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Optimizing Drone-Based IoT Networks: The ISCT Approach

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Abstract: - The use of a cognitive technique to handle network management is an interesting area of solution in a drone-based Internet of Things environment. Through cognitive capabilities, we can alleviate multiple networking issues associated with the IoT environment. In current research, focuses to address networking drawbacks in a drone-based IoT scenario through a self-organized cluster-based networking solution termed Innovative Self-organized Clustering Technique (ISCT), aiming to increase network efficiency and effective network performance. The ISCT is an integrated solution which incorporates the concept of Enhanced Coyote Optimization Algorithm (ECOA). The ISCT we proposed includes an ECOA-based cluster formation and cluster head selection process. Moreover, the dead cluster member identification mechanism is processed within the maintenance procedure to stabilize the network. Additionally, one of the crucial mechanisms we introduce in our proposed ISCT is the routing mechanism that facilitates data transmission to the next hop neighbors through the route selection function that increases the communication process efficiency. To analyse the presented ISCT performance, as the proposed fusion bio-inspired clustering algorithm, we consider the duration of the cluster build, energy consumption, cluster lifetime, and the delivery ratio as the ISCT performance metrics. These metrics are compared with the existing fusion bio-inspired clustering schemes to analyse the comparative performance of the ISCT.

Keywords: Innovative Self-organized Clustering Technique (ISCT), Enhanced Coyote Optimization Algorithm (ECOA).

I. INTRODUCTION

The development in wireless communication technologies has turned IoT, an abbreviation for the Internet of Things, into a mainstream intelligent service and applications technology. Over time, with the growing interconnection of a wide array of devices and items, there has been immense production of data. The current Internet of Things applications, however, are not at advanced stages to allow such a device to make decisions on its own and reason without a human mind involved [1]. This, in effect, has made the cognition computing area more appealing to most researchers in the Internet of Things field. The term "Cognitive Internet of Things," abbreviated "CIoT," denotes advanced Internet of Things technologies endowed with cognitive abilities. Internet of Things refers to the cognition-enabled devices and things to learn amid data collected from various sources, such as linked gadgets and drones, among others. Due to the sensing, processing, storage, and communication capabilities in-built within them, Unmanned Aerial Vehicles, popularly known as UAVs, are becoming a very cutting-edge technology [2]. The use of these unmanned aerial vehicles is gaining popularity in an increasing number of fields, including intelligent transportation systems, smart cities, and Internet of Things environments. They are considered to be valuable assets in different industries since they can independently collect and analyze data.

Typical applications of drone swarms for IoT services include materialization, in packages and letters, public safety, search and rescue missions, tracking, and surveillance. With the emergence of applications endowed with IoT technologies, the Internet of drones is a new concept that emerges: INTERNET of DRONES (IoD) [3]. The latter enables networking between drones for communication with users and other drones using the internet. Communication tasks are well-suited for drones due to their easy deployment and high mobility. Being mobile by nature, drones behave like data couriers, taking data to its required destination. If a destination is not directly reachable from a drone, data is forwarded in multiple hops across the drone network [4]. In a swarm, drones collaborate to establish a network that will effectively relay information to an expected source. IoD is known to be robustly scalable and reliable but imposes significant challenges in drone communication and networking as drones are highly mobile from one point to another in the environment, which brings about rapid changes in the network topology and can potentially lead to communication problems. By implementing this self-organization-based approach, the foreseen challenges can be taken care of in cognitive IoT systems, and drones can easily adjust the environment accordingly to ensure smooth communication under varying conditions [5].

Clustering can be defined as breaking down a network into smaller physical subgroups, which are finally known as clusters. Each cluster comprises a cluster head (CH) and some number of cluster members (CMs). The CH is a representative of the cluster and must manage to ensure that the activities of the cluster are handled effectively

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and sustainably. He is chosen through a democratic process by all of the members within the cluster [6]. As a result, which, leadership by a CH is a fundamental responsibility in the clustering process, and every CM has the potential to manage this nominated position. Networking from multi-hop cluster-based and single-hop communication networking tends to produce so much higher performance, scalability, and even energy efficiency than the latter. The procedures that define an effective cluster topology for these algorithms include the generation of clusters and the election of the CH [7]. Such operations must be strongly constrained because any changes in the relative placements of the CMs can seriously disturb the overall cluster architecture. IoD involves a very challenging task, mainly due to the high mobility of drones, causing a topology to be very dynamic. It is this construction and maintenance of clusters that become very strenuous due to changes that happen so frequently, and much energy gets lost from the drones through this frequent change [8]. Clustering algorithms under this context must be designed as more effective. All these algorithms should be competent enough to handle rapid changes in topology that is a general characteristic of the Internet of Things environment. This shall make the algorithms more scalable and the usage of energy resources more efficient [9]. These intelligent algorithms can enhance the global effectiveness and efficiency of the network by optimizing the processes of cluster formation and election of CHs. In short, the network will be increasingly robust and sustainable to dynamic conditions.
The following are the main contribution of the proposed research work,

