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Performance of an Adaptive Trajectory Prediction Algorithm for Climbing Aircraft

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Aircraft climb trajectories are difficult to predict, and large errors in these predictions reduce the potential operational benefits of some advanced concepts in the Next Generation Air Transportation System. An algorithm that dynamically adjusts modeled aircraft weights based on observed track data and predictions of atmospheric conditions improved trajectory prediction accuracy for climbing flights across the National Airspace System. Overall, the algorithm reduced both altitude and top-of-climb time prediction root mean square errors by about 20 percent. Although the algorithm improved climb trajectory prediction accuracy in all Centers, results indicate that additional gains may be possible by tuning the algorithm's parameters on a per-Center basis. Miami, Fort Worth, and Houston Centers were investigated more thoroughly because they represented the lower, middle, and upper end of the algorithm's performance range. The degree of improvement at the Center level was dependent on the aircraft types.

Nomenclature

D	=	drag (lbf)
$\dot{E}_{obs}$	=	observed energy rate
$\dot{E}_{model}$	=	modeled energy rate
$\Delta\dot{E}$	=	energy rate difference, $\dot{E}_{obs} - \dot{E}_{model}$
g	=	gravitational acceleration (ft/sec^2)
h	=	altitude, (ft)
$\dot{h}$	=	rate of climb (ft/min)
T	=	thrust (lbf)
V_T	=	true airspeed (kt)
W	=	aircraft weight (lbf)
W_l	=	horizontal wind speed (kt)
β	=	sensitivity parameter
ψ_{rel}	=	relative wind angle (degrees), $\psi_i - \psi_w$
ZAB	=	Albuquerque Air Route Traffic Control Center
ZAU	=	Chicago Air Route Traffic Control Center
ZDC	=	Washington Air Route Traffic Control Center
ZDV	=	Denver Air Route Traffic Control Center
ZFW	=	Fort Worth Air Route Traffic Control Center
ZHU	=	Houston Air Route Traffic Control Center
ZLA	=	Los Angeles Air Route Traffic Control Center
ZMA	=	Miami Air Route Traffic Control Center
ZMP	=	Minneapolis Air Route Traffic Control Center
ZOB	=	Cleveland Air Route Traffic Control Center

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I. Introduction

AIR traffic demand is expected to more than double over the next 20 years,[1] but air traffic controller workload limits airspace capacity. It is expected that more automation will be necessary to accommodate future growth. Trajectory prediction error has been shown to be a major limiting factor on the level of safety and efficiency that can be achieved. For instance, previous research observed late and missed conflict detections due to errors in climb trajectory predictions.[2-4] This is due to the wide range of error sources[5-7] in the atmospheric models (e.g., wind, temperature) and climb profile and their respective magnitudes in current operations.[8-10]

A recently investigated approach that adjusts the modeled aircraft weight parameter in the underlying aircraft performance model on a per-flight basis based on observed track and atmospheric data has reduced climb trajectory prediction errors.[11-12] The adaptive weight algorithm does not require any additional data from Airline Operational Control (AOC) or aircraft unlike other previously investigated approaches.[8-9] Also, since it is derived from the point-mass equations of motion and is applied on a per-flight basis, it is more flexible than a method that applies the same statistical model of engine thrust and climb Calibrated Airspeed (CAS) to all flights of the same aircraft type.[10]

The adaptive weight algorithm was tuned in a prior study using 12 hours of Fort Worth Center traffic data before being evaluated with a separate data set of 20 hours of data.[11] Results showed that it was able to reduce both altitude and top-of-climb time prediction errors by 20 percent. However, it was not clear that the algorithm as-is could improve climb trajectory prediction accuracy (to the same extent) at all Centers and for aircraft types that do not typically depart out of Fort Worth Center. The current study seeks to answer these questions by analyzing twenty-four hour data sets at ten different Centers.

It should be emphasized that the objective of the adaptive weight algorithm is not to estimate actual aircraft weight[13] or fuel burn.[14] In fact, due to the wide array of sources of uncertainty that cause climb trajectory prediction errors, the modeled aircraft weight may be adjusted away from the true aircraft weight. Rather, the algorithm seeks to modify the modeled aircraft weight parameter such that the resulting climb trajectory prediction more closely matches the observed track data in general. Adjusting aircraft weight exclusively will not be sufficient to fully compensate for all sources of climb uncertainty, and the resulting trajectory predictions will never perfectly match subsequent radar track data. Regardless, the adaptive weight algorithm is expected to improve overall climb trajectory prediction accuracy.

Comparable adaptive thrust approaches were also shown to improve climb trajectory prediction accuracy for a handful of actual climbing flights in Fort Worth Center.[15-16] Still, the adaptive weight approach is preferred because engine thrust is computed using altitude data that are discretized in 100-ft increments. Also, within any 12-second track update cycle, multiple ground stations may receive altitude data from the same flight but at different times and possibly having different values. Since the data from exactly one of these ground stations is selected at each track update and the data source could change over time, adjusting the modeled thrust is most likely less precise than adjusting the modeled aircraft weight, which is an independent parameter.

The remainder of this paper is organized as follows. The next section has a high-level description of the adaptive weight algorithm. Following that is an overview of the experimental setup. Then, the results of analyzing adapted and non-adapted trajectory predictions generated in real-time using NASA's Center/TRACON Automation System (CTAS)[17] Trajectory Synthesizer (TS) are presented. This study compared trajectory predictions for climbing flights in ten (Air Route Traffic Control) Centers across the National Airspace System (NAS) to actual radar track. Three of these Centers were investigated more thoroughly because they spanned the range of algorithm performance and had some aircraft types in common: Fort Worth Center (ZFW), Miami Center (ZMA), and Houston Center (ZHU). These aircraft types were examined in greater detail to determine the extent to which different operational procedures by different carriers affected algorithm performance. Lastly, the findings of this research are summarized.

