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# Assuring Autonomous UAS Traffic Management Systems Using Explainable, Fuzzy Logic, Black Box Monitoring

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***Abstract*—Researchers have shown via simulation and early flight tests the feasibility and safety benefit of adding autonomy to the concept of unmanned aircraft system (UAS) Traffic Management (UTM), which is the Federal Aviation Administration's (FAA) vision for air traffic management below 400 feet. Such simulations are a complex interaction between UAS, UAS operators, and the UTM system. Autonomy in this system is achieved through the algorithms used for strategic de-confliction (UAS launch scheduling) and flight planning (creates waypoints from delays introduced by scheduling), which have been shown to improve safety in congested UAS airspace. However, autonomous algorithms have been known to make poor decisions without notice, and thus need to be constantly monitored to prevent these decisions from negatively affecting airspace performance and safety. This is the impetus for developing and implementing a fuzzy assurance black box monitor. Using a rule set generated from parameters that have been shown to improve safety in congested airspace, this monitor only considers the inputs and outputs of the autonomous UTM system to estimate the risk of the autonomous algorithms making poor decisions. Fuzzy rules that fire during the operation of the fuzzy assurance monitor help identify offending algorithms and their poor decisions, and thus provide a level of explainable artificial intelligence (AI) capability. The goal is to use fuzzy inference rules to evaluate the performance of strategic de-confliction algorithms in the UTM simulation. We investigate several airspace operational use cases (i.e., normal and rogue behavior in congested airspace) and several different autonomous UTM configurations (No Strategic de-confliction and Strategic de-confliction). The simulation data is analyzed with the help of the fuzzy inference system rules to help identify offending algorithms and poor decisions that lead to unsafe airspace. Our results show that the fuzzy assurance monitor is able to use the inputs and outputs of the autonomous UTM system to assign safety risks appropriately across use cases and autonomous UTM configuration. The fuzzy assurance monitor can also provide insight on the performance trade-offs of black-box algorithms.**

***Index Terms*—drone, UAS, UTM, autonomy, assurance**

## I. Introduction

In recent years, the use of UAS and other air vehicles has expanded from mostly military/government applications to commercial and personal applications. The demand for small unmanned aircraft is still growing to the point that the Federal Aviation Administration (FAA), NASA, other federal agencies and industries are exploring potential operation of unmanned aircraft system (UAS) traffic management. Currently the general concept of UAS traffic management (UTM) [7] includes FAA systems and operators communicating real-time. UAS statuses and airspace restrictions are exchanged between FAA systems and UAS operators. Researchers have recently shown that autonomy can be added to the UTM concept through the use of algorithms for strategic de-confliction and flight planning, which improve safety in congested airspace.

In [4], the authors introduce an autonomous version of UTM via simulation. The authors investigate the feasibility of replacing some of the human-in-the-loop operations of UTM with autonomy. They found that in a congested airspace (i.e., 300 airspace operations per hour or more), autonomous strategic de-confliction improves safety (i.e., Dynamic near mid-air collisions are almost zero) by sacrificing mission completion performance [4]. However, because of the known intermittent aberrant behavior of autonomy [9], it is becoming increasingly necessary to monitor and assure these algorithms [10]. This is the impetus for the development of our fuzzy assurance monitor.

The overall goal of autonomy assurance is to provide efficacy in autonomous systems [11]. A system without certain efficacy creates distrust. Thus, the distrust of autonomous systems may hinder the progress of AI applications until the research community can bridge the gap of distrust and reach a satisfying equilibrium of AI usage and desired results [9] [10]. We posit that the explanability of AI [13] decisions is a step in the direction of system efficacy and assurance.

The UTM architecture is still in concept stage and thus there are no production systems [7]. In this paper we chose to take a black box monitoring approach and use fuzzy logic to assess the risks of the algorithms in autonomous UTM of making bad decisions. Below are works that are related to our efforts.

The authors in [3] and [2] investigated the use of fuzzy logic for UAS control in strategic and tactical de-confliction. Their approach is similar to our own, except their use of a fuzzy inference system is to implement an autonomous version of UTM rather than risk evaluation. To our knowledge, there are no other recent works that apply fuzzy logic to the UTM concept.

