

Advancing evolutionary coordination for fixed-wing communications UAVs

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Abstract. In this paper we present advances to our previously proposed coordination system for groups of unmanned aerial vehicles that provide a network backbone over mobile ground-based vehicles. Evolutionary algorithms are employed in order to evolve flying manoeuvres that position the aerial vehicles. The updates to the system include obstacle representation, a packing mechanism to permit efficient dynamic allocation of ground-based vehicles to their supporting aerial vehicles within large-scale environments, and changes to time synchronisation. The experimental results presented in this paper show that the system is able to adaptively form sparse formations that cover as many ground-based vehicles as possible, optimising the use of the available power.

Keywords: Evolutionary algorithms, unmanned aerial vehicles, coordination strategies.

1 Introduction

This paper presents advances to the autonomous coordination of multiple unmanned aerial vehicles (UAVs) that provide network coverage for multiple independent ground-based vehicles, initially introduced in [5]. The advances include a way to overcome the known problems of imperfect communication due to the mobility of ground-based vehicles (leading to long distances between them and the aerial vehicles), limited radio frequency power, and other communication failures related to large distances between communicating devices. The aim of the system is to define flying strategies that allow groups of autonomous aerial vehicles to react to topological changes and to ensure that relaying of data between ground-based vehicles is achieved. The use of evolutionary algorithms for similar complex problems has been previously explored, showing great potential ([1, 3, 7, 8]). The system's ultimate objective is to maximise the number of supported ground-based vehicles with respect to the given limited power available to the communication. To achieve such emergent behaviour while staying below the power threshold, a sophisticated method for allocating which ground-based vehicle is to be covered by which unmanned aerial vehicle (referred to as packing) needs to be employed.

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In this paper the incorporation of obstacle representation and the use of a packing mechanism that allow simulations of realistic and large-scale scenarios to be achieved, are introduced. A new mechanism for providing coverage considers the limited available power when allocating ground-based vehicles to their supporting aerial vehicles. This mechanism replaces our previous evolutionary algorithm fitness function initially presented in [5]. The original fitness function (equation 1) only considered two objectives; a) maximisation of the network coverage by minimising the overlap between the footprints of the aerial vehicles, and b) minimisation of their average altitudes. The latter ensured that minimum power will be consumed in achieving network coverage.

$$f = \frac{C_{net} - C_{overlap}}{G} \times \left(1 - \text{norm} \left(\frac{\sum_{i=0}^U (h_i)}{U} \right) \right) \quad (1)$$

Although the equation proved its effectiveness through experiments, it assumes that no power hard limit exists, thus leading to unbalanced situations where some aerial vehicles end up providing network coverage to more ground-based vehicles than others in a stochastic way, independent of the physical positions of the ground-based vehicles. This phenomenon brings to light two important issues. Firstly, in reality, the aerial vehicles have limited power available for communications and thus a method that encourages a balanced way of ground-based vehicles to aerial vehicles allocation is desired. Secondly, using such a fitness function the resulting physical topologies will ultimately lead to communication networks prone to congestion due to bottleneck effects. That is, routing protocols will explore those paths containing overloaded aerial vehicles and thus the traffic will eventually be routed via particular overloaded relays.

The latest system puts emphasis on enhancements that allow large-scale scenarios to be realised (i.e., the obstacle representation and the sophisticated packing mechanism) and a study of analysing the flying formations that emerge.

The structure of the paper is as follows. Section 2 presents the enhancements made to the system. Section 3 is dedicated to the results and their analysis. The paper concludes in section 4, where an overview of the findings is given.

2 Methods

In this section, the key components of the proposed system are briefly discussed with respect to the enhancements made to the new version of the coordination system. Namely, the obstacle representation into the communication model, the chromosome codification with respect to time synchronisation in the system and the packing mechanism that replaces the fitness function of the previous initial work, allowing the system to work efficiently in large-scale dynamic environments.

2.1 Communication model and obstacle representation

As in the initially proposed system, an aerial vehicle is treated as a point object in three-dimensional space with an associated direction vector. At each time step, the position of an aerial vehicle is defined by a latitude, longitude, altitude and heading $(\phi_c, \lambda_c, h_c, \theta_c)$ in the geographic coordination system. Detailed descriptions of the kinematic model responsible for the flying of the fixed-wing aerial vehicles can be found in [6] and in [5].

