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Aircraft Mass Estimation Using Cruise Flight Profile

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Abstract

Aircraft mass estimation is a challenging problem in aircraft operations, because it often requires confidential data available only to aircraft operators. While most researchers use climb profile to estimate the aircraft mass, this paper proposes a mass estimation method using the cruise flight data. Here, we exploit the fact that the cost-optimal altitude depends on the aircraft mass to estimate the aircraft mass. However, the aircraft does not necessarily fly on the cost-optimal altitude. Therefore, this paper uses a clustering technique to extract the flight segment where the aircraft appears to fly near the cost-optimal altitude. The proposed method is evaluated using 39 flights operational data, and the mean absolute error of 3.29 % is achieved.

Keywords: clustering; Ward's method; cruise altitude; aircraft weight;

1. Introduction

The aircraft mass (weight) is a key parameter in the aircraft operation, because it affects trajectory and fuel consumption predictions [1][2]. However, the aircraft mass information is usually not openly-available, because it is often airline's confidential data. Therefore, it is a challenge to estimate the aircraft mass using other available data.

Most past studies focus on the aircraft climb trajectory to estimate aircraft mass[3][4][5][6][7]. Past existing researches avoid relying on the cruise phase to estimate aircraft mass because the aircraft vertical movement is small during the cruise phase. To the best of the author's knowledge, there is only one research to estimate the aircraft mass using cruise phase flight[8]. This work estimates the flight dynamics parameters (e.g. lift/drag coefficients) directly from the detailed flight data. Although the obtained result is compared to that in quick access recorder (QAR) data, the accuracy is inferior compared to other works. This result infers that the cruise flight is not suitable for mass estimation.

However, the author argues that the cruise phase data can be used to estimate aircraft mass with sufficient accuracy. The optimal cruise altitude of aircraft increases as the mass decreases, which causes the aircraft to perform a step-up climb to fly at the optimal altitude. This information can be potentially used for mass estimation, which is the main target of this study. If the aircraft mass is well estimated with the cruise flight phase only, the further accuracy improvement may be possible by combining other estimation methods.

However, the aircraft does not necessarily fly at the optimal altitude due to various reasons, e.g. airspace congestion and turbulence. Therefore, the author proposes that only a limited segment of the flight is used for mass estimation, where the aircraft appears to fly at its optimal altitude. The cruise flight is segmented using a clustering technique, and the appropriate segment is selected based on the operational knowledge of the cruise flight. The estimated mass is also compared to the mass recorded in QAR data, and its accuracy is also investigated. The aircraft performance model of BADA is used to calculate the optimal altitude of the aircraft.

2. Aircraft mass estimation from cost-optimal altitude perspective

2.1 Data used for this analysis

The target of this study is to estimate the aircraft mass without using any sensitive operational data. To estimate the aircraft mass the author focuses on the cruise phase. For a more accurate estimating, sufficiently-long cruise segments data are preferable. Therefore, in this paper, as a first step, we limit the investigation to long-haul flights. North Pacific (NOPAC) routes are the busiest oceanic routes in Japan, so the flight track data on NOPAC routes are used in this estimation. Since these routes are busy, aircraft often fly below the cost-optimal altitude, which makes it difficult to estimate the mass. On oceanic routes, most aircraft send ADS-C reports, which include the reported time, aircraft position (latitude, longitude), barometric altitude, and the current mach number[9]. All this information is accessible for air traffic control (ATC). For safety reasons this ADS-C report is recommended to be sent at least every 15 minutes[10], but more frequent position reports are observed in actual operation. This time, this position report is assumed to be obtained every 10 minutes. In addition to ADS-C, wind forecast data are also used, which is provided by Japan Meteorological Agency (JMA) as Global Spectral Model (GSM) numerical prediction data[11].

Also, for validation purposes, QAR flight data are used. QAR data are obtained in the airline fleet, and includes precise data every second. The QAR includes all ADS-C signals as well as the aircraft mass. The aircraft mass recorded in QAR is assumed to be the true value, and therefore it is compared to the estimated value. This time, 39 flight data of B787-8 are used.

