Using Next-Generation GPS Technology for Fuel Efficient Flight Path Optimization

ABSTRACT

Air navigation serves as a method to ensure the safety and efficiency of aircrafts. Airlines must develop flight plans, which seek to optimize fuel usage. This is not a simple task as wind patterns affect the groundspeed of aircrafts in the sky. Historically, flight planning has been heavily regulated by the Federal Aviation Administration by limiting paths to airways (highways in the sky) and waypoints (checkpoints in the sky) to prevent collisions between aircrafts due to limits of radar-based tracking technology. However, new next-generation GPS technology is anticipated to become the standard in aviation, which allows for new techniques for optimizing flight paths. This research attempts to take advantage of such technology by designing next-generation flight paths that follow the rules set in place by air traffic control. The focus of our methodology is to develop a model that optimizes fuel utilization by interpolating wind data and overlaying it on the various possible flight paths. Using a shortest-path formulation between origin and destination, this model designs a path that flies through waypoints, but is not constrained to traditional airways. This allows to create paths that are not dramatically different than historical paths. Our model showed a possible 8-9% decrease in fuel usage, which corresponds to huge environmental and economic savings. When scaled globally, these savings can have a huge impact for both carbon emissions and cost savings. These results demonstrate the potential of new optimization techniques for flight planning.

Keywords: shortest-path, Gaussian process, flight-path optimization, fuel utilization, operations research, civil engineering, industrial engineering

Introduction

Air navigation serves as a way to ensure the safety and efficiency of air transportation [26]. Over the last half-century, new laws about the procedures for flight paths have been regulated by the Federal Aviation Administration (FAA) to ensure the safety of aircraft operations in the air. While many provisions dictate the "laws of the sky," airlines still look to develop effective flight plans that minimize cost for the company. Planning a flight is not a trivial task. In order to optimize fuel efficiency, aircrafts simply cannot follow the greater-circle route from origin to destination as weather patterns may hinder the effectiveness of such a route. Airlines look to optimize routes for fuel efficiency using the wind and weather to their advantage. Currently, flight planning has to adhere to two critical constraints: calculate fuel loads to adequately reach the destination, and follow air traffic control procedures imposed by the FAA in order to avoid collisions in the sky [11].

Over the past twenty years, fuel efficiency has become a major cause of concern for the airline industry. With fuel prices on the rise, and accounting for nearly 28% of annual costs [21], companies are seeking new technologies and techniques to optimize fuel usage based on wind data, to maximize profit. Currently, the available flight paths are limited to certain airways – highways in the sky. Air traffic control has approved usage of these airways to reduce possible collisions mid-air as well as monitor the position of the aircraft throughout the flight [10]. In order to allow the FAA to track the location of the aircraft, they are required to go through a set of waypoints in the airspace. New GPS technology is rapidly becoming the standard in airspace navigation. GPS increases the accuracy of location tracking, which can allow for more free-form flight while still being able to avoid collisions. Aircrafts are no longer restricted to the waypoints set in place by the FAA.

The Next Generation Air Transportation System (NextGen) is a new airspace navigation system anticipated to be implemented across the country sometime between 2012 and 2025 [15]. Using GPS based technology, NextGen seeks to supersede current ground-based radar technology [15], which is limited in its ability to track the movements of aircrafts in the sky. With this new technology, airline companies are now able to develop more free-form flight paths because of the precise tracking ability of GPS. Planes are able to fly closer together, and take more direct routes from origin to destination [16]. This new wave of technology enables the airlines to re-evaluate traditional methods for flight planning and consider new techniques for optimization to design free-form flight paths which take into consideration wind speed and direction. This paper provides preliminary steps towards modeling flights paths that are not constrained to traditional airways and a way to evaluate potential fuel cost savings.

For our flight path model, we pose the following objective: Design a flight path that is more fuel-efficient than the flights that are routinely used between origin and destination. Our engineering goal is to evaluate the extent to which flight paths can be optimized. The approach taken here is to design a model that generates new-generation flight paths that may be taken in place of the traditional airway transport, while satisfying the constraints of air traffic control. The problem is formulated as a shortest path problem between origin and destination. The choice of this path is restricted to intermediate points in the airspace that are derived from the current feasible fly zone for the O-D pair. Two additional considerations are handled: 1) the travel time between any two points depends on the local wind velocity, and 2) the travel between any two points is a greater-circle path. Based on data from flight paths between Atlanta and Seattle (later described), we note that our model does show that there is significant room for improvement in terms of fuel utilization. This approach provides preliminary research into the use of optimization techniques that take advantage of NextGen air navigation technology.

