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Enabling Metaheuristics with Deep Learning based Resource Allocation in Unmanned Aerial Vehicles Wireless Networks

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Abstract

Unmanned aerial vehicle (UAV) network offers a variety of applications in public safety, disaster management, advertising and broadcasting, overload situation, etc. Due to the dynamic characteristics of MU, it is challenging to provide robust transmission services to mobile users (MU). Resource allocation (RA), including sub-channel, serving user, and transmit power, is a crucial problem; also, it is critical to enhance the coverage and energy efficiency of UAV-enabled communication protocol. Furthermore, system resources are limited (for example, spectrum, and transmission power) and UAV transmission coverage and on-board energy are limited. In order to meet the QoE of any user with limited UAV energy and limited resource system, we jointly enhance UAV trajectory, user communication scheduling, and bandwidth allocation and transmit power to satisfy user QoE requirements and increase energy efficiency. Thus, the study proposes a new mud ring optimization with deep belief network-based resource allocation scheme (MRODBN-RAS) technique for UAV-enabled wireless networks. The proposed MRODBN-RAS approach focuses on the effectual accomplishment of the computational and energy-effective decision. Besides, the MRODBN-RAS technique assumed the UAV as a learning agent by forming RA decisions as actions. In addition, the MRODBN-RAS technique designed a reward function to reduce the weighted resource utilization. The MRODBN-RAS technique uses DBN model with hyperparameter tuning using MRO algorithm to allocate the resources. The design of the MRO algorithm helps in the optimal selection of the hyperparameter related to the DBN model. The simulation results of the MRODBN-RAS method are examined under various measures. The extensive comparison study highlighted the better performance of the MRODBN-RAS approach over existing techniques.

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1. Introduction

With fast development and higher mobility of data traffic, unmanned aerial vehicles (UAVs) enabled wireless communication is involved significant focus [1]. In comparison with standard wireless communication, UAV-assisted wireless communication is provided larger wireless connections in fields without architecture coverage. Moreover, higher throughput is continuously attained in UAV-assisted wireless communications owing to a great possibility of line-of-sight (LoS) communication connections among UAVs and user equipments (UEs) [2]. Due to the aforementioned differences, UAVs are employed for several applications like UAV-based data collection, UAV-based relaying, UAV-assisted collecting networks, UAV-based wireless power transmitted networks, and UAV-based device-to-device communication protocol [3]. For fully utilizing the configuration degrees of freedom for UAV-assisted communication, it can be important for analysing the location and track optimization in UAV-aided wireless communication protocol [4]. The height of UAVs is improved for providing extreme radio coverage of the environment. For maximizing the count of enclosed users, employing less transmission power, an optimum altitude and location placement method is studied for base station (BS) [5].

With various quality-of-service (QoS) necessities of the user, researchers considered the 3D UAV-BS placement, which can increase the covered user count [6]. The UAV quantity diminution is studied since, the adaptable location of the UAVs. The UAV's trajectory is enhanced by combination of considering both UAV's energy consumption and communication throughput. More optimizing user-UAV links, considered the sum power reduction issue of UAVs [7]. Distinct from fixed-beamwidth antenna, the directional antenna beamwidth is improved with fixed bandwidth distribution for enhancing the system throughput. By combination of optimizing bandwidth and beamwidth, the sum power is reduced. Connecting the above-mentioned aids of UANs is no easy task as it should address several undermined technical difficulties with respect to resource distribution patterns [8]. The aim to resource allocation (RA) in UAV-aided wireless network is efficiently assigned the accessible power, time, spectrum, and other resources between the ground users and UAVs in a manner that increases network dimensions, reduces interference, and make sure service quality [9]. Study in UAV-enabled wireless networks includes machine learning (ML) approaches, optimization algorithms, and developing complex methods and these are to face challenges. ML techniques are trained for predicting user requests, channel conditions, and UAV mobility patterns, and assisting in dynamic RA decisions [10].

The study proposes a new mud ring optimization with deep belief network-based resource allocation scheme (MRODBN-RAS) technique for UAV-aided wireless networks. Besides, the MRODBN-RAS method assumed the UAV as a learning agent by forming RA decisions as actions. In addition, the MRODBN-RAS technique designed a reward function to reduce weighted resource utilization. To allocate the resources, the MRODBN-RAS technique uses DBN model with hyperparameter tuning using MRO algorithm. The design of MRO algorithm helps in the optimal selection of the hyperparameter related to the DBN model. The simulation outcomes of the MRODBN-RAS method are examined in terms of different measures.

