

A Multi-Objective Harris Hawks Optimization Framework for Bandwidth Allocation and Power Control in Multi-UAV'S Enabled 6G Networks

Sana Sateesh¹, K. Srinivasa Rao²

1.PG Scholar, Department of ECE, JNTUA Collage of Engineering, India.

2.Assistant Professor (Ad-hoc), Department of ECE, JNTUA Collage of Engineering, India.

E-mail: sateeshsana0@gmail.com, Srinivas.kollimarla.ece@jntua.ac.in.

1. <https://orcid.org/0009-0006-5543-2347>, 2. <https://orcid.org/0000-0001-5076-0591>.

Abstract—Allocating spectrum and choosing transmit powers in a 6G network made up of several unmanned aerial vehicles (UAVs) is a coupled, non-convex problem. A recent two-stage remedy [1] first divides the band with a graph-colouring model that is solved by Sequential Quadratic Programming (SQP), and then reduces the transmit powers with an M-matrix procedure. SQP is a local, gradient-driven method: where it ends up depends on where it starts, and its iteration count grows as the network becomes denser. In this paper the bandwidth stage is given to a Multi-Objective Harris Hawks Optimization (MO-HHO) algorithm, a derivative-free, population-based global search that works directly on the maximal-independent-set (MIS) space of bandwidth reuse, while the M-matrix power stage is retained unchanged. A rule-based natural-language-processing (NLP) front end is added as well, so that a ground operator can describe mission needs in everyday English, for example “guarantee at least 5 Mbps for the rescue-team relay and favour UAV-3”. The module extracts UAV identifiers and quality-of-service (QoS) keywords and turns them into the minimum-rate constraints used by the optimizer, which removes the need to edit constraint vectors by hand. Monte Carlo simulations for network densities of 0.5, 0.8 and 1.0 and for 3–8 UAVs report improvements of up to 32.8% in data rate and up to 26.1% in energy efficiency over SQP, and convergence in 2–3 iterations against 90–100 for SQP.

Key words—6G, multi-UAV networks, Harris Hawks optimization, M-matrix theory, bandwidth allocation, power control, spectral efficiency, energy efficiency.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) are widely considered as flying relay nodes for 5G-and-beyond systems. Because their air-to-air channels are largely line-of-sight, they suit disaster recovery, traffic offloading from ground base stations, temporary event coverage and the collection of data from Internet-of-Things devices [2]–[5]. Once a large fleet has to share a limited band while each aircraft is held below a battery-imposed power ceiling, the management of spectrum and power becomes a central design issue. The two decisions interact through the signal-to-interference-plus-noise ratio (SINR), which makes the joint problem both non-convex and non-linear. The customary way out is to split it into two parts: bandwidth is assigned first, with every UAV transmitting at full power, and the powers are afterwards lowered to the smallest values that still satisfy the SINR targets implied by that assignment.

Alnakhlī *et al.* [1] followed this path. They modelled the UAV network as a colouring graph in which maximal independent sets (MIS) identify groups of links that may reuse one band, solved the bandwidth stage with SQP, and closed with an M-matrix power-adjustment stage. SQP is a local method driven by gradients, so the solution it returns depends on the starting point, and it may need about a hundred iterations. That is a handicap when UAV

motion keeps altering the topology. The present work preserves the two-stage layout and the M-matrix power stage but swaps SQP for Harris Hawks Optimization (HHO), a population-based technique that requires no derivatives. A lightweight NLP interface is added through which plain-language operator instructions are converted into the numerical QoS targets the optimizer needs. The main contributions are the following.

- A Multi-Objective HHO (MO-HHO) formulation of the colouring-graph/MIS bandwidth problem, intended to avoid early convergence to local optima and to cut the number of iterations that SQP demands.
- Unmodified reuse of the M-matrix power-control stage, so that transmit powers stay minimal for the adjusted per-link SINR requirement and the energy-efficiency behaviour of the original design is retained.
- A rule-based NLP front end that converts free-text mission instructions into UAV-indexed minimum-rate and priority constraints, a capability absent from the reference schemes.
- A Monte Carlo study over three network densities (0.5, 0.8, 1.0) and 3–8 UAVs that quantifies the data-rate and energy-efficiency gains of MO-HHO over SQP, with MASPECT and random selection (RS) as further references, both with and without power control.

The remainder of the paper is organized as follows. Section II reviews related work, Section III presents the system model, Section IV describes the proposed method, Section V discusses the simulation results, and Section VI concludes the paper.

II. RELATED WORK

Resource management for UAV fleets has been approached from many directions. Reviews of non-terrestrial 6G technology [6], an energy-aware bandit-learning scheme for link selection with UAV-mounted reconfigurable surfaces [7], and a hierarchical multi-agent reinforcement-learning method for frequency reuse and power control [8] each address a portion of the problem. The study most closely related to ours is the graph-based bandwidth allocation scheme that couples a reuse model with iterative power control [1]. Its MIS bandwidth model was later extended by taking advantage of correlation among sources to improve spectral efficiency [2], and resource allocation under imperfect channel knowledge has been examined for NOMA-enabled satellite-UAV-terrestrial networks [9]. For the power stage, M-matrix theory yields a non-negative closed-form solution once the SINR target of each link has been fixed [10]. These works share one feature: a gradient-based solver is used for the discrete bandwidth-reuse decision, and such a solver can become trapped in local optima on the non-convex SINR landscape created by the mutual interference of the UAVs.

