Genetic Algorithm-based Path Planning for an Unmanned Aerial Vehicle Considering Energy Consumption and Payload

HDI Piyumini[1#] and CH Hsu[2]

[1]Department of Mechanical Engineering, General Sir John Kotelawala Defence University, Sri Lanka

[2]Department of Mechanical Engineering, National Kaohsiung University of Science and Technology, Taiwan

#piyuminihdi@kdu.ac.lk

Abstract: *Unmanned Aerial Vehicles (UAVs), more commonly known as drones, have a wide range of applications spread across various industries. Drones are plagued with several challenges concerning their limited battery life and payload. Until researchers come up with a much more advanced and long-lasting battery solution, drones must use the most optimum path for delivery, which will increase battery efficiency and reduce overheads. This study analyses the battery energy consumption, velocity, and flight time of the quadcopter for varying payloads and develops a suitable mathematical relationship for path planning problem formulation. This paper proposes a Genetic algorithm -based path optimization to obtain the most energy optimal path for the drone carrying a certain payload for a set of specified destinations.*

Keywords: *Path planning, Unmanned Aerial Vehicle,Genetic Algorithm, Energy Consumption, Simulation, Payload*

1. Introduction

Despite its many advantages, a significant drawback in using an Unmanned Aerial Vehicle (UAV) or a drone is its battery life limitation and payload. The limited power supply restricts the drone's flight duration. Researchers have invested a considerable effort to minimize the weight of the rotorcrafts by adopting improvements. As payload is a crucial factor affecting the drone's flight duration, lack of sufficient battery power brings out a worse scenario of drone malfunction or drone crash before the completion of delivery. Until researchers develop a much more advanced long-lasting battery solution, research on optimizing routes and battery consumption has become an exciting area.

Much existing literature has not considered the case of drone failure before it completes the journey due to the loss of battery power. As most researchers used commercially available drones for their research, they have determined the energy consumption by considering the Battery Consumption Rate (BCR) of the drone (Yacef et al., 2017; Torabbeigi et al., 2o2o). In contrast to these, this paper considers the battery power, energy consumption, and varying payloads to formulate the optimization problem. The contributions of this paper are as follows:

i. An energy model is derived from the power consumption and the flight time of a LiPo battery used by a custom-made drone for different payloads. Here, path is planned by considering payload as a significant factor affecting the drone's energy consumption.

ii. A Genetic Algorithm (GA) approach is used to search for the optimal energy-efficient path.

iii. The operation is visualized using a Python-based simulation.

2. Literature Review

Many researchers presented several approaches to analysing the range and endurance of battery-powered quadrotors. Traub (2011) has examined and validated (Traub, 2013) the effect of battery

discharge rate and the voltage drop on its adequate capacity. An experiment (Abdilla et al., 2015) to validate the endurance model for LiPo battery-powered UAV was conducted to characterize the consumption of power of rotorcrafts. Kim and his team (2018) proposed a robust method to find the most optimal flight schedule considering uncertain battery duration. Morbidi and his team (2016) addressed UAVs' battery power limitation by determining the minimum energy paths by utilizing the electrical model of a BLDC motor for a commercial quadrotor.

The rising issue of determining energy-optimal paths for a drone considering the power and payload has not received the related literature's required attention. Several path planning approaches have been studied by many researchers worldwide, considering the state-of-health of the battery (Schacht-Rodríguez et al., 2018), the coverage and resolution (Di Franco and Buttazzo, 2015), and wind condition (Yacef et al., 2020). The paper presented by Torabbeigi and his team (2020) claims that the payload is a linear function of the battery consumption rate using linear regression.

Algorithms such as Greedy (Ahmed et al., 2016), Particle Swarm Optimisation (PSO) (Huang et al., 2016), Dijkstra algorithm (Bekhti et al., 2017), Bellman-Ford algorithm (Samar and Kamal, 2012), and Genetic Algorithm (GA) (Shivgan and Don, 2020; Bagherian and Alos, 2015) are among the most used algorithms for UAV path planning. When these researchers compared their results with different algorithms for the same conditions, GA has provided a more accurate solution. According to Bagherian and Alos (2015), GA provides a much better solution to the problem, even with more calculations.