2. Related Works

In [11], developed a fixed-wing UAV-assisted wireless network method for providing mobility coverage for MGUs. The low-average throughput was increased among users by collectively enhancing the user planning, UAV trajectory control to limit the users' QoS requests, and RA, UAV trajectory transmitting, and communication resources. Li et al. [12] presented a new method of UAV-based wireless-powered MEC (WP-MEC) but, numerous IoT networks utilize the energy receiver from UAV's RF signals. A 2-weighted sum computation bits (WSCB) optimization issue was developed on the binary and partial off-loading correspondingly by combining improving the local computing time and frequencies. Ahmad et al. [13] introduced a dynamic collaborative RA technique for MEC-UAV-assisted wireless networks named joint optimization of trajectory, altitude, delay, and power (JO-TADP) employing anarchic federated learning (AFL). Primarily, the proposed model is optimally located through the beluga whale optimizer (BLWO) method. Through the triple-mode density peak clustering (TM-DPC) approach, optimum clustering could be executed. Besides, the hovering time, altitude, and trajectory of MEC-UAVs were augmented and predicted by the self-simulated inner attention-LSTM (SSIA-LSTM) method.

Cai et al. [14] introduced a scheme of RA and trajectory for collecting UAV-assisted data in WSNs. This technique targets to optimize the average data gathering rate by collectively developing the SN arrangement for gathering information, UAV's trajectory, and power transmission. In [15], an Enhanced Slime Mould Optimizer with DL-based RA Approach (ESMOML-RAA) method was introduced in UAV-based wireless network. This approach studies a UAV as a learning representative with the development of a RA resolution as an activity and scheme. For RA, this method utilizes a highly parallelized LSTM (HP-LSTM) with an ESMO technique as a hyper-parameter optimization. Yahya and Maghsudi [16] designed a technique that reduces the communication period and FL computation in all global iterations: initially, the method adapts the UAVs' positions for controlling the average quantity of sensor devices connected with UAVs to optimize coverage and decrease computational period.

A multi-criterion technique for energy-effective RRM in a collaborative IoT system was suggested by Ramzan et al. [17]. This algorithm is accepted as a power splitting (PS) based EH method for RF-EH at UAV switching and develops a joint optimization issue for source power distribution, PS ratio selection, UAV relay allocation, and IoT device collection. An outer approximation algorithm (OAA) was also developed. In [18], a multi-UAV-assisted wireless communication system was studied but, several UAV aerial BSs have been utilized to work a kind of UEs on BS. This algorithm optimizes the fully uploaded rates of overall BS UEs in the uplink transmittance by maximizing the transmission links among UAVs and UEs collectively.

3. System Model

Given that wireless transmission protocol comprising of M users as $m = \{1, \dots, M\}$, with the position of m user represented as $u_m \in R^{2\times 1}, m \in M$ [19]. The distribution of users is uniform and random. Consider the user location is fixed and already known by the UAV. The QoE requirement of user is arbitrarily distributed, with diversity and changes per period T. The user data was gathered from the cloud server at any time. Without losing generalization, we examined the trajectory design, bandwidth allocation and user communication schedule and association, in each time period T. We assume a downlink scenario where UAV combines time divide multi-access (TDMA) protocol with frequency divide multi-access (FDMA) protocol to interact with user over successive periods at each time $T > 0$. The time-varying coordinate of UAV is represented as $(t) = \big(x(t), y(t), z(t)\big)$. The total bandwidth of the system is BW, the maximal power transmission is $p_{\max}$, and the maximum speed for UAV mobility is $v_{\max}$. The UAV trajectory must satisfy the following limitations.

$$\|q(t)\| <= v_{\max}, \tag{1}$$

$$R_m(t) \geq R_{th}^m. \tag{2}$$

Where the minimal constant data rate for the user m at any time period is R_{th}^m and the maximal velocity of the UAV is $v_{\max}$. Then, the time-dependent distance between GTs and the UAV is formulated by Eq. (3),

$$d_m(t) = \sqrt{(x(t) - x_m)^2 + (y(t) - y_m)^2 + (z(t))^2}. \tag{3}$$

$$\lambda_m(t) = \begin{cases} 1, & R_m(t) \geq R_{m,th} \\ 0, & otherwise \end{cases}. \tag{4}$$

