Journal of Intelligent & Robotic Systems (2022) 105:31
https://doi.org/10.1007/s10846-022-01590-8

REGULAR PAPER

Hybrid Route Optimisation for Maximum Air to Ground Channel Quality

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Received: 25 February 2021 / Accepted: 2 February 2022

Abstract
The urban air mobility market is expected to grow constantly due to the increased interest in new forms of transportation. Managing aerial vehicles fleets, dependent on rising technologies such as artificial intelligence and automated ground control stations, will require a solid and uninterrupted connection to complete their trajectories. A path planner based on evolutionary algorithms to find the most suitable route has been previously proposed by the authors. Herein, we propose using particle swarm and hybrid optimisation algorithms instead of evolutionary algorithms in this work. The goal of speeding the route planning process and reducing computational costs is achieved using particle swarm and direct search algorithms. This improved path planner efficiently explores the search space and proposes a trajectory according to its predetermined goals: maximum air-to-ground quality, availability, and flight time. The proposal is tested in different situations, including diverse terrain conditions for various channel behaviours and no-fly zones.

Keywords Aerial robotics · Nature-inspired optimisation · Hybrid optimisation · Path planning · Channel model · Wireless communications

1 Introduction

Recent trends in aerial vehicle (AV) development show an increasing interest in developing new urban transportation forms. It is expected that the Urban Air Mobility (UAM) market will continuously grow [12]. This market growth will be shared among various UAM platforms: air taxis, personal AVs, aerial cargo vehicles and air ambulances. Moreover, these vehicles are expected to perform tasks not only in urban environments but also in non-urban environments, e.g., for search and rescue [44].

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Among the main technologies needed to enable these new types of vehicles are sense and avoid systems, automated ground control stations and artificial intelligence (AI) [41]. Sense and avoid provide manoeuvre capability in tight places without any prior knowledge of the environment. It also ensures that AVs do not collide with nearby vehicles and obstacles. Owing to the increase in the number of AVs flying simultaneously, currently, centralised airspace management means are insufficient and distributed ground control stations will be required. Last but not least, AI is a technology expected to enable this AV to perform all types of tasks with little to no supervision.

Some enabling technologies, such as AI and automated ground control stations, require constant communication between an AV and ground control to exchange AV positions, and flight plans or perform collision avoidance activities [35]. These operations will occur in an environment already known for causing communication problems. Global navigation systems' performance can be degraded due to the canyon effect [51] caused by nearby buildings. This type of structures can also produce shadowing, multipath and, together with the emitter's movement, the Doppler shift [21, 34].

The command and control (C2) link is used for operation related communications and ensures a safe AV flight. This

Published online: 20 May 2022

link operates based on communication transactions, and its performance is described by the communication transaction time, continuity, availability and integrity [9]. Channel performance must be maximised to ensure safe flight operations because it directly affects the C2 link parameters. To the extent that even the maximum throughput of the channel is insufficient to meet operational requirements, this information can be given to flight operators, and decisions can be made on that basis. These decisions could include a change in the destination or revision of the mission.

The effect of the urban environment on the channel performance has been studied before, but the effect of using a ground network designed in favour of ground users has received insufficient attention. Antennas are tilted to the ground to improve reception quality on ground users, making AVs in the sky connect under suboptimal conditions [17]. For a system that heavily relies on communications, mission completion can be endangered, and hazardous situations can occur when the AV flies over areas with low signal quality.

Our route optimisation for maximum air to ground (A2G) channel quality can be applied to many situations. Among these situations, Fig. 1 illustrates an AV with a simple route departing from A and arriving at B. As seen in the figure, along the route, there is an area with low received power. Using our route optimisation, the AV finds a new route with optimal flight time and uninterrupted connection to the ground network. Other objectives, such as obstacle avoidance, are implemented.

Simulations are a great tool that allows the easy and low-cost modelling of the network's behaviour in different settings and situations. Thanks to these advantages, simulated results will be used as the first approach to test the optimisation algorithm. This simulation covers all aspects of the optimisation: real flight dynamics, airframe shape, channel modelling, and the optimisation algorithm. The presentation of the simulation environment and a first optimisation algorithm have been discussed in reference [18]. Therefore, this work aims to extend what has been presented by studying alternatives to the previous optimisation and selecting the one that provides better results and reduces computational resources.

This work's novelty proposes an optimisation algorithm that outperforms the evolutionary approach used in [18]. Our contribution to the field is to propose the optimisation algorithm and prove its performance under different challenging scenarios and against other promising optimisation algorithms.

The remaining paper is organised as follows: Section 2 introduces the related work in channel modelling and route optimisation for AVs and flying ad-hoc networks. Section 3 provides an overview of the necessary building blocks for a successful optimisation. Section 4 presents the results of using the particle swarm optimisation algorithm under different conditions and scenarios. Hybrid optimisation is proposed in Section 5, and results are discussed in the same section. Section 6 is dedicated to the conclusions.

2 Related Work

The channel must be studied and characterised to mitigate the environment's effects on the wireless channel. Erik Haas is the main contributor to the field of wireless channel modelling. He uses the signal delay and Doppler distribution to generate a new kind of A2G channel model in his main work. David Matolak is the main contributor to the field of channel modelling. He has co-authored several A2G channel modelling publications for different environments [32–34, 42, 47, 48]. With the results of these measurements, he proposes a series of site-specific channel models. Despite this extensive work on channel modelling, to the best of the author's knowledge there is no universal deterministic channel model for AVs.

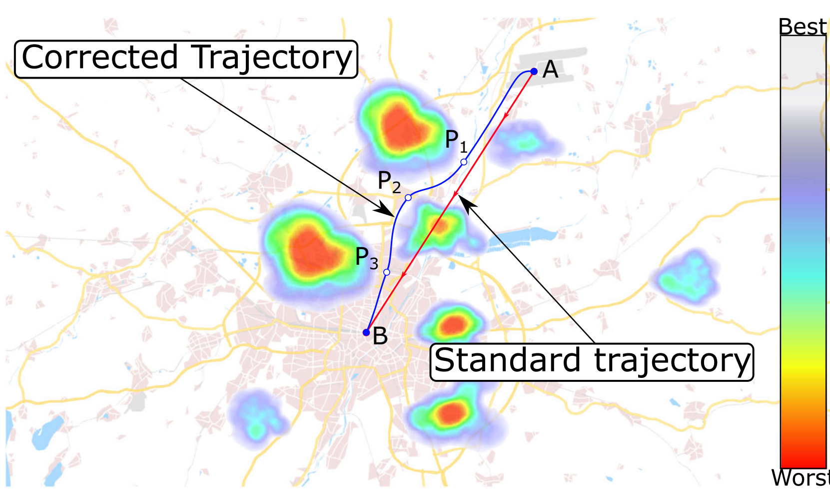


Fig. 1 optimised trajectory avoiding areas with low channel performance. The proposed novel route optimisation proposes new waypoints to avoid low connectivity areas

Coverage enhancement in disaster areas is one of the applications for AV that has received significant attention from the community. Reference [19] proposes modifying the AV position to reduce the end-to-end delay using a control loop. In reference [50], those efforts are extended by optimising the AV trajectory to serve multiple users in a given 2D area. Convex optimisation is used in [53] to maximise the end-to-end throughput. A common factor is to treat the AV trajectory only in a two-dimensional space. Reference [54] focuses on minimising the flight time and keeps the signal-to-noise (SNR) under a defined threshold.

Optimisation of the route as a method to enhance signal reception and improve other mission parameters such as obstacle avoidance or terrain-following has not been extensively treated. MILP is used in [22] for route optimisation, with the disadvantage that the success of the algorithm relies on the trajectory used as a starting point. A potential risk associated with mixed-integer linear programming (MILP) optimisation is that the algorithm might focus on a local minimum. References [13] and [10] also propose to apply an evolutionary algorithm (EA) to realistic environments and achieve to generate a trajectory that safely navigates the AV through a hostile environment. Reference [24] coordinates a swarm of AVs in a search and rescue mission using EA. In this case, the objective is to lower the required time to complete the mission and set up a communication path.

