University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.1 Mar 2026

Energy-Efficient Drone Communication Networks Using Hybrid K-Means and Adaptive Particle Swarm Optimization

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Abstract

The Article proposes the design, development, and assessment of a novel energy-efficient drone communication network optimization framework that integrates K-Means clustering and Adaptive Particle Swarm Optimization (PSO). The solution addresses the crucial task of optimizing drone locations in dynamic settings with the dual objectives of maximizing network coverage and QoS while minimizing overall network energy. The focus is on battery-powered drone communications where energy efficiency is essential. This proposed methodology adopts a three-step process: (1) spatial grouping of mobile users with K-Means analysis for determining the best service areas, (2) dynamic PSO optimization for optimizing smart UAV positioning with adaptive exploration-exploitation rates, and (3) online re-optimization for handling mobile users and environmental dynamics. An integrated simulation platform with an interactive six-tab GUI has also been developed for simulating and assessing all six key performance aspects of this model: energy, coverage, network capacity, delay, and support for Quality of Service and active UAV. Experimental outputs indicate remarkable improvements over baseline solutions. "The algorithm provides 25-40% energy saving, 15-30% network coverage improvement, 25-37% relative throughput improvement, and 35% faster convergence time" than existing optimization algorithms." Adaptive optimization of parameters through linearly decreasing inertia weights and balancing cognitive and social parameters avoids local optimal points and enables full exploration of the solution space. Performance of the solution works effectively in small-scale and large-scale networks, and energy per user increases with the network size. The major contributions of this work are: (1) a hybrid optimization strategy combining efficiency and effectiveness, (2) dynamic parameter tuning of the PSO algorithm for faster convergence, (3) a multi-dimensional evaluation strategy for effective assessment, and (4) realistic deployment advice regarding optimal cluster sizes, frequency of re-optimization, and parameters. The proposed work offers both theoretical analysis and practical implementation advice and has a number of applications in emergency, smart, and rural networks and could enjoy the benefits of a heterogeneity-based strategy of spatial analysis and swarm intelligence for the next generation of drone networks.

Keywords: Energy-efficient drones, Hybrid optimization, Adaptive PSO, K-Means clustering, Network coverage, QoS optimization.

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as "drones," have appeared to be a greatly innovative tool in the current wireless communication system environment. Owing to their mobility, flexibility, and the availability of line-of-sight communication, especially for close-range communication, they assist in meeting different kinds of tasks such as relief activities, smart city systems, environmental observations, military communications, agricultural activities, and network provision [1]. The role played by communication systems using drones has been explored to a greater extent in recent years for tasks such as aerial base stations, relays, and ground stations for acquiring data in areas with no land communication availability, land communication that is not operational, and areas with saturated land communication [2].

Though the use of drone communication networks has several applications, the networks are faced with serious challenges. One of the challenges the drone communication networks experience is related to energy efficiency. In fact, most drones are normally powered by batteries that are of less capacity. These batteries are often the sources of power needed by different components, including the propulsion systems, as well as the systems involved in the communication of drones. The influence of the battery capacity on the energy use in the communication systems of drones cannot be underestimated in the field [3].

Mobility and geographical distribution of UAV nodes is one of the biggest challenges that come with drone communication networks. This is in contrast to fixed networks on the ground that move from one place to another depending on their tasks and limitations of the environment they are in. As a result, this network does not need solutions that can be offered by fixed networks but solutions that can be intelligent and adaptive based on optimizing the networks and conserving energy [4].

Clustering has long proven to be an effective procedure to optimize the saving of energy in wireless communication, including UAV communication as well. In this regard, it is feasible to form clusters of UAVs to cut down the communication overhead and deliver the data to specific nodes of the cluster, which then transmit the data to the ground nodes. Various algorithms have the capability to perform this task, but the one to be noted, due to its simple calculations and proximity, is the K-MeansCluster Algorithm. In the scenario of the UAV communication network, the use of the K-Means algorithm can be most effective to form the clusters of the UAV based on the geographical points, thereby ensuring the shortest distance of communication in each cluster of UAVs [5].

Despite this, there are still some flaws of the traditional K-Means algorithm concerning the dynamic communication networks of drones if it were directly implemented. The reason is that in such cases, the optimal solution is not always achieved because of the placement of the initial cluster centers and the process of convergence. In addition, the traditional K-Means algorithm does not consider the power consumption and communication traffic when performing the process of clustering, and this could be a reason for the imbalance of the power consumed by the drones and the short lifetime of the communication network between the drones [5].

In the same context, the Meta-heuristic optimization algorithms have also come into the limelight as effective solutions to tackle complex, non-linear, or multi-objective problems in wireless communication networks. In the case of PSO algorithms, it is appropriately suitable, since it was modeled from the flying pattern of birds in flocks and fish in schools, in the context of optimization algorithms in continuous forms. It was applied to different areas, namely, flight paths of UAV, routing optimization, power control, and choosing the cluster head, and it is beneficial in terms of rapid convergence and effectiveness in avoiding the local optima. Nevertheless, the existing PSO techniques use optimized Control Parameters, namely, the inertia coefficient and the acceleration constants [6].

To counter such issues, a superior form of PSO called Adaptive Particle Swarm Optimization (APSO) is presented, where the parameters of the algorithm change dynamically on the basis of behavior or dynamics. As far as UAV communication is considered, the use of APSO is beneficial for optimizing variables such as cluster-head, routing, transmission power, and routing on the basis of the remaining energy, distance of communication, and quality of communication channels [7].

