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GA-based Energy Aware Path Planning Framework for Aerial Network Assistance

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Abstract

Aerial networks have enormous potential to assist terrestrial communications under heavy traffic requests for a predictable duration. However, such potential for improving both the performance and the coverage through the use of drones can face a major challenge in terms of power limitation. Hence, we consider the energy consumption characteristic of the components in such networks to provide energy aware flight path planning. For this purpose, a flight path planning scheme is proposed on an underlying topology graph that models the energy consumption of path traversals in the aerial network. In the proposed model, we offer to seek for the minimum energy consumption on a global problem domain during the entire operational time. Thus, we provide a concrete problem formulation and implement a flight path planning with Genetic Algorithms (GA) approach. Moreover, a novel end-system initiated handover procedure is illustrated to preserve connectivity of terrestrial users in the network architecture. In the end, the evaluation of the proposed model is conducted under three different scales of social event scenarios. A comparison with a dummy path planning scheme without energy awareness concerns is presented according to a set of parameters. The evaluation outcomes show that the proposed model is able to save 20% energy consumption, provides 15% less number of terrestrial replenishment, and 18% more average endurance for the topology. Besides, another energy aware path planning scheme in the literature offering a deployment with Bellman Ford algorithm is also included in the evaluation to evaluate the feasibility of the proposed framework for the enhanced problem domain.

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1. Introduction

According to Cisco Annual Internet Report [1], the total number of networked devices will be 29.3 billion by 2023 and this will be more than three times the global population. When considered fast mobility growth, the data traffic requests generated by such devices have recently begun to overwhelm conventional network infrastructures, especially in urban areas. Thus, as a prominent solution, the use of drones have received growing attention to support communication infrastructure. Especially, their use is beneficial for terrestrial network assistance, such as in use cases where providing permanent terrestrial components are costly and redundant. These two concepts have been interacting with each other, and aerial networks have become a popular technology that deploys Aerial Base Stations (ABS) to increase wireless coverage and capacity. In this context, social event scenarios such as concerts, festivals, soccer games, etc. are convenient scenarios for aerial network assistance where a huge crowd generates abnormal traffic requests within a specific geographical area for a short duration. The appeal for aerial network assistance in such environments provides flexible, efficient, and advanced management of traffic requests with a mission-specific temporary intention.

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There has been several attempts in the literature to offer aerial networks as an extension to conventional terrestrial infrastructures, recently. [2] studies an aerial network deployment for disaster scenarios as an assistant component. In [3], the authors aim to provide a proper coverage for terrestrial users in such an environment with a delay tolerant networking approach. [4] offers aerial networks as an offloading mechanism for cellular communication to especially alleviate the burden of user density in cell edges. Another application of aerial network emerges with Internet of Things (IoT) concept as in [5]. The authors propose ABSs to collect data from terrestrial nodes so as to reduce transmit power in IoT network; thus, an increased system reliability is obtained with enhanced lifetime. There are also commercial applications such as the one proposed by AT&T, [6], for social events such as football games and Super Bawl in which they deploy a complementary aerial infrastructure that results an enhanced coverage and service. Besides the opportunities provided in aerial networks, there are some major challenges as the details surveyed in [7] and [8]. The energy limitation challenge of aerial networks comes forward against the others since ABSs' limited battery capacity affects the flight endurance and, thus network lifetime. Hence, the deployment purpose and energy awareness of such networks should be carefully recognized to provide the existence of the network in a reasonable and proper way.

An efficient way to save energy is directly related with a proper path planning during the maintenance. There is also a considerable amount of interest in the literature to provide energy efficiency for flight path planning whenever an ABS requires a replenishment because of a dead battery. In [9], the authors present a propulsion energy consumption model for UAVs and provide a UAV trajectory scheme where flight radius and speed are optimized in order to minimize the energy consumption. [10] proposes a joint flight path planning and a task assignment problem for aerial networks consist of fixed-wing UAVs according to an energy effectiveness scheme. In [11], a novel energy aware path planner algorithm is given for a UAV swarm responsible for geographical inspection mission. [12] studies on a battlefield communication environment and proposes a flight planning under a set of constraints. In [13], an energy aware path planning framework is proposed for aerial networks considering an underlying topology graph that includes a distance-related energy consumption model for path traversals. However, in these studies, the authors do not have an effort to track the dynamicity in the network as time passes and all possible, energy aware opportunities during the entire operational time. A proper flight planning mechanism should consider an enhanced search space to fully utilize possible opportunities until the termination of network deployment.

In addition to considering the entire operational time, it is an obligatory for the flight planning approach to respond within a feasible amount of time. The entire search space grants a global optimum solution, against all possible replenishment requests, by using a systematic approach such as Bellman Ford's algorithm (in [13]), A-Star algorithm (in [12]); however, such approaches used in the literature suffer from the state space explosion. Thus, they cause huge response time to investigate each probable solution candidate even most of them is too far to be optimum. On the other hand, the running time complexity of an implementation plays an important role to get a response in a reasonable amount of time, especially for the problems with extensive search space. There are some studies to overcome this challenge in the literature by applying evolutionary approaches. As indicated in [14], traditional approaches give place to evolutionary mechanisms to solve complex real world problems within a reasonable amount of time and the authors implement GA for robot path planning. In [15], capabilities and characteristic of GA approach are inquired to solve path planning problems for extensive environments in robotic domain. Hence, such approaches should be utilized for a proper flight planning scheme on the enhanced problem domain to meet feasibility concern in terms of the response time to the system.