The TDMA technique is used for UAVs to design sufficient trajectory and to serve the M ground user. Random parameter $\lambda_m(t)$ represents whether the user m is scheduled for transmission with UAV at any time t, with $\lambda_m(t) = 1$ or else the user m is scheduled for transmission at any time t and $\lambda_m(t) = 0$. Assume that the UAV connects several users at any time period, and user can serve more frequently than once, thereby the constraints of users' communication schedule and association are written as follows:

$$\int_{t=0}^{T} \lambda_m(t)dt \geq 1, \forall m, t$$

$$\lambda_m(t) \in \{0,1\}. \tag{5}$$

Eq. (4) has two functions, in the first case, it determines the user communication schedule and association, and then, it defines the priority of user service. Consider $p_m(t)$ signifies the transmit power assigned to user m at any time t. UAV connects several users at any time, FDMA protocol is used to interact with the user at any given time. $b_m(t)$ represents the bandwidth assigned to user m at any time period t,

$$\sum_{m=1}^{M} \lambda_m(t) b_m(t) \leq BW,$$

$$\sum_{m=1}^{M} \lambda_m(t) p_m(t) \leq p_{\max}. \tag{6}$$

The ground-to-air path loss mechanism considered the location of ground user and the type of environment with greater difference (for example, suburban, rural, high-rise urban, urban, and so on) that are accurately available in the real scenario.

4. The Proposed Model

In this work, a new MRODBN-RAS method was established for UAV-enabled wireless networks. The proposed MRODBN-RAS approach focuses on the effectual accomplishment of the computational and energy-effective decision. The MRODBN-RAS technique uses DBN model with hyperparameter tuning using MRO algorithm to allocate the resources. Fig. 1 depicts the entire flow of MRODBN-RAS algorithm.

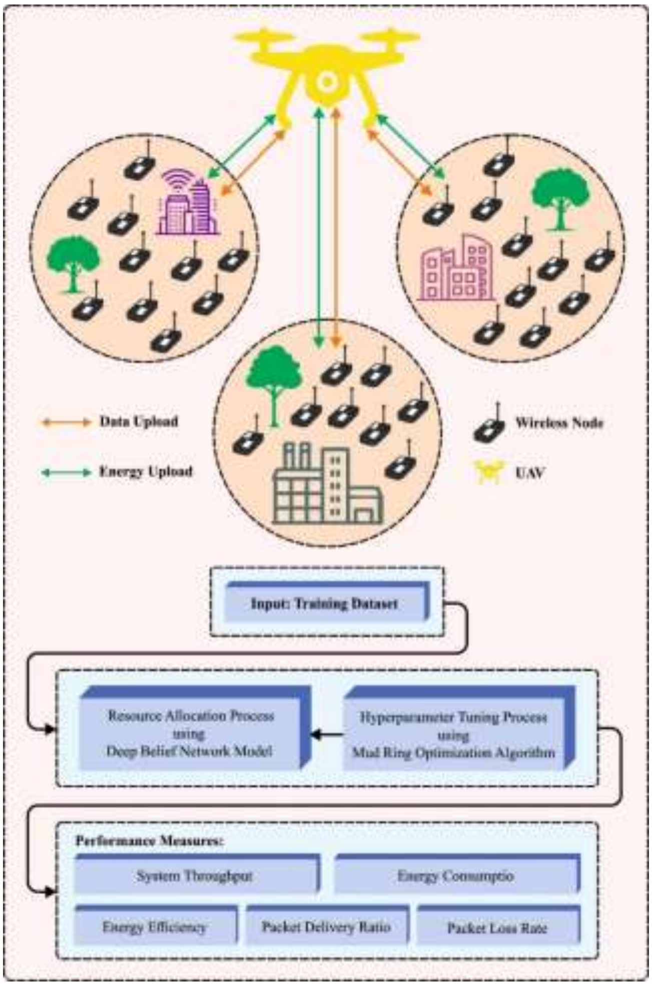

Figure 1: Overall flow of MRODBN-RAS algorithm

A. Problem Formulation

The study was used to minimalize the service delay of MU, and the overall energy depletion of the UAVs while serving the communication and computation requirements of the MU [20]. We make the following assumptions to describe the service delay of MU: 1) the UAV cannot split the tasks until receiving its input dataset to ensure accurateness; 2) the ECs and UAV cannot start the processing of task until the end of transmission between the UAV and ECs or MUs and the UAV to ensure the reliability of computation outcomes; and 3) the computation at the UAV can simultaneously proceed with the communication of task to EC because the computation and transmission modules are frequently partition at the UAV, the service delay of MU i is written as follows:

$$T_i = t_i^{G2A} + \max_{j \in \mathcal{J}} \{ t_i^{UAV}, t_{ij}^{A2G} + t_{ij}^{EC} \}. \tag{7}$$

