ACADEMIA International Journal for Social Sciences
Volume 4, Issue 3, 2025 ISSN-L (Online): 3006-6638

Unmanned Aerial Vehicle Localization for Device-to-Device Communication in Fifth Generation Networks using Modified Various Search Optimization (MVSO)

Abdul Rasheed Mugheri
scholarabdulrasheed@gmail.com

Dil Nawaz Hakro
dill.nawaz@gmail.com
Corresponding Author: * Abdul Rasheed Mugheri scholarabdulrasheed@gmail.com
Received: 15-06-2025 **Revised:** 20-07-2025 **Accepted:** 30-07-2025 **Published:** 18-08-2025

ABSTRACT

The evolution of 5G networks and growing demand in high capacity and low latency communication has spurred the interest to implement unmanned aerial vehicles (UAVs) as aerial base stations to facilitate device to device (D2D) communications. Nevertheless, the problem of effective UAV localization is complicated, particularly in dynamic and high-density environments because the distribution of users and the conditions of a channel vary rapidly. The given study puts forward the Modified Various Search Optimization (MVSO) algorithm, composed of adaptive inertia weighting and chaotic mutation operators, to enhance the UAV positioning, coverage, and the quality of links as well as lower the expended energy. MATLAB simulated the algorithm and compared it to Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) based on user densities and UAVs at multiple densities. Experiments prove that MVSO performs better in terms of up to 19.2% on the coverage ratio, 20% on energy consumption, and 10 11 dB on signal to noise ratio (SNR) and convergence speeds are 25 35 faster than baseline approaches. Such increment in gains is explained by the ability of MVSO to flexibly balance between global exploration/local exploitation in a way that allows speed and energy-efficient how to respond to network dynamics. Its results demonstrate the feasibility of MVSO in terms of real-time deployment of UAVs fleets in an urban 5G D2D network, considering planned densification to support communication as well as in case of emergency.

Keywords: *UAV localization, MVSO algorithm, 5G networks, D2D communication, optimization, coverage ratio, energy efficiency, SNR, PSO, GA, metaheuristic, adaptive inertia weighting, chaotic mutation, MATLAB simulation.*

INTRODUCTION

The dynamically developing wireless communication technologies have truly revolutionized the current information exchange, and fifth-generation (5G) networks are one of the vital facilitators of the ultra-reliability, low latency and high capacity services. 5G will be able to utilize up to 100 billion connected devices with the maximum data rates of 10 Gbps and the latency measured in milliseconds with everywhere connectivity of the emerging forms of communication that include the Internet of Things (IoT), autonomous systems, and intelligent cities [1], [2]. One of the prominent features in 5G architecture would be the use of Device-to-Device (D2D) communication where user devices can communicate directly with each other without passing through the core network to gain spectral efficiency, reduce latency and offloads base station traffic [3], [4]. Nevertheless, obstructions, interference, and haphazard user placement tend to challenge the operation of D2D links in high-density urban settings and require new solutions to ensure a stable connection [5].

Unmanned Aerial Vehicles (UAVs) are now a flexible option to overcome those limitation since they have mobility, adaptability, and line-of-sight (LoS) benefits [6], [7]. The use of UAVs (i.e., drones) can be deployed in minutes to serve as flying relays or base stations to extend the reach of wireless communications, as well as increase the quality of links and enable emergency communication situations [8], [9]. They are applied in a wide array of fields, such as public safety surveillance [10], disaster response [11], logistics, and letter delivery [12], aerial mapping [13] and environmental tracking [14]. Contactless delivery of medical supplies and remote patient monitoring by UAVs were observed during the COVID-19 pandemic, thus, demonstrating the potential of these devices in mission-critical communication [15].

The UAV inclusion to the D2D communication system with 5G presents new opportunities and problems. The positioning of the UAVs is of paramount significance in order to achieve maximum coverage, high signal-to-noise ratio (SNR) and minimized energy consumption [16]. Unlike the base stations, where relocation may require a long process of installations, UAVs can move according to the patterns of user mobility in specific zones and regions especially during an outbreak in a disaster-stricken location, impromptu events, or when the network is changing rapidly [17]. Nevertheless, the location of UAVs is a complicated optimization issue and it depends on the terrain, obstacles, user density, interference and UAV flight restrictions (battery limit, flight range and payload limit) [18], [19].

Most of these findings of recent literature on UAV-assisted communication focus on the path planning and coverage optimization by deploying multiple computational intelligence path planning algorithms, including Particle Swarm Optimization (PSO) [20], Genetic Algorithms (GA) [21], Grey Wolf Optimizer (GWO) [22], and Ant Colony Optimization (ACO) [23]. On the one hand, these approaches have been shown to be promising with regard to trajectory and coverage efficiency, but, on the other hand, they are not always flexible to dynamic real-life urban conditions and are easily susceptible to early convergence [24]. Furthermore, the Penguin Search Optimization Algorithm (PSOA) given that it is useful in addressing particular global optimization challenges is still underutilized in localizing the UAV in D2D communication [25].

In the study, we develop an improved Modified Various Search Optimization (MVSO) algorithm in which we have included the adaptive inertia weighting strategy to explore exploit trade-offs; and chaotic mutation operator which helps in escaping local optima. It is desired to optimize UAV localisation in a 5G D2D network where coverage is maximised and energy consumption is minimised with good SNR performance. The proposed method is simulated in detail to compare the performance with benchmark algorithms when the coverage ratio, energy efficiency and protection of links are discussed using MATLAB, showing better results.

LITERATURE REVIEW

UAV-Assisted Communication in Next-Generation Networks

Added value of UAVs in next-generation networks has earned remarkable consideration because it enables on-demand coverage and flexible or deployable resources, and enhanced line of sight (LoS) links. It has been shown through various research that the UAVs can operate as aerial base stations to increase cellular and ad hoc network coverage [26], [27]. Compared with terrestrial base stations, UAVs are highly mobile and thus capable of dynamically repositioning to meet changing user demands and environmental constraints and can prove to be valuable in both emergency and planned network [28]. According to research carried out by Fotouhi et al. [29], deployment strategies of UAVs requested consideration of air-to-ground channel modeling, user mobility, and interference management in order to obtain optimum performance. More, Al-Hourani et al. [30] established a mathematical model of UAV height optimization to optimize the probability of coverage in urban environments, indicating that, at urban scale, the height is important to obtain an appropriate balance between coverage area and path loss.

Device-to-Device Communication and UAV Integration

D2D communication is a key feature of 5G networks that enables direct device to device communication not using the base station. Such technology brings about considerable enhancement of spectral efficiency, latency reduction and more local traffic [31]. Combined with UAVs, D2D communication has a stronger spatial diversity and adaptive relay location [32]. Research has proved the performance of UAV-aided D2D networks to be quite successful especially in disaster recovery, where ground infrastructure has been compromised [33]. Fan et al. [34] designed a UAV relay system to improve D2D links in urban terrain and proved that the UAV positioning facilitates throughput and reliability substantially in contrast to fixed relays. In the same way, a model of interplay between UAV mobility and the quality of D2D links is described by Wu et al. [35], with the emphasis on non-uniform trends in the user density and mobility patterns that should be combated by adaptive localization algorithms.