Networking is achieved by maintaining communication links between the aerial backbone and as many ground-based vehicles as possible. The communication links are treated independently and a transmission is considered successful when the transmitter is able to feed its antenna with enough power, such that it satisfies the desirable quality requirements. In terms of the ground-based vehicles, it is assumed that they have a Global Positioning System (GPS) device and are able to broadcast their own position information at some reasonable interval (the default value is 3 seconds). This data is used by the evolutionary algorithms in order to make appropriate predictions and relocate the aerial vehicles. It is the only way the aerial vehicles can sense the presence of ground-based vehicles and their moving patterns. In terms of the aerial vehicles it is assumed that they are equipped with two radio antennae. One isotropic able to transmit to all directions and a horn-shaped one able to directionally cover an area on the ground. Also, all flying vehicles are equipped by a GPS device and can broadcast information about their current position and directionality at a reasonable interval (default 3 seconds). Here, focus is primarily given to the communication between aerial vehicles and ground-based vehicles using the former horn-shaped antennae, as it dictates the effectiveness of the communication coverage of the mission and the power consumption of a flying mission.

Starting from the initial communication model [5], a link between an aerial vehicle and a ground-based vehicle antennae is considered of a good quality if the ratio of the energy per bit of information E_b to the thermal noise in 1 Hz bandwidth N_0 (normalized signal to noise ratio E_b/N_0) is maintained. The transmitting power P_t that an aerial vehicle is required to feed to its horn-shaped antenna in order to cover a ground-based vehicle in distance d is expressed by the following version of the Friis equation:

$$P_t = p \times d^2 R_b \frac{E_b}{N_0} \frac{1}{G_r G_t} \left(\frac{4\pi f}{c} \right)^2 T_{sys} K \quad (2)$$

- R_b is the desired data rate on the link (bit/s),
- E_b/N_0 is the target ratio of energy in one bit to the noise in 1 Hz,
- G_r is the receiver's antenna gain (assuming omnidirectional),
- G_t is the transmitter's antenna gain equal to $\frac{2\eta}{1-\cos(HPBW/2)}$, where η and $HPBW$ are the efficiency and the half-power beamwidth angle of the horn-shape antenna,
- T_{sys} is the total system noise temperature,
- K is the Boltzmann K constant,

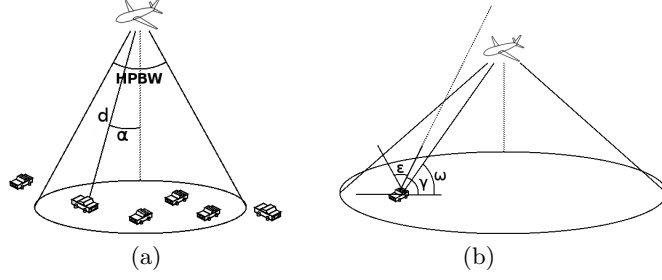


Fig. 1. Slant distance d and angle α of a communication link (a) and angle ϵ defines the area within which links are possible (b). Elevation angle γ is user-defined.

- p is the coverage profile (will be explained below), and
- d is the slant range defining the distance between the aerial vehicle and the ground-based vehicle on the ground.

and has to be reduced from the time step power available threshold P_{max} . In equation 2, most of the terms are known and remain constant during the mission, apart from the slant distance d and coverage profile p .

The latter describes whether a ground-based vehicle is covered by a supporting aerial vehicle. Its value is 1 if the ground-based vehicle lies within its supporting aerial vehicle's footprint, determined using the packing algorithm described in section 2.3. In the new system, there are two criteria that need to be fulfilled so that the coverage profile p of a ground-based vehicle is set to 1. The first criterion is depicted in figure 1(a) and is related to the aerial vehicle's footprint w.r.t. its current altitude as well as its antenna's half-power beamwidth (HPBW) angle. The higher the aerial vehicle flies, the wider its footprint on the ground. The second criterion is related to the existence of obstacles in the system, an enhancement that allows realistic simulations to be conducted. Obstacles are introduced by the use of an elevation angle, as shown in figure 1(b). The two criteria are combined mathematically so as the profile p is written:

$$L(p) = \begin{cases} 1, & \alpha < HPBW/2 \quad \text{and} \quad \omega \geq \gamma \\ 0, & \alpha \geq HPBW/2 \quad \text{and} \quad \omega < \gamma \end{cases} \quad (3)$$