3. Methodalogy

C. Hardware Setup

The drone used in this experiment is an X-shaped quadcopter. The Carbon fiber frame holds four Gemfan 9047 Carbon Nylon CW/CCW propellers, four brushless DC motors, and four multirotor brushless electronic speed controllers. The system is powered by a three-cell 11.1V LiPo (5C) Battery. The flight controller used in the study is Radiolink Mini Pix V1.0, which includes a processor, barometer, accelerometer, and compass. Fight control is achieved by the communication between the hand-held Transmitter (TX) and the receiver (RX) attached to the flight controller. The radio transmitter is a Flysky FS i6X model joystick controller, and the receiver is a Flysky FS iA6B 2.4 GHz 6 channel receiver.

Figure 2. Drone used in this experiment

The Ground Control Station (GCS) used for this study is the Mission Planner for Radiolink 1.3.50, an open-source platform. The ground control station can create different missions via a flight plan. Once this mission is loaded, the quadcopter flies according to the given commands autonomously. An image captured while the drone was on air is shown in Fig. 1.

D. Experimental Data Analysis

Two experiments were performed to obtain the data required for the research at the open-space playground of Sirindhorn International Institute of Technology, Thailand. Gathered data was used to study the relationship of battery life, flight time, and velocity to an added payload to the drone's existing weight.

The first experiment was performed to understand the LiPo battery's behaviour with the drone's flight time. The quadcopter's battery consumption was measured during hovering mode (or "altitude hold mode" in Mission Planner). As there is a translational lift, the power consumption is relatively higher in hovering mode. Compared to hovering mode at the corresponding mass, vertical, and/or translational flight indicated the minimum difference, leading to the adoption of hovering as the nominal flight mode (Abdilla et al., 2015). The required experimental data was read from the flight data screen in Mission Planner using a radio connection with a baud rate of 57600.

In the first experiment, the battery voltage, power, and current consumption were recorded and plotted against the flight time for varying payloads. The experiment was conducted for a total weight ranging from 1.174 kg (net weight of the drone) to 1.674 kg (maximum weight the drone can withstand). The experiment was repeated by adding 50 g weight in each trial and aborted when the drone cannot take off any further or is hovering unstably. A total number of eleven (11) tests were performed.

The LiPo cell used for the experiment has a nominal voltage of 3.7 V. The battery has three cells in series, which accounts for a voltage of 11.1 V. The battery was discharged following the 80% rule, i.e., the battery should never be discharged down past 80% of its full capacity to prevent any damage. At 80% charge, the LiPo cell provided an approximate open-circuit voltage of 3.73-3.75 V. With this battery voltage, the maximum flight time without a payload for the drone was 620 s, and the maximum flight time with a payload of 500 g was 210 s. Low battery voltage was detected using a BX100 battery voltage buzzer. By observing the R squared value of the regression models, the following Eq. (1) was obtained, which showed that there is a linear relationship (according to Eq. (2)) between the battery voltage (B_v) and the flight time (t).

$$B\_v = -0.0056t + 12.172 \quad (1)$$

The above equation is in the form of

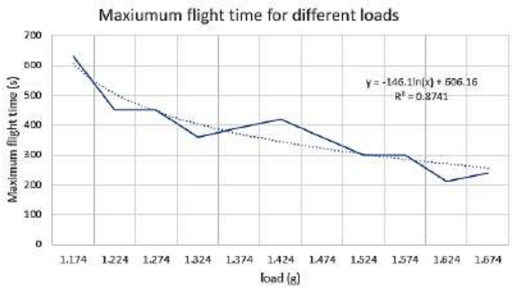
$$B\_v = \alpha t + \beta \quad (2)$$

where α is the slope and β is the intercept.

E. Experimental Results

Using the data from the experiments, another analysis was performed to study how the flight time varies with increasing load. Due to the drone's additional power to lift the payload, the flight time showed a reducing pattern with an increasing load (w), as shown in Fig. 2.

Figure 2. Variation of maximum flight time of



the drone with the total load of the drone

Here, the continuous line shows the experimental values while the dotted line represents the best fit curve. For the plot, the logarithmic fit showed the best R squared value of 0.8741. Therefore, it was concluded that the load w and the flight time t_max of the drone have a logarithmic relationship shown by the Eq. (3).

$$t\_max = -146.1 \ln(w) + 606.16 \quad (3)$$

To obtain the data required to find the relationship between drone velocity (v), power (p), and load (w), the UAV was flown in a straight line with a constant distance of 50 m and maintaining an altitude of 10 m. The data was gathered for payloads varying from 50 g to 500 g. The constant distance and the flying altitude were set using the Mission Planner software.

