Energy Aware Enhanced Krill Herd Algorithm Enabled Clustering for Unmanned Aerial Vehicles

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Abstract

Recently, unmanned aerial vehicles (UAV) have gained maximum interest in diverse applications ranging from military to civilian areas. The presence of numerous energy-constrained UAVs in an adhoc manner poses several design issues. At the same time, the limited battery, high mobility, and adaptive characteristics of the UAVs need effective design of clustering techniques for UAVs. In this manner, this paper presents a levy flight with a krill herd optimization algorithm (LF-KHOA) for energy-efficient clustering in UAVs. The proposed LF-KHOA technique integrates the concepts of LF to the KHOA to enhance efficiency and search space exploration. In addition, the LF-KHOA technique derives a fitness function involving three input parameters to elect cluster heads (CHs) and organize clusters. The energy consumed by the UAVs depends on the distance from UAVs to nearby nodes. Therefore, the fitness function aims to decrease communication distance, which mitigates energy utilization when transmitting the information. To ensure the better performance of the LF-KHOA technique, an extensive set of simulations takes place, and the results are inspected in terms of different measures. The experimental results highlighted the betterment of the LF-KHOA technique over the current state of art techniques.

Keywords: Unmanned aerial vehicles, Energy efficiency, Clustering, Levy flight, Metaheuristics

1. Introduction

In recent years, because of the features of high mobility, high adaptability, and low cost, unmanned aerial vehicles (UAVs) are involved in a wide range of applications [1]. For instance, these aircraft are involved in urban management, disaster relief, agricultural monitoring, and environmental protection using remote sensing. With the rapid development of wireless communication network technology, UAV-enabled wireless networks (UeWNs) are gaining popularity in research [2-4]. Compared to UAV point-to-point communication, UeWNs can take advantage of distributed clustering to improve performance in applications. For instance, distributed UAVs in UeWNs could be deployed as relays for the construction of non-line-of-sight (NLOS) transmission links to overcome the obstacle and extend the coverage [5]. Fig. 1 shows the structure of UAV. However, the assistance of UAVs with wireless communications and

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networks brings a lot of new challenges in terms of transmission security, multiple access, energy efficiency, interference cancellation, network optimization, and channel estimation [6, 7].

In the UAVs assisted data collection and dissemination, the communications among UAVs and the sensor nodes must be implemented but not in a P2P method however in a broadcast/multicast method. It is due to various UAVs is small compared to various sensors, and the UAVs pass through the sensor nodes, gather information from the sensors, or data dissemination to the sensor nodes. Hence, integrating the network of sensors to any logical group and only make the group leader interact with UAVs are chosen to save power utilization of the sensors and extend lifespan of the network. Integrating neighboring sensor nodes into logical groups is denoted as clustering [8-10]. Clustering is separated into CH selection and cluster formation. Make logical groups of neighboring nodes are known as the cluster formation and the groups are known as a cluster [11, 12]. On the other hand, selecting leaders in a cluster that play as a data disseminator/collector is denoted as the CH selection. The CH selection and cluster formation are corresponding to one another. In few clustering systems, CH is initially selected and the cluster formations are finalized afterward a CH broadcast a declaration method and its member responds to it through a join message. After this, they referred to these cluster formation systems as first CH systems. In another clustering system [13], cluster is initially made by exchanging of few messages, and CH of the cluster is then selected based on a condition or various criteria.

Khan et al. [14] proposed a smart CRSF for adhoc networks. CH election in this presented method depends on fitness, i.e., based on the location and UAV residual energy. For an effective managing of UAVs swarm, clustering management mechanisms were introduced, stimulated from MOA approach. Pustokhina et al. [15] projected a new energy effective clustering based UAV network using DL dependent scene classification algorithm. The presented method includes a C-PTRN method that operates on 2 main stages like scene classification and cluster construction. At first, the UAV is clustered by the T2FL method based residual energy, distance to UAV degree, and neighboring UAV. [16] proposed a SIL method and cluster systems in UAVs network for emergency communication. Initially, proposed a novel 3D SIL method according to PSO method which uses the particle search space in a constrained edge through the bounding box technique. In 3D search spaces, anchor UAVs node is arbitrarily assigned and SIL algorithms measure the range to present anchor node to estimate the position of the targeted UAVs node.