A. Introduction of Innovative Self-organized Clustering Technique (ISCT):

This paper introduces ISCT, an innovative technique for solving networking issues in the context of a drone-based IoT. ISCT is a cluster-based networking solution that has been self-organized to support network efficiency and performance. This represents the designing and development of a custom solution that eliminates the hosting of networking issues related to this type of drone-based IoT scenario.EASE OF USE

B. An enhanced coyote optimization algorithm:

In this context, the simulation of a bio-inspired algorithm for optimizing the cluster formation process and its respective cluster heads selection process at ISCT is a significant development. The integrated ECOA in ISCT makes it more capable of autonomously organizing clusters and selecting optimal cluster heads to contribute to better stability and performance of the network.

C. The Advanced Maintenance and Routing Mechanisms Introduction:

This section introduces advanced mechanisms of ISCT within this study for enhancing network stability and communication efficiency. For instance, ISCT incorporates a dead cluster member identification mechanism in its maintenance procedure to achieve network stabilization. In another aspect, it introduces a routing mechanism to help accomplish the efficient message delivery process to neighboring nodes, which enhances the efficiency of the communication process. These contributions present a holistic view of the addressing of the different components of network management within drone-based IoT environments.

II. LITERATURE SURVEY

Recently, much investigation work has been done in clustering in ad hoc networks to overcome routing challenges associated with them. [10] Proposes a flexible weighted clustering technique based on battery power. So, one approach that clarifies the issue is this. The main objective of this algorithm is to prevent nodes with low battery power from being left as CH. This is the primary goal of this algorithm. The different thing it has done compared to the current efforts is that another research [11] proposed a mobility prediction-based clustering algorithm. In this system, the relative rates of the nodes to one another are used to achieve proper results from its calculations. By exchanging Hello packets, all nodes calculate the average relative speed of the surrounding nodes. Then, the node with the least relative mobility is chosen to be the cluster head (CH), and the other nodes are selected from as cluster members (CMs). In contrast, high mobility of the nodes tends to shorten the lifetime of the CH. The Mobility Prediction Clustering Algorithm (MPCA) provided in [12], this algorithm is drone-specific and combines dictionary structure prediction fused with the LET. The location and mobility data of both drones are utilized to calculate the LET between any two drones. When the CH is elected, it announces all the drones in its surroundings. The election of CH is among those drones with the highest weight within the neighbors. Upon receiving different such messages, the drone will take into account the CH that has the longest LET.
In [13], a cluster-based location-aided dynamic source routing (CBLADSR) approach is presented. This approach follows the weight-based schemes in clustering the network. In the CBLADSR scheme, the appointment of the cluster head (CH) is picked based on some factors, which include the energy state of the drone, the velocity concerning it, and the number of drones that are situated around it. More specifically, the CH is elected from drones that have the highest energy level, lowest relative speed, and most drones in close vicinity to it. Every drone creates and maintains a neighbor table which contains data of each other drone in its immediate vicinity. This table is absolutely necessary for the sake of communication and the CH election process. The CH is determined to be the drone that has the maximum weight factor determined by performing calculations based on these parameters. Another explained approach in detail is the weighted centroid localization-based clustering, as described in [14], where the localization is done precisely by utilizing fuzzy logic that is, finding the position of each drone. The received signal strength indicator (RSSI) between drones is employed for calculating the location

to find out the CH election location. Subsequently, at the creation of the cluster, the distances between all the drones are computed by finding the RSSI values present in each drone. When elected, CH has the responsibility of sending information of the CMs to the BS, which is at a farther distance. This not only indicates the requirement for good communication within the cluster for an effective communication rate, but also indicates the parameter where data can be consistently conveyed at preferably long distances to the BS. This approach utilizes RSSI to produce accurate location estimations and an effective election for CH. Therefore, the overall efficiency and reliability of the network increase.