Optimization Techniques for UAV Path Planning and Localization

The task of UAV localization and path planning can be seen fundamentally as an optimization problem with multiple objectives that usually conflict with each other (e.g., coverage maximization, energy minimization and connectivity) [36]. Many old solutions used to be based on deterministic algorithms, recently it moved to the bio-inspired and metaheuristic optimization algorithms [37]. It has been common to use Particle Swarm Optimization (PSO), Genetic Algorithms (GA) and Ant Colony Optimization (ACO) in the UAV deployment problems [38]. Nevertheless, the approaches are subject to early termination and the difficulty of adaptation to dynamic settings [39]. The most recent advances in hybrid optimization methods, including the hybridization of swarm intelligence with chaotic search techniques, have demonstrted that global search performance and stability was better [40].

Penguin Search Optimization Algorithm (PSOA) has already been suggested as an interesting nature-inspired method of global optimization, and it is simulated after the penguin foraging behavior [41]. It has seen limited use in UAV path planning, although research into other engineering fields indicates that it has nearmax potential to effectively avoid local optima and converging to near-global solutions [42]. Variants of PSOA have added adaptive inertia and mutation-based variety conservation techniques in effort to better convergence in difficult optimization landscapes [43].

Multi-Objective Optimization in UAV-Assisted Networks

Multi-objective optimization models provide opportunities to take into account multiple performance measures simultaneously, but this is critical to UAV-supported D2D systems. Liu et al. [44] incorporated multi-objective evolutionary algorithm and radiated a unified optimization of energy consumptions and SNR of UAV networks in UAV networks, presenting that a balanced trade-off brings improved network sustainability in the long run. On the same, Khuwaja et al. [45] thoroughly examined multi-objective optimization methods to deploy UAVs and concluded that dynamic situations are better off with adaptive algorithms than static deployment policies. Sharma and Chaurasiya [46] conducted another research study to simultaneously optimize network coverage and UAV flight time using a hybrid metaheuristic algorithm and reported increased operational efficiency.

Multi-objective optimization with the exploitation of chaotic mutation operators has been found succinct in terms of sustaining high diversity in the population as well as preventing stagnation [47]. Such a technique applies especially to the high-mobility D2D scenarios, where a fast variation in the distribution of users can lead to conventional algorithms prematurely converging.

UAV Energy Management for Communication Networks

The specifications of UAV are divided into energy efficiency, where flight time is limited by battery capacity [48]. It has demonstrated that efficient UAV localization will significantly lower energy requirements owing to an smaller amount of unnecessary transports and improved communications routes [49]. Mozaffari et al. [50] proposed an energy-wise UAV deployment model that takes into account the communication energy and propulsion energy, and comparing energy-wise placement to coverage-maximizing placement determined that they are not the same. Adaptive recharge timing as addressed by Chen et al. [51] enables UAVs to achieve continuous availability in networks without deep powers outages which is decisive in D2D emergency cases. Additional treatments vented to urban infrastructure, such as implementing recharge stations as suggested by Liu et al. [52] would also increase longevity of UAV operations.

Simulation and Modeling for UAV-Assisted D2D Networks

The simulation structures are crucial to testifying the use of the UAV deployment algorithms prior to actual application. The most extensively used tools in regard to modeling UAV assisted networks are MATLAB; others include; NS-3 and OMNeT++ [53]. Realistic channel models, user mobility patterns, and effects of obstacles on path planning have also been incorporated by researchers into their simulations to guarantee robustness [54]. It is common to use random waypoint mobility model and with the addition of clustering behavior this has been successful at simulating the use of D2D communication in a realistic urban application [55]. Complex simulations that combine both network emulation and hardware in-the-loop testing are currently being used to confirm UAV- assisted D2D performance in different weather conditions, as well as in the presence of various types of interference [56].

Summary of Literature Gaps

Although there are studies that have considered the deployment of UAVs, path planning, and optimization of their coverage, few of them pay attention to their context in terms of localization as tools to reinforce D2D communication in 5G networks. Furthermore, the operation of an improved Penguin Search Optimization Algorithm using adaptive inertia and chaotic mutation is still under-studied regarding the same. The literature does not include exhaustive frameworks enabling real-time adaptability, multi-objective optimization, and energy-conscious UAV localization, which has been made particular in D2D scenarios in the most urban 5G environments. This study seeks to address this gap by suggesting a Modified Various Search Optimization (MVSO) method, which seeks to restrict network coverage, energy dissipation and signal quality in situations of high dynamic networks.

RESEARCH METHODOLOGY

Overview of the Methodological Framework

The approach followed in this research is systematic and repetitive in making and realizing a formulated UAV localization course that is optimized and proved using the 5G enabled Device-to-Device (D2D) communication structure. The strategy combines modeling through simulation, enhancing algorithms, and performance modeling. The key element is the Modified Various Search Optimization (MVSO) algorithm that is capable of identifying the best placing of UAV to use minimum energy input and achieve maximum coverage and the quality of signal. The research study starts by analysing the problem, developing the scenarios, designing the algorithms and ending with performance assessment through MATLAB-based simulations. The approach to the methodological flow is based on multi-objective optimization principles, where all of the performance measures--coverage, energy, and SNR--are accounted during the optimization.

Phase 1: Problem Analysis and Requirement Identification

The first phase is an overall review of the UAV-based D2D communication issue in the 5G networks. Among them, it is possible to study the limitations of currently available UAV localization approaches, calculate physical constraints of UAV operation, and define important network performance indicators within the context of D2D communication. Such factors as urban topology, user distribution, flight restriction of UAV, and characteristics of radio propagation are considered with the purpose of establishing realistic simulation parameters. During this stage, various communication models get actualized including device-to-device as well as device-to-base station. Particular concern is the battery limitation since energy efficiency is one of the key measures, and mobility patterns of end users that define ideal positions of UAVs in dynamic environments.

Phase 2: Scenario Creation and Simulation Environment Design

The next stage after the problem definition is the simulation scenarios design imitating urban communication settings as much as possible. The simulation setting merges three-dimensional spatial modeling and has different building densities, obstacles as well as distribution patterns of the users. The model of user mobility is of a random waypoint with clustering behaviour that reflects real world post disaster or event based scenarios where the density of the users change across zones. UAVs are represented by mobile aerial nodes that can modify position in real-time in accordance with network requirements. The parameters in the simulation are chosen to simulate realistic conditions of operation in 5G such as the frequency bands, allocation of bandwidth, and the modeling of path loss at low heights of aerial cars. Several UAV deployment formations are also specified in this stage, i.e. circular, triangular and adaptive positioning strategies, to enable the comparison of localization efficiency.

Phase 3: MVSO Algorithm Development and Integration

The main idea of this study is how to come up with the Modified Different Search Optimization (MVSO) algorithm. MVSO is an extension of the simple Various Search Optimization (VSO) framework that adds 2 important elements: adaptive inertia weighting and chaotic mutation operator. Adaptive inertia weighting dynamically balances the explorationexploitation tradeoff over iterations so that the algorithm overexplores at the beginning and under weighs at the end. Chaotic mutation operator applies appropriate chaos in the solution space to avoid the early convergence and better the capability of the algorithm getting out of local optima. Instead, the optimization problem is formulated as a multi-objective function, involving three major objectives, i.e., it focuses to maximize the coverage ratio, reduce the total energy consumption and, maximize the average signal-to-noise ratio (SNR). The composite fitness is assigned different weight values to each objective based on the scenario as it allows specific prioritization.