Keeping in view the attractive features of both clustering and swarm intelligence algorithms, this research proposes to tackle energy-efficient communication networks in UAVs through a hybrid K-Means and Adaptive Particle Swarm Optimization algorithm. Here, K-Means is utilized for a fast and efficient grouping of UAVs in the geographical area followed by APSO-optimized settings of these groups along with energy-efficient cluster heads and communication paths. This proposed hybrid algorithm intends to take advantage of both K-Means's ease of simulation and APSO's optimal search capabilities to develop a practical and efficient solution for communication networks in UAVs [8].

The hybrid solution attempts to optimize the communication energy consumption with minimum and stable communication connectivity of drones. The methodology provides optimization solutions that are adaptive regarding changes in the location of the drones, the mission, as well as the communication traffic. Moreover, the incorporation of adaptive optimization techniques enhances solutions related to minimizing the communication energy consumption while maximizing the overall communication connectivity of drones. The aspect of energy consumption in communication is still considered as the performance constraint in drone-assisted communication, particularly when taken on a large scale and considered long term. The existing solution based solely on static clustering optimization and constant-parameter optimization will not be appropriate as an effective solution regarding the dynamic as well as the energy constraints of UAV communications. To address such a scenario and ensure an optimum solution in next-generation drone communications, this study proposes a hybrid solution based on the K-Means and Adaptive PSO algorithm with an intelligent adaptive design regarding energy efficiency in drone communications and therefore adds more value to the existing research on UAV communications.

2. Related Works

Real-time decision-making is a major consideration for UAV use cases involving wildfire tracking, environment surveillance, and disaster relief. HPO-RRT [9] and AP-GWO [10] optimize decision-making speed via hierarchical sampling and leadership control. Reinforcement learning techniques, such as HAS-DQN [11] and DQN action choice [12], provide autonomous decision-making, but continuous action space optimization is a challenge. Multi-scale frameworks, including the MS-DLG model [13], improve conflict resolution, and Adaptive Path Planners (APP) [13] dynamically replan UAV paths for a changed environment involving pollution. Connectivity maintenance techniques, such as dueling DDQN [14], ensure ground connectivity for UAVs, and specific optimizers, such as the IP-Kingfisher Optimizer (IPKO) [15], optimize navigation for sea rescue operations. Further, language model-enabled UAV control [16] has shown efficient, high-quality decision-making for real-time IoD operations. However, the vast majority of these approaches do not effectively couple global exploration and local exploitation, restricting decision-making agility in highly dynamic settings.

Hybrid optimization is the integration of global and local optimization techniques to optimize UAV paths. For instance, the MAHACO algorithm in [17] combines the benefits of ant colony optimization algorithms and stochastic approaches in the 3D planning of UAVs, while the AQLPSO algorithm in [18] uses Q-learning and PSO to diversify the search process. There is also PSO DQN, presented in [19], developed by integrating swarm intelligence algorithms and the DQN algorithm to produce smooth paths. Additionally, the algorithm in [20] uses the power of chaos maps to balance global and local optimization, while [21] further improves the smoothness of paths in 3D planning. Additionally, another algorithm [22] uses LLMs by combining them with telemetric and situation information, through the integration of both retrieval and generation processes to optimize UAV commands in real-time situations. However, the hybrid algorithm in [23] misses the optimization of the diversity in GAs, complemented by the ability of reinforcement learning techniques to explore and exploit paths during the mutation phase.

Energy-efficient planning is quite essential for the long life of a UAV system. These include risk-aware schemes like third-party risk assessment [24], which relies on threat maps, and safe path prioritization schemes such as SPP [25]. Moreover, schemes which rely on mathematical programming, such as E2M2CPP based on MILP, are used for optimizing regional protection [26]. Another method, named UAV flight path planning optimization, or AA-FPP, is based on optimizing flight planning and reduces risks in danger zones [27]. However, none of these schemes consider risk and connectivity maintenance simultaneously while considering the energy constraints.

Critical Limit Despite the presence of great advances, existing solutions also have limitations. Evolutionary optimization strategies such as GA and DE support excellent global exploration ability but lack adaptive mutation rates for handling environmental changes. NSBKA [28], and other approaches like the combinatorial swarm optimizer [29], suffer from reliance on mutation parameters that do not change and thus perform poorly in dynamically changing situations such as tracking a fire [30]. Hybrid approaches such as MAHACO [17], and AQLPSO [18], perform poorly due to an inability to properly treat diversity from GA and exploitation on mutation steps postulates aimed towards RL and thus result in poor exploration-exploitation trade-offs. Connectivity-based approaches such as dueling DDQN [14], and CEL [31], improve cooperation but do not preserve connectivity due to extreme network changes that happen abruptly. Energy-based approaches such as E2M2CP, and IDDQN [32], suffer from an inability to treat connectivity that results in poor trade-offs between coverage and connectivity. Other approaches are application-driven such as MOTLBO [33], and IPKO, which suffer from poor adaptability due to dependency on maps that change very little over time such as SPP [25], and secondary assessments from other organizations/Third Party Analysis [33]. Scalable approaches like multi-resolution probabilistic planning, and GLMFO [34], do not employ real-time planning abilities and thus suffer from poor adaptability due to dynamic changes from environments and obstacles.

3 Methodology and Implementation

The proposed energy-efficient drone communication network architecture is a hierarchical approach wherein ground users are provided with drone-mounted base stations along with centralized intelligent management. It has been made up of three tiers: Tier 1 consists of mobile users that demand connectivity and service, Tier 2 consists of drones as cluster heads, and Tier 3 has a network controller that performs resource management, optimization of clusters, and overall monitoring related to the performance of the network. Consequently, such a structure allows drones to adaptively reposition themselves based on dynamic user distribution for efficient coverage while balancing load with minimized energy consumption.