The results showed that the drone's velocity remained at an average value of 3.23 ms^{-1} for every different weight attached. This is mainly due to the electronic speed controller's function connected to the drone that supplies the adequate instantaneous current to maintain a constant velocity. The following graph in Fig.3 shows the relationship between the load and the drone velocity.

The average velocity remained unchanged with varying loads. However, when considering power variation with flight time for all the weights added, it was observed that the power consumption has increased with every added payload. The weight limit of the drone depends on the thrust produced by the motors.

The variation of power consumption with payload is given by the Eq (4).

$$p = 0.1288w - 27.303 \quad (4)$$

The trendline for velocity variation is given by,

$$v = 0.0003w + 2.794 \quad (5)$$

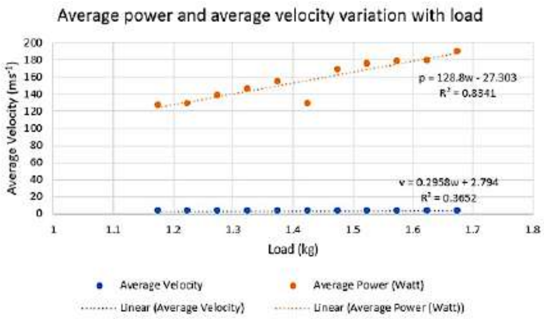


Figure 3. Variation of average velocity and the average power with a varying total load

In addition to this, the maximum distance for each flight was obtained by multiplying the corresponding velocity with the flight time.

F. Determining the Energy Consumption of the Drone

As energy consumption depends on the drone speed, the energy consumption model must consider the different flight stages, including acceleration, deceleration, and hovering. The energy consumption at different speeds and distances can be calculated by the Eq. (6).

$$E_{(v,d)} = \int_0^{t1} P_a \, dt + \int_{t1}^{t2} P_v \, dt + \int_{t2}^{t3} P_d \, dt \quad (6)$$

Here, P_a denotes the power consumed during acceleration, P_v denotes power consumed when the drone is flying with uniform velocity v, P_d denotes the power consumed during deceleration, d is the distance traveled, and $t1, t2$, and $t3$ is the time duration of the acceleration phase, constant speed flight phase, and deceleration phase, respectively. The particular current draw and the battery voltage data were obtained from the first experiment. The consumed power was then derived by multiplying the absorbed current by the supply voltage for each payload. The corresponding power consumption was plotted in a graph for every flight. The energy consumed by the total flight was calculated by obtaining the area under the curve, according to Eq. (7).

$$E_w = \int_{t=0}^{t=T} P(t)dt \quad (7)$$

In the Eq (7), E_w represents the energy consumed by a drone with a weight w. Fig. 4 shows that the energy level has reduced with added weights. This was considered as an energy loss. The energy consumption for different loads was plotted in the graph, and the best fit's eligibility was observed. The fit with the R squared value closest to one (1) was selected as the most suitable energy model equation.

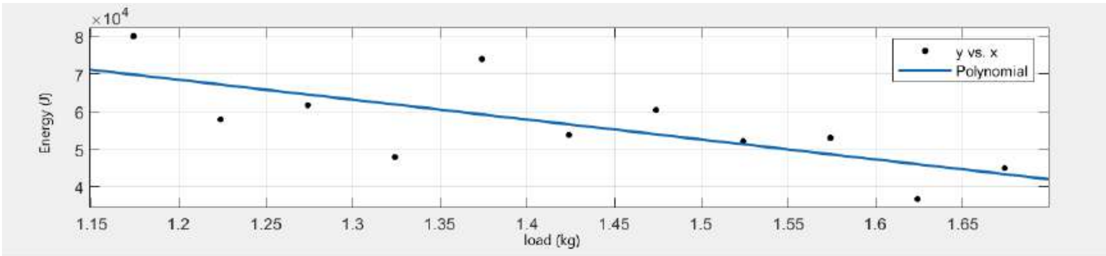


Figure 4. Energy consumption of the drone with varying load

Since there were four types of fits with an R squared value of more than 50%, cross-validation was performed to check which fit is more likely to give out the closest value to the actual energy value. The average percentage error for linear fit, polynomial fit of degree 1, polynomial fit of degree 2, and polynomial fit of degree 3 was 46.8%, 2.14%, 19.63%, 26.3%, respectively. As the model with a one-degree polynomial provided a closer value, it was selected as the energy model of the problem.