II. Adaptive Weight Algorithm Description

The adaptive weight algorithm improves altitude prediction accuracy by dynamically adjusting the modeled aircraft weight for each climbing flight using observed track data and predictions of atmospheric conditions. The algorithm is only applied between 15,000 and 25,000 ft, where flights are typically in the constant CAS portion of their climb profile. The algorithm was derived in detail in a previous study of the adaptive weight algorithm.[11] Figure 1 is a high-level overview of the adaptive weight algorithm, where the weight adjustments are based on the modeled energy rate ($\dot{E}_{model}$, which is calculated based on the thrust, drag, and weight parameters in the CTAS aircraft performance models as shown in equation 1) and the observed energy rate ($\dot{E}_{obs}$, which is calculated from rate of climb and true airspeed estimated from radar track data and prediction of wind magnitude and direction as shown in equation 2). The energy-rate difference is then calculated (equation 3) and if the observed energy rate is greater than the modeled energy rate, the algorithm will reduce the modeled weight (equation 4) for that particular flight. If the opposite is true, then the algorithm will increase the modeled weight to reduce the energy-rate difference. The algorithm begins with a baseline of 90 percent of the maximum gross takeoff weight. A lower limit of 80 percent and an upper limit of 100 percent of the maximum gross takeoff weight were used to reduce the possibility of trajectory prediction integration failures. The algorithm was unchanged from the previous study that analyzed Fort Worth Center climbing flights.[11]

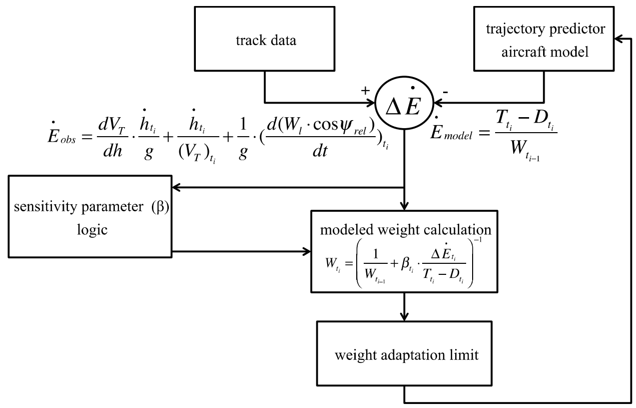


Figure 1. High-level overview of adaptive climb algorithm.

The right-hand side of the energy-rate difference equation:

$$\dot{E}_{model} = \frac{T - D}{W} \tag{1}$$

The left-hand side of the energy-rate difference equation:

$$\dot{E}_{obs} = \frac{dV_T}{dh}\frac{\dot{h}}{g} + \frac{\dot{h}}{V_T} + \frac{1}{g}\frac{d(W_l\, cos(\psi_{rel}))}{dt} \tag{2}$$

The energy-rate difference equation:

$$\Delta\dot{E} = \left(\frac{dV_T}{dh}\right)_{t_i}\frac{\dot{h}_{t_i}}{g} + \frac{\dot{h}_{t_i}}{(V_T)_{t_i}} + \frac{1}{g}\left(\frac{d(W_l\, cos(\psi_{rel}))}{dt}\right)_{t_i} - \frac{T_{t_i} - D_{t_i}}{W_{t_{i-1}}} \tag{3}$$

The modeled weight calculation equation:

$$W_{t_i} = \left(\frac{1}{W_{t_{i-1}}} + \beta_{t_i}\frac{\Delta\dot{E}}{T_{t_i} - D_{t_i}}\right)^{-1} \tag{4}$$

III. Experiment Setup

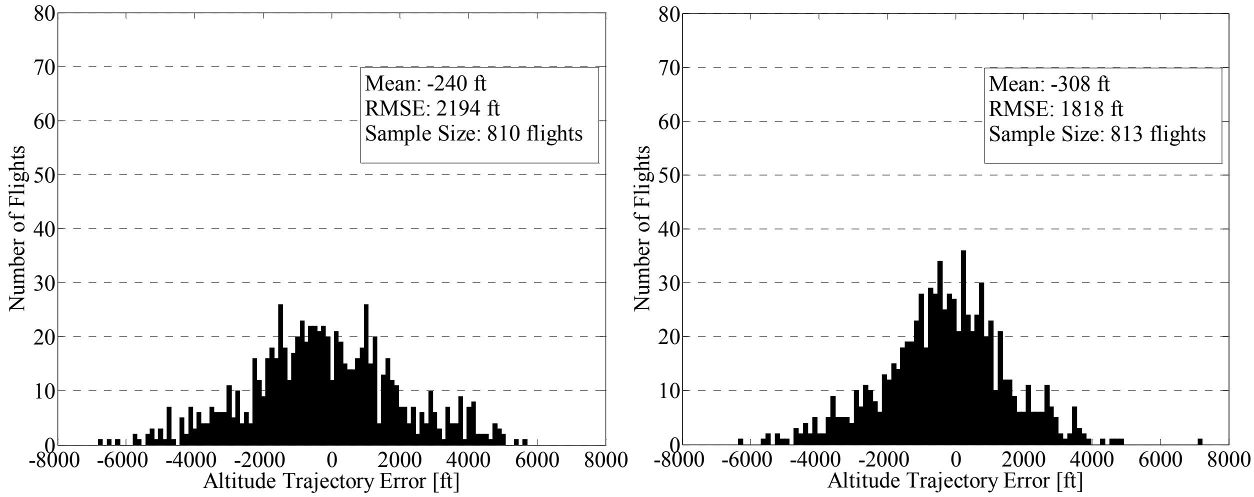
Radar track and adapted and non-adapted trajectory prediction data were collected using CTAS, NASA's real-time Air Traffic Control (ATC) research system. In this study, CTAS generated 4D-trajectories using Center Host flight plan and radar track data from 10 Centers in the NAS and atmospheric condition forecasts from the National Oceanic and Atmospheric Administration Rapid Update Cycle for an average traffic day (November 16, 2011). The 10 Centers analyzed were: Albuquerque (ZAB), Chicago (ZAU), Washington (ZDC), Denver (ZDV), Fort Worth (ZFW), Houston (ZHU), Los Angeles (ZLA), Miami (ZMA), Minneapolis (ZMP), and Cleveland (ZOB).