Population-based meta-heuristics such as HHO [11] have been strengthened through augmented variants [13] and used for UAV resource allocation together with other swarm-intelligence techniques [12]. By examining many candidate solutions simultaneously and moving gradually from exploration to exploitation, they rely less on the starting point and are better able to escape a local optimum. This observation motivates the use of HHO for the bandwidth stage in this paper, whereas the analytically optimal M-matrix procedure continues to handle the power stage.

On the interface side, NLP has been employed to translate an operator's intent into network policy. An NLP-based intent manager was demonstrated for private 5G networks [14]. Subsequent studies depend on large language models for intent life-cycle handling [15], zero-touch configuration [16] and attention-based hierarchical reinforcement-learning pipelines for intent processing [17], while [18] and [19] supply wider overviews of intent-based networking and ChatGPT-style network management. We carry this idea over to UAV mission-QoS specification in a deliberately simple, rule-based form, which avoids the computational cost of running a language model.

To place the present work among these studies, Table I summarizes the technique and scope of the principal related contributions as they are described above. None of them combines a global search for the bandwidth-reuse decision with an analytical power stage and a plain-language mission interface, which is the gap this paper addresses.

TABLE I
SUMMARY OF RELATED WORK

Ref.	Main technique	Scope
[1]	Colouring-graph MIS, SQP, M-matrix power control	Bandwidth and power, multi-UAV 6G
[2]	MIS model with source-correlation exploitation	Spectral efficiency, multi-UAV 6G
[8]	Hierarchical multi-agent reinforcement learning	Frequency reuse and power control
[9]	NOMA-based allocation with imperfect CSI	Satellite-UAV-terrestrial networks
[12], [13]	Swarm intelligence, augmented HHO	UAV resource allocation, path planning
[14]–[17]	NLP- and LLM-based intent handling	Network management and configuration
This work	MO-HHO, M-matrix, rule-based NLP	Bandwidth, power and mission QoS

III. CONCEPTUAL FRAMEWORK AND SYSTEM MODEL

Fig. 1 shows how the three parts of the proposed system are connected. The operator states mission intent in plain language and the NLP module converts it into numerical QoS constraints. These constraints enter the fitness function of the MO-HHO search over the MIS bandwidth space. The resulting allocation is passed to the M-matrix stage, which returns the smallest feasible power vector, and the combined bandwidth and power decisions are then used to select routing paths for data delivery. Because language understanding, combinatorial bandwidth search and analytical power control are kept apart, any one of them can be replaced later without disturbing the others.

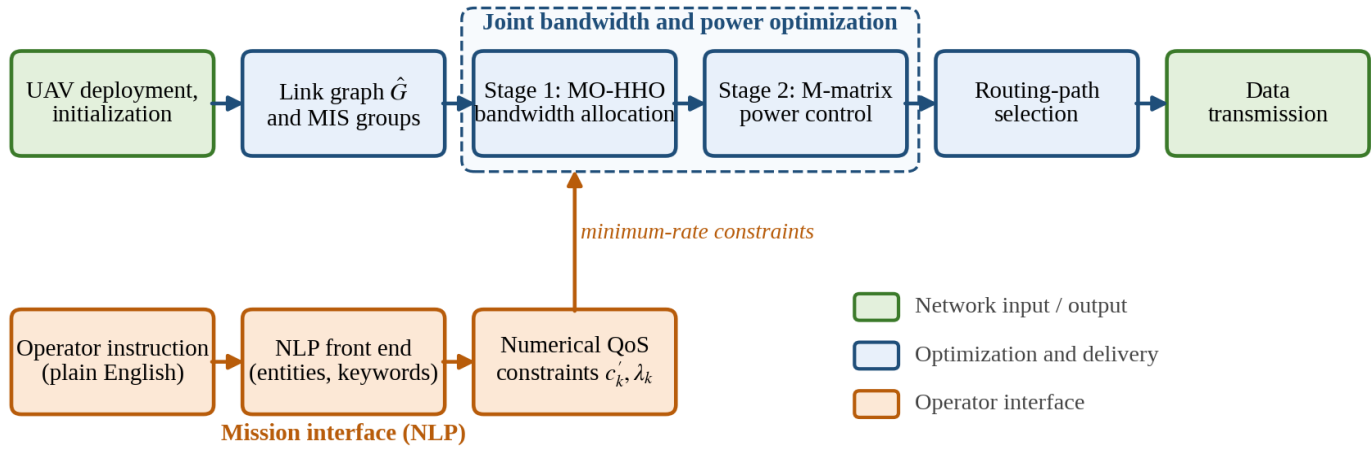


Fig. 1. Block diagram of the proposed framework. The NLP front end turns operator instructions into minimum-rate constraints for Stage 1 (MO-HHO bandwidth allocation); Stage 2 (M-matrix power control) then reduces the transmit powers before routing and data transmission.