Na et al. [17] proposed a synergetic system for UAVs route formation and subslots distribution. The aim is to increase the uplinked average attainable rates of IoTs terminal through synergistically plan UAVs route as well as subslots period when assuring the uplink attainable rates and UAVs mobility constraint. Since the formulating problems suffer complications and nonconvexity, effective iterative algorithms were introduced for addressing the problem.

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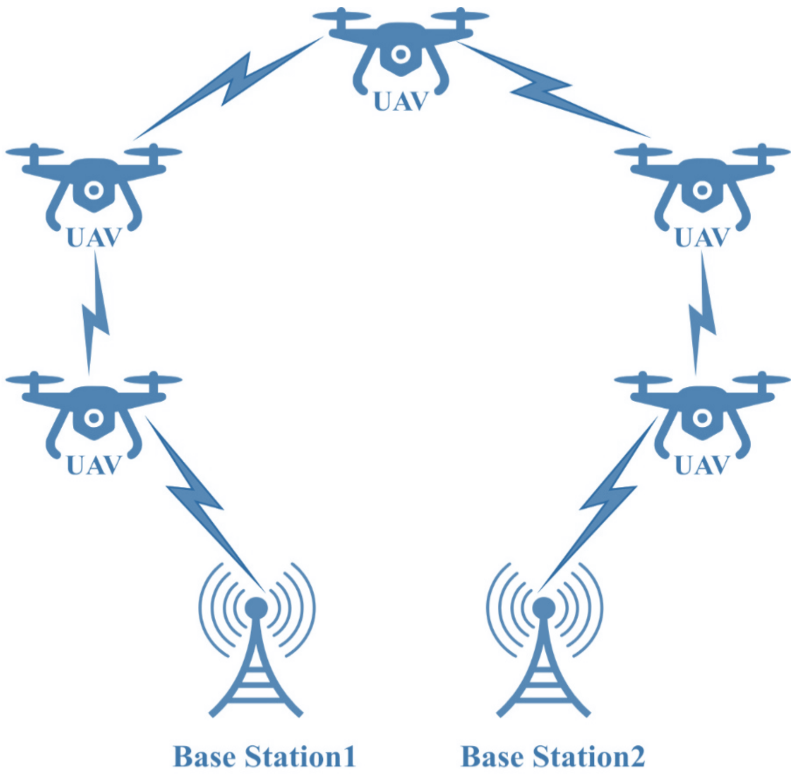

Fig. 1. Structure of UAVs Networks

This paper presents a levy flight with krill herd optimization algorithm (LF-KHOA) for energy efficient clustering in UAVs. The proposed LF-KHOA technique integrates the concepts of LF to the KHOA to enhance efficiency and search space exploration. In addition, the LF-KHOA technique derives a fitness function involving three input parameters to elect cluster heads (CHs) and organize clusters. The energy consumed by the UAVs depends on the distance from UAVs to nearby nodes. Therefore, the fitness function aims to decrease the communication distance which tends to mitigate the energy utilization on transmitting information. In order to ensure the better performance of the LF-KHOA technique, an extensive set of simulations take place and the results are inspected interms of different measures.

2. The Proposed Model

In the recently proposed method, the UAV is assumed as mobile and modifies the location when it is placed. In addition, it is similar that denotes that it is consists of transmission radius, symmetric sensing range, basic energy, and data buffer size. After that, the UAV depends on the well-trained GPS technique. The placed UAV can able to measure the location information, and data sink gathers the complete information about the location of UAV. Moreover, the BS is attentive to alternative variables included in UAV are buffer size and primary energy. Additionally, the main goal of clustering is to demonstrate the paths of data collectors. Therefore, mobile data collectors are made up of effective transceivers and higher mobility. It is appropriate to collect the sensed information at the time of varying to UAVs. When the traversal is finished, the mobile data collectors send and receive the collected information to BS [18].

Most of time, energy is used by UAVs when carrying out the data transceiving procedure. Generally, the power applications on sensing are minimal than transceiving. Thus, the researchers have focused on energy consumed for data transceiving. Therefore, power used on transmitting a k-bit message via distance d is represented by,

$$E_{Tx} = E_{elec} \times k + \varepsilon_{amp} \times k \times d^2, \tag{1}$$

Whereas E_{elec} represents power cost for an individual bit on performing transceiver circuit and ε_{amp} means the efficiency of an amplifier. Energy utilization on getting a k-bit message is demonstrated as,

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$$E_{Rx} = E_{elec} \times k. \tag{2}$$

The power concept exhibits the energy employed by UAVs depends on the distance from UAVs to nearby models. Thus, decreasing the communication distance tends to mitigate the energy utilization on transmitting information. Moreover, since the delay in UAVs based method depends on the travelling time of UAVs, delays in UAV based method is assumed as unavoidable. Next, rather than assigning a complex delay, prior methods are used in the delay constraints of data transmission in UAVs based methods using certain thresholds.