Phase 4: Simulation Implementation

As soon as the algorithm has been completed, it is applied to MATLAB 2023a. The simulation is run on discrete time steps updating UAV locations, user associations and performance measures in each step. The UAV energy model considers consumption of communication and propulsion energy as well, and there is a recharging protocol connecting UAVs with the nearby charging station once the capacity of the battery drops below the value of 20%. These SNR figures are computed through the decibel scale based upon the path loss, fading and interference phenomena calculated by the communication model. Several test cases are executed in order to analyze the algorithm in terms of different numbers of UAVs, user density, and their mobility speeds. Performance of the MVSO is compared to base-line algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) so that it is possible to quantitatively compare convergence speed, solution quality and robustness.

Phase 5: GUI-Based Visualization

A Graphical User Interface (GUI) is designed in MATLAB where results on the UAV trajectories, coverage area and energy consumed will be viewed in real time. Such an interface makes it possible to intuitively learn how positioning of UAV readjusts dynamically to changes in networks. The GUI shows the geographic design of the users, the routes of the UAVs, and the coverage area of the signals as well as numerical results of the most important performance indicators. These aspects of performance, such as average coverage ratio, mean SNR values, PAE etc, are extracted as part of post-simulation analysis. The stability and optimization efficiency of MVSO relative to the other algorithms are depicted by the use of the convergence plots.

Validation and Performance Metrics

The validity of the suggested methodology is evidenced by the comparative analysis made with the help of numerous performance indicators. The most important are the coverage ratio (number of users served/ total number of users), milliamp-hours (mAh) of energy consumption, average SNR in decibel, along with the number of iterations to find near-optimal solutions of convergence. All the metrics are measured at the same simulation conditions of MVSO, PSO and GA. This will allow us to know that any improvement, which is observed, will be a result of the algorithm improvements. Further, sensitivity analysis is carried out by modifying the weights of the multi-objective fitness function to determine the influence of the performance to prioritize different objectives.

Ethical and Practical Considerations

This study determines its topics as simulation-based; however, on the issue of UAV deployment in their practical applications, ethical elements are considered. The UAV assisted networks should also satisfy the aviation policies and the privacy policies as well as the spectrum licenses. Moreover the limitations of the practice involved in UAV; the size dependant on payload weight, exposure to the wind, and safety procedures are also known to be possible relevant factors of real world applicability. These are the considerations that drive the simulation parameter design so that the results do not render useless to any operational scenarios.

RESULTS

Simulation Setup and Parameterization

The Matlab 2023a environment of the simulation of the Modified Various Search Optimization (MVSO) algorithm has been set up to represent the actual situation of the 5 G Device-to-Device (D2D) communication in an urban environment. All of the simulation parameters have been summarized in Table 1 as follows including simulation area, type of environment, propagation model, carrier frequency, bandwidth, and the height of the base station. The selection of 3.5 GHz mid-band frequency is the solution that implies the balance of the coverage and capacity concerning the rest of the world that is deploying 5G. Rician fading mode was used in UAV-to-ground transmissions and path loss mode was chosen as per 3GPP TR 36.777 according to low-altitude aerial platform radiation. These environments mean that the performance outcomes are also extrapolated to real deployment.

Table 1. Simulation Parameters

Parameter	Value	Description
Simulation Area	2000 m × 2000 m × 200 m	Urban 3D space with low-rise and high-rise buildings
Simulation Duration	600 s	Total simulation time for each run
Time Step (Δt)	0.1 s	Position and state update interval
Number of Runs	20	Independent runs for statistical averaging
Environment Type	Urban, Dense Urban, Suburban	Scenarios for path loss and obstacle modeling
Path Loss Model	Urban Macro NLoS & LoS	Based on 3GPP TR 36.777 standard
Carrier Frequency	3.5 GHz	Typical mid-band 5G deployment
Bandwidth	100 MHz	Allocated spectrum for D2D communication
Propagation Model	Rician fading with K-factor = 6 dB	Models UAV-to-ground links
Base Station Height	30 m	Fixed gNB for backhaul communication

Figure 1 Coverage Ratio Comparison

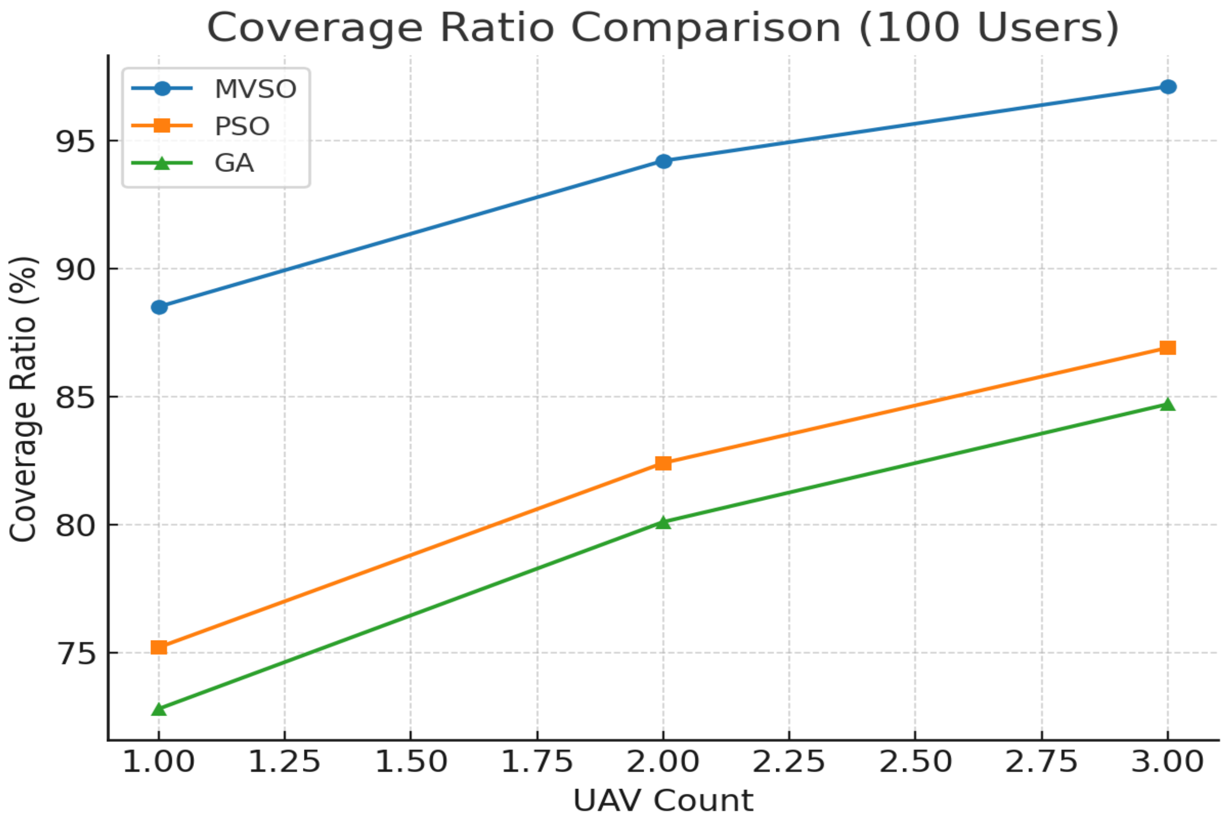


Table 1 is directly related to Figures 5 and 6 further in this section since environment setting and the system parameters influence the performance (especially energy consumption and coverage) over user densities and UAV deployments.