Another novel approach can be found in [15], which describes a hybrid clustering scheme using RSSI. Hybrid clustering with RSSI makes the drone a mobile sink that collects data in WSNs. The cluster heads can be selected based on this plan, considering the residual power and distance between the drone and nodes. With a consideration of the distance from the node to the drone, therefore, the nodes within the drone's range can communicate directly with it, while the nodes outside its range connect to the CH after many hops. The sensor nodes continuously monitor the RSSI values provided by the drone beacons to help in clustering. The highest RSSI value recorded in the CH election is put into consideration in the process. This ensures optimization in the clustering process. A bio-inspired mobility prediction clustering technique is implemented in a separate development discussed in [16]. This mechanism is designed by merging the characteristics of drones in their mobility with the foraging model of Physarum polycephalum. In this method, all of the drones in the area compute the mobility values of the drones that are found in the surrounding environment to provide information for a CH election process. By this innovative synthesis of bio-inspired principles, the predictive ability of the clustering mechanism is enhanced, thereby culminating in an increase in the overall efficiency and flexibility of the drone network.

In the first step, the configuration of the CH is chosen by the drone with the maximum probability, and the other drones become its members. An efficient routing strategy for the drone network has also been presented in [17], which combines the clustering traits of WSN with drones. The network is divided into several numbers of clusters and each cluster consists of stationery and location-aware sensor nodes. The drones are equipped with the location details of all the CHs inside the clusters. The drone is updated with information from these CHs while in motion and does data routing through the use of an ACO-based routing approach. Moreover, [18] offers hybrid communication between drones based on Boid Reynolds method and Ad-hoc On-demand Distance Vector Protocol. Their solution usually contains three prominent phases: AODV is utilized to find reactive routing computation, the boid Reynolds method is used for connectivity creation, and the ground-based Base Stations (BSs) are found. Originating from bird flocks or fish schools; the Boid-Reynolds method has three basic principles: separation, alignment, and cohesion. This hybrid bio-inspired approach is based on integrating the bio-inspired tenets with conventional routing protocols to enhance communication efficiency and network performance in the drone environment.

III. Proposed Fusion Self-Organized Clustering Technique

Here, we are presenting a new model under the name Innovative Self-organized Clustering Technique (ISCT), for enhancement of efficiency and adaptability in cluster-based networking in the IoD. Since this technique is an ECOA approach, it gives an efficient way to manage swarm-based networks. The overall structure of the ISCT model contains three stages, which was given in Figure 1.

A. Selection of Cluster Head and Formation of Clusters Phase: The ECOA approach is used to select CHs and form clusters. The CH is chosen by considering connectivity with the base station, and the estimation of the CH is based on the fitness function, which estimates the residual energy and luciferin value from drone positions. The CH is elected as the node or drone with the highest fitness value, while the rest become cluster members.

B. Cluster Management Phase: In this phase, cluster management is motivated by ECOA in drone positioning. At the same time, the CH updates the positions of the drones and transmits the cluster topology table to all its CMs for effective cluster management.

C. Cluster Maintenance Phase: It reviews the status of all cluster members for network stability. A routing mechanism is also suggested that sends sensed data to the BS by selecting an optimum route.

The proposed ECOA algorithms, ISCT provides a comprehensive approach to manage swarm-based networks in IoD environments, easing the process of cluster formation, management, and maintenance toward optimum data transmission to the BS.

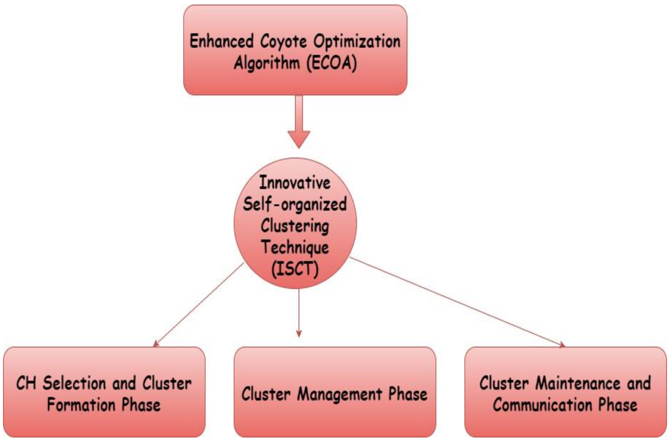

Figure 1. Overview of Proposed work

IV. ENHANCED COYOTE OPTIMIZATION ALGORITHM FOR SELECTION AND FORMATION OF CLUSTER HEAD:

COA Developed COA is a population-based algorithm influenced by the species Canis latrans behavior, classified under both swarm intelligence and evolutionary heuristics [19]. Unlike the GWO (Grey Wolf Optimizer), which takes its cues from the Canis lupus species and places an emphasis on social hierarchy and dominance, the COA makes use of a different structural configuration. One of the things that COA does not put across is norms of dominance, as much as the alpha coyote is said to be the leader in a pack. Unlike the Global Work Overlay, which is all about the act of hunting prey, COA has a focus on the social structure of coyotes and ways through which they share their experiences with others.

