Fuel Consumption Optimization in Three-Dimensional (3D) Flight Planning Using Genetic Algorithm

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Abstract

Flight Planning is a document prepared by airline which consist of aircraft information, planned route, required fuel, carried load, weather forecast, etc. Optimization in flight planning aims in reducing fuel consumption to reduce cost and emission. The purpose of this research is to optimize the flight planning route in Three-Dimensional approach using Genetic algorithm.

The algorithm uses population size of 500 individuals that generated with 0.01 mutation rate, 100 generation cycle, and 20 elite sizes. The case study covers flights of Jakarta – Tanjung Pinang, Jakarta – Makassar, and Jakarta – Manado. The aircraft gross weights are analyzed to study the effect on the resulted flight route. The aircraft performance database from Flight Crew Operating Manual (FCOM) of A320 aircraft was used.

It is concluded that the algorithm able to find the optimal flight route at the range of cruise altitude from 35,000 to 39,000 ft. Results from Jakarta - Tanjung Pinang flight showed an average of fuel reduction of around 2.29% followed by Jakarta – Makassar flight with 13.28% and Jakarta – Manado flight with 15.68%. Although, the resulted altitude profile shows a fluctuation in the middle of route, in average it is a climb.

Keywords: *3D Flight Planning, Fuel Consumption Optimization, Genetic Algorithm, Flight Crew Operating Manual, Fuel Saving.*

1. Introduction

Flight planning has been used by pilots to select the best route from departure airport to destination airport. With the recent Flight Planning application, it can predict the estimate time arrival, distance, speed, altitude, and how much fuel to be carried. Flight planning itself is the process of producing a flight plan to describe a proposed aircraft flight. It involves fuel calculation, to ensure that the aircraft can safely reach the destination, and compliance with air traffic control requirements, to avoid the risk of midair collision. The characteristics of different types of aircrafts also must be taken into account. For example, the fuel capacity, Engine Thrust, MTOW (Maximum Take-off Weight), the gross weight, etc.

Since, the emission gas produced by aircraft is also considered dangerous for the environment, reduction of fuel burn is become essential. Emissions generated by aircraft engines contains approximately 70% carbon dioxide (CO2), less than 30% water vapor (H2O) and less than 1% nitrogen compounds (NOx), carbon monoxide (CO), sulfur oxides (SOx) and others (Slamet, 2006). There are many ways to reduce emissions on aircraft, one of which is to reduce excessive use of aircraft fuel. (SURATMAN, Eman, Dr.Ir. Sigit Priyanto, 2004) developed the implementation of RVSM (Reduced Vertical Separation Minimum) method and had the result for short haul flight about 0.8% fuel savings, and 1.1% for medium haul flight.

The selection of altitudes greatly affects fuel consumption. However, in real flight aircraft does not always fly in optimal altitudes. Therefore, this research aims to optimize the fuel consumption in a 3D Flight Planning. The 3D aspect of this optimization includes 2D lateral and the altitudes. In this case the algorithm will search for a route based on the lowest fuel burn by taking different routes and altitudes. Genetic algorithm is selected for eliminating complex computational constraints. This manuscript consists of methodology in chapter 2, result and analysis in chapter 3 and conclusion and recommendation in chapter 4.

2. Methodology

This section describes methodology used in the research. It may describe a review of related works, problem definition, and methods used in this research.

2.1. Related Works

In a flight trajectory optimization, the performance boundaries (the fuel burn and the flight time) for the trip along a given trajectory are determined through a simulation. This calculation is performed utilizing the aircraft performance model and design, anticipated climate condition, speed, altitude, and navigation constraint. The atmosphere conditions (air temperature and winds) experienced during a flight might be not the same as the assessed/anticipated qualities utilized in the optimization. The extent of the contrast between the anticipated and the real atmospheric function of the precision of the atmospheric data forecast, and of the difference between the time when the forecast is generated and the time instance for which the atmospheric conditions are estimated. This distinction will affect the flight trajectory performance boundaries assessment results (fuel consume, flight time, absolute expense), and, as an outcome, the advancement calculation results (for example determination of a non-ideal or close ideal flight profile, non-compliance with the time limitation, and so forth)

The factors that must be considered are the performance of an aircraft and the lateral & vertical navigation profiles. (Dancila, 2019) presented the arrangement of assessed vertical navigation profiles are portrayed by indistinguishable altitudes and speed at their initial and last waypoints, a limit of one altitude step and flown at consistent speed. (Mendoza et al., 2016) concluded that trajectory optimization represents a significant occasion to diminish fuel consumption from the flights that don't fly at their ideal speed and altitude.

(Félix Patrón et al., 2014) presented the mix between two distinct trajectories' optimization types: one improving the vertical navigation profile, and the other upgrading the lateral navigation profile. The lateral and vertical navigation profiles are analyzed to get the ideal cruise trajectory as far as fuel consumption. (Legrand et al., 2018) build up an approach to optimize the trajectory in presence of wind. He utilized Bell algorithm to process the ideal trajectory dependent on the wind forecasts.

In the literature (Ng et al., 2014) investigated that flying in wind ideal trajectories with a fuel-ideal vertical profile lessens average fuel burn of international flights cruising at a single altitude by 1–3%. The wind effects during a flight are a very important factor to consider in the creation of flight trajectories. (Lindner et al., 2020) investigated the benefit of en-route weather updates and got 17% of fuel saving in return. (Franco et al., 2017) build up an optimization of the aircraft course considering wind vulnerability. The examination is centered on a cruise flight made out of a few fragments interfacing certain waypoints. Results are introduced for a model of B767-300 airplane, for a given trans-maritime route, considering a genuine gathering weather forecast, and with the goal of limiting the normal complete fuel consumption.

(Hartjes et al., 2016) combined a develop optimization algorithm with a point mass aircraft model to optimize 3-dimensional long-haul aircraft trajectories in a wind field. It was the point of limiting the flight time in which the arrangement of constant build-up trails may occur, while considering the consequences for flight time and absolute fuel burn. (Sridhar et al., 2011) developed a wind-optimal trajectory for aircraft while avoiding the regions of airspace that facilitate persistent contrails formation. Although there was an increase in terms of fuel about 2%, the tradeoff for reducing 70% of travel time through contrail regions when altitude is optimized, satisfactory.

2.2. Problem Definition

The selection of altitudes greatly affects fuel consumption. However, in real flight aircraft does not always fly in optimal altitudes. Therefore, this research aims to optimize the fuel consumption in a 3D Flight Planning. The 3D aspect of this optimization includes 2D lateral and the altitudes. In this case the algorithm will search for a route based on the lowest fuel burn by taking different routes and altitudes. Genetic algorithm is selected for eliminating complex computational constraints. Such as finding the route with the closest distance, the lowest fuel burn, and the altitude where the climb and descend fuel are also calculated.

2.3. Method

The study aims to solve the fuel optimization problem using genetic algorithm for selecting the routes and altitudes with the lowest fuel consumption. This chapter will explain the methodology used and how to apply it with the tools and data available. It will start with explaining the genetic algorithm used in this optimization. Next is the aircraft performance database (PDB). And finally, is the vertical and lateral navigation profile optimization.

2.3.1 Genetic Algorithm

A genetic algorithm is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction to produce offspring of the next generation. In this section we will explain the original theory and implementation of Genetic algorithm.

2.3.1.1 Original Theory

The cycle of natural selection begins with the choice of fittest individuals from a population. They produce offspring which acquire the attributes of the parents and will be added to the next generation. On the off chance that parents have better fitness, their offspring will be superior to parents and have a better possibility of surviving. This cycle continues repeating and toward the end. At the end, a generation with the fittest individuals will be found.

There are five phases in a genetic algorithm: Initial population and individuals, Fitness function, Selection, Crossover, and Mutation.

- *Initial Population and individuals*

The initial population is a set of individuals can be seen in Figure 2-1. The number of initial populations is defined by number of combinations of its properties and computing capabilities of used hardware. (Note that the initial population is supposedly determined by the algorithm, however the population size in the input will limit the number of individuals since the hardware is not capable in searching for thousands of individuals).

The individuals are basically the function of combination and permutation however it will generate thousands of individuals and since the author computer is not capable in iterating it, therefore the population size is limiting the number of individuals.

- *Fitness function*

The fitness function determines how fit the individual is (the individual's ability to compete with other individuals). It provides a fitness score for each individual.

- *Selection*

This selection aims to select the fittest individual and let them pass their genes to the next generation.

- *Crossover*

This stage is the most significant phase in the genetic algorithm. After the selection is done, the surviving individuals will reproduce to create new set of individuals with combination of different flight levels and waypoints. Its aim is the same to create new set of trajectories with minimum fuel burn. A uniform crossover method was used to create the new individuals.

- *Mutation*

In certain newly formed offspring, some of their genes may mutate with low random probability. This implies that some of the waypoints will be randomly selected and changed from the list of routes as well as the altitudes.

2.3.1.2 Algorithm Implementation

In this section the implementation of algorithm is explained in the same five phases:

- *Initial Population*

In this case the individuals are the routes from starting point to destination point. Each individual consists of gene which are latitudes, longitudes and altitude. The distance and fuel burn between waypoints will be calculated by the algorithm. The altitudes in each route as mentioned before has 6 different flight levels varying from 29,000 ft. to 39,000 ft. as shown in Figure 2-1.