Methods and Models for Flight Path Optimization

In this paper we seek to examine flight paths between two airports and to create an effective and optimal route between the two cities. We examine paths between the cities of Atlanta and Seattle because of their geographic locations; the route is an east-west and north-south flight. In this paper, we implement a shortest path algorithm to model fuel consumption along the different possible routes available between the two cities. The solution approach is modeled as follows:

1) For a given O-D pair, we first identify the feasible waypoints using historical data.
2) We introduce arcs between the waypoints to get a network that represents all possible routes between the O-D pair.
3) We need to associate the travel time for each arc. In order to do this we (a) first calculate the wind velocity at each point along the arc using interpolation techniques for wind data and (b) calculate the travel time given the wind velocity, assuming a constant optimal cruising speed for the plane.
4) We solve the network for shortest travel time to identify the optimal flight path. This flight path minimizes fuel usage since ground speed is assumed constant (hence fuel consumption rate is held constant.) Therefore, shortest travel time yields a fuel-optimal route.

The methodology can be broken down into three sections: Data Collection; Model for Wind Interpolation and Application of a Shortest Path Algorithm. The methods proposed in this paper were coded in *python* for the analysis and *matlab* for data collection.

Data Collection:
Two different classes of data were collected from public sources for the purpose of this analysis:

1) The historical flight path data. This is needed in step 1 of the solution approach to create a feasible region for the flight to navigate through.
2) The weather needed for wind calculations in step 3 of the solution approach.

Wind Data: Aviation Weather Center
The Aviation Weather Center updates wind information at approximately 300 airports and weather stations located around the continental United States [2]. There are certain time allocations for the data that indicate the time frame during which the wind data is accurate. For this research, the time allocations directly correspond to the time of the flight. Furthermore, this research focuses on cruising altitude, so the data was restricted for altitudes above 24,000 feet. Using a Web HTML Scrapper Tool in *matlab,* wind data was daily collected between July 15 and August 15. For each day, the wind data was used to model and design an optimal flight path network (later described). The data set for any given day can be broken down as follows:

- Altitudes of 24,000, 30,000, 34,000 and 39,000 feet are given as column headings
- Row Headings are the various airports and weather stations where the data is actually collected
- The data contains wind speed, wind direction and temperature at any given altitude and weather station within the continental United States.

For the purposes of this analysis, we randomly sampled ten days between July 15 and August 15 to compare the efficiency of our model to the actual flight path.

Waypoint Data: Flight Aware

The FlightAware database contains actual and planned flight plans for several routes within the continental United States [12]. For this paper, we looked at flight DAL1929 between Atlanta and Seattle for reasons previously mentioned. Each planned flight path has waypoints indicating the planned route the flight would take. Using those waypoints, a data file was created, containing all the waypoints between Atlanta and Seattle given the planned flight paths between April 2015 and August 2015. The following data set was created:

- The column heading consisted of waypoint title, latitude and longitude
- Each row had the title of the waypoint and the latitude and longitude for that given waypoint
- A total of 92 waypoints were collected for this specific route

These waypoints can be visually represented on a United States map shown in figure 1.1. For our problem, the waypoints create a set of nodes in which the aircrafts must fly through in order to reach the destination. Further description is provided later in this section.

A Model for Wind Interpolation

The weather data provided by the AWC gives us a fairly course resolution for our needs where we need the wind velocity at twenty-mile intervals along paths between waypoints. This allows us to consider techniques in spatial statistics to interpolate wind data at the given locations. Our data can be modelled using geostatistical techniques in which the observations are continuously varying throughout the US. For our problem, we don't take into account the temporal aspect of modelling because we assume that the given weather data is constant and accurate for a given time frame (which correlates with the flight time.) Furthermore, our problem can be thought of as a mixture of two types of spatial structures: large-scale structures and small-scale structures. The weather and wind patterns across the continental United States cause our problem to take a large-scale structure, which corresponds to the definition of a mean function [13]. However, since we interpolate weather points based on distance, this causes our problem to also take a small-scale structure, which corresponds to a covariance function [13]. The objective of our interpolation model is to predict the wind velocity along twenty mile intervals on the arcs between two waypoints. The prediction of unobserved variables is referred to as kriging.

For our research problem, we use a simple kriging approach to estimate the wind velocity at the known points given in our network. A simple kriging model is equivalent to a Gaussian Process Regression because in both cases the mean function is often assumed to be zero. Gaussian process models are a non-parametric method for modeling data where we do not need to make assumptions of a functional form with the parameters [20].

A GP is characterized as follows: GP = *(m(x), k(x,x'))*, where *m(x)* is the mean function and *k(x,x')* is the covariance function that defines the properties of the functions considered for inference [20]. A popular choice for the covariance function is the squared exponential. This covariance function makes points very close to each other similar and distant points to have very small correlations. This is suitable for our setting since the wind patterns for neighboring points are alike and this will provide a smooth prediction curve. The squared exponential function is shown below:

$$K_{ij} = k(x_i, x_j) = \alpha exp(-(x_i - xj)^2/2\sigma^2) + \sigma_n^2\gamma_{ij}$$

$\alpha = signal\ variance$

$\sigma = lengthscale$

$\sigma_n^2\gamma ij = prediction\ noise$

$\theta(hyperparamater) = (\alpha, \sigma)$

We seek to optimize the hyperparameters, using a multivariate optimization algorithm such as Nelder-Mead simplex or conjugate gradients on the log likelihood function [7].