The population of coyotes is organized in packs with the COA, and there is a coyote in each pack. These packs are represented by the packs: $N_p \in \mathbb{N}^*$ packs with $N_c \in \mathbb{N}^*$. A first claim is that the number of coyotes in each pack is identical to pack-to pack, and constant throughout all the packs. As a consequence of this, the total population in the algorithm is equal to the product of the values of N_p and N_c. This version of the algorithm ignores the existence of single coyotes, also known as subrogatory coyotes, just for computational simplicity. This is where a coyote can be regarded as a potential solution to the optimization problem. In contrast, the social state of a coyote represents the cost of the objective function.

The behaviors of coyotes depend on a set of parameters that may be grouped into either those that are intrinsic, such as sex, social status, and membership in a pack, or extrinsic, such as snow depth, snowpack hardness, humidity, and biomass of carcasses. For this reason, the Coyote Optimisation Algorithm has included social-science factors equivalent to the choice variables $\vec{x}$ of a global optimization problem. Therefore, the social situation, the set of decision factors of the c^{th} coyote at time t^{th} from pack p^{th}, is written as

$$\mathrm{soc}_c^{p,t} = \vec{x} = (x_1, x_2, \dots, x_D) \qquad \{1\}$$

In this first stage of the Coyote Optimisation Algorithm, an alternative name for the algorithm, the global population of coyotes is set up. Since COA is a stochastic algorithm, the initial social conditions that each coyote is bestowed with are left to chance. This is realized for the c^{th} coyote of the p^{th} pack along the j^{th} dimension by assigning random values in the search space as follows:

$$soc_{cj}^{p,t} = lb_j + r_j \cdot \left(ub_j - lb_j\right) \qquad \{2\}$$

In the following, let lb_j and ub_j denote the lower and upper bounds of the j-th choice variable, in this regard, the letter D is used to denote the search space dimension, and the letter r_j denotes an actual random number that is generated within the interval [0,1] through the use of the uniform probability law. Right after this initialization, a decision is taken as to how much coyotes have acclimatized themselves to their respective modern social environments.

$$fit_c^{p,t} = f\left(soc_c^{p,t}\right) \qquad \{3\}$$

In the beginning, the coyotes are assigned to packs by random selection. And it is, of course, possible over time for some of the coyotes to drop out from their pack to become solitary or to join other packs. According to the results in, the eviction of a coyote from a pack depends on the size of the pack and occurs with a given probability, P_e, such that:

$$P_e = 0.006 \cdot N_c^2 \qquad \{4\}$$

Since P_e can have values above 1 for Nc ≤ 200, the maximum number of coyotes that can be taken into a pack is only 14. This ensures that the COA promotes diverse contacts among all its members in the group, and this way, it facilitates cultural exchange among all the others.

There are generally two alphas in one coyote pack in nature. This one alpha selected by the COA lessens the complexity of that the best possible adaptation of a coyote towards its surroundings. The p-th pack's alpha at the t-th time step is then defined by using the following equation for the minimization problem:

alpha $a^{p,t} = \left\{\mathrm{soc}_c^{p,t} \mid \arg_{c=\{1,2,\ldots,N_c\}} \min f\left(\mathrm{soc}_c^{p,t}\right)\right\}$ {5}

The COA is an algorithm based on the assumption that the coyotes are organized enough to share social settings and collaboratively help maintain their pack. This is because there are clear indicators that this species possesses swarm intelligence. In this regard, the COA fully considers any information provided by an individual coyote and processes it to find out the cultural trend of the pack. The collective computation represents the level of resonance between information and experiences shared among the coyotes and forms part of the general flexibility and operation of a pack.

$$\text{cult } j_j^{p,t} = \begin{cases} O^2_{\frac{(N_c+1)}{p,t},j}, & N_c \text{ is odd} \\ \dfrac{O^{p,t}_{\frac{N_c}{2},j} + O^{p,t}_{\left(\frac{N_c}{2}+1\right),j}}{2}, & \text{otherwise} \end{cases} \quad \{6\}$$