The replenishment process of ABSs for topology maintenance is also affects the terrestrial users in aerial networks. There is a quite difference between the handover requirement for such networks and existing mobility management schemes in the literature (e.g. [16], [17]). For instance, a handover process is required for user clusters served by an ABS with drained battery, and in this case, the handover procedure should be initiated from the end-system even the corresponding terrestrial users are immobile. On the other hand, conventional handover studies mainly focus on the mobility pattern of end-users in dense environments and offer some novelties for the handover procedure from the end-user perspective. Thus, a proper handover mechanism should also be considered while fulfilling the missing aspects of energy awareness in flight path planning schemes.

As a consequence of the motivations provided, in this paper, we offer a path planning model for commercial aerial network assistance that collects data from aerial components, schedules possible future replenishment requests and provides an energy aware flight path. Moreover, the connectivity of terrestrial users is also taken into account with a novel handover procedure. The contribution of the study is summarized as listed below:

- A concrete optimization problem considering the time variable is provided based on an energy consumption graph model given in [13] to present an objective function with respect to the energy consumption which affects the number of terrestrial replenishment and average endurance.
- A feasible flight planning framework with GA implementation is proposed on the enhanced search space obtained from the entire operational time of the aerial network.
- A novel end-system initiated handover procedure is defined to maintain the connectivity of corresponding terrestrial users during a replenishment process for an ABS with drained battery.

The rest of the paper is organized as follows. The network architecture studied in the paper is given in Section II. The proposed system model for flight path planning is introduced and its components are described in Section III. Performance evaluation of the study is presented in Section IV by illustrating a comparison with existing flight path planning strategies over a set of evaluation metrics. Eventually, the conclusion and future research directions are given in Section V.

2. Network Architecture

The network architecture used in the study is given with Figure 1. In the architecture, there are users, base stations embedded drones called ABSs, and a centralized Terrestrial Drone Controller (TDC). It is assumed that the users come together for a social event (e.g. a concert, music festival, etc.), have a linear mobility model with no initial speed as given in [18], and generate a variety of traffic requests.

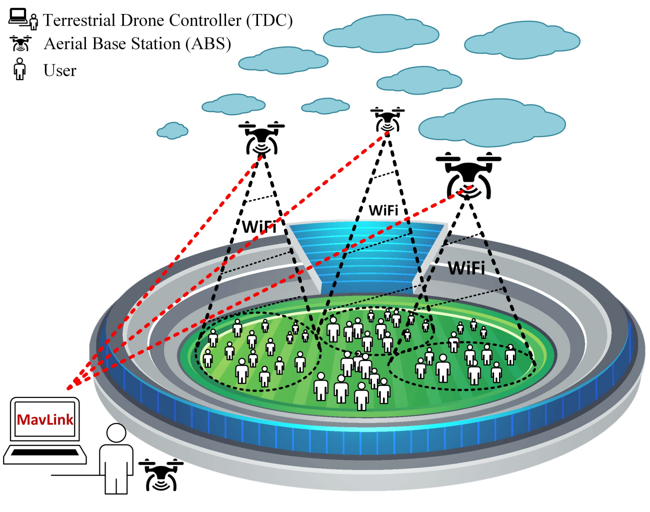

Figure 1. The network architecture

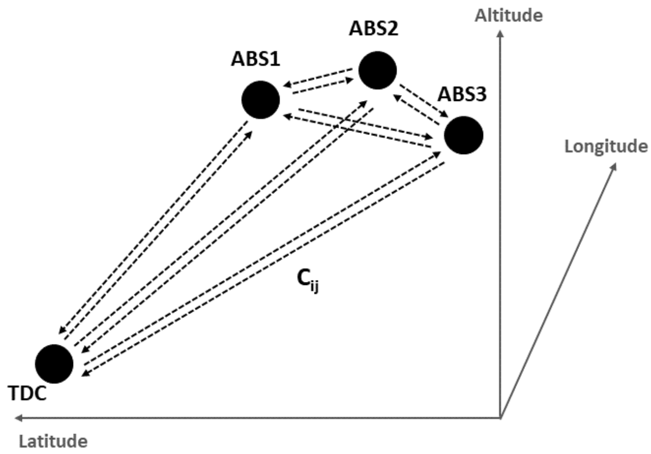

Figure 2. Corresponding topology graph for the network architecture

Each of the ABSs covers a specific area with WiFi protocol and serves corresponding users to alleviate terrestrial network components that are not shown in the architecture for the sake of simplicity. An exact location for each ABSs in the topology is determined according to previous studies in the literature (e.g. [19], [20], [21], [22]), and given as an input to the proposed system model studied in this work. The drone controller is capable of commanding drones using Micro Air Vehicle Link (MAVLink) protocol to manage them with a set of commands. The architecture given in the figure should be maintained during the estimated time of the event scenario. Thus, each of the ABSs with a drained battery should be replenished with redundant ones by the terrestrial controller. For this purpose, the proposed system model is consulted for a path planning with minimum energy consumption cost in the topology.