Nature-inspired optimisation algorithms such as the EAs are a great tool when applied to a search field with many local minima. The many applications that can benefit from nature-inspired optimisation algorithms involve imaging as in reference [28, 29, 46], structure optimisation as in reference [27] and one of the most common applications, search for the shortest path [15]. Despite the popularity of these methods in a stand-alone version, their performance can be significantly improved by combining these algorithms with direct search algorithms such as the Nelder-Mead simplex algorithm [31], the Direct Search with Coordinate Rotation (DSCR) or simulated annealing [25]. To the best of the authors' knowledge, the number of publications covering hybrid optimisation is limited. The authors in [43] combine the EA with a complex algorithm, a kind of direct search method sensitive to the initial guess, applied to the lunar soft landing trajectory optimisation problem. On lower altitudes, [11] combines the simulated annealing with hill-climbing to plan 4D aircraft trajectories and avoid collision situations. In a 2D scenario, hybrid optimisation (EA and simulated annealing) is applied to the speed trajectory of a train in [45]. The authors of [37] compare the performance of different hybridisation techniques combined with automated computed aided design tools to design microwave waveguide filters.

From the literature review, it is manifested that evolutionary approaches have been applied to optimise the route of an AV [10, 13, 40]. Furthermore, references [23, 33] and [48] prove that effort is being made to improve link performance. Our previous work [18] proposes a novel EA that maximises A2G channel performance based on a channel model's output. This article aims to extend this work by proposing a more suitable optimisation strategy that requires fewer evaluations of the cost function with better-optimised trajectories. The final cost function value and the compliance with objectives and restrictions define the proposed AV route's performance.

The paper requires simulations to prove the convergence of the proposed optimisation algorithm. It is worth dedicating a few lines to the challenges faced in an actual implementation even though implementation won't be covered in this work but might be covered in future ones. The main one is how the algorithm copes with disturbances, modelling errors, and uncertainties when incorporated in a close loop control system. Authors in [38] solve the problem by applying particle swarm to determine uncertainties in the system. Neural network linea differential inclusion techniques are used in reference [20] to linearise unknown nonlinear parameters. In [16], the method applied is to design a robust fault detection filter to stabilise against external disturbances. Last but not least, reference [52] uses adaptive dynamic programming to solve optimal control problems in dynamic systems. These could be potential solutions and appear as research directions for future development in the final section.

3 Mission Modelling

Laying down the scenario's fundamentals is the first step to achieve route optimisation. These fundamentals include channel model (3.1), terrain profile (3.2), flight dynamics (3.3), generation of the waypoints (3.4) and the characterisation of the aircraft and the antennas used in the scenario (3.5) [18].

3.1 Channel Model

Terrain profile, flight dynamics of the AV and antenna characterisation are part of the channel model. This model allows the optimiser to calculate the channel's state at any given point of the flight trajectory. The state of the channel is calculated with Eq. 1. This equation represents the radiated electric field at the receiver. Quantities such as the position of the reflected ray (x, y, and z) are obtained from the terrain profile and flight dynamics. Parameters α and β represent the angles of arrival of the wave on the horizontal and vertical planes, respectively. The flight dynamics determine the speed (v) of the AV. The term $(2\pi/\lambda)v\Delta t\cos[\alpha[t]-\delta]\cos[\beta[t]]$ constitutes the Doppler shift part of the equation, $A[t]$ is the amplitude, and $E_R[t]$ is the radiated field at the observation point. Terms Φ_n and ω_c are the Doppler phase shift and carrier angular frequency, respectively. Equation 1 is applied for every reflection found on the terrain and the direct line of sight ray.

$$E_R[t] = A[t]\exp\left[\omega_c t - \frac{2\pi}{\lambda}\left[x[t]\cos[\alpha[t]]\cos\left[\beta[t]\right]\right.\right. \\ +y[t]\sin[\alpha[t]]\cos\left[\beta[t]\right] + z[t]\sin\left[\beta[t]\right] \\ \left.\left. +v\Delta t\cos[\alpha[t]-\delta]\cos\left[\beta[t]\right]\right] + \Phi_n\right] \quad (1)$$

3.2 Terrain Profile

The described channel model can be applied to all tested scenarios because it considers the terrain profile and terrain characteristics. Terrain models are used not only to calculate the channel response but also to assess whether the AV is within the allowed height. The necessary maps are achieved by combining Google Maps [4–6] information and the results of the TanDEM-X mission [39]. This data fusion results in a map with terrain reflection properties and terrain elevation.

3.3 Flight Dynamics

Analytical Graphics Inc. Systems Tool Kit (AGI-STK) [1] is the selected simulator to obtain the AV's position and behaviour through the proposed route. As in our previous work in [18], to ensure a compromise between granularity and calculation times, the route is sampled 12 times per minute. Due to this sampling rate, the number of points per route (M) will always be greater than the number of points (N). Position (x, y, z), attitude (ϕ, θ, ψ), and speed vector (Vx, Vy, Vz) are computed and collected in L_i and $\mathcal{L}$. L_i represents the state vector of the AV on a given time. As in Eq. 3, $\mathcal{L}$ represents the AV's location, attitude, and speed during the flight.

$$L_i = [x_i, y_i, z_i, \phi_i, \theta_i, \psi_i, Vx_i, Vy_i, Vz_i], i \in [1, M] \quad (2)$$

$$\mathcal{L} = \{L_1, L_2, \ldots, L_M\} \quad (3)$$

3.4 Route Generation

The optimiser proposes a route to guide the flight of the AV. The route optimiser uses azimuth (Az), elevation (Elev) and range (R) values to determine the next waypoint. How Az, Elev, and R translate into a waypoint can be found in Figure 3 of [18]. This method minimises the search space, but modifying a waypoint will alter the route. Route alteration can affect online planners but not our route planner as the optimiser will generate the collection of waypoints for evaluation at once.

This work uses a vertical takeoff and landing model for the AV. As the name indicates, these AVs can takeoff and land vertically, which results in a reduction of space because no runway is needed. As every route starts at a certain height, the initial waypoint (WP_0) is always located 150 m above the ground.

The straight-line route is the route used by the AV to go from WP_{start} to WP_{end}. R's maximum value is defined as one-third of the distance the AV covers on the straight line route. This upper boundary is designed to keep proposed trajectories close to the straight line route, minimising the route's time. R's minimum value is 1 km to give the AV enough distance to adapt to the next waypoint. Maximum and minimum values for Az and $Elev$ are ±30 and ±0.1 degrees, respectively. These values are designed to avoid abrupt changes in the horizontal plane and height. The algorithm uses certain restrictions and objectives to assess how good is a route. One of the objectives is to have a route with a length as close as possible to the straight-line route's length.

$$\text{Route} = \left\{ \begin{array}{c} WP_{start} \\ WP_1(Az_1, Elev_1, R_1) \\ WP_2(Az_2, Elev_2, R_2) \\ \vdots \\ WP_N(Az_N, Elev_N, R_N) \\ WP_{end} \end{array} \right\} \quad (4)$$

3.5 Aircraft and Antenna Characteristics

The AV and antenna characteristics are the missing pieces to finish the scenario's fundamentals. AV characteristics are its shape and the antenna used. The shape of the AV enables the calculation of structural shadowing conditions. With this information, the optimiser can avoid situations where the shape of the AV itself obscures the signal. As for the antenna characteristics, the antenna is located below the fuselage and presents a dipole radiation pattern, as depicted in Fig. 2.

The ground segment follows a design commonly used in wireless communication networks [14]. Typically, the ground station's radiation pattern is composed of 3 sectors spaced 120 degrees. One of the assumptions explained earlier is that the AV connects to a ground network optimised for ground users. An antenna's tilt is -15 degrees to provide maximum coverage for those users. Figure 2 illustrates the resulting radiation pattern of the ground's station antenna.

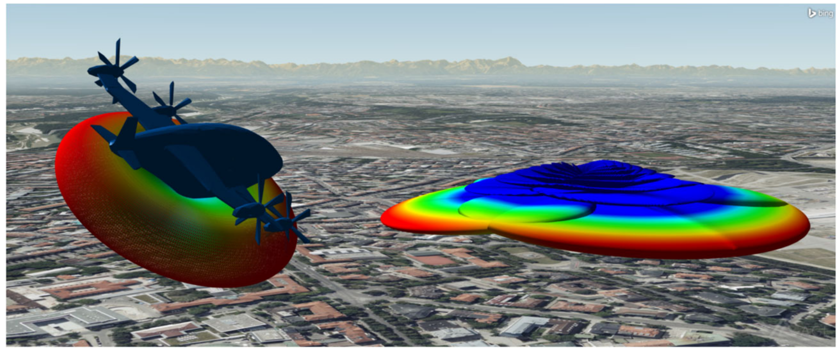


Fig. 2 UAS CAD Model, UAS radiation pattern and ground station radiation pattern used for simulations

4 Optimisation Approaches

This section describes how optimisation approaches have been designed. All approaches share the restrictions and objectives (4.1) applied by the optimiser to evaluate a route. Based on the literature review, the particle swarm algorithm is proposed as an alternative to EA (4.2). The shortcomings of the linear cost function (Eq. 5) are discussed, and a new, logarithmic cost function is proposed in Section 4.3. Finally, two hybridisation techniques are proposed and described (4.4).

