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Novel Hybrid Deep Optimized Machine Learning Model for Energy Efficient Cluster Selection in Unmanned Aerial Vehicle Networks

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Abstract: - Unmanned Aerial Vehicles (UAVs) have grown into a more powerful type of data transmission due to this rapid progress of evolution of wireless communication technology. In addition, UAVs have been proven to be effective in a variety of applications, including intelligent transport, disaster risk management, surveillance, and environmental monitoring. When UAVs are deployed randomly, however, they can effectively accomplish challenging tasks because of the UAVs' has low battery capacity, quick mobility, and dynamic in nature orientation. Due to this reason, a new technique must be designed for an optimal energy efficient UAV clustering as well as data routing protocols. In this work proposes a new hybrid model of Emperor penguin-based Generalized Approximate Reasoning Based Intelligent Control (EP-GARIC) cluster-based network topology. Furthermore, the optimal routing function is achieved by the proposed Artificial Jellyfish Optimization (AJO). The implementation of this research is carried out using Network Simulator (NS2). The simulation results displays the effective performance of the suggested approach in terms of reduced energy consumption, improved packet delivery ratio, reduced loss, and so on over compared to the conventional approaches.

Keywords: Clustering, Neural Network, Fuzzy method, Energy Efficiency, Parameter Tuning.

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I. INTRODUCTION

Unmanned Aerial Vehicle (UAV), also referred as a drone, is a plane that does not have a human operator or passengers aboard [1]. In unmanned aerial systems, control systems [2] such as ground control station (GCS) control linkages, and other relevant support devices [3] are all part of the UAV system. The concept “unmanned aerial vehicle” (UAV) refers to a military aircraft that is guided autonomously and remotely and contains sensors, target designators, and electronic sources [4]. Aerodynamic drones and remotely controlled vehicles are among the offensive weapons used to disrupt or destroy terrorist objectives, although ballistic and semi-ballistic weapons, mortars, and missile systems, which are considered atomic delivery systems, are not included [5].UAVs are used in a variety of real-world applications, including traffic monitoring [6], payload distribution of moving items in a potentially hazardous situation, and surveillance [7]. The altitude ranging, durability, and weight represent a large set of uses, including commercial and military [8].

Unmanned Aerial vehicles are monitored the weather conditions, environment, traffic problems, and improvement of smart cities[9]. The most important areas for the research part of smart cities using a mobile network and information are gathered [10]from surveillance cameras. Internet of things platform that will provide the information of various smart cities such as smart UAV[11],the smart device will improve and work with demands of customer[12].Moreover, Killer drones [13], attack drones, spy drones, and surveillance drones are examples of unmanned aerial vehicles (UAVs) that are controlled by computers to carry out specific tasks without the need for direct human piloting [14]. The various challenging crises and issues for the UAV communication model suffer[15]. The major problems where UAV is used for battery replacement[16], recharging that limits the endurance of drone[17].In UAV wireless systems, energy efficiency (EE) is an essential performance parameter [18].

For UAV-based data transmission, data collection, and data response, cluster routing techniques were used [19]. As a result of the frequent separation of UAV components, routing were developed [20]. Multi-UAV sets are built out of a network of different communication connections [21]. The IEEE 802.11 standard model has been used in the UAV system [22]. The IEEE 802.14.4 specification is suitable for UAV-to-UAV communications in cases when bandwidth is constrained [23]. Recently, various kinds of methodologies are utilized for the optimal clustering and routing of data transmission such as distributed clustering [24], deep learning [25], Multi-layer perception method [26], hybrid of deep and neural method [27] and heuristic algorithms like electrBio-inspired method [28] and so on [29]. However, the conventional methods are not performed up to the level in terms of different performance measures.

In this article, a new Emperor penguin-based Generalized Approximate Reasoning Based Intelligent Control (EP-GARIC) is developed for optimal energy efficient clustering in UAV network. The EP-GARIC model used three input parameters such as for the selection of Cluster Heads (CHs) and topology creation, the average distance to neighbouring UAVs, residual energy (RE) in UAVs, and UAV degree are used. Besides, the Artificial Jellyfish Optimization (AJO) is proposed for a set of routes for UAVs communication and improves the energy efficiency performance. The simulation findings reveal that the proposed strategies perform better in terms of various performance metrics.

The following is an overview of this article is organised. Section 2 discusses recent studies relevant to the study. Section 3 explores into the system model and associated issue formulations. Section 4 explains the suggested framework. In Section 5, the results, discussion, and comparative analysis for this study are explained. Consequently, Section 6 gives the conclusion of this article.

II. RELATED WORK

The following is a list of some of the research that has been done in order to conduct the study: Reduce the number of duplicate sensors talking with the UAV by grouping sensors inside the beacon signal's coverage region into distinct priority groups. Circularly Optimized Frame Selection (COFS) defines priority segments in which transmission of data is continually steered from higher to lower transmission priority cycles. As a result, Nazib, Rezoan Ahmed, and SangmanMoh [30] highlighted the need of achieving low energy usage while also extending the lifetime of sensors inside the network. Wireless Sensor Networks with Unmanned Aerial Vehicles (WSN-UAN) is a data collection and communication technology that is both successful and energy-efficient.

In UAV networks, Bio-Inspired Localization (BIL) and Bio-Inspired Clustering (BIC) systems are used to identify and monitor wildfires in distant places. Establish a Hybrid Gray wolf optimization (HGWO) that decreases localization mistakes, prevents flip confusion in limited distance error margins, and provides accurate results in localization. As a result, Arafat, Muhammad Yeasir, and SangmanMoh [29] proposed a GWO-based Compressive Sensing (CS-GWO) method of information transmission from CHs to base stations (BS). Although there are certain cost and complexity implications, many antennas can be used to boost the effectiveness of UAV networks.

In domains like the Internet of Things (IoT), sensor networks, and three-dimensional (3D) wireless networks, UAVs have been widely embraced to make optimal use of network capacity. According to data collection and UAV travelling distance limits, the maximum and least remaining energy of sensors during transmitting data for energy-efficient UAV routing. A Node-link diagram is modified to locate a collection of UAV hovering positions, according to Baek, Jaeuk, et al [31]. This is an extremely low computational burden performance.

In UAV networks, novel 3D joint transmission architecture is employed for user-centric air-to-air communication. As a result, Humadi, Khaled, et al [32] develop on a framework that allows Aerial Base Stations (ABSs) to collaborate on a dynamic basis, consequently improving the performance of Aerial User Equipment (AUEs). The best cluster size is one that maximises energy efficiency (EE).

Unmanned aerial vehicles (UAVs) have opened up a world of possibilities for perception outdoor operations. Detecting visual objects is one of the most important tasks among them. However, because to the constraints of energy consumption, precision, and speed. It is challenging to really install detectors on embedded systems. After that, Deng, Jianing [33] obtained a speed of 28.5 FPS as well as 2.7 FPS /W energy efficiency on the set of data with Low Power Object Detection Challenges (LPODC).

A revolutionary technique for UAV-based WSNs to solve the problem of short lifespan produced by clustering networks without addressing their dispersal and substantial package losses incurred by storage restriction. When sensor nodes are clustered, the energy consumption is reduced, and the lifespan of the WSN is extended. Thus, Zhu, Botao, et al. [34] suggested an incorporated Soft-K-means clustering algorithm to upsurge the lifespan of sensor network and lessen transmitting data package loss.

III. SYSTEM MODEL

The system model of UAV in WSN is illustrated in Figure 1. Considering down-link communication in UAV assisted wireless connections, where many UAVs serve as aerial base stations to serve users in a certain region. The symmetric sensor range, transmission radius, data storage capacity, and fundamental energy are all part of UAV. Following that, UAVs rely on a well-trained GPS technique. The distributed UAV may measure position parameters, and the information sink collects all of the information about the UAV's location. Furthermore, the base station is aware of extra UAV factors such as starting energy and buffer size. Also, the primary goal of clustering is to display the path taken by data providers. As a result, it is appropriate for gathering sensed data while switching to UAV. The wireless data collection then delivers and receives the obtained data to the base station after the transmission is done.