In order to solve for θ, we must calculate the covariance function among all possible combinations of the observed data points, among all points $y*$ at which we need predictions. The matrix representations are shown below [7]:

$$K = \begin{bmatrix} k(x_1,x_1) & k(x_1,x_2) & \cdots & k(x_1,x_n) \\ k(x_2,x_1) & k(x_2,x_2) & \cdots & k(x_2,x_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(x_n,x_1) & k(x_n,x_2) & \cdots & k(x_n,x_n) \end{bmatrix}$$

$$K_* = \begin{bmatrix} k(x_*,x_1) & k(x_*,x_2) & \cdots & k(x_*,x_n) \end{bmatrix} \qquad K_{**} = k(x_*,x_*).$$

Now the predictions at $y*$ are provided as follows [7]:

$$y_*|\mathbf{y} \sim \mathcal{N}(K_*K^{-1}\mathbf{y},\ K_{**} - K_*K^{-1}K_*^{\mathrm{T}}).$$

$$\overline{y}_* = K_*K^{-1}\mathbf{y} \qquad \mathrm{var}(y_*) = K_{**} - K_*K^{-1}K_*^{\mathrm{T}}.$$

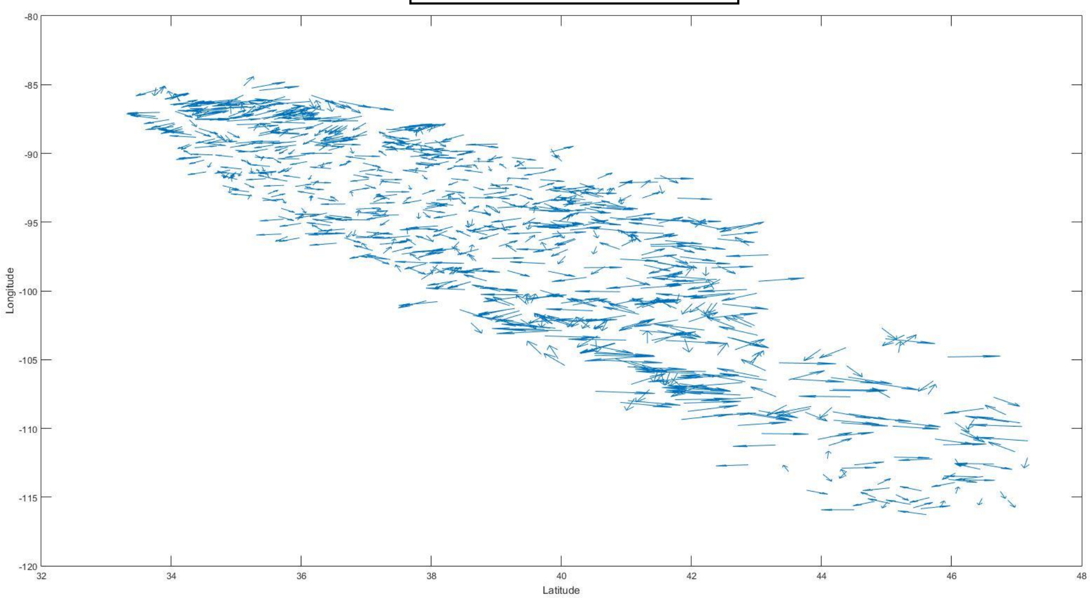
All methods in this sub-section were coded using the Gaussian Process package in python [18]. The package allows to select a kernel that uses the squared exponential equation to calculate the covariance matrix K. Our covariance matrix K is a square 300x300 matrix, with individual correlations between all given weather data points (as shown above). We look to predict $y*$, which are all known geographic points along 20 mile intervals between waypoints in the flight path network. Two regression tasks are defined: one for speed and one for direction. Table 1 below shows the average means and standard deviations across all points for the ten sampled days.

Dates	Average Mean (compass °)	Average std. dev (compass °)	Average Mean (mph)	Average std. dev (mph)
15-Jul	278.36	71.22	32.62	12.2
20-Jul	274.15	65.65	36.42	13.5
22-Jul	264.49	48	38.94	13.5
25-Jul	226.68	69.25	38.95	14.28
31-Jul	280.85	59.67	44.98	12.58
3-Aug	283.01	59.23	45.55	13.61
6-Aug	273.14	66.16	43.82	14.84
7-Aug	289.37	64.39	47.58	13.96
8-Aug	271.66	62.34	34.55	12.2
11Aug	288.12	57.73	55.36	12.48

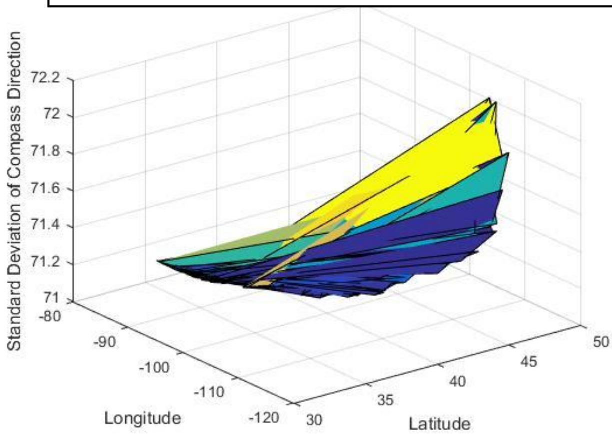
Table 1 – Reported Means and Standard Deviations of GP Regression