Finally, at each time step the transmission of 3 UDP datagrams from each aerial vehicle down to any ground-based vehicle it currently supports is simulated, using a downline data rate of 2Mbit/s and frequency of 5GHz to finally ensure a ratio E_b/N_0 of 10db. Ultimately, the number the available communication links that can be accessed depends on the position of the aerial backbone and the number of ground-based vehicles being currently allocated to each of them. In this way, the power consumption per time step is measured and subtracted from the available power to the communication which is set to $P_{max} = 50\text{Watts}$.

2.2 Chromosome codification and time synchronisation

A centralised, on-line, EA-based approach is considered for the coordination of the group of aerial vehicles. The decision making for the next set of manoeuvres for the group is made by a single aerial vehicle, nominated as the master. Taking advantage of the underlying network, it is assumed that every 3 seconds the master is able to receive messages carrying the last known positions and direction vectors of the flying group as well as those of the ground-based vehicles. Data updates may be received from relaying aerial vehicles and directly from the ground-based vehicles within the master's footprint, and are tagged such that the master, and in turn the EA decision unit, are fed with up-to-date knowledge of the topology.

Once the EA has evolved a new set of manoeuvres, the master aerial vehicle is responsible for broadcasting the solutions to the whole group, using the network. As this work mainly focuses on providing network coverage to ground customers, it is assumed that there is no packet loss and that a dynamic routing protocol allows flawless data relaying within the topology.

A flying manoeuvre is described by a Dubins path of 3 segments [5]. Each segment comprises a bank angle and the duration for which the segment's manoeuvre is to be performed. Furthermore, a Dubins path may request a change to the vertical plane, thus require an alteration to the current altitude. The information is stored to the chromosome's genes in a form of " $\beta_1, \delta t_1, \beta_2, \delta t_2, \beta_3, \delta t_3, b, \delta h$ " sequences. The first six genes describe the horizontal motion and the duration of each of the 3 segments of the Dubins path and are stored as floating point values. The seventh gene b , as well as the last δh , control the vertical behaviour of the aerial vehicle. When the former is set to 0, the aerial vehicle flies at the same altitude (level flight). If it is set to 1, then the vertical motion is considered and the aerial vehicle is expected to change its altitude by δh within the duration of the Dubins path, $\sum_{i=1}^3 (\delta t_i)$.

The decision of including two dedicated genes related to the altitude changes instead of just representing the altitude with a single floating point value, is explained when one carefully investigates both the influence and type of parameter each gene represents. When encoding and decoding chromosomes, e.i., constructing flying solutions for the aerial vehicles so they can be evaluated, the genes' values are bounded within pre-defined ranges, according to their nature and meaning. Bank angles drive an aerial vehicle to bank either to the left or to the right, allowing it to gradually change its heading. If β_{min} and β_{max} are the minimum and maximum values, that is -48° and $+48^\circ$ respectively, then the values of the corresponding genes (β_1, β_2 and β_3) are encoded within the range of $[0, 1]$ and decoded after being normalised in the range of $[\beta_{min}, \beta_{max}]$. Similarly, the δh value is decoded after being normalised in the range of $[h_{min}, h_{max}]$, with $h_{min} = -h_{max}$. Clearly, if the 7th gene was not present, the chances of flying level, e.i., $\delta h = 0$, would not be probabilistically fair compared to $\delta h \neq 0$. With the binary gene present, flying level has an equal probability to ascending and descending, thus affecting the power consumption by changing the distance between the transmitting and receiving antennae. Ta-

ble 1 depicts an example of chromosome codification, where $C0$ and $C1$ are chromosomes before and after decoding. In this example, the EA-based system proposes that for the next manoeuvre $C1$ will gradually change its altitude by flying -147 metres lower. In this example, the duration of a manoeuvre is set to $\delta t_1 + \delta t_2 + \delta t_3 = 134.164848 + 106.131113 + 71.704039 = 312.0$ seconds.

