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Aircraft-Based Complexity Assessment for Radar Controllers in the Multi-Sector Planner Experiment

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I. Introduction and Motivation

New technologies and automation tools under development in Next Generation Air transportation System (NextGen) will change controllers tasks, roles, and responsibilities. However, controllers cognitive complexity will remain one of the limiting factors on system capacity. To better understand cognitive complexity in future Air Traffic Control (ATC) environments, an investigation of cognitive complexity factors was performed for radar controllers in the Multi-Sector Planer (MSP) II experiment.

A large amount of work in ATC complexity has been performed to identify factors and influences that make an air traffic situation more or less complex. Summaries of these studies can be found in the review papers.[1–4] Most of the complexity factors identified can be grouped into two categories: the distribution of aircraft in the air traffic situation and properties of the underlying structure in a sector.[5] Indicators for the distribution of aircraft in the air traffic situation can be measured directly with parameters, such as traffic density, the proportion of aircraft changing altitudes, and number of conflicts, etc. However, indicators for the properties of the underlying structure in a sector cannot be readily calculated, for example, sector shape, the configuration of airways, and the impact of restricted areas of airspace, etc.

A number of quantifiable metrics based on the identified complexity factors have been proposed to describe ATC complexity or the limit of controller workload. For instance, Dynamic Density is intended as an objective measure to identify situations that are complex enough such that centralized control would still be required in the concept of Free Flight.[6] Kopardekar et al.[7] defines Dynamic Density as the collective effect of all factors, or variables, that contribute to sector level air traffic control complexity or difficulty at any given time. Multiple metrics related to Dynamic Density have been proposed using various sets of variables representing complexity factors.[8–12] These metrics formulates the relationship between complexity factors and controller indicated complexity level. Four popular Dynamic Density metrics are examined by Kopardekar and Magyarits[13] . Twelve complexity factors with high weightings from the four metrics have been identified and incorporated into one single metric. Further study indicates that the Dynamic Density metric performs better than aircraft count.[7] However, using Dynamic Density also has its shortcomings. Factors weightings are applicable only to the sector in which the data are collected and validated.[3] Some other complexity models also attempt to capture intrinsic complexity factors. For example, Delahaye and Puechmorel[14] use factors derived directly from the locations and speeds of aircraft.

In this study, cognitive complexity was measured through controller's evaluation of the complexity contribution of each individual aircraft. A few studies have proposed complexity metrics based on aircraft count.[15–19] However, no complexity measure used in the past has the ability to explicitly assess each aircraft's contribution to controller's cognitive complexity to support the development of those aircraft-based complexity metrics. An aircraft-based complexity assessment method was developed to obtain aircraft specific information. In this method, experiment participants were asked to identify specific aircraft in a traffic

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situation that contribute higher complexity load to the overall complexity level than a standard aircraft. This paper presents the procedure of the aircraft-based complexity assessment and the analysis of complexity factors using the data obtained from this complexity assessment.

II. Methodology

An aircraft-based complexity assessment, different from the most common used complexity assessment methods, was developed to explicitly assess each aircraft's contribution to controller's overall cognitive complexity level. Most common techniques and measures used to develop, validate or calibrate complexity metrics are summarized in Table 1. Among these measures, system performance and physiological measures can only indirectly reflect controller cognitive complexity level. Controller activities can indicate how busy a controller is, but not how complex the situation is. The measures of controller perceptions and reported workload are most often based on aggregated information of a traffic situation, for example, the workload rating is always a combined effect of all the aircraft and various complexity factors.

Table 1. Example Measures Used to Validate Complexity Metrics

Measure Group	Measure Example	Used in
System performance	Operational errors, delays, fuel burn, efficiency	17, 20–22
Physiological measures	Eye blink rate, pupil diameter, visual fixation frequency, EEG, EMG, EOG, heart rate measures, respiration, biochemical activity	23–25
Controller activities	Number and duration of communications, interface interactions, coordination events, handoffs	9, 26
Controller perceptions and reported workload	Air Traffic Workload Input Technique (ATWIT), NASA TLX, expert judgment/over the shoulder ratings, complexity factor rankings	8, 9, 26, 27

The aircraft-based complexity assessment was designed to assess the complexity contribution of individual aircraft in post-simulation reviews. In this method, experiment participants were asked to identify which aircraft were contributing high complexity load to the overall cognitive complexity level. Aircraft that under jurisdiction of the air traffic controller but did not need additional monitoring were considered as the standard aircraft. Any aircraft that contribute more complexity load than the standard aircraft were considered as high complexity aircraft. The assessment was conducted in post-simulation reviews to prevent interfering with participants' on-going activities. A simulation replay capability was used to help the participants to recall the traffic situation. The replay was paused at predefined times and participants were asked to identify high complexity aircraft in those traffic situations. Figure 1 is a sample screen-shot obtained from the aircraft-based complexity assessment.