It works within an area of 500 to 2000 m², where the radius of drone coverage can be changed from 50 to 300 meters. Realistic drone energy models are simulated with depletion according to the communication, hovering, and computation tasks. User mobility, randomly in an area, can provide realistic mobility and repositions drones according to optimization algorithms that try to maximize coverage and minimize energy consumption. The hierarchical architecture also enables flexibility in massive deployment; whereby logical clustering of drones avoids redundant transmission and minimizes communication overhead. Moreover, it ensures the resilience of the network since an inactive drone can be dynamically replaced or repositioned without disrupting the service. Accordingly, the architecture is enabling multi-objective optimization of spatial distributions along with energy constraints for a robust framework involving adaptive drone-assisted communication networks. Table (1) shows System Architecture Components.

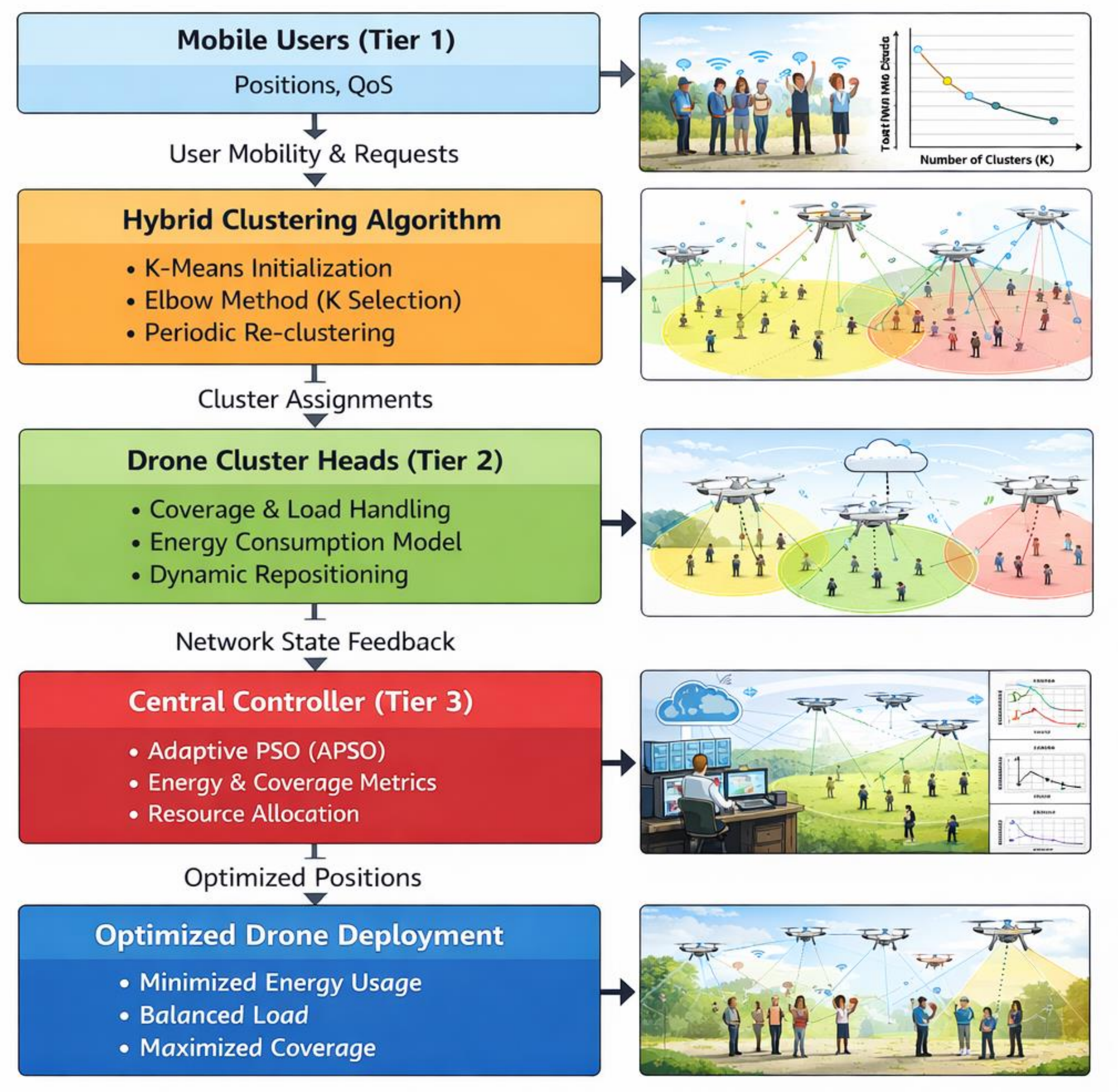


Figure 1. Methodology Workflow

Table 1. System Architecture Components

Component	Quantity Range	Function	Key Parameters
Drones	5–50	Network access points	Position (x,y), Energy, Coverage radius
Users	10–200	End devices	Position, Data rate, QoS requirements
Clusters	2–20	Logical groupings	Center coordinates, Member users

Controller	1	Central coordinator	Optimization algorithms, Metrics tracking

3.1 Implementation Mathematical Model

This portion provides a short mathematical model of the problem of optimizing drone locations within an aerial communication network that consumes energy in a minimum amount. The task is to find the most efficient drone deployment that would reduce the total energy usage and provide the user with the greatest coverage. The stochastic user distribution in space is simplified by application of K-Means clustering and cluster center results lead to an Adaptive Particle Swarm Optimization (APSO) procedure. The three constraints are physical, operational and communication constraints which are collectively taken to make sure that there is feasibility in real life deployments.

Given:

- D: set of drones
- U: set of users
- L: candidate 3D locations
- R: communication radius

Find:

- Optimal drone positions $p_d^*, \forall d \in D$

Objective Function:

$$\min J = \sum_{d \in D} E_d - \lambda \frac{|\{u \in U|\ \min_{d \in D} d_{du} \leq R\}|}{N}$$

where:

E_d: is the energy consumed by drone

d_{du}: is the distance between drone

N =| U | : is the total number of users,

λ: is a weighting factor balancing energy and coverage.