The corresponding topology graph for the network architecture is also provided in Figure 2. There are four nodes labeled as TDC, ABS1, ABS2, ABS3 in the graph, i.e. the representatives for the components in Figure 1, and virtual-directed-weighted edges between them. A complete digraph is used and energy consumption related costs are assigned to each of the edges in the graph. The nodes and edges are denoted as V and E in the graph, respectively. A cost assignment strategy stated in [13] is utilized such that a Manhattan Distance value is considered to assign a cost for an edge w.r.t $cost(s,d) = (\sum_{i=1}^{2} |(d_i - s_i)|) + (d_3 - s_3)$ where s is the source node, d is the destination node, and i, j are the index values representing the latitude-longitude tuple, respectively; and, the third dimension for (d_3 and s_3) is altitude. The distance value between each node is labeled as c_{ij} to illustrate the cost of energy consumption during the traversal between node V_i and V_j. Whenever a drone in the network drains its battery, the proposed framework offers an energy aware path planning for the replacement process in order to maintain the topology and connection of the terrestrial users. Moreover, the estimated operational time for the aerial network is also taken into account to provide the minimum energy consumption traversal not only for the moment of replacement process but also for the future state of the topology. For this purpose, a concrete problem formulation is presented below with respect to an objective, i.e. minimizing the power consumption against a set of constraints. The objective function and constraints for the problem can be listed below to find the shortest path between V_s i.e. the terrestrial control point as the source node, and V_d i.e. the ABS on the network with a drained battery as the destination node:

$$\text{minimize} \quad C_t = \sum_{V_i,V_j \in V} c_{ij} \cdot d_{ij,t} \tag{1}$$

$$\text{subject to} \quad \sum_{V_i \in V} d_{ij,t} = \sum_{V_i \in V} d_{ji,t}, \;\; V_j \notin \{V_s, V_d\} \tag{2}$$

$$d_{ij,t} = \begin{cases} 1, & \text{the edge } E_{ij} \text{ is traversed} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$\sum_{0}^{t^-} C_t + C_t \le \sum_{0}^{t^+} C_t, \;\; 0 < t^- < t < t^+ < t_e \tag{4}$$

where Eq. 1 represents the objective function as the sum of the corresponding costs for a path traversal; Eq. 2 corresponds to the equality of incoming and outgoing traversal for a node; Eq. 3 indicates the decision variable for an edge to indicate it is included in the solution or not; and Eq. 4 shows that the cost for a path traversal of the current replenishment prevents a deterioration for the total energy consumption in the future. In Eq. 1, C_t is the cost of a path traversal decision at time t, i.e. the moment a replenishment is requested, V represents the nodes, c_{ij} is the cost of edge between V_i and V_j, $d_{ij,t}$ is the decision variable for the corresponding edge is included in the traversal or not at time t. In Eq. 2, decision variables, $d_{ij,t}$ are used to grant that there is exactly one ABS in the predefined locations in the topology. In Eq. 3, possible discrete values for each $d_{ij,t}$ is presented. Finally, in Eq. 4, it is shown that the cumulative energy consumption cost up until time t should not worsen the total cost in the future when the traversal with C_t is included in the flight planning. As a consequence for the problem formulation, we provide an algorithmic system model to satisfy the objective of the given optimization problem under the constraints presented.

The proposed handover procedure for corresponding terrestrial users throughout a drone replenishment in the architecture is performed according to the flow chart given in Figure 3. The flow of the procedure

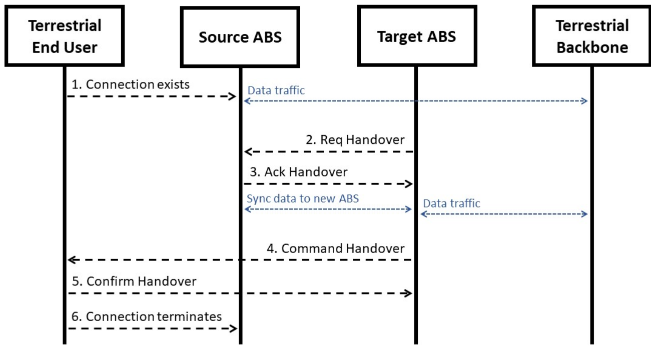

Figure 3. A single handover procedure between ABSs

is labeled with numbers in the figure. Firstly, there is an ongoing connection between a terrestrial user and an ABS with drained battery, the source ABS in the figure, and the data traffic is delegated to the terrestrial backbone through the connection. Whenever a replenishment is required, a new ABS, the target ABS in the figure, is sent to the topology and inform the source ABS about the handover procedure initialization. After that, the source ABS responses and ACK and data sync are started between ABSs to delegate the data traffic to the terrestrial backbone through the target ABS. Subsequently, the target ABS command a handover to all users connected to the source ABS and the handover procedure is completed for a terrestrial user after handover confirmation to the target ABS and connection termination to the source ABS. The main difference of the proposed procedure is that, the mobility pattern of users in the architecture is constant and the end-system initializes handover process because of the fact that an ABSs with drained battery is the main cause for a handover. As a consequence, an end-system initiated handover procedure is presented in the study to maintain the connectivity of all corresponding terrestrial users during a replenishment process.