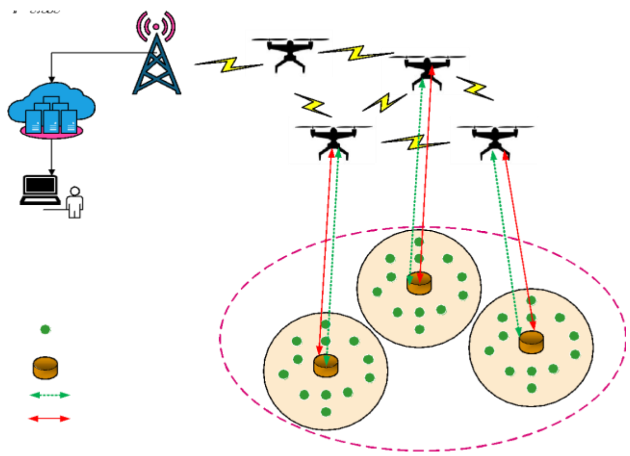

Figure.1 System model of UAV in WSN

3.1 Problem statement:

Cluster head and cluster node are the two primary components in which the sensor node operates. Sensor networks are causing uneven energy consumption since the data traffic for each cluster node and cluster head is highly different. Few nodes may expire very soon which eventually affects the overall network operation. Cluster heads are free to leave the store since they must store tens of sensor nodes relaying data to the UAV. Whenever the storage capacity is reached, newly received data is lost, causing the UAV to retrieve incomplete data to the base station. So, storage should also be considered when choosing a cluster head. Furthermore, the data transmission layer must indicate concerns such as packet delay, excessive interaction between UAVs, exceptional network utilization, increased mobility, and varied link quality.

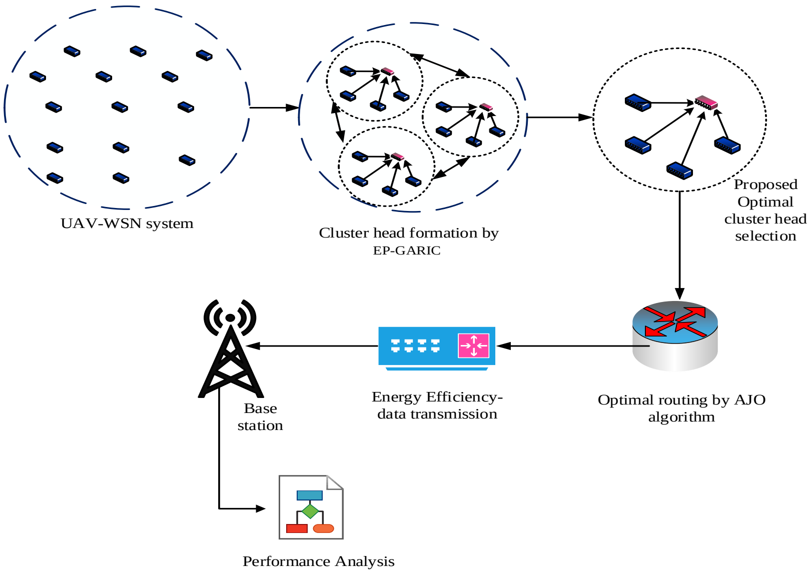

Figure.2 Suggested EP-GARIC with AJO model in energy efficient CH selection is UAV

IV. PROPOSED SYSTEMS

The suggested EP-GARIC with AJO model in Energy efficient CH selection is UAV is depicted in Fig. 2. After the UAVs have been positioned and started, the next step is to select the best customary of CHs for transmission of data with the least amount of energy loss. To begin, BS uses the created model to pick the optimal CH size in order to evenly divide the load. Second, the chosen CH is used to create clusters with neighbouring nodes. The key purposes in the development of a UAV are optimal energy efficiency and maximum lifespan; the Cluster head selection procedure employs the EP-GARIC approach with three input parameters. For the choice of Cluster Formation, the mean distance to close UAVs, the UAV's residual energy (RE), and the UAV's degree were used. Following that, it will exchange the information about the election of CHs with additional UAVs in the system and construct a cluster based network topology. Following that, the CHs are in charge of data transmission to other CHs and, as just a response to BS. The AJO method is used to choose the best fixed of routes for clustering UAV broadcast.

4.1 EP-GARIC based CH selection

The EP-GARIC method is the combination of Emperor penguin optimization and improved neural fuzzy inference function. The GARIC function is operated with three conditions such as action selection, action evaluation and stochastic action. The parameters of the GARIC approach are optimized by the EP method. Learning takes place by EP fine-tuning the free parameters in the two networks like the weights in the action evaluation are altered, while the parameters specifying the fuzzy membership functions in the action selection change. The proposed EP-GARIC method in an optimal CH selection is illustrated in figure 3.

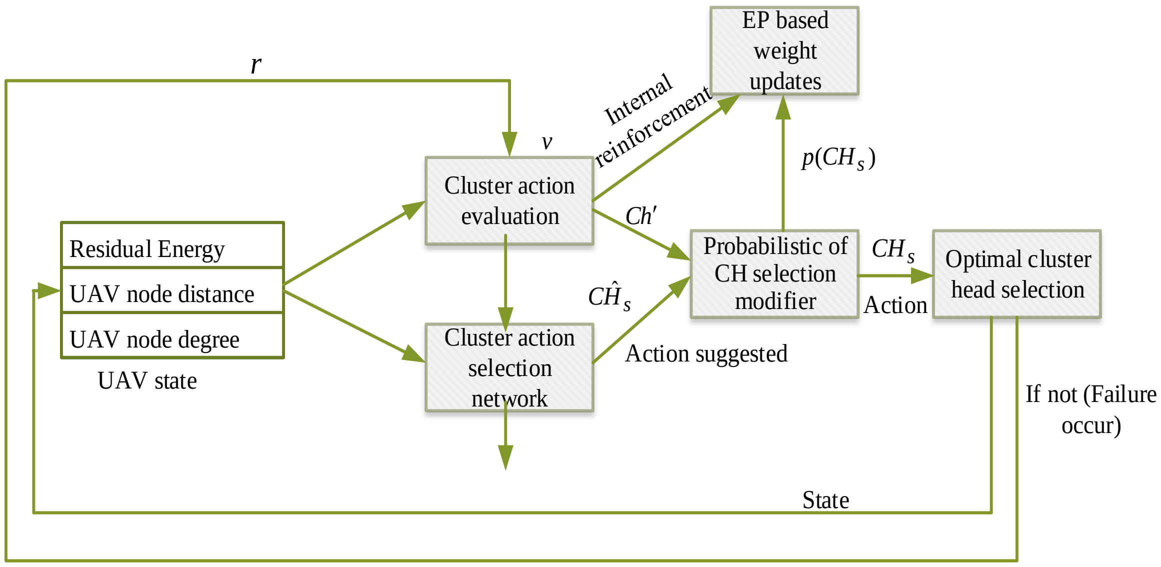

Figure.3 Proposed EP-GARIC method in an optimal CH selection

4.1.1 Cluster action evaluation

The action evaluation acts as an adaptive evaluative factor, continually predicting reinforcements in response to various input states. The action evaluation receives only additional information such the state of the UAV system in terms of state variables and if or not a problem has happened. The state of the UAV is the input, and the output is a score evaluation. The action assessment yields estimation reinforcement for a specific state, and adjustments in this estimate are utilized to direct the stochastic activity in clustering actions selection. If this function goes from a configuration with low reinforcement probability to one with higher reinforcement probability then, EP is employed to encourage the clustering activity that generated the transfer. An evaluation program's framework consists of q hidden nodes, m input groups from the UAV-WSN environment, and a bias nodes $y_0, y_1, \ldots\ldots y_m$. Moreover, the hidden nodes output is estimated using eqn. (1),

$$z_i(n, n+1) = h(\sum_{k=1}^{m} b_{kl}\,[n] y_k[n+1]) \tag{1}$$

Here, the successive time steps are denoted as n and $n+1$. The evaluation network's output node takes inputs from both hidden node nodes and nodes in the input layer directly. The probability of clustering is expressed using eqn. (2),

$$c(n, n+1 = \sum_{k=1}^{m} f_k[n] y_k[n+1] + \sum_{k=1}^{m} g_k\,[n] y_k[n+1] \tag{2}$$