In the context of this discussion, the notation $O^{p,t}$ signifies the ranked social conditions of all of the coyotes that are part of the $p-th$ pack during the $t-th$ time step, for each j that falls within the range [1, D]. This essentially indicates that the cultural inclination of the pack can be identified by computing the median of the social situations of all of the coyotes that are a part of that particular pack

The COA takes into consideration the two most important biological occurrences, which are birth and death. The system also monitors the age of every individual coyote, which is expressed in years and is denoted by the symbols age $p,t\ c \in N$. To ensure an authentic representation of population dynamics, the birth of a new coyote is modelled through integrating the social circumstances of two randomly selected parents with an additional environmental effect. This ensures that the birth scenario is as accurate as possible. As a mathematical description, this process can be stated as follows:

$$pup_j^{p,t} = \begin{cases} \mathrm{soc}^{p,t}_{r_1,j}, & rnd_j < P_s \text{ or } j = j_1 \\ \mathrm{soc}^{p,}_{r_2,j,j,} & \mathrm{rnd}_j \geq P_s + P_a \text{ or } j = j_2 \\ R_j, & \text{otherwise} \end{cases} \quad \{7\}$$

For this algorithm, let r_1 and r_2 be the symbols for two randomly chosen coyotes from the p-th pack, respectively. Similarly, let j_1 and j_2 be the symbols for two random dimensions of the problem.

P_s is the Scatter Probability abbreviated, Pan is the abbreviation for Association Probability; R_j is the abbreviation for a random number has which lies between the limits of the decision variable for the $j-th$ while $rand(j)$ is a randomly generated number with probability uniformly distributed over the $interval$ [0,1]. These are scatter and association probabilities, and they depict the cultural diversity that exists among the coyotes present in the pack.

In this first round of the COA, values for P_s and R_j present themselves as pre-determined; it is the first time their values have been defined.

$P_s = 1/D$ {8}

$P_a = (1 - P_s)/2$ {9}

Algorithm 1: Proposed coyote optimisation algorithms

1 $\boldsymbol{Initialization}$:
- $Create\ N_p\ packs, each\ containing\ N_c\ coyotes\ (Equation\ 2)$.

2 $\boldsymbol{Adaptation\ Verification}$:
- $Evaluate\ the\ adaptation\ of\ each\ coyote\ (Equation\ 3)$.

3 $\boldsymbol{Main\ Loop}$:
- $Condition: Continue\ until\ the\ stopping\ criterion\ is\ met.$

4 $\boldsymbol{Pack\ Processing}$:
- $\boldsymbol{For}\ each\ pack\ p$:
  1 $Alpha\ Coyote\ Identification$:
  - $Determine\ the\ alpha\ coyote\ of\ the\ pack\ (Equation\ 5)$.

  2 $\boldsymbol{Social\ Tendency}$:
  - $Calculate\ the\ social\ tendency\ of\ the\ pack\ (Equation\ 6)$.

  3 $\boldsymbol{Coyote\ Update}$:
  - $\boldsymbol{For}\ each\ coyote\ c\ in\ pack\ p$:
  - $Update\ the\ social\ condition\ of\ the\ coyote\ (Equation\ 7)$.
  - $Evaluate\ the\ new\ social\ condition\ (Equation\ 8)$.
  - $Adaptation\ process\ (Equation\ 9)$.

  4 $\boldsymbol{Birth\ and\ Death}$:
  - $Execute\ the\ birth\ and\ death\ process\ (Equation\ 7\ )$.

5 ***Pack Transition***:
- *Handle the transition of coyotes between packs (Equation 4).*

6 ***Age Update***:
- *Update the ages of the coyotes.*

7 ***End Loop.***

8 ***Best Adaptation Selection***:
- *Choose the coyote with the best adaptation.*

V. EXPERIMENTATION AND DISCUSSION

Several critical performance criteria are used to exhaustively evaluate the developed ISCT—Innovative Self-organized Clustering Technique—namely: time consumed during cluster formation, energy consumed, longevity of clusters, and probability of effective data transmission. Related to ISCT effectiveness and efficiency, the indicators are compared to those of the one BICSF scheme described in more detail in [20].

The simulations are conducted using MATLAB to guarantee controlled environments to measure and compare the performances of the two different clustering algorithms. The ISCT is further comprehensively tested under diverse environments using a variety of grid sizes and drones within the network, keeping in view real-world scenarios and resulting challenges. This leads to a complete evaluation of the ISCT.