Our problem becomes jointly optimizing the $G2A$ uplink communication RA B_i^{UL}, UAV location Q^{UAV}, task partition variables β_{i0} and β_{ij}, total service delay of all MUs, computation RA of UAV f_i^{UAV} and ECs f_{ij}^{EC} to minimalize the weighted amount of energy depletion of UAVs:

$$\min_{\substack{Q^{UAV}, B_i^{UL}, \beta_{i0}, \\ \beta_{ij}, f_i^{UAV}, f_{ij}^{EC}}} \sum_{i \in \mathcal{N}} E_i^{UAV} + \rho \sum_{i \in \mathcal{N}} T_i \tag{8}$$

$$s.t. \sum_{i \in \mathcal{N}} B_i^{UL} \le B^{UL} \tag{9}$$

$$\beta_{i0} + \sum_{js \in \mathcal{J}} \beta_{ij} = 1 \; \forall i \tag{10}$$

$$\sum_{i \in \mathcal{N}} f_i^{UAV} \leq F^{UAV} \tag{11}$$

$$\sum_{i \in \mathcal{N}} f_{ij}^{EC} \leq F_j^{EC} \; \forall j \tag{12}$$

$$0 \leq \beta_{ij} \leq 1 \; \forall i, j \tag{13}$$

$$0 \leq \beta_{i0} \leq 1 \; \forall i \tag{14}$$

$$B_i^{UL}, f_i^{UAV} \geq 0 \; \forall i \tag{15}$$

$$f_{ij}^{EC} \geq 0 \; \forall i, j \tag{16}$$

where $\rho > 0$ is a parameter describing the relative weight of energy and delay, and ensures that the RA for UAV, uplink bandwidth and EC CPU frequency is non-negative and no more than their limits while constrains that the offloading task of MU is processed completely by ECs and UAV, and the value of partition variable lies within [0,1].

B. DBN-Based Resource Allocation Approach

The MRODBN-RAS technique uses DBN model to allocate the resources. A DBN is a probabilistic productive network that comprises multiple RBM layers [21]. An RBM is an unsupervised nonlinear feature extractor based on Markov random field, involving two important layers: a hidden unit layer and a visible cell. The output of RBM hidden unit is fully connected to the next RBM unit through symmetric undirected synapses. This RBM property leads to conditional independence between hidden and visible cells. Fig. 2 illustrates the architecture of DBN.

The joint likelihood distribution recognized by the RBM's weights used an energy-based function of $\{v, h\}$, as follows:

$$En(v, h; \theta) = -v^T W h - a^T v - b^T h = -\sum_{i=1}^{D_v} \sum_{j=1}^{D_h} w_{ij} \, v_i h_j - \sum_{i=1}^{D_v} a_i \, v_i - \sum_{j}^{D} b_j \, h_j, \tag{17}$$

Where $\theta = \{b_i, \, a_j, w_{ij}\}, sw_{ij}$ indicates the weight from i^{th} visible cell to j^{th} hidden cells, and a_i and b_j correspondingly show the bias of i and j units. The joint likelihood distribution of the RBM model over the visible-hidden cells is evaluated as follows:

$$P(v, h; \theta) = \frac{1}{Z(\theta)} exp\big(-E(v, h; \theta)\big), \tag{18}$$

In Eq. (18), $Z(\theta)$ denotes the normalizing constant value or partition function attained from the summary of each possible energy allocation combining i^{th} and j^{th} cells.

$$Z(\theta) = \sum_{v} \sum_{h} e\,xp\big(-E(v, h; \theta)\big) \tag{19}$$

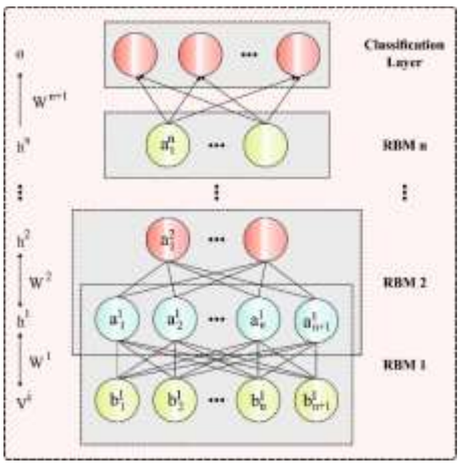

Figure 2: DBN architecture

The RBM attain the probability of input dataset via the energy equation. Based on the joint likelihood distribution, the conditional probability function of i and j cells are attained using the subsequent functions:

$$P(h_j = 1|v) = \delta\left(b_j + \sum_i v_j w_{ij}\right), \tag{20}$$

$$P(v_i = 1|h) = \delta\left(a_i + \sum_j h_j w_{ij}\right) \tag{21}$$

$$\delta(x) = \frac{1}{1 + exp(-x)} \tag{22}$$

The input state is recreated by arranging v_i to 1 with the probability provided by Eq. (21). Therefore, the hidden cell state is gradually renewed to represent the reconstructed features.