The network contains M UAVs hovering at height h and joined by line-of-sight air-to-air links. For UAVs i and j separated by the three-dimensional distance d_{ij} , path loss and received power follow a log-distance model:

$$PL_{ij} [\text{dB}] = PL(d_0) + 10\alpha \log_{10}(d_{ij} / d_0) \quad (1)$$

$$P_{r,ij} [\text{dB}] = P_{t,i} [\text{dB}] - PL_{ij} [\text{dB}] \quad (2)$$

where $PL(d_0)$ is the path loss at the reference distance d_0 , α is the path-loss exponent and $P_{t,i}$ is the transmit power of UAV i . With all powers converted to linear units, the SINR and the spectral efficiency of the link $i \rightarrow j$ are

$$\text{SINR}_{ij} = P_{r,ij} / (\sum_{v \neq i} P_{r,vj} + \rho_0) \quad (3)$$

$$R_{ij} = \log_2(1 + \text{SINR}_{ij}) \quad (4)$$

where ρ_0 denotes the noise power. The goal is to maximize the total data rate

$$\max \sum_i \sum_j \eta_{ij} B_{ij} R_{ij} \quad (5)$$

The total data rate is R_{total} and the energy efficiency of a configuration is defined as

$$\text{EE} = R_{\text{total}} / \sum_i P_{t,i}$$

subject to (a) the total-bandwidth constraint $\sum_i \sum_j \eta_{ij} B_{ij} = B_{\text{tot}}$ and (b) the power limit $0 < P_{t,i} < P_{t,\text{max}}$, where η_{ij} is a pre-assigned connectivity indicator. Since (5) is non-convex, it is broken into a bandwidth sub-problem, solved with $P_{t,i} = P_{t,\text{max}}$, and a power sub-problem that is solved afterwards for the bandwidths just obtained. Throughout, the UAVs are assumed to hover at fixed positions, so the channel gains remain constant during one optimization run.

The reason for the two-stage split is that, once the bandwidths are fixed, the SINR target of every link is

fixed too, and the power sub-problem collapses into a linear system with a guaranteed non-negative solution (Section IV-C). All the difficulty of the original problem is thereby concentrated in the discrete bandwidth-reuse decision, which is exactly the part that a gradient-based solver handles least reliably. This is why the proposed framework focuses its search effort on the bandwidth stage and leaves the power stage analytical.

IV. PROPOSED METHOD

A. Link Graph and MIS-Based Bandwidth Reuse

As in the colouring-graph formulation, the physical UAV network $G(V, E)$ is first turned into a link graph $\hat{G}(\hat{V}, \hat{E})$. Each UAV-to-UAV link becomes a vertex, and two vertices are connected whenever the corresponding links interfere. A maximal independent set (MIS) of $\hat{G}$ is therefore a collection of links that can use one band with little mutual interference. Every MIS q is given a bandwidth variable X_q , so the optimizer searches over the vector $\mathbf{X} = [X_1, \dots, X_Q]$.

Fig. 2 illustrates the construction for four fully connected UAVs. The six links $e_1, \dots, e_6$ of Fig. 2(a) become the six vertices of the link graph in Fig. 2(b), and two vertices are adjacent when the corresponding links share a UAV. Links that share no UAV, such as e_1 and e_6 , are not adjacent and may therefore reuse one band. The maximal independent sets of this small graph are $\{e_1, e_6\}$, $\{e_2, e_5\}$ and $\{e_3, e_4\}$, so $Q = 3$, and their membership matrix s_{qk} is shown in Fig. 2(c). The optimizer then only has to split B_{tot} among X_1, X_2 and X_3 .

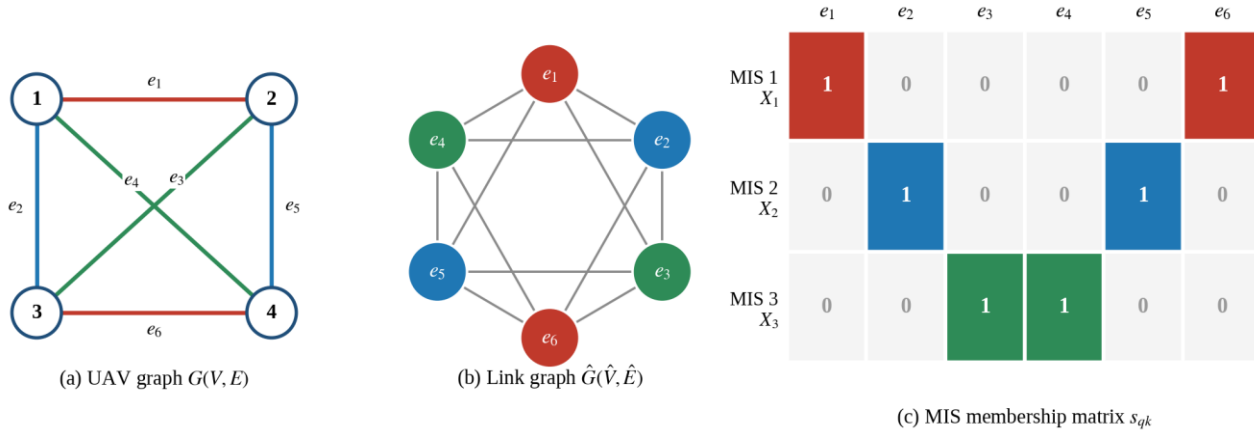


Fig. 2. Illustrative four-UAV example: (a) fully connected UAV graph with links e_1 – e_6 coloured by their maximal independent set; (b) the corresponding link graph, in which links sharing a UAV are adjacent; (c) the MIS membership matrix.