2.2 Calculation of cost-optimal altitude

The airline usually tries to minimize the direct operating cost (DOC) of the flight. The DOC consists of the fuel cost and the time cost, and is calculated by the following form.

$$DOC = \int_0^{t_f} \left(C_t - \dot{m}C_f\right) dt \tag{1}$$

where m is the aircraft mass, t_f is the flight time of a fixed segment, C_t and C_f are the unit time cost and the unit fuel cost, respectively. Once the cost index (CI) is defined asC_t/C_f, the minimization of the following objective function J is equivalent to the minimization of DOC.

$$J = \frac{DOC}{C_f} = \int_0^{t_f} (CI - \dot{m})\, dt \tag{2}$$

The cost index indicates the proportion of the time cost over the fuel cost, and the unit of [100 lb / flight hour] is often used for Boeing aircraft[12]. Since t_f is the total flight time to reach a certain distance r, the instantaneous objective function $J(t)$ can be calculated by the following form using the instant ground speed V_{GS} and fuel flow $FF(t) = -\dot{m}(t)$.

$$J(t) = \int_0^{r/V_{GS}(t)} (CI + FF(t))\, dt = \frac{CI + FF(t)}{V_{GS}(t)} r \tag{3}$$

Since r is the constant, the cost-optimal altitude and speed can be calculated by minimizing $J(t)/r$. The cost index of the typical value of 30 is used in this analysis, and the actual mach is obtained via ADS-C report. In terms of the optimization, both mach number and cruise altitude are the optimization parameters. However, the actual cost index is unknown, so the mach number is not optimized, and the actual mach number is used instead in the calculation. The fuel flow data can be calculated by BADA model assuming the equilibrium of forces of at level flight. Finally, the optimal altitude can be simply calculated by using a gradient method. The ground speed is calculated by the following equation when mach number, route direction, temperature and wind components are known.

$$V_{GS} = w\cos(\Omega - \phi) + \sqrt{v^2 - w^2 \sin^2(\Omega - \phi)} \tag{4}$$

$$v = Ma_0\sqrt{\frac{T}{T_0}} \tag{5}$$

where w is the wing magnitude, Ω is the aircraft track angle, ϕ is the wind direction, v is the true air speed, M is the Mach number, a_0 is the sound speed at sea level, T is the temperature, and T_0 is the temperature at sea level.

2.3 Calculation of aircraft mass based on the cruise altitude

When the aircraft flies at the cost-optimal altitude, the current aircraft mass can be estimated by iterative calculation of the cost-optimal altitude with the aircraft mass. Fig. 1 shows an example of the calculation of the optimal altitude of each aircraft mass. This calculation assumes M=0.82, no wind, and international standard atmosphere (ISA). The aircraft mass is assumed to be between 360,000 lb and 460,000 lb. The objective function J can be calculated in for each cruise altitude and each mass based on Eq. (3). The altitude which shows the minimum objective function becomes the cost-optimal altitude in each aircraft mass. Therefore, once the actual cruise altitude is assumed to be the cost-optimal altitude, the corresponding aircraft mass can be calculated. In this example (Fig. 1), if the aircraft flies at 38000 ft, the aircraft mass is estimated as 420,000 lb assuming the aircraft flies at cost-optimal altitude.

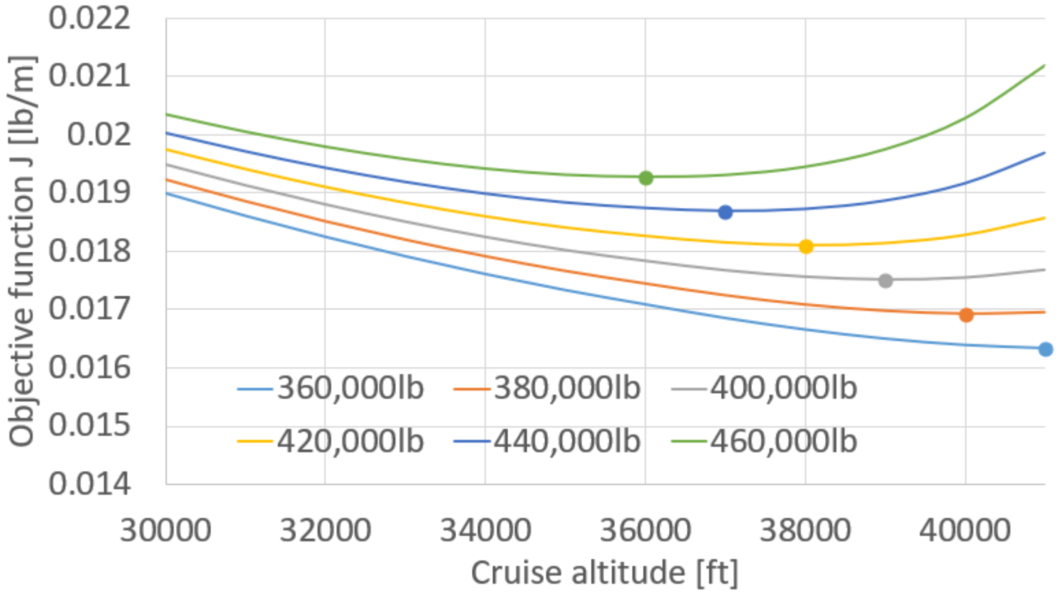

Figure 1 – The objective function vs. cruise altitude with various aircraft mass. (The dots indicate the optimal altitude in each aircraft mass.)