The waypoint here actually obtained from the previous research (Sentoso & Ruseno, 2021) who tries to find the optimal routes in the horizontal plane (latitude and longitude). The distance is needed to find the total fuel burn in each individual which has the important role in the next section.

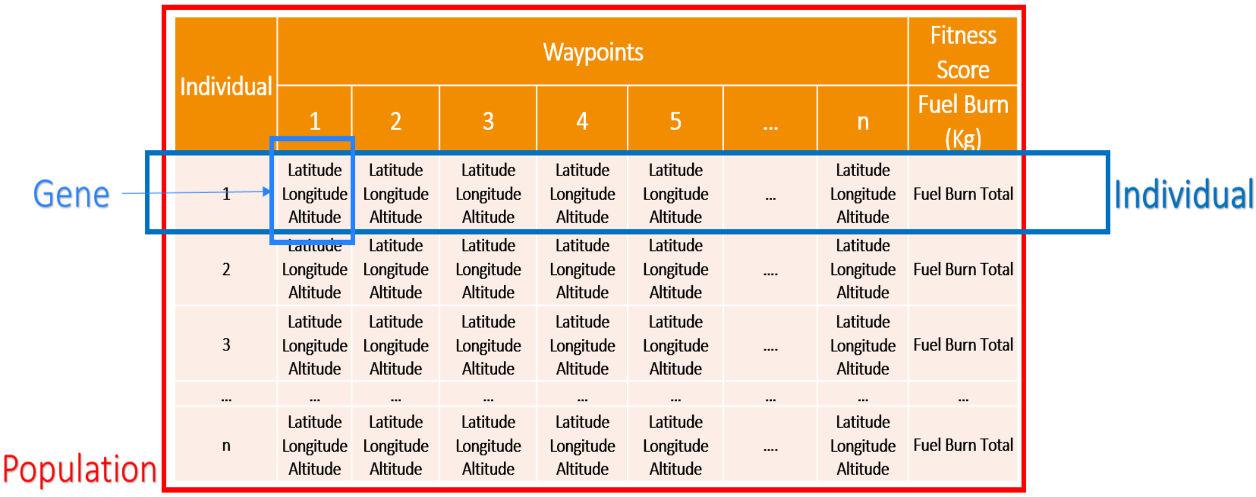


Figure 2-1: Visualization of individual properties in Genetic Algorithm

- *Fitness Function*

In this segment, each of the individuals are being evaluated for the minimum fuel burn from each route with its flight level. To calculate the fuel burn, a performance database of a certain aircraft is needed, in this case it is A320 type aircraft. By using the linear and exponential interpolation to find the total fuel burn per individuals. Then the individuals will be sorted from the minimum fuel burn to maximum fuel burn.

- *Selection*

This process will select the best route with smallest fuel burn used in the cruising section. There are different methods in selecting the individuals. In this paper we use the rank selection which will sort the individuals according to the fuel burn whereas only top 20 as the elite size of the fittest individual will be chosen. The visualization of the unsorted and sorted individuals is shown in Figure 2-2 and 2-3. After the individuals are survived, they are begun to reproduce to create next stronger generation.

Individ	Route	Flight Level	Fuel Bu
1	['CKG', 'DKI', 'BIKAL', 'BIDAK', 'PKP', 'KIRDA', 'TPG']	[0, 37000, 39000, 37000, 29000, 35000, 0]	3739
2	['CKG', 'DKI', 'DOMIL', 'BIDAK', 'TODAK', 'KIRDA', 'TPG']	[0, 35000, 29000, 39000, 35000, 37000, 0]	4022
3	['CKG', 'DKI', 'DOMIL', 'PLB', 'PKP', 'NE', 'TPG']	[0, 29000, 31000, 31000, 31000, 37000, 0]	3920
4	['CKG', 'DKI', 'DOMIL', 'BOSLO', 'TODAK', 'KIRDA', 'TPG']	[0, 37000, 37000, 35000, 29000, 37000, 0]	3878
5	['CKG', 'DKI', 'DOMIL', 'BIDAK', 'TODAK', 'NE', 'TPG']	[0, 33000, 29000, 31000, 29000, 35000, 0]	3822
6	['CKG', 'DKI', 'BIKAL', 'PLB', 'PKP', 'KIRDA', 'TPG']	[0, 39000, 39000, 35000, 33000, 29000, 0]	3177
7	['CKG', 'DOLTA', 'DOMIL', 'PLB', 'TIAMA', 'NE', 'TPG']	[0, 35000, 37000, 37000, 31000, 39000, 0]	3841
8	['CKG', 'DKI', 'DOMIL', 'BOSLO', 'TIAMA', 'NE', 'TPG']	[0, 33000, 35000, 31000, 39000, 31000, 0]	3670
9	['CKG', 'DOLTA', 'DOMIL', 'BOSLO', 'PKP', 'KIRDA', 'TPG']	[0, 35000, 37000, 29000, 37000, 37000, 0]	3900
10	['CKG', 'DKI', 'DOMIL', 'BIDAK', 'TIAMA', 'NE', 'TPG']	[0, 31000, 31000, 29000, 35000, 35000, 0]	3932
....	....	....	....
100	['CKG', 'DOLTA', 'DOMIL', 'BIDAK', 'TIAMA', 'NE', 'TPG']	[0, 33000, 31000, 37000, 29000, 31000, 0]	3638

Figure 2-2: Unsorted Individuals

- *Crossover*

The comparison of several crossover methods is shown in Figure 2-4. For each parent pair to be mated, the point of crossing is randomly selected from within the genes. However, the first and the last genes will not be cross-overed. The crossover points will be random but the position of the waypoints keep the same so there will not be any illogically routes. After the individuals are created, they will be evaluated again then reproduce again until a predefined number of generations are reached.

Individu	Route	Flight Level	Fuel Bu
6	['CKG', 'DKI', 'BIKAL', 'PLB', 'PKP', 'KIRDA', 'TPG']	[0, 39000, 39000, 35000, 33000, 29000, 0]	3177
100	['CKG', 'DOLTA', 'DOMIL', 'BIDAK', 'TIAMA', 'NE', 'TPG']	[0, 33000, 31000, 37000, 29000, 31000, 0]	3638
8	['CKG', 'DKI', 'DOMIL', 'BOSLO', 'TIAMA', 'NE', 'TPG']	[0, 33000, 35000, 31000, 39000, 31000, 0]	3670
1	['CKG', 'DKI', 'BIKAL', 'BIDAK', 'PKP', 'KIRDA', 'TPG']	[0, 37000, 39000, 37000, 29000, 35000, 0]	3739
5	['CKG', 'DKI', 'DOMIL', 'BIDAK', 'TODAK', 'NE', 'TPG']	[0, 33000, 29000, 31000, 29000, 35000, 0]	3822
7	['CKG', 'DOLTA', 'DOMIL', 'PLB', 'TIAMA', 'NE', 'TPG']	[0, 35000, 37000, 37000, 31000, 39000, 0]	3841
4	['CKG', 'DKI', 'DOMIL', 'BOSLO', 'TODAK', 'KIRDA', 'TPG']	[0, 37000, 37000, 35000, 29000, 37000, 0]	3878
9	['CKG', 'DOLTA', 'DOMIL', 'BOSLO', 'PKP', 'KIRDA', 'TPG']	[0, 35000, 37000, 29000, 37000, 37000, 0]	3900
3	['CKG', 'DKI', 'DOMIL', 'PLB', 'PKP', 'NE', 'TPG']	[0, 29000, 31000, 31000, 31000, 37000, 0]	3920
10	['CKG', 'DKI', 'DOMIL', 'BIDAK', 'TIAMA', 'NE', 'TPG']	[0, 31000, 31000, 29000, 35000, 35000, 0]	3932
2	['CKG', 'DKI', 'DOMIL', 'BIDAK', 'TODAK', 'KIRDA', 'TPG']	[0, 35000, 29000, 39000, 35000, 37000, 0]	4022
....	....	....	....

Figure 2-3: Sorted Individual

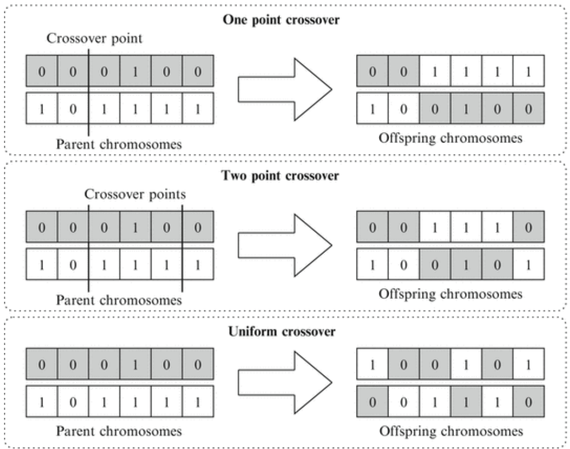


Figure 2-4: Methods of Crossover

- *Mutation*

The mutation function is to swap the altitude and waypoints to find the chance of changing it to find the optimal fuel burn. The altitude and waypoints will be randomly picked by the algorithm. This research used the 0.01 mutation rate. It means that the mutation will be only possible for 5 individuals from 500 populations.