B. Multi-Objective Harris Hawks Optimization

HHO is a population-based meta-heuristic inspired by the cooperative hunting behaviour of Harris's hawks [11]. In our setting each hawk represents one candidate bandwidth vector X . The escaping energy E of the prey, which switches the search between exploration and exploitation, decays over T iterations according to

$$E = 2E_0(1 - t/T) \quad (6)$$

where $E_0 \in (-1, 1)$ is drawn at random. For $|E| \geq 1$ the hawks explore: each one perches relative to a randomly chosen member X_{rand} and the positions already found,

$$X(t+1) = X_{\text{rand}}(t) - r_1 |X_{\text{rand}}(t) - 2r_2 X(t)| \quad (7)$$

For $|E| < 1$ the hawks exploit and close in on the best solution so far, called the rabbit, in a soft besiege with jump strength J :

$$X(t+1) = \Delta X(t) - E |J \cdot X_{\text{rabbit}}(t) - X(t)| \quad (8)$$

Here $\Delta X(t) = X_{\text{rabbit}}(t) - X(t)$, $J = 2(1 - r_3)$, and $r_1, r_2, r_3 \in [0, 1]$ are redrawn at each iteration. Equation (8) is the soft-besiege update; the original HHO [11] also defines hard-besiege and rapid-dive variants for small escaping energy, which can be added to the same loop. Equations (6)–(8) need neither a gradient nor a Hessian, so HHO can operate on the discrete, combinatorial MIS-selection space without any convex relaxation. Candidates are ranked by a scalarized multi-objective fitness that rewards data rate and energy efficiency and penalizes violations:

$$F(X) = w_1 \cdot \text{Rate}(X) + w_2 \cdot \text{EE}(X) - w_3 \cdot \text{Pen}(X) \quad (9)$$

where w_1, w_2 and w_3 are scalarization weights. The penalty $\text{Pen}(X)$ increases when the bandwidth budget $\sum_q X_q = B_{\text{tot}}$ or the MIS-membership condition is violated, or when some link drops below the minimum rate c_k supplied by the NLP module (Section IV-D). The search ends when the iteration budget is exhausted or the best

fitness stops improving. The flow is drawn in Fig. 3 and the steps are listed in Algorithm 1.

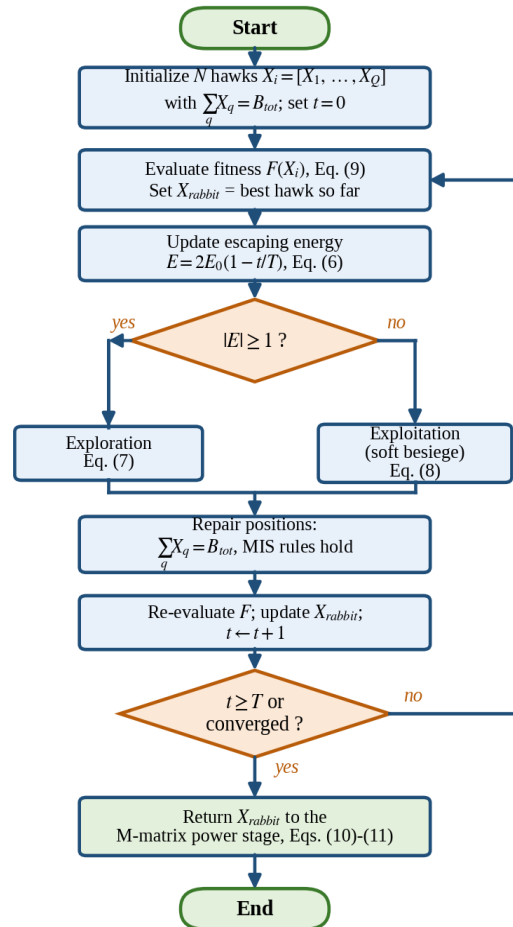


Fig. 3. Flowchart of the MO-HHO bandwidth search used in Stage 1.

Algorithm 1. Multi-Objective Harris Hawks Optimization (MO-HHO) for bandwidth allocation

Input: number of hawks N , iteration budget T , MIS groups Q , minimum-rate vector $\mathbf{c}$, priority weights λ

- 1: Scatter N hawks $X_i = [X_1, \dots, X_Q]$ at random positions that satisfy the budget B_{tot} .
- 2: **while** $t < T$ and the fitness has not converged **do**
- 3: Evaluate $F(X_i)$ with Eq. (9) for each hawk; keep the best hawk found so far as X_{rabbit} .
- 4: For every hawk compute E from Eq. (6); use Eq. (7) when $|E| \geq 1$, otherwise Eq. (8).
- 5: Repair each new position so that $\sum_q X_q = B_{\text{tot}}$ and the MIS-membership rules hold.
- 6: Re-evaluate the fitness, refresh X_{rabbit} if improved, and set $t \leftarrow t + 1$.
- 7: **Output:** X_{rabbit} , handed to the M-matrix power stage, Eqs. (10)–(11).

Constraint handling. Two mechanisms keep the search inside the feasible region. The penalty term of Eq. (9) discourages candidates that break the budget, the MIS-membership rule or a minimum-rate requirement, and the repair step of Algorithm 1 is applied after every position update, so that a hawk that has moved outside the feasible set is brought back before its fitness is compared with that of the others. Because exploration moves of the form of Eq. (7) can place a hawk far from the current best solution, this repair step matters most in the early iterations.