2.4 Weight estimation based on cruise altitude

Using the method described in the previous subsection, the aircraft mass can be estimated at each position report. Fig. 2 shows an example of the mass estimation of a single flight. This flight includes 27 data points corresponding to 4.5 hours of flight. At each data point, the aircraft mass is estimated based on the calculation explained in Sec. 2.3. During this period, the aircraft flew at FL 400 and did not change its cruise altitude. Here, the actual mass is considered to be the mass data recorded in QAR flight data. Since the flight altitude remains 40,000 ft, the estimated aircraft mass becomes constant when the other conditions are not changed. However, in the real world, the mach number, wind, and the air temperature change as the flight proceeds, and those affect the mass estimation. The wind, in particular, has the greatest impact. According to the figure, however, the estimated mass is close to the actual at the beginning, and its error increases with time. This infers that the cost-optimal altitude in general increases as time proceeds, and the aircraft did not change the flight altitude. This also means that the weight can be estimated with high accuracy if it is known whether the aircraft flies close to the cost-optimal altitude. This method will be considered in the next section.

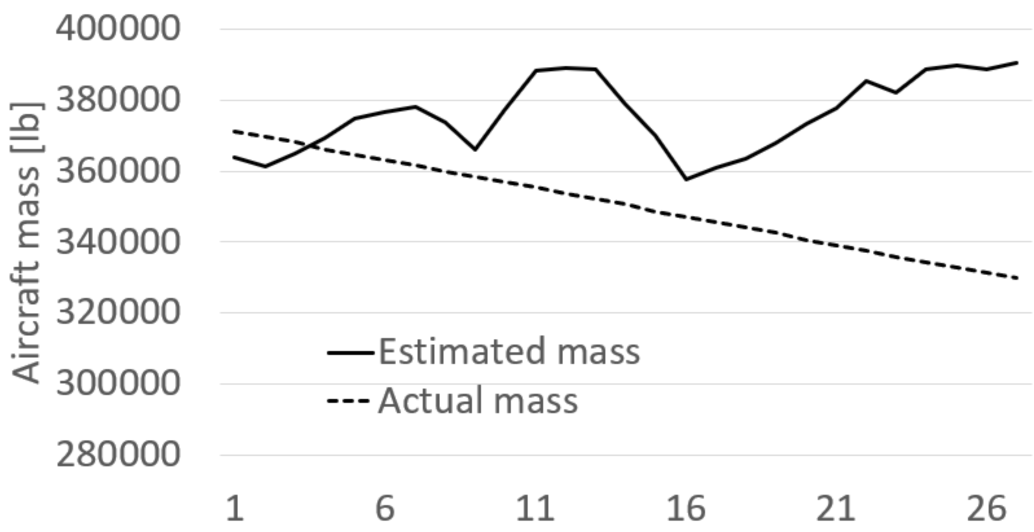

Figure 2 – Mass estimation on a single flight. (Flight ID: 4)

3. Mass estimation by clustering

3.1 Selection of cruise altitude

Although the cost-optimal cruise altitude can be calculated as shown in the previous section, the aircraft does not necessarily fly at this cost-optimal altitude. First, the ATC minimum vertical separation is set to 1000 ft, so the aircraft can choose only discrete values for its cruise altitude, namely every 1000 ft only. Second, the cost-optimal altitude is not necessarily available due to other traffic or turbulence. In such a case, the aircraft usually flies below the cost-optimal altitude. It is very rare that the aircraft flies above the cost-optimal altitude because of the fuel efficiency and reduced safety margin due to the limited range of available speed. Third, the aircraft does not frequently change the cruise altitude. The cost-optimal altitude depends on the wind as well as the aircraft mass, and it does not necessarily increase gradually. Even if the cost-optimal altitude is 1000 ft higher than the current altitude, the aircraft does not change the flight altitude if the cost-optimal altitude becomes lower in the future.