The energy model for the above analysis is given by Eq. (8).

$$E = p_1 w + p_2 \quad (8)$$

Where E is the energy consumption in Joules and w is the payload in Kilograms. $p1$ and $p2$ are two coefficients provided as $p_1 = -5.306 \times 10^4$ and $p_2 = 1.321 \times 10^5$.

G. Path planning

The path planning approach in this research was conducted as a Travelling Salesman Problem (TSP) to minimize energy consumption. Given a set of random cities or locations and the travel cost between each site, the TSP can find the cheapest route to visit all the cities and return to the initial starting point. A Genetic Algorithm (GA) approach was used to evaluate the shortest path that the drone travel using optimized energy and distance using the derived energy model.

In the proposed GA, the initial population is the set of all possible traveling routes for the drone which is defined by user input. A solution or a route is characterised by a set of parameters (genes) which links together to form a solution (chromosome). In this case, the fitness value was calculated based on the energy consumed along the path drone takes. For selecting the parent, this research used the Elite selection method. As the objective is to minimize the energy consumption, the parent with a smaller fitness value used in GA to push the hypothesis towards an optimal solution. The swapping is selected, which corresponds to the higher energy efficient path. New offspring are created by applying a crossover operator to the parents.

```
Input: No of waypoints, Weight of the drone, Population size, velocity
P = -128.8w-27.30
E = P * (d/v)
Initialize population
function evaluate_function
for i =1: n do
    for j=1: n do
        dij= sqrt((x_i - x_j)^2 + (y_i - y_j)^2)
    end for
end for
return E, dij
end function
while iteration < num_Iter do
    for p=1:popul_size do
        for K=1:chrom_size do
            N(p,k),e(p,k) = evaluate function
            D=D+d(p,k)
            E=E+e(p,k)
        end for
    Total D(P) =D
    Total E(P)=E
    end for
if iteration > num_Iter then
    break
else
    repeat total energy calculation using cross over and mutation
end if
for P=10: 10: popul_size do
    Use Elite selection to find parents
    Apply crossover to find new solution
    save in temp_pop
    for k=1: size(temp_pop) do
        select previously separated solution from temp_pop
        apply swapping mutation
        if solution is feasible then
            save it in new_pop
        end if
    end for
    update solution in pop
end for
maximum_energy=-53063.39459*(w/1000) + 132107.63396
if drone_energy<maximum energy
    Print maximum_energy, total energy, total distance, drone energy, maximum_energy-drone_energy
else print maximum energy is not enough to complete path
end if
```

Figure 5. Pseudocode for the simulation program

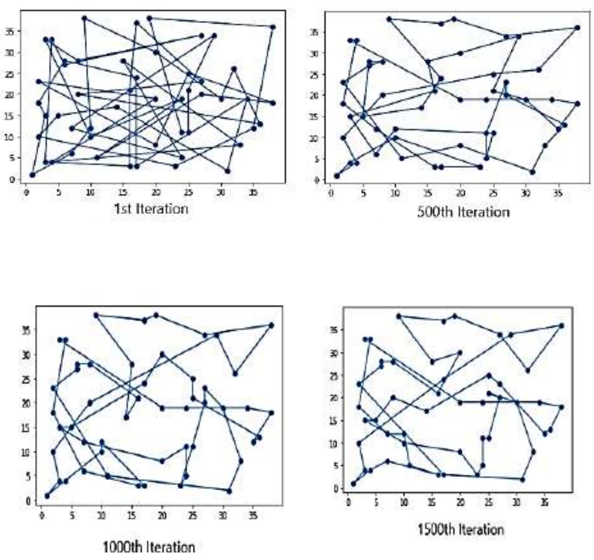
New offspring are created by applying a crossover operator to the parents. The two-point crossover method was used in our study. This method uses two points randomly selected, and these points are applied to a pair of chromosomes

The two-point crossover method was used in our study. This method uses two points randomly selected, and these points are applied to a pair of chromosomes. Mutations aremechanism was used for mutation, which selects two or more random genes from a chromosome to be swapped. The mechanism selects two random positions on the chromosome and interchange the values. The termination process determines when the GA process ends. Every iteration in the GA process brings out a better solution, but the progression starts to saturate when the improvements are minimal. The process is terminated when the solution becomes closer to the optimal.

The path planning process was simulated using Python 3.7 V based genetic library [17]. The computer used for this consisted of an Intel® Core™ i5-6200U CPU with a speed of 2.40 GHz. The system used a 64-bit Windows operating system with an x64 -based processor. The pseudocode for the program is provided in the Fig 5.