	β_1	δt_1	β_2	δt_2	β_3	δt_3	b	δh
C0:	0.058745	0.345754	0.258386	0.260568	0.997280	0.888298	0	0.587347
C1:	0.197602	0.835057	0.560083	0.565502	0.092618	0.234472	1	0.428889
C0:	-42.360511	88.144913	-23.194961	79.285621	47.738864	144.569466	0	180.807804
C1:	-29.030183	134.164848	5.767955	106.131113	-39.108657	71.704039	1	-147.199089

Table 1. An example of two chromosomes being decoded into meaningful values for the flying of two aerial vehicles.

An evolutionary algorithm using linear ranking is employed to set the parameters of the paths [4]. We consider populations composed of $M = 100$ teams, each consisting of $N = 4$ individuals (the number of aerial vehicles in the flying group). At generation 0 each of the M teams is formed by generating N random chromosomes. For each new generation, the chromosomes of the best team (“the elite”) are retained unchanged and copied to the new population. Each of the chromosomes of the other teams is formed by first selecting two old teams using roulette wheel selection. Then, two chromosomes, each randomly selected among the members of the selected teams are recombined with a probability of 0.3 to reproduce one new chromosome. The resulting new chromosome is mutated with a probability of 0.05. This process is repeated to form $M - 1$ new teams of N chromosomes each.

The concept of time and time synchronisation plays a important role in the system. The aerial vehicles are allowed to perform two types of manoeuvres; i) a turn circle manoeuvre of a fixed bank angle, and ii) the resulting evolved manoeuvre generated by the EA decision unit.

As the system does not consider noise at the current, abstract stage (e.g., wind force and variations to cruising speed), an aerial vehicle is expected to perform perfect circles and always reach the same final latitude, longitude, and altitude when completing a revolution. In terms of the manoeuvres generated by the EA, all aerial vehicles are expected to complete their flying at an equal time, due to the Dubins manoeuvres’ equal durations. Since the resulting decision that dictates the next move is communicated from the master to the rest of the group using the network, it is understood that there are delays that may affect the transmissions, such that not all of the aerial vehicles will be informed on time. This brings a synchronisation problem which is addressed by increasing the number of revolutions required before a Dubins path is implemented by the aerial vehicles. The significance of this rule is two-fold. Not only it allows all aerial vehicles to successfully receive the next manoeuvre information, depending on the number of repeated revolutions set, but it also ensures that the EA has enough time to reach a solution.

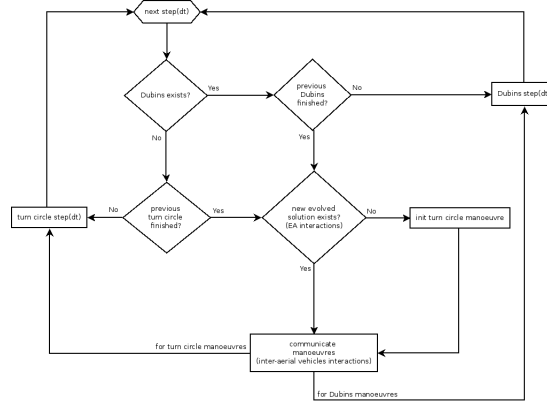


Fig. 2. Process flow for a master aerial vehicle.

After solving the time synchronisation issues the EA is able to run in parallel with the rest of the controller, which is responsible for keeping the aerial vehicle flying in order to complete its previous action, either a turn circle or a Dubins manoeuvre. Figure 2 depicts the algorithm flow at the master aerial vehicle. At every time step dt , the algorithm takes a step further to the previous unfinished manoeuvre (as long as it is not completed). If no Dubins manoeuvre is available and a turn circle manoeuvre has been performed, the master interacts with the EA decision unit to receive a freshly evolved solution (set of manoeuvres for all of the aerial vehicles in the group). Notice that in case when the EA has not been successful in evolving a good solution, the master communicates turn circle manoeuvres to the rest group. This allows synchronisation between the aerial vehicles as they are bound to make a revolution, whilst giving more time to the EA algorithm to produce a result.