To visually represent the interpolated data, a quiver and surface plot are shown below. The quiver plot shows a graph of vectors of the wind velocity for a subset of our sampled data points (else the figure gets too crowded). This visualization helps show the general pattern of the winds, which can be useful for the flight planners. The surface plot shows the variation of standard deviation across all sampled data points. The errors are highest around the Seattle area – this might be partly due to the Cascade Mountains which strongly influence the local wind patterns. Both graphs are shown for July 15th, but the means and standard deviations reported in table 1 are based on samples across ten days.

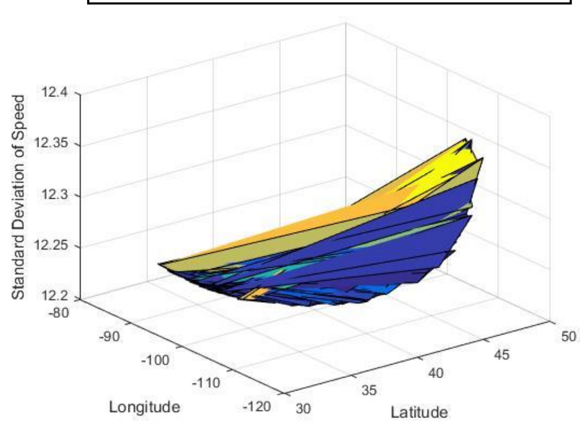
Quiver Plot of Wind Vectors



Coordinates vs. Standard Deviation of Compass Direction



Coordinates vs. Standard Deviation of Speed



An Application of a Shortest Path Algorithm

In this section, we look at the application of a Shortest Path Algorithm to a flight route network. This research seeks to minimize fuel consumption for the aircraft when flying from origin to destination through the available waypoints. Networks as typically modeled as directed graphs, *G(V,E)* where *V* are the nodes and *E* are edges between nodes [5]. In this section we look at a network for flight paths and the implementation of a Shortest Path Algorithm.

Flight Path Network

In order to evaluate the proposed approach, we will restrict our analysis to designing fuel optimal flight paths between Atlanta and Seattle. A map of the United States is shown in Figure 1.1, including all the waypoints collected from FlightAware (previously mentioned).

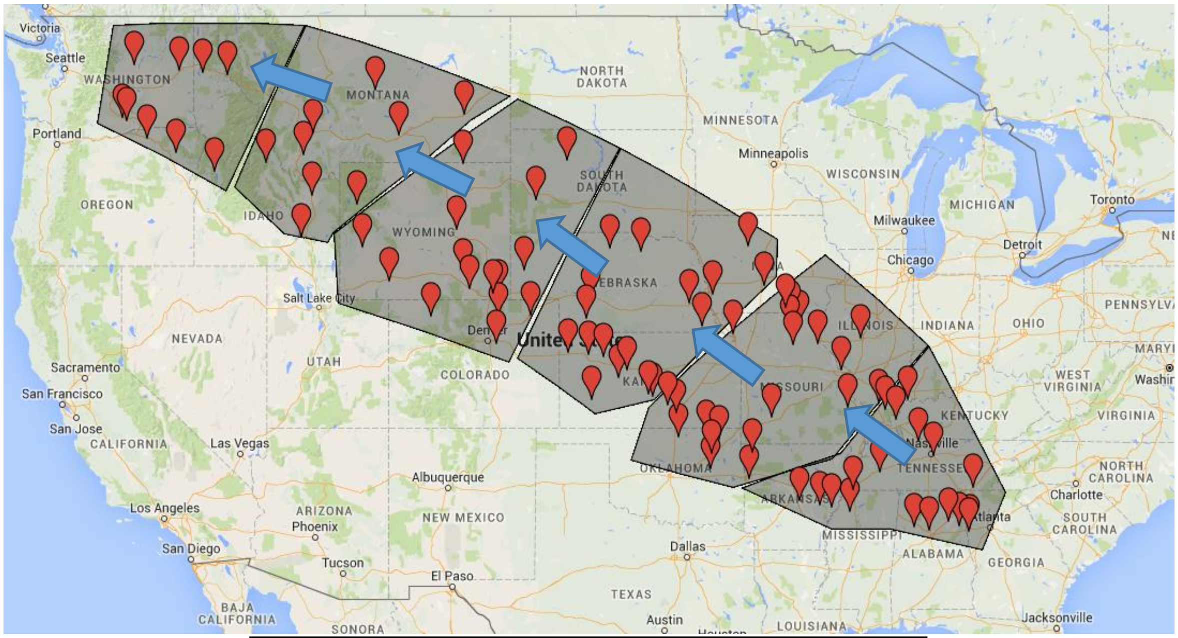


Figure 1.1 – United States Map with Waypoints and Zones

In order to ensure a proper flight trajectory, geographic zones were created. The introduction of zones allows for a few benefits for the network. First, it ensures a proper flight trajectory, forcing the aircraft to move in a way that is always approaching the destination. Second, it allows airlines to set the number of waypoints in any given route. This could be useful as airlines move towards GPS technology to explore the effect of adding or reducing the number of waypoints for any flight path. Finally, it reduces the complexity of the problem by reducing the number of edges four-fold. This is achieved by only allowing edges between adjacent zones. Although taking this approach might constrain the search for optimal routes, this would be a more pragmatic way for airlines to start exploring new flight paths without dramatically changing current practices. For our research, six zones were made by dividing the area between Atlanta into six equal sections and assigning all the waypoints within each section to a zone.