3. The Proposed System Model

The proposed system model is presented in Figure 4. It is offered in the study that the entire operational time of the assistant terrestrial network should be considered. Otherwise, future path planning opportunities that may decrease overall energy consumption may be missed. To this end, a feasible, intelligent, and flexible flight path planning scheme is required. The arrows in the figure indicate data flow, each slice of the circle includes an explanation about the flow, and each rectangle illustrates a module of the system model in which the data are processed. A set of inputs is given to the proposed model when replenishment of an ABS is required to maintain the topology. These inputs contain the coordinate values (x, y, z) and attributes

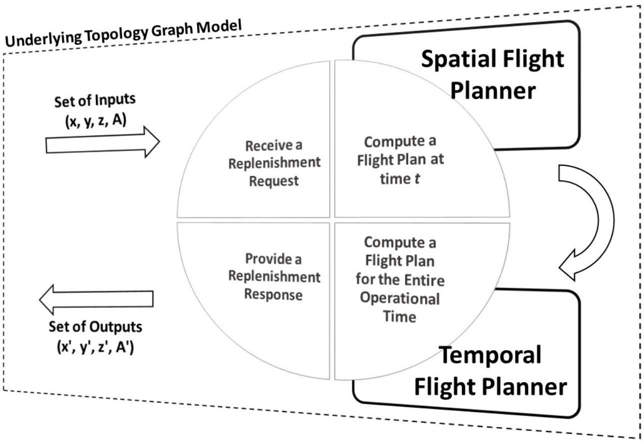

Figure 4. GA-based energy aware flight path planning framework

(A) of an ABS such as remaining battery percentage, flight duration, the total amount of consumed energy, number of connected end-users, etc. In the proposed model, there are two modules dealing with incoming requests named as *replenishment request scheduler* and *flight path planner*. The scheduler records statistics about each nodes in the graph, updates them against the changing circumstances in the topology, and retrieves the data to delegate for path planning. The flight path planner provides a feasible implementation of energy-aware path planning approach considering the entire operational time of the aerial network assistance. Eventually, a set of outputs is responded to provide an energy-aware replenishment for the entire deployment duration.

3.1. Replenishment Request Scheduler

The scheduler is responsible for keeping the statistics about the nodes (the position of ABSs) in the topology up to date against the changing circumstances in the network environment. The endurance for different ABSs deployed at the same node may not be the same during the network existence because of facing dynamic environmental conditions such as wind, rain, etc. Thus, a set of node driven statistics is stored for a proper replenishment request schedule. For this purpose, it is offered that data storage is required in order to record, update, and retrieve flight characteristics of each node in the topology whenever a replenishment is demanded. The mean value for the entries is considered for history information kept in the framework against the dynamic behaviour of the environment. In this way, a proper analysis/estimation for the upcoming replenishment requests can be utilized by the flight path planner throughout the entire presence of the assistant aerial network. Hence, the scheduler for the path planner is a vital part of the proposed energy-aware flight path planning framework.

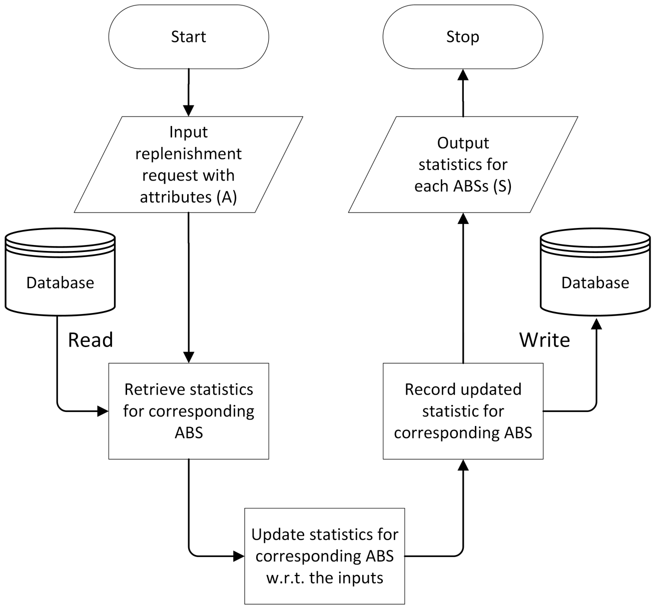

Figure 5. Flowchart for replenishment request scheduler implementation.

Replenishment request scheduler is implemented according to the flow chart given with Figure 5. In the flow chart, first, inputs for the incoming request are taken and previous statistics about the corresponding node in the topology are retrieved. Then, the average endurance for the node is computed. When it is the first time i.e. there is no data in the database storage, then the average endurance is taken according to device specification employed for the ABS. In this study, it is determined as 30 minutes for the ArduCopter instance introduced in Section 4.1. Finally, the computed statistics based on the node history is recorded in the storage and delegated to the flight path planner.