The main metric used to gauge the performance of the algorithm was the root-mean-square of altitude errors (altitude RMSE). A flight was analyzed only if it did not have any flight plan amendments or non-climbing segments between the time the trajectory prediction was made and the time its flight plan cruise altitude was attained. This was done to mitigate the effects of controller intervention in the analysis. Altitude errors were computed for trajectory predictions generated at the first track update at or above 18,000 ft, 21,000 ft, and 24,000 ft. The attitude trajectory errors were computed by taking the difference of the altitude from the track at some given time, from the altitude that was predicted for that time.

IV. Results

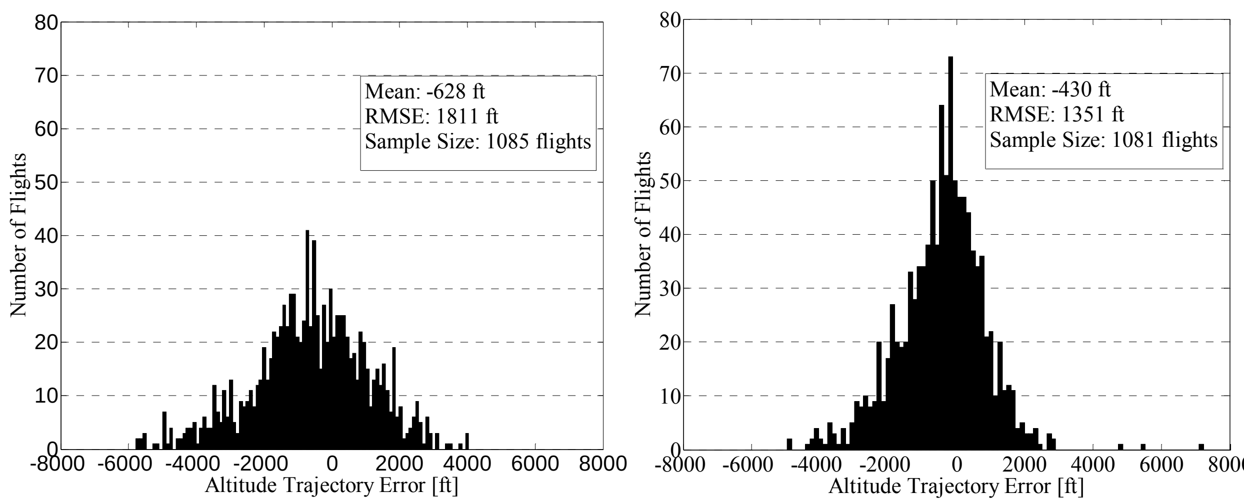
A. Aggregate Results

The adaptive weight algorithm reduced altitude RMSE in the 10 Centers analyzed in this paper by 17 percent overall for trajectory predictions generated at 18,000 ft on a 5-minute look-ahead time; this is illustrated in Figures 2a and 2b. It should be noted that this was achieved with just one to two minutes of adaptation. This increased to 24 percent for trajectory predictions made at 24,000 ft as the algorithm had additional time to operate (see Figures 3a and 3b). The errors of the adapted trajectory predictions were more tightly clustered around zero compared to the non-adapted predictions at both 18,000 and 24,000 ft. It was successful at reducing the number of flights at the tails of the distribution, especially on the positive side. These results corroborate with previous analysis of Fort Worth Center traffic that also observed a decrease of about 20 percent.[11]



a) **b)**

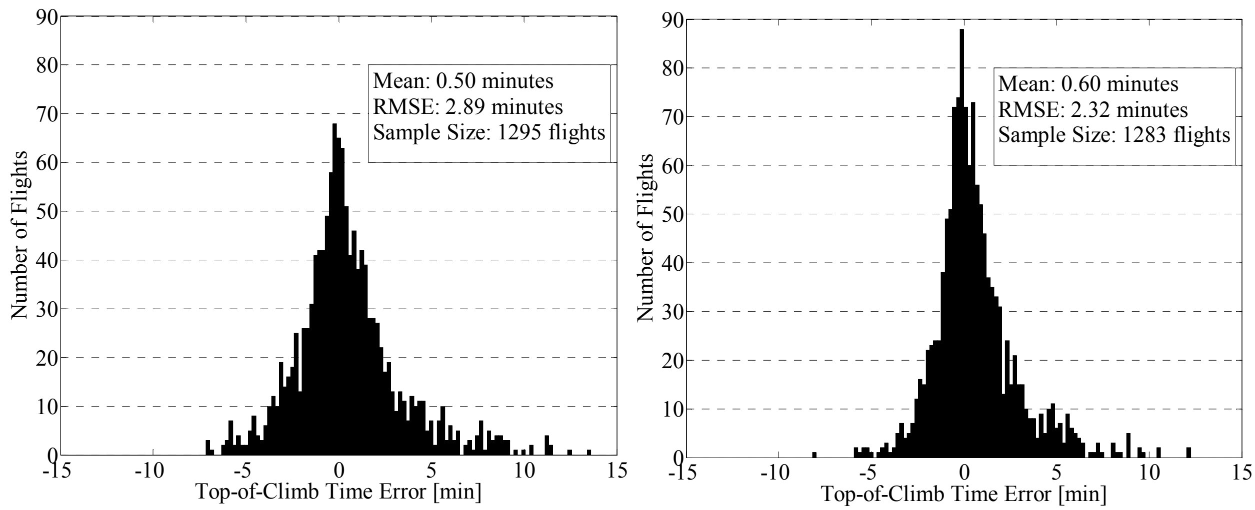
Figure 2. Altitude trajectory prediction errors generated at 18,000 ft on a 5-minute prediction look-ahead time for all Centers a) without adaptation, and b) with adaptation.



a) **b)**

Figure 3. Altitude trajectory prediction errors generated at 24,000 ft on a 5-minute prediction look-ahead time for all Centers a) without adaptation, and b) with adaptation.

The adaptive weight algorithm also decreased top-of-climb (TOC) prediction time errors by 20 percent for trajectory predictions generated at 18,000 ft (see Figures 4a and 4b), which is also about the same as in the previous study of Fort Worth Center departures.[11] The distribution of the TOC time errors is narrower in the adapted case compared to the non-adapted case while still being centered near zero. At 24,000 ft, the TOC-time RMSE was 1.75 minutes with the algorithm compared to 2.50 minutes without it. This decrease of 30 percent exceeds the 20 percent reduction observed in the Fort Worth Center study. This metric is important because air traffic controllers need reliable predictions of times to climb to different altitudes when evaluating possible conflict resolution maneuvers to keep aircraft safely separated.



a) b)

Figure 4. Top-of-climb time errors for trajectory predictions generated 18,000 ft for all Centers a) without adaptation and b) with adaptation.