This setup allows us to model the flight path network where we only allow edges between adjacent zones in the direction toward the destination. To simplify the problem, the optimization will only occur at cruising altitude, as much of the takeoff and landing sequence is decided by a complex set of maneuvers imposed by the FAA. The two nodes – source and target – are added as the start point for cruising speed and end point for cruising speed, respectively.

Along each edge in the network, we look at attributes of distance, bearing and heading. We assume that the aircraft is travelling at a groundspeed that corresponds to optimal fuel utilization (i.e. 543 mph [3]). However, the groundspeed is adjusted based on the effect of the wind velocity. After the adjusted speed is calculated, the time taken to travel along each edge is calculated. The fuel consumption for each edge is estimated by multiplying time by the fuel consumption rate. Finally, a shortest path algorithm is used to find the route with minimal travel time. Minimal travel time directly corresponds to minimal usage, as we are assuming the aircraft to be traveling at a constant cruising rate. This process is enumerated below.

- For air travel around the globe, the flight path between two points is a circular arc and not a straight line. Therefore, along every edge, the distance is calculated by using the haversine formula, which gives the greater circle distance between any two points given the latitude and longitude [13]. The formula is given below:

$$d = 2r\,\mathrm{arcsin}(\sqrt{(}\sin^2(\alpha_2 - \alpha_1)/2) + \cos(\alpha_2) * \cos(\alpha_1) * \sin^2(\beta_2 - \beta_1)/2)$$ Haversine Formula

$\beta_1, \beta_2 = longitude\ of\ points\ 1\ and\ 2$

$\alpha_1, \alpha_2 = latitude\ of\ points\ 1\ and\ 2$

$r = radius\ of\ earth$

- Along every edge, an adjusted groundspeed must be calculated. In order to do so, the edge is broken up into intervals of twenty miles where the wind data will be collected. In order to determine location and orientation at these twenty mile intervals, bearing and heading must be used. The initial bearing is calculated between the two nodes along an edge, and given that bearing a destination point is given in multiples of twenty miles away from the origin. The formulas for bearing and destination point given bearing are shown below [14]:

$$\theta = atan2(\sin(\beta_2 - \beta_1) * \cos(\alpha_2), \cos(\alpha_1) * sin(\alpha_2) - \sin(\alpha_1) * \cos(\alpha_2) * \cos(\beta_2 - \beta_1))$$ Bearing Formula

$$\alpha_2 = asin(\sin(\alpha_1) * \cos(\gamma) + \cos(\alpha_1) * \sin(\gamma) * \cos(\theta))$$ Final latitude

$$\beta_2 = \beta_1 + atan2(\sin(\theta) * \sin(\gamma) * \cos(\alpha_1), \cos(\gamma) - \sin(\alpha_1) * \sin(\alpha_2))$$ Final longitude

$d = desired\ distance\ travelled$

$\gamma = angular\ distance(d/R)$

$\theta = bearing$

$r = radius\ of\ earth$

$\beta_1, \beta_2 = longitude\ of\ points\ 1\ and\ 2$

$\alpha_1, \alpha_2 = latitude\ of\ points\ 1\ and\ 2$

- After the twenty mile intervals along each edge are calculated, the wind speed is overlaid with the plane's speed to create the adjusted speed. The horizontal and vertical components for the plane's speed and wind speed are calculated at all twenty mile intervals. The horizontal components and vertical components of the plane and wind speeds are added, and the adjusted groundspeed is derived.
- The groundspeed for each edge is calculated by averaging all the adjusted speeds along any given edge.

- Time is calculated by dividing distance of each edge by average adjusted groundspeed for each edge.