C. Hyperparameter Tuning using MRO Algorithm

The MRO technique is applied for the hyperparameter tuning process to optimize the performance of the DBN model. Bottlenose dolphin collaborates by working together for maximizing their hunting strength to attain food [22]. Accordingly, the bottlenose dolphin forms swarm and later the individuals from the swarm swim in a circle nearby the target (school of fish), swinging its tail up and down along the sand for making a plume or ring of mud that throws the fish-off balance. Dolphin employs a different hunting strategy. This approach change based on the target and surrounding circumstance. Mud plume fishing (or mud Ring feeding), is a unique foraging approach introduced in 1999 as researcher workers were observing the behaviors of dolphins in the shallow water nearby Florida's Atlantic coast. The MRO algorithm was stimulated by the foraging behaviors of bottlenose dolphins, such as formation of mud rings for eating and echolocation-based food search. These behaviors are determined as the optimal way of attaining prey. The parameter K is the backbone of the optimization technique because it demonstrates how they move nearby the prey once the hunting method commences. Such parameters control the transition amongst the exploitation and exploration by decreasing the sound whenever the swarm get closer towards the target. This section provides mathematical modeling of mud plume fishing and foraging for food. The phases of MRO algorithm was explained below.

Foraging—Exploration Phase: Echolocation

Echolocation randomly applies bottlenose dolphin with kinetic energy (K) and exploration velocity (V) at place DE that doesn’t produces sound to alert the target. Also, echolocation applies sound. The assumption is that the r pulse rate varies over time within $[0,1]$ intervals, in which no pulse emission indicates 0 and the maximal emission rate indicates 1. Dolphin adapted the sound volume in line with the vicinity of the target. The vector $K's$ computation is shown below:

$$K = 2a \cdot r - a \tag{23}$$

$$a = 2\left(1 - \frac{c_{iter}}{\text{Max}_{iter}}\right) \tag{24}$$

Generic solution explores (hunting target) in d-dimension space determined by the vicinity K is used for causing divergence and searching for the optimum target, which randomly changes with values > 1 or < 1. Instead of the better dolphin, a dolphin randomly selected is preferred.

$$D(t) = D(t-1) + V \tag{25}$$

In Eq. (25), V is an initial state random vector. The random velocity from the range $[Vmin, Vmax]$ is allotted to the bottlenose dolphin according to the magnitude of the target issue.

Mud Ring Feed—Phase: Exploitation

The bottlenose dolphin detects and surrounds the target. Mud ring feed exploits the optimum or closest target as the current best solution. The optimum searching agent is chosen, and the other individuals change their locations accordingly:

$$A = |C \cdot D(t-1) - D(t-1)| \tag{26}$$

$$D(t) = D(t-1) \cdot \sin(2\Pi l) - K \cdot A \tag{27}$$

In the equation, DE indicates the location vector with the optimum solution at t^{th} iteration with coefficient vectors CE and KE. Similar to a sign, the dolphin quickly wiggles its tail periodically for making a plume while the other individuals surround the target. The vector CE is evaluated by using the following expression:

$$C = 2 \cdot r \tag{28}$$

By finding out the random vector rE, any location in the search area was attained. The dolphin defends their locations regarding either the randomly chosen time step or better position. Consequently, a parameter depends on the transition phase between exploration and exploitation.

5. Results and Discussion

This section investigates the performance of the MRODBN-RAS technique under various measures. Table 1 offers the detailed performance of the MRODBN-RAS technique under varying numbers of BSs.

Fig. 3 presents a comparative result of the system throughput (THRO) values of the MRODBN-RAS technique with and without UAVs. The results show that the THRO values get increased under THRO values under varying numbers of BS. With 3 BS, the THRO value under UAV is 122Mbps whereas without UAV is 31Mbps. In addition, with 9 BS, the THRO value under UAV is 376Mbps whereas without UAV is 72Mbps. Besides, with 15 BS, the THRO value under UAV is 618Mbps whereas without UAV is 127Mbps.

Table 1: Classifier outcome of MRODBN-RAS approach under differing numbers of BSs

No. of BSs	UAV		Without UAV	
	System Throughput (Mbps)	Energy Consumption (j)	System Throughput (Mbps)	Energy Consumption (j)
3	122	156	31	56
5	211	276	42	60
7	298	359	58	79
9	376	458	72	105
11	470	543	88	125
13	537	627	106	145
15	618	678	127	158

In Fig. 4, the energy consumption (ECON) outcomes of the MRODBN-RAS method are compared with and without UAVs. The results show that the ECON values get improved in the absence of UAVs. It is also noticed that the ECON values get increased with a rise in the number of BSs.