It depends on the how many generations is defined; the new set of population will go through the same process until a predefined number of generations are reached. Since the algorithm is based on randomness, the possibility of best solution is not fixed but vary. The algorithm is implemented in Python programming language version 3.

2.3.2 Fuel Consumption Optimization

This section discussed about how to optimize the fuel consumption. We used a FCOM (Flight Crew Operating Manual) data as database for calculation including the ISA (density), Aircraft Speed and the fuel burn per altitudes and per distance. This research used aircraft performance data based on the FCOM of Airbus A320. The used data tables are shown in Appendix A-1. This data includes precise information on the phases of climb, cruise, and descend as shown in Figure 2-5. Each one of the data tables gives the data of fuel burn, speed, and specific range. In this optimization will only use the specific range in long range cruise data, and fuel burn and distance for the climb and descend. Each of the calculation in the table to get the fuel burn (kg) used the exponential and linear interpolation.

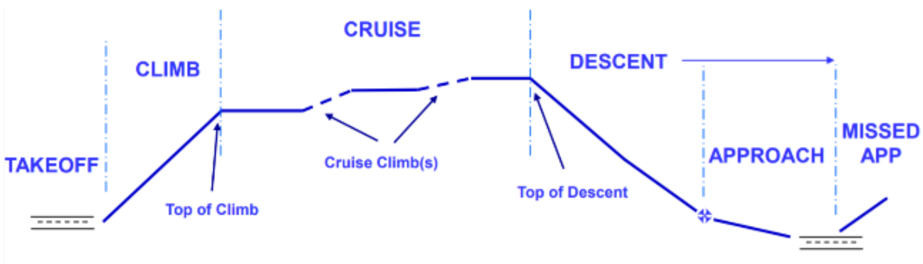


Figure 2-5: Flight Phases

There are several phases during flight, however in this optimization will only focus on climb until descend phases. Notice that in the cruise segment, there will be step descend or step climb which also will be calculated. The input and the output in this calculation as shown in table 2-1.

Table 2-1: Input and Output of aircraft performance calculation

Phases	Input	Output
Climb	Gross Weight [Kg] Altitude [ft.]	Fuel Burn [Kg]
Cruise	Gross Weight [Kg] Altitude [ft.]	Specific Range [NM/1000kg]
Descend	Gross Weight [Kg] Altitude [ft.]	Fuel Burn [Kg]

The purpose of solving the problem is to determine the fuel consumption of each route and altitudes that can be selected in order to achieve the minimization of the total fuel consumption. The constraints start from equation (2-1). Where the total fuel (TF) is calculated by the sum of cruise fuel and climb or descend fuel. The maximum fuel capacity of A320 is 21,448 Kg. Therefore, any number greater than that will not be selected in the genetic algorithm.

$$TF = Fcr(w, alt) + Fuel_{(FC,FD)} \tag{2-1}$$

Next constraint is from the equation (2-2) where we can see it is the fuel cruise. Here we set the weight can vary from its maximum 74,000 Kg, 70,000 Kg, 65,000 Kg, 60,000, and to its minimum 55,000 Kg since the weight is decreasing in each waypoint because of the fuel loss. And the altitude range is from 29,000 ft. to 39,000 ft. the cruising calculation is to calculate the fuel between each waypoint at a certain altitude.

Note that in the cruise segment, specific range will be used to calculate the fuel burn. Therefore, the equation to calculate it is as follows:

$$Fcr(w, alt) = \frac{dw}{D} \tag{2-2}$$

Where Fcr: fuel consumption in cruise (Kg), dw: distance between waypoints (NM) and D: Specific Range (distance/1000kg) and (w, alt) means that fuel consumption is a function of weight and altitude. Another constraint is from equation (2-3) and (2-4) which are the fuel consumption where the aircraft is climbing or descending. The input will be the same as the cruising phase which are the altitude and gross weight. Using the climb and descend data from FCOM as shown in Appendix A-1, to calculate the fuel at climb and descend will be as follows:

$$FC = FL(w, alt)_N - FL(w, alt)_C \tag{2-3}$$

$$FD = FL(w, alt)_C - FL(w, alt)_N \tag{2-4}$$

Whereas FC is Fuel Climb, FD is Fuel Descend, N is next segment and C is current segment and FL(w,alt) is the function of weight and altitude according to the interpolation and the FL is the fuel required for that flight level (Kg). This however has a different interpolation; the climb data and cruise data are using exponential interpolation while the descend data is using linear interpolation. Since, the flight in the optimization is able to climb or descend during cruise phase, thus it could lead to fluctuation in vertical navigation profile (altitude). In the calculation, the constraint that we assumed to be constant is the Long-Range Cruise Speed (300-396 kts), ISA CG = 33%, and Maximum Cruise Thrust Limits.

2.3.3 Flight Route as a Grid

We used the resulted optimal and alternate routes from (Sentoso & Ruseno, 2021) in 2D as the base grid. The resulted lateral routes are shown in figure 2-6. The other 2 routes are shown in Appendix A-2. Each of the routes has its optimal and alternate routes which then creating a 3D Grid. The alternate routes acting as the available route from starting point to destination point.

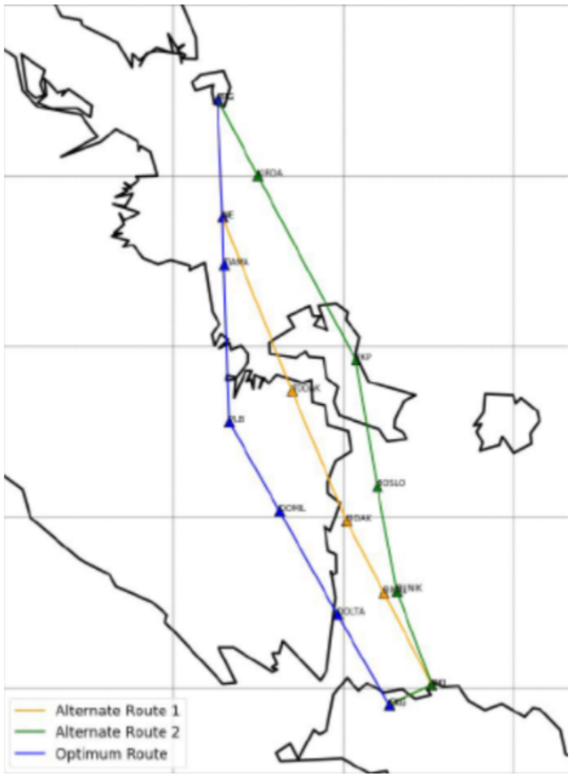


Figure 2-6: Jakarta – Tanjung Pinang Optimum 2D flight routes (Santoso, 2020)

The 3D grid is created when the altitude is implemented in the lateral grid. From the paper of (Mendoza et al., 2016), the grid visualization will be shown in the figure 2-7.

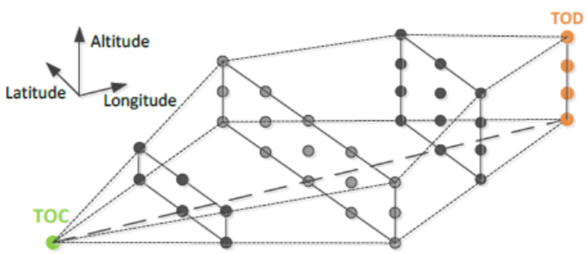


Figure 2-7: 3D Grid Visualization (TOC: Top of Climb, TOD: Top of Descend)

Here the range of altitude will be from 29,000 ft. to 39,000 ft. with separation of 2,000 ft. between altitudes. Note that the starting point or departure and arrival airport will be considered as 0 ft. The cruise altitude begins in TOC which is 1 waypoint after start point and ends 1 waypoint before destination airport.

The case study covers in this research consist of 3 scenarios:

- Scenario 1 is to analyze the effect of the generation number into the convergence of the result.
- Scenario 2 is to analyze the effect weight difference to the selection of optimum route.
- Scenario 3 is to analyze the altitude selection by the algorithm and compare it with the optimal altitude from other sources.

The specification of hardware and Software used in this simulation is as follows:

- Operating System : Win 10 Pro
- System Manufacture : HP
- Processor : i5 9th Gen
- Memory : 8 Gb
- VRAM : 128 MB
- Application : Python 3.6

3. Result and Analysis

The main result is presented along with the analysis. The result will be divided into 3 scenarios.

3.1. Scenario 1

In this scenario, the route we take starts from Jakarta to Tanjung-Pinang with its alternate routes. The inputs of the algorithm are:

- Initial Population = 500
- Elite Size = 20
- Mutation Rate = 0.01
- Generation numbers = 5, 25, 50, 100
- Maximum Take-Off Weight (MTOW) = 74,000 Kg

Supposedly the initial population is not limited by the author and will generate itself. However, due to low specification of the hardware it took 3 hours to generate 100 generations without limiting the population. Thus, the initial population is limited to speed up processing time.

To find the generation number that produce convergence value, we run several numbers of generation as 5, 25, 50 and 100 in one case of scenario which are from Jakarta – Tanjung Pinang.

As seen in Figure 3-1, respectively the 5, 25, 50 and 100 generation has a different value in initial fuel burn. They are 3117 Kg, 3195 Kg, 3112 Kg and 3162 Kg respectively. It is because the initial population are generated randomly by the algorithm. Thus, the calculated fuel burns are not always the same. However, it converged in the final generation.