4.1 Optimisation Restrictions and Objectives

Similar to our previous work in [18], the mission is fulfilled when the cost function meets the restrictions and objectives value is minimised. If restrictions are not satisfied, the objectives are not considered. A restriction is satisfied when its value is precisely zero. When the restrictions reach this value, the cost function value decreases, and the optimisation seeks to minimise objectives value.

The following text describes the cost function restrictions that drive the optimisation. More detail on how these restrictions and the following objectives are implemented can be found in previous work [18].

- Altitude (r_1): the AV trajectory $\mathcal{L}$, as described in Eq. 3, is not allowed to have points that are higher than the AV higher limit and below the lower limit. This restriction is bounded between 0 as best-case scenario (the AV respects the altitude limits in all points of the trajectory) and 1 as worst-case scenario (the AV is out of the altitude limits in all points of the trajectory).
- Area (r_2): the AV can only fly on the allowed airspace; it cannot cross any no-fly zone (NFZ). The vehicle is also not allowed to go beyond map limits. This restriction is bounded between 0 as the best-case scenario (the AV does not enter any NFZ) and 1 as the worst-case scenario (all the trajectory is crossing an NFZ).
- Minimum received power (r_3): the minimum receiver power along the route must be improved above the system's sensitivity to improve the quality of the A2G channel. This restriction is bounded between 0 as the best-case scenario (received power in all points in the trajectory is above the receiver sensitivity) and 1 as the worst-case scenario (below sensitivity in all points of the trajectory).

The three objectives, only tackled if restrictions reach the zero value, are:

- Trajectory distance (a_1): the distance covered by the AV is minimised. The optimiser rewards trajectories with a length as close as possible to the straight-line trajectory. This objective is bounded between 0 as the best-case scenario (straight trajectory) and 1 as the worst-case scenario.
- Vertical variation (a_2): this objective minimises height variations. This objective is bounded between 0 as the best-case scenario (no height variation along the trajectory) and 1 as the worst-case scenario.
- Average received power (a_3): this objective improves the average power through the AV trajectory. It uses the maximum received power on the straight-line trajectory; the closer the average received power is to this value, the lower the value of the objective. This objective is bounded between 0 as the best-case scenario (received power in all points of the trajectory is the same, and therefore equal to the average received power) and 1 as the worst-case scenario.

The A2G channel model's complexity and multiple restrictions and objectives determine that standard route planning techniques are not suitable. Reference [49] states that the problem to be solved is NP-Complete, and given the optimisation nature, heuristic approaches are best suitable to solve the problem.

4.2 Particle Swarm

Different optimisation approaches will be proposed and studied to improve the results obtained in our previous work [18]. All of these approaches are discussed to highlight each one's strengths and weaknesses and select the one that better performs among the designed scenarios. Based on the literature review, the particle swarm algorithm is the most promising candidate. This optimisation algorithm's foundations can be found in [26], which is a brief description of the algorithm. A more detailed explanation of the algorithm can be found in reference [36]. The main parameters configuring particle swarm algorithm and its implementation can be found in [8].

Particle swarm will find a local unconstrained minimum for the cost function based on bird flocking, fish schooling, and swarming theory. Swarming theory describes many animal's behaviours such as birds collaborating and finding resources more efficiently. This algorithm starts with a specific swarm size that explores the search space, proposing new positions or waypoints for the AV to follow. In our work, the number of particles that better perform is 50, ten times the number of waypoints. It is worth noting that the number of individuals in the evolutionary method is the same, 50 individuals. Other relevant parameters and its implementation can be found in [3]. After the initialisation phase, the particle swarm chooses new velocities based on current velocity, best locations and neighbour's best locations. Iterations continue until a stopping criterion has been reached. To ensure a fair comparison between particle swarm optimisation and the EA used in our previous work, the same cost function will be used as in Eq. 5.

$$c = \begin{cases} \frac{1}{3}\sum_{i=1}^{3} a_i, & \text{if } \sum_{j=1}^{3} r_j = 0 \\ \frac{1}{3}\sum_{i=1}^{3} a_i + \frac{1}{3}\sum_{j=1}^{3} r_j + 10, & \text{otherwise} \end{cases} \tag{5}$$

4.3 Logarithmic Cost Function

Further analysis of the current linear cost function as in Eq. 5 shows that it has room for improvement. Figure 3a displays the linear cost function issues in a simplified way. Values have been given to the restrictions and objectives between 0 and 1 to calculate the cost function's possible values in a simplified search space. It becomes clear that the majority of the search space does not vary significantly until the restriction takes a value of 0; only after that are the objectives of any significance. With Eq. 6, we introduce the logarithmic cost (LC) function, with a higher gradient towards the cost function's minimum theoretic value. Figure 3b displays the values that the LC function can take. This new function eases the cost function's minimisation and enables a higher interaction between the restrictions and objectives.

$$c = \frac{1}{3}\sum_{i=1}^{3} a_i + \log\left[\frac{100}{3}\sum_{j=1}^{3} r_j + 1\right] \tag{6}$$

4.4 Hybridisation Techniques

The presented LC function has the potential to improve results obtained with the linear cost function. Another technique, hybridisation, is a suitable candidate and worth applying to the route optimisation as in reference [37]. The basis of this approach is to combine two different optimisation algorithms instead of using a single one. The first algorithm performs an efficient global search and stops when the cost function's value reaches a threshold value (0.25). When the value is reached, optimisation is stopped, and the second optimisation algorithm starts. This second optimisation algorithm, which is more eager in finding the minimum in the cost function, and less exploratory of the search space than particle swarm, uses the solution of the first algorithm to search for a solution and finds the closest optimum as quick as possible. The candidate optimisation algorithms are the Nelder-Mead simplex algorithm and the DSCR, both fall in the direct search optimisation methods category. Readers can find other relevant parameters and the implementation of the optimisation algorithms in reference [7] and [2], respectively.

The first algorithm, the Nelder-Mead algorithm, can be found in reference [30]. This optimisation algorithm should not be confused with the simplex algorithm of Dantzig for linear programming. The method used in this work focuses on unconstrained optimisations and is one of the most used for nonlinear optimisations. The second tested algorithm, the DSCR, can also be used on non-continuous functions. This algorithm varies the route by following successful pattern moves.

The starting point of the optimisation workflow is the initial trajectory; in our work, the straight trajectory is the initial one. The state vector is obtained using the AV flight dynamics and the route proposed by the optimiser. The already described aircraft model, antenna radiation patterns, AV state vector, terrain type and elevation, are used to compute the channel's state. The current route score is obtained using the cost function, as in Eqs. 5 or 6. The last step is for the optimisation algorithm to propose a new trajectory. The optimisation algorithm's output is a new trajectory composed of N (Az, Elev and R)-triplets, where N is the number of waypoints, leading to $3N$ design parameters.

In order to ensure a fair comparison between results obtained with different optimisation approaches, the methodology of all simulations is the same. Each algorithm relies on a random number generator to propose new waypoints. The random number generator seed changes on every simulation to ensure that each algorithm is non-deterministic. Each algorithm uses the straight-line route as a starting point for the optimisation. The scenario is

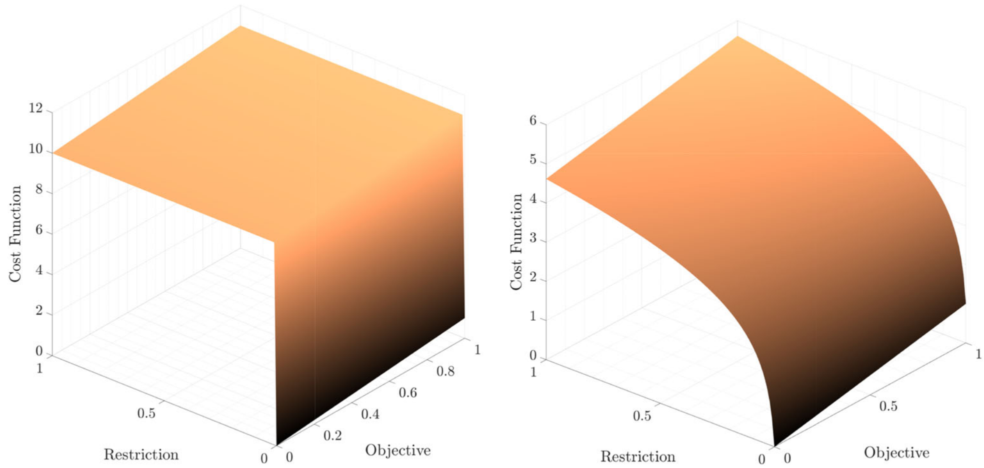


Fig. 3 Cost functions comparison

(a) Linear cost function as in Equation 5

(b) Logarithmic cost function as in Equation 6

evaluated 10 times to assure that we have a good picture of the optimisation algorithm's possible outcomes.