In general, KHOA [19] is defined as a novel metaheuristic optimization approach used for resolving the optimization process which depends upon the herding behavior of krill swarms by responding to the specific biological as well as ecological processes. The time-based location of an individual krill in 2D space is selected by 3 major functions namely, movement influenced by alternate krill individuals, foraging movement, as well as random diffusion. Also, KHO model has applied Lagrangian method in d-dimensional decision space as given below (3):

$$\frac{dX_i}{dt} = N_i + F_i + D_i, \tag{3}$$

where N_i, F_i, and D_i implies the motion of adjacent krill individuals, foraging action, and physical diffusion of ith krill individual, correspondingly. Initially, the direction of motion, α_i is processed by the target effect (target swarm density), local impact (local swarm density) as well as a repulsive effect (repulsive swarm density). Thus, the movement of krill individual is measured by,

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old}, \tag{4}$$

and N^{max} means the speed induced, ω_n refers the inertia weight of motion projected from [0, 1], and N_i^{old} defines the final motion.

Followed by, foraging action is evaluated by 2 major elements. The initial one is food location and alternate module is advanced knowledge regarding the food location. For ith krill individual, this action is approximately derived as given below:

$$F_i = V_f \beta_i + \omega_f F_i^{old}, \tag{5}$$

Where
$$\beta_i = \beta_i^{food} + \beta_i^{best}, \tag{6}$$
and V_f indicates the foraging speed, ω_f defines the inertia weight of foraging action from 0 and 1, F_i^{old} implies the final foraging action. Also, random diffusion of krill individuals is processed randomly. It is defined by means of high diffusion speed as well as random directional vectors. Then, it is represented by:

$$D_i = D^{max}\delta, \tag{7}$$

Where D^{max} means the high diffusion speed, and δ illustrates the random directional vector and random values are ranged from $[-1, 1]$. According to the 3 pre-defined movements, diverse attributes of action in time and position vector of a krill individual from the interval t to $t + \Delta t$be depicted by the given expression:

$$X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \tag{8}$$

The proposed LF-KHOA technique integrates the concepts of LF to the KHOA to enhance efficiency and search space exploration. LF was initially presented by the French arithmetician in 1937 called Paul Levy. A varied kind of natural and artificial phenomena is defined based on Levy statistics [20]. The LF is a well-considered class of stochastic non Gaussian walk in which step length value must be distributed regarding Levy stable distribution. It is obtained as:

$$Levy(\beta) \sim u = t^{-1-\beta}, 0 < \beta \leq 2 \tag{9}$$

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β denotes important Levy index for adjusting the stability. The Levy arbitrary amount is estimated by:

$$Levy(\beta) \sim \frac{\varphi \times \mu}{|v|^{1/\beta}} \tag{10}$$

Whereas μ & v denotes regular distribution, Γ represents normal Gamma function, $\beta = 1.5$, & φ is given by:

$$\varphi = \left[\frac{\Gamma(1+\beta) \times \sin\left(\pi \times \frac{\beta}{2}\right)}{\Gamma\left(\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}\right)}\right]^{\frac{1}{\beta}}. \tag{11}$$

For obtaining a tradeoff among the exploitation and exploration abilities of metaheuristic method, LF method is utilized for updating search agent location that can be given by:

$$X_i^{levy} = X_i + r \oplus levy(\beta) \tag{12}$$

where X_i^{levy} denotes novel location of ith search agents X_i afterward upgrading also r denotes arbitrary vector in zero and one $\oplus$ indicates dot product (entry wise multiplication). In addition, the LF-KHOA technique derives a fitness function using three input parameters.