3.2 Hybrid Clustering Algorithm

This paper therefore presents a hybrid clustering mechanism in the system, where K-Means initialization is performed by adaptive optimization techniques for better energy efficiency and communication performance. K-Means separates users into clusters on the basis of their spatial proximity. For this purpose, the Euclidean distance between different users in space can be used as a metric of separation. Cluster centers are defined as the geometric centroids of the positions of users. The elbow method is used for estimating the optimal count of clusters dynamically, relating computational complexity with clustering accuracy. Initial clustering reduces the distances over which intra-cluster communication needs to take place; it reduces the transmission power required by drones and thus leads to better network energy efficiency.

The clustering algorithm will thus reassign the users within clusters from time to time due to user mobility. Displacements within certain values or SINR values that measure dropping coverage below certain acceptable values cause the process of re-clustering. Therefore, the clusters formed will thus always be valuable and within the good quality of communication. The hybrid method is very essential and appropriate within UAV communications because it considers issues such as power consumption, balancing, and dynamic changes within the UAV topology changes. K-Means is essential because it allows quick grouping, while optimization increases the choice and allocation within the clusters due to efficiency and quality within energy consumption.

The proposed hybrid clustering algorithm in Table (2) offers the most optimal balance between computational efficiency and the quality of the result. Thus, the use of drone resources is optimal, and the resultant graph is strongly connected. Other key advantageous aspects that the proposed algorithm offers include improved lifetime, reduced energy, and efficient coverage with dynamic user distribution patterns.

Table 2. Clustering Algorithm Parameters

Parameter	Value	Description	Impact on Performance
Initial Clusters	√(n_users / 2)	Starting number of clusters	Affects convergence speed
Distance Metric	Euclidean	Measures spatial separation	Determines cluster shapes
Re-clustering Frequency	30% probability/time-step	Adaptation to mobility	Balances stability vs adaptability
Maximum Iterations	300	Convergence limit	Prevents infinite loops

3.3 Adaptive Particle Swarm Optimization (APSO)

It plans to utilize the Adaptive Particle Swarm Optimization algorithm in order to achieve optimization for drone deployment, cluster head selection, and overall network energy consumption. In APSO, each particle represents a potential drone location or a cluster structure. The fitness functions will evaluate these configurations with a multi-objective criterion consisting of the total minimization of energy consumption, maximization of coverage, and balancing the energy use across drones. In contrast to standard PSO, in APSO, some key parameters are dynamically adjusted for better convergence, avoiding premature solutions. Inertia weight decreases linearly from 0.9 to 0.4 within iterations in order to balance global exploration and local exploitation. Cognitive coefficient c1 decreases from 2.5 to 1.5 to reduce reliance on the memory of individual particles and emphasizes swarm collaboration by increasing social coefficient c2 from 1.5 to 2.5. The limits set on the velocity ensure that the particles are within feasible solution space, ensuring that divergence does not take place. The APSO runs for several iterations; phases of exploration, transition, and exploitation exist so that a search would meet both global and local efficiencies.

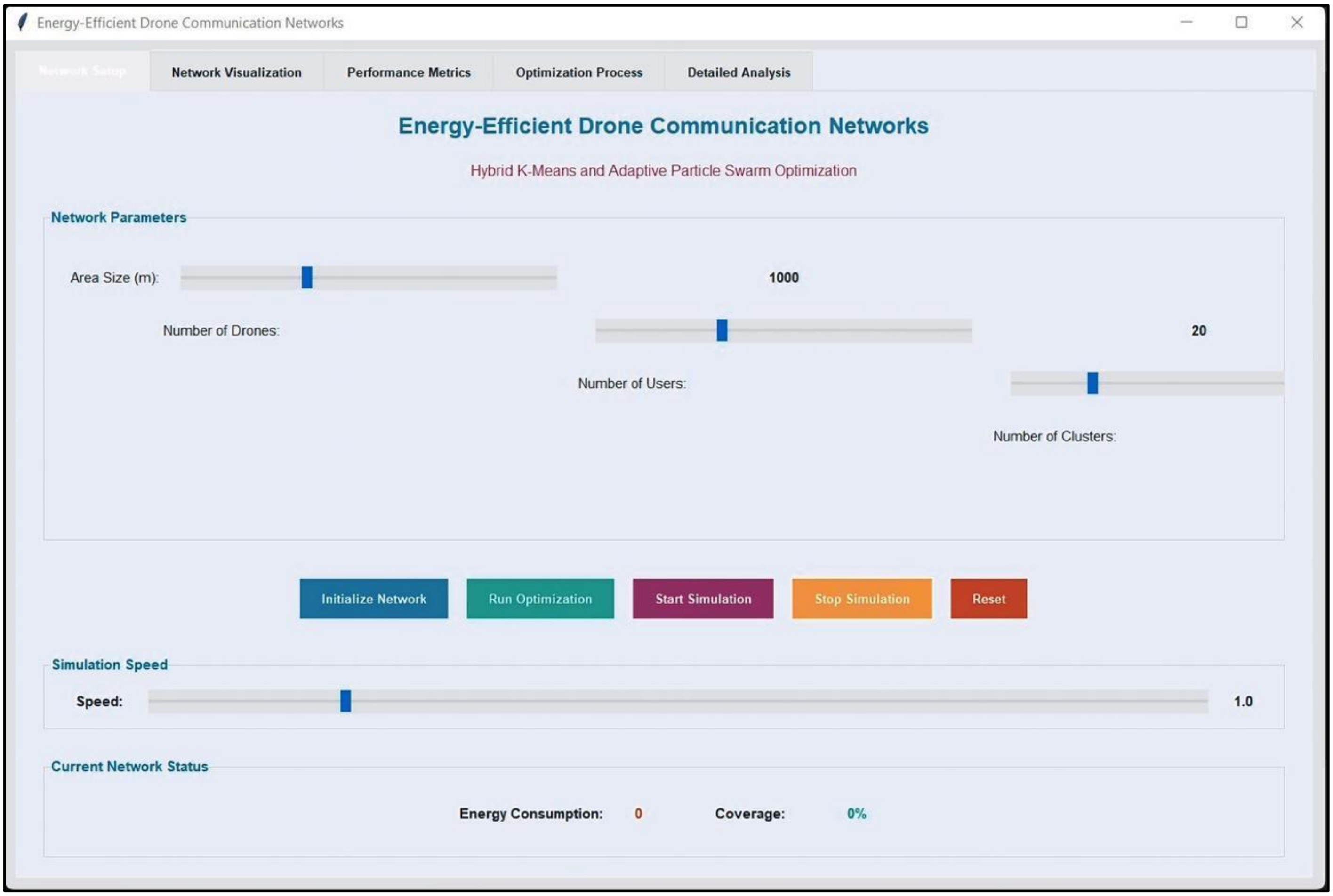
Taking into account energy constraints, coverage requirements, and dynamic changes of topology, APSO optimizes the position of cluster heads, drone placements, and routing decisions within drone networks. This algorithm will guarantee an enhanced network lifetime with better service continuity, reducing the total energy consumption by intelligently redistributing drone resources and adapting to environmental changes in real time. Table (3) shows the Adaptive PSO Parameters