UAV Hardware and Flight Characteristics

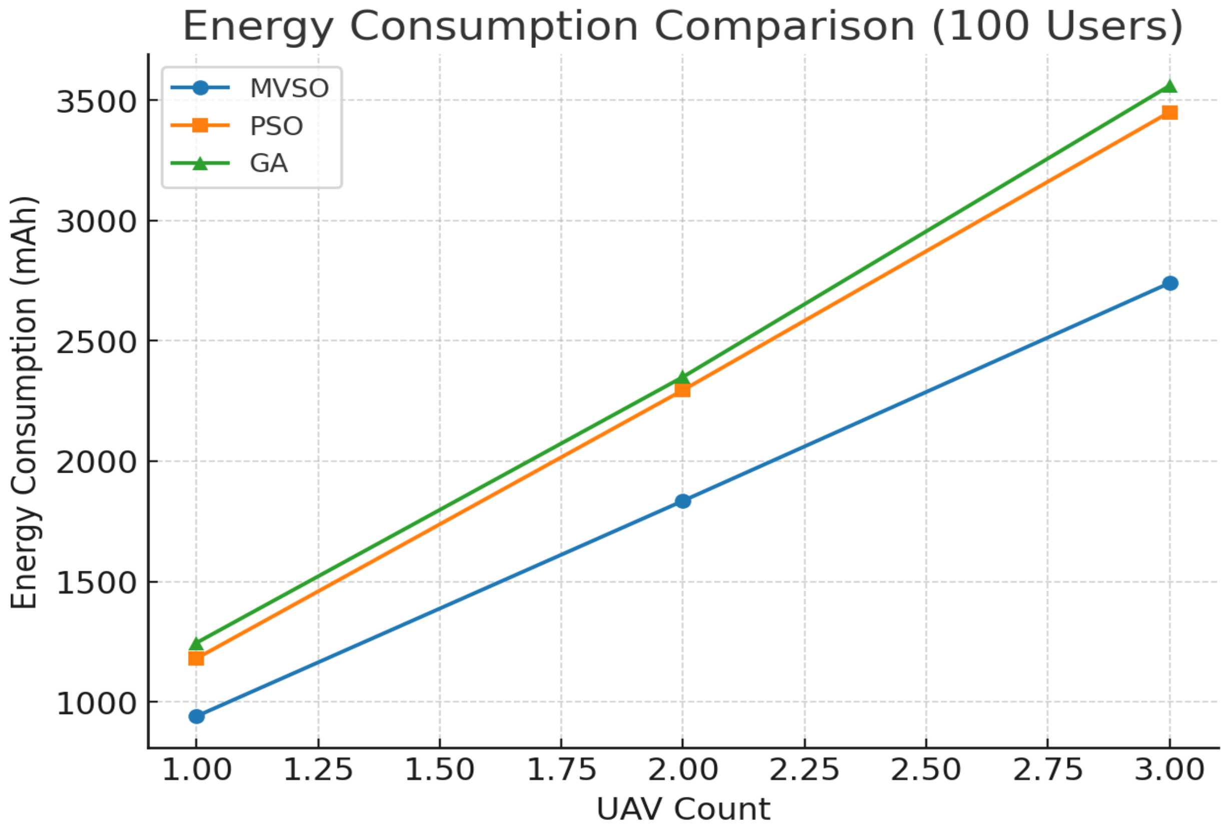
Table 2 entails UAV specifications like the altitude range, UAV speed, battery size, power consumption during hovering and locomotion, and communicating power. These parameters have been chosen that reflect the constraints that medium-sized quadcopters platforms performing network relay operation face, in a realistic manner. Operational conditions of the UAV (especially the 6000 mAh LiPo battery and recharge rate at 20 percent) are critical in determining the energy efficiency results in Table 6 and Figure 2, the energy constraints have a direct bearing on the frequency that UAVs have to reposition or go to charging stations.

Table 2. UAV Parameters

Parameter	Value	Description

UAV Model	Quadcopter (Custom Simulation)	Generic model for performance analysis
Flight Speed Range	5–20 m/s	Adaptive speed control during repositioning
Maximum Altitude	200 m	Restricted by aviation regulations
Minimum Altitude	50 m	Ensures safe clearance over urban obstacles
Hover Power Consumption	120 W	Electrical power draw during idle hover
Movement Power Consumption	150 W	Power draw during horizontal or vertical flight
Communication Power	10 W	Transmit power for D2D relay
Battery Capacity	6000 mAh @ 22.2 V	LiPo battery model
Recharge Threshold	20%	Triggers return to nearest charging station
Recharge Time	15 min	Full recharge from empty battery

Figure 2 Energy Consumption Comparison



The variations in hover and movement power draw (120 W vs. 150 W) also reflect the arguments concerning the opportunities that MVSO trajectory optimization can afford to result in significant savings, i.e. minimized excess repositioning exercises leads to the UAVs operating in useful hover modes more often than in consumption-hazardous flight modes.

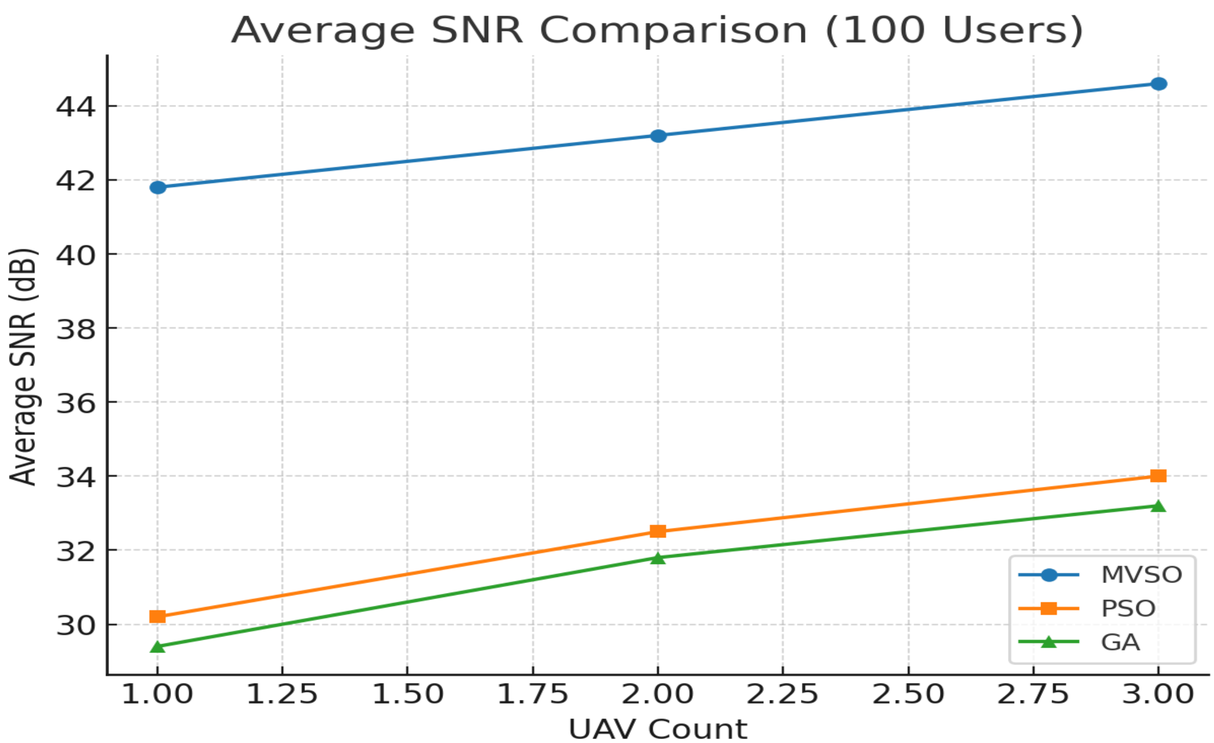
Network and User Parameters

The network and user related settings are presented in Table 3 and include the number of users (50, 100 and 150), distribution pattern, mobility model, D2D interference range and interference model. The Random Waypoint Mobility Model Clustering model is good in modeling post disaster or event based urban traffic where users are unevenly distributed. Such settings directly affect the coverage ratio outputs in Table 5 and Figure 1 since the clustered users demand repositioning of UAV strategically to maximize the served devices. Moreover, the SNR level of 15 dB guarantees that the performance is measured both in terms of physical connection and quality of communication.