This knowledge can be used to determine whether the aircraft is flying close to the cost-optimal altitude or not. In this paper, this selection is done via a clustering technique.

3.2 Calculation of the cost-optimal altitude

Before applying the clustering technique, the cost-optimal altitude is calculated. Once the initial mass is determined, the cost-optimal altitude can be calculated at each data acquisition time. The fuel consumption is calculated between the two data acquisition times when the aircraft is assumed to fly at the latest observed mach number and altitude. The wind and the temperature are obtained via JMA GSM numerical weather forecast data.

Fig. 3 shows the cost-optimal altitude for various values of the initial mass vs. the actual altitude. The initial mass indicates the mass at the first data acquisition time. The flight data used in Figure 2 is used here. For each initial mass, the fuel consumption at each data acquisition point is also calculated, so the mass also decreases gradually as the data number progresses. As mentioned before, the cost-optimal altitude should gradually increase if mach number, wind, and temperature are constant. However, this is not the case in the real world. According to the figure, although the cost-optimal altitude increases with time in general, it drops around data number is 13-15. After data number is 16, the cost-optimal altitude increases gradually. In such a case, the pilot usually selects a single altitude up to data number = 15, and changes the flight level after that depending on the flight conditions. This pilot altitude selection strategy is modeled by a clustering technique.

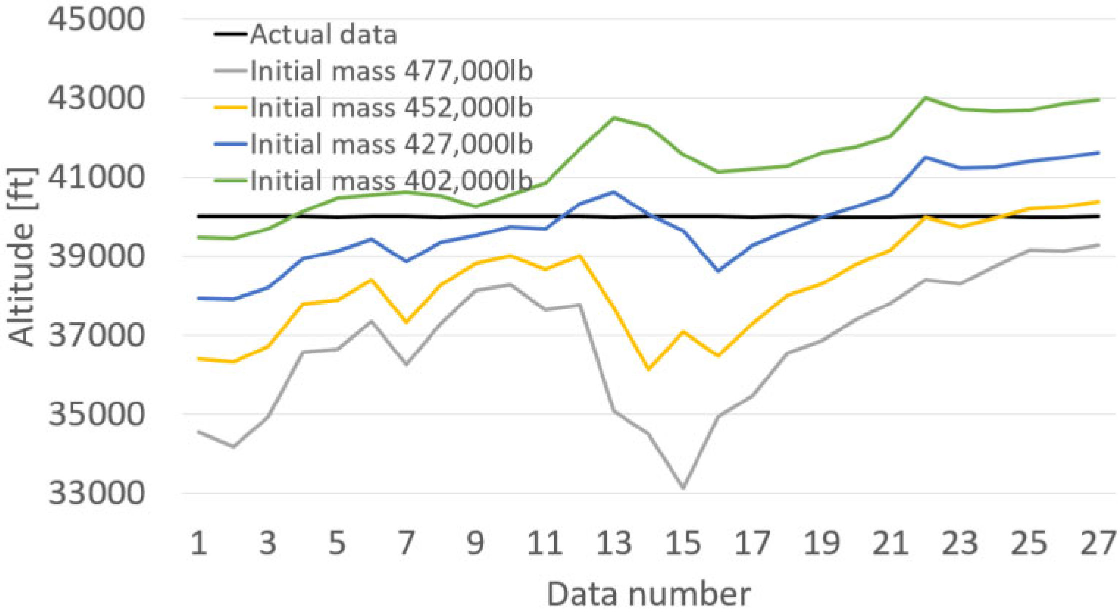

Figure 3 – Actual altitude and the cost-optimal altitude in each initial mass. (Flight ID: 4)

3.3 Proposed clustering method

The proposed clustering method will improve the mass estimation accuracy in the following way, summarized in Fig. 4. In Step 1) several discrete initial masses are assumed, and the cost-optimal altitude is calculated at each data for each initial mass. Next, 2) the initial mass where the actual altitude matches the cost-optimal altitude the best is chosen. To improve the prediction accuracy, in step 3) the time histories of cost-optimal altitude are categorized into several groups by clustering. In this sample case, four groups (A[1,2,3], B[4,5], C[6,7,8], D[9,10,11,12]) are created. In step 4) in each group, the initial mass is estimated using the actual altitude as shown in Table 1. The initial mass is estimated at each data point, and its average within the group is considered to be the estimated result for each group. As for group D, the estimated initial mass is 420,000 lb for 9,10 and 400,000 lb for 11,12, so its average becomes 410,000 lb. To determine the initial mass by the proposed method, we use the knowledge that the aircraft does not usually fly above the cost-optimal altitude. If the aircraft flies lower than the cost-optimal altitude, the estimated mass becomes larger than the actual mass. In other words, the estimated mass will never be smaller than the actual mass if the aircraft does not fly above the cost-optimal altitude. This implies that the minimum estimated initial mass should be chosen. Therefore, 5) the estimated initial mass of group C[6,7,8] provides the answer where the estimated initial mass is minimum among groups.