B. Center-Level Analysis

The performance of the adaptive weight algorithm at different Centers varied as seen in Figure 5, which plots the altitude RMSE for the 10 Centers in this study with and without the algorithm enabled for trajectory predictions generated at 18,000 ft and a prediction look-ahead time of five minutes. Although the 10 Centers had smaller altitude errors with the algorithm enabled, the reduction was only 4 percent in ZAB. By comparison, ZHU was most improved at 28 percent.

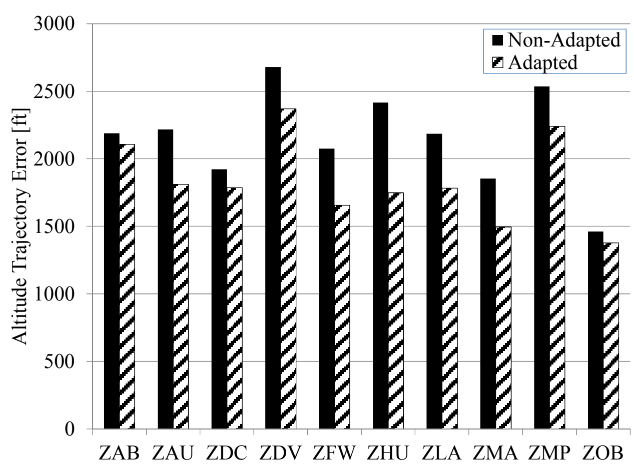


Figure 5. Altitude RMSE for trajectory predictions generated at 18,000 ft on a 5-minute look-ahead time.

Analysis of trajectory predictions computed at 21,000 ft and 24,000 ft also showed wide performance ranges, but the adaptive weight algorithm continually improved trajectory prediction accuracy throughout the climb phase. The reductions in altitude RMSE were greater at 21,000 ft than at 18,000 ft for eight of the 10 Centers (with no change at ZDC and ZMA), ranging from 5 percent at ZDC to 31 percent at ZHU. Similar results were observed for the trajectory predictions generated at 24,000 ft, with altitude RMSE improvements ranging from 12 percent at ZOB to 38 percent at ZMP. Although the adaptive weight algorithm reduced altitude RMSE at all 3 analysis altitudes and in all 10 Centers, it is still important to take a closer look at the results for specific Centers to identify the possible causes for the diversity in performance. The overall results are illustrated for 21,000 and 24,000 ft in Figures 6a and 6b.

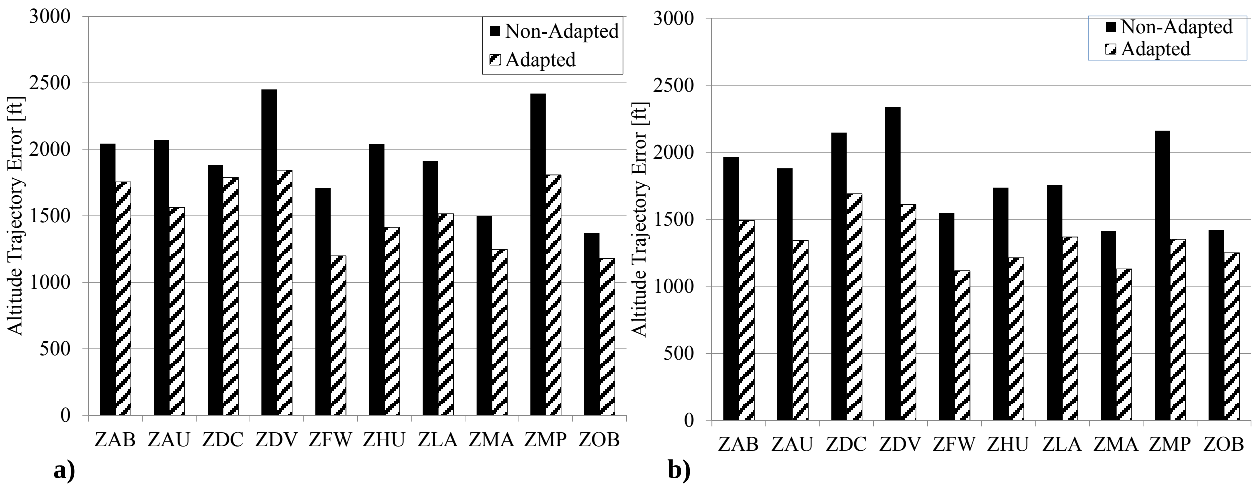


Figure 6. Altitude RMSE for trajectory predictions generated at 21,000 a) and 24,000 b) ft for a 5-minute look-ahead time.

C. Aircraft-Type Results in Specific Centers

The 10 Centers were categorized into 3 groups based on the adaptive weight algorithm's performance relative to the 20 percent improvement observed in the earlier Fort Worth Center study.[11] The improvement was lower in 4 Centers (ZAB, ZDC, ZMA, and ZOB), about the same in 4 Centers (ZAU, ZDV, ZFW, and ZLA), and higher in 2 Centers (ZHU and ZMP). In the end, Fort Worth (ZFW), Miami (ZMA), and Houston (ZHU) Centers were selected from these sub-groups based on their respective sample sizes and common aircraft types (E145 in ZFW and ZHU, and B738 in ZHU and ZMA).

i. Fort-Worth Center (ZFW) Results

The results for ZFW were similar to the earlier research findings[11], with a reduction in altitude RMSE of roughly 20 percent for trajectory predictions computed at 18,000 ft on a 5-minute prediction time. Figure 7 illustrates how the algorithm improved the accuracy of these trajectory predictions across all look-ahead times. There is a widening gap between the adapted and non-adapted results as look-ahead time increases, which is significant because trajectory prediction errors do not necessarily increase monotonically as a function of prediction look-ahead time due to the wide range of error sources[5-7] and their respective magnitudes in current operations.[8-10]