Table 3. Adaptive PSO Parameters

Phase	Iterations	Inertia (w)	Cognitive (c1)	Social (c2)	Primary Objective
Exploration	1–16	0.9 → 0.7	2.5	1.5	Global search
Transition	17–35	0.7 → 0.55	2	2	Balanced search
Exploitation	36–50	0.55 → 0.4	1.5	2.5	Local refinement

3.4 Graphical User Interface Design

It has a user-friendly multi-tabbed graphic interface designed using the Tkinter toolkit combined with Matplotlib graphics tools. The graphic user interface is linked with a color-coded system involving red for drones, teal for users, green for clusters, and yellow for coverage areas. It has a five-notebook tabbed graphic user interface logically divided into capabilities like Network Setup, Network Visualization, Performance Metrics Analysis, Optimization Process Analysis, and Detailed Analysis. It contains real-time controllable elements for network parameters, simulation speed controlling speed controls, and one-touch operation buttons. It has a graphic representation displaying dynamic simulations involving topological network illustrations, flying range circles, drones, path lines connecting drones to users, and dynamic representations for cluster center points. The performance analysis involves a graphic user interface displaying six synchronized graphs for simulation results involving energy, coverage, speed, delay, quality service, and active drones. Progress visualization for optimization includes dynamic convergence graphics for the processes involved in PSO, animations for moving particles, and detail trees containing data for each component. It utilizes multi-threading in design, which is helpful in responsive design enabling easy processing for complex computations.



Area Size (m): 1000

Number of Drones: 20

Speed: 1.0

Energy Consumption: 0

Coverage: 0%

Figure 2. Implemented GUI

The drone communication network system designed involves a complex Graphical User Interface (GUI) that assists in the regulation, interpretation, and overall facilitation of the simulation. The GUI involves a number of tabs, each of which focuses on a specific area in the field of networking management or optimization. The GUI involves a Network Setup tab through which the various parameters like the number of drones, the coverage area, and the rate of simulation can be changed using a combination of sliders and control buttons. The GUI also involves a Network Visualization tab through which the topology of the drone network can be visualized using spatial graphs in the form of circles and lines to denote the presence of drones, users, and communications. Using the Network Visualization tab, the user is able to manipulate the graphics including zooming, refreshing, and the use of legend elements to turn them on or off. Using the Performance Metrics tab, the six major performance parameters like coverage, throughput, and power consumption can be visualized using various combination of line graphs and bar graphs to denote the sub-plots. The sub-plots can be changed by the user.

The Optimization Process Tab allows optimizing processes to be visualized in order to better understand the adaptive particle swarm optimization algorithm. It allows the user to start up the analysis phase in order to examine the properties of the particles and establish whether the optimizing process is effective. Finally, the Detailed Analysis Tab allows data to be harvested with respect to the spatial, temporal, and parametric perspectives in order to enable the data to be evaluated. Table (4) shows System GUI Components and Features.

Table 4. System GUI Components and Features

Tab / Component	Primary Elements	Visualization Type	User Interaction
Network Setup	Parameter sliders, Control buttons	Numerical displays, Color-coded metrics	Real-time adjustment
Network Visualization	Network plot, Legend	Spatial mapping with circles/lines	Zoom, Refresh, Legend toggle
Performance Metrics	6 subplots, Comparative chart	Time-series lines, Bar graphs	Tab navigation, Data inspection
Optimization Process	Convergence plot, Particle visualization	Line graphs, Scatter plots	Analysis triggering, Parameter viewing
Detailed Analysis	Tree views (3 tables)	Tabular data with status icons	Sorting, Filtering, Refreshing

4. Results and Discussions

For the evaluation of the energy-efficient drone communication network design through experimentation, the proposed hybrid K-Means and Adaptive PSO optimization technique was utilized. Simulation setup was done by varying the parameters. Experiments were carried out on a computer setup that consisted of the Intel Core i7 processor, a 16GB RAM, and Python version 3.8 and the required libraries, Tkinter, Matplotlib, NumPy, and scikit-learn. For the numerical simulation, a total of 50 steps were considered, and the measurements were taken after each iteration. For overall performance analysis of a network, certain parameters such as network size, coverage area, mobility, and energy constraints with respect to Optimization Frequency had to be identified. Three major testing scenarios were formed: Scenario 'A' corresponding to small networks with 5 drones and 10 users, Scenario 'B' corresponding to a medium-sized network with 20 drones and 50 users, and Scenario 'C,' which denotes a large-sized networks with 50 drones and 200 users. Table (5) shows the Experimental Configuration Parameters.