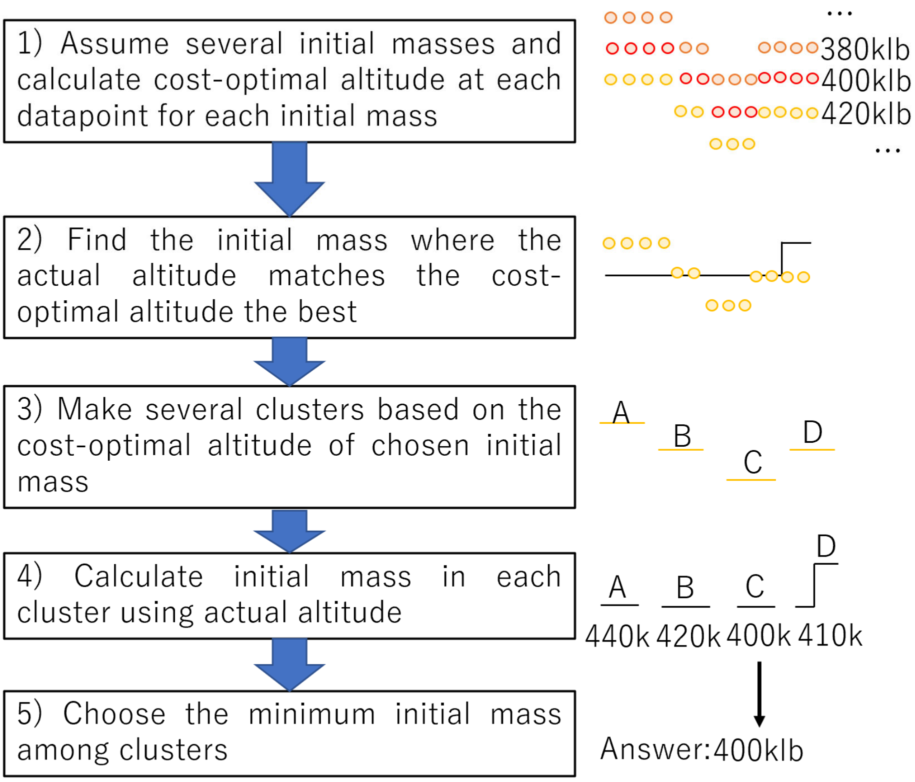

Figure 4 – Example of flight altitude and cost-optimal altitude of various mass.

Table 1 –Categorized groups and estimated aircraft mass.

Groups	Used data points	Estimated initial mass
A	1,2,3	440,000 lb
B	4,5	420,000 lb
C	6,7,8	400,000 lb
D	9,10,11,12	410,000 lb

3.4 Clustering method

Clustering is the method of grouping the of objects, which share similar propertiesand the objects are expected to be similar within each group. The clustering is the a type of unsupervised learning, so the grouping is possible even if no answer label is included in the data. This time, a clustering technique is used to estimate the aircraft mass more accurately considering the time histories of the cost-optimal altitude.

There are several directions of clustering; hierarchical clustering and non-hierarchical clustering. As for hierarchical clustering[13], a single data is defined as a single group first, then two groups are combined into a single group where the distance is minimum among all two combination of existing groups. It is important how to define the distance between groups, and simple Euclidean distance (L2 norm) or Ward's criterion[14] are two popular approaches. This hierarchical clustering requires $O(n^2 \log n)$, so it can be applied only to the a small number of data. As for non-hierarchical clustering, the number of groups is defined first, and the core data of each group are defined. Other data are categorized into one of the groups where the distance is minimum. k-means clustering[15] is the most famous method here. Although this non-hierarchical clustering can be applied to large data sets, the result highly depends on the initial solution.

It should be noted that the altitude selection problem has a time-dependent characteristic. Since it is difficult to change the flight altitude frequently, data within each group should be time-continuous. Therefore, time series clustering is can be used here. one of the categories of clustering, and There are many extended methods applied to time series data[16]. Among time series clustering, this altitude selection problem can be categorized into time point clustering. In time point clustering, the penalty term is often added to the calculation of the distance between groups. For example, the number of changes of the group through the whole time series is added as a penalty[17].