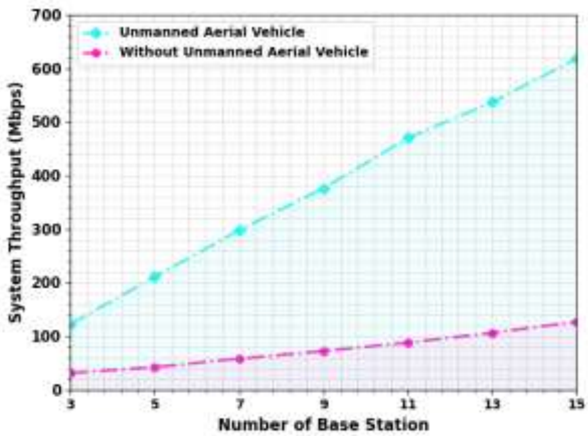

Figure 3: System THRO outcome of MRODBN-RAS approach under varying numbers of BSs

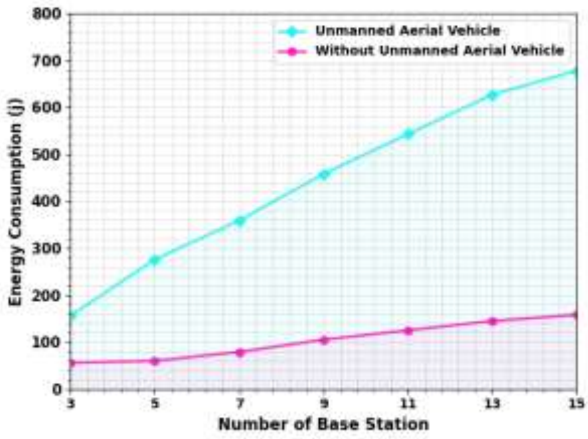

Figure 4: ECON outcome of MRODBN-RAS approach under varying numbers of BSs

In Table 2 and Fig. 5, the energy efficiency (EE) outcomes of the MRODBN-RAS technique with recent models under varying numbers of users [15]. The results highlight that the MRODBN-RAS technique reaches decreasing EE values over other models. With 10 users, the MRODBN-RAS technique provides increasing EE of 167826971bit/j. In addition, with 15 users, the MRODBN-RAS method provides increasing EE of 61808332bit/j. Besides, with 20 users, the MRODBN-RAS system provides an increasing EE of 40408658bit/j. Also, with 25 users, the MRODBN-RAS technique provides increasing EE of 28564735bit/j.

Table 2: EE outcome of MRODBN-RAS technique with recent methods under varying numbers of users

Energy Efficiency (bit/j)						
No. of Users	MRODBN-RAS	ESMOML-RAA	DQN	Q-Learning	Random	Maximum
10	167826971	147715341	141671116	117116436	94450581	84250947
15	61808332	59696271	54407571	45718991	35519359	31741715
20	40408658	39296999	37030415	29097365	21542084	19653261
25	28564735	26453015	23808668	18519969	17764441	15875619

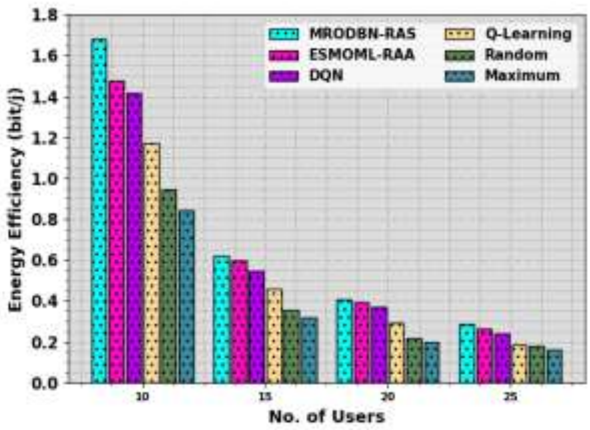

Figure 5: EE outcome of MRODBN-RAS technique under varying numbers of users

In Table 3 and Fig. 6, the EE outcomes of the MRODBN-RAS technique with recent models under differing numbers of BSs. The results highlight that the MRODBN-RAS technique reaches decreasing EE values over other models. With 3 BS, the MRODBN-RAS technique provides increasing EE of 41213832bit/j. In addition, with 5 BS, the MRODBN-RAS method provides increasing EE of 49654674bit/j. Besides, with 7 BS, the MRODBN-RAS system provides an increasing EE of 56496196bit/j. Also, with 8 BS, the MRODBN-RAS technique provides an increasing EE of 58362073bit/j.