5 Designed Test Scenarios

In this section, the four scenarios that will challenge the optimisation approaches are shown. As in our previous work [18], the selected scenarios represent various geographical locations, NFZs and ground network (GN) distribution. The differences between the scenarios allow us to determine which optimisation approach performs better under different conditions and restrictions.

Scenario 1 challenges the AV to avoid flying over a temporal NFZ. This situation is particularly challenging because the optimal trajectory with respect to flight time crosses both NFZs. From a coverage point of view, the southern part of the map is more favourable since more GNs stations are available. For a route to be optimal, it must avoid the NFZs while improving the straight line route's channel conditions. Figure 4 illustrates GN locations and the described scenario.

Scenario 2 adds a further layer of complexity to the optimisation; one of the GN base stations is malfunctioning, as shown in Fig. 5 by the missing base station. The AV must find a route that avoids the existing NFZs and improves the channel conditions.

The Bavarian Alps (Scenario 3) are an environment with deep valleys and high mountains. This scenario has no NFZ, the significant variation of altitude challenges the evolutionary and particle swarm optimisation algorithms. Mountains have different side effects, namely the low visibility and limited coverage; the AV will not see more than one GN base station at a time, as depicted in Fig. 6. The restrictions and objectives are the same as before: the aircraft must avoid crashing into the ground and fly higher than the 1200 m limit, and improve the channel performance while reducing the flight time.

Finally, Scenario 4 displays our approach's versatility by optimising a route through two very different environments. Figure 7 displays the GN coverage affected by signal propagation over water and land. Since the ability to avoid NFZ and terrain has been proven in previous scenarios, this scenario focus solely on channel quality maximisation.

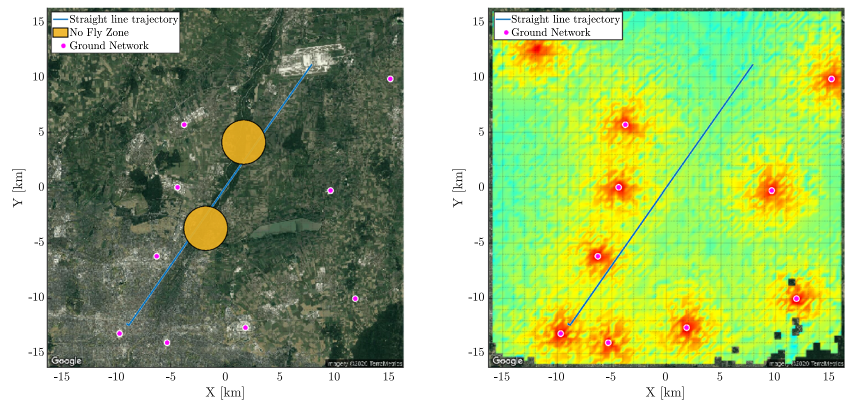
6 Results

This section is devoted to describing the obtained results on the designed scenarios with the various optimisation approaches. We start by comparing the EA and particle swarm algorithm's performance applied to the described scenarios. The best algorithm is used to analyse how good is the LC function and if the hybridisation provides better results.

Optimisation algorithms are compared based on performance evaluation indicators: calculation time [h], cost function final value, cost function evaluations and average received power improvement [%]. The first indicator, calculation time, determines which approach will require shorter times to produce a result. The second indicator, cost function final value, is used together with the calculation time. It is essential to obtain a route in a shorter time and obtain one with the lowest cost function final value.

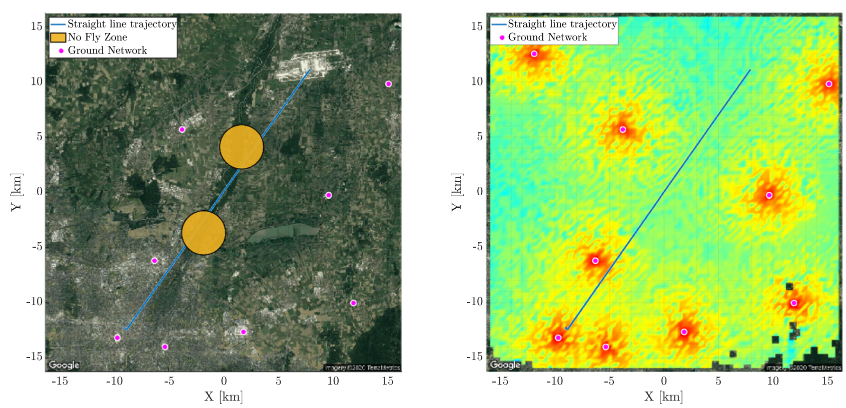
For the second part, the hybridisation, the analysis of results requires a different set of performance evaluation indicators. The main reason is that the optimisation algorithms use various cost functions. Hence, the cost function final value is no more a suitable indicator. Average receiver power improvement is a quantity that better displays channel

Fig. 4 Scenario 1: Munich Airport to Munich central station scenario [6]



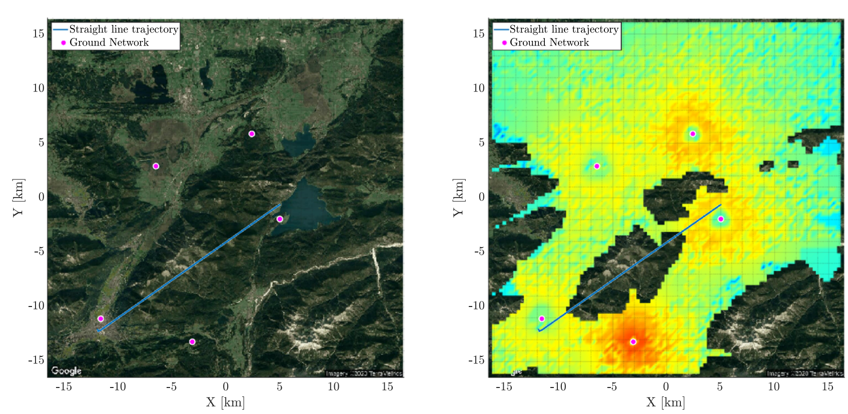
(a) Terrain view (b) Ground network coverage

Fig. 5 Scenario 2: Munich Airport to Munich central station with an antenna failure scenario [6]

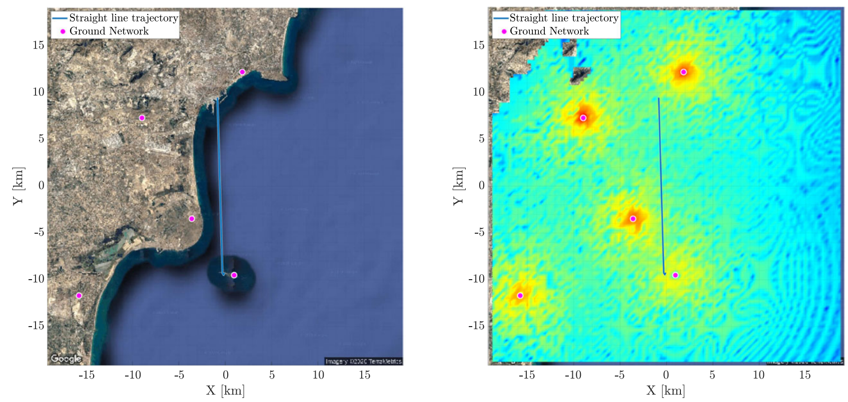


(a) Terrain view (b) Ground network coverage

Fig. 6 Scenario 3: Flight on the Bavarian alps scenario [5]



(a) Terrain view (b) Ground network coverage



(a) Terrain view

(b) Ground network coverage

Fig. 7 Scenario 4: Flight coast to island scenario [4]

improvement. The analysis uses the number of evaluations to display the number of iterations required to obtain a result. The most suitable approach is the one compliant with restrictions and objectives, which obtains a result with fewer iterations and the one with maximum air to ground channel quality.