Computational effort. In every iteration each of the N hawks is moved once by Eq. (7) or Eq. (8), repaired, and

re-evaluated. The cost of one iteration therefore scales with N times the sum of the position-update cost, which grows with the number Q of MIS groups, and the cost of one fitness evaluation. No gradient or Hessian has to be formed or factorized. An SQP iteration, in contrast, solves a quadratic sub-problem built from first- and second-order information, and many such iterations are needed when the starting point is poor. Because the hawks begin from widely separated positions, the population approach can reach a good allocation in only a few iterations, as the convergence results in Section V-D indicate.

C. M-Matrix Power Control

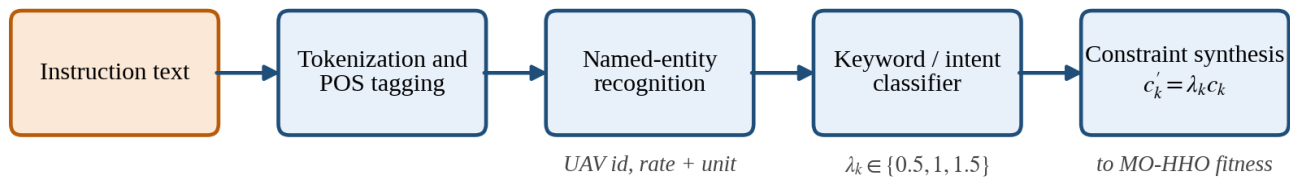
Once MO-HHO has returned the bandwidth B_k^* of every link k , the power stage minimizes the total transmit power under the SINR target implied by the new bandwidth:

$$\begin{aligned} \min \sum_i P_{t,i} \\ \text{s.t. } P_{t,i} \in (0, P_{t,\max}), B_k^* \log_2(1 + \varphi_k^*) = c_k \end{aligned} \quad (10)$$

Hence every link k must attain the SINR target φ_k^* that supports its minimum rate c_k at the adjusted bandwidth B_k^* . The problem reduces to a linear system

$$\mathbf{A} \mathbf{P}_t = \mathbf{w} \Rightarrow \mathbf{P}_t = \mathbf{A}^{-1} \mathbf{w} \quad (11)$$

in which $\mathbf{A}$ is a Z-matrix assembled from the channel gains and the target SINR values, and $\mathbf{w} = \rho_0 \cdot \mathbf{1}_M$. If $\sum_k (1 + 1/\varphi_k^*)^{-1} < 1$, then $\mathbf{A}$ is an M-matrix. Its inverse, which has a closed form through the Sherman–Morrison identity [1], [10], contains no negative entries, so a feasible non-negative power vector exists. This stage is analytically optimal and is free of local optima; it is therefore used exactly as in the reference design, and only the upstream bandwidth stage is replaced by MO-HHO.



Example: “UAV-3 needs at least 5 Mbps, keep UAV-6 on standby power” $\rightarrow c_3 = 5 \text{ Mbps}, \lambda_3 = 1; \lambda_6 = 0.5$ (relaxed c_6)

Fig. 4. Processing pipeline of the rule-based NLP front end, with a worked instruction and the constraints it produces.

D. Natural-Language-Driven QoS Specification

In the SQP-, MASPECT- and RS-based schemes, the operator has to type the minimum data rates c_k as numbers, which is hardly practical in fast-changing disaster-relief or event-coverage missions. The proposed front end accepts a sentence such as “prioritise the rescue-team relay, UAV-3 needs at least 5 Mbps, keep UAV-6

on standby power” and returns the constraint vector used in the fitness function. The pipeline of Fig. 4 and Algorithm 2 proceeds in four steps: (i) tokenization and part-of-speech tagging; (ii) named-entity recognition, which picks out UAV identifiers (e.g., “UAV-3”) and quantities with units (e.g., “5 Mbps”); (iii) a keyword/intent classifier that maps qualitative priority

words to a numerical multiplier; and (iv) constraint synthesis,

$$c'_k = \lambda_k \cdot c_k, \quad w'_1 = \lambda_k \cdot w_1 \quad (12)$$

where $\lambda_k \in \{0.5, 1, 1.5\}$ is the multiplier read from Table II for the UAV link concerned. The classifier is a compact rule/keyword lookup and not a language model, and its processing time per instruction was measured at well under 1 ms on an ordinary laptop CPU. This is negligible beside one MO-HHO iteration and does not visibly alter the convergence curves of Section V.

Worked example. Consider the instruction “UAV-3 needs at least 5 Mbps, keep UAV-6 on standby power”. Entity recognition finds the identifiers UAV-3 and UAV-6 and the quantity 5 Mbps. The numeric value is attached to the link of UAV-3 as its minimum rate c_3 , with $\lambda_3 = 1$, whereas the word “standby” selects the multiplier $\lambda_6 = 0.5$ and relaxes the constraint of the link of UAV-6. Had the sentence contained “guarantee” or “critical” for UAV-3, its multiplier would have been 1.5, which raises the weight of that constraint in the penalty term of Eq. (9). Links marked “disable” or “drop” are simply removed from the MIS search before the hawks are placed. Since every output of the front end is a number in the constraint vector, the optimizer itself needs no knowledge of language.