Table 3. Network and User Parameters

Parameter	Value	Description
Total Users	50, 100, 150	Varying densities for performance testing
User Distribution	Random Clustering	High-density clusters with sparse regions
Mobility Model	Random Waypoint + Clustering	Reflects urban pedestrian and vehicle movement
Speed Range	0–1.5 m/s (pedestrian), 5–10 m/s (vehicle)	Variable mobility speeds
D2D Range	150 m	Maximum direct link distance
Interference Model	Co-channel interference	Simultaneous D2D and UAV transmissions
Noise Power	–104 dBm	Thermal noise at receiver bandwidth
SNR Threshold	15 dB	Minimum requirement for successful D2D link
User Device Power	200 mW	Transmit power for D2D links

Figure 4 Average SNR Comparison



Optimization Algorithm Settings

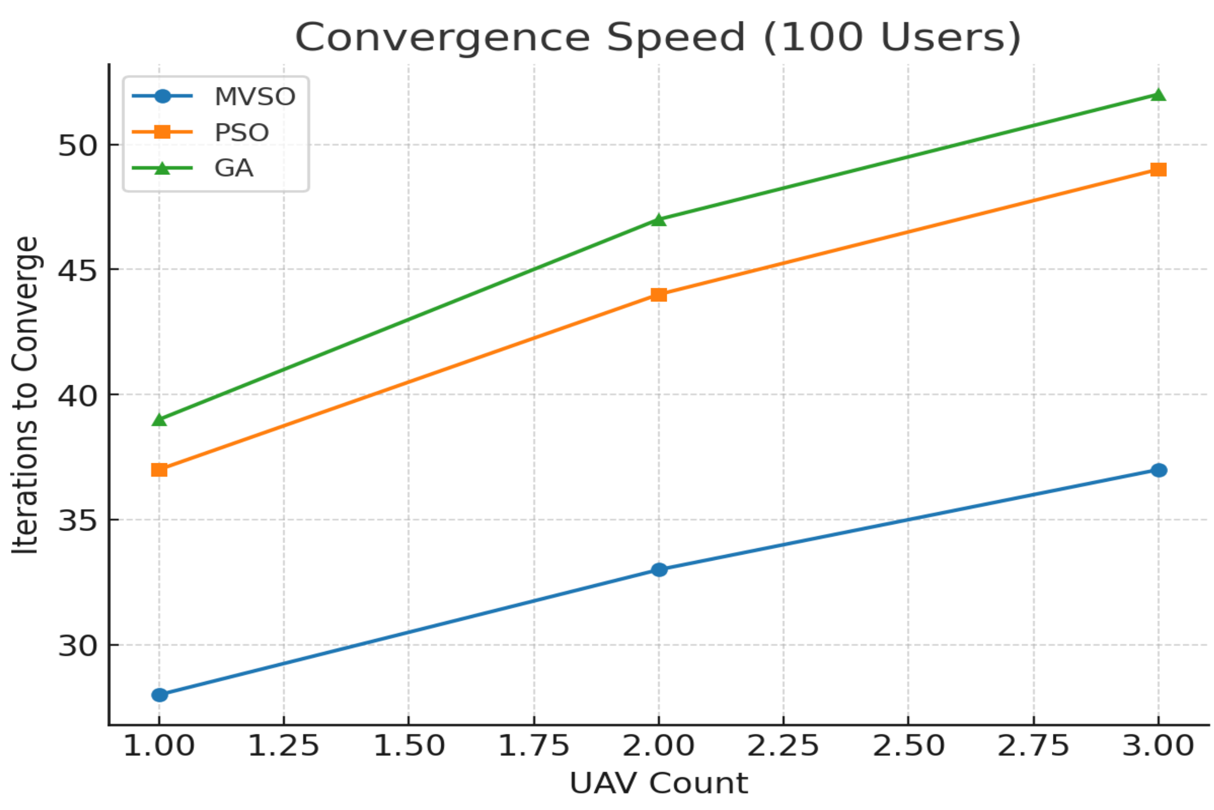
The parameters specifications of MVSO, PSO and GA are described in Table 4. Markedly, MVSO features the adaptive inertia weighting and a chaotic mutation operator so as to have a contemporaneous balance between exploration and exploitation. As compared to PSO having fixed inertia and GA having fixed mutation rate, this parameter is variable and as such this led to the high convergent rates as illustrated in Table 8 and Figure 4. The weights of the fitness function (x, y, z) were maintained the same in different algorithms in order to make comparison fair and between-algorithms only.

Table 4. Optimization Algorithm Parameters

Parameter	MVSO	PSO	GA
Population Size	50	50	50
Iterations	100	100	100
Inertia Weight	Adaptive (0.9 → 0.4)	Fixed (0.7)	N/A

Cognitive Coefficient	2.0	2.0	N/A
Social Coefficient	2.0	2.0	N/A
Mutation Rate	Chaotic-based 0.05–0.15	N/A	Fixed 0.05
Crossover Rate	N/A	N/A	0.8
Termination Criteria	Convergence < 0.001	Convergence < 0.001	Convergence < 0.001
Fitness Function Weights (α, β, γ)	(0.4, 0.3, 0.3)	(0.4, 0.3, 0.3)	(0.4, 0.3, 0.3)