6.1 Comparison Between Evolutionary Algorithm and Particle Swarm

As shown in Table 1, the evolutionary and particle optimisation methods use of the linear cost function as in Eq. 5. Because they use the same cost function, they can be compared, and a decision can be made on which algorithm is best. The LC function, as in Eq. 6, and the hybridisation methods are applied to the resulting best optimisation algorithm.

Table 1 gathers the result obtained through the 10 simulations with EAs and the 10 simulations with particle swarm. Interesting metrics are the number of iterations needed until the algorithm stops, and the final value is achieved. Due to space limitations, only the maximum (max), minimum (min) and average (avg) values of the total calculation time in hours and the final value of the cost function in each simulation are presented.

The first indicators that the particle swarm algorithm outperforms in Scenario 1 are the cost function's final values. Said values are below 1 for the max and min, which indicates that all restrictions have been satisfied in all simulations. The EA does not achieve this performance. Furthermore, some simulations end without satisfying the restrictions. Not only the EA does not satisfy the restrictions, but it also requires higher times to converge to the final value.

In Scenario 2, evolutionary and particle swarm have a similar performance in terms of the achieved cost function value. Moreover, max, min and avg values are very close to each other. The difference can be seen in the number of

Table 1 Results comparison between the evolutionary and particle swarm optimisation method for each scenario

	Optimisation method	Calculation time [h]			Cost function final value		
		Max	Min	Avg	Max	Min	Avg
Scenario 1	Evolutionary	18.6824	4.8749	9.0902	10.2524	0.1583	4.1856
	Particle	14.3173	2.5868	5.4143	0.2103	0.1635	0.1827
Scenario 2	Evolutionary	5.3395	3.1762	4.3425	0.1636	0.1274	0.1460
	Particle	4.5325	1.2945	2.7709	0.1556	0.1298	0.1396
Scenario 3	Evolutionary	4.5987	3.0829	3.7282	10.1871	0.1074	7.1381
	Particle	12.5108	3.1496	5.7959	0.1168	0.0928	0.1036
Scenario 4	Evolutionary	10.1358	5.6554	7.6369	0.2268	0.1929	0.2054
	Particle	5.6402	2.9157	4.5967	0.2386	0.1876	0.2155

Values have been obtained using the linear cost function as in Eq. 5

iterations needed to converge. While EAs need a max of 5.34 and a min of 3.18 h, particle swarm requires a max of 4.53 h. For this scenario, particle swarm finds similar solutions with lower times.

The values in Table 1 for Scenario 3 highlight the superiority of the particle swarm optimisation over the EA. The min final cost function value is similar for both algorithms. Nevertheless, the max final cost function value is above one for the EA. Particle swarm optimisation delivers results in similar max and min final cost function values, both below one. A final value higher than one means that the restrictions have not been satisfied, and an average of 7.1381 implies that restrictions are not satisfied in several simulations. An analysis of the calculation time shows that particle swarm requires more time on average to converge on a solution, but the minimum time required is similar on both algorithms. This higher number of time can be solved by modifying the function tolerance, so the particle swarm algorithm finishes the optimisation earlier in case of stalling.

In Scenario 4, the particle swarm algorithm shows a better performance. An example of this higher performance is that the particle swarm takes half the time than the evolutionary approach. The max, min and avg values are smaller for particle swarm optimisation. Final cost function values for both approaches indicate that they achieve a solution that complies with restrictions and improves the objectives. Particle swarm optimisation achieves a better result, although the difference is almost negligible.

6.2 Hybridisation on Particle Swarm

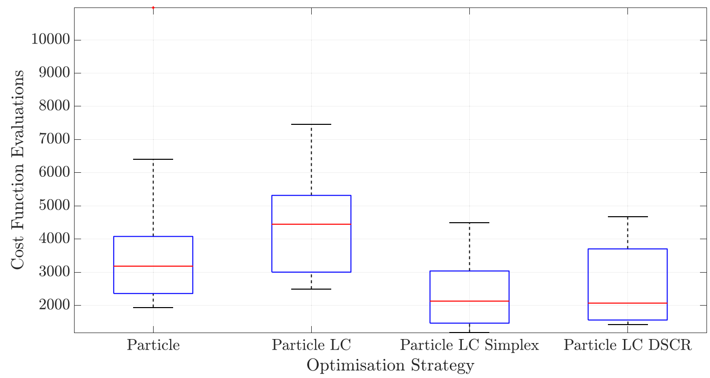
As said at the beginning of this section, the LC function and hybridisation techniques are applied to the best optimisation algorithm. Particle swarm has been shown to perform better than the evolutionary approach presented in our previous work [18]. Since different cost functions will be commented on, comparing the cost function's final values is not appropriate. Channel improvement is used for comparison instead, together with the number of iterations required for convergence.

Table 2 collects the results obtained from the different optimisation strategies used in Scenario 1. As in the previous subsection, each row in Table 2 gathers the results obtained after applying the optimisation method 10 times to the corresponding scenario. Looking at the number of iterations used by each optimisation algorithm, the LC function applied to particle swarm optimisation brings no improvement. On the contrary, the number of iterations needed is increased. Figure 8a supports this view. The median of the number of cost function evaluations (red line) is one of the highest compared with other used optimisation strategies and close to the number of cost function evaluations of the EAs.

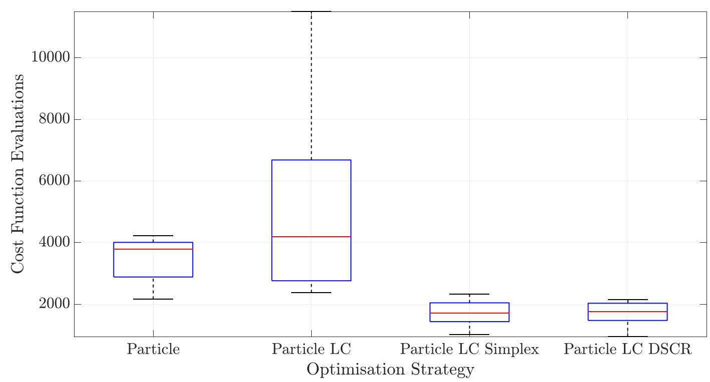
Table 2 Results obtained after applying particle swarm with the linear cost function (5), particle swarm with the LC function (6), particle swarm with LC function plus simplex and particle swarm with LC function plus DSCR on each scenario

	Optimisation method	Cost function evaluations			Average received power improvement [%]		
		Max	Min	Avg	Max	Min	Avg
Scenario 1	Particle	10973	1940	4107	5.2395	2.5395	4.0679
	Particle LC	7458	2493	4533	4.4093	−0.9819	2.0289
	Particle LC Simplex	4491	1182	2428	4.2835	−0.5076	1.9855
	Particle LC DSCR	4679	1429	2533	4.6488	0.2557	3.0768
Scenario 2	Particle	4225	2162	3458	3.6757	0.2281	2.0513
	Particle LC	11494	2372	5016	3.8040	0.4744	2.1827
	Particle LC Simplex	2326	1017	1698	4.1481	0.4971	2.0899
	Particle LC DSCR	2152	948	1678	4.2101	0.4917	2.2649
Scenario 3	Particle	15294	3847	7083	32.0707	30.8897	31.3656
	Particle LC	12875	3411	7291	32.2998	29.5095	31.3610
	Particle LC Simplex	937	669	795	29.3207	27.5215	28.3835
	Particle LC DSCR	1728	666	932	29.4115	27.5848	28.6093
Scenario 4	Particle	5541	1547	3348	4.7013	3.1495	3.7473
	Particle LC	5768	3235	4195	4.0894	3.4459	3.8468
	Particle LC Simplex	659	558	598	2.2709	−1.4652	1.0580
	Particle LC DSCR	1020	542	698	3.3751	0.8613	1.8997