3.5 Clustering algorithm used in this research

Considering all of the above, hierarchical clustering is used in this study because the number of data samples is small (up to 30) in this problem. Ward's criterion is used to calculate the distance between groups to merge the closest two groups.

In hierarchical clustering, initial groups are created with each single data sample. Therefore, the number of groups is equal to the number of data samples. Two groups where the distance is minimum are merged into a single group, so the distance of all combinations of every two groups must be calculated. The distance of two groups in Ward's criterion is calculated by the following form.

$$d(P,Q) = E(P \cup Q) - E(P) - E(Q) \tag{6}$$

$$E(P) = \sum_{i \in P} (x_i - \bar{x})^2 \tag{7}$$

When the number of groups reaches the target number of groups, the calculation terminates. In each group, the initial mass can be estimated by the average of the estimated initial masses within the group. Since the cost-optimal altitude is given discretely with various initial masses as shown in Fig. 3, the cost-optimal altitude is interpolated by spline interpolation. Finally, the initial mass can be estimated in each group. Considering the operational knowledge that the aircraft rarely fly above the cost-optimal altitude, the answer of the initial mass becomes the minimum initial mass among the groups.

3.6 Consideration of time series data

As shown in Fig. 3, when the cost-optimal altitude frequently changes, the simple clustering using Ward's criterion leads to the frequent change of the group along the time sequences. Therefore, the number of group swaps along the time sequences is counted, which is included in the distance calculation among groups. This penalty is added defined by the following equation.

$$\Delta = \sum_{i=1}^{n-1} \delta_{g(i),g(i+1)} \tag{8}$$

where $g(i)$ is the assigned group of i th data sample, and $\delta_{i,j}$ is the Kronecker delta. The distance calculation is replaced by the following formula:

$$d_{new}(P,Q) = d(P,Q) + a(\Delta(merged\ P,Q) - \Delta(independent\ P,Q)) \tag{9}$$

where a is the weight factor to penalty. The penalty is calculated for independent P, Q and merged P, Q, respectively, and the penalty is added to the distance calculation. a is set sufficiently large, which means that the group are merged so that the penalty is minimized first. If the penalty is the same, the minimum distance of Ward's criterion is applied.

4. Estimation results

4.1 Estimation with whole flight data

First, the mass is estimated using the entire flight data up to 4 hours. This estimation can be easily done by setting the target number of clusters to 1. Fig. 5 shows the estimation result for each flight (total 39 flights). The mass is compared at the first report point between the estimated mass and the actual mass recorded in QAR data. In general, the estimated mass is greater than the actual mass. That is because the aircraft tends to fly below the cost-optimal altitude when the aircraft cannot fly on the cost-optimal altitude. If the aircraft flies below the cost-optimal altitude, the mass is estimated greater than the actual. MAE is often used as an index of the mass estimation accuracy, and it is 5.32 %. This is an acceptable result when compared with other references. This infers that the simple mass estimation using the whole flight data can be used for the initial guess.

Also, the orange bars indicate the flights where the cruise altitude changes within data samples. MAE of such flights is 4.40 % while MAE of other flights (no flight level change) is 6.57 %. It is easier to estimate the mass when the aircraft changes the cruise flight level during the flight.

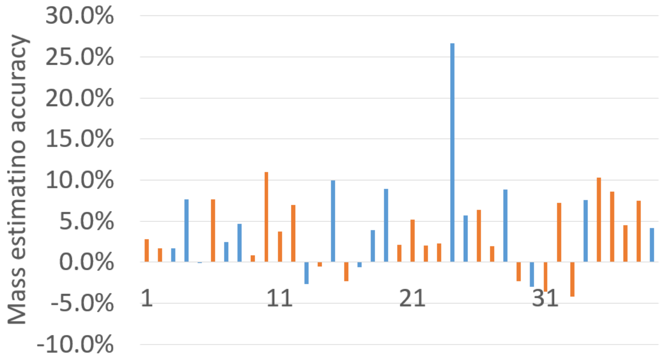

Figure 5 – Mass estimation with whole flight data. (MAE=5.23%) Orange bars indicate the flights where the cruise altitude changes within data samples.