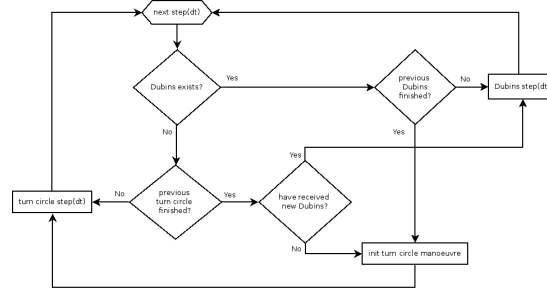


Fig. 3. Process flow for a non-master aerial vehicle.

As a non-master aerial vehicle (shown in figure 3) does not interact with an EA decision unit at the current stage of the system, it constructs and performs

turn circle manoeuvres only when no Dubins (or turn circle manoeuvre) is received from the master. This feature is rather unusable as the aerial vehicles will always receive a manoeuvre due to the perfect network conditions discussed before. Nevertheless, in reality this will allow a non-master aerial vehicle to continue flying in a controlled attitude and give it time to synchronize with the rest of the group. It is empirically found that a double turn circle manoeuvre of 6 seconds (75 degrees bank angle) gives enough time for the EA decision unit to produce reasonable results for a group of 6 aerial vehicles. Ultimately, the group's flying pattern is as follows: turn circle $\rightarrow$ turn circle $\rightarrow$ Dubins $\rightarrow$ turn circle $\rightarrow$ turn circle $\rightarrow$ Dubins $\rightarrow$... and so on.

2.3 Packing mechanism for energy efficiency

Another major enhancement to the proposed system is the use of a packing mechanism which is responsible for allocating ground-based vehicles to supporting aerial vehicles. In order to understand the importance of a packing mechanism and its use in the context of network coverage and coordination of aerial vehicles, it is necessary to deeply understand the internal mechanisms of the evolutionary algorithms while travelling within the search space to converge to an optimal solution. Each population, when generated, has at some point to be evaluated so as the survival of the fittest is ensured. In the context of the proposed system, the evaluation is performed at a group level, where the performance of the group of aerial vehicles is examined in a collective manner. Thus, similarly to the previous fitness function, an optimal solution is a solution that maximises the cumulative network coverage. Still, the influence the altitude of an aerial vehicle has to the amount of power required to achieve communication with ground-based vehicles needs to be incorporated in the system. This is achieved by a packing mechanism.

In this work, a similar packing algorithm used in [2] is adopted. The ability of an aerial vehicle to support ground-based vehicles is described by its packing array, a list of ground-based vehicles that are allocated to this particular flying vehicle. The aim of the packing algorithm is to make the most efficient allocation in terms of the power consumption. In more detail, a general logical map is first built so as to accommodate all aerial vehicles along with all the ground-based vehicles that lie within their footprints, coupled with the power required to support each the intermediate link. Notice that the ground-based vehicles sorted by the power requirement and thus the least expensive lie first. Algorithm 1 is employed ensuring that the number of ground-based vehicles allocated to each aerial vehicle is maximised while the power consumption is minimised, by firstly concentrating on the centre of each aerial vehicle's footprint and gradually expanding to its edges.

Consequently, the group fitness function f is the sum of the packing arrays, i.e., $\sum_{i=1}^N (packing[i])$. The bigger that number becomes, the most fitted that particular set of manoeuvres is when implemented. This process allows the EAs to evolve solutions that maximise the network coverage by assigning ground-based vehicles to those aerial vehicles that are able to spend less power to support

Algorithm 1 Packing algorithm

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1: let  $G$  be a sorted logical map
2: initialize  $\text{packing}[N]$  as empty packing arrays for  $N$  aerial vehicles
3: while  $G$  is not empty of ground-based vehicles do
4:   for each  $u$  in logical map  $G$  do
5:     let  $g$  be the first ground-based vehicle found in  $u$ 's sorted list
6:     let  $p$  be the power required to support  $g$ 
7:     if  $\text{powerbudget}(u) - p \geq 0$  then
8:        $\text{packing}[u] \leftarrow g$ 
9:        $\text{powerbudget}(u) = \text{powerbudget}(u) - p$ 
10:    remove remaining instances of  $g$  from  $G$ 