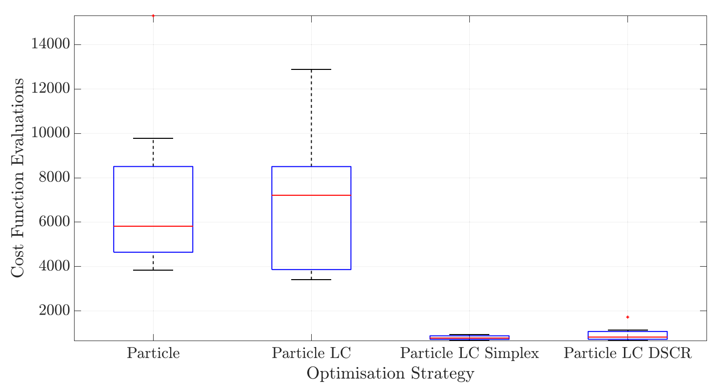
Fig. 8 Number of evaluations to achieve a solution for each scenario and each optimisation method described in Table 2



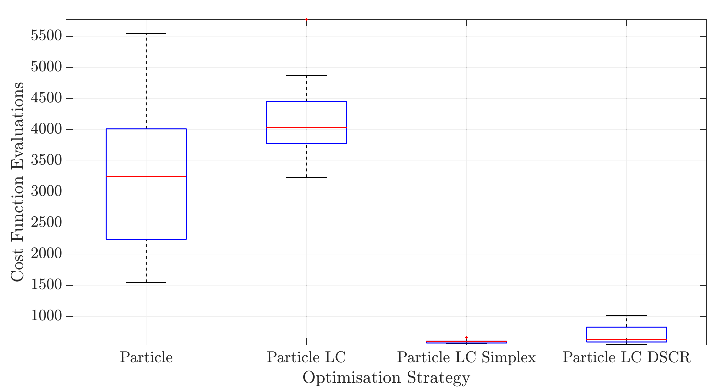
(a) Scenario 1



(b) Scenario 2

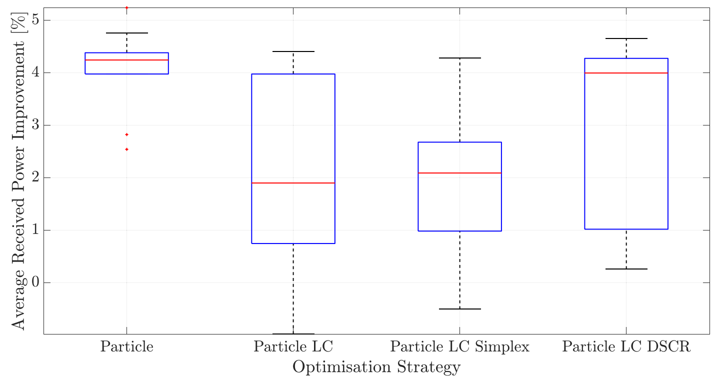


(c) Scenario 3

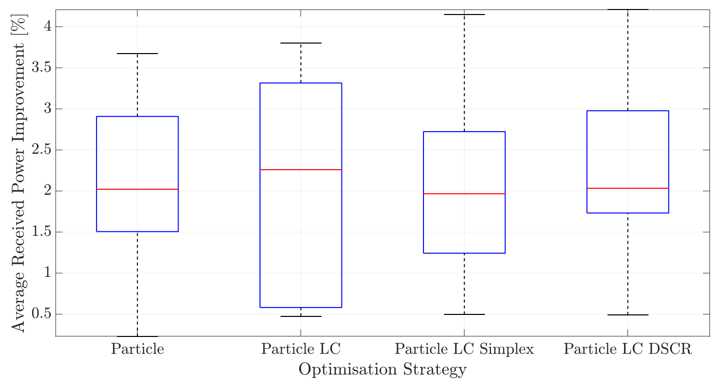


(d) Scenario 4

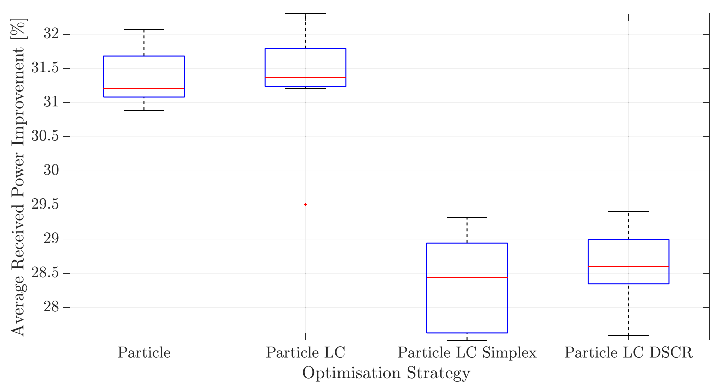
Fig. 9 Average received power improvement achieved for each scenario, and each optimisation method described in Table 2



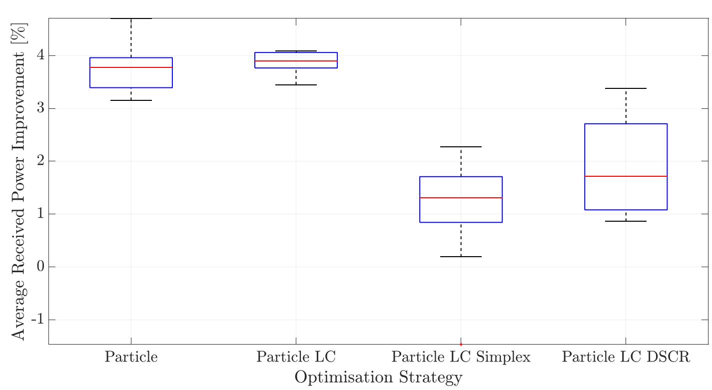
(a) Scenario 1



(b) Scenario 2



(c) Scenario 3



(d) Scenario 4

The LC function with particle swarm optimisation is insufficient to improve previous results alone. Nevertheless, it becomes effective in hybrid optimisation. The first proposed hybrid algorithm combines particle swarm, the LC function, and the simplex method. This combination improves the results already obtained; it requires half the amount of iterations on average. Maximum and minimum values are also improved with respect to previous optimisation strategies, as shown in Fig. 8a. There is no significant variation in the number of iterations when the DSCR is applied instead of the simplex algorithm.

Channel improvement values give an advantage to the hybridisation with the DSCR algorithm. Not only the average channel improvement is better but also the median channel improvement too, as seen in Fig. 9a. Another point favouring the DSCR algorithm is that the minimum value obtained is above zero, which implies that there is always a route that improves the average received power. A negative value does not imply that restrictions are violated. Since the shown channel improvement is calculated with the average received power, the minimum value may be improved, but the average is not.

In Scenario 2, the AV must fly from the airport to the city's centre with malfunctioning antennas. The obtained results are shown in Table 2. The number of iterations required by particle swarm with the LC function is one of the highest, only surpassed by the EA. The maximum number of iterations is the highest among all optimisation strategies. The required number of iterations is shown in Fig. 8b.

As with Scenario 1, the LC function is most effective with the simplex and DSCR hybridisation. The number of iterations to converge is lower than those of the previous three optimisation strategies (evolutionary, particle and particle with LC). It is essential not only to achieve a solution faster but also to achieve a better or at least equally good solution. DSCR improves the average received power on all simulations and with an average, maximum and minimum value higher than the other tested optimisations. This achievement is also displayed in Fig. 9b.

Previous scenarios focused on avoiding present NFZ under different connectivity conditions. Scenario 3 focuses on terrain avoidance and channel improvement. The results obtained from the various simulations and optimisation approaches are summarised in Table 2. On the one hand, using particle swam with the new LC does not improve the results when compared to the evolutionary optimisation and the particle swarm that uses the linear cost function. On the other hand, hybrid optimisation with simplex and DSCR algorithm on average converges much faster than the other optimisation strategies. Figure 8c also highlights that the hybridisation algorithms outperform the rest of the optimisation strategies in the number of cost function evaluations.

One additional challenge in this scenario is that the straight-line route has areas where no signal is received, a challenge for the EA. A closer inspection of the proposed hybrid algorithms results shows that all simulations are compliant with the restrictions. Channel average received power improvement, shown in Fig. 9c, indicates that the simplex and DSCR algorithm have lower performance than the others. This data, when compared with Fig. 8c, indicates that both hybridisation combinations achieve similar results with much lower cost function evaluations.

Scenario 4 is designed to test the ability to find a suitable route under fewer restrictions. Table 2 summarises the results obtained through the various simulations and optimisation approaches. The results display the same behaviour as in previous scenarios; when using the new LC function with particle swarm optimisation, the number of cost function evaluations is not reduced. Simplex and DSCR converge with less than 700 cost function iterations on average, which is lower than the 5507 or 3348 required by evolutionary or particle swarm optimisation, respectively.