Table 3: EE outcome of MRODBN-RAS technique with recent methods under varying numbers of BSs

Energy Efficiency (bit/j)

No. of BSs	MRODBN-RAS	ESMOML-RAA	DQN	Q-Learning	Random	Maximum
3	41213832	39213822	36459441	33882759	32016889	28995955
4	45389827	43389821	40368887	37259101	33971611	31217233
5	49654674	47654669	43745223	40990838	37259103	34415864
6	53741824	51741815	48632029	44278332	40102332	36903692
7	56496196	54496191	51919518	46677302	43656373	39213824
8	58362073	56362064	54762749	50497902	46499604	42856716

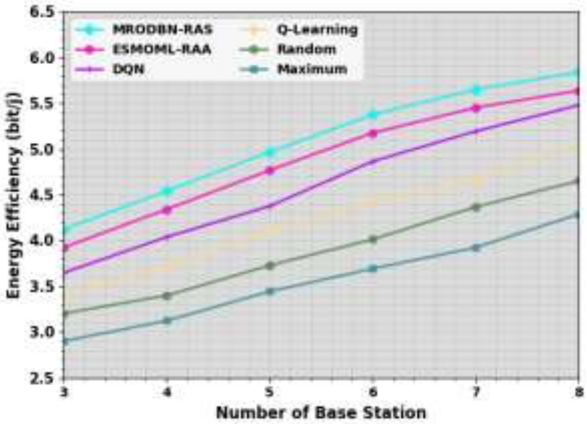

Figure 6: EE outcome of MRODBN-RAS technique under differing numbers of BSs

Table 4 and Fig. 7 portray the computation time (CT) results of the MRODBN-RAS technique with existing approaches. The obtained values presented that the MRODBN-RAS technique accomplishes minimal CT values. With 3 BS, the MRODBN-RAS technique offers reduced CT of 167s while the ESMOML-RAA, DQN, Q-learning, random, and maximum models obtain increased CT values of 189s, 224s, 264s, 324s, and 373s respectively. Moreover, with 15 BS, the MRODBN-RAS method provides reduced CT of 367s while the ESMOML-RAA, DQN, Q-learning, random, and maximum models obtain increased CT values of 397s, 457s, 461s, 489s, and 513s correspondingly.

Table 4: CT outcome of MRODBN-RAS technique with recent methods under varying numbers of BSs

Computational Time (sec)						
No. of BSs	MRODBN-RAS	ESMOML-RAA	DQN	Q-Learning	Random	Maximum
3	167	189	224	264	324	373
5	173	202	260	297	349	404
7	205	225	322	352	387	441
9	236	260	353	389	432	468
11	275	304	390	427	463	496
13	348	372	420	440	482	511
15	367	397	457	461	489	513

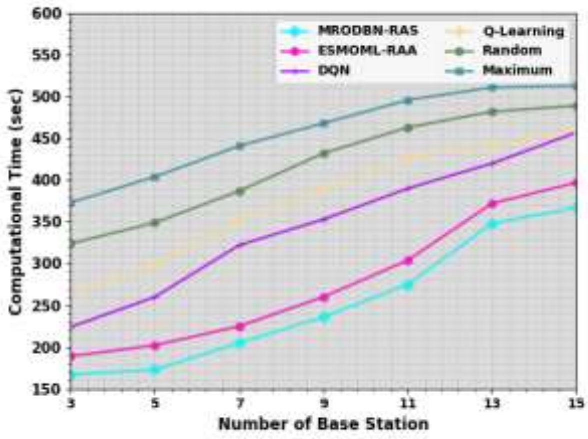

Figure 7: CT outcome of MRODBN-RAS technique under varying numbers of BSs

Table 5 and Fig. 8 portray a packet delivery ratio (PDR) result of the MRODBN-RAS technique with existing approaches. The obtained values presented that the MRODBN-RAS technique accomplishes maximum PDR values. With 3 BS, the MRODBN-RAS technique offers higher PDR of 77.42% while the ESMOML-RAA, DQN, Q-learning, random, and maximum models obtain lesser PDR values of 70.10%, 63.21%, 47.82%, 34.75%, and 24.23% respectively. Moreover, with 15 BS, the MRODBN-RAS technique offers higher PDR of 97.94% while the ESMOML-RAA, DQN, Q-learning, random, and maximum models obtain lesser PDR values of 91.14%, 81.65%, 72.68%, 67.54%, and 61.16% correspondingly.

