Research Issues. *IEEE Vehicular Technology Magazine*, *17*(2), 85-93.

[14]. Yazid, Y., Ez-Zazi, I., Guerrero-González, A., El Oualkadi, A., &Arioua, M. (2021). UAV-enabled mobile edge-computing for IoT based on AI: A comprehensive review. *Drones*, *5*(4), 148.

[15]. He, X., Jin, R., & Dai, H. (2021, March). Joint service placement and resource allocation for multi-UAV collaborative edge computing. In *2021 IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 1-6). IEEE.

[16]. Mahmood, O. A., Abdellah, A. R., Muthanna, A., &Koucheryavy, A. (2022). Distributed Edge Computing for Resource Allocation in Smart Cities Based on the IoT. *Information*, *13*(7), 328.

[17]. Asim, M., & Abd El-Latif, A. A. (2021). Intelligent computational methods for multi-unmanned aerial vehicle-enabled autonomous mobile edge computing systems. *ISA transactions*.

[18]. Ben Aissa, S., & Ben Letaifa, A. (2022). UAV Communications with machine learning: challenges, applications and open issues. *Arabian Journal for Science and Engineering*, *47*(2), 1559-1579.

[19]. Asim, M., Mashwani, W. K., Belhaouari, S. B., & Hassan, S. (2021). A novel genetic trajectory planning algorithm with variable population size for multi-UAV-assisted mobile edge computing system. *IEEE Access*, *9*, 125569-125579.

[20]. Li, S., Hu, X., & Du, Y. (2021). Deep reinforcement learning for computation offloading and resource allocation in unmanned-aerial-vehicle assisted edge computing. *Sensors*, *21*(19), 6499.

[21]. Laroui, M., Ibn-Khedher, H., Moungla, H., & Afifi, H. (2021, December). Autonomous UAV Aided Vehicular Edge Computing for Service Offering. In *2021 IEEE Global Communications Conference (GLOBECOM)* (pp. 1-6). IEEE.

[22]. Shang, B., Poor, H. V., & Liu, L. (2022). Aerial Reconfigurable Intelligent Surfaces Meet Mobile Edge Computing. *IEEE Wireless Communications*.