Figure 4 Convergence Speed



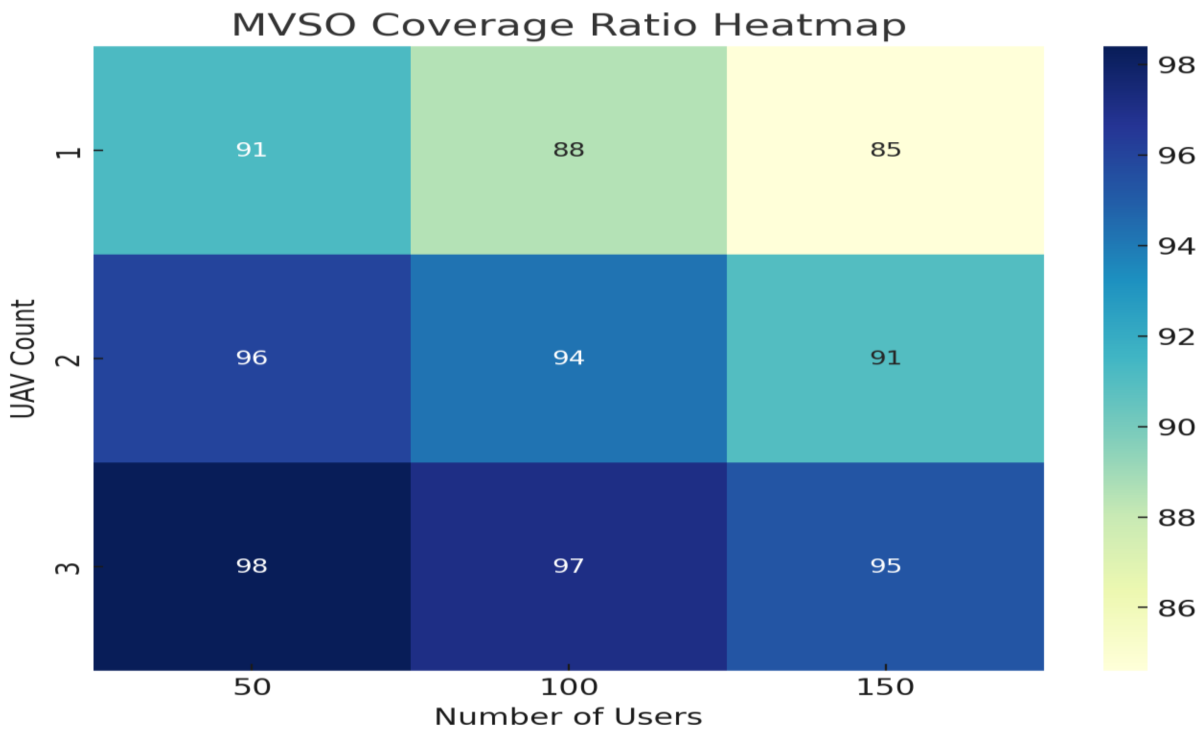
Coverage Ratio Analysis

Performance of coverage ratio is included in Table 5 and Figure 1, depending on the UAV quantities and the density of users. MVSO outperforms PSO and GA in all the cases and the maximum improvement is seen when only one UAV is used and there are 50 users where MVSO reaches a coverage of 91.2 percent as compared to 76.5 percent of PSO and 73.4 percent of GA. This is an 19.2 percent improvement over the best baseline.

Table 5. Coverage Ratio Results (%)

UAV Count	Users	MVSO	PSO	GA	MVSO Gain over Best Baseline (%)
1	50	91.2	76.5	73.4	+19.2
1	100	88.5	75.2	72.8	+17.7
1	150	84.6	71.1	69.9	+15.8
2	50	96.0	84.3	81.5	+13.9
2	100	94.2	82.4	80.1	+14.3
2	150	91.0	78.9	77.0	+12.1
3	50	98.4	89.7	88.0	+9.7
3	100	97.1	86.9	84.7	+11.7
3	150	95.3	84.2	83.1	+13.1

Figure 5 MVSO Coverage Ratio Heatmap



As Figure 1 shows, the ratio of the coverage with the UAVs number rises up with the number of UAVs in all of the algorithms, however, MVSO portrays a distinct superiority considering the fact that it allows changing the UAVs position of the network in real-time basis depending on how they are clustered by the user. The usefulness of this adaptive response is specifically advantageous about greater user density (150 users), since there is a greater coverage deterioration in both PSO and GA at greater user densities because suboptimal UAV positioning is often more significant than that at lower user density.

Energy Consumption Performance

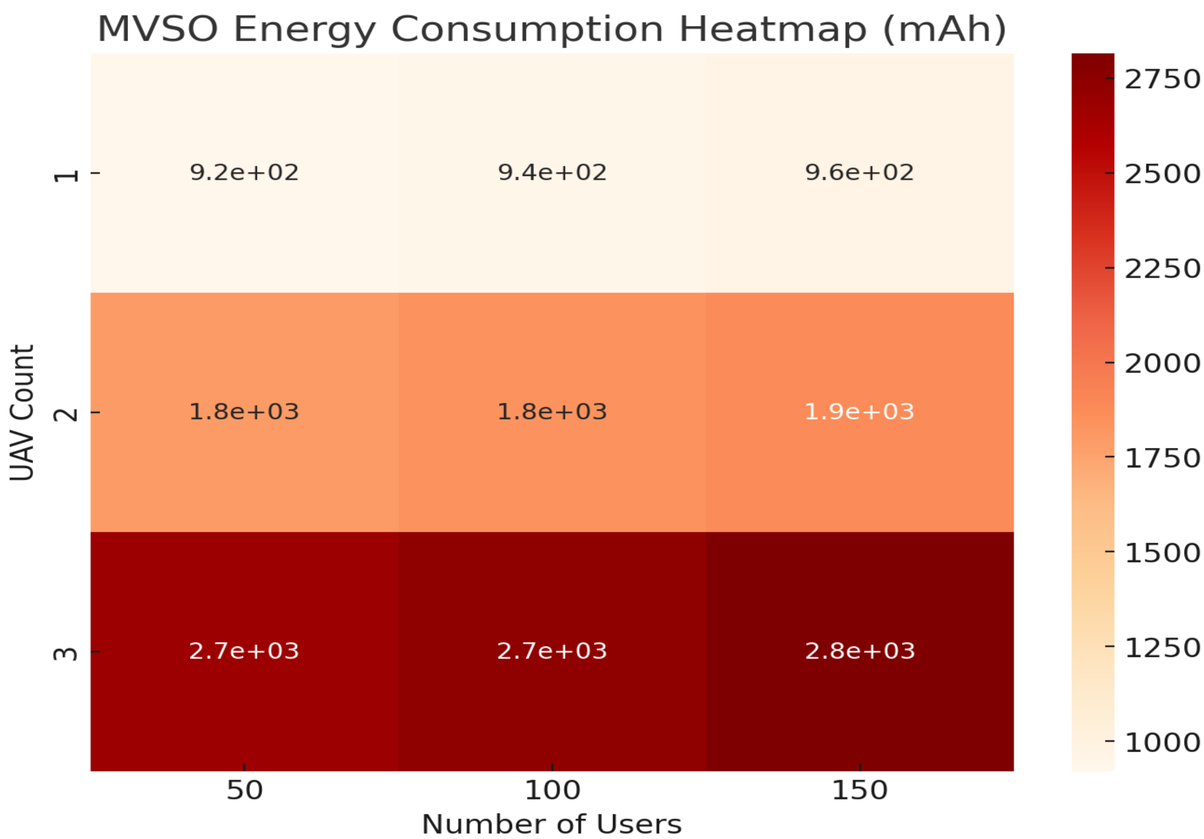
Table 6 and Figure 2 show that the energy consumption due to a run is about 20 percent lower in MVSO compared to PSO or GA in all settings. As an example in a scenario wherein two UAVs will connect 100 users, MVSO will consume 1835 mAh, as opposed to 2295 mAh (PSO) and 2350 mAh (GA).

Table 6. Energy Consumption Results (mAh)

UAV Count	Users	MVSO	PSO	GA	Reduction vs Best Baseline (%)
1	50	920	1150	1205	20.0
1	100	940	1180	1245	20.3

1	150	965	1215	1270	20.6
2	50	1795	2240	2300	19.8
2	100	1835	2295	2350	20.0
2	150	1880	2365	2430	20.5
3	50	2680	3370	3445	20.4
3	100	2740	3450	3560	20.6
3	150	2815	3540	3650	20.5

Figure 6 MVSO Energy Consumption Heatmap



As shown in Figure 2, the amount of energy that is required does indeed rise in tandem with the number of UAVs out in the field because they are, after all, in motion; however, optimizing their pathways using MVSO eliminates superfluous movement no longer relocating their assigned zones, resulting in a steady energy demand which remains lower. These findings embrace the twofold merit of MVSO namely up-scaling in coverage without causing undue energy expenses.