The Figure 3-1 shows that the convergence value reached in the 12th generation. It was confirmed by the altitude profile that remain the same from the 25 generation until 100 generations. It means that it reached the best solution generated by the algorithm.

The optimum lateral route selected by the algorithm is shown in Figure 3-2. It is the same route as the generated route from Dijkstra Algorithm from the research of (Santoso, 2020) shown in Figure 2-6.

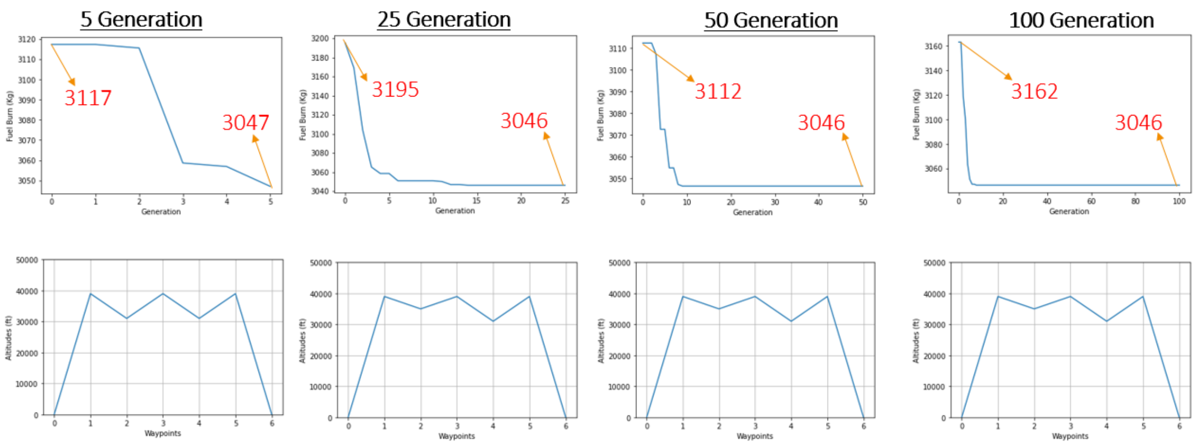


Figure 3-1: Fuel Burn and Altitude Profile of the best Route in 5, 25, 50 and 100 generations

The next routes to be observed are the Jakarta-Makassar and Jakarta-Manado route. The used routes are shown in Appendix A-2. The detail results are shown in Appendix B-1. In general, it has the similar result with flight Jakarta-Tanjung Pinang. The 100 generations provided convergence result.

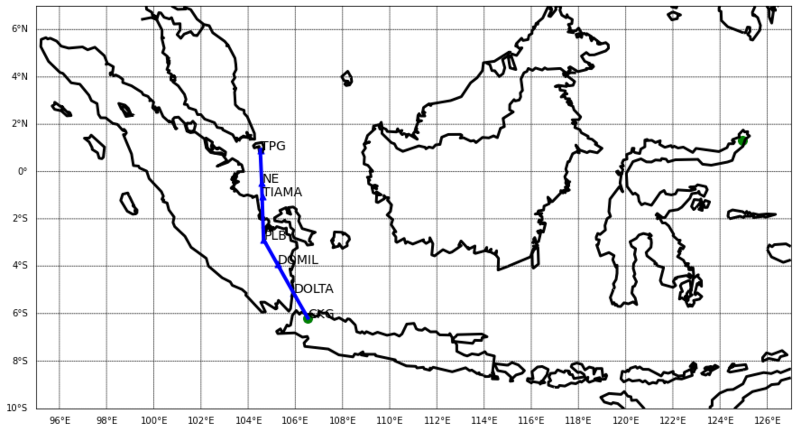


Figure 3-2: Lateral Optimum Route generated by 5, 25, 50 and 100 generations

For Jakarta-Makassar route, the genetic algorithm able to reduce fuel burn from 5,407Kg into 5,010Kg. The optimum route selected is like the result of previous research (Sentoso & Ruseno, 2021).

For Jakarta-Manado route, the genetic algorithm able to reduce fuel burn from 8,979Kg into 7,320Kg. However, the optimum route selected is the alternate 1 which has a little bit longer around 1207 NM compared to the optimum route from the previous research. It means that with the combination of more optimum altitude, it could lead to the changes in the selection of optimum route.

3.2. Scenario 2

For this scenario, 5 aircraft weights have been analyzed starting from 74000 kg, 70000kg, 65000kg, 60000kg and 55000kg for 3 routes. The fuel saving is calculated from the difference between fuel burn at final generation and initial generation. The complete of resulted fuel burn is shown in Appendix B-3. The summary of fuel burn is shown in Figure 3.3.

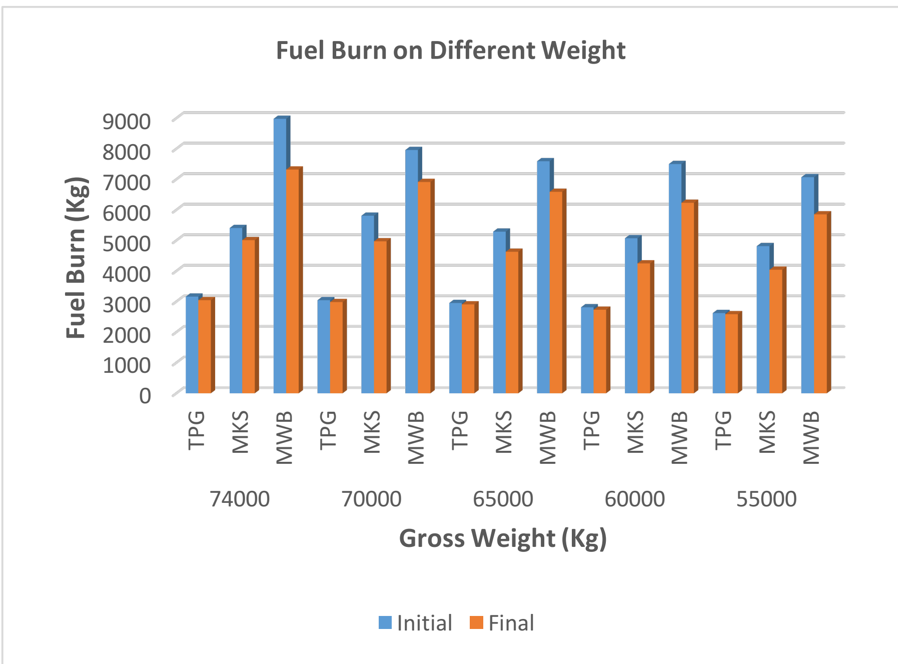


Figure 3-3: Reduction of Fuel Burn per aircraft weights: 74000Kg, 70000Kg, 65000Kg, 60000Kg, 55000Kg

The Figure 3-4 shows the resulted fuel saving for different aircraft weights. The fuel savings are not proportional to the weight of the aircraft at heavy conditions but changed at lighter conditions. From the figure 3-3, in Jakarta - Tanjung Pinang, the amount of fuel that is reduced is relatively lower and has fluctuations. Starting with a weight of 70000kg decreased by 1.97%, a weight of 65000kg has decreased by 1.5%, a weight of 60000kg has decreased by 2.84% and finally with a weight of 55000kg has decreased by 1.48%.

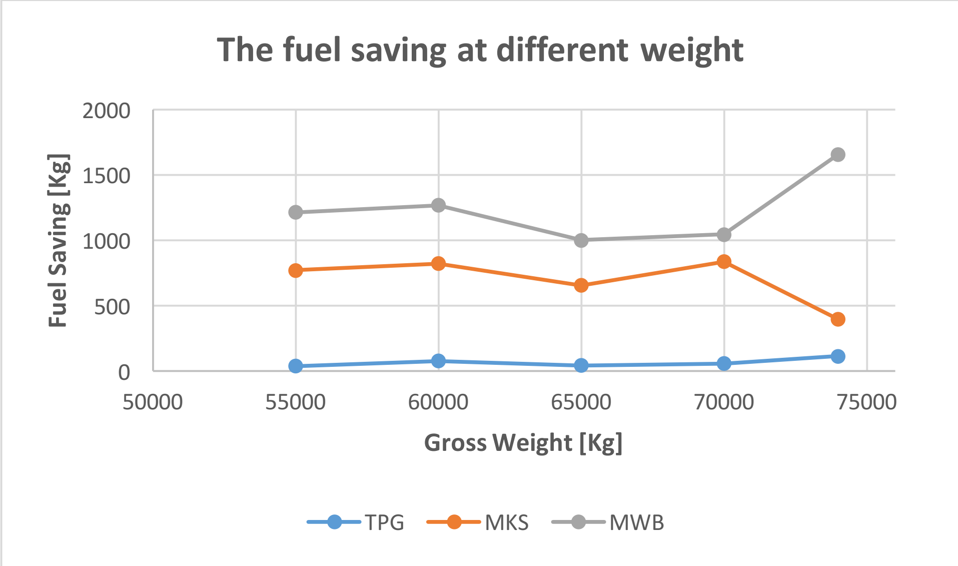


Figure 3-4: Reduction of Fuel Burn on Different Weight

Next is the route of Jakarta – Makassar starting with a weight of 74000kg, 70000kg, 65000kg, 60000kg, and 55000kg. The reduced fuel on the Jakarta Makassar route is quite interesting because at the beginning the weight of 74000kg experienced a quite low fuel drop but became large at lighter weight. The fuel burn on weight 74000kg has drop to 7.34%, weight 70000kg drop to 14.4%, weight 65000kg drop to 12.44%, weight 60000kg drop to 16.22% and lastly weight 55000kg drop to 16.03%. This happen because the initial population of starting generation is picked randomly by the system. The waypoints and altitudes were picked randomly to create the initial individuals. Therefore, the initial fuel burn could be higher or lower.