Furthermore, using multiple time steps in a clustering operation allows comparing different c throughout time and seeing if the system has improved or deteriorated in clustering. This network examines the clustering action suggested by the action network as a combination of the failure message and the change in energy state analysis based on the system's current energy state at time $n+1$. The clustering head formation is evaluated based on the energy state and appropriated condition using eqn. (3),

$$Ch'(n+1) = \begin{cases} 0 & startCHstate \\ Ch[n+1] - c[n,n] & FailureCHstate \\ Ch[n+1] + \delta c[n, n+1 - c[n,n]] & Otherwise \end{cases} \tag{3}$$

Where δ is denoted as the discount value in the range of [0,1]. Thus, this function of evaluating CH formation provides a suitable performance of clustering UAVs.

4.1.2 Cluster Head Selection Network

The UAV network selects a CH depending on the current energy level by developing an inference approach based on fuzzy control constraints. It may be seen as a five-layer network with each unit doing one phase of the fuzzy inference procedure. The real-valued input parameters are used in the input step. These might also be referred to as the variables of interest in linguistics. These nodes do not perform any computations. Here, the linguistic variables of input parameters are given like the linguistic variables of residual energy is high, low and average, for distance is farthest, far and near also for node degree is high, low and medium. Consequently, the probability of CH selection is considered based on the linguistic variables such as very strong, strong, medium, above medium, below medium, poor and very poor of CH selection. In the second stage, a node computes $\eta_{high}(y)$ to the subsequent phase and corresponds to one potential value of a few of the linguistic variables in stage 1. For example, if large is one of the values that y can take, a node computes $\eta_{high}(y)$. It will only have one input and will provide its result to every rules that employ the if clause y is high in their if component. The expression of this stage is provided in eqn. (4),

$$n_{m_v}, l_{vs}, r_{vs}(y) \tag{4}$$

Where v is the linguistic variables (eg. High, far, medium, etc.) m_v is the middle of the fuzzy membership function (MF), l_{vs} and r_{vs} are the left and right side of the fuzzy MF v. The MF has been smoothening using eqn. (5),

$$n(y) = \frac{1}{1+\left|\frac{y-m}{s}\right|^{d}} \tag{5}$$

Where $s = l_{vs}$ or r_{vs} therefore $y < m$ or $y \geq m$ and b is the curvature mechanism. Then, the triangular MF is executed using eqn. (6),

$$n_{m_v}, l_{vs}, r_{vs}(y) = \begin{cases} 1 - \frac{|y-m|}{r_{vs}} & y \in [m, m + r_{vs}] \\ 1 - \frac{|y-m|}{l_{vs}} & y \in [m, m + r_{vs}] \\ 0 & otherwise \end{cases} \tag{6}$$

The middle and side may be thought of as weights on the input connections, similar to how radial-basis-function units are used in machine learning. Furthermore, in a rule of the third stage, it is used to combine all of the preceding criteria. A rule in the fuzzy rules is represented as a node in third part. All nodes in second part that participate in the “if” component of that rule provide input to it. The min operation is performed by the node itself, and it has been softened to the following differentiable softmin action:

$$f_r = \frac{\sum k\, n_k e^{-lnk}}{\sum k e^{-lnk}} \tag{7}$$

Where η_k is the degree of correspondence between a fuzzy label that occurs as one of rule r antecedents and the related input variable. This soft min procedure returns f_r, the degree of rule r application. The soft min operation's hardness is controlled by the parameter l, and when set it to $r \rightarrow \infty$, then get the ordinary min operator back. However, For r bounded one obtain a differentiable value of the inputs, that enables computing gradients throughout the process of learning much easier. The value of l isn't relevant.

A subsequent label refers to a four stage node. It gets its inputs from all rules that employ this specific consequent label. This node calculates the relevant output action for each of the f_r provided to it, as recommended by rule r. This mapping is expressed in the following eqn. (8)

$$n^{-1}_{m_v,\ l_{vs},\ r_{vs}}(y) \tag{8}$$

Where v is a specific subsequent label, m_v, l_{vs} and r_{vs} denote MF parameters, and the inverse denotes a proper defuzzification technique applicable to a certain regulation. In this case, the inverse technique is used to defuzzify the technique; if the goal is monotonic, the inverse method η^{-1} is not used. In the eqn. (9), the inverse method is then examined.

$$n_v^{-1}(f_r)\ is\ the\ synchronized\ CH\ of\ \{y: n_v^{-1}(y) \geq f_r\} \tag{9}$$

Because sharing of subsequent labels is possible, a unit in layer 4 can have many outputs holding distinct values, which is a unique feature. It should provide an actual output CH choosing action for each rule supplying it a degree, which is then provided to the next phase. For several types of MF, this incorrect functionality can be removed. Such a node simply needs to output the response for triangular operators.

$$CH_v = \left(m_v + \frac{1}{2}(r_{vs} - l_{vs})\right)\left(\sum_r f_r\right) - \frac{1}{2}(r_{vs} - l_{vs})\left(\sum_r f^2{}_r\right) \tag{10}$$

In general, when $\eta^{-1}(y)$ is polynomial in y, depending on the number of inputs, only one output is necessary. This transition is achievable due to the structure of the calculation performed in the following layer. Furthermore, the fifth stage will contain the same number of nodes as the output CH selection action variables. The suggestions from all of the proposed fuzzy norms in the rule base are combined at each output stage using the appropriate weighted sum, with the weights representing the rule expertise:

$$CH_S = \frac{\sum_{r=1} f_r n_v^{-1}(f_r)}{\sum_{r=1} f_r} \tag{11}$$

The node simply adds all of the inputs together and calculates the difference. This generates an output parameter score that represents the CH selection action.

4.1.3 Probabilistic of CH selection modifier

This stochastically generates a CH selection action $C\hat{H}_s$, which is a Gaussian random variable with mean CH_s and standard deviation $\sigma(Ch'(n+1))$, using the values of Ch' from the previous iteration and the action CH_s advised by the action selection system. This $\sigma()$ function is a monotonically decreasing non - negative real variable. The UAV is really exposed to the CH selection action $C\hat{H}_s$. The recommended action's probabilistic modification allows for improved exploration of data transmission routing and generalisation capabilities. When Ch' is low, the magnitude of the divergence $\left|C\hat{H}_s - CH_s\right|$ is great, and when Ch' is high, the size of the variation $\left|C\hat{H}_s - CH_s\right|$ is small. When the last CH selection action taken is undesirable, the operator takes a significant random step back from the suggestion, but when the prior CH selection action taken is excellent, the system stays true to the fuzzy control principles. At each sampling interval, the perturbation is indicated by eqn. (12),

$$p(CH_S) = \frac{|CH_S(n) - CH_S(n)|}{\sigma(Ch\prime(n+1))} \tag{12}$$

The exact shape of the function $\sigma()$, particularly its magnitude and degree of reduction, must anticipate the output variable's measures and range of variability.

4.1.4 EP based Learning model

Only the input connections to layers two and four have modifiable weights. The other weights are all set to one. As a result, the Emperor penguin procedure only works with two layers of weights. The goal of computing CH_s is to maximise v such that the system remains in a good condition and does not fail. As a result, given the state, v is the objective function that must be maximised as a function of all weights in the system. Let's assume there are two layers named as to two and four. Moving is always from a v in need of higher to a v that is higher. Because the v second layer weight is higher in this situation, the spiral movement is from two and four is expressed using eqn. (13),

$$O = xe^{j\theta} \tag{13}$$

Where x and j are the constant and θ is the x-axis angle. During the absorption phase, the v spiral movement is not monotone and has a divergence from a uniform distribution. Therefore, the weights of the GARIC method is optimized and updated in the significant layer.