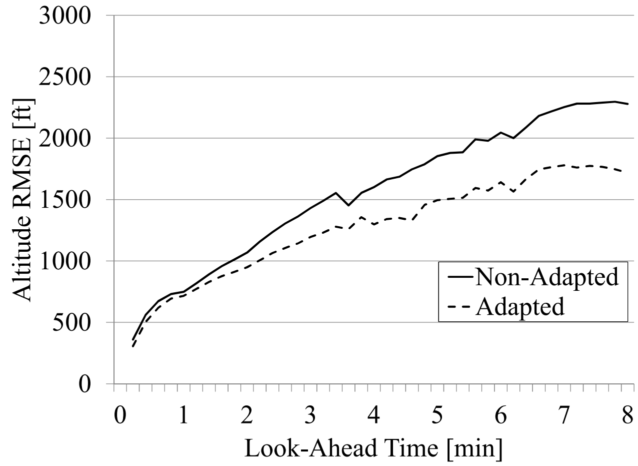


Figure 7. Altitude RMSE for trajectory predictions generated at 18,000 ft in ZFW.

Three aircraft types were investigated more closely because they accounted for approximately half of the flights in ZFW: 1) McDonnell Douglas MD-82, 2) MD-83, and 3) Embraer E145. The adaptive weight algorithm improved climb trajectory prediction accuracy by at least 20 percent for each of these three aircraft types, with the E145 having the greatest improvement: 30 percent for trajectory predictions generated at 18,000 ft for a 5-minute prediction time, 44 percent at 21,000 ft, and 38 percent at 24,000 ft (see Figure 8). The altitude RMSE for E145 flights decreases toward the 1000-ft vertical separation threshold between 18,000 ft and 24,000 ft, with a decrease from 2070 ft to 1064 ft with the adaptation compared to the reduction from 2974 ft to 1706 ft without it.

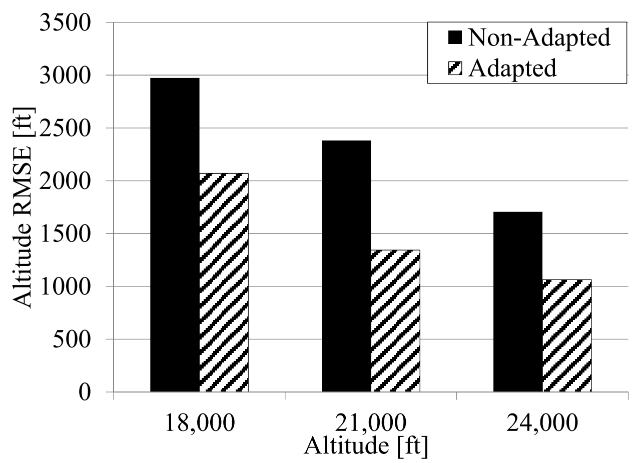


Figure 8. Altitude RMSE for E145 flights in ZFW at different altitudes (5-minute look-ahead).

ii. Miami Center (ZMA) Results

The adaptive weight algorithm reduced altitude RMSE for climb trajectory predictions generated at 18,000 ft on a prediction look-ahead time of five minutes in Miami Center by about 12 percent, which was in the bottom 1/3 of the Centers analyzed in this study. As expected, the improvement is limited at shorter look-ahead times and greater at longer prediction times (see Figure 9).

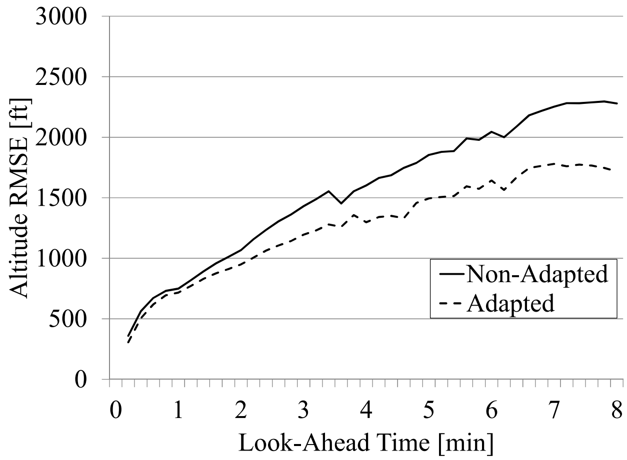


Figure 9. Altitude RMSE for trajectory predictions generated at 18,000 ft in ZMA.

Three aircraft types comprised about half of the climbing flights analyzed in ZMA: 1) Boeing 757-200 (B752), 2) Boeing 737-800 (B738), and 3) Boeing 767-300 (B763), in decreasing order of frequency. ZMA was selected for additional analysis because its B738 flights could be compared to those in ZHU to determine the extent to which the adaptive weight algorithm was affected by different operational procedures by different carriers.

The algorithm reduced the altitude RMSE of B738 flights at 18,000 ft by 24 percent from 1514 to 1156 ft (see Figure 10). It continued to improve climb trajectory prediction accuracy at 21,000 ft, where the altitude RMSE in the adapted case was 696 ft, which was a reduction of about 20 percent compared to the non-adapted trajectory predictions. However, at 24,000 ft. the altitude RMSE was only 14 percent lower with the algorithm enabled than without it. Note that there was actually a small increase in altitude RMSE between 21,000 ft and 24,000 ft for both the adapted and non-adapted trajectory predictions. A closer investigation found that the algorithm reached the lower weight limit of 80 percent of the gross maximum takeoff weight for roughly one-third of the B738 flights in ZMA. Otherwise, the algorithm likely would have continued to improve climb trajectory prediction accuracy.