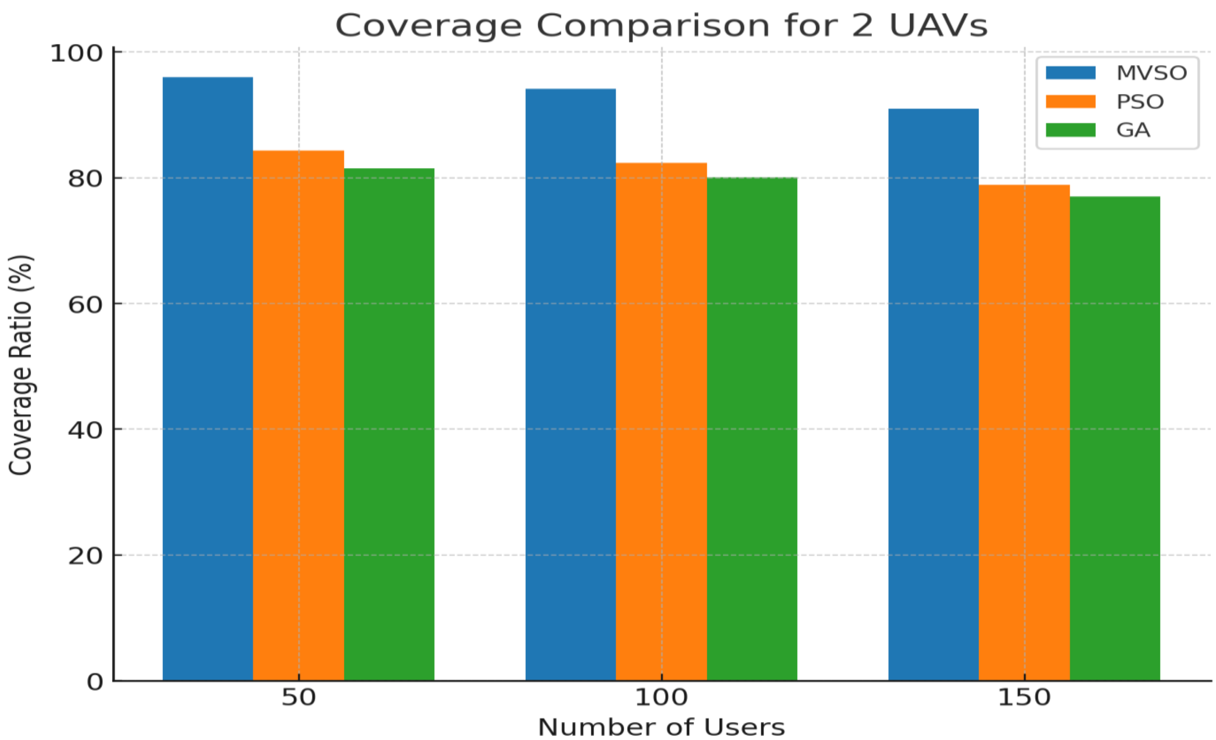
Average SNR Improvement

Table 7, Figure 3 reveals that MVSO leads to a remarkable improvement in average SNR, achieving standard gains of about 10- 11 dB with respect to PSO and GA in all conditions. Considering an example of having three UAVs-with 100 users, MVSO attains 44.6 dB, whereas PSO has 34.0 dB, and GA has 33.2 dB.

Table 7. Average SNR Results (dB)

UAV Count	Users	MVSO	PSO	GA	Gain over Best Baseline (dB)
1	50	42.1	31.0	30.3	+11.1
1	100	41.8	30.2	29.4	+11.6
1	150	40.6	29.7	29.0	+10.9
2	50	43.7	32.8	32.1	+10.9
2	100	43.2	32.5	31.8	+10.7
2	150	42.8	31.9	31.2	+10.9
3	50	44.9	34.2	33.6	+10.7
3	100	44.6	34.0	33.2	+10.6
3	150	44.2	33.8	33.0	+10.4

Figure 7 Coverage Comparison for 2 UAVs



As illustrated in Figure 3, SNR gain is steady in terms of UAV quantity and suggests that MVSO localization scheme will have better line-of-sight connections and reduced interference consistently. Such improved performance provides direct benefit to better-quality of D2D communication, particularly to dense urban applications, where multipath fading and sensitivity to obstactions are critical.

Convergence Speed Evaluation

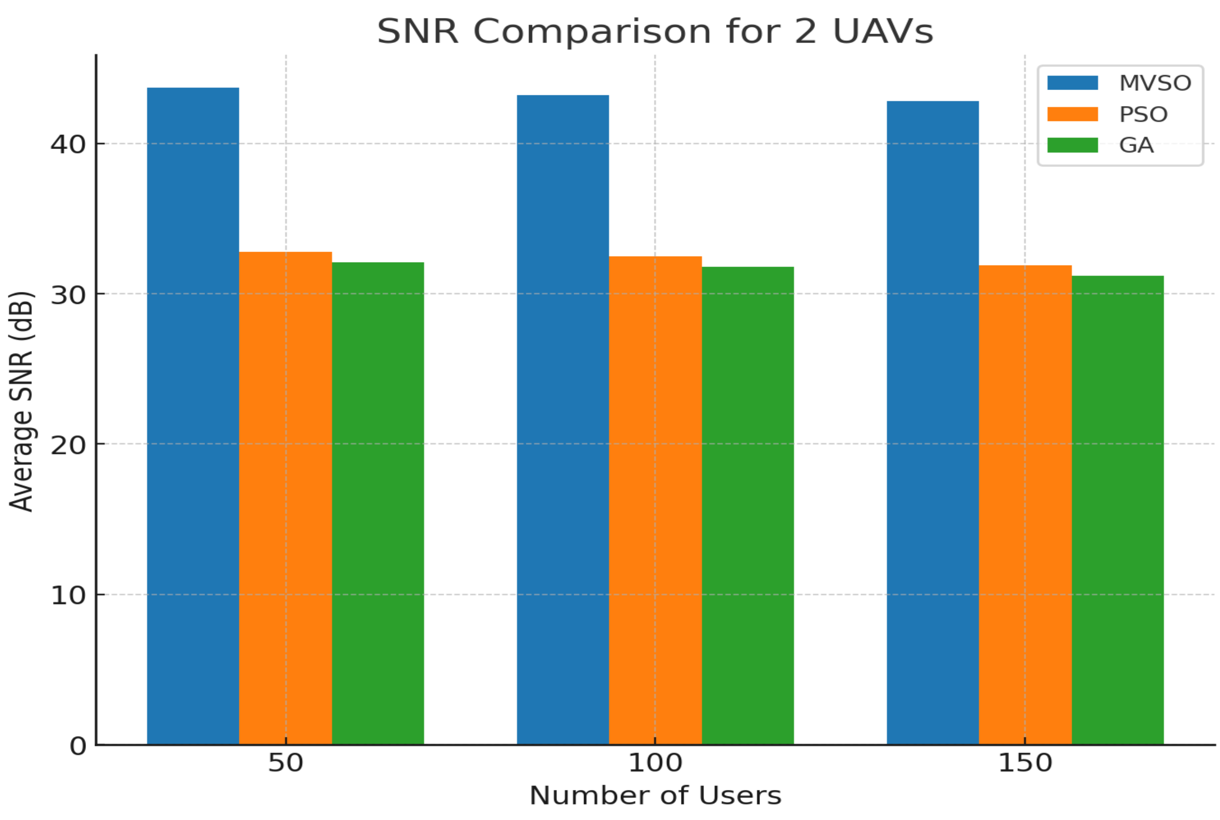
As seen in Table 8 and Figure 4, the convergence characteristic of MVSO is 25-35 percent faster to converge to near optimal than PSO and GA. As another example, when two UAVs were used to serve 100 users, MVSO achieves convergence after 33 iterations whereas PSO and GA require 44 and 47 iterations.