4.3 AJO based Routing

The flowchart of AJO based optimal routing is shown in figure 4. Following the selection of CHs among UAVs, the multiple routing procedures are used to find the best data transmission pathways among clustering UAVs. An efficient AJO-based routing for UAV networks is defined in this study as routing with the shortest transmits power. This approach dramatically minimizes the quantity of data transmissions while also balancing the network's traffic burden. Without employing AJO, the CM nodes send data to the CH in the same cluster. To send data to the base station or the closest CH, the CHs use AJO routing.

4.3.1 Network initialization

Initially, the random is usually used to start the UAV of CH data. The logistic map, which generates more varied beginning groups than random assortment and has a reduced probability of early convergence, which is used to increase the variety of the initial population. The initialization map of the data is expressed using eqn. (14)

$$Y_{k+1} = \propto Y_k(1 - Y_k), \qquad 0 \le Y_0 \le 1 \tag{14}$$

Where Y_k is the logistic chaotic variable of the Y_k data position; X 0 is utilised to generate the starting data group.

4.3.2 Network Boundary conditions

The WSN is surrounded by UAV systems. Because the WSN is roughly spherical, data that travels outside the restricted search region returns to the opposite boundary.

$$\begin{cases} Y_{k,d} = (Y_{k,d} - A_{l,d}) + B_{l,d}(d) & if\ Y_{k,d} > A_{l,d} \\ Y_{k,d} = (Y_{k,d} - B_{l,d}) + A_l(d) & if\ Y_{k,d} > B_{l,d} \end{cases} \tag{15}$$

The position of the k^{th} CH in the d^{th} dimension is $Y_{k,d}$; the revised position is $Y_{k,d}$ after boundary constraints have been checked. In problem domains, $A_{l,d}$ and $B_{l,d}$ are the top and bottom limits of the d^{th} dimension, respectively.

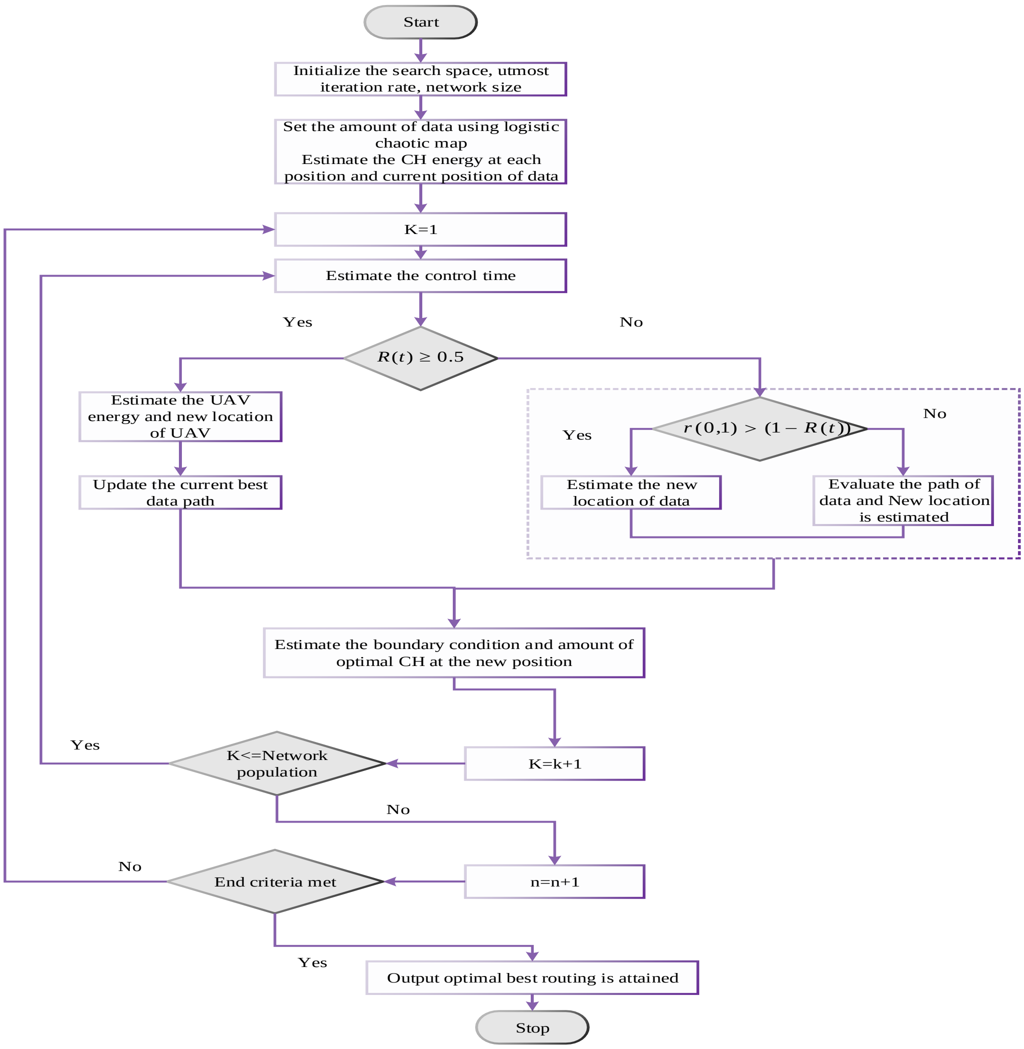

Figure 4 Flowchart of AJO based optimal routing

4.3.3 Time control function

Because the UAV includes a big number of energy-efficient CH, it attracts data. More data accumulates over time, becoming a swarm. The data in the swarm moves toward another UAV CH and a new data swarm is produced when the network environment changes in the UAV-WSN network. Type one (passive motions) and type two (active motions) data movements exist within a CH population and the data switches between categories. In the start, kind one is chosen; when time passes, type two is selected. To replicate this circumstance, the Delay mechanism is used.

The time control method contains a time control function $R(t)$ and a fixed R_0 to manage data transfer between observing the UAV network and travelling within the CH swarm. The random variable of the time control process varies from 0 to 1 throughout duration. The time control function is evaluated using eqn. (16),

$$R(t) = \left| \left(1 - \frac{t}{M_t}\right) * 2 * r(0,1 - 1) \right| \tag{16}$$

Where, the particular time period is for the number of iteration is denoted as t and the utmost number of iteration is denoted as M_t. The data follows the UAV network whenever the value crosses R_0. They go within the CH when its value is smaller than R_0. The time control fluctuates arbitrarily from 0 to 1, and the R_0 value is unknown. As a result, R_0 is set to 0.5, the average of 0 to 1. The function $(1 - R(t))$ is used to replicate the movement inside a CH in the same way as $R(t)$ is (type one or two). The data moves in type one routing when r(0, 1) is greater than

$(1-R(t))$. Then data move in type tow routing when $r(0,1)$ is less than $(1-R(t))$. Because $(1-R(t))$ rises from zero to one over time, the likelihood of $r(0,1) > (1-R(t))$, initially outnumbers the probability of $(1-R(t)) > r(0,1)$. As a result, type one motion is favoured over type two routing. As time passes, $(1-R(t))$ approaches one, and the likelihood that $(1-R(t)) > r(0,1)$ eventually exceeds $r(0,1) > (1-R(t))$ increases. As a result, type two routing is preferred.