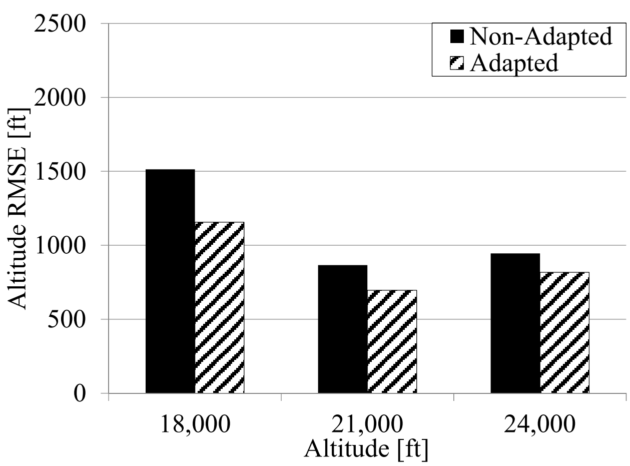


Figure 10. Altitude RMSE for B738 flights in ZMA at different altitudes (5-minute look-ahead).

iii. Houston Center (ZHU) Results

Houston Center had the greatest overall improvement in climb trajectory prediction accuracy among the 10 Centers analyzed in this study. For a 5-minute prediction look-ahead time, the improvement in altitude RMSE was roughly 28 percent at 18,000 ft and 30 percent for 21,000 and 24,000 ft. The magnitude of this improvement was partially due to the fact that ZHU non-adapted trajectory prediction errors were among the highest (see Figure 5). As shown in Figure 11, the propagated as a function of look-ahead time.

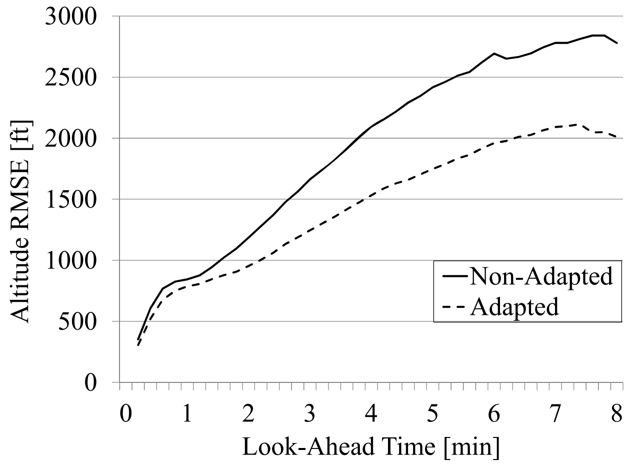


Figure 11. Altitude RMSE for trajectory predictions generated at 18,000 ft in ZHU.

Three aircraft types accounted for 58 percent of the climbing flights in ZHU that were analyzed: 1) Embraer E145, 2) Embraer E45X, and 3) Boeing 737-800 (B738), in order of decreasing frequency. ZHU was selected for additional investigation because E145 and B738 were also among the three most common aircraft types in ZFW and ZMA, respectively.

E145 trajectory predictions were among the most improved predictions by the adaptive weight algorithm. At 18,000 ft, for a 5-minute look-ahead time, there was an initial reduction of 35 percent, bringing the altitude RMSE down from 3367 ft to 2179 ft (see Figure 12). The algorithm further reduced the altitude RMSE to 1276 ft by 21,000 ft (45 percent decrease) and 680 ft at 24,000 ft (55 percent decrease). The behavior of the algorithm with the E145 was an ideal case where the algorithm approached the observed weight of the aircraft in a predictable way, and eventually brought the altitude RMSE within the legal vertical separation limit.

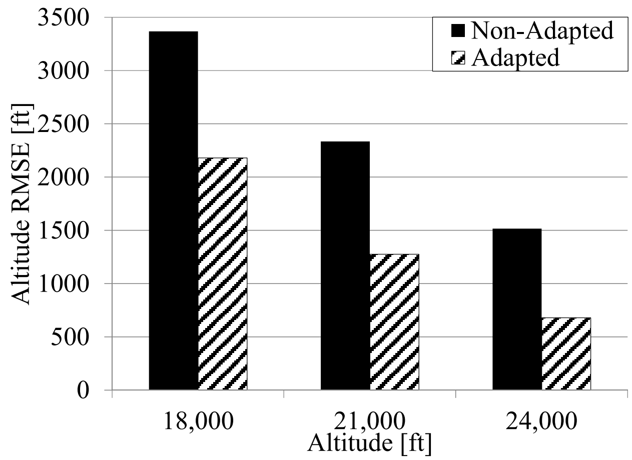


Figure 12. Altitude RMSE for E145 flights in ZHU at different altitudes (5-minute look-ahead).

The adaptive weight algorithm also consistently improved climb trajectory prediction accuracy for B738 flights throughout the climb phase as seen in Figure 13. However, the B738 did not fall below the 1000-ft standard in ZHU at any of the three analysis altitude unlike in ZMA. For a 5-minute prediction look-ahead time, the altitude RMSE of the adapted trajectory predictions was 16 percent less than their non-adapted counterparts at 18,000 ft (1757 ft vs. 2084), 29 percent smaller at 21,000 ft (1495 ft vs. 2092) , and 31 percent lower at 24,000 ft (1298 ft vs. 1877)

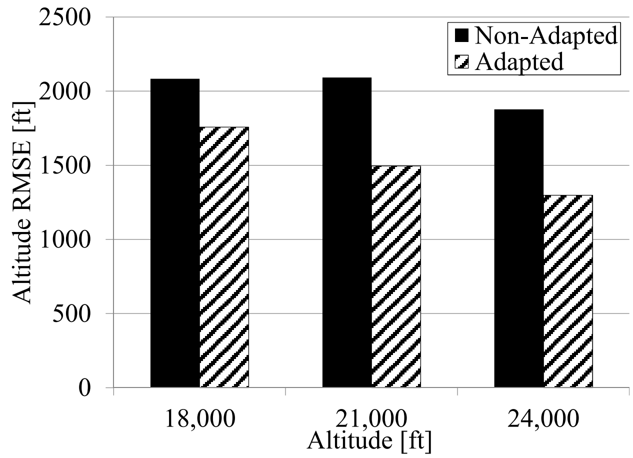


Figure 13. Altitude RMSE for B738 flights in ZHU at different altitudes (5-minute look-ahead).

V. Discussion

The adaptive weight algorithm typically reduced altitude trajectory prediction errors for all prediction look-ahead times and analysis altitudes. One notable exception were Embraer E45X flights in ZHU, which had greater altitude RMSE with adaptation. Their adapted weight values and actual vertical flight paths were examined more closely. Another atypical case were Boeing 767-300 (B763) flights in ZMA, whose altitude RMSE for the adapted trajectory predictions actually increased as a function of analysis altitude. A side-by-side comparison with the altitude RMSE of the non-adapted predictions indicates that the algorithm is highly dependent on the trajectory predictor. Lastly, this section also looks at the extent to which different operational procedures by different carriers affects algorithm performance for B738 flights in ZHU and ZMA and E145 flights in ZFW and ZHU.