Then finally the last route of the analysis, route from Jakarta to Manado. The reduced fuel on the Jakarta-Manado route is almost the same as the Jakarta-Tanjung Pinang route, except that the Jakarta-Manado route has decreased drastically from a weight of 74,000 kg to a lighter weight. Starting with a weight of 74000kg, 70000kg, 65000kg, 60000kg, 55000kg. The decrease in fuel burn at the weight listed as follows:

- Weight 74000 Kg = 18%
- Weight 70000 Kg = 13.12%
- Weight 65000 Kg = 13.18%
- Weight 60000 Kg = 16.90%
- Weight 55000 Kg = 17.20%

Since the algorithm generate the initial population randomly therefore if you can see in the appendix, in the 60000kg of gross weight it has a spike on the fuel burn per generation in each route. Means that the early generation had bad genes, therefore the algorithm will continue to iterate so that the best generation is produced in the 100th generation. The mutation rate also plays a role in this problem. Since the mutation rate is 0.01 from 500 individuals, there are 5 individuals that are mutated.

3.3. Scenario 3

In the choice of altitude, it is done randomly by a genetic algorithm. The altitude is selected in the list that has been created. List of altitudes is as follows: [29000, 31000, 33000, 35000, 37000, and 39000] each individual will have altitude at each waypoint. In this optimization, altitude is still viewed per altitude, not per distance. From 3 case examples Jakarta - Tanjung Pinang, Jakarta - Makassar, and Jakarta - Manado will analyze the effect of altitude on this optimization. Figures 3-5, 3-6, and 3-7 show the routes with different altitudes in different weights.

In the route of CKG – TPG (Figure 3-5), the optimal selection of altitude generated by GA in weight 74000kg, 70000kg, 65000kg, 60000kg and 55000kg has a fluctuation from the waypoint 2 until waypoint 6. However, in the fluctuation has the average of altitude 35000ft and 37000ft. The result reaches the optimal altitude but with fluctuation. In the weight of 65000kg, shows the reasonable altitude with only descend in the waypoint 4.

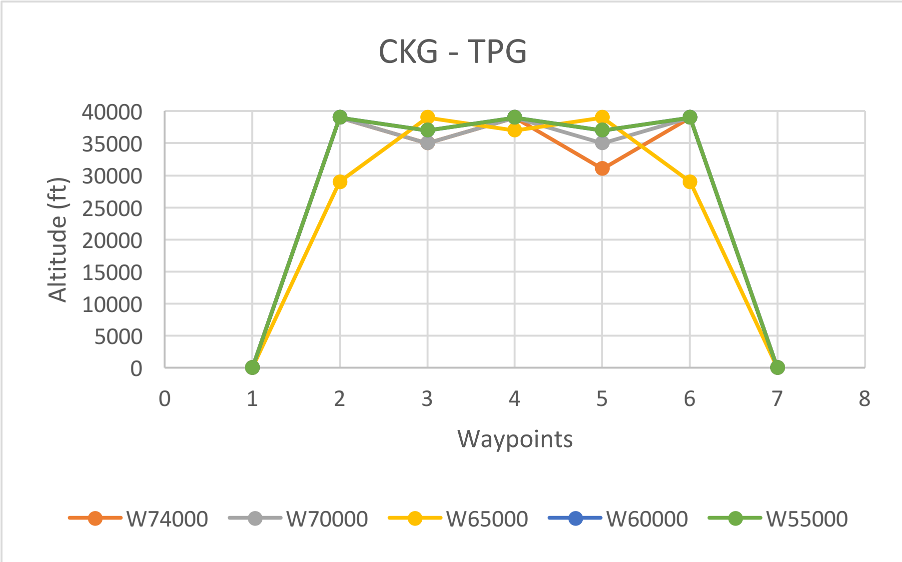


Figure 3-5: Altitude Profile in each Weight for Jakarta – Tanjung Pinang

Next is from CKG – MKS (Figure 3-6), at a weight of 74000 kg and 70000 kg has the same altitude from start to end with a fluctuating range from 30000 ft. to 39000 ft. from waypoint 3 to waypoint 10. There goes again in the weight of 60000kg has already begin to reach the optimal with a bit of fluctuation same goes with the weight of 55000kg.

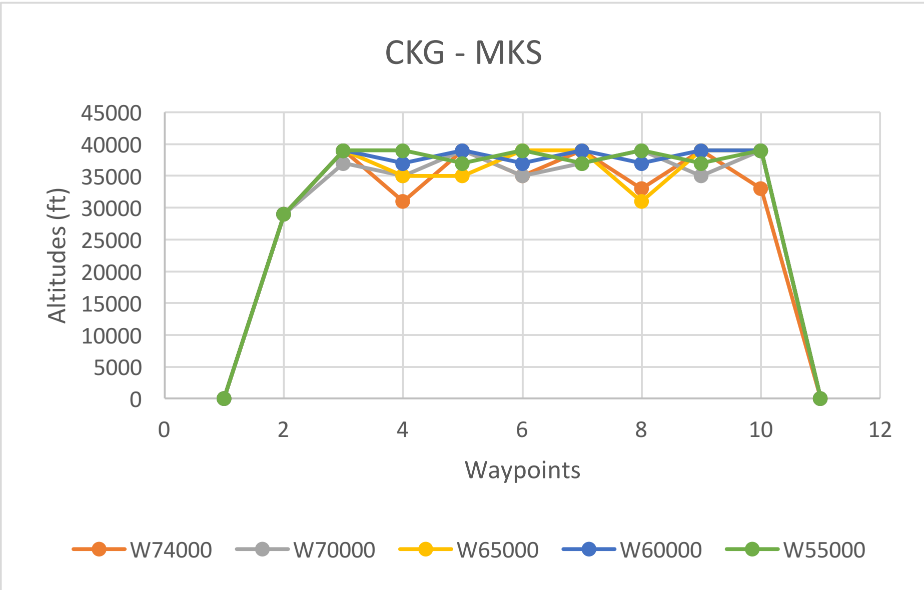


Figure 3-6: Altitude Profile in each Weight for Jakarta – Makassar

On the last route CKG – MWB (Figure 3-7), there is something unique about the choice of altitude. At a weight of 74000 kg to 55000 kg having the same fluctuating range of altitude from 35000 ft. to 39000 ft. It is already reaching the optimal altitudes.

From the result we can see that the GA has already reach the optimum altitude, this concludes that the algorithm succeeds in choosing the altitude for the optimal one. However, the fluctuation is due to selection of altitude in the cruising path. Here we make it possible that the aircraft can choose the altitudes freely without any restriction in the cruising phase. Therefore, this cannot be compared to the real flight data since the constraint is not dynamic.

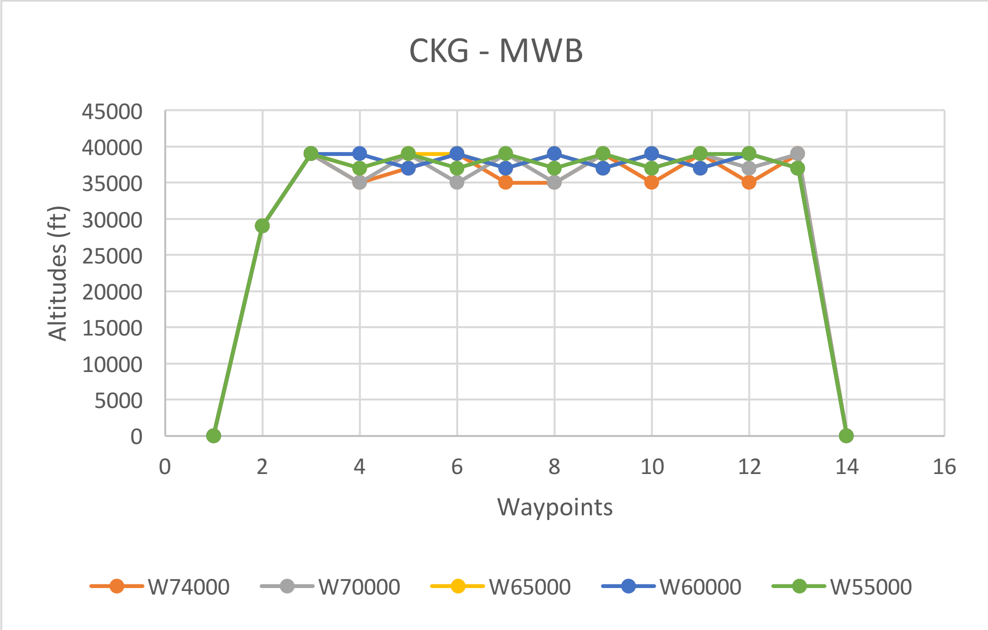


Figure 3-7: Altitude Profile in each Weight for Jakarta – Manado

Now, if we can see that in these three routes there is a decrease in altitude at the last waypoint and an increase or constant in the waypoint before the last one. It can be concluded that this algorithm is looking for altitudes with the least fuel burn. Therefore, it can be interpreted that the route with that altitude is more fuel optimal than the other altitudes. In this case only analyzed 100 generations. There is a possibility that the altitude changes in the generation 200 or 300 or more. Which then lead to the longer the route and the more the selection of waypoints the better the result is.