3.2. Flight Path Planner

The proposed flight path planner is responsible for providing a feasible path planning implementation considering the input dynamics taken by the scheduler. For this purpose, an implementation of GA approach is performed considering the entire operational duration as given in Figure 6. The algorithm starts with taking the statistics from the scheduler as the inputs. Immediately after, an initial population is computed on the topology graph for the minimum energy flight path traversal considering current statistics when the replenishment is requested. Taking the initial population based on these statistics is sensible, because such an attempt eliminates most of the redundant solution candidates for GA that are far from optimum. In this way, a pruned search space is obtained around likely optimum solution candidates. Then, a

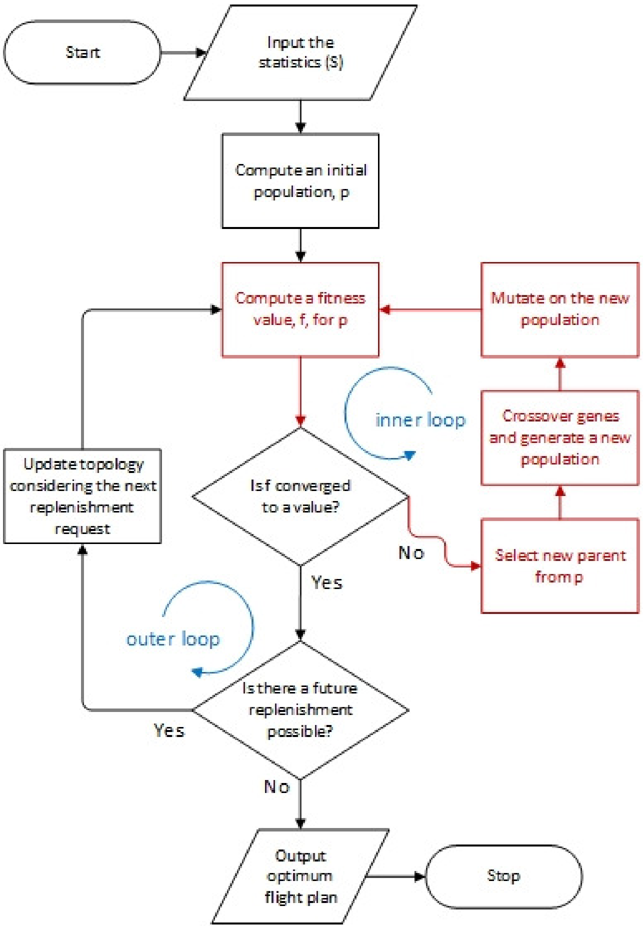

Figure 6. Flowchart for flight path planner implementation.

fitness value is computed with respect to the traversal cost of the corresponding population. Afterward, the operational time is taken into account and a possible future replenishment request is investigated (indicated with the outer loop) considering the aforesaid attributes and statistics of the ABSs in the topology. If there is at least one possible future replenishment, then GA procedure indicated with red color starts: a new population is selected, genes crossover is performed to generate a new population, and mutation is applied, respectively. As a consequence, a new fitness value is calculated on the recent population and these steps are repeated (illustrated with the inner loop) until the value convergence is achieved. Finally, a set of outputs is responded to the corresponding ABSs to inform them about the forthcoming replenishment process, a backup ABS is sent to the topology, and the ABS requesting the replenishment comes down to the location of the terrestrial controller. In this way, each of the ABSs included in the traversal moves at most one edge, starting with the redundant ABS on the ground and the replenishment process terminates when the ABS with drained battery is taken to the ground.

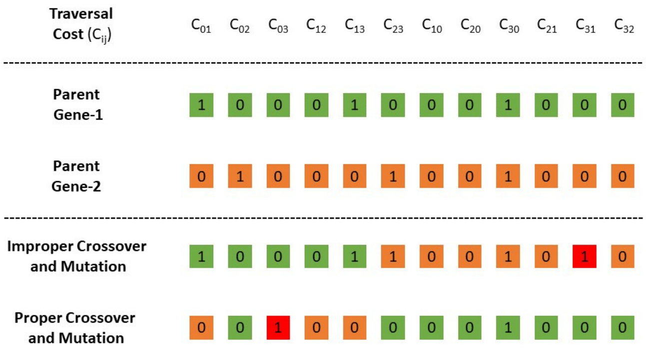

Figure 7. Illustration for a sample run of flight path planner

A sample run for the GA implementation is summarized in Figure 7. Assume that an index value is given for each of the nodes in the topology graph such that TDC is represented by 0, ABS1 is represented by 1, ABS2 is represented by 2 and ABS3 is shown by 3. Thus, the cost C_{01} corresponds to the cost between TDC and ABS1, whereas C_{10} is the cost between ABS1 and TDC in the opposite direction. Similarly, C_{12} represents the cost between ABS1 and ABS2 and so on. Consider that Parent Gene 1 in the figure includes C_{01}, C_{13}, and C_{30} in the flight planning with 100010001000 that means a new ABS is sent instead of ABS1, ABS1 is moved to the position of ABS3, and ABS3 is taken down. An alternative way of taking ABS3 down is also given with Parent Gene 2. It sends a new ABS to the topology instead of ABS3 and changes the position of ABS2 with 010010010000. The proposed GA implementation runs the red parts in the flowchart and provides alternatives for ABS replacement considering the fitness value convergence and objective function constraints. As a result of gene crossover and mutation phases of the algorithm, two new genes are given in Figure 7. The crossovers from the parent genes are indicated with the same color as in parents, and the mutation on the produced genes is given with red color. The first one is labeled as an improper gene because 100011001010 offers multiple ABSs for the position of drained ABS3 and this violates the constraint given in Eq. 2. On the other hand, the second one, 001000001000, is a proper solution candidate that offers a direct replenishment between a new ABS and ABS3. If the fitness value has a lower energy consumption cost than ever before, then 001000001000 is marked as a solution and a convergence around the corresponding value is sought. To summarize the application logic, the components of the proposed framework are triggered for each of the replenishment request in order to update statistics and eliminate the environmental effects with re-computation of the path planning.