In this paper we assure autonomous UTM by using a fuzzy risk monitor for black box strategic de-confliction. The monitor is based on a set of fuzzy rules derived from parameters and concepts [4] that have shown to provide safety in congested airspace. Also, the fired rules from this fuzzy inference system (FIS) are used to identify offending algorithms and explain their poor decisions.

Our contributions are as follows: (1) we use insight from parameters that have been shown to provide safety in congested airspace to design fuzzy rules for an explainable autonomous UTM fuzzy assurance monitor, (2) we implement this fuzzy assurance monitor using MATLAB, and (3) we use several airspace use cases and autonomous UTM configurations to demonstrate the efficacy of this approach. The rest of this paper is organized as follows. In Section 2 we introduce fuzzy inference systems, and in Section 3 we discuss our fuzzy assurance monitor implementation. In Section 4 we introduce the experimental evaluation, Section 5 we discuss our results, and in Section 6 we conclude the paper with a summary.

## II. Fuzzy Inference Systems

A fuzzy FIS is a human-readable ruled-based system meant to provide inferences while considering uncertainty [12]. The inputs and outputs of a FIS are real numbers called crisp values. Crisp values belong to bounded sets associated with chosen ranges [1]. Human-readable labels are used to describe the ranges. Each FIS input is called a fuzzy member and the human-readable labels are called membership functions [12]. Membership functions are created based on expert knowledge of data that represents the numerical ranges of members with human-readable labels. The ranges can overlap to represent uncertainty in labeling. Membership function labels are used to create rules. These rules tie input label combinations to output labels and result in human-readable conditional statements.

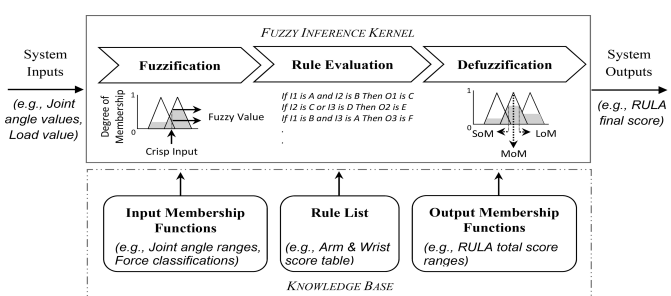


Fig. 1. Example Fuzzy Inference System diagram [14]

In operation, numerical values are feed into a FIS. The values are labeled based on the membership functions. The process of translating from numbers to labels is called fuzzification. Rules are fired based on the input labels which provides output labels. The reverse of fuzzification (defuzzication) takes output labels and translates them to numbers. The two most common types of FIS are Mamdani and Sugeno. In this paper, we implement a Mamdani FIS using Matlab.

The example in Figure 1 illustrates a Mamdani FIS, where crisp values come into the system and get mapped to the membership function (i.e., become fuzzified) in the Fuzzification step. Then, every rule that corresponds to fuzzified values are said to have fired during the Rule Evaluation step. Finally, during the Defuzzification step, the ”fired” rules are evaluated and produce a crisp output using defuzzification methods such as centroid (center of mass), Fuzzy Or (maximum value), or some other method [15].

## III. Fuzzy Assurance Monitor Implementation

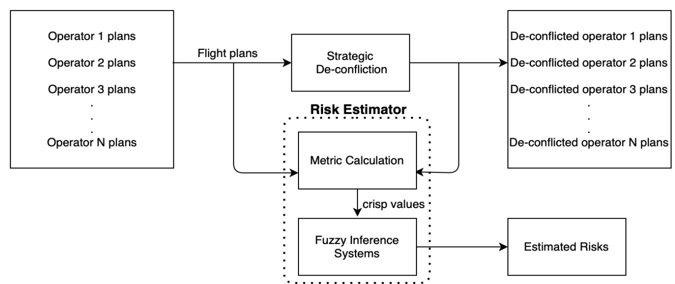


Fig. 2. Placement of fuzzy inference systems in UTM

The illustration in Figure 2 shows a diagram of the mapping of the fuzzy risk estimator to the inputs and outputs of the autonomous UTM strategic de-conflictor (i.e., scheduler). The risk estimator uses these inputs and outputs to begin Further and Closer Warning percentage calculations (described in sections 5A - 5B) and De-confliction Distance and Time Impact metric calculations (described in sections 5C - 5D). Then, these crisps metric calculations and percentages are passed to the FIS to compute estimated risks.