Implementation of a Shortest Path Algorithm

In graph theory, the shortest-path problem is to find a network path between two nodes, source and target, such that the sum of the weights of all the edges is minimized over all such paths [23]. For this problem, we look to find the shortest path between the origin and destination, with the path flying from zone to zone. Since we restrict the path to fly zone to zone, this structure allows us to model the path as a bipartite graph. An example is shown below:

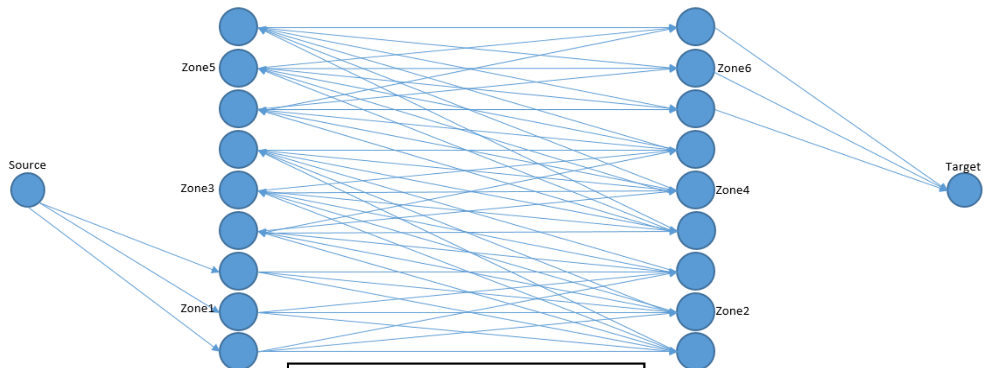


Figure 1.2 – Bipartite Graph

In this formulation, we look to solve a single-pair shortest path problem; we are trying to find a route that minimizes time across all edges in the graph. Many algorithms can be used to find the shortest path such as: Dijkstra's algorithm, A* search algorithm and Bellman-Ford algorithm [8]. However, we can use a much simpler algorithm that exploits the inherit structure of the bipartite graph.

Our graph is structured with *n* zones, where there exists edges only between adjacent zones. We restructure our graph to make it a linear path, in which each vertex is a zone, and all the edges between vertices represent all the edges between respective zones. For our problem, the edges represent all possible waypoint to waypoint paths between adjacent zones. An example of the liner path graph for a zone-based flight path is shown below in Figure 1.3:

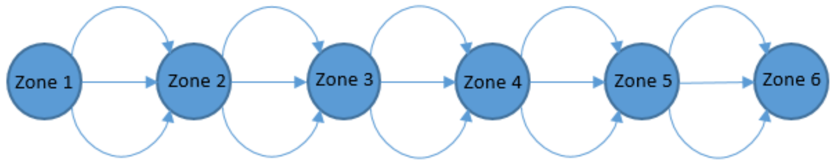


Figure 1.3 – Linear Path (Without Source and Target)

As previously mentioned, we are seeking to minimize time across the path. Since the graph does not branch, one can simply choose the cheapest edge between every vertex in the linear path. This yields a worst-case linear complexity with $O(|E|)$.

Results and Discussion

In this section, we look at different approaches used to evaluate the efficacy of our flight path model. First, we look at different days with different wind data and present some basic statistics of the flight path, such as distance, waypoints, time, and average speed. Secondly, we compare the fuel consumption of our proposed route to the actual flight path and what environmental benefits our results provide. Finally, we compare the average cost of fuel for our proposed flight path to what was actually flown.

General Statistics

Using our approach to find an optimal flight path, we look at the distance, waypoints used, time, and average speed across several days in the summer of 2015. Ten random days between July 15 and August 15 were chosen for this analysis.

For our proposed flight path, average groundspeed was determined by taking the optimal cruising speed of Boeing 747-800 (543 MPH [3]-aircraft used for this route) and adding the additional wind components to it. Time was simply distance over speed, and the waypoints were the latitude and longitude markers for the course of this flight. Looking at the actual flight path, we again limit the distance to only the cruising altitude. As mentioned in the data section, the actual flight paths were collected for these days and the latitude and longitude markers are given for all points in the path. Based on that data, we were able to calculate cruising distance and time, and speed was determined by dividing total distance by total time. The distances reflect only paths that were at cruising altitude, which explains why the distance may be less than the actual greater-circle distance between Atlanta and Seattle. Table 1.1 and 1.2 are below, comparing the distance, time and average speed between the proposed and actual paths:

Dates	Distance(Mi)	Time(Hr)	Avg.Speed(MPH)	Waypoints
15-Jul	1984.2	3.604	550.57	GAD,SGF,HCT,DDY,HIA,TEMPL
20-Jul	1975.8	3.542	557.84	LAJUG,STL,ONL,RAP,BIL,HILIE
22-Jul	1987.1	3.504	567.03	LAJUG,SKBOZ,ANW,KD9OU,BIL,HILIE
25-Jul	1974.68	3.544	557.21	BNA,MCM,ONL,RAP,BIL,HILIE
31-Jul	1976.96	3.535	559.29	BNA,TINGS,OVR,RAP,HIA,TEMPL
3-Aug	1975.6	3.532	559.3	RMBLN,FAM,ANW,KD9OU,BIL,MLP
6-Aug	1983.1	3.548	558.93	HANKO,MKL,HCT,DDY,DLN,TEMPL
7-Aug	1977.8	3.553	556.61	BNA,DENNI,LNK,RAP,BIL,TEMPL
8-Aug	1980.3	3.608	548.82	BNA,PLESS,ANW,KD9OU,HIA,TEMPL
11-Aug	1973.9	3.489	565.81	LAJUG,TINGS,ONL,KD9OU,BIL,GEG