On the channel improvement, results are similar to those in Table 2. Hybridisation using the simplex and DSCR obtain improvement in the same order of magnitude as previously tested optimisation algorithms. DSCR proves to have a better performance than simplex since the later had a negative improvement in this scenario. The average received power loss of the hybridisation using the simplex algorithm can be interpreted in Fig. 9d as an outlier.

7 Conclusion

Through this work, several optimisation methods have been shown to optimise a route for maximum connectivity that complies with the given objectives and restrictions. When compared with our previous work in [18], particle swarm optimisation achieves an optimal solution for all scenarios and all simulations, simulations where the evolutionary algorithm could not always find a solution compliant with all objectives and restrictions. Two hybrid optimisation approaches that combine particle swarm optimisation with the Nelder-Mead simplex algorithm or the Direct Search with Coordinate Rotation (DSCR) are proposed, and its results studied. The new hybrid approach requires a new cost function since the one used before is not suitable any more. Results confirm that the new cost function is necessary for the hybrid approach's good performance.

The results show that the hybrid optimisation with Nelder-Mead simplex or DSCR provides better and faster results. Using a hybrid approach can reduce the number of cost function evaluations by a factor of 10. Not only the number of evaluations to convergence is critical, but also the improvement on the average received power. This significant improvement in the number of evaluations before achieving a solution reduces the time required to find a suitable and compliant route.

The use of particle swarm combined with the DSCR is the more suitable of the two hybrid optimisation strategies. This combination has similar results to the combination with the Nelder-Mead simplex. Nevertheless, the use of DSCR always provides an improvement in the average received power. The particle swarm algorithm combined with DSCR always provides a flying route with the maximum connectivity in any of the scenarios investigated in this paper. In conclusion, through this work, we have proposed different optimisation methods to outperform our previous work in [18]. These methods have been applied to a plethora of situations and locations. The results have been studied, the performance of the various optimisation methods have been proved on critical scenarios, and particle swarm with DSCR is proposed as the most suitable approach. With this proposed optimisation approach, we have full filled the main objective of this work; to find an optimisation approach that outperforms the results obtained in our previous work.

Some aspects remain unclosed and constitute excellent candidates for further studies and development of the‘optimisation approach. First of all, new scenarios can be designed to test the system's robustness against disturbances, modelling errors and uncertainties. We have identified possible research directions to be followed concerning this topic. The next topic is the validation of the proposed routes as part of the necessary activities to validate the simulation. At least, the straight, best and worst routes should be flown and compared with the results obtained in the simulation to verify it. Verification of the results, along with the time required to obtain a route, air traffic management and technology readiness level of some elements, constitute limitations to the applicability of the proposed method. Undoubtedly, the optimisation approach can be further improved; candidate techniques to be studied in the future include other metaheuristic techniques such as tabu search or simulated annealing.

Author Contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Adrian Expósito Garcia. The first draft of the manuscript was written by Adrián Expósito García, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding This study was funded by Airbus Defence and Space gmbh. Universitat Politecnica de Valencia will cover publication costs.

Availability of data and material no applicable.

Code Availability no applicable.

Human/Animal Rights This article does not contain any studies with human or animal subjects performed by any of the authors.

Declarations

Ethics approval and consent to participate no applicable.

Consent for Publication no applicable.

Conflict of Interests Adrián Expósito García, Héctor Esteban González and Dominic Schupke declare that they have no conflict of interest.

References

1. Analytical Graphics, Inc. www.stk.com. Accessed: 2021-02-23
2. DCSR algorithm implementation by Matlab. https://cutt.ly/HY45SP8. Accessed: 2021-12-18
3. Genetic algorithm implementation by Matlab. https://cutt.ly/OY47O56. Accessed: 2021-12-18
4. Google Maps, Aerial view of the Alicante area. https://cutt.ly/DjnLvqA. Accessed: 2021-02-23
5. Google Maps, Aerial view of the Alps area. https://cutt.ly/KjnLWuw. Accessed: 2021-02-23
6. Google Maps, Aerial view of the Munich area. https://cutt.ly/1jnLnyu. Accessed: 2021-02-23
7. Nelder-mead algorithm implementation by Matlab. https://cutt.ly/DY45Wxl. Accessed: 2021-12-18
8. Particle swarm implementation by Matlab. https://cutt.ly/PY47TPC. Accessed: 2021-12-18
9. Ali, S.F., Nguyen, L.: UAS C2 data link performance for safe automatic flight guidance and control operation. In: AIAA/IEEE Digital Avionics Systems Conference - Proceedings (2016). https://doi.org/10.1109/DASC.2016.7778017
10. Besada-Portas, E., De La Torre, L., De La Cruz, J.M., De Andrés-Toro, B.: Evolutionary trajectory planner for multiple UAVs in realistic scenarios. IEEE Trans. Robot. **26**(4), 619–634 (2010). https://doi.org/10.1109/TRO.2010.2048610
11. Chaimatanan, S., Delahaye, D., Mongeau, M.: A hybrid metaheuristic optimization algorithm for strategic planning of 4d aircraft trajectories at the continental scale. IEEE Comput. Intell. Mag. **9**(4), 46–61 (2014)
12. Cotton, W.B., Wing, D.J.: Airborne trajectory management for urban air mobility. In: 2018 Aviation Technology, Integration, and Operations Conference (2018). https://doi.org/10.2514/6.2018-3674
13. de la Cruz, J.M., Besada-Portas, E., Torre-Cubillo, L., Andres-Toro, B., Lopez-Orozco, J.A.: Evolutionary path planner for UAVs in realistic environments. In: Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation - GECCO '08, p. 1477 (2008). https://doi.org/10.1145/1389095.1389383