The RE of UAVs (x) when transmitting k bits to the end UAVs (y) on a distance d, as follows

$$RE = E - \left(E_T(k,d) + E_{R(k)}\right) \tag{13}$$

Whereas E indicates the present energy of the UAVs and E_T signifies the energy expended to sense information.

$$E_T(k,d) = kE_e + KE_a d^2 \tag{14}$$

In which E_e represents the energy of electrons and E_a denotes the needed amplified energy, $E_{R\text{-}(k)}$ indicates the energy dissipated to obtain information, as follows

$$E_{R(k)} = kE_e \tag{15}$$

The 3 variables for CH selection are the average distance (AvgD) to adjacent UAV. The AvgD signifies the average of the distance value to the UAV to its single hob neighbouring UAV, as follows

$$AvgNBDist_i = \frac{\sum_{j=1}^{NB_i} dist(i, nb_j)}{NB_i}, \tag{16}$$

Whereas $dist(i, nb_j)$ denotes the distance from the UAVs to the adjacent jth UAVs. It's neighbour nb_j. The degree of UAVs denotes the numbers of nearby node which present in the UAVs. It is determined by

$$\mathrm{Deg}_x = |N(x)| \tag{17}$$

In which $N(x) = \{n_y / dist(x,y) < trans_{range}\} x \neq y$, and $dist(x,y)$ signifies the distance between 2 UAVs n_x & n_y, $trans_{range}$ indicates the broadcast range of the UAV.

3. Performance Validation

This section inspects the energy efficient performance of the LF-KHOA technique with existing techniques. Table 1 and Fig. 2 investigates the energy consumption (EC) analysis of the LF-KHOA technique with existing ones under varying UAV counts. The figure demonstrated that the PSOA technique has gained ineffectual outcomes with the maximum EC whereas the ACOA, GWOA, and KHOA techniques have obtained moderate performance with the slightly reduced EC. However, the LF-KHOA technique has shown better outcomes with minimal EC. For instance, with 10 UAVs, the LF-

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KHOA technique has gained a lower EC of 31 while the KHOA, GWOA, ACOA, and PSOA techniques have obtained a higher EC of 37, 41, 43, and 52 respectively. Also, with 50 UAVs, the LF-KHOA approach has obtained a lesser EC of 101 whereas the KHOA, GWOA, ACOA, and PSOA methods have reached a raised EC of 123, 133, 143, and 162 individually. Moreover, with 100 UAVs, the LF-KHOA manner has increased a lower EC of 142 while the KHOA, GWOA, ACOA, and PSOA techniques have reached a superior EC of 171, 193, 210, and 219 correspondingly.