4. Performance Evaluation

4.1. Evaluation Environment

A summary of evaluation environment parameters is given in Table 1. Three different scales of social event scenarios are considered in the performance evaluation. It is assumed that there is a temporary event of 4 hours long duration for which putting additional terrestrial components is costly and redundant. The validation of the proposed system model is investigated with:

- a small scale scenario with 3 ABSs and 3000 users within 5000 m^2 area,
- a medium scale scenario with 6000 users, 6 ABSs with 10000 m^2 coverage, and
- a large scale scenario with 12 ABSs and 12000 users inside 15000 m^2 area.

In this way, we achieve an evaluation environment for the proposed system model by covering different size of geographical areas and experiencing a different number of replenishment requests. A linear mobility model with 0 km/h initial speed is chosen for terrestrial users, i.e. the location of each user is constant during the event simulation. Hence, the ABSs in the topology graph can be thought that they maintain the same position during the simulations to serve these users. We compare the proposed study with an existing approach considering the same scenarios. To this end, at first, a dummy path planning scheme is implemented that considers no information about the topology and directly replenishes an ABS with a new one alongside the terrestrial controller. Moreover, the flight planner performance is also investigated with single spatial flight planner implementation that does not consider the entire operational time into account.

Table 1. Simulation Environment for Different Scale of Scenarios.

	Small	Medium	Large
Number of Users	3000	6000	12000
Number of ABSs	3	6	12
Coverage Area (m^2)	5000	10000	15000
Duration (min)	240	240	240
User Mobility Model	Linear Mobility Model with NO Initial Speed		

A set of tools is used to provide an evaluation environment for the proposed system model. The evaluation outputs obtained from corresponding flight planning implementations are recorded for the entire operational time of the aerial network assistance. To introduce technical details of the evaluation environment, 64-bit Windows 10 operating system is used as the underlying operating system. The hardware specification of the machine includes 16 GB RAM, 1 TB HDD memory, Intel Core i7 processor with 2.40 GHz clock speed and 8 virtual cores. Cygwin software is set up to emulate UNIX commands for MAVProxy drone controller, and Software in the Loop (SITL) simulator software is utilized to perform simulations of the evaluation environment. The SITL simulator creates an ArduCopter instance to emulate a quad rotor ABS on Google Map API. This ABS is controlled from the MAVProxy command line with corresponding commands during the simulation. Whenever a replenishment is required in the topology, three different approaches are separately consulted for a proper flight plan and the simulation logs are recorded. After simulating the scenarios, log files are dumped from the controller in two different formats as binary disc images and binary telemetry log files. Finally, Ardu Pilot Mission Planner software is used to analyze and display flight data for each of the corresponding path planning strategies.

4.2. Evaluation Results

Three different evaluation metrics are defined and used to provide a comparison between evaluated path planning approaches. Firstly, A normalized energy consumption value is introduced to show the relative amount of total energy consumed with respect to different flight path planning strategies. Moreover, the number of total terrestrial ABS replenishment is considered as another performance metric because it includes information about the effort to maintain the topology during the mission. Additionally, average endurance for an ABS, i.e. another metric to show the effectiveness of a flight path planning approach, is also computed.

A further investigation is also conducted for the response time of each implementation when we try to seek the solution in the entire operational time. GA implementation in the proposed framework has a stochastic progress as stated in [23]. On the other hand, it is obvious that conventional implementations such as DP have a systematical, but massive computational progress. Moreover, it is stated in [13] that DP approach has a running time complexity in terms of the number of vertexes as $O(|V|)^3$ for a single run at time t considering the graph model provided. When the problem search space is extended into the time domain, the number of inputs to the algorithm increases and its third-order exponent for the running time complexity results in a huge execution time. Thus, a stochastic evolutionary algorithm, GA, with running time complexity of $O(g \cdot p \cdot i)$ becomes more feasible because it is obviously has at most the same running time complexity even if there is not any convergence and all of g (the number of generations), p (the population size) and i (the size of individuals) equals to $|V|$. Moreover, the value can be decreased dramatically with a proper initial population selection for GA approach. As a consequence, the execution time for both approaches is also evaluated and the results are presented to highlight the performance gap between the existing approach and the proposed one.