The fuzzy members and bounded values for the risk estimators are illustrated in Table 1 and described below in 5A - 5E. The 12 fuzzy rules for Collision Risk, which involve Closer and Further Warning, are derived from Table 2. Similarly, there are 75 fuzzy rules for Efficiency Risk, which involve the use of de-confliction Distance and Time Impact and Priority, but because of space limitations, they are not listed.

TABLE I
Pre-planning fuzzy members

| Name | Input/Output | Minimum | Maximum |
|---|---|---|---|
| Further Warning | I | 0 | 1 |
| Closer Warning | I | 0 | 1 |
| Deconfliction Distance Impact | I | -∞ | ∞ |
| Deconfliction Time Impact | I | -∞ | ∞ |
| Priority | I | 0 | 9 |
| Collision Risk | O | 0 | 1 |
| Efficiency Risk | O | 0 | 1 |

### *A. Further Warning*

Further Warning is a fuzzy member that receives bounded inputs (0-1) in 2-dimensional space from the autonomous UTM system as shown in Table I. The warnings are distance checks between UAS and all obstacles (fixed and moving). The values in Figure 3 are percentages of UAS mission waypoints that come within 60 m of obstacle. The 60 m horizontal threshold is chosen to be bigger than a Dynamic Near Midair Collision (Dynamic sNMAC), which is the number of times UAS breach the same area (15.24 meters horizontally) [4].The further warning memberships are very clear (VC), mostly clear (MC), partially clear (PC) and barely clear (BC).

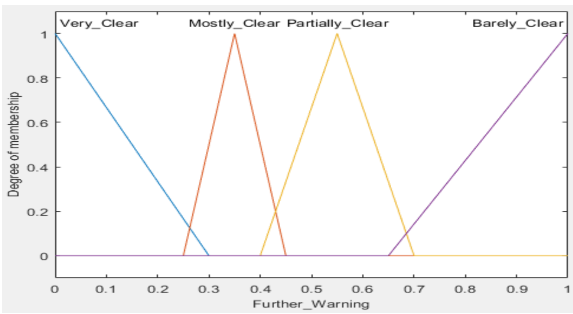


Fig. 3. Further warning membership

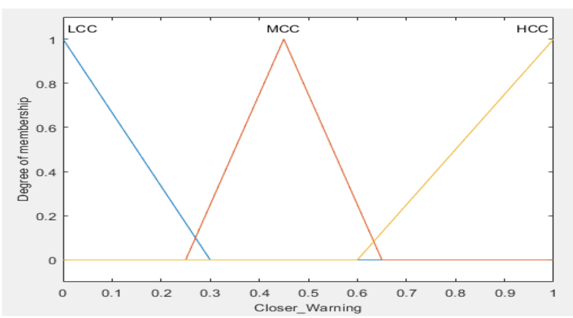


Fig. 4. Closer warning membership

### *B. Closer Warning*

Closer Warning is also a fuzzy member that receives bounded inputs in 2-dimensional space similar to further warning (0-1). The values in Figure 4 are percentages of UAS mission waypoints that come within 40 m of any obstacle. The 40 m threshold is chosen to be bigger than a Dynamic sNMAC. The closer warning memberships are light close collisions (LCC), many close collisions (MCC), and heavy close collisions (HCC). The ranges for each member are chosen to slightly increase from light to heavy to increase the rate that the collision risk increases.

### *C. De-confliction Distance Impact*

De-confliction Distance Impact is a fuzzy member that receive bounded inputs from the autonomous UTM system. The De-confliction Distance Impact metric represents a percent increase or decrease from the original distance, the percentages are not bounded from 0 to 100 but from $-\infty$ to $\infty$. The distance of a flight plan is calculated using the euclidean distance between adjacent points as shown in Equation 1 where N is the number of waypoints and W = [W1, W2, W3, … Wn] is the list of ordered waypoints.

***Eq 1. Distance*** = $\sum_{i=1}^{N-1}((W_{i+1,x} - W_{i,x})^2 + (W_{i+1,y} - W_{i,y})^2 + (W_{i+1,z} - W_{i,z})^2)^{1/2}$

The distance impact is found by calculating the distance of a flight plan before and after de-confliction. Then the differences are calculated through subtraction of the final and initial distances which are then divided by the initial distances. This process is shown through Equation 2.