4.3.4 UAV position for optimal CH

The AJO are attracted to the UAV-WSN network because it includes a lot of CH. The UAV's direction is calculated using eqn. (17) to average all the vectors from each data point in the network to the UAV that is currently in the optimum place.

$$b = Y^* - f_a \frac{\sum Y_k}{N} = Y^* - f_a \propto \tag{17}$$

Here $D = f_a \alpha$ N is the number of UAV clusters, Y^* is the data now in the swarm's optimal position, D is the difference between the current perfect location of the data and the average position of all data, f_a is the component that influences the attractiveness, α is the average position of all data. A distance of around the average position comprises a particular probability of all data based on the assumption of a normal spatial distribution of data in all dimensions. The new position of each data is provided using eqn. (18),

$$Y_k(n+1) = Y_k(s) + r(0,1) * (Y^* - \delta * a(0,1) * \alpha) \tag{18}$$

The data distribution coefficient is denoted as $\delta > 0$.

4.3.5 Swarm of Data to optimal CH

In swarm, data is routed in two ways: passive (type one) and active (type two). Once the swarm is first established, the majority of data follows type one routing. They are progressively exhibiting type two routing throughout period. The transportation of data around their own CH locations is known as type one routing, and the associated updated position of each data is provided by

$$Y_k(n+1) = Y_k(s) + \propto * r(0,1) * (A_l - B_l) \tag{19}$$

where A_l and B_l are the top and bottom bounds of search spaces, correspondingly and $\alpha > 0$ is a speed parameter proportional to the distance of mobility around the sites of CH. To model type two routing, a data (k) other one than of involvement is chosen at random, and the direction of routing is determined using a variable from the data of attention I to the selected data (k). When the volume of optimal CH obtainable to the selected data (k) exceeds that accessible to the data of concern (s) the latter keeps moving it towards the past; if the volume of optimal CH available to the data sample (k) is lower than that obtainable to the data of involvement (s) latter moves straight ahead from the past. As a result, each piece of data in a swarm goes in the direction of the best CH. Then, the path of mobility and the updated position of data are expressed as follows

$$Path = \begin{cases} Y_k(n) - Y_s(n) & if\ f\ (Y_S) \geq f\ (Y_K) \\ Y_S(n) - Y_k(n) & if\ f\ (Y_S) \geq f\ (Y_K) \end{cases} \tag{20}$$

Where f is represented as the objective function of position Y. For this reason, the movement of data path is considered as follows:

$$Y_k(n+1) = Y_k(n) + r(0,1) * path \quad (21)$$

A time control scheme is used to identify the kind of mobility throughout time. It manages not just to type one and two CH routing, and yet also data flows to and from UAV networks.

Table 1: Simulation parameter settings for the EP-GARIC with AJO model

Parameter	**Value**
Area of Communication network	1000m*1000m
Transmission and Sensing range of UAV	250m
Number of rounds	1000
Nearby node distance	110m
Type of traffic	CBR
Energy consumed the sending and receiving	5nJ/bit and 40nJ/bit
Base station number	1
Mobility	10 to 50m/s
MAC protocol	IEEE 802.1 ln
Number of UAV	100
Threshold in the free space mode	243m
Number of clusters	[5,6,…..25]
Data packet size	4500 bits

V. 5. RESULT AND DISCUSSION

The performance of the proposed model was tested using the Network Simulator-2 programme on an i5 CPU running Ubuntu with 4 GB RAM. The EP-GARIC with AJO model performed a number of computations in terms of energy consumption, convergence, clustering time, longevity, throughput, and average latency, among other things. In this simulation, a 1000m*1000m region was evaluated, with the UAVs deployed evenly over the network. The UAVs had an operational range of around 250m. The BS was installed outside of the sensing field. The UAVs' lowest and highest speeds varied from 10 to 50m/s. Table.1 shows the parameter settings for the EP-GARIC with AJO model.

5.1 Case study

Assume that M represents the deep forest and Y represents the service provider. Assume the deep forest M, which has a variety of UAV nodes ranging from M1 to M100. The data from the deep forest is gathered via UAV. Nevertheless, energy efficient of CH selection is a major problem while data transmission via UAV. Thus, a new EP-GARIC with AJO method is developed for improving the energy function is UAV with WSN network. The proposed EP-GARIC method has been formed and selected the optimal CH and the data transmission has been provided using AJO routing algorithm.

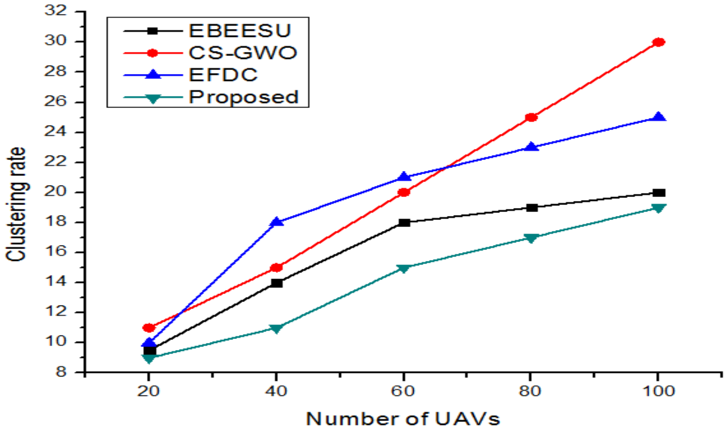

Figure 5 Clustering rate analysis with different UAVs

5.2 Performance Analysis

The performance of proposed EP-GARIC with AJO method has been compared with the existing methods like EBEESU[28], CS-GWO [29] and energy-efficient and fast data collection (EFDC) [30]in terms of different metrics such as throughput, packet delivery ratio, energy consumption, network life span, convergence, clustering time, etc.

5.2.1 Clustering Rate

The clustering rate in the UAV refers to how rapidly a large number of clusters can be generated to accommodate network demand. As this study boosts the dynamic clustering function across UAV applications, the whole heterogeneous networks become more effective due to the continual proposed clustering.

As a result, energy consumption will be lowered as a function of system response, leading to more efficient resource distribution. It implies that resource distribution would be just as successful as clustering degree. The recommended approach, as illustrated in Fig. 5, has the lowest clustering rate. However, EBEESU [28], CS-GWO [29], and EFDC [30] approaches are all produced highest clustering rates than the recommended strategy.

5.2.2 Cluster formation time

All node broadcasts its location and energy state at the start of each round in the clustering algorithm, and every CH node sends a communication to announce itself within the network. The cluster development time, which refers to the time required by the clustering method to generate clusters and choose CHs, relates to the clustering method's computational burden. As the number of devices in the system grows, the clustering system's time to create the cluster expands are shown in figure 6.

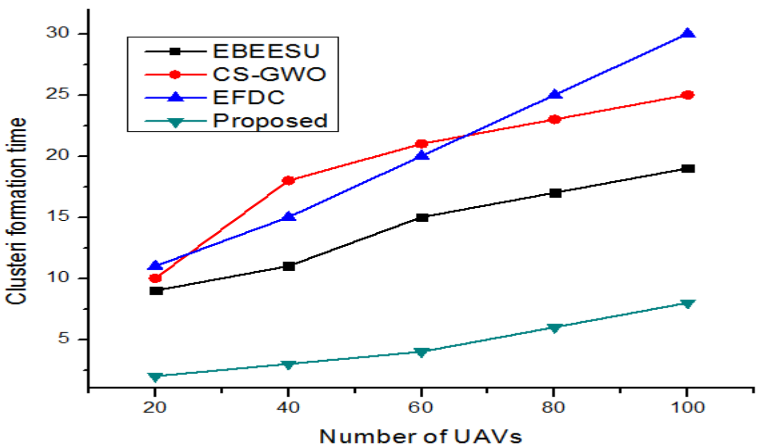

Fig.6 Clustering time analysis with different UAVs

As a result, the suggested technique outperforms other algorithms because it takes less time to establish clusters, which minimises the optimal routing delay.

5.2.3 Throughput

The volume of data acquired at the received signal is measured by the time it requires for transfer of data in the method, which is referred to as throughput in eqn. (22).

$$T = \frac{\text{Amount of data received to the users}}{Delay\ of\ time} \tag{22}$$

Figure 7 compares the proposed technique's obtained throughput to current models for varied numbers of UAVs. The proposed approach provides a throughput of 0.982 Mbps for a total number of UAVs. As the number of UAVs grows, the throughput value drops. However, the comparison shows that the proposed technique exceeds previous models, such as all-UAV variation, in terms of effective performance.