14. Dandanov, N., Al-Shatri, H., Klein, A., Poulkov, V.: Dynamic self-optimization of the antenna tilt for best trade-off between coverage and capacity in mobile networks. Wirel. Pers. Commun. **92**(1), 251–278 (2017)
15. Di Caprio, D., Ebrahimnejad, A., Alrezaamiri, H., Santos-Arteaga, F.J.: A novel ant colony algorithm for solving shortest path problems with fuzzy arc weights. Alexandria Engineering Journal (2021)
16. Dong, X., He, S., Stojanovic, V.: Robust fault detection filter design for a class of discrete-time conic-type non-linear markov jump systems with jump fault signals. IET Control Theory Applic. **14**(14), 1912–1919 (2020)
17. Elouadih, A., Oulad-Said, A., Hassani, M.M.: Design and Simulation of a PIFA Antenna for the Use in 4G Mobile Telecommunications Networks. International Journal of Communications, Network and System Sciences. https://doi.org/10.4236/ijcns.2013.67035 (2013)
18. Exposito, A., Schupke, D., Esteban, H.: Route optimisation for maximum air to ground channel quality. IEEE Access **8**, 203619–203630 (2020). https://doi.org/10.1109/ACCESS.2020.3037075
19. Fadlullah, Z.M., Takaishi, D., Nishiyama, H., Kato, N., Miura, R.: A dynamic trajectory control algorithm for improving the communication throughput and delay in UAV-aided networks. IEEE Network. https://doi.org/10.1109/MNET.2016.7389838 (2016)
20. Fang, H., Zhu, G., Stojanovic, V., Nie, R., He, S., Luan, X., Liu, F.: Adaptive optimization algorithm for nonlinear Markov jump systems with partial unknown dynamics. Int. J. Robust Nonlinear Control **31**(6), 2126–2140 (2021)
21. Greenberg, E., Levy, P.: Channel characteristics of UAV to ground links over multipath urban environments. In: 2017 IEEE International Conference on Microwaves, Antennas, Communications and Electronic Systems, COMCAS 2017 (2017). https://doi.org/10.1109/COMCAS.2017.8244753
22. Grøtli, E.I., Johansen, T.A.: Path planning for UAVs under communication constraints using SPLAT! and MILP. Journal of Intelligent and Robotic Systems, Theory and Applications. https://doi.org/10.1007/s10846-011-9619-8 (2012)
23. Haas, E.: Aeronautical channel modeling. IEEE Trans. Veh. Technol. **51**(2), 254–264 (2002). https://doi.org/10.1109/25.994803, http://ieeexplore.ieee.org/document/994803/
24. Hayat, S., Yanmaz, E., Brown, T., Bettstetter, C.: Multi-objective UAV path planning for search and rescue, 5569–5574. https://doi.org/10.1109/ICRA.2017.7989656 (2017)
25. Ingber, L.: Adaptive simulated annealing (asa): Lessons learned arXiv preprint cs/0001018 (2000)
26. Kennedy, J., Eberhart, R.: Particle swarm optimization. In: Proceedings of ICNN'95 - International Conference on Neural Networks, vol. 4, pp. 1942–1948 (1995)
27. Kumar, S., Tejani, G.G., Pholdee, N., Bureerat, S., Jangir, P.: Multi-objective teaching-learning-based optimization for structure optimization. Smart Science, 1–12 (2021)
28. Kurban, R., Durmus, A., Karakose, E.: A comparison of novel metaheuristic algorithms on color aerial image multilevel thresholding. Eng. Appl. Artif. Intel. **105**, 104410 (2021)
29. Kurban, T., Civicioglu, P., Kurban, R., Besdok, E.: Comparison of evolutionary and swarm based computational techniques for multilevel color image thresholding. Appl. Soft Comput. **23**, 128–143 (2014)
30. Lagarias, J., Reeds, J., Wright, M., Wright, P.: Convergence Properties of the Nelder–Mead Simplex Method in Low Dimensions. SIAM J. Optim. **9**, 112–147 (1998). https://doi.org/10.1137/S1052623496303470
31. Lagarias, J.C., Reeds, J.A., Wright, M.H., Wright, P.E.: Convergence properties of the Nelder-Mead simplex method in low dimensions. SIAM J. Optim. **9**(1), 112–147 (1998)
32. Matolak, D.W., Sun, R.: Air-ground channel characterization for unmanned aircraft systems: The Hilly suburban environment. In: 2014 IEEE 80th Vehicular Technology Conference (VTC2014-Fall), pp. 1–5. IEEE (2014). https://doi.org/10.1109/VTCFall.2014.6965861, http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6965861
33. Matolak, D.W., Sun, R.: Air-ground channel characterization for unmanned aircraft systems - part III: The suburban and near-urban environments. IEEE Trans. Veh. Technol. **66**(8), 6607–6618 (2017). https://doi.org/10.1109/TVT.2017.2659651
34. Matolak, D.W., Sun, R., Jamal, H., Rayess, W.: L- and C-band airframe shadowing measurements and statistics for a medium-sized aircraft. In: 2017 11th European Conference on Antennas and Propagation (EUCAP 2017), pp. 1429–1433. https://doi.org/10.23919/EuCAP.2017.7928054 (2017)
35. Meyer, D., Wypych, T., Petrovic, V., Strawson, J., Kamat, S., Kuester, F.: An air traffic control simulator for test and development of airspace management schemes. In: 2018 IEEE Aerospace Conference, pp. 1–8 (2018). https://doi.org/10.1109/AERO.2018.8396575
36. Mezura-Montes, E., Coello, C.A.C.: Constraint-handling in nature-inspired numerical optimization: Past, present and future. Swarm Evol. Comput. **1**(4), 173–194 (2011). https://doi.org/10.1016/j.swevo.2011.10.001, http://www.sciencedirect.com/science/article/pii/S2210650211000538
37. Morro, J.V., Esteban, H., Soto, P., Boria, V.E., Bachiller, C., Cogollos, S., Gimeno, B.: Automated design of waveguide filters using aggressive space mapping with a segmentation strategy and hybrid optimization techniques. In: IEEE MTT-S International Microwave Symposium Digest, 2003, vol. 2, pp. 1215–1218 (2003)
38. Nedic, N., Prsic, D., Dubonjic, L., Stojanovic, V., Djordjevic, V.: Optimal cascade hydraulic control for a parallel robot platform by pso. Int. J. Adv. Manuf. Technol. **72**(5), 1085–1098 (2014)
39. Rizzoli, P., Martone, M., Gonzalez, C., Wecklich, C., Borla Tridon, D., Bräutigam, B., Bachmann, M., Schulze, D., Fritz, T., Huber, M., Wessel, B., Krieger, G., Zink, M., Moreira, A.: Generation and performance assessment of the global TanDEM-X digital elevation model. ISPRS J. Photogram. Remote Sens. **132**, 119–139 (2017). https://doi.org/10.1016/j.isprsjprs.2017.08.008, https://linkinghub.elsevier.com/retrieve/pii/S092427161730093X
40. Sahingoz, O.K.: Generation of bezier curve-based flyable trajectories for multi-UAV systems with parallel genetic algorithm. J. Intell. Robot. Syst. Theory Applic. **74**(1-2), 499–511 (2014). https://doi.org/10.1007/s10846-013-9968-6
41. Scherer, J., Yahyanejad, S., Hayat, S., Yanmaz, E., Vukadinovic, V., Andre, T., Bettstetter, C., Rinner, B., Khan, A., Hellwagner, H.: An autonomous multi-UAV system for search and rescue. In: DroNet 2015 - Proceedings of the 2015 Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use (2015). https://doi.org/10.1145/2750675.2750683
42. Schneckenburger, N., Matolak, D., Jost, T., Fiebig, U.c., del Galdo, G., Jamal, H., Sun, R.: A geometrical-statistical model for the air-ground channel. In: 2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC), pp. 1–6. IEEE (2017). https://doi.org/10.1109/DASC.2017.8102054, http://ieeexplore.ieee.org/document/8102054/
43. Sha, J., Xu, M.: Applying hybrid genetic algorithm to constrained trajectory optimization. In: Proceedings of 2011 International Conference on Electronic Mechanical Engineering and Information Technology, vol. 7, pp. 3792–3795 (2011)
44. Shakhatreh, H., Sawalmeh, A.H., Al-Fuqaha, A., Dou, Z., Almaita, E., Khalil, I., Othman, N.S., Khreishah, A., Guizani, M.: Unmanned Aerial Vehicles (UAVs): A Survey on Civil Applications and Key Research Challenges. https://doi.org/10.1109/ACCESS.2019.2909530 (2019)
45. ShangGuan, W., Yan, X., Cai, B., Wang, J.: Multiobjective optimization for train speed trajectory in ctcs high-speed railway with hybrid evolutionary algorithm. IEEE Trans. Intell. Transp. Syst. **16**(4), 2215–2225 (2015)

46. Singh, S., Mittal, N., Thakur, D., Singh, H., Oliva, D., Demin, A.: Nature and biologically inspired image segmentation techniques. Archives of Computational Methods in Engineering, 1–28 (2021)
47. Sun, R., Matolak, D.W.: Air-ground channel characterization for unmanned aircraft systems part II: Hilly and mountainous settings. IEEE Trans. Veh. Technol. **66**(3), 1913–1925 (2017). https://doi.org/10.1109/TVT.2016.2585504
48. Sun, R., Matolak, D.W., Rayess, W.: Air-ground channel characterization for unmanned aircraft systems-part IV: Airframe shadowing. IEEE Trans. Veh. Technol. **66**(9), 7643–7652 (2017). https://doi.org/10.1109/TVT.2017.2677884
49. Szczerba, R.J.: Threat netting for real-time, intelligent route planners. In: 1999 Information, Decision and Control. Data and Information Fusion Symposium, Signal Processing and Communications Symposium and Decision and Control Symposium. Proceedings (Cat. No.99EX251), pp. 377–382 (1999)
50. Wu, Q., Zeng, Y., Zhang, R.: Joint trajectory and communication design for multi-UAV enabled wireless networks. IEEE Trans. Wireless Commun. **17**(3), 2109–2121 (2018). https://doi.org/10.1109/TWC.2017.2789293, http://arxiv.org/abs/1705.02723, http://ieeexplore.ieee.org/document/8247211/
51. Xie, P., Petovello, M.G.: Measuring GNSS Multipath Distributions in Urban Canyon Environments. IEEE Trans. Instrum. Meas. **64**(2), 366–377 (2015)
52. Xin, X., Tu, Y., Stojanovic, V., Wang, H., Shi, K., He, S., Pan, T.: Online reinforcement learning multiplayer non-zero sum games of continuous-time markov jump linear systems. Appl. Math. Comput. **126537**, 412 (2022)
53. Zeng, Y., Zhang, R., Lim, T.J.: Throughput maximization for mobile relaying systems. 2016 IEEE Globecom Workshops. GC Wkshps 2016 - Proceedings **64**(12), 4983–4996 (2016). https://doi.org/10.1109/GLOCOMW.2016.7849066
54. Zhang, G., Wu, Q., Cui, M., Zhang, R.: Securing UAV communications via trajectory optimization. 2017 IEEE Global Communications Conference GLOBECOM 2017 - Proceedings 2018-Janua, pp. 1–6. https://doi.org/10.1109/GLOCOM.2017.8254971 (2018)

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