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them. Artificial evolution awards those sets of manoeuvres that achieve a better score and when all generations complete, the solution is communicated to the flying group for implementation along with the suggested packing arrays used for the fitness score calculations. The receiving aerial vehicles are then forced to fly according to their Dubins path and serve those ground customers that are stored into their packing arrays. It is important to notice that evolution uses information retrieved from frequent broadcast messages sent by all vehicles. In order to ensure that the manoeuvres are generated according to valuable positional information, distances between antennae and in turn power estimation is calculated based on predicted positions.

3 Experiments and results

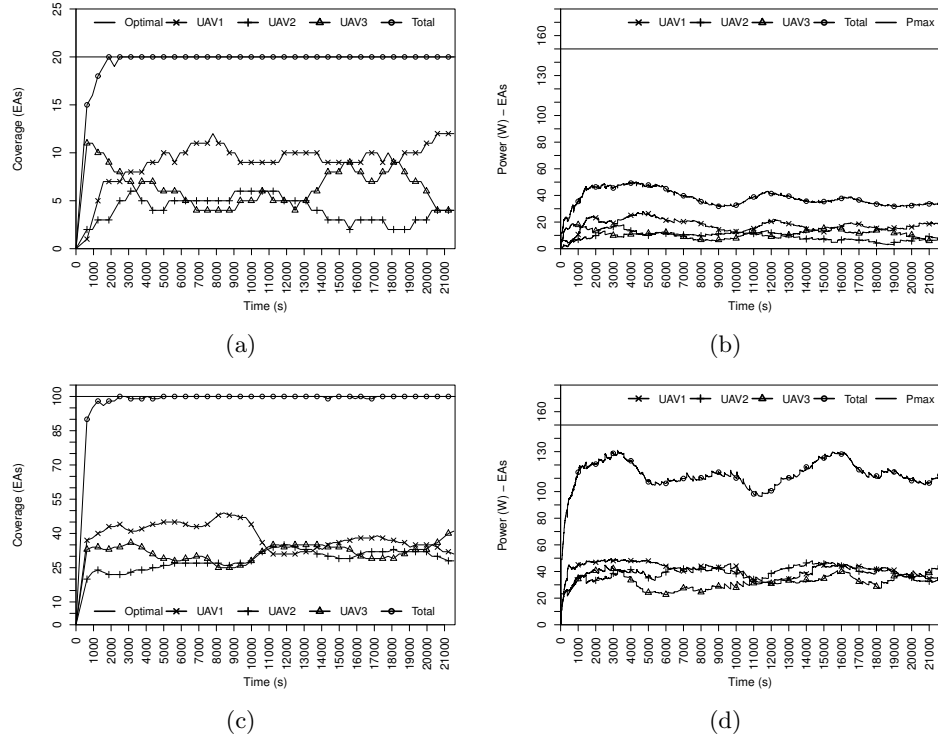
The performance of the enhanced proposed system is shown and discussed in this section. The study encompasses an experimental scenario in which groups of three aerial vehicles with limited available communications power are deployed to fulfil the network requirements of several ground-based vehicles. The ultimate aim of the study is to investigate the ability of the system to manage and utilise the aerial vehicles by repositioning them, such that the network coverage is maximised in a power-aware fashion. Also, their performance is evaluated in terms of autonomous flying flexibility, resulting in formations and manoeuvres, in order to challenge its applicability to real world applications. Results related to the aerial vehicles ability to separate and thus allow higher manoeuvring flexibility are included. The configuration settings and simulation conditions are similar in both scenarios and are summarised in table 2.