Table 1.1 – Statistics of our proposed flight path

Dates	Distance(Mi)	Time(Hr)	Avg.Speed(MPH)
15-Jul	1952.35	3.883	502.79
20-Jul	2007.7	3.733	537.82
22-Jul	1941.7	3.833	506.57
25-Jul	1981.6	3.783	523.82
31-Jul	2034.3	3.983	510.75
3-Aug	2030.69	4.117	493.25
6-Aug	1993.1	3.900	511.05
7-Aug	1723.6	4.033	427.37
8-Aug	2049.76	3.833	534.77
11-Aug	1953.2	3.817	511.71

Table 1.2 – Statistics of the actual flight path

When comparing the difference between the proposed flight path and actual flight path, it is apparent that the proposed seems to be a better candidate than the actual. Time and average speed stand out as the variables that have the greatest difference between actual and proposed. The average time for the actual flights was 3.84 hours compared to just 3.55 hours for the proposed paths. Similarly, the average speed for the actual paths was 515.5 miles per hour compared to 558.1 miles per hour for the proposed paths. In the next section, we look at a breakdown of how this loss of optimality corresponds to fuel efficiency and energy conservation.

Fuel Efficiency

Air transportation is one of the premier transport networks for globalization. However, the airline industry accounts for nearly 11% of the energy consumed by transportation [25]. Because of aircraft's high speeds, they are commonly linked to high levels of consumption [25]. In this section we look at the fuel consumed by our proposed flight plan versus the actual flight plan. We then describe the effect the savings will have on carbon emissions into the atmosphere.

For this specific path, we again take into consideration the use of a Boeing 737-800. The consumption rate for this aircraft is 2526 kg/h [3]. We are able to determine the time taken for the flight for both the proposed and actual paths. Using this information, we are able to compare the efficiency of our proposed model to the efficiency of the actual routes flown. Table 1.3 below compares the fuel efficiency of our model versus the actual flight path.

Dates	Actual (Kg)	Proposed (Kg)	Difference(Kg)	Percentage Difference
15-Jul	9808	9103	705	7.2%
20-Jul	9430	8947	483	5.1%
22-Jul	9682	8852	830	8.6%
25-Jul	9556	8952	604	6.3%
31-Jul	10061	8929	1132	11.3%
3-Aug	10400	8923	1477	14.2%
6-Aug	9851	8962	889	9.0%
7-Aug	10187	8976	1211	11.9%
8-Aug	9682	9115	567	5.9%
11-Aug	9642	8812	830	8.6%
Average	9830	8957	873	8.9%

Table 1.3 – Fuel Consumption Comparison

Looking at the difference between the actual fuel consumed for the proposed and actual routes, we see that across the board the proposed route provides a more optimal solution in terms of fuel usage. We can measure the difference in two ways: difference and percentage. The difference indicates how many kilograms of fuel were saved using our proposed model, while the percentage difference indicates the actual increase of efficiency for fuel utilization. For our subset of paths, the actual fuel usage was 9830 kilograms compared to the proposed usage of 8957 kg, which marks an 8.9% decrease in fuel usage.

Another interesting metric we can look at is what effect the savings in fuel (kg) has on carbon emissions into the atmosphere. A few calculations must first be made in order to determine the amount of CO_2 that was released. We must find the density of JET fuel, convert the mass to volume and finally see how much CO_2 is released into the atmosphere based on the volume of JET fuel being released in the aircraft.

Now looking at Table 1.4 shown below, we can see how much carbon dioxide could be saved if our model was adopted for planning flight paths between Atlanta and Seattle.

Dates	Actual CO2 Emissions(kg)	Proposed CO2 Emissions(kg)	Difference(kg)
15-Jul	29849	27704	2145
20-Jul	28696	27227	1469
22-Jul	29465	26939	2526
25-Jul	29080	27242	1838
31-Jul	30618	27172	3446
3-Aug	31648	27153	4495
6-Aug	29980	27274	2706
7-Aug	31002	27315	3687
8-Aug	29464	27737	1727
11-Aug	29341	26817	2524
Average	29914	27258	2656

Table 1.4 – CO_2 Emission Comparison

Based on the table above, on any given day our proposed model could save between 1469 kg and 3687 kg, and on average saves 2656 kg of carbon emissions into the atmosphere. When these savings are scaled to account for all flights in the US, the emissions savings could have a huge global impact.

In order to scale this on a per yearly basis, a few key data pieces are needed: number of annual flights (US) and average length per flight. We first convert our savings from kilograms per route to metric tons per mile. Second, we multiply that by the average stage length (the average non-stop distance flown in miles). Finally, we take that and multiply it by the number of flights in a given year. All the data was collected by the Bureau of Transportation Statistics [4].

Based on this raw interpolation, we estimate that using such an optimization technique for fuel efficiency can save about 9.78 million metric tons of CO_2 per annum. In 2014, the United States aviation industry emitted 140 million metric tons of CO_2 [9], which indicates that such an optimization model for flight path could yield a savings of 7%. These results indicate that there may be room for optimization across all routes in the United States.