The results obtained from the aircraft-based complexity assessment gave us the opportunity to associate possible complexity factors with the identified high complexity aircraft. Potential complexity factors were evaluated based on the characteristics of the identified high complexity aircraft. Two approaches were applied to analyze the factors that made aircraft contributing high complexity load. First, the complexity factors reported by controllers were evaluated using aircraft-based complexity assessment data. Then, a database for all the aircraft evaluated in the aircraft-based complexity assessment was constructed. Each aircraft had a complexity level of high or low based on whether it was considered as high complexity or not by the participants. Each aircraft also had a series of observable states, which were derived from the spatial and temporal information of the traffic situation. Classification tree analysis was then used to identify the characteristics of an aircraft and its relationship to the air traffic situation that determined its complexity level. The results are helpful to better understand the factors that impact controller cognitive complexity.

III. Experiment

In this work, we leveraged on the human-in-the-loop high fidelity ATC simulation in the Multi-Sector Planner (MSP) II experiment conducted at NASA Ames Research Center. The experiment was designed by NASA and FAA to assess a coordination position (Multi-Sector Planner) that bridges the gap between the traffic strategic planning and the sector tactical operations. The simulation provided an advanced ATC environment to assess cognitive complexity of radar controllers. The focus of our work is to measure the

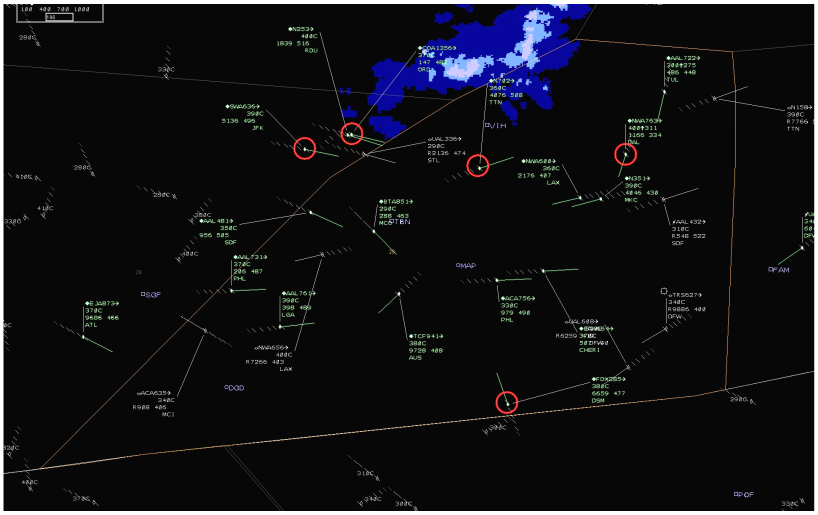

Figure 1. A sample screen-shot obtained from the aircraft-based complexity assessment. A controller evaluated all the aircraft under jurisdiction. Aircraft contributing high complexity were identified in red circles.

cognitive complexity of radar controllers based on the contribution of individual aircraft. Thus, the aircraft-based complexity assessment was integrated in the MSP II experiment; however, this work was only a separate and small part of the MSP II experiment.

A. ATC Environment and Simulation Capabilities

The ATC environment in the MSP II experiment included several proposed NextGen technologies: ground-ground and air-ground digital data communications; enhanced automation tools to detect traffic conflicts and weather penetrations; tools for trajectory and flow manipulation.[28,29] Sectors controlled by participants in the simulation were high-altitude, trajectory-based airspace (Figure 2). All aircraft were flown by pseudo pilots. Roles and responsibilities of radar controllers in the experiment remained the same as they are in current operations.