Now when compared with the optimal altitude of the FCOM, it shows that the lower the weight the higher the altitude should be. As shown in the Figure 3-8 the dotted line represents the optimal altitude at different weights. Why is it different from genetic algorithm? Because the first, here the data used is not dynamic. Basically, it just searches for the lowest fuel consumption in different altitudes and routes. Second in the genetic algorithm, only the altitude that has a low fuel burn is selected randomly, if the last descend is selected, it indicates that the minimum fuel burn is achieved with that altitude.

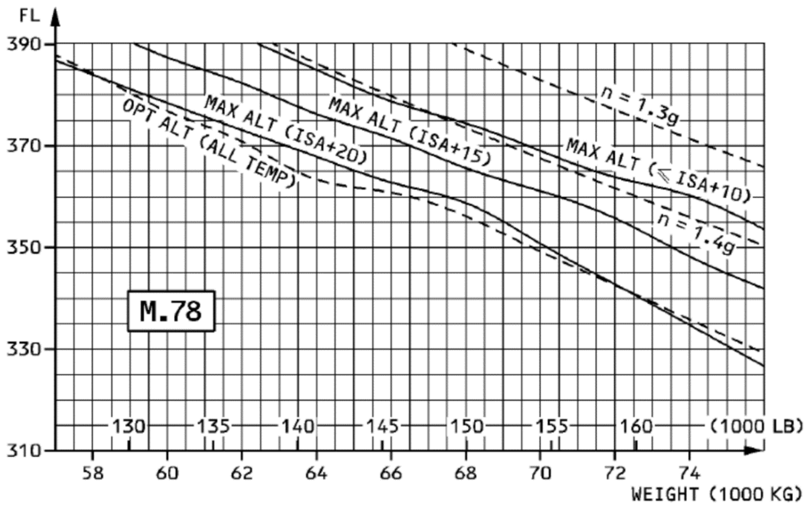
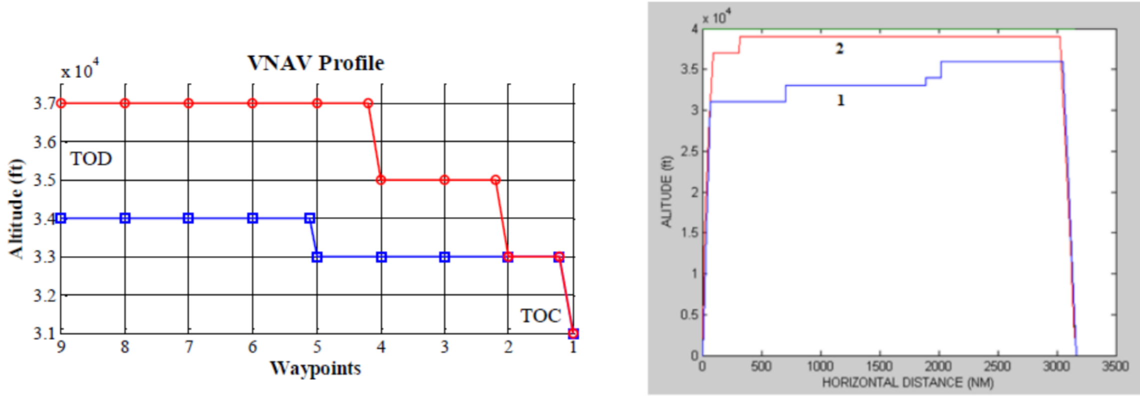


Figure 3-8: Optimal Altitude From FCOM Data (Airbus, 2019).

From the paper of (Patrón & Botez, 2015) and (Félix Patrón et al., 2014) the altitude or VNAV were resulted climbing not descending as shown in Figure 3-9 (a) and (b). It because first they did not calculate the descent in the cruise phase. However, the descend calculation happened in the last waypoint which represent actual descend not cruise descend. Second, the selection of altitudes in their paper can be assume that the next altitude must be higher or same with the previous altitude which means there is a limitation in the altitude so the aircraft cannot descend in the cruise phase. Last, they used the interpolation of wind data and considered the external factor such as the weather and climb and descend acceleration



(a) (b)

Figure 3-9: VNAV Profile: a. (Patrón & Botez, 2015), b. (Félix Patrón et al., 2014)

Based on the result, the smaller the weight has the stable in altitude. It is because the crossover point in the individuals are using the uniform crossover where the altitude before and after could be different. Also, the descend data from the FCOM is not sufficient in weight 74000 kg to 65000 kg. By comparing it to the resulted altitude from (Patrón & Botez, 2015), they are not using descend in the optimization.

Means they are not considering a descent in the cruise segment, however only in the last waypoint happened to be a descend segment. An assumption is made by the author that in their paper there's a limitation to the selection of altitude. When the altitude is selected the next altitude must be higher or same as the previous altitude so that will not be any descend in the cruise segment.

4. Conclusions and Recommendation

The algorithm performs well to find the optimal fuel burn routes with changing in altitudes. The 100 generations of genetic algorithm are more than enough to generate a convergence result. After several gross weights were tested, the results showed changes in the optimum route chosen by the genetic algorithm. It can also be seen that the farther the route, the more significant the changes to the fuel.

Results from Jakarta - Tanjung Pinang flight showed an average of fuel reduction of around 2.29% followed by Jakarta – Makassar flight with 13.28% and Jakarta – Manado flight with 15.68%. The resulted altitude profile shows a fluctuation in the middle of route. However, most of it ends with a climb. This happen because the algorithm calculates the value of fuel burn in each altitude point by considering possibility of step climb or descend.

For the better result of this algorithm, it is recommended to use better hardware to run the program without having a BSOD (Blue Screen of Death). In addition, dynamic data such as time and speed could produce a better result in the route selections. Also, considering the wind data could make it comparable to the real flight data.

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Appendix A-1: Flight Crew Operating Manual (FCOM) Data of A320

LONG RANGE CRUISE						
MAX. CRUISE THRUST LIMITS NORMAL AIR CONDITIONING ANTI-ICING OFF				ISA CG=33.0%	N1 (%) MACH KG/H/ENG IAS (KT) NM/1000KG TAS (KT)	
WEIGHT (1000KG)	FL290	FL310	FL330	FL350	FL370	FL390
50	74.9 .673 1012 258 196.8 398	75.3 .676 960 248 206.8 397	76.6 .698 946 245 214.6 406	78.2 .726 941 245 222.4 419	79.6 .752 939 242 229.7 431	81.6 .778 946 240 236.0 446
52	75.3 .676 1031 259 194.0 400	76.0 .684 989 251 202.9 401	77.5 .710 983 250 210.2 413	78.9 .736 976 248 217.5 424	80.4 .764 977 247 224.2 438	82.3 .782 975 242 230.0 449
54	75.7 .676 1047 259 191.3 400	76.8 .693 1023 255 198.9 407	78.5 .723 1021 254 205.9 420	79.6 .748 1013 252 212.7 431	81.1 .775 1015 251 218.9 444	82.8 .785 1006 243 223.8 450
56	76.2 .680 1068 260 188.3 402	77.6 .703 1058 258 195.0 413	79.1 .731 1054 258 201.7 425	80.2 .757 1047 256 208.2 436	81.8 .781 1048 253 213.8 448	83.4 .785 1035 243 217.4 450
58	76.9 .689 1103 264 184.8 408	78.5 .715 1096 263 191.3 419	79.8 .741 1089 261 197.7 431	81.0 .769 1088 260 203.6 443	82.4 .784 1076 254 208.8 449	84.0 .786 1071 243 210.5 451
60	77.7 .698 1137 268 181.5 413	79.3 .725 1133 267 187.8 426	80.4 .750 1125 265 193.8 436	81.6 .778 1126 264 199.2 449	82.9 .786 1108 255 203.5 451	84.7 .786 1106 243 203.8 451
62	78.4 .707 1174 272 178.3 419	79.9 .734 1168 270 184.3 430	81.0 .759 1161 268 190.0 441	82.2 .782 1156 265 195.0 451	83.4 .786 1137 255 198.2 451	85.4 .786 1144 243 197.1 451
64	79.2 .719 1214 276 175.2 425	80.5 .742 1204 274 180.9 436	81.6 .770 1203 273 186.1 448	82.7 .784 1184 266 190.8 452	84.0 .786 1172 255 192.4 451	86.1 .785 1180 243 190.9 450
66	80.0 .727 1249 280 172.2 430	81.0 .750 1240 277 177.6 440	82.3 .779 1241 276 182.5 453	83.2 .786 1215 267 186.5 453	84.6 .786 1207 255 186.9 451	
68	80.5 .734 1284 283 169.3 435	81.6 .759 1277 281 174.4 445	82.8 .782 1271 277 178.9 455	83.7 .786 1245 267 182.0 453	85.2 .787 1245 255 181.3 451	
70	81.0 .742 1319 286 166.5 439	82.2 .770 1319 285 171.2 452	83.3 .784 1300 278 175.4 456	84.2 .786 1278 267 177.3 453	85.9 .787 1286 255 175.7 452	
72	81.5 .750 1355 289 163.7 444	82.8 .778 1358 288 168.0 456	83.7 .785 1330 279 171.8 457	84.7 .786 1312 267 172.7 453	86.3 .781 1304 253 171.9 448	
74	82.0 .756 1390 292 161.0 448	83.3 .782 1389 290 165.1 459	84.2 .787 1362 280 168.1 458	85.3 .787 1350 267 167.9 453		
76	82.6 .766 1433 296 158.3 454	83.8 .784 1419 291 162.1 460	84.6 .786 1391 279 164.3 457	85.9 .787 1389 267 163.3 454		
LOW AIR CONDITIONING ΔFUEL = −0.6 %			ENGINE ANTI ICE ON ΔFUEL = +2.5 %		TOTAL ANTI ICE ON ΔFUEL = +4.5 %	