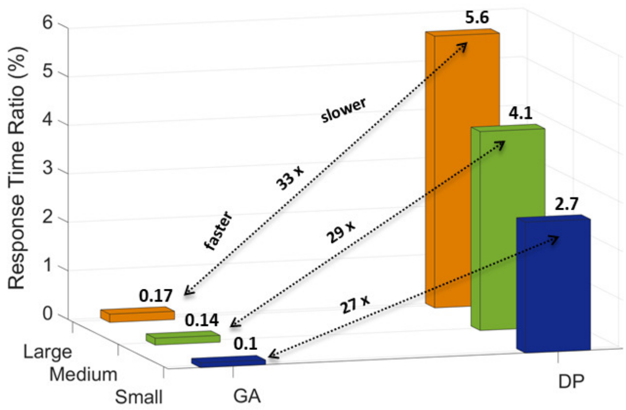

Figure 8. Response time ratio to the corresponding endurance with respect to different approaches under different scenarios

In Figure 8, a percentage value with respect to the corresponding average endurance for the corresponding scenario is presented for each of the evaluated scenarios. The values for the dummy strategy is not shown in the figure, because of the fact that the dummy approach does not have any running time complexity due to its simple/stupid replenishment scheme. Hence, the execution times obtained for the dummy strategy are considered small enough to be neglected. According to the figure, in the small scenario, a flight planning can be responded by the proposed system model in 0.1% of average endurance (approximately 1.6 seconds) with GA implementation; on the other hand, this value reaches to 2.7% of the endurance (approximately 48 seconds) with DP implementation. In other words, DP implementation is 27 times slower than GA implementation to handle a single replenishment request. Moreover, the performance gap between these two implementations grows when the components in the scenario increase. DP approach becomes 29 times and 33 times slower than GA implementation on average for medium and large scenarios, respectively in which GA approach needs 0.14% and 0.17%; DP approach requires 4.1% and 5.6% of the corresponding average endurance. In the evaluation, the percentage of the response time to the average endurance increases when the scenario grows for both implementations because of two reasons: i) the execution time of the flight planner algorithm is increasing with respect to the growing number of inputs, ii) average endurance is decreasing because a more amount of energy required to cover the growing geographical area. To sum up, the response time for DP implementation exceeds a minute for the large scenario showing that it is not feasible to apply such systematic approaches to be responded in a reasonable amount of time, considering the total endurance of an ABS. It can be asserted that the difference between both implementations arises from pruning some of the search space in GA implementation owing to its stochastic search mechanism. Moreover, it can be concluded that using evolutionary algorithms is a necessity based on the deployment purposes of aerial networks considering the feasibility perspective of the strategies being compared.

The normalized energy consumption outcomes are presented in Figure 9 with respect to different approaches and scale of scenarios. The amount of total energy consumed grows for a larger scenario because of the increasing number of users and extending geographical area coverage. Hence, a normalization is provided within each individual scenario with respect to the values obtained from the dummy path planning strategy to clearly identify the change in energy consumption for different scale of scenarios. According to the evaluation result, it is seen in the small scenario that the proposed approach with DP implementation consumes 6% less energy than the dummy approach owing to the path planning strategy offered. Moreover, the energy consumption gain reaches to 9% and 15% in medium scenario and large scenario, respectively. On the other hand, GA implementation also provides around 5% less energy consumption than the DP implementation because of the fact that the proposed framework takes the entire operational time into account with an enhanced set of probable solutions. Hence, the energy consumption gain reaches to 10%,14%, and 20% when GA implementation is used instead of dummy approach for small, medium, and large scenarios, respectively. Furthermore, GA implementation is clearly more feasible than the DP implementation as represented in Figure 8, especially for larger scenarios. As a consequence, it can be stated that the dummy strategy is useless against the proposed framework in terms of energy consumption and DP implementation is also useless against the GA implementation in terms of not only performance but also feasibility perspective. Hence, it can be inferred from the evaluation that the proposed GA implementation is the most suitable approach to obtain a feasible response time with a remarkable energy awareness.

The number of terrestrial ABS replenishment is presented in Figure 10 with respect to different approaches and scenarios. This metric is directly related to the total energy consumption in the network and according to the evaluation results, it is clearly seen that the number of terrestrial ABS replenishment increases

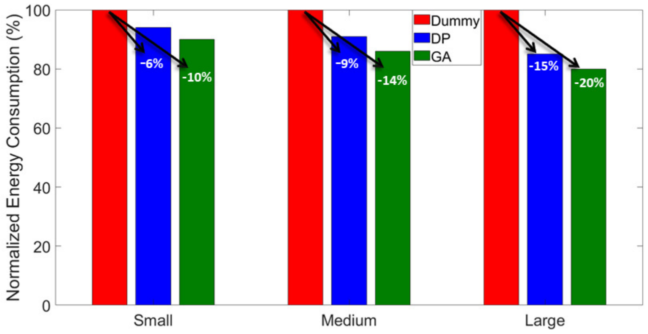

Figure 9. The normalized energy consumption with respect to different approaches under different scenarios

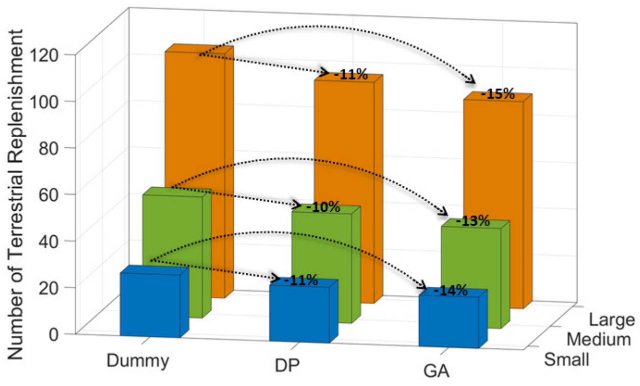

Figure 10. The number of terrestrial ABS replenishment with respect to different approaches under different scenarios