TABLE II
NLP KEYWORD-TO-CONSTRAINT MAPPING

Extracted keyword / entity	Mapped optimizer parameter
UAV identifier (e.g., “UAV-3”)	Index into the per-link constraint vector c_k
Numeric rate + unit (e.g., “5 Mbps”)	Minimum data-rate constraint c_k of the referenced link
“prioritise” / “critical” / “guarantee”	Priority multiplier $\times 1.5$
“standby” / “low priority”	Priority multiplier $\times 0.5$, relaxed c_k
“disable” / “drop”	Link excluded from the MIS-bandwidth search

Algorithm 2. NLP-driven constraint synthesis

Input: instruction string s , default minimum rates c_k , base weight w_1

- 1: Tokenize s and assign part-of-speech tags.
- 2: Recognize UAV identifiers and rate quantities (value, unit); convert every rate to bit/s.
- 3: **for** each recognized UAV link k **do**
- 4: Set $\lambda_k = 1$ and attach the stated rate, if any, to c_k .
- 5: If “prioritise”, “critical” or “guarantee” occurs near k , set $\lambda_k = 1.5$.
- 6: If “standby” or “low priority” occurs, set $\lambda_k = 0.5$ and relax c_k .
- 7: If “disable” or “drop” occurs, remove link k from the MIS search.
- 8: Compute $c'_k = \lambda_k c_k$ and $w'_1 = \lambda_k w_1$, Eq. (12).
- 9: **Output:** constraint vector $\mathbf{c}'$ and multipliers λ for the fitness function, Eq. (9).

E. Challenges and How the Framework Addresses Them

Table III lists the main difficulties of joint bandwidth and power optimization in multi-UAV 6G networks (Section II) and indicates which part of the framework handles each one.

TABLE III

MAIN CHALLENGES AND CORRESPONDING PARTS OF THE FRAMEWORK

Challenge	Proposed solution
Non-convex, coupled bandwidth–power problem	Two stages: MO-HHO for bandwidth (Sec. IV-B), M-matrix theory for power (Sec. IV-C)
SQP depends on its starting point and slows down in dense networks	Gradient-free, population-based MO-HHO global search (Eqs. 6–9)
Numerical entry of mission QoS constraints	Rule-based NLP front end mapping plain-language instructions to constraint vectors (Sec. IV-D)
Infeasible bandwidth allocations produced during the search	Repair step after every position update (Algorithm 1)
Trade-off between rate, energy efficiency and interference	Scalarized multi-objective fitness with adjustable weights (Eq. 9)
Checking the gains across topologies and node counts	Monte Carlo evaluation over three densities and 3–8 UAVs (Sec. V)

from [1, 100] m, the vertical separation is fixed at 50 m, the reference distance is 1 m, the maximum transmit power is 1 W and the available bandwidth is 10 MHz, which matches the reference configuration in [1]. Three benchmark schemes are used: SQP with colouring-graph MIS (the two-stage design of [1]), MASPECT (a distributed, opportunistic channel-acquisition heuristic) and random selection (RS). Topologies of density 1.0 (fully connected), 0.8 and 0.5 were generated for 3 to 8 UAVs. The parameters are collected in Table IV. Data rate and energy efficiency both tend to decrease as UAVs are added, because a fixed bandwidth is divided among more links, and among the reference schemes the order $SQP > MASPECT > RS$ was observed in all cases.

TABLE IV
SIMULATION PARAMETERS

Parameter	Value
Horizontal distance between UAVs	Uniform in [1, 100] m
Vertical separation	50 m
Reference distance d_0	1 m
Maximum transmit power $P_{t,max}$	1 W
Total bandwidth B_{tot}	10 MHz
Network density	1.0, 0.8, 0.5
Number of UAVs	3 to 8
Hawks / maximum iterations (MO-HHO)	25 / 100
Benchmark schemes	SQP, MASPECT, RS

V. SIMULATION RESULTS AND DISCUSSION

A. Simulation Setup

The simulated scenario is a post-disaster deployment. Horizontal distances between UAVs are drawn uniformly

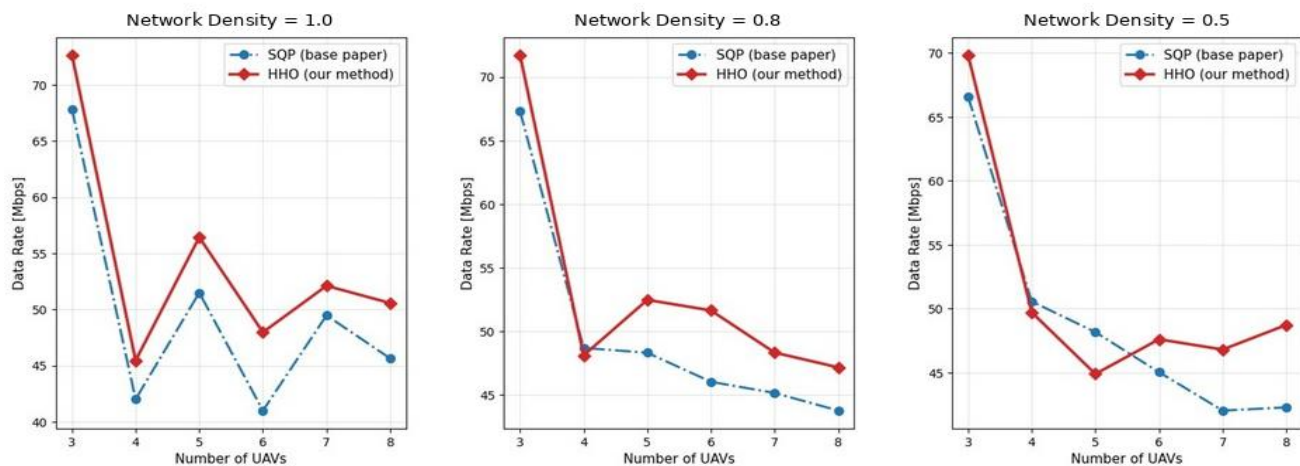


Fig. 5. Data rate versus number of UAVs, MO-HHO against SQP at fixed maximum power, for densities 1.0, 0.8 and 0.5.