A. Analysis of Algorithm Performance for Embraer E45X in ZHU

The E45X had significant improvements in altitude RMSE of 32 percent at 18,000 ft on a 5-minute prediction look-ahead-time (see Figure 14). At 21,000 ft, this dropped to 21 percent. By 24,000 ft, though, the altitude RMSE for the non-adapted trajectories of the E45X flights were similar on a 3-minute look-ahead time and actually 17 percent higher than their non-adapted counterparts in the 5-minute case. In fact, the altitude RMSE of the adapted trajectories at 24,000 ft were at least as much as the non-adapted predictions at all look-ahead times (see Figure 15).

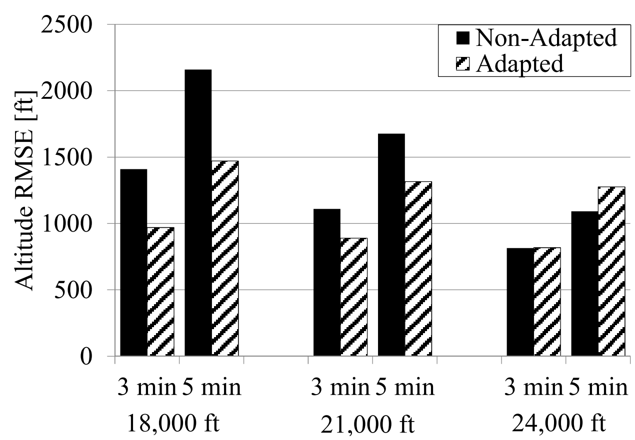


Figure 14. Altitude RMSE for E45X flights in ZHU at different altitudes and look-ahead times.

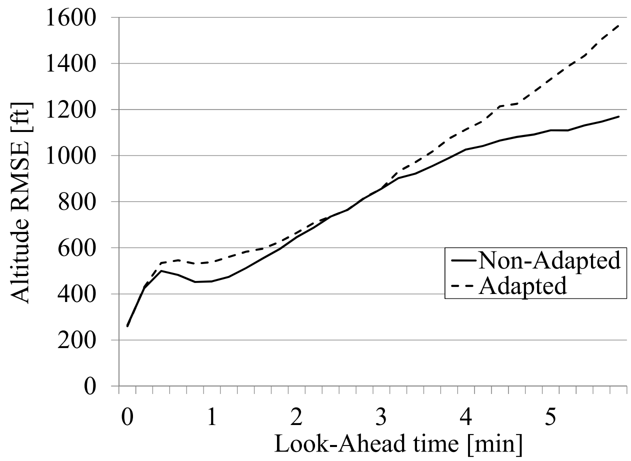


Figure 15. E45X Altitude RMSE to look-ahead time, 24,000 ft.

One reason for this behavior is the difference between the modeled and actual speeds of E45X flights. The E45X aircraft performance model uses faster speeds than what were actually flown. As a result, the algorithm increases the modeled weight until it reaches the upper bound limit of 100 percent of the gross maximum takeoff weight. This is illustrated in Figure 16, which is a plot of the median adapted weight values as a function of altitude.

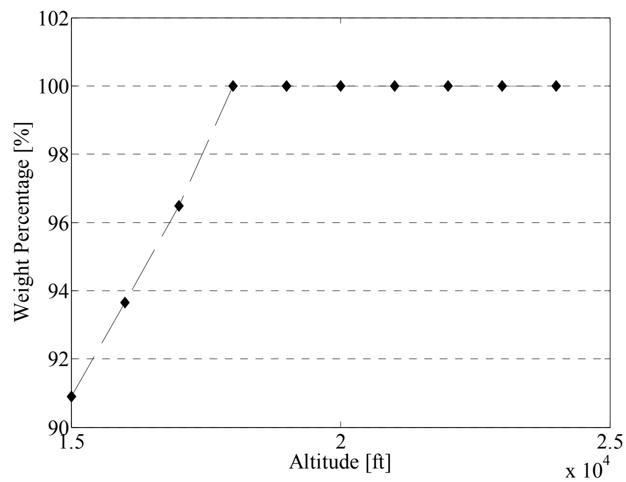
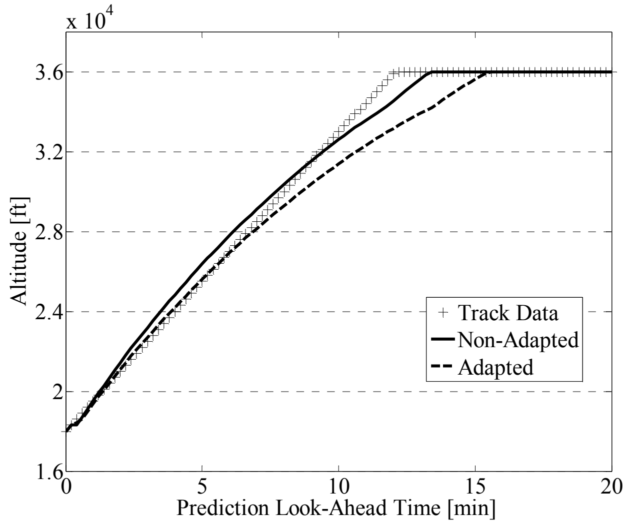
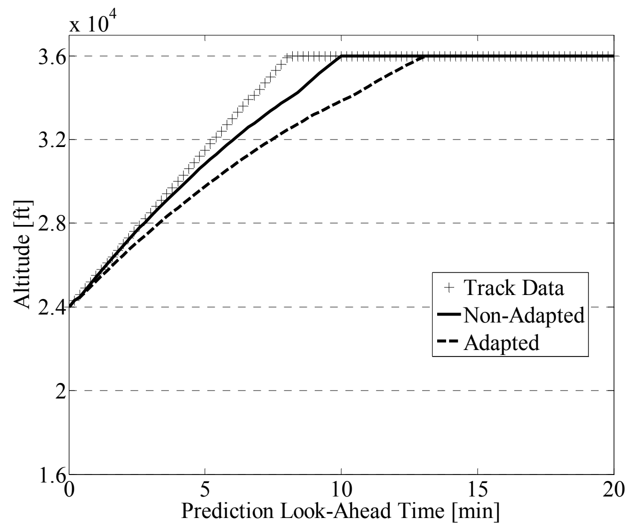


Figure 16. E45X median adapted weight percentage at different altitudes.