This rigid approach ensures that the assessment will touch on a wide variety of operational scenarios and, therefore, highlight the strengths of the ISCT scheme and potential areas for development over the currently implemented BICSF framework.

A. Overall Energy Consumption

The total energy consumption is thus defined as the energy consumed by the algorithm over the entire network. Energy consumption in drones is primarily through two principal mechanisms: the energy utilized during their operation and the energy sensors utilized when placed on themselves. Further, activities in communication consume a significant amount of energy, which consequently forms a large portion of the overall amount of energy consumed.

Figures 2 and 3 show that increasing the number of drones in the network increases the energy consumed. One can easily infer from the results that our ISCT significantly outperforms the other schemes available in terms of energy savings. Less energy use is achieved due to the selection of an energy-aware cluster head (CH) and an efficient cluster management procedure in our proposed strategy.

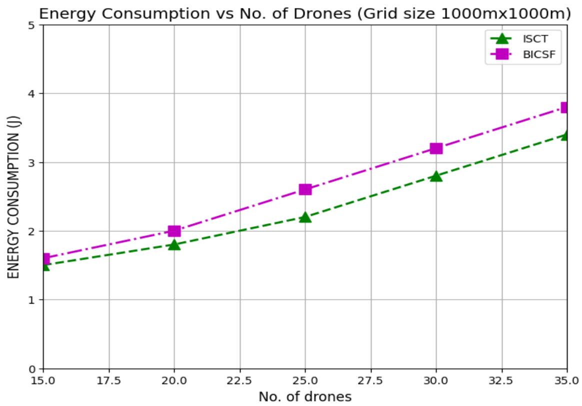

*Figure 2. Consumption of energy over Total quantity of drones (size of grid = 1000*1000m)*

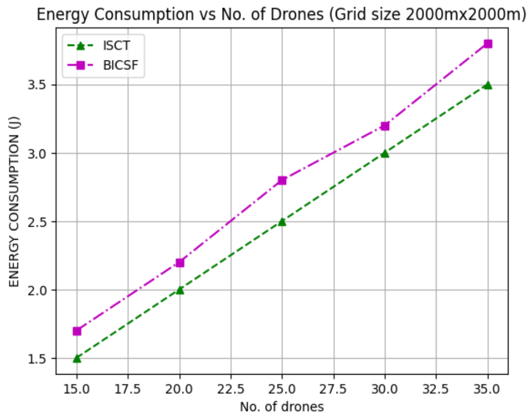

*Figure 3. Consumption of energy over Total quantity of drones (size of grid = 2000*2000m)*

B. Lifespan of cluster

The duration from the formation of a cluster until its death is called the cluster's lifetime. During the running of a clustering method, a drone having a high fitness value becomes the cluster head (CH). Owing to the large number of operational steps, the fitness value of this CH drone will gradually decrease with time. If the fitness value falls below a predefined threshold that is configured beforehand, the process of selecting CHs is carried out again. A short cluster lifetime means the clustering algorithm will have to run more frequently. This results in increased communication and processing overheads within the network.

The ISCT scheme we developed shows good performance compared to the BICSF scheme, as deduced from Figures 4 and 5. In addition, the results show that the cluster lifetime decreases with the increase in the number of drones employed in the network. The increase in the number of cluster members increases the cluster's lifetime, hence reducing the lifetime because of the increased changes in topology in the network. Therefore, modifications of methods lead to an increase in overhead.

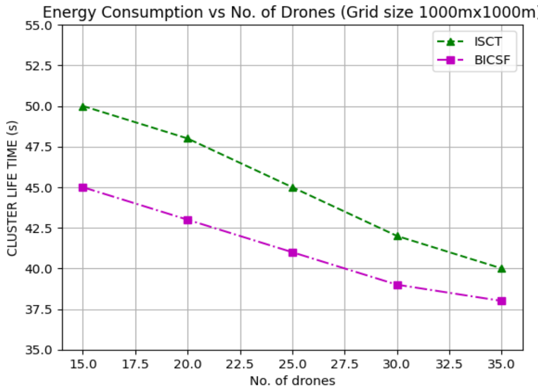

Figure 4. Life span of cluster over Total quantity of drones (size of grid = 1000*1000m)