Figure A-1: Cruise Data (Airbus, 2019)

CLIMB - 250KT/300KT/M.78							
MAX. CLIMB THRUST NORMAL AIR CONDITIONING ANTI-ICING OFF			ISA CG=33.0%		FROM BRAKE RELEASE TIME (MIN) FUEL (KG) DISTANCE (NM) TAS (KT)		
FL	WEIGHT AT BRAKE RELEASE (1000KG)						
	50	52	54	56	58	60	62
390	17 1235 108 385	18 1302 114 385	19 1373 121 386	20 1449 129 387	21 1531 138 389	23 1620 147 390	24 1721 158 392
370	15 1160 95 378	16 1220 101 378	17 1282 106 379	18 1347 112 380	19 1416 118 381	20 1489 125 382	21 1566 132 382
350	14 1095 86 371	15 1150 90 372	15 1207 95 372	16 1267 100 373	17 1328 105 374	18 1393 111 374	19 1460 116 375
330	13 1036 77 364	13 1087 81 365	14 1140 86 365	15 1195 90 366	15 1251 94 366	16 1310 99 367	17 1371 104 367
310	12 978 70 356	12 1025 73 357	13 1074 77 357	14 1125 81 358	14 1177 85 358	15 1231 89 359	16 1287 93 359
290	11 915 62 346	11 959 65 347	12 1005 68 347	12 1051 71 348	13 1099 75 348	13 1149 78 349	14 1200 82 349

Figure A-2: Climb Data (Airbus, 2019)

CLIMB - 250KT/300KT/M.78							
MAX. CLIMB THRUST NORMAL AIR CONDITIONING ANTI-ICING OFF			ISA CG=33.0%		FROM BRAKE RELEASE TIME (MIN) FUEL (KG) DISTANCE (NM) TAS (KT)		
FL	WEIGHT AT BRAKE RELEASE (1000KG)						
	64	66	68	70	72	74	76
390	26 1835 172 394						
370	22 1650 141 384	23 1740 150 385	25 1840 160 387	27 1952 172 389	29 2081 186 391		
350	20 1531 123 376	21 1606 129 377	22 1686 137 378	23 1773 145 379	24 1867 153 381	26 1970 163 383	27 2086 175 385
330	18 1435 109 368	19 1502 115 369	20 1571 120 370	20 1645 127 371	22 1724 133 372	23 1808 141 373	24 1899 149 375
310	16 1346 97 360	17 1406 102 360	18 1469 107 361	19 1534 112 362	19 1604 117 363	20 1677 123 364	21 1755 130 365
290	15 1254 86 350	15 1308 90 350	16 1365 94 351	17 1424 98 352	17 1487 103 352	18 1552 108 353	19 1620 113 354

Figure A-3: Climb Data Continued (Airbus, 2019)

DESCENT - M.78/300KT/250KT									
IDLE THRUST NORMAL AIR CONDITIONING ANTI-ICING OFF			ISA CG=33.0%		MAXIMUM CABIN RATE OF DESCENT 350FT/MIN				
WEIGHT (1000KG)	45				65				
FL	TIME (MIN)	FUEL (KG)	DIST. (NM)	N1	TIME (MIN)	FUEL (KG)	DIST. (NM)	N1	IAS (KT)
390	16.1	208	101	68.2	17.7	173	108	IDLE	241
370	14.6	177	90	69.4	16.9	169	102	IDLE	252
350	12.9	136	77	71.5	16.2	165	97	IDLE	264
330	12.1	125	71	IDLE	15.6	161	92	IDLE	277
310	11.7	123	68	IDLE	15.0	157	88	IDLE	289
290	11.2	120	64	IDLE	14.4	154	83	IDLE	300

Figure A-4: Descend Data (Airbus, 2019)

Appendix A-2: 2D Optimum and Alternate Flight Route used

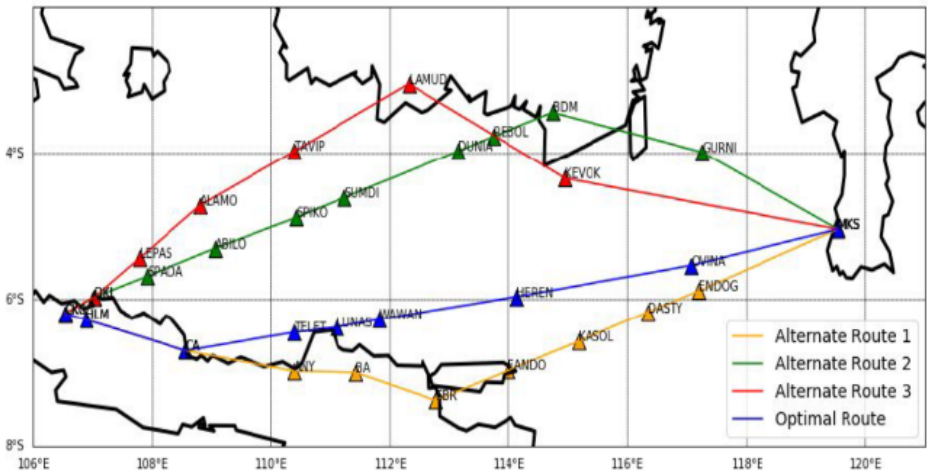

Figure A-5: Jakarta – Makassar flight routes (Santoso, 2020)

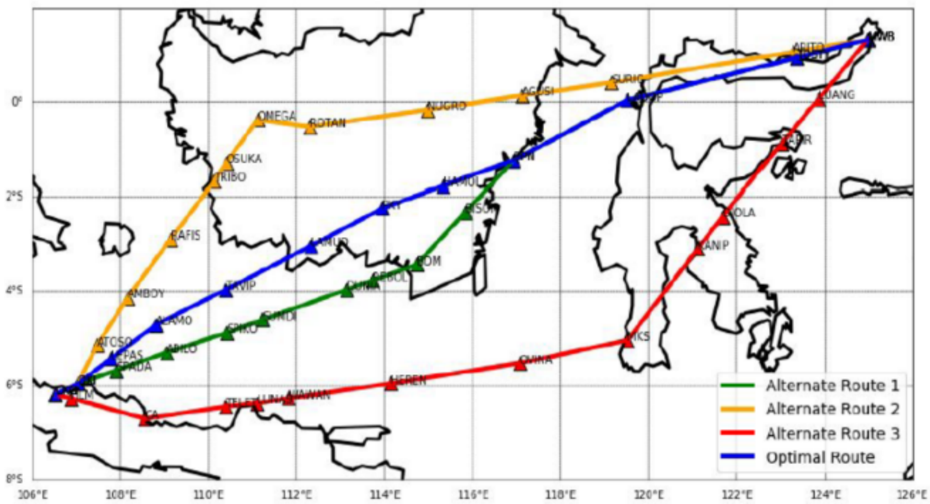

Figure A-6: Jakarta – Manado flight routes (Santoso, 2020)