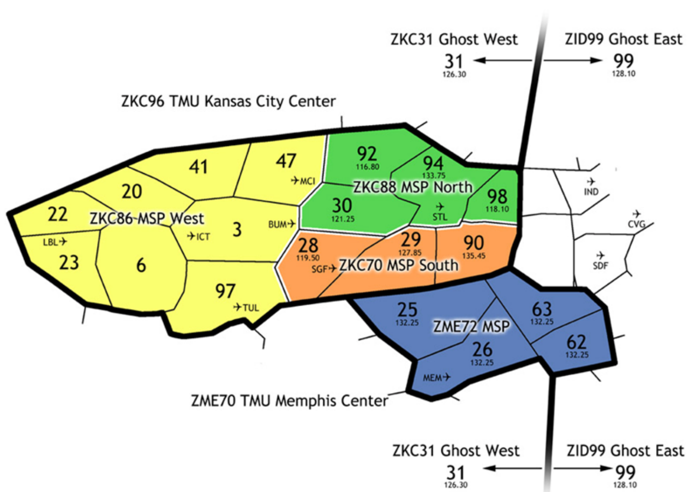

Figure 2. Airspace involved in the MSP II experiment.[28] The sectors which had active controllers were sectors 28, 29, 30, 90, 92, 94, and 98.

B. Participants

The MSP II experiment focused on the coordination positions, including radar controllers and several MSP coordination controllers. Meanwhile, this work focused on the sector radar controllers. The sectors which had active controllers were sectors 28, 29, 30, 90, 92, 94, and 98 (Figure 2). All seven radar controllers (6 male, 1 female) who participated in the aircraft-based complexity assessment were Certified Professional Controllers (CPCs).

C. Procedure and Data Collection

There were 16 simulation runs in the MSP II experiment to test different scenarios and different team configurations. Each run was 75 minutes long. After each 75-minute simulation run, a screen recording of this run was replayed to the controller who was in position. The screen recording was paused at three predefined times. At each sample time, the controller was asked to identify aircraft that contributing higher cognitive complexity than a standard aircraft in that sector. To identify those high complexity aircraft, the controller only needed to click on the screen-shot of that sample time.

During the experiment, 336 sample screen-shots (7 controllers x 16 runs x 3 specified times in a run) were collected. In these samples, there were 5581 aircraft observable; of these, 776 (13.9%) aircraft were identified as high complexity aircraft. The information of traffic situation was recorded during the whole simulation, including each aircraft's position, heading, speed, flight plan, time to traffic conflict, time to weather penetration, and data link communications. The information of sector boundaries and weather impact areas was also available.

Besides the aircraft-based complexity assessment, a paper-and-pencil questionnaire was administered to each of the seven participants at the end of the 16 simulation runs. The participants were asked to identify the reasons they had used to identify high complex aircraft from a list of potential reasons. There was an opportunity for them to identify additional reasons.

IV. Aircraft-Based Complexity Factors Analysis

A. Controller Reported Complexity Factors

Potential reasons for considering aircraft as high complexity were collected through the questionnaire. Table 2 summarizes all the reasons reported by the controllers. The top five complexity factors are Potential traffic conflict, Climbing/Descending, Potential weather penetration, Requests from ATC agents, and Crossing a major flow. These complexity factors were highlighted by most of the controllers.

Potential traffic conflicts and weather penetrations were detected and recorded by the automation tool embedded in the simulation. The automaton tool could detect traffic conflicts within 12 minutes and weather penetrations within 30 minutes. The requests from ATC agents were 4-dimensional re-routing data-link requests sent to radar controllers by traffic management coordinators or multi-sector planners to adjust flow strategies in the area. Radar controllers could reject or implement the re-routing requests according to the local traffic situation and their workload limits.

Table 2. Complexity Factors Reported by Controllers

Reason for aircraft considered as high complexity	Controllers highlighted	
	Number	Percentage
Potential traffic conflict	7	100%
Climbing/Descending	7	100%
Potential weather penetration	6	86%
Requests from ATC agents	6	86%
Crossing a major flow	4	57%
Entering the sector	2	29%
Helping overloaded sector	1	14%

B. Correlation of Controller Reported Complexity Factors with Aircraft-Based Complexity Assessment Data

Controller reported complexity factors were examined by using the results obtained from the aircraft-based complexity assessment procedure. This analysis involved the four most significant complexity factors reported: potential traffic conflict, climbing/descending, potential weather penetration, and requests by ATC agents; all highlighted as relevant factors by more than 80% of the controllers. First, several graphs are shown (Figure 3(a), 3(b), 3(c), 3(d)), representing the percentage of high complexity aircraft in the subsets characterized as matching and non-matching each complexity factor individually. Then, a more rigorous assessment of correlation based on the chi-square test was performed.