4.2 Detailed results of mass estimation using clustering

Next, the mass is estimated using the proposed clustering method. First, the detailed result is shown using the data of flight ID = 4. In this example, the mass estimation error is 7.62 % when the entire flight data are used for the estimation. Fig. 6 shows the clustering result when the target number of clusters is set to 6.

A to F are the assigned groups, and the initial mass is estimated in each group. According to Fig. 6, the aircraft flies the highest relative to the cost-optimal altitude at group A. Fig. 2 also shows that the minimum initial mass is estimated in group A, and the initial mass estimation result at group A becomes the final result. Using the data of group A only, the mass estimation error is 0.51 %, which is significantly below that estimated by the entire data (7.62 %).

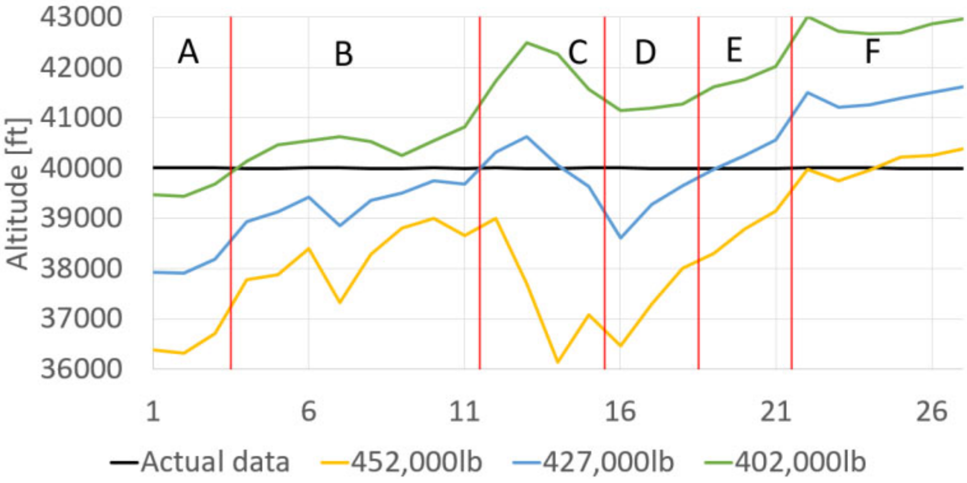

Figure 6 – The assigned groups (A-F) by clustering.

These six groups are merged as follow as the target number of clusters becomes small.

6: A-B-C-D-E-F

5: A-B-CD-E-F

4: A-B-CDE-F

3: A-BCDE-F

2: ABCDE-F

1: ABCDEF

In this example, BIC is minimum when the number of clusters is 6. However, group A is independent when the number of clusters is between 3 and 6, so the estimation result is the same when the number of clusters is between 3 and 6.

Another example is shown in Fig. 7 by using flight ID = 24. In this example, the cost-optimal altitude gradually increases with time, and the green (initial mass = 452,000 lb) or blue line (initial mass = 477,000 lb) seems to fit the actual altitude data. However, according to the mass estimation result, the actual and the estimated mass differ significantly. This is because this aircraft seemed to fly much below the cost-optimal altitude throughout this period. In such a case, the clustering technique does not work because none of data can estimate the correct mass. Actually, using the whole flight data the mass estimation error is 26.67 % while the error is 22.04 % using clustering. Although there is only one such a flight among all 39 flights, we should keep in mind that the proposed method potentially causes such a large mass estimation error. However, such a large estimation error can be corrected by other methods (e.g., rough mass estimation by the distance to the destination).