Appendix B-1: Result for Jakarta – Makassar flight

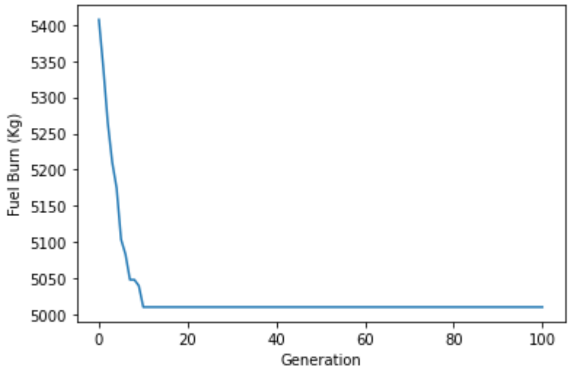

Figure B-1: Fuel Burn per Generation

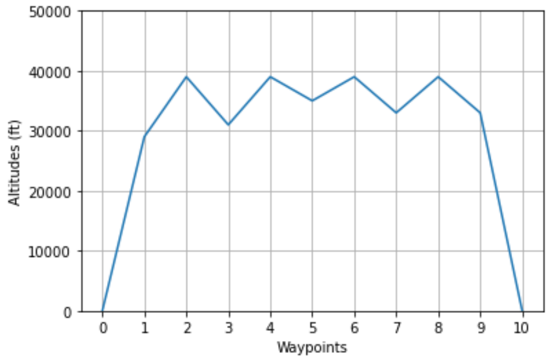

Figure B-2: Vertical Navigation Profile

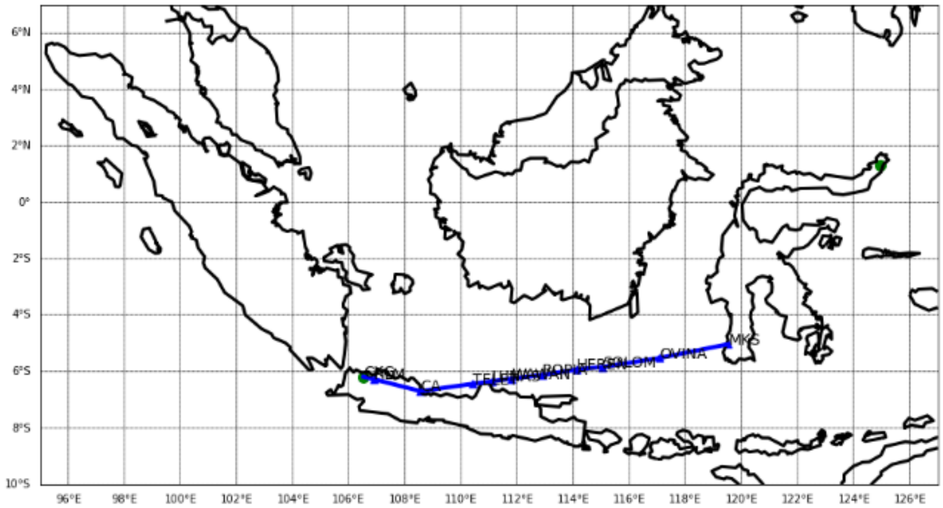

Figure B-3: Route Generated at 100th Generation

Appendix B-2: Result for Jakarta – Manado flight

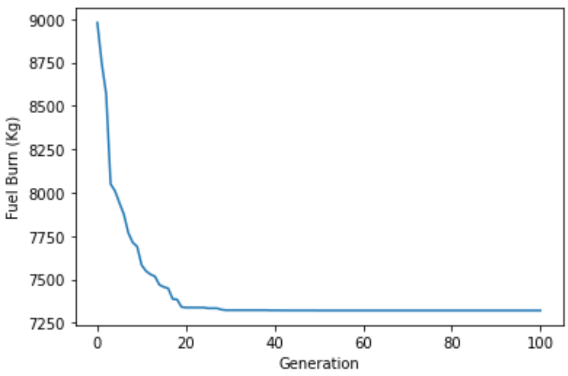

Figure B-4: Fuel Burn per Generation

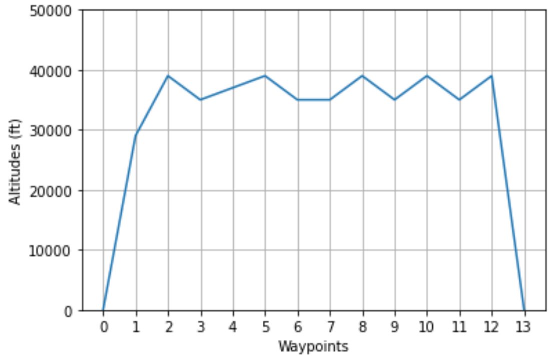

Figure B-5: Vertical Navigation Profile

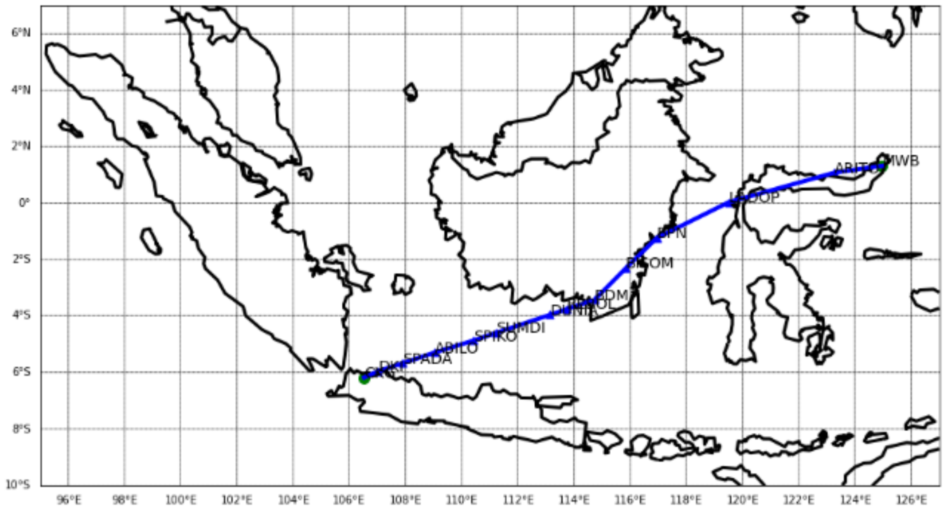

Figure B-6: Route Generated at 100th Generation

Appendix B-3: Fuel Burn results used for Weight Analysis

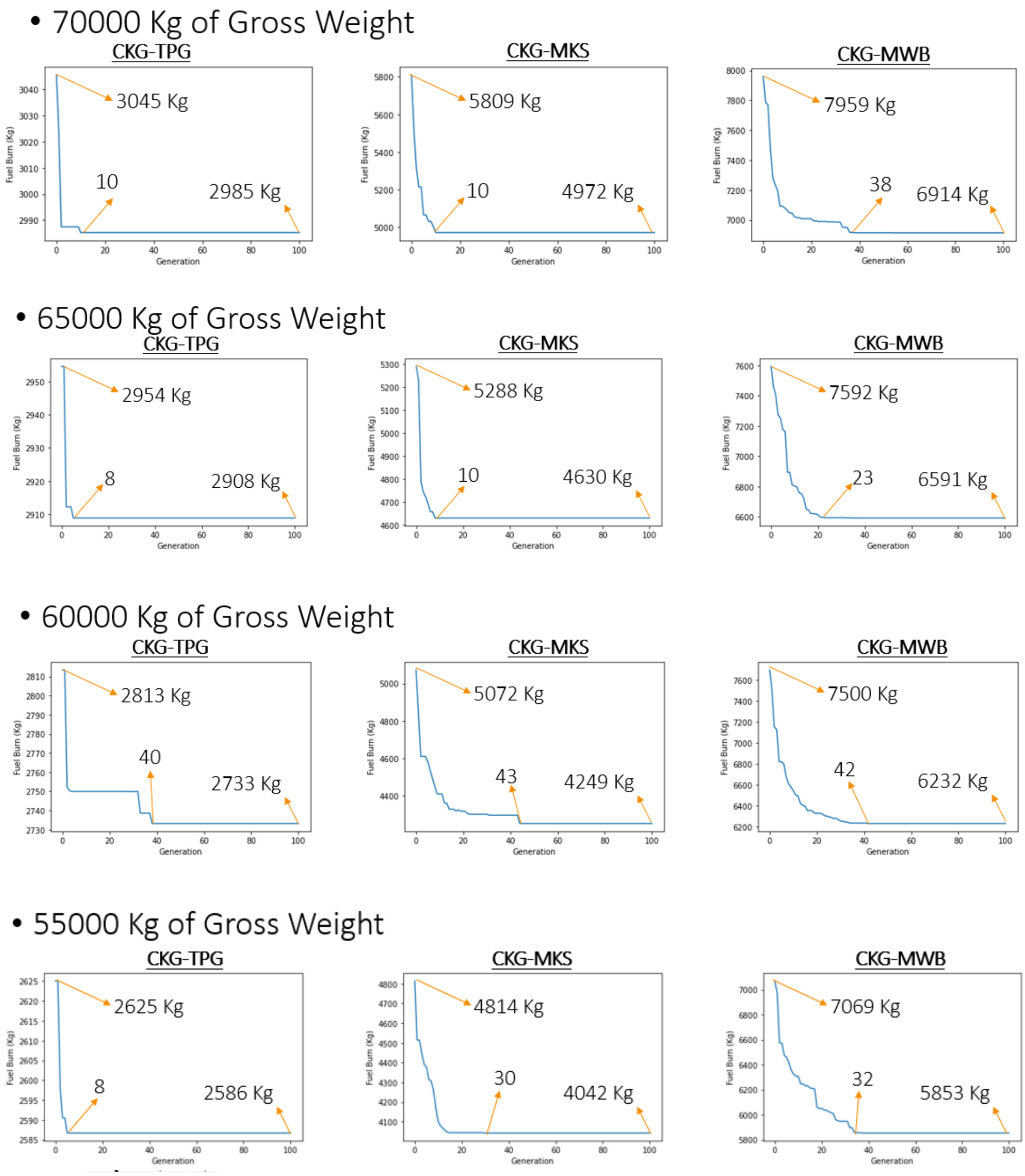

Figure B-7: Result of Fuel Burn per Generation for aircraft weights: 70000Kg, 65000Kg, 60000Kg, 55000Kg