Results of experiments with three aerial vehicles are presented in figures 4 for both coverage (a, c) and power consumption (b, d). The system is shown to achieve optimal coverage results when covering a small as well as large number of ground-based vehicles. It is also observed that the flexibility in implementing flying manoeuvres, as a result from the design, allows the aerial vehicles quickly find a good formation according to the way their customers are positioned on the ground. This is observed in conjunction with separation results depicted in fig-

Simulation parameters			
Terrain size	100 km^2		
Duration	6 hours of flying		
Aerial vehicles' parameters			
Init altitude	15000 feet		
Init latitude, longitude and heading	#1	52.8636, -2.6373	270°
	#2	52.0512, -1.4219	270°
	#3	52.8605, -1.4219	270°
Ground-based vehicles's parameters			
Number of units	50 and 200		
Mobility model	Random WayPoint		
Speed	30 mph		

Table 2. Table of parameters and configuration settings

ure 5. The aerial vehicles fly far away from each other and gradually gain altitude so that more ground-based vehicles lie within their cumulative footprints.

**Fig. 4.** Coverage and power results as a function of time, when covering 20 (a, c) and 100 (b, d) ground-based vehicles.

Power consumption is shown in figures 4(b) and 4(d) for small and large number of ground-based vehicles, respectively. In the case of 100 ground-based

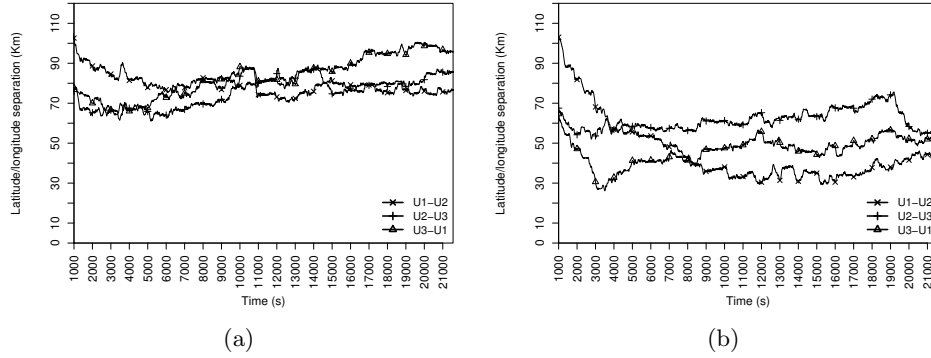


Fig. 5. Separation between all possible pairs of aerial vehicles as a function of time, when covering 20 (a) and 100 (b) ground-based vehicles.

vehicle participants the system, as expected, consumes more energy yet the packing mechanism balances the number of ground-based vehicles allocated to each aerial vehicle and does not allow aerial vehicles to reach the limit of 50 Watts per time step. The effect is less obvious in the case of supporting only 20 ground-based vehicles as due to the large scenario area, the ground vehicles are sparsely positioned, a physical fact that requires wider footprints to be generated.

Finally, the manoeuvrability of the system is examined by presenting the separation of three aerial vehicles during the course of the mission. Notice that the initial 1000 seconds have been omitted from the plots, as they constitute a bootstrap period with unstable flying formations present.

Figures 5(a) and 5(c) show the separated distance between all possible aerial vehicle pairs during the autonomous flying. It is clearly shown that the EAs tend to fly the aerial vehicles far apart from each other, in almost triangle formations. In both scenarios they reach the ceiling (maximum altitude of 22000 feet). This is because the positions of the ground-based vehicles are quite sparse and the aerial vehicles need to increase their altitudes so as to capture as many or them as possible. However, in the case of covering 100 ground-based vehicles the aerial vehicles fly closer to each other as they are able to find clusters of ground-based vehicles and amendments between consecutive evolutions do not make a significant difference to the fitness score of the new solutions.

4 Conclusion

This paper presents enhancements made to the initially proposed autonomous coordination system found in [5]. The new design includes an obstacle representation for realistic communication in large-scale scenarios, as well as the employment of a packing mechanism that considers limited available power. Emphasis is also given to the design in terms of time synchronisation and chromosome codification.

The experimental results show that the system is able to fulfil the main objective, i.e., to optimise the network coverage while utilising efficiently the power given to the communications. In addition, this paper shows an analysis of the flying behaviour emerging by the use of EAs, in terms of separation in flying. The aerial vehicles are found to quickly adopt sparse formations, a valuable trait for covering large-scale areas.

Acknowledgements

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