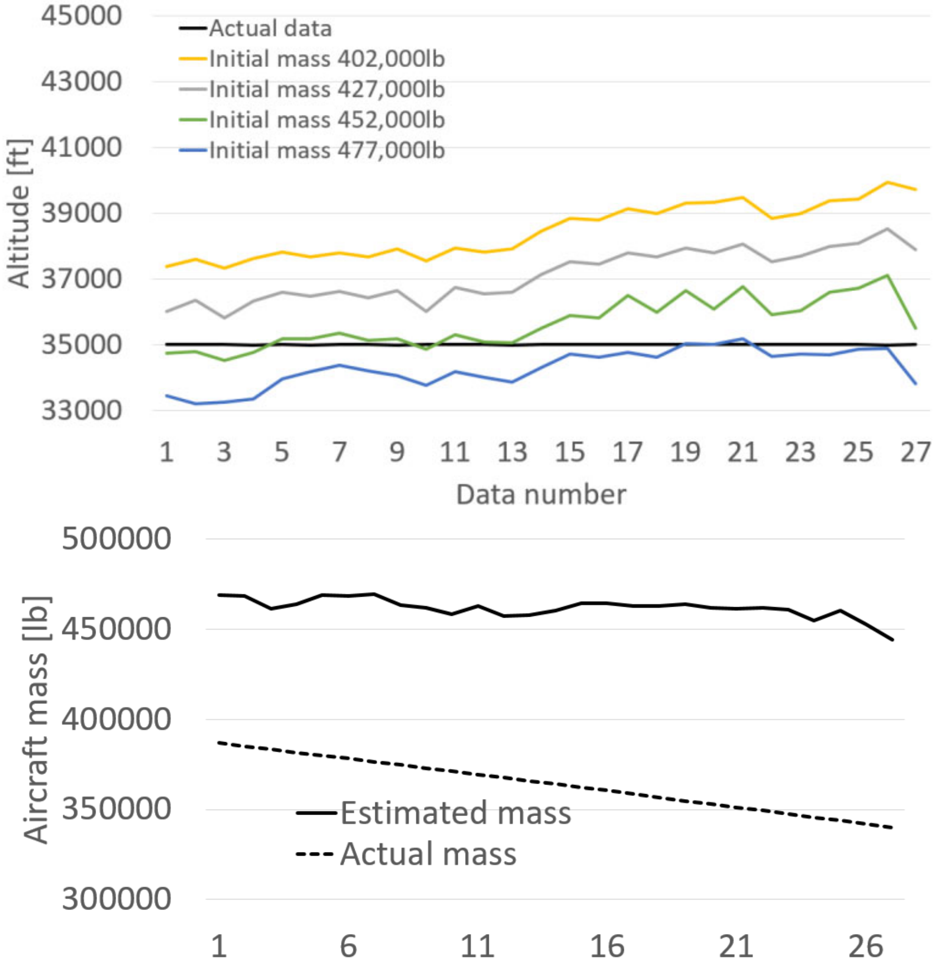

Figure 7 – The cost-optimal altitude and actual altitude, and the mass estimation result.

4.3 Mass estimation result using clustering

Fig. 8 shows the mass estimation result using clustering method. For the comparison purpose, the result using the whole flight data (which is exactly the same shown in Fig. 4) is also shown. Using the clustering method, MAE is reduced from 5.23 % to 3.29 %. In all cases, the estimated mass is smaller than that estimated with entire flight data. This is understandable because the clustering method uses the minimum estimated mass among the groups. The aircraft mass seems to be estimated with high accuracy.

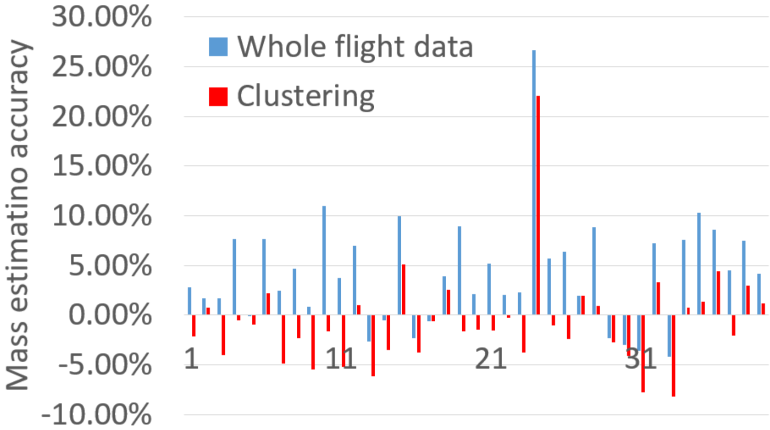

Figure 8 – Comparison of mass estimation error with usnig whole flight data and clustering method. (MAE = 3.29 % for clustering)

5. Conclusions

The aircraft mass estimation is a challenging problem, and this paper proposed a method to estimate the aircraft mass using the cruise flight data history with data available to ATC and numerical weather forecast only. Since the aircraft tends to fly below the cost-optimal altitude, the cruise flight was segmented by clustering to improve the mass estimation accuracy. The estimation result was compared to the actual mass data recorded in QAR data, and 3.29 % of MAE was achieved. Once flight performance data, ATC data, and numerical weather forecast data are available, the aircraft mass can be estimated without training the estimation model. This time, only a single aircraft type with limited number of QAR data (39 flights) are available, so this method will further be tested on more various data. Also, it will be investigated whether the proposed method can be applied to shorter flight data samples.

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8. References

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