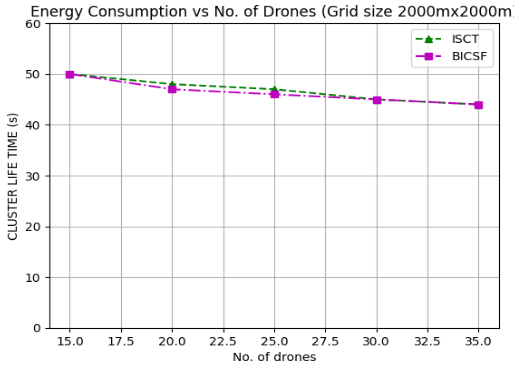

Figure 5. Life span of cluster over Total quantity of drones (size of grid = 2000*2000m)

C. Overall Energy Consumption vs Lifespan of cluster vs Quantity of drones

Figure 6 shows a dynamic relationship between the number of drones, the energy amount consumed, and the longevity of the cluster. Notably, both the number of drones and the time required to build a cluster impact the longevity of the cluster. It becomes abundantly clear from here that the developed Hybrid Self-organized Clustering Scheme is better than BICSF in terms of the average lifetime of the cluster. As the number of drones within the network increases, the time it requires to build the clusters also starts rising, which will lead to the growth in consumed energy consumption. However, through this intensified energy usage based on the additional drones being integrated into the network, lifespan decreases. In essence, the energy requirement rises when more drones are integrated into the network because the drones with resource constraints are performing a variety of functions, which in turn increases the energy demand.

Thus, the clustering method must be carried out more frequently in proportion to the resources demand that eventually leads to less lifetime given to the cluster.

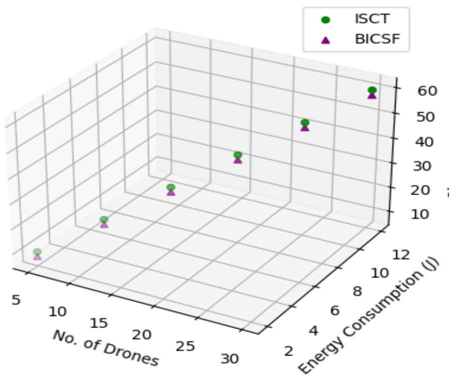

Figure 6. Overall Energy Consumption vs Lifespan of cluster vs Quantity of drones

VI. Conclusion

The Innovative Self-Organized Clustering Technique (ISCT) is an advancement in network operations management within drone-based IoT environments. It uses cognitive features to solve numerous networking problems typically related to such scenarios. In cases of cluster head selection and cluster formation, efficient, energy-conscious cluster management is guaranteed using the Enhanced Coyote Optimization Algorithm (ECOA). It includes a mechanism for identifying and managing dead cluster members, thereby further stabilizing the network and improving performance overall. In addition, the routing mechanism of the ISCT enhances data transmission efficiency by selecting an optimal route to forward data to next-hop neighbors. The following simulation performance evaluation of the ISCT, based on metrics for consideration like cluster build duration, energy consumption, cluster lifetime, and delivery ratio, elucidates the improvement in the bio-inspired fusion-based clustering scheme concerning the existing fusion bio-inspired clustering schemes. These improvements highlight that the ISCT has a high potential for continuous improvement in network efficiencies and performance in drone-based IoT applications.

REFERENCES

[1] Wang, Huanchi, He Fang, and Xianbin Wang. "Safeguarding cluster heads in UAV swarm using edge intelligence: Linear discriminant analysis-based cross-layer authentication." IEEE Open Journal of the Communications Society 2 (2021): 1298-1309.

[2] Salam, Abdu, Qaisar Javaid, and Masood Ahmad. "Bioinspired Mobility‐Aware Clustering Optimization in Flying Ad Hoc Sensor Network for Internet of Things: BIMAC‐FASNET." Complexity 2020, no. 1 (2020): 9797650.

[3] Ghdiri, Oussama, Wael Jaafar, Safwan Alfattani, Jihene Ben Abderrazak, and Halim Yanikomeroglu. "Offline and online UAV-enabled data collection in time-constrained IoT networks." IEEE Transactions on Green Communications and Networking 5, no. 4 (2021): 1918-1933.

[4] Wang, Gicheol, Byoung-Sun Lee, Jae Young Ahn, and Gihwan Cho. "A UAV‐Aided Cluster Head Election Framework and Applying Such to Security‐Driven Cluster Head Election Schemes: A Survey." Security and Communication Networks 2018, no. 1 (2018): 6475927.

[5] Khanmohammadi, Elnaz, Behrang Barekatain, and Alfonso Ariza Quintana. "An enhanced AHP-TOPSIS-based clustering algorithm for high-quality live video streaming in flying ad hoc networks." The Journal of Supercomputing 77, no. 9 (2021): 10664-10698.