***Eq 2. PercentDistanceImpact*** = $(D_F - D_I) \div D_I$
***Eq 3. PercentTimeImpact*** = $(T_F - T_I) \div T_I$

Figure 5 shows the membership functions for de-confliction distance impact. De-confliction distance impact has the following membership functions: major improvement (MI), partial improvement (PI), negligible difference (ND), partial deterioration (PD) and major deterioration (MD). The ranges increase away from the middle member to create dramatic increases in risk as the mission is inflated or deflated.

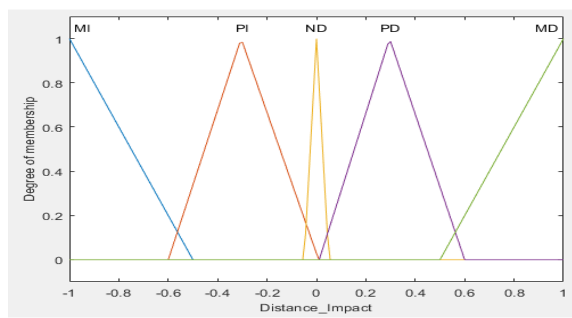


Fig. 5. De-confliction distance impact membership

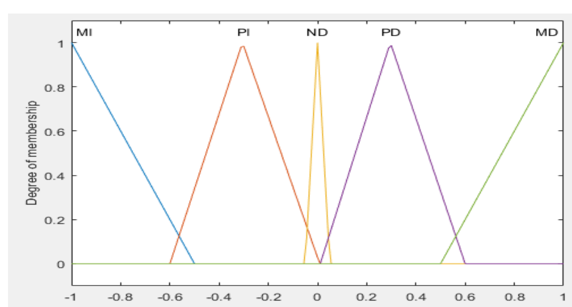


Fig. 6. De-confliction time impact membership

### *D. De-confliction Time Impact*

De-confliction Time Impact is another fuzzy member that receive bounded inputs ($-\infty$ - $\infty$) as shown in Table 1.

Similarly to distance impact, the De-confliction Time Impact metric represents the percent changes in flight plan time from before and after strategic de-confliction. The time is the number of waypoints in a flight plan minus 1 for coding logic (first waypoint is the start location at time 0 seconds). Then the differences in time are calculated through subtraction of the final and initial times. The differences are then divided by the initial times. This process is shown through Equation 3.

The illustration in Figure 6 shows the membership functions for de-confliction time impact. The membership functions are similar to Distance Impact.

### *E. Priority*

UAS priority is another fuzzy member that could receive bounded (i.e., 0 - 9) input from the autonomous UTM system. This fuzzy member allows different priorities to be placed on UAS. The membership plots are shown in Figure 7. The experiments use priority as a control to exhibit the sensitivity of Efficiency Risk. In this paper, we fixed the priority to the highest value (i.e., 9) for all UAS.

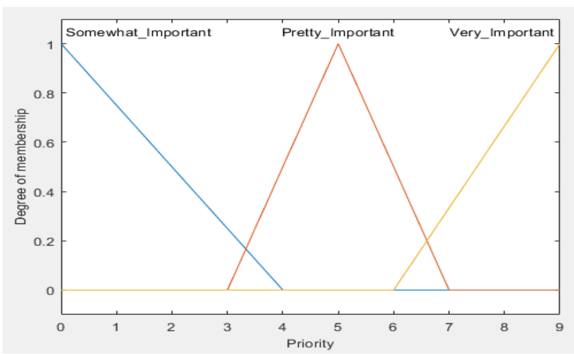


Fig. 7. Priority membership

### *F. Collision and Efficiency Risks*

TABLE II
COLLISION RISK FUZZY RULE MATRIX

| | | **Further Warning** | | | |
|---|---|---|---|---|---|
| | | Very clear | Mostly Clear | Partially Clear | Barely Clear |
| **Closer Warning** | Light Close Collisions | Barely Risky | Barely Risky | Somewhat Risky | Somewhat Risky |
| | Many Close Collisions | Risky | Risky | Very Risky | Very Risky |
| | Heavy Close Collisions | Too Risky | Too Risky | Too Risky | Too Risky |

The output risks are percentages as seen in Figure 8 for Collision and Efficiency Risks, which have the same membership functions. The membership functions are: barely risky (BR), somewhat risky (SR), risky (R), very risky (VR) and too risky (TR). The memberships are chosen arbitrarily such that the first four ranges are similar in length and the last (TR) is larger than all the rest . For our FIS, we tuned the membership functions based on parameters and insight from [4], which have been shown to improve safety in simulated congested airspaces.