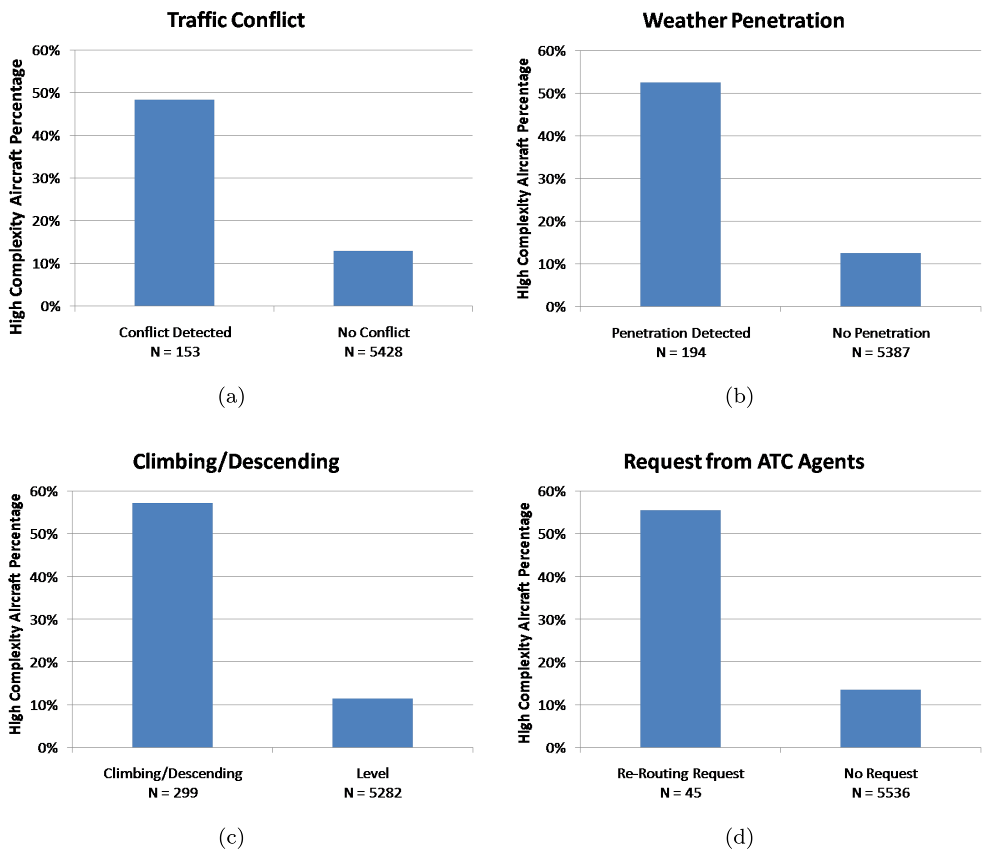

Figure 3. The impact of each controller reported complexity factor on the percentage of high complexity aircraft. Aircraft with traffic conflicts were more likely to be considered as high complexity percentage-wise than aircraft without traffic conflicts. Similar results were obtained for weather penetrations, climbing/descending, and requests from ATC agents.

As shown in Figure 3(a), aircraft with traffic conflict detected had a larger percentage (nearly 50%) to be considered high complexity by controllers in the complexity assessment procedure. In addition, in the set of events in which traffic conflicts were not detected, only 12 percent of them were considered as high complexity. A chi-square test of independence was performed to examine the relation between high complexity aircraft percentage and the traffic conflict factor. The test result showed a significant correlation between the percentage of high complexity aircraft and the traffic conflict factor, $\chi^2(1, N = 5581) = 156.07, p < .001$. Consequently, aircraft with traffic conflicts were more likely to be considered as high complexity than aircraft without traffic conflicts. However, this factor alone does not explain all the cases of aircraft considered high complexity, so it will be necessary to combine this information with other factor as it is shown in the following sections.

For the weather penetration, similar results were obtained as shown in Figure 3(b). More than half (53%) of aircraft with potential weather penetrations were considered as high complexity, while only 13 percent of aircraft with no weather penetrations were considered as high complexity. The result of chi-square test showed the correlation between high complexity aircraft percentage and the weather penetration status was significant, $\chi^2(1, N = 5581) = 251.10, p < .001$.

Similar results were obtained for aircraft in climbing or descending and aircraft with re-routing requests. As shown in Figure 3(c), fifty-seven percent of aircraft in climbing or descending were considered as high complexity, while only 11 percent of aircraft flying level were considered as high complexity. The result of chi-square test showed the percentage difference was related to aircraft's vertical motion status, $\chi^2(1, N = 5581) = 494.49, p < .001$. For aircraft with re-routing requests, 56 percent of them were considered as high complexity, comparing to 13 percent for the aircraft without re-routing requests (Figure 3(d)). The chi-square test of independence showed high complexity aircraft percentage was related to the re-routing requests, $\chi^2(1, N = 5581) = 65.74, p < .001$.