The first generation, also known as the initial population, generates several paths possible. This number (population size) is defined by the user in popul_size, which is the set of all possible paths a drone can follow. The genetic algorithm process starts at this point. The initial population and selection algorithm is described in a class called GeneticAlgorithm. The primary role calls it for the GA process, which is initiated by the run function. The initial population is then sorted according to the fitness value in ascending order.

4. Results



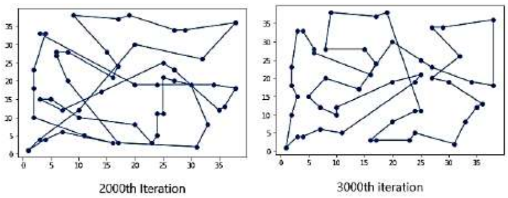


Figure 6. Simulation results for 50 waypoints with different iterations for 1374 g

The fitness value is generated by obtaining the sum of the

total energy (E(P)) consumed by the drone when it is moving from one point to another for all the points and the total distance (D(P)). Then the selection process is done using the elite selection model. The selection model sorts the initial population into sets of 10, and the set with the best fitness is considered as the new population. This new population is returned to the GA function. This set is subjected to mutation and crossover and calculates the fitness value again. This cycle is repeated until the best solution is obtained.

Results for path planning simulation were tested on several conditions. Tests were conducted for 50 waypoints, 20 waypoints, and 10 waypoints to observe the fitness value behaviour. The distance coordinates were chosen to be in the range of 0 m to 40 m, and the experiment was repeated for three selected weights (1174 g, 1374 g, 1424 g, and 1674 g). For each drone weight, five tests were conducted by changing the number of iterations.

The maximum energy calculated by the program for each given weight was close to the energy values for the tested payloads obtained using the Eq. (8). The results also showed the amount of energy consumed by the drone battery and the remaining energy. A sample simulation results for drone carrying a load of 1374 g with 50 waypoints with 3000 iterations is shown in Fig. 6.

Test simulations were conducted with a load of 1374 g for 10,20 and 50 waypoints to observe the iteration at which the fitness value reaches a minimum. Results are shown in Table 1.

Table 1: Results of test simulation for 1374g.

No. of waypoints	Iteration at which the fitness value reaches minimum
10	60
20	100
50	3000

For 50 waypoints, as 1000 iterations were not enough to obtain an acceptable optimized solution, the no of iterations were increased to 3000. Then the fitness value started to stabilize at approximately 2000th iteration. Therefore, for higher number of waypoints, it is required to increase the number of iterations, which increases the number of generations to obtain an accepted fitness value.

The results in Table 1 were obtained only when the total distance travelled by the drone along the path generated is less than the maximum distance that the drone can travel with the available battery capacity. If the generated total distance is more than the drone's travel capacity, a message is displayed to show that the drone cannot cross the generated path.

5. Future Work

As an extension of this work, a real-time rescheduling based on real-time battery capacity reduction can be studied. An alternative flight path can be developed to minimize the unmet demand in a scenario where the remaining battery capacity falls below a threshold value due to temperature changes. As the drone's battery life is limited to approximately 10 minutes, new approaches such as battery swapping or autonomous battery recharging can be utilized at different depots on the map. These can be accounted to the path planning problem formulation for a much more realistic scenario. Furthermore, this research can be conducted for higher loads to derive standard model for higher weight range.

6. Conclusion

Since long-lasting batteries for UAVs are still under research, this project has developed an optimized flight routing algorithm considering the available battery energy and the payload the drone can carry. Initially, data analysis on battery consumption, velocity, and flight time with the payload was conducted on a custom-made drone. The relationship between each parameter was developed, and an energy model was created. Using the developed energy model and relationships generated from the data analysis, the path planning algorithm was formulated and optimized. Then using a GA approach, the problem was simulated. The results obtained provided an energy-efficient path plan for each payload carried by the drone around a set of user-defined locations. This approach can be utilized for drones deployed in various industrial and domestic applications.

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Author Biography

Ms. HDI Piyumini received her MSc in Engineering and Technology from Thammasat University, Thailand. She is currently serving as a Lecturer (probationary) in the Department of Mechanical Engineering, KDU.

Dr. CH Hsu received his PhD from Texas A&M University and he is currently serving as an academia in the Department of Mechanical Engineering, National Kaohsiung University of Science and Technology, Taiwan.