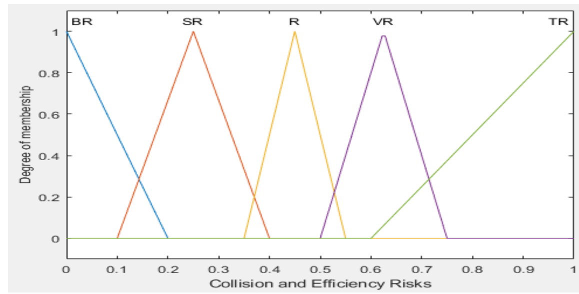


Fig. 8. Collision and Efficiency Risk membership

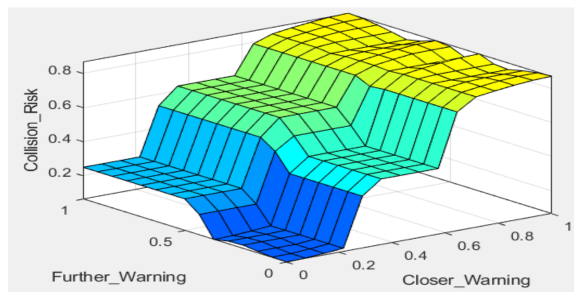


Fig. 9. Pre-planning collision risk rules

*1) Collision Risk System:* The risk increases as both the Closer and Further warning increase. The Closer Warning is weighed more than the Further Warning so the risk increases faster when it goes up. The Collision Risk graph provides a visual representation of the crisp input to output relationship, see Figure 9.

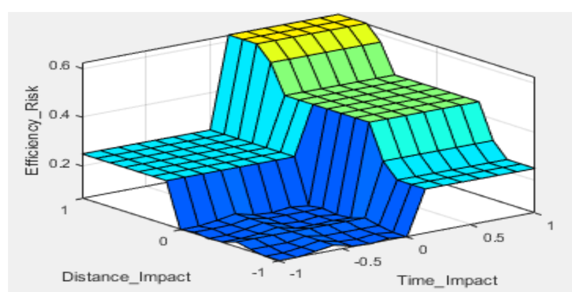


Fig. 10. Pre-planning efficiency risk rules

*2) Efficiency Risk System:* The risk of losing mission efficiency is based on the amount of distance and time inflation. The risk jumps as the missions are inflated and stays around zero when deflated, as seen in Figure 10. The system is tuned to be more sensitive to time than distance because UAS velocity is kept constant for the experiment, so increases or decreases in time imply similar affects on distance.

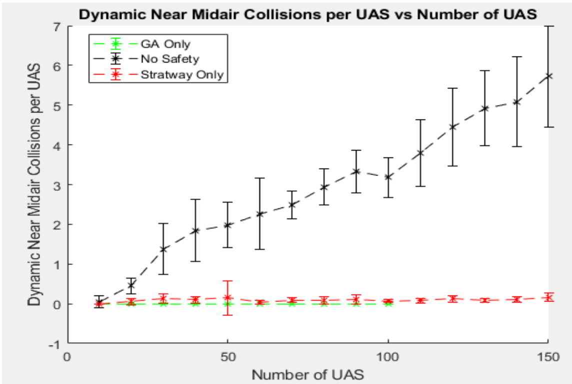


Fig. 11. Dynamic sNMAC results

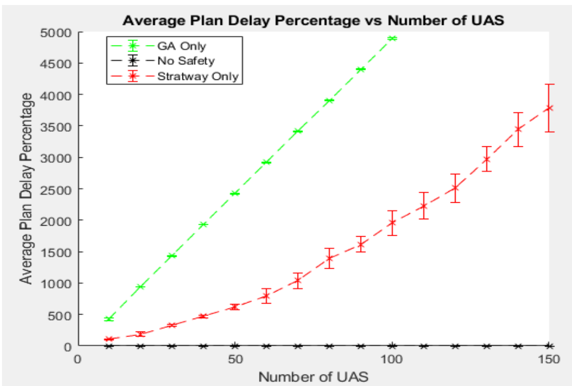


Fig. 12. Plan Delay results

## IV. Experimental Evaluation

### A. Experimental Setup

Our experimental setup is composed of an autonomous UTM simulation taken from [4]. In our simulations we used strategic de-confliction via a genetic algorithm (GA) [6] based scheduler and a scheduler based on the NASA Stratway algorithm [5]. Also, flight planning was done using the RRT* algorithm [8]. We implemented our black box fuzzy inference monitor using MATLAB (Mamdani). We received results from