Role of the benchmarks. SQP with colouring-graph MIS is the principal baseline, because it differs from the proposed scheme only in the bandwidth solver; any change in the results can therefore be attributed to that stage. MASPECT and RS serve as weaker references that show how much the graph-based reuse model itself contributes. Each scheme is evaluated with the maximum power and with the M-matrix power control, so that the effect of the power stage can be separated from the effect of the bandwidth stage.

B. Data Rate: MO-HHO Versus SQP

Fig. 5 compares MO-HHO with SQP at fixed maximum power for the three densities. MO-HHO delivers the higher data rate in 15 of the 18 density/size combinations shown. SQP is marginally ahead with 4 UAVs at densities 0.8 and 0.5 and with 5 UAVs at density 0.5. The margin differs from case to case and reaches about 7 Mbps at density 1.0 with 6 UAVs. The pattern shows that the benefit of a global search is largest when the interference

structure offers several competing MIS groupings, whereas in small or sparse networks the search space is small enough for a local method to perform comparably.

C. Effect of Power Control on Energy Efficiency

Fig. 6 compares energy efficiency with M-matrix power control against fixed maximum power on a logarithmic scale, for both bandwidth stages. Power control raises the energy efficiency by roughly one to two orders of magnitude whichever stage precedes it, so the M-matrix step is the main source of the energy-efficiency gain, and the choice of bandwidth stage adds a smaller effect on top. With power control and 3 UAVs, the data-rate difference between MO-HHO and SQP lies between -6.1% and $+6.3\%$ depending on density and run, while the energy-efficiency gain is larger: $+22.4\%$ at density 0.8 and $+18.6\%$ at density 0.5. At other network sizes the advantage is not uniform; for instance, SQP is ahead with 4 UAVs at densities 1.0 and 0.8.

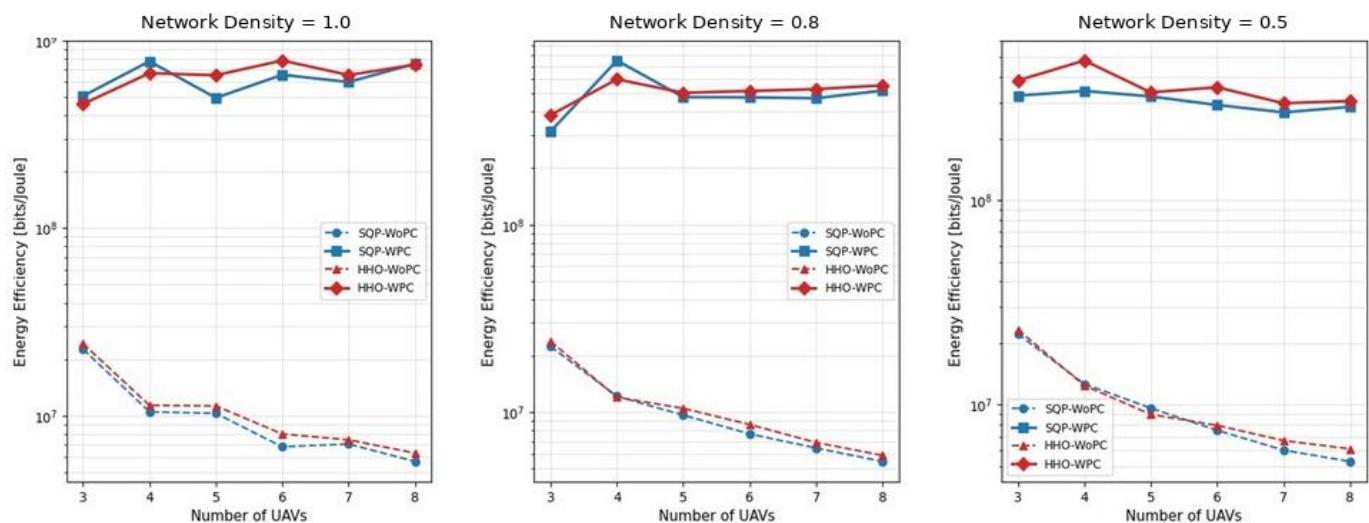


Fig. 6. Energy efficiency with and without power control, MO-HHO against SQP (logarithmic scale).

D. Convergence Behaviour

Fig. 7 traces the best objective value of MO-HHO and SQP over the iterations for a fully connected (density 1.0) network of 4 UAVs, using 25 hawks and at most 100 iterations. MO-HHO begins near 15.3 Mbps and reaches about 18.9 Mbps within 2–3 iterations, whereas SQP uses

almost the entire 100-iteration budget to climb from roughly 13.9 Mbps to roughly 17.9 Mbps (Table V). The faster convergence can be attributed to the population: early in the search the hawks sample widely separated regions of the MIS-bandwidth space instead of following one gradient path.