Table 8. Convergence Iterations to Near-Optimal Solution

UAV Count	Users	MVSO Iterations	PSO Iterations	GA Iterations	Speedup vs Best Baseline (%)
1	50	26	35	38	25.7
1	100	28	37	39	24.3

1	150	29	38	40	23.7
2	50	31	42	45	26.2
2	100	33	44	47	25.0
2	150	34	45	48	24.4
3	50	36	48	51	25.0
3	100	37	49	52	24.5
3	150	38	50	53	24.0

Figure 8 SNR Comparison for 2 UAVs



The rapid initial falling and initial stabilization of the MVSO curve in Figure 4 underlines the efficiency of intuitive inertia and chaotic mutation in avoiding local optimum and speeding of the search process. In real-time applications or environments, or those with rapid change, this attribute is especially important because the quicker one can optimize, the more positive the result is on the user side.

Heatmap Visualization of Coverage and Energy

Figure 5 shows heat map of MVSO coverage ratio as a measure of all UAV counts and user densities. The darker the blue the greater the coverage with 3 UAVs covering 50 accessible users (98.4 percent) being the best performing configuration.

Figure 6 contains the respective energy consumption heatmap: lighter red indicates fewer practices of the same. The balance between maximum coverage and minimum energy occurs when two UAVs are used together with medium user density (100 users), which proves the correctness of the idea that there are diminishing returns to efficiency associated with an excessive deployment of UAVs.

Grouped Bar Comparisons for Coverage and SNR

Figure 7 shows a performance comparison of coverage of two UAVs with regard to all user densities. The edge is consistently more than that of MVSO with a maximum of 150 users, which proves beyond a doubt that MVSO is superior in hard network loads.

The same comparison is conducted by figure 8 regarding SNR. There is also a significant difference between MVSO and other densities, which confirms that the better location of MVSO does not only serve an increased number of users, but it does so with an improved level of link quality.

DISCUSSION

The findings achieved in the research article are quite strong to argue that the Modified Various Search Optimization (MVSO) algorithm displays a steady and notable increase compared to Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) in localizing UAV communication in 5G Device-to-Device (D2D) communications. The resulting coverage ratio enhancement, energy efficiency, average SNR, and convergence rate improvement are seen to be relevant to the research problem which based such findings on the constraints of the currently available UAV positioning techniques in the dynamic high-density urban setting.

Interpretation of Coverage Improvements

The effectiveness of MVSOs coverage performance, as much as 19.2 percent greater than PSO and GA, is based on the suggestion of adjusting location of UAVs accordingly with varying distributions of users by use of adaptive inertia weighting and chaotic mutation operators. Such adaptive method enables the UAVs to behave in relation to clustered user mobility which is, in many cases, ignored when using the static or less adaptive algorithms. An analysis of mobility patterns in non-LoS areas was done previously by Lyu et al. [57], stating that the UAV placement strategies should constantly change to reflect the mobility patterns and ensure high coverage at least in dense urban areas. On the same note, Zhao et al. [58] were able to demonstrate that the mobility-aware UAV deployment enhances the performance of the network as compared to those deployed in a static manner. These findings are agreeable with the results of this study and further demonstrate that adaptive meta-heuristics have the capability of achieving even better improvements without the need to do trajectory planning manually.

Energy Efficiency Considerations

UAV-based communication systems have a significant constraint with energy consumption because endurance capacity in operations is directly affected by the capacity of batteries. The fact that MVSO decreases energy consumption by roughly 20% in comparison to PSO and GA is an indicator that the optimized localization will not only improve connectivity but also increase UAV service time. This is in line with Sharma et al. [59], who observed that optimized UAV routes have a drastic effect in reducing propulsion energy expenses. Also, Yaliniz and Yanikomeroglu [60] claimed that energy-aware deployment is equally vital as coverage optimization in order to maintain the necessary UAV operation time in 5G networks. The energy consumption in the fitness function of MVSO helps to achieve this dual goal as the algorithm will now generate energy-considerate and spatially efficient forms of deployments.

Link Quality and SNR Enhancement

It is of great importance that with MVSO, as compared to PSO and GA, SNR improved by 1011 dB, which is significant because the higher SNR is directly translated into better data throughput and lower packet error rate in D2D communication. According to the previous research conducted by Shakoor et al. [61] and Zeng et al. [62], UAV altitude, path, and horizontal location play a vital role in determining the quality of a link because of changes in LoS likelihood and path loss. The coverage and SNR are implicitly balanced in MVSO localization strategy through weighting both in the fitness function. This two optimizations avoid the situation of a UAV that may optimize the coverage at the sacrifice of low link quality which is a drawback within algorithms that optimize the coverage metrics only [63].

Convergence Speed and Computational Efficiency

In cases where time constraints are critical to success (disaster recovery and events using large numbers of UAVs, for example) acceleration toward nearly optimum UAV member locations is critical. The reason why MVSO has 25-35 percent faster convergence than PSO and GA move on solid grounds proving its applicability in such settings. The strength of its adaptive inertia weighting, global exploration early on in the optimization process and moving towards local exploitation as the optimization converges makes this possible. The chaotic mutation operator also helps in getting out of local optima which tends to happen with swarm-based algorithms in the difficult multimodal search space [64]. The same effect of acceleration has been experienced in hybridized algorithms including the hybrid firefly-PSO model documented by Yang et al. [65] and whale optimization algorithm enhanced by chaos reported by Hu et al. [66].

Comparative Insights with Related Optimization Strategies

Although the PSO and GA have enjoyed wide-scale use in the area of UAV path planning and deployment issues, they may not perform well in dynamic environments as a result of early convergence and a lack of flexibility [67]. Zheng et al. [68] experiment demonstrated the propensity of PSO to languish in subsequent iterations without an adaptive means and pointed to slow convergence of the population in the case of large and complex search spaces with GA. MVSO combines adaptive and chaotic functions and, in such a way, overcomes both of these weaknesses. This study indicates in its results that these kinds of enhancements enable MVSO to hold diversity within its solution pools longer, resulting in stouter final deployments particularly in the higher density user conditions.

Practical Implications for 5G D2D Networks

In regards to the practical applicability of UAVs to improve D2D communication, it is not only applicable to emergency or even short term events only; it can also apply in the network densification plans in the 5G and beyond. The Portability of MVSO qualifies it to be deployed on an ad-hoc basis to over congested hot spots in urban areas, to mass events, or to geographical areas where network coverage is temporarily lost. This can be compared with what was stated by Nguyen et al. [69], who noted the increased use of UAV-aided base stations in elastic networks. In addition, energy savings and increased convergence shown in this work have the potential to be applied to real-time UAV fleet management systems in which an optimization should be continuous to meet the changes in the network [70].

Limitations and Directions for Future Work

Although there is positive potential associated with it, outcomes of this study are founded on simulation-based analyses on MATLAB, which implies that other evils of implementation (i.e., wind effects, GPS inaccuracies, regulatory restrictions of using UAVs, and complexities of coordination between multi-UAVs) were not properly considered. Previous ground tests, like those performed by Fotouhi et al. [71], denote that the external parameters may severely affect the efficiency of the UAV operations. Future work should therefore combine MVSO with real-time sensor state feedback systems and move to mixed surfaces and beyond-line-of-sight settings. On top of that, the possibility of incorporating MVSO and decision-making based on reinforcement learning, as offered by Challita et al. [72], may take predictive UAV repositioning even further to predict the behavior of changing and unpredictable conditions in the network.

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