Table 5: PDR outcome of MRODBN-RAS technique with recent methods under varying numbers of BSs

Packet Delivery Ratio (%)						
No. of BSs	MRODBN-RAS	ESMOML-RAA	DQN	Q-Learning	Random	Maximum
3	77.42	70.10	63.21	47.82	34.75	24.23
5	86.39	79.36	67.28	56.80	47.56	40.13
7	90.18	84.22	73.19	61.39	54.48	44.50
9	92.67	87.03	75.74	61.42	56.02	47.30
11	96.37	89.06	76.51	66.78	59.61	51.90
13	96.72	89.86	77.02	69.33	63.95	53.70
15	97.94	91.14	81.65	72.68	67.54	61.16

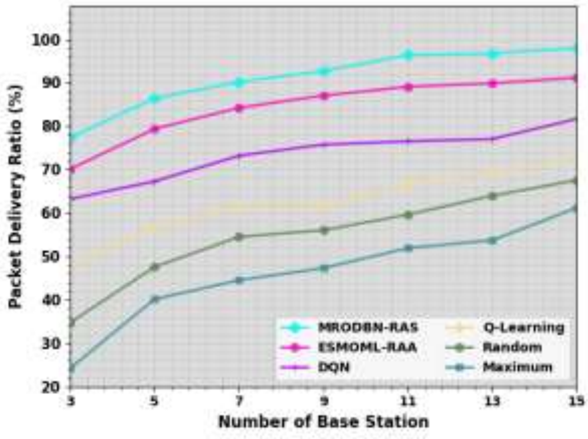

Figure 8: PDR outcome of MRODBN-RAS technique under varying numbers of BSs

Table 6 and Fig. 9 portray the packet loss rate (PLR) results of the MRODBN-RAS technique with existing approaches. The obtained values presented that the MRODBN-RAS method accomplishes minimal PLR values. With 3 BS, the MRODBN-RAS method offers reduced PLR of 24.70% whereas the ESMOML-RAA, DQN, Q-learning, random, and maximum models obtain increased PLR values of 31.73%, 38.74%, 54.07%, 67.17%, and 77.51% correspondingly. Furthermore, with 15 BS, the MRODBN-RAS technique offers reduced PLR of 3.48%

while the ESMOML-RAA, DQN, Q-learning, random, and maximum methods attain maximum PLR values of 10.64%, 20.04%, 29.01%, 34.20%, and 40.68% correspondingly.

Table 6: PLR outcome of MRODBN-RAS technique with recent methods under varying numbers of BSs

Packet Loss Rate (%)						
No. of BSs	MRODBN-RAS	ESMOML-RAA	DQN	Q-Learning	Random	Maximum
3	24.70	31.73	38.74	54.07	67.17	77.51
5	16.40	22.49	34.47	45.15	54.32	61.79
7	11.62	17.59	28.58	40.24	47.20	57.32
9	8.66	14.86	26.05	40.42	45.71	54.44
11	6.13	12.66	25.36	34.89	42.30	49.93
13	5.89	11.98	24.74	32.46	37.90	48.02
15	3.48	10.64	20.04	29.01	34.20	40.68

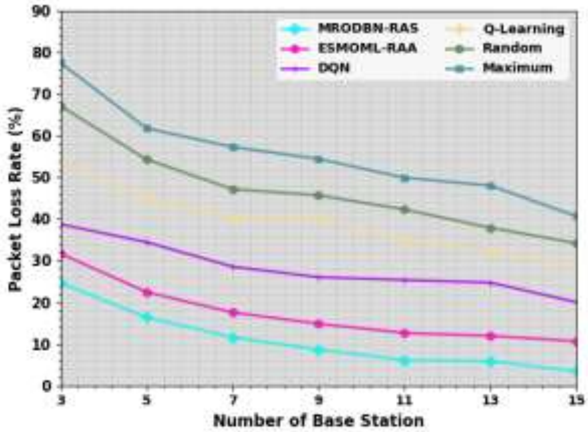

Figure 9: PLR outcome of MRODBN-RAS technique under varying numbers of BSs

These results portrayed that the MRODBN-RAS technique accomplishes enhanced performance over other models.

6. Conclusion

In this study, we have developed the MRODBN-RAS technique for UAV-enabled wireless networks. The proposed MRODBN-RAS approach focuses on the effectual accomplishment of the computational and energy-effective decision. Besides, the MRODBN-RAS technique assumed the UAV as a learning agent by forming RA decisions as actions. In addition, the MRODBN-RAS technique designed a reward function to reduce the weighted resource utilization. The MRODBN-RAS technique uses DBN model with hyperparameter tuning using the MRO algorithm to allocate the resources. The design of the MRO algorithm helps in the optimal selection of the hyperparameters related to the DBN model. The simulation results of the MRODBN-RAS method are examined in terms of different measures. The extensive comparison study highlighted the greater performance of the MRODBN-RAS system over existing techniques.

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