when the scenario gets bigger, as a result of more overall energy demand for coverage and service. For all scenarios, the DP implementation causes a less number of replenishment compared to the dummy strategy, and the decrease is reached to 11% in the large scenario. Moreover, there is a decrease up to 4% that corresponds to a few less numbers of terrestrial ABS replenishment when GA is used in the large scenario instead of DP implementation. A similar relation between DP, GA, and dummy approaches also exists for medium and small scenarios. DP implementation causes 10% and 11% less number of terrestrial replenishment than the dummy strategy in medium scenario and small scenario, respectively. Furthermore, the values achieved by using GA implementation are also less than the ones obtained with DP implementation with a ratio of 3%, in small and medium scenarios. In addition, there is a remarkable advantage of GA implementation from the feasibility perspective, considering the gain in response time. It can be concluded that DP implementation outperforms the dummy approach because of having an energy aware flight planning strategy; and, GA implementation outperforms DP implementation because of offering a flight path planning by considering the entire operational time with more solution opportunities. As a result, it can be claimed that DP and GA implementations provide a much less number of replenishment than the dummy one considering an entire deployment for the aerial network assistance. Moreover, it can also be stated that GA implementation can be preferred to DP in order to take advantage of lower response time in practice in addition to the slight performance improvement.

Figure 11 provides a comparison between different flight path planning approaches with respect to average endurance for an ABS. According to evaluation results, it can be claimed that DP and GA implementations provide higher endurance in all scenarios compared to the dummy path planning scheme which uses no information about a flight route. The difference between DP implementation and the dummy approach is approximately 5%, 9%, and 13% for small, medium, and large scenarios, respectively. Again, GA implementation of the proposed framework has a better performance on average endurance value compared with DP implementation. The superiority of GA implementation versus DP implementation reaches to 5% in large scenario. Thus, as seen in the figure, average endurance per ABS values by the proposed GA implementation reaches 6%, 11%, and 18% more than the ones obtained by dummy approach in different scale of scenarios. Furthermore, it can also be declared that there is also a gain with GA implementation in terms of decreasing response time. Consequently, it can be asserted that the superiority of the proposed model with GA implementation versus two other strategies is validated according to the average endurance parameter for an ABS.

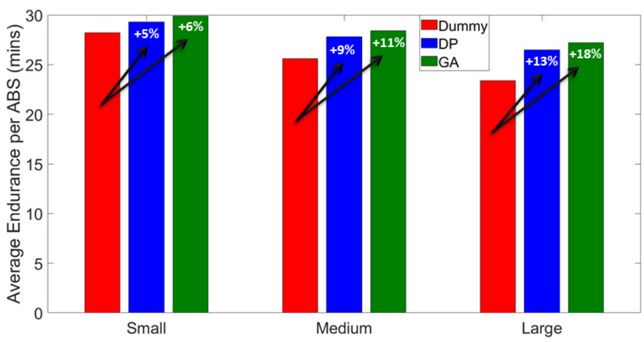

Figure 11. Average endurance per ABS with respect to different approaches under different scenarios

To sum up the evaluation, it can be asserted that both of flight path planning models implemented in the study outperforms the dummy strategy with respect to the evaluation metrics presented. A lower amount of energy consumption, less number of terrestrial replenishment, and more average endurance per ABS are obtained by applying the flight path planning models that take the energy consumption characteristic of an aerial network into account. Moreover, the proposed framework with GA implementation considering the entire operational time yields better evaluation outcomes than the DP implementation not only from the energy awareness perspective, but also from feasibility of real world deployment according to the response time of the end-system. Hence, it is shown in the study that a feasible and faster flight planning can be obtained owing to GA implementation used in the proposed framework also with less energy consumption, less terrestrial drone replenishment, and more average flight time per ABS.

5. Conclusions

In the study, we propose an energy aware flight path planning framework in aerial networks deployed for assistance considering the enhanced problem domain so long as the entire operational time. For this purpose, social event scenarios such as a festival, concert, soccer game, etc. with predictable operational time are targeted as the use case. A distance-related energy consumption model in the literature is utilized for the network topology and a problem formulation is presented. In the proposed system model, an *end user application wrapper* and a *flight path planner* is implemented using GA approach to seek the minimum energy consumption value under the constraints of the problem formulation. A novel handover procedure is also presented to maintain the connectivity of terrestrial users whenever a replenishment is required for one of the ABSs in the topology. For the evaluation, the proposed system model and a conventional approach are both simulated. Three different scales of social event scenarios are presented and according to the evaluation results, it is shown that up to 20% less energy is consumed with the proposed framework that leads to 15% decrease in the number of terrestrial replenishment and 18% increase in average endurance for an ABS. Moreover, compared to an energy aware approach presented in the literature, it is also evaluated that the proposed framework implemented with GA approach that prunes the search space and provides much faster response is more feasible alongside improved evaluation metrics.

It is spotted during the evaluation that the proposed system model offers some inner replacement of ABSs in the topology considering traversal costs in the underlying energy consumption graph model. Thus, it is expected that there is more number of terrestrial user handovers compared to a conventional path planning scheme. As a future work, a performance investigation of end-user parameters will be scheduled and the effect of the proposed system model on terrestrial user satisfaction will be studied under different type of traffic loads.

5.1. Acknowledgements

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