With nearly 95% of the airline industry's carbon emissions coming from the burning of JET fuel [23], maximizing fuel efficiency is becoming a primary concern for airlines. This research indicates that the newer GPS technology for flight planning can aid the optimization of fuel efficiency. If aircrafts are able to optimize their routes, the results, when scaled globally, can be large for carbon emissions.

Cost Savings

To this day, fuel continues to be the largest cost for the airline industry [17]. JET fuel prices nearly quadrupled from 2002 to 2013, going from $.72 per gallon to $2.98 per gallon [17]. As a result of this, airlines' annual fuel related costs went from $14 billion to $50 billion in the same time period. Fuel costs accounted for 28% of operating costs for the airline industry in

2013 [20]. All of this data indicates that fuel optimization is not only beneficial environmentally, but also can make a huge difference in terms of monetary savings for the airline industry.

Understanding the cost incurred by JET fuel prices, we can go back to Table 1.3 to understand how much an airline can save by optimizing a flight path route. We can take the difference in consumed fuel between the proposed, the actual and derive the number of liters saved on each flight. Furthermore, we can calculate the actual costs saved through fuel efficiency. Table 1.5 (shown below) shows the average savings per flight, comparing our proposed route to the actual route.

Dates	Difference(Kg)	Difference(L)	Cost(Per L)	Savings($)
15-Jul	705	848	$0.41	$347.84
20-Jul	483	581	$0.41	$238.19
22-Jul	830	999	$0.41	$409.53
25-Jul	604	727	$0.41	$298.02
31-Jul	1132	1362	$0.41	$558.62
3-Aug	1477	1777	$0.37	$657.64
6-Aug	889	1070	$0.37	$395.86
7-Aug	1212	1458	$0.37	$539.52
8-Aug	568	683	$0.37	$252.73
11-Aug	829	998	$0.37	$369.32
Average	873	1050.	$0.39	$409.67

Table 1.5 – Cost Savings per Flight

Table 1.5 is indicates that on average, using our proposed optimization model, an airline can save about $410 on each flight of this distance. The cost per liter for JET fuel is different because the cost changed from July to August, dropping about 4 cents. These savings correspond to 8-9% of the total fuel cost for the airlines. Such improvements can be significant to the bottom-line profit of airlines, with regards to fuel cost savings.

Similar to the calculations done in determining carbon emissions savings, we can scale the monetary savings. We first calculate dollar savings per mile, multiply it by average stage length, and finally multiply again by total number of flights per year. For this example, we limited all the data for just Delta Airlines, as each individual airline company will be looking to maximize profit through fuel savings. All of the data was collected from the MIT Airline Data Project [1]. The total savings per year to Delta Airlines was approximately 481 million dollars. Delta's annual spending on fuel in 2014 was about 13 billion dollars, which shows that our model could potentially save nearly 4% of fuel costs. While these percent savings do not represent the same level of savings on a per-route basis, we must understand that fuel prices have dropped from 2014-2015, which would translate to lower spending for fuel in 2015.

With the airline industry already having extremely low profit margins, decreasing fuel costs by 8.8% for a route would have a huge impact on the total profit for each individual airline. Further research needs to be done with regard to the use of newer technologies, but this research indicates that there may be new ways to optimize flight paths in order to maximize fuel consumption that can lead to monetary savings and environmental benefits.

Conclusion and Future Research

With the growth of GPS based tracking technology, airlines are moving toward new methods and models for flight path optimization. This model provides a preliminary step in designing flight plans that move away from traditional airway transport. Based on a mixture of free-form and waypoint based transport, this model incorporates the use of new and old technologies to create a more efficient flight path. Furthermore, this research shows the room for improvement with regard to fuel efficiency within the airline industry. Our results indicate that small savings in fuel usage could translate into big savings economically and environmentally. Such a tool could be useful for airline companies as well as aircraft makers, to enable growth in flight planning technology. This model serves as a tool to predict which flight path is the most optimal, and can in fact be turned into a software that can aid pilots' mid-flight. This research indicates possibilities of future research and future improvement for flight path optimization, with the availability of state-of-the-art technology (NextGen).

The scope of this paper is limited to a weather model based on data from the AWS. For more accurate results, different weather models (with higher resolution data) could be used to predict wind data and measure the effect this would have on the predicted flight path route. Another next step for this project would be to define an optimal control problem for non-linear flight paths. This optimization technique would be able to take full advantage of the NextGen GPS technology and potentially create flight paths that are nearly one hundred percent optimized. However, these paths might alter very significantly when compared to current flight paths. Also, in order to calculate true fuel utilization, an analysis could be done with passenger flow through a network. This will allow for a more complete analysis of the fuel usage because of the added weight on each flight, given the capacity. This total cost analysis for the airline must be done to understand the benefits of upgrading to NextGen technology.

This model provides several directions for the application of graph theory and machine learning to evaluate current flight paths and to create more efficient ones. It provides insight into the benefits attributed to the use of GPS technology, and explores a new area of research for airlines. Further research may allow us to improve on the models and techniques for optimization that may yield better results for flight paths.

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