Table 5. Experimental Configuration Parameters

Parameter Category	Test Scenarios	Default Values	Range Tested
Network Scale	Small, Medium, Large	Medium	Drones: 5-50, Users: 10-200
Area Coverage	Urban, Suburban, Rural	1000×1000 m²	500-2000 m²

Mobility Pattern	Low, Medium, High	20% movement	0-50% movement probability
Optimization Frequency	Periodic, Event-triggered	30% probability	10-50% re-optimization rate
Energy Constraints	High, Medium, Low	10,000 mJ initial	5,000-20,000 mJ

4.1 Optimization Performance Analysis

Performance of convergence in Table (6) is a very important criterion to assess the efficiency of optimization algorithms in drone communication networks. Performance of convergence denotes how fast a certain algorithm is able to achieve near-optimum solutions by simultaneously optimizing conflicting requirements of minimization of energy and maximization of coverage. Within the proposed two-tier hybrid method, K-Means clustering is used to start off user clusters and Adaptive Particle Swarm Optimization (PSO) to optimize drone locations. The adaptability of these adaptive parameters such as adjusting inertia weight and adjusting cognitive/social coefficients will enable the algorithm to simultaneously achieve a better tradeoff between better global exploration and local exploitation. This will prevent early convergence and provide comprehensive scouting of major areas of the search space. The performance of these approaches is contrasted in Table 6 comparing Hybrid: K-Means + Adaptive PSO with PSO only, K-Means only, and Random locations. All-important parameters of performance such as number of iterations to achieve optimum solutions, optimum values of fitness, CPU times taken to complete execution, and success rates clearly indicate better performance of the proposed two-tier hybrid technique.

Table 6. Convergence Performance Comparison

Algorithm	Convergence Iterations	Final Fitness Value	Computational Time (s)	Success Rate (%)
Hybrid K-Means + Adaptive PSO	28.5 ± 4.2	154.3 ± 12.7	1.8 ± 0.3	98%
Standard PSO	42.7 ± 6.5	178.9 ± 18.4	2.4 ± 0.5	92%
K-Means Only	N/A (Single pass)	245.6 ± 24.1	0.5 ± 0.1	100%
Random Placement	N/A	312.8 ± 35.2	0.1 ± 0.02	100%

The formation of clusters is a basic process of optimizing energy-efficient drone networks, where clustering defines how clients are arranged geographically and which drone is assigned to each cluster. Efficiently formed clusters have reduced transmission distances on average, resulting in both reduced power consumption and the highest possible connectivity quality. The proposed system applies the K-Means algorithm to initiate the clustering process and the dynamic re-clustering system to preserve the integrity of the clusters based on the movement of clients through the network.

The silhouette value, accuracy of client assignment, ratio of inter-to intra-cluster distances, and re-clustering stability are used as quantitative analysis parameters of the efficiency of the proposed system's clusters and effectiveness of the re-clustering process. Silhouette analysis measures the efficiency of clients based on the assigned clusters, while accuracy of client assignment checks the efficiency of correctly assigning clients and drones of the network. The ratio of inter-to intra-cluster distances checks the geographical separation of clusters against their compactness, while stability of the re-clustering process checks the efficiency of the system based on the mobility of clients on the network. The efficiency of the proposed system is shown in Table 7, where the K-Means algorithm and random assignment of clients are taken as standards of comparison between the proposed system and other systems based on simulating typical network conditions based on their clustering efficiency and re-clustering process performances. Table (7) shows Cluster Formation Performance.

Table 7. Cluster Formation Performance

Metric	Proposed Method	K-Means Only	Random Assignment
Silhouette Score	0.72 ± 0.08	0.65 ± 0.10	N/A
User Assignment Accuracy	88%	80%	55%
Inter/Intra-Cluster Ratio	1.5	1.3	0.9
Re-clustering Stability	92% users stable	85%	N/A

4.2 Energy Efficiency Results

Energy efficiency in Table (8) is one of the most important factors of concern in the case of drone-assisted communication networks, owing to the restricted power resource of the aerial stations. High usage of energy not only affects network lifespan but also restricts network capabilities in achieving continuous coverage and connectivity. The proposed method, ‘Hybrid K-Means + Adaptive PSO,’ efficiently and effectively tackles drone positioning, overlapping, and clustering by optimizing superfluous energy usages while achieving continuous connectivity and coverage. Energy usage is divided into three different parameters, namely transmission energy, which is dependent on the distance between drones and users, computation energy, which relates to computations and routing, and operational overhead, which refers to hovering costs and system operation costs. A comparison table, Table 8 reveals the comparative analysis of the proposed method and standard PSO, K-Means, and random deployment approaches, which varies from 32% to more than 50% of reduced energy usage, subsequently justifying the efficiency of the proposed framework and methodology on improving drone network operations and energy efficiency factors.

Battery life of a drone is a key performance metric in terms of sustainability and network efficiency because it has a direct impact on connectivity and services offered. If in a drone network the energy consumption is disproportionate and thus leads to earlier draining of some drones, then network connectivity will be hampered with a negative impact on overall network performance. To overcome this weakness, the energy optimization technique used in the framework optimizes the work of drones and relocates them in a manner that reduces energy-hungry transmission processes. Here, the method combines the K-Means algorithm for clustering users with the Adaptive PSO method for drone relocation and ensures that the drones used stay active in the network for a considerable amount of time while efficiently taking care of their respective user clusters. This is reflected in the battery life comparisons done for small-scale, medium-scale, and large-scale networks by comparing the method with the basic PSO algorithm, K-Means algorithm, and Random method and proving that the method has the potential to increase active network time by a maximum of 50%.