Figure 17a illustrates a typical E45X flight from this analysis. In figure 17a, it climbed at a constant rate of about 1500 ft/min (+ points), which was slower than what was modeled by the underlying trajectory predictor (solid line). As a result, the adaptive weight algorithm correctly increased the modeled weight parameter to reduce the vertical rate (dotted line) until it reached the upper bound of 100 percent of the gross maximum takeoff weight. The algorithm continued to keep the modeled aircraft weight at this level because the modeled speeds in the underlying trajectory predictor were always greater than the actual speed. This produced results where the algorithm enabled trajectory predictions were less accurate than their non-adapted counterparts at 24,000 ft. This becomes more apparent at 24,000 ft, where only case of the algorithm-enabled performance lags behind the non-adapted predicted trajectories as illustrated in 17b. However, despite the fact the algorithm resulted in trajectory predictions that were less than their non-adapted counterparts, ZHU was still one of the Centers with the most improvement overall.



a)



b)

Figure 17. Example track data and trajectory prediction for typical E45X flight in ZHU.

B. Analysis of Algorithm Performance for Boeing 767-300 Flights in ZMA

The results for B763 flights in ZMA stood out because the altitude RMSE of the adapted trajectory predictions in this case actually increased as a function of altitude. At 18,000 ft, the adaptive weight algorithm reduced the altitude RMSE by 39 percent to 489 ft for a 5-minute prediction look-ahead time (see Figure 18). However, this improvement was less at both 21,000 ft (18 percent) and 24,000 ft (21 percent). In fact, the altitude RMSE for the adapted predictions was noticeably higher at both of those analysis altitudes unlike the other aircraft types in this paper. The behaviors of the adapted and non-adapted results are actually similar, which indicates that the performance of the adaptive weight algorithm is highly dependent on the accuracy of the underlying trajectory predictor.

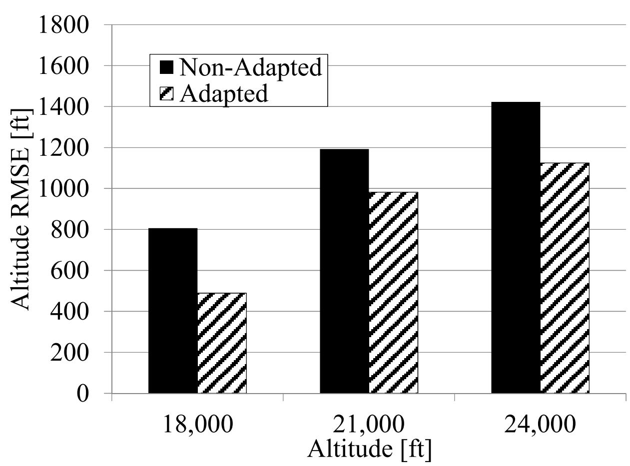


Figure 18. Altitude RMSE for B763 flights in ZMA at different altitudes (5-minute look-ahead).

C. Comparison of Boeing 737-800 Flights in ZHU and ZMA

The adaptive weight algorithm improved climb trajectory prediction accuracy for B738 flights in both ZHU and ZMA as seen in Figures 10 and 13. In both cases, it was generally more effective at higher altitudes as it had more time to work except at 24,000 ft in ZMA. The algorithm reached the lower weight limit of 80 percent of the gross maximum takeoff weight for roughly one-third of the B738 flights in ZMA or else it may have continued to improve climb trajectory prediction accuracy. Despite this, the altitude RMSE for the adapted trajectory predictions was still lower in ZMA than in ZHU. This is mainly because the underlying trajectory predictor was more accurate in ZMA than in ZHU as seen in the altitude RMSE of the non-adapted predictions. Further investigation also found that different carriers operated B738 flights in ZHU compared to ZMA. These findings further reinforce the fact that the performance of the adaptive weight algorithm is contingent on the accuracy of the trajectory predictor used.

D. Comparison of Embraer E145 Flights in ZFW and ZHU

The results for E145 flights in ZFW and ZHU were similar in terms of the magnitude of their altitude errors as shown in Figures 8 and 12. At 18,000 ft and 21,000 ft, the altitude RMSE of the adapted trajectory predictions in these two Centers were within 100 ft of each other. At 24,000 ft, the difference in altitude RMSE was roughly 300 ft, but both were close to or below the 1000-ft vertical separation threshold. Closer inspection found that all of the E145s in ZFW and ZHU were actually operated by the same carrier (under different names). The similarity of the results indicates that algorithm performance also depends on the accuracy of the underlying trajectory predictor and, specifically, how well it models the specific operational procedures of an airline. Last, but not least, the large altitude RMSE for the non-adapted trajectory predictions (e.g., greater than 3000 ft at 18,000 ft on a 5-minute look-ahead time) in both Centers indicates that improvements to the underlying E145 aircraft performance model are needed.

VI. Conclusions

The adaptive weight algorithm improved climb trajectory prediction accuracy in all ten Centers analyzed in this study using only the radar track and atmospheric forecast data currently available; it did not require any additional information from Airline Operations Centers or aircraft. Overall, the algorithm reduced both altitude and top-of-climb time prediction root-mean-square errors by about 20 percent. The smallest decrease in altitude errors was 4 percent in Albuquerque Center while the largest was 28 percent in Houston Center. Although further gains may be achieved by tuning the algorithm's parameters (e.g., the lower and upper bound limits on the adapted weights) for specific aircraft types and/or Centers, algorithm performance primarily depends on the accuracy of the underlying trajectory predictor (particularly for Boeing 767-300 and Embraer E145 flights). Overall, though, the results of this study indicate that the adaptive weight algorithm could serve as a foundation for improving the trajectory prediction accuracy of climbing flights across the National Airspace System to the level required for the Next Generation Air Transportation System.

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