C. Analysis of Complexity Factors by Classification Tree Method

A multi-dimensional classifier was needed to explore various potential factors that contribute to aircraft-based complexity. The complexity level of an aircraft could be the result of multiple complexity factors. For instance, controllers might consider an aircraft as high complexity because that aircraft was in climbing, while identified another aircraft as high complexity because that aircraft was going to have a conflict. Some other high complexity aircraft could be chosen as a result of the combined effect of multiple factors. A classification and regression tree method was chosen as the multi-dimensional classifier to explore various potential complexity factors, since the results can be interpreted easily by the graphically displayed decision tree.

The classification tree technique created a tree-like decision model to classify the complexity status of each aircraft based on observable states, which were derived from the spatial and temporal information of the traffic situation. The hierarchy of decision nodes in the tree provides a visual representation of the observable states used and the relationship among them. For each aircraft in the screen-shots, the complexity status of that aircraft was either high or low, depending on whether the aircraft was identified as contributing high complexity or not by the controller. The observable states were the measures of possible complexity factors calculated using the traffic situation information. The classification and regression tree algorithm in Breiman et al.[30] was used to create and test the trees. The data was split into two sets: 70% as the training data set and 30% as the test data set.

As a preliminary analysis, 18 observable states were included to develop the classification tree. Four of them were measures of the four complexity factors reported by controllers, which were vertical motion, traffic conflict status, time to weather penetration, and re-routing requests status. All the 18 observable states are summarized in Table 3.

Table 3. Observable states included to develop the classification tree

Sector	Altitude
Future altitude change within 5 minutes	Vertical motion*
Speed	Heading
Traffic conflict status*	Time To weather penetration*
Weather at current location	Re-routing requests status*
Distance from origination	Distance to destination
Direction to destination	Time to entering boundary
Distance to nearest sector boundary	Outside or in the sector

* Observable states related with controller reported complexity factors

A cost matrix needs be specified in the classification tree algorithm to create a decision tree that best suits the user's need. Each element in the cost matrix ($C(i, j)$) specifies the cost of classifying a point into class j if its true class is i. The algorithm creates a decision tree to classify all the points in the data set which minimizes the total cost. The default setting of the cost matrix uses a cost of one for both miss detection [a] and false alarm [b] ($C(\textit{low, true high}) = C(\textit{high, true low}) = 1$), and a cost of zero for correct classification ($C(\textit{high, true high}) = C(\textit{low, true low}) = 0$). However, since the objective of this study is to identify all the

[a] Miss detection: high complexity considered by controllers, but classified as low complexity by the classification tree
[b] False alarm: low complexity considered by controllers, but classified as high complexity by the classification tree

potential factors contributing to high complexity, a larger penalty was placed on the miss detections than the false alarms. The cost matrix was specified as two for miss detection ($C(low,\ true\ high) = 2$) and one for false alarm ($C(high,\ true\ low) = 1$). The objective was to maximize the correct classification rate for high complexity aircraft, while keeping the correct classification rate for low complexity aircraft at a reasonable level.

A classification tree was created using the 18 observable states and a cost matrix specified above. The classification tree after pruning (a standard procedure to avoid over-training) is shown in Figure 4. The decision nodes in the tree could be used to understand what the most influential observable states were. Initially, 18 observable states were included to develop the classification trees; however, only five of them remained in the tree, since the other observable states were eliminated during pruning. The most influential observable states are listed in Table 4. Observable states measuring three of the four complexity factors reported by controllers (Climbing/Descending, Weather penetrations, Traffic conflicts) were remained in the tree.