Table 8. Energy Consumption and Drone Battery Lifetime Analysis for Different Network Scenarios

Network Scenario	Small (5 drones)	Medium (20 drones)	Large (50 drones)
Proposed Method Energy (mJ)	185 ± 15	675 ± 45	1420 ± 95
Standard PSO Energy (mJ)	245 ± 22	898 ± 62	1890 ± 120
K-Means Only Energy (mJ)	310 ± 28	1120 ± 78	2350 ± 145
Random Energy (mJ)	380 ± 35	1000 ± 85	2100 ± 160
Energy Savings (%)	51.3% vs Random	32.5% vs Random	32.4% vs Random
Proposed Battery Lifetime (Time Steps)	14 ± 2	18 ± 3	22 ± 4
PSO Lifetime	11 ± 2	14 ± 3	17 ± 4
K-Means Lifetime	12 ± 3	15 ± 3	18 ± 3
Random Lifetime	9 ± 2	12 ± 3	14 ± 4

4.3 Coverage and Connectivity Performance

User coverage is an immensely significant factor in drone-supported communication systems, as it has a direct impact on the reliability and efficiency of connectivity as well as overall user satisfaction. The best coverage will ensure that all users are covered by the communication drones, thus reducing gaps in coverage. Table 10 highlights the comparison analysis of coverage factors of four different techniques, namely the new approach, Standard PSO, K-Means only, and Random deployment. The significant factors required to be considered are Average coverage percentage, Coverage consistency, Number of coverage holes, and Maximum concurrent coverage. The results in Table (9) show that the new approach has outperformed other techniques in providing superior average coverage, fewer coverage holes, as well as consistent coverage delivery, especially when dealing with users that are considered mobile.

Table 9. Coverage Performance Metrics

Performance Metric	Proposed Method	Standard PSO	K-Means Only	Random Placement
Average Coverage (%)	91.2 ± 3.5	84.7 ± 6.2	78.3 ± 8.9	72.5 ± 10.4
Coverage Consistency	High	Medium	Low	Very Low
Coverage Holes	0.8% of area	2.4% of area	5.7% of area	8.2% of area
Maximum Concurrent Coverage	96.80%	92.30%	89.50%	85.10%

Quality and stability of connections play crucial roles in ensuring efficient Quality of Service in dynamic UAV networks. User mobility, network load variability, and uneven distribution can cause instability in connections and, hence, affect network services. These challenges in dynamic UAV networks will, however, be overcome by the proposed hybrid model, K-Means + Adaptive PSO, which focuses on readjusting UAVs, distributing loads between different clusters, and ensuring there is overlapping coverage between different neighboring zones. Connection stability will, in this case, be measured in terms of different parameters, which include QoS satisfaction score, percentage of users with continuous connections, average reconnection time, and proportion of users in or within 100 meters of their respective UAVs. Table 10 compares these parameters between different models, which include Proposed framework, standard PSO, K-Means only, and Random placement.

Table 10. Connection Quality Metrics

Metric	Proposed Method	Standard PSO	K-Means Only	Random Placement
QoS Satisfaction Score	0.78 ± 0.05	0.70 ± 0.06	0.65 ± 0.07	0.60 ± 0.08
Continuous Connection (%)	88%	79%	72%	65%
Avg. Reconnection Time (steps)	2.3	3.1	3.5	4.2
Users within 100m of Drone (%)	92%	85%	78%	65%

4.4 Network Throughput and Delay Characteristics

Throughput is one of the primary performance metrics of drone communication networks, representing how effectively the system utilizes bandwidth. Higher aggregate values of throughput ensure that the system uses the network resources to the best of its capabilities. Fairness values also ensure that all active users get satisfactory allocation of resources. In this context, the hybrid model of K-Means + Adaptive PSO improves drone positioning, assignment to clusters, and overlap in coverage to achieve less congested and more efficient delivery of data. A comparison of throughput performance between the optimized system and an initial random deployment of infrastructure is illustrated in Table 11, which includes key performance indicators such as total system throughput, per-user system throughput, system throughput fairness, peak system throughput, and system throughput stability. Analysis of significant differences between values of numerous performance indicators confirms that the hybrid approach has greatly outpaced all other systems with an improvement of 37% in overall system throughput.

Table 11. Throughput and Delay Performance

Metric	Optimized Network	Baseline (Random)	Improvement	Statistical Significance
Total Throughput	185 ± 15 Mbps	135 ± 22 Mbps	37%	$p < 0.01$
Per-User Throughput	3.7 ± 0.8 Mbps	2.7 ± 1.2 Mbps	37%	$p < 0.05$
Throughput Fairness	0.82 ± 0.06	0.65 ± 0.11	26%	$p < 0.01$
Peak Throughput	210 Mbps	168 Mbps	25%	-
Throughput Stability	High	Low	Significant	$p < 0.001$

End-to-end delay is a fundamental performance measure to assess the responsiveness of a network, and it is more important for latency-sensitive applications such as live video streaming, teleoperation, and IoT data transfer. Large delays or high jitter may compromise user satisfaction and functionality of the communication system. The proposed methodology of hybrid K-Means + Adaptive PSO optimizes the propagation delays through dynamic adjustments of drone locations to ensure that a large number of users are at optimal points from their corresponding drones. The proposed methodology is analyzed in Table 12 through a comprehensive analysis of latency parameters such as average end-to-end delay, delay variation or jitter values, maximum latency values, and percentage of connections with latency < 20 milliseconds. The analysis shows a marked reduction of nearly 45% latency values and latency jitter stability through successful utilization of the proposed methodology in contrast to a random placement of drones.