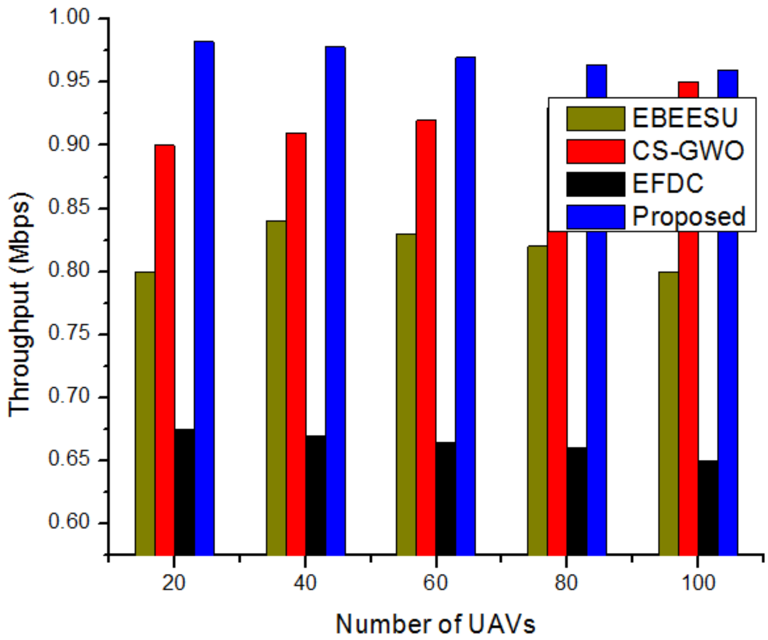

Figure 7 Throughput analysis with different UAVs

In terms of throughput, the EBEESU and CS-GWO models have both exceeded the EFDC model. When 10 UAVs are present, the EP-GARIC with AJO method model obtains the highest throughput of 0.982Mbps, while the EBEESU, CS-GWO, and EFDC models reach the lowest throughput of 0.8Mbps, 0.9Mbps, 0.675Mbps, and 0.82Mbps, respectively. When 100 UAVs are present, the EP-GARIC with AJO method model obtains the highest throughput of 0.996Mbps, while the EBEESU, CS-GWO, and EFDC models reach the lowest throughputs of 0.8Mbps, 0.95Mbps, 0.65Mbps, and 0.96 Mbps, respectively.

5.2.4 Energy consumption

To communicate correctly, each UAVs in the network requires a specific quantity of energy. The quantity of energy required for data transmission is stated in eqn. (23), which represents the system's energy consumption.

$$Energy\ consumption = E_D * quantity\ of\ nodes + E_S \tag{23}$$

The energy at the transmission point is indicated by E_S, whereas the energy at the destination point is denoted by E_D. The energy consumption with different UAVs are shown in fig.8.

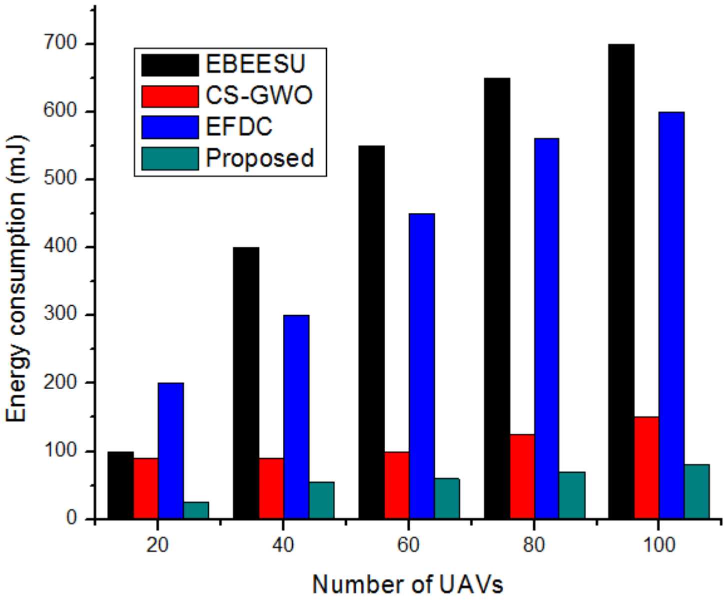

Figure. 8 Energy consumption analyses with different UAVs

Furthermore, EBEESU and CS-GWO models have shown higher energy use than the EFDC model. For example, when 10 UAVs are present, the EP-GARIC with AJO technique model consumes less energy than the EBEESU, CS-GWO, and EFDC models. Similarly, when 100 UAVs are present, the EP-GARIC with AJO technique model has a subordinate energy consumption of 80mJ, but the EBEESU, CS-GWO, and EFDC model have the lowest energy consumption of 700mJ, 150mJ, and 600mJ, respectively.

5.2.5 Network lifetime

A few UAVs fail after each cycle due to the drain on their battery power. Figure 9 depicts a comparative examination of network lifespan. The observation demonstrates that EP-GARIC with AJO maintains a higher number of live nodes and is more durable than other techniques.

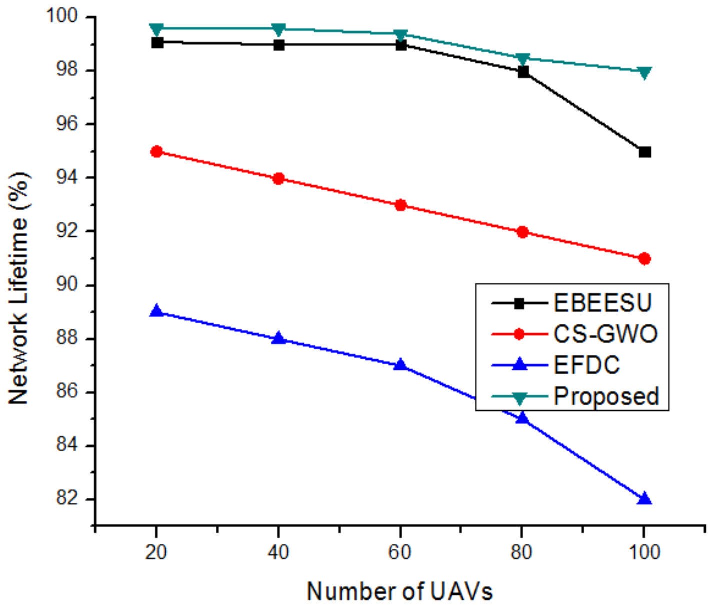

Figure. 9 Network life time analyses with different UAVs

For contrast, with 10 UAVs, the EP-GARIC with AJO technique model has a maximum network lifespan of 99.6 percent, while the EBEESU, CS-GWO, and EFDC models have high network life spans of 99.1 percent, 95 percent, and 89 percent, respectively. Similarly, when 100 UAVs are present, the EP-GARIC with AJO technique model has maximum t network longevity of 98 percent, but the EBEESU, CS-GWO, and EFDC model have the shortest network life spans of 95 percent, 91 percent, and 82 percent, respectively. The proposed technique selects CHs by integrating node residual energy and ideal cluster centres, extending the network's lifespan to more cycles and delivering a 99.6% improvement over previous methods.

5.2.6 Accuracy

Another essential parameter for accurate energy management assessment methods is accuracy. It describes the accurate percentage of energy management; when the accuracy reaches 100%, the regulated energy is said to be the best, and it is approximated using eqn. (24),

$$\text{Accuracy} = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \tag{24}$$

The accuracy of recommended and current models is depicted in Figure 10. In terms of accuracy, the recommended technique surpassed other strategies, according to the comparison. The high accuracy value illustrates the proposed method's significant performance in precise, energy-efficient, and optimum UAV network routing. The recommended model's accuracy for all 100 UAVs is 96 percent, which is a high figure when compared to other methodologies.