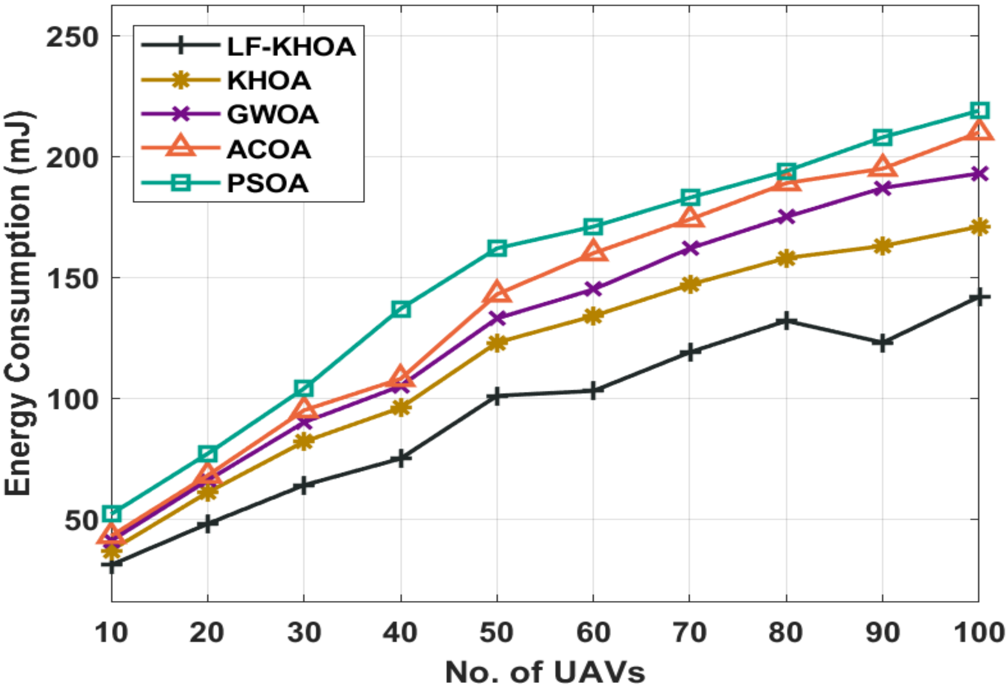

Fig. 2 EC analysis of LF-KHOA technique

Table 2 and Fig. 3 demonstrate the NLT analysis of the LF-KHOA technique with existing ones. The results depicted that the LF-KHOA technique has accomplished improved performance with the higher NLT. For instance, with 10 UAVs, the LF-KHOA technique has resulted in an increased NLT of 5900 rounds whereas the KHOA, GWOA, ACOA, and PSO techniques have offered a reduced NLT of 5600, 5300, 5000, and 4700 rounds. Also, with 40 UAVs, the LF-KHOA method has resulted in a maximum NLT of 5500 rounds whereas the KHOA, GWOA, ACOA, and PSO techniques have obtainable a reduced NLT of 5000, 4900, 4500, and 4400 rounds. Besides, with 70 UAVs, the LF-KHOA manner has resulted in an enhanced NLT of 4700 rounds whereas the KHOA, GWOA, ACOA, and PSO techniques have accessible a minimal NLT of 4200, 4000, 3600, and 3500 rounds. Additionally, with 100 UAVs, the LF-KHOA approach has resulted in a maximum NLT of 4000 rounds whereas the KHOA, GWOA, ACOA, and PSO methods have obtainable a lower NLT of 3400, 3200, 3100, and 3000 rounds.

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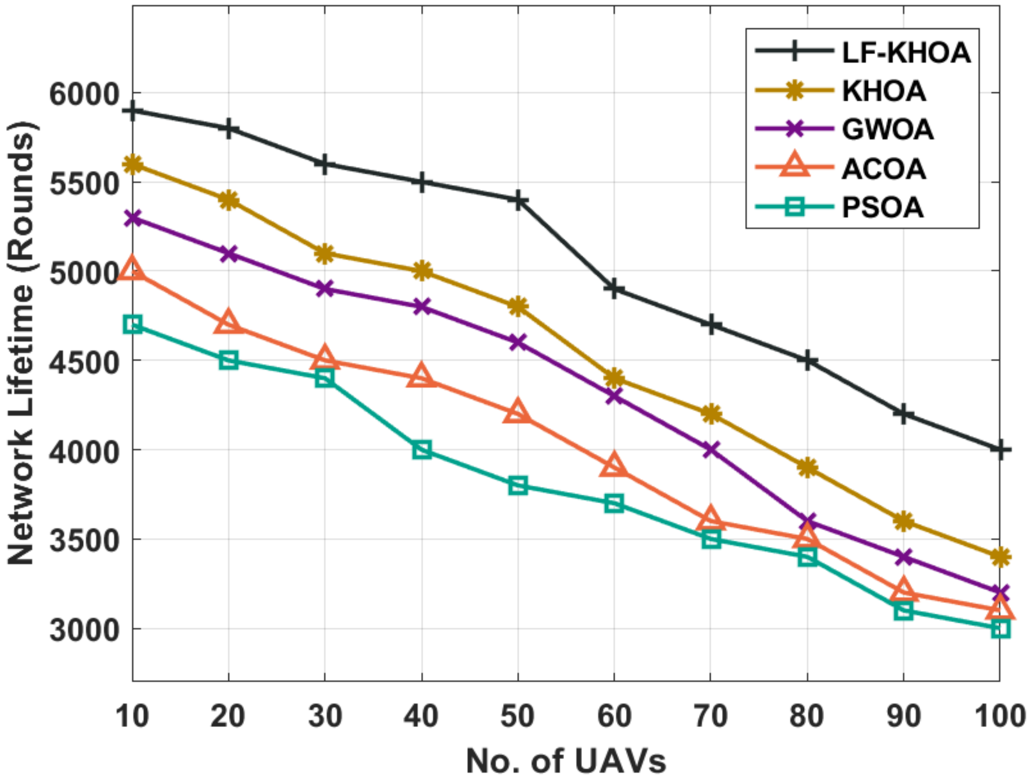