[6] Banerjee, Anuradha, Abu Sufian, Krishna Keshob Paul, and Sachin Kumar Gupta. "Edtp: Energy and delay optimized trajectory planning for uav-iot environment." Computer Networks 202 (2022): 108623.

[7] Elkamchouchi, Dalia H., Jaber S. Alzahrani, Hany Mahgoub, Amal S. Mehanna, Anwer Mustafa Hilal, Abdelwahed Motwakel, Abu Sarwar Zamani, and Ishfaq Yaseen. "Intelligent Optimization-Based Clustering with Encryption Technique for Internet of Drones Environment." CMC-COMPUTERS MATERIALS & CONTINUA 73, no. 3 (2022): 6617-6634.

[8] Kiruba, K., P. Hemalatha, J. Manikandan, M. Madhin, and Raj S. Mohan. "Revolutionizing secure commercialization in agriculture using blockchain technology." In 2021 International Conference on System, Computation, Automation and Networking (ICSCAN), pp. 1-6. IEEE, 2021.

[9] Bhandari, Sabin, Xianbin Wang, and Richard Lee. "Mobility and location-aware stable clustering scheme for UAV networks." IEEE Access 8 (2020): 106364-106372.

[10] Haider, Syed Kamran, Aimin Jiang, Ahmad Almogren, Ateeq Ur Rehman, Abbas Ahmed, Wali Ullah Khan, and Habib Hamam. "Energy efficient UAV flight path model for cluster head selection in next-generation wireless sensor networks." Sensors 21, no. 24 (2021): 8445.

[11] Gheisari, Mehdi, Mahdi Safaei Yaraziz, Jafar A. Alzubi, Christian Fernández-Campusano, Mohammad Reza Feylizadeh, Saied Pirasteh, Aaqif Afzaal Abbasi, Yang Liu, and Cheng-Chi Lee. "An efficient cluster head selection for wireless sensor network-based smart agriculture systems." Computers and Electronics in Agriculture 198 (2022): 107105.

[12] Zhu, Botao, Ebrahim Bedeer, Ha H. Nguyen, Robert Barton, and Jerome Henry. "Joint cluster head selection and trajectory planning in UAV-aided IoT networks by reinforcement learning with sequential model." IEEE Internet of Things Journal 9, no. 14 (2021): 12071-12084.

[13] Haider, Syed Kamran, Muhammad Ali Jamshed, Aimin Jiang, Haris Pervaiz, and Qiang Ni. "UAV-assisted cluster-head selection mechanism for wireless sensor network applications." In 2019 UK/China Emerging Technologies (UCET), pp. 1-2. IEEE, 2019.

[14] Aftab, Farooq, Ali Khan, and Zhongshan Zhang. "Hybrid self-organized clustering scheme for drone based cognitive Internet of Things." IEEE Access 7 (2019): 56217-56227.

[15] Refaee, Eshrag A., and Shermin Shamsudheen. "Trust-and energy-aware cluster head selection in a UAV-based wireless sensor network using Fit-FCM." The Journal of Supercomputing (2022): 1-16.

[16] Aftab, Farooq, Ali Khan, and Zhongshan Zhang. "Bio-inspired clustering scheme for Internet of Drones application in industrial wireless sensor network." International Journal of Distributed Sensor Networks 15, no. 11 (2019): 1550147719889900.

[17] Raj, Bryan, Ismail Ahmedy, Mohd Yamani Idna Idris, and Rafidah Md. Noor. "A survey on cluster head selection and cluster formation methods in wireless sensor networks." Wireless Communications and Mobile Computing 2022, no. 1 (2022): 5322649.

[18] Tazibt, Celia Yasmine, Mustapha Bekhti, Tounsia Djamah, Nadjib Achir, and Khaled Boussetta. "Wireless sensor network clustering for UAV-based data gathering." In 2017 Wireless Days, pp. 245-247. IEEE, 2017.

[19] Reddy, Chada Sampath, and G. Narsimha. "Adaptive squirrel coyote optimization-based secured energy efficient routing technique for large scale WSN with multiple sink nodes." Intelligent Decision Technologies 17, no. 4 (2023): 1207-1232.

[20] A. Khan, F. Aftab and Z. Zhang, "BICSF: Bio-Inspired Clustering Scheme for FANETs," IEEE Access, vol. 7, pp. 31446-31456, 2019.