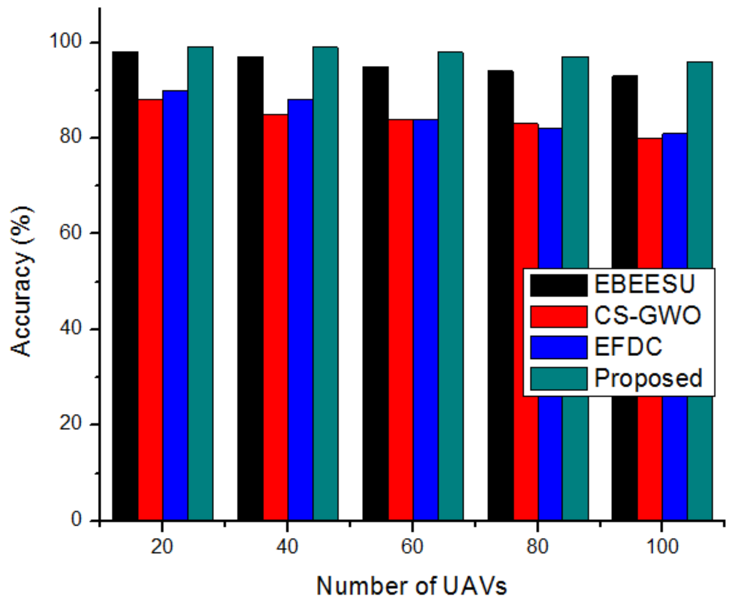

Figure. 10 Accuracy of analysis with different UAVs

For illustration, when 10 UAVs are present, the EP-GARIC with AJO technique model has a maximum accuracy of 99.2 %, but the EBEESU, CS-GWO, and EFDC models have high accuracy of 98 %, 88%, and 90 %, respectively. Furthermore, when 100 UAVs are present, the EP-GARIC with AJO method model has the highest accuracy of 96 %, while the EBEESU, CS-GWO, and EFDC model have the lowest accuracy of 93 %, %, and %, respectively.

5.2.7 End to End delay

It is defined the significant time between the formation of the transmission source and the destination of significant purpose and process at the target UAV node. Furthermore, all conceivable delays in the source and each intermediary UAV node, such as data forwarding, distribution, and waiting time, were assessed. The time it takes for data to go from one head to the other is known as end-to-end delay, and it may be estimated using eqn. (25).

$$\text{End} - \text{to} - \text{End delay} = \frac{\sum_{j=1}^{v}(E_j - S_j)}{v} \tag{25}$$

Where v is the quantity of successful data transmission delivered, j is the package recognizer, E_j is the transmission destination time of UAV i^{th} node and S_j is the network sending time UAV i^{th} node. It estimates all conceivable delays at the beginnings and downstream UAV nodes, as well as queue time and diffusion, and MAC layer tape delays, and provides the appropriate information. Network congestion or the inability to access critical pathways might lengthen the wait. When the number of UAVs increases, then the End-to-End delay changes. Figure 11 depicts the end-to-end latency for several UAVs.

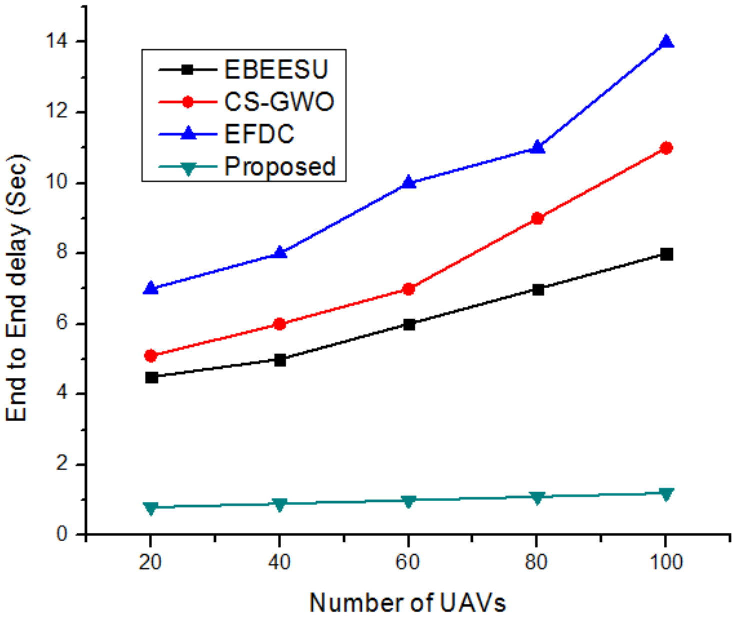

Figure. 11 End-to-End delays of analysis with different UAVs

For instance, with 10 UAVs, the EP-GARIC with AJO technique model has a lower End-to-End delay of 0.8 sec, but the EBEESU, CS-GWO, and EFDC models have higher End-to-End delays of 4.5 sec, 5.1 sec, and 7 sec. Moreover, when 100 UAVs are present, the EP-GARIC with AJO technique model has a lower End-to-End latency of 1.2sec, but the EBEESU, CS-GWO, and EFDC model have high End-to-End delays of 8sec, 11 sec, and 14 sec.

5.2.8 Routing overhead

When a system or process's authorised boundaries are exceeded, routing overflow occurs. Furthermore, all data must pass through the routing overhead, also defined as the quantity of routing system interactions, while being sent. As a result, traffic in communication cables is replicated, and the efficiency of UAV node power distribution is reduced. Furthermore, network congestion is more likely if the features have a high routing overhead. The overhead of routing is indicated by eqn. (26).

$$\text{Routingoverhead} = \frac{S_j+T_j}{E_j} \tag{26}$$

Where the transmitting data quantity is indicated by S_j, the forward data quantity is denoted by T_j, and the destination data quantity is denoted by E_j. The comparison of routing overhead over several UAVs is shown in fig.12.

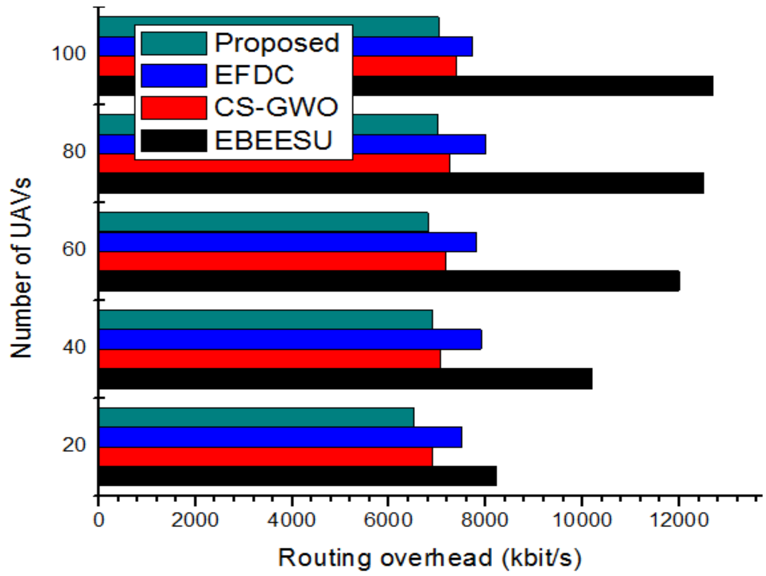

Figure. 12 Routing overhead of analysis with different UAVs

The findings show that the suggested solution has the greatest performance in terms of lowered overhead for UAV routing traffic flow regulation at 7020kbit/s at 100 UAVs when compared to the current EBEESU, CS-GWO, and EFDC approaches. Consequently, when 10 UAVs are present, the EP-GARIC with AJO technique model has a routing overhead of 6500kbit/s, but the EBEESU, CS-GWO, and EFDC models have significant routing overheads of 8200 kbit/s, 6900 kbit/s, and 7500 kbit/s, respectively. Likewise, when 100 UAVs are present, the EP-GARIC with AJO technique model has a lower routing overhead of 7020 kbit/s, but the EBEESU, CS-GWO, and EFDC model have large routing overheads of 12700 kbit/s, 7400 kbit/s, and 7706 kbit/s, respectively.