Fig. 3. NLT analysis of LF-KHOA technique

Table 3 and Fig. 4 showcases the throughput analysis of the LF-KHOA technique with existing ones. The results depicted that the LF-KHOA technique has accomplished increased performance with superior throughput. For instance, with 10 UAVs, the LF-KHOA methodology has resulted in an enhanced throughput of 0.97Mb/s whereas the KHOA, GWOA, ACOA, and PSO techniques have attainable a least throughput of 0.94Mb/s, 0.93Mb/s, 0.91Mb/s, and 0.87Mb/s. Likewise, with 40 UAVs, the LF-KHOA technique has resulted in an increased throughput of 0.90Mb/s whereas the KHOA, GWOA, ACOA, and PSO techniques have accessible a lesser throughput of 0.73Mb/s, 0.67Mb/s, 0.61Mb/s, and 0.54Mb/s. Followed by, with 70 UAVs, the LF-KHOA technique has resulted in a maximum throughput of 0.80Mb/s whereas the KHOA, GWOA, ACOA, and PSO techniques have presented a lower throughput of 0.63Mb/s, 0.56Mb/s, 0.54Mb/s, and 0.45Mb/s. Eventually, with 100 UAVs, the LF-KHOA method has resulted in an increased throughput of 0.74Mb/s whereas the KHOA, GWOA, ACOA, and PSO manners have offered a diminished throughput of 0.58Mb/s, 0.50Mb/s, 0.49Mb/s, and 0.40Mb/s.

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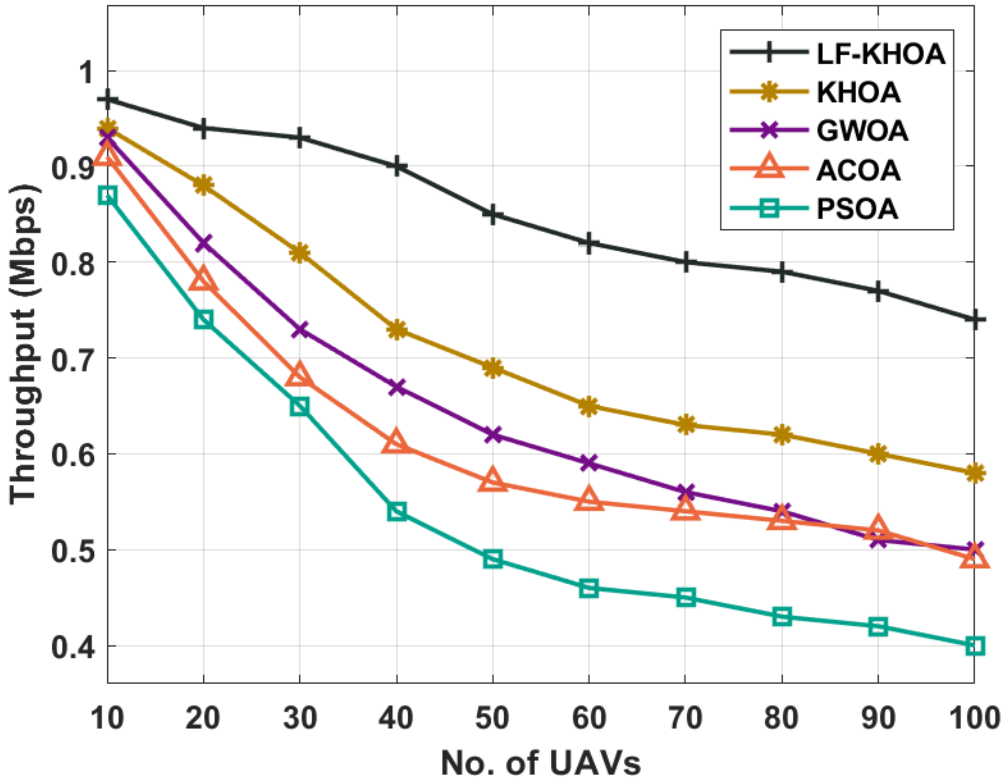

Fig. 4. Throughput analysis of LF-KHOA technique

4. Conclusion

This paper has developed a new LF-KHOA technique for energy efficient clustering in UAVs. The proposed LF-KHOA technique integrates the concepts of LF to the KHOA to enhance efficiency and search space exploration. In addition, the LF-KHOA technique derives a fitness function involving three input parameters to elect CHs and organize clusters. The energy consumed by the UAVs depends on the distance from UAVs to nearby nodes. Therefore, the fitness function aims to decrease the communication distance which tends to mitigate the energy utilization on transmitting information. For ensuring the improved outcomes of the LF-KHOA technique, an extensive set of simulations take place and the results are inspected interms of different measures. As a part of future scope, the performance of the LF-KHOA technique is derived interms of different aspects.

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