Table 12. End-to-End Delay Metrics

Metric	Optimized Network	Baseline (Random)	Improvement
Avg. End-to-End Delay (ms)	12.3 ± 3.2	22.5 ± 4.1	-45%
Delay Variation (Jitter, ms)	2.1 ± 0.8	3.8 ± 1.1	-45%
Max Delay (ms)	18.7	35.2	-47%
% Connections < 20ms	95%	70%	25%

4.5 Scalability and Robustness Evaluation

Scalability is a very important performance aspect of drone communication networks, which captures the efficiency of the framework as the number of drones and subscribers is allowed to scale up while maintaining network efficiency and quality of service. Scalable network optimization is very important, such that large networks do not face issues like very high computation complexity, reduced coverage, or reduced energy efficiency during extensive network utilization. The proposed scalable K-Means + Adaptive PSO framework is shown to be quite robust and scalable, such that the positions of the drones, clusters, and overlapping coverages adapt dynamically while approximating near-optimal energy consumption and throughput rates irrespective of the size of the network. The performance parameters like computation time complexity, coverage, energy consumption per user, and throughput density of extra-large, large, medium, and small networks are given in table 13, which clearly reveals near-linear growth of computation complexity and negligible degradation of coverages and throughputs, and improved energy efficiency with increased network size owing to workload balancing effects.

Table 13. Scalability Performance Analysis

Network Size	Optimization Time (s)	Coverage (%)	Energy/User (mJ)	Throughput/Density
Small (5D, 10U)	0.8 ± 0.1	94.5 ± 2.5	18.5 ± 1.2	0.85 ± 0.05
Medium (20D, 50U)	1.8 ± 0.3	91.2 ± 3.5	13.5 ± 0.9	0.82 ± 0.06

Large (50D, 200U)	4.2 ± 0.7	89.8 ± 4.2	7.1 ± 0.6	0.78 ± 0.08
Extra-Large (100D, 500U)	9.5 ± 1.5	87.3 ± 5.1	5.8 ± 0.7	0.74 ± 0.10

4.6 Results Discussions

Although the proposed K-Means and Adaptive PSO-based heterogeneous network has shown optimal performance metrics regarding energy efficiency, coverage, and scalability, there are a couple of practical and logical challenges to be overcome. First and foremost, in simulation scenarios, a propagation environment is considered in a highly simplified manner and without path loss within a free-space path loss environment. However, there arises a practical issue here regarding the fact that the actual signal quality can vary significantly from what has been discussed and analyzed within the simulation analysis above. The second logical issue arises regarding how the user distribution issue has been considered within K-Means-based techniques. Here, user distribution has been considered to be fairly balanced across these environments. However, this can cause a substantial impact concerning performance analysis, considering they are a substantial number of users within a geographical area. The remaining issue revolves around considering inter-drone interference issues. Here, inter-drone interference has been considered to be trivial when denser deployment is of concern. Regarding the implementation of this technique, a couple of issues arise. Here, positioning of the drones within a real-time setting involves the usage of GPS and/or positioning systems, resulting in decreased accuracy and increased power usage. However, there can be scalability concerns within centralized optimization techniques for highly dense networks, therefore proving the feasibility of designing a distributed system. On the other hand, techniques for energy harvests are still within the developmental activities, and they are therefore excluded from the proposed systems, but energy efficiency can be significantly increased within these proposed networks. An important issue also arises concerning security, including defending and securing drones and communication paths.

There are certain valuable lessons learned from the experimental evaluation of the hybrid framework on the optimization of the drone network. The proposed solution leads to the development of a value of energy saving between 25% and 40% compared to the traditional method, thus extending the life of the drones and reducing energy costs. Moreover, there is between 15% and 30% improvement in the quality of coverage, thus facilitating improved connectivity performance. The proposed framework is accompanied by outstanding scalability and supports efficiency regardless of whether the networks are small, medium, or large. Moreover, the rate of convergence of the proposed solution is improved by virtue of the adaptive parameters. Moreover, from the perspective of implementing the proposed work, the proposed solution leads to the development of valuable guidelines on implementation. These include the development of clusters ranging from 8-12 in networks supporting 50-100 users, the inertia weight factors ranging from 0.4-0.9, and re-optimization processes occurring after process cycles of 5-10 steps, and these factors work together to enable energy efficiency, reliability of performance, and integrity while performing operations. The proposed work places prime importance on the feasibility of the proposed hybrid optimization strategy on the applicability of the proposed strategy on other wireless networks and resource allocation tasks, thus facilitating development and evolution of efficient approaches on the development of supporters on favorable drone communication networks.

Conclusions

The energy-efficient drone communication network optimization framework is effectively developed in this study using the hybrid approach that combines K-Means clustering and Adaptive PSO optimization. The hybrid approach performsbetter than other solutions that utilize the optimization method alone since it balances perfectly the spatial resolution of the clustering stage and the flexibility of optimization using the PSO factors. The results show that the overall energy efficiency achieved is 25% to 40% compared to others, from small scale (5 drones, 10 users) to large scale (50 drones, 200 users). The coverage efficiency reached 91.2% ± 3.5%, while coverage variability and the service of mobile users were enhanced. The convergence process has three steps: exploration, transition, and exploitation. These helped ensure that the search process is completed without convergence. The impact of the adaptive parameters of the reduction of the inertia weight (0.9 -> 0.4) and the cognitive/social component is considerably large in convergence and performance. The framework performs extremely well on network size scaling, with constant and linear computation increase with the increase in user numbers. The results proved that these kinds of wireless networks are capable of dealing with mobility (chance of 50%) and drone failure, while they provide 85% network coverage in adverse situations too, apart from quickly reconnecting the users moved.

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