VI. CONCLUSIONS

In this article, the described EP-GARIC based clustering and AJO based routing methods model obtained ideal energy efficiency. After the UAVs have been deployed and started, the next step is to determine the best clustering procedure for data transmission with the least amount of energy loss. Immediately after the selection of CHs, the information will be available with other members of the network, forming a cluster-based network topology. Moreover, AJO is used to choose the best routes for inter-cluster transmission. A range of modelling procedures was carried out to ensure that the EP-GARIC with AJO algorithm produced an energy-efficient output, and the findings were inspected in a range of methods. The simulation results show that the proposed method has achieved the finest performance in terms oflessenergy consumption, clustering time, clustering rate, routing overhead, delay, high packet delivery ratio, throughput, network lifetime and high accuracy over traditional approaches. Data analysis and network segmentation solutions can be devised in the future to optimise overall network allocation.

REFERENCES

[1] Renduchintala, Ankit, et al. "A comprehensive micro unmanned aerial vehicle (UAV/Drone) forensic framework." Digital Investigation 30 (2019): 52-72.

[2] Torres-Sánchez, Jorge, et al. "Assessing UAV-collected image overlap influence on computation time and digital surface model accuracy in olive orchards." Precision Agriculture 19.1 (2018): 115-133.

[3] Outay, Fatma, Hanan Abdullah Mengash, and Muhammad Adnan. "Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges." Transportation research part A: policy and practice 141 (2020): 116-129.

[4] Ahmed, Syed Affan, MujahidMohsin, and Syed Muhammad Zubair Ali. "Survey and technological analysis of laser and its defense applications." Defence Technology 17.2 (2021): 583-592.

[5] Altmann, Jürgen. "New Military Technologies: Dangers for International Security and Peace." S&F Sicherheit und Frieden 38.1 (2020): 36-42.

[6] Bisio, Igor, et al. "Unauthorized amateur UAV detection based on WiFi statistical fingerprint analysis." IEEE Communications Magazine 56.4 (2018): 106-111.

[7] Um, Jung-Sup. "Drone Flight Ready." Drones as Cyber-Physical Systems. Springer, Singapore, 2019. 21-57.

[8] Hassanalian, Mostafa, and AbdessattarAbdelkefi. "Classifications, applications, and design challenges of drones: A review." Progress in Aerospace Sciences 91 (2017): 99-131.

[9] Mohamed, Nader, et al. "Unmanned aerial vehicles applications in future smart cities." Technological Forecasting and Social Change 153 (2020): 119293.

[10] Ullah, Zaib, et al. "Applications of artificial intelligence and machine learning in smart cities." Computer Communications 154 (2020): 313-323.

[11] Alsamhi, Saeed H., et al. "Survey on collaborative smart drones and internet of things for improving smartness of smart cities." Ieee Access 7 (2019): 128125-128152.

[12] Mohamed, N., Al-Jaroodi, J., Jawhar, I., Idries, A., & Mohammed, F. (2020). Unmanned aerial vehicles applications in future smart cities. Technological Forecasting and Social Change, 153, 119293.

[13] Billings, Charles E. Aviation automation: The search for a human-centered approach. CRC Press, 2018.

[14] Alsamhi, Saeed H., et al. "Survey on collaborative smart drones and internet of things for improving smartness of smart cities." Ieee Access 7 (2019): 128125-128152.

[15] Sungheetha, Akey, and Rajesh Sharma. "Real time monitoring and fire detection using internet of things and cloud based drones." Journal of Soft Computing Paradigm (JSCP) 2.03 (2020): 168-174.

[16] Suzuki, Koji AO, Paulo Kemper Filho, and James R. Morrison. "Automatic battery replacement system for UAVs: Analysis and design." Journal of Intelligent & Robotic Systems 65.1 (2012): 563-586.

[17] Lin, Na, et al. "A novel multimodal collaborative drone-assisted VANET networking model." IEEE Transactions on Wireless Communications 19.7 (2020): 4919-4933.

[18] Pustokhina, I. V., Pustokhin, D. A., Kumar Pareek, P., Gupta, D., Khanna, A., & Shankar, K. (2021). Energy-efficient cluster-based unmanned aerial vehicle networks with deep learning-based scene classification model. International Journal of Communication Systems, 34(8), e4786.

[19] Torres-Sánchez, Jorge, et al. "Assessing UAV-collected image overlap influence on computation time and digital surface model accuracy in olive orchards." Precision Agriculture 19.1 (2018): 115-133.

[20] Li, Yabo, et al. "Joint resource allocation and trajectory optimization with QoS in UAV-based NOMA wireless networks." IEEE Transactions on Wireless Communications (2021).

[21] Wu, Jiehong, et al. "A multi-UAV clustering strategy for reducing insecure communication range." Computer Networks 158 (2019): 132-142.

[22] Valadares, Dalton, et al. "Performance Evaluation of an IEEE 802.11 g Network in an Industrial Environment." IEEE Latin America Transactions 18.05 (2020): 947-953.

[23] Azari, M. Mahdi, et al. "UAV-to-UAV communications in cellular networks." IEEE Transactions on Wireless Communications 19.9 (2020): 6130-6144.

[24] Saif, Abdu, et al. "Distributed Clustering for User Devices Under Unmanned Aerial Vehicle Coverage Area during Disaster Recovery." arXiv preprint arXiv:2103.07931 (2021).

[25] Pustokhina, Irina V., et al. "Energy-efficient cluster-based unmanned aerial vehicle networks with deep learning-based scene classification model." International Journal of Communication Systems 34.8 (2021): e4786.

[26] Annepu, Visalakshi, and Anbazhagan Rajesh. "An unmanned aerial vehicle-aided node localization using an efficient multilayer perceptron neural network in wireless sensor networks." Neural Computing and Applications 32.15 (2020): 11651-11663.

[27] Miranda, Julien, et al. "Hybridization of deep and prototypical neural network for rare defect classification on aircraft fuselage images acquired by an unmanned aerial vehicle." Journal of Electronic Imaging 29.4 (2020): 041010.

[28] Bensalem, Amina, and DjallelEddineBoubiche. "EBEESU: ElectriBio-inspired Energy-Efficient Self-organization model for Unmanned Aerial Ad-hoc Network." Ad Hoc Networks 107 (2020): 102236.

[29] Arafat, Muhammad Yeasir, and SangmanMoh. "Bio-inspired approaches for energy-efficient localization and clustering in UAV networks for monitoring wildfires in remote areas." IEEE Access 9 (2021): 18649-18669.

[30] Nazib, Rezoan Ahmed, and SangmanMoh. "Energy-Efficient Data Gathering Schemes in UAV-Based Wireless Sensor Networks." (2020).

[31] Baek, Jaeuk, Sang Ik Han, and Youngnam Han. "Energy-efficient UAV routing for wireless sensor networks." IEEE Transactions on Vehicular Technology 69.2 (2019): 1741-1750.

[32] Humadi, Khaled, et al. "Energy-Efficient Cluster Sizing for User-Centric Air-to-Air Networks." IEEE Communications Letters 25.4 (2020): 1308-1312.

[33] Deng, Jianing, Zhiguo Shi, and Cheng Zhuo. "Energy-efficient real-time uav object detection on embedded platforms." IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems 39.10 (2019): 3123-3127.

[34] Zhu, Botao, et al. "Improved soft-K-means clustering algorithm for balancing energy consumption in wireless sensor networks." IEEE Internet of Things Journal 8.6 (2020): 4868-4881.

[35] Nazib, Rezoan Ahmed, and SangmanMoh. "Energy-efficient and fast data collection in UAV-aided wireless sensor networks for hilly terrains." IEEE Access 9 (2021): 23168-23190.