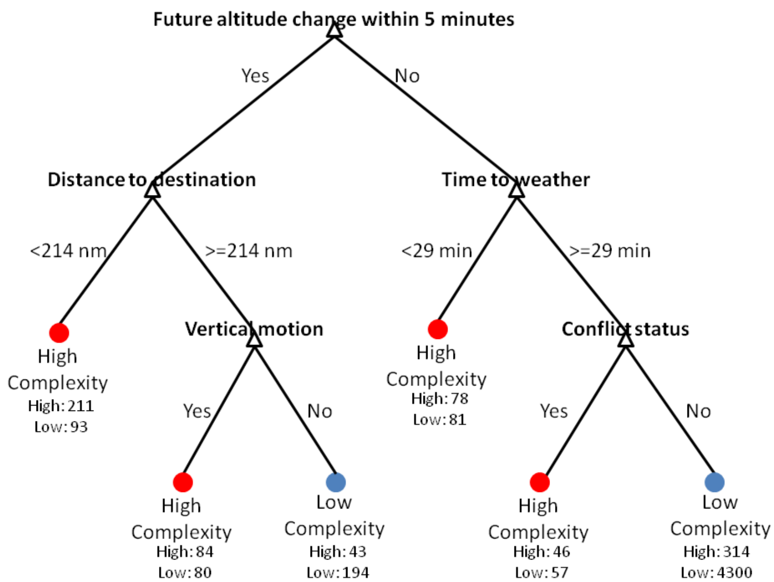

Figure 4. Classification tree trained with 18 observable states. The numbers under each node are the counts of true high complexity aircraft and the true low complexity aircraft for the whole data set including training data and test data.

Table 4. Observable states remained in the classification tree

Future altitude change within 5 minutes
Time to weather penetration*
Distance to destination
Vertical motion*
Traffic conflict status*

* Observable states related with controller reported complexity factors

The hierarchal relationship of the decision nodes in the classification tree could explain what the relationship was among the observable states. From the classification tree as shown in Figure 4, one observes that the most effective observable state to separate high complexity aircraft from all the aircraft was future altitude change within 5 minutes. Aircraft that would change its altitude within 5 minutes were likely to be considered as high complexity except when it was far from the destination and was in level flight. For aircraft without future altitude change, they would be considered as high complexity either if they were going to enter a weather impacted area within 29 minutes or if they were going to have a conflict with other traffic.

The results of decision tree evaluated with the whole set of data show that 419 out of 776 high complexity aircraft (54%) were correctly classified. However, 314 high complexity aircraft were classified into the low complexity node at the bottom right of the tree (these are missed events). In addition, there were several non-complex events classified as high complexity, which represented the number of false alarms. In total, the results of the decision tree involves 357 misses and 311 false alarms, therefore 668 mistakes over 5581 events or 12%. The results of the decision tree are encouraging if compared with using any of the complexity factor as the only criteria for classifying aircraft. Vertical motion attained the best results as single complexity factor, but a classifier based only on this factor is able to detect only 170 (22%) of high complexity aircraft with 735 (13.2%) mistakes (misses plus false alarms).

Although the decision tree has been very useful to identify complexity factors, the classification accuracy suggests that the current 18 observable states do not contain enough information to explain the complexity status of an aircraft. There are various other potential complexity factors that are not captured by the 18 observable states, for example the structure-based complexity factors. Several studies pointed out that one important aspect of controller cognitive complexity is the impact of structure.[5,8,31–33] One of the hypotheses is that aircraft is usually more complex when it is near a critical point where several major flows merge or intersect. Another hypothesis is that aircraft is less complex when it belongs to a standard flow in the sector. The performance of classification tree might be improved if appropriate measures of complexity factors considering the impact of structure are included in the observable states.

V. Conclusion and Future Work

The aircraft-based complexity assessment was found to be an effective tool to explore and evaluate the aircraft-based complexity factors contributing to controller's overall cognitive complexity level. This complexity probe technique allowed specific aircraft that contributed high complexity load to be identified. An investigation of possible complexity factors associated with those specific aircraft was performed. Complexity factors were examined based on the questionnaire results and then evaluated by correlating them with the results obtained from aircraft-based complexity assessment. Four complexity factors (potential traffic conflict, vertical motion, potential weather penetration, and re-routing requests) identified by controllers were observed to correlate with the percentage of high complexity aircraft.

As a second step, the classification tree method was applied to classify the complexity state of each aircraft based on the observable states derived from the information of the aircraft and the airspace. Preliminary results revealed the combinations of observable states that likely influence the complexity contribution of an aircraft. The most influential complexity factors found so far are future altitude change within 5 minutes, time to weather penetration, distance to destination, vertical motion, and potential traffic conflict status.

As stated earlier, a primary motivation of this study is to understand factors that are contributing to controller cognitive complexity in future air traffic control environment. The current available observable states contain limited information to explain all the different situations when an aircraft to be considered as high complexity. Additional observable states that can represent complexity factors to classify the high complexity aircraft will be identified and developed . Implications on cognitive complexity metrics in future operations may be addressed building on the results of this study.

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