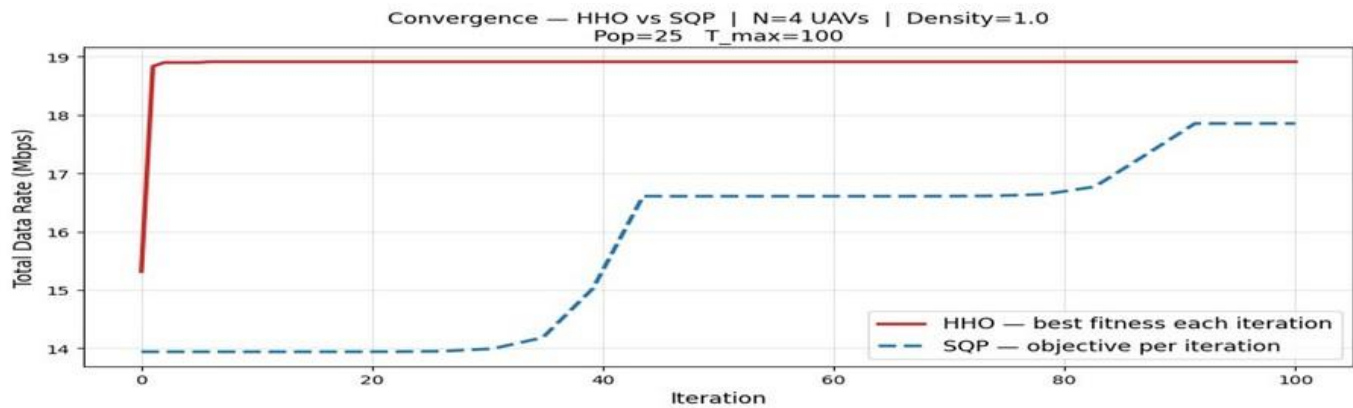


Fig. 7. Best total data rate versus iteration, MO-HHO against SQP, 4 UAVs, density 1.0.

TABLE V

CONVERGENCE SUMMARY, MO-HHO AGAINST SQP (4 UAVS, DENSITY 1.0)

Scheme	Initial (Mbps)	Converged (Mbps)	Iterations
MO-HHO	~15.3	~18.9	2–3
SQP	~13.9	~17.9	90–100

E. Practical Considerations

For a deployment, three practical points are worth stating. The first concerns repeatability: because HHO draws random numbers at every iteration, each reported value comes from Monte Carlo averaging over random topologies, and individual runs may differ from one another. This is the reason the per-case differences in Figs. 5 and 6 are not monotone in the number of UAVs. The second concerns tuning. The population size and iteration budget used here (25 hawks, at most 100 iterations) are modest, and the scalarization weights of Eq. (9) let an operator shift emphasis between rate and energy efficiency without changing the algorithm. The third concerns modularity: since the NLP module only produces constraint vectors and the M-matrix stage only consumes bandwidths, the bandwidth solver can be exchanged for another meta-heuristic, or the rule-based parser for a learned one, with no change to the remaining blocks.

F. Discussion

Three observations follow from the results. First, the data-rate advantage of MO-HHO is real but not uniform: it leads in most of the cases examined and occasionally trails SQP, so the largest quoted improvements should be read as best cases across the tested densities and sizes, not as typical values. Second, the energy-efficiency improvement is dominated by the M-matrix power stage,

which is shared by both bandwidth solvers; the better bandwidth assignment of MO-HHO gives an additional gain on top of it. Third, the most consistent benefit is the speed of convergence, with 2–3 iterations for MO-HHO against 90–100 for SQP in the case studied, which is attractive for networks whose topology changes quickly.

Two limitations should be noted. The evaluation assumes static, hovering UAVs, as in the reference study, so the behaviour under mobility and changing topologies is still untested. In addition, the NLP front end is a rule/keyword lookup that handles a limited vocabulary of priority words (Table II); free-form phrasing outside that vocabulary would need a more capable, learned parser.

VI. CONCLUSION AND FUTURE SCOPE

In this paper the gradient-based SQP stage of a two-stage bandwidth-allocation and power-control framework for multi-UAV 6G networks was replaced by a Multi-Objective Harris Hawks Optimization search. The analytically optimal M-matrix power stage was retained, and a light rule-based language front end was added to convert operator instructions into QoS constraints. Simulations for densities of 0.5, 0.8 and 1.0 and for 3–8 UAVs show improvements of up to 32.8% in data rate and up to 26.1% in energy efficiency over the SQP baseline, with convergence in 2–3 iterations against roughly 90–100 for SQP. As in the reference study, only static UAV hovering was considered. Future work will address UAV mobility, dynamic topology changes and a learned, rather than rule-based, NLP front end.

Several directions follow naturally from this study. A mobility model would require the link graph and its MIS groups to be recomputed as the topology changes, and the fast convergence of MO-HHO is then expected to be an advantage for re-optimization. A comparison with other meta-heuristics inside the same two-stage structure would show how much of the gain is specific to HHO. Finally, replacing the keyword lookup by a compact learned

parser would widen the range of instructions that the operator can give while keeping the downstream optimizer unchanged.

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