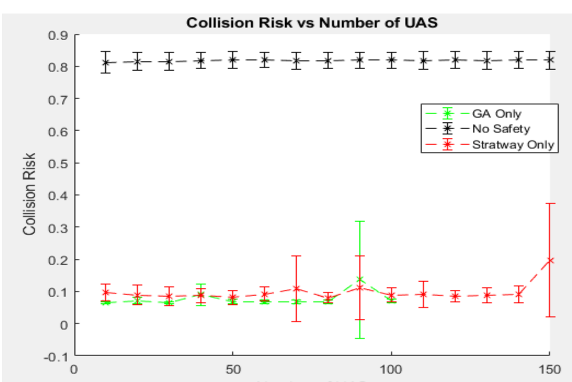


Fig. 13. Collision Risk results

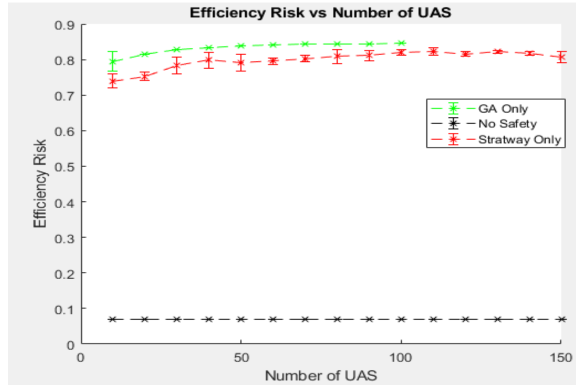


Fig. 14. Efficiency Risk results

our fuzzy monitor by running autonomous UTM Monte-Carlo experiments using a multi-node cluster that had 8 operational nodes, which collectively provided 384 available CPUs.

### B. Experimental Procedure

In order to test the fuzzy assurance monitor's ability to properly assess autonomous UTM airspace safety, several experiments were done with different autonomous UTM configurations. (1) No strategic de-confliction (i.e., No Safety), (2) Strategic de-confliction (i.e., GA Only), and (3) Strategic de-confliction (i.e., Stratway Only). These experiments were done using both normal UAS behavior (i.e., UAS conforming to de-conflicted flight plans) and rogue UAS behavior (i.e., UAS deviating +/- 1000m in 2-dimensional space from de-conflicted flight plans). Specifically, Monte-Carlo autonomous UTM simulations were run with the probability of a UAS going rouge varying from 0% to 90% (chose randomly) and the number of UAS varying from 10 to 150.

## V. Results and Discussion

The experiments are designed to test the ability of the black box fuzzy assurance monitor to analyze the inputs and outputs of the autonomous UTM system and determine if there is an impact to safety or efficiency and then to assign the associated risk. In this phase of our work, we only test the fuzzy risk monitor on safe operation (i.e., strategic de-confliction or fully functioning autonomy algorithms) or unsafe (i.e., no strategic de-confliction or fully failed autonomy algorithms). In future work we plan to develop realistic models of varying levels of failing autonomous algorithms to further test our fuzzy risk monitor.

We know from [4] that when strategic de-confliction is used in a congested airspace, Dynamic sNMACs are reduced to almost zero, see our own results in Figure 11. Also, the authors in [4] state that this safety comes at the cost of the mission completion time being significantly affected, see our own results in Figure 12.

### A. Collision Risk

The results in Figure 13 suggests that Collision Risks are extremely high (approximately 80%) when neither schedulers are used in the autonomous UTM system, but are extremely low (approximately 10%) when either scheduler is used. This aligns well with results from [4].

To explain the decisions made by our risk monitor, we look into the fired fuzzy rules that produced: (1) the extremely high risk percentage when no strategic de-confliction was used in the autonomous UTM system and (2) the low risk percentage when strategic de-confliction was used for one of the runs of the Monte-Carlo simulation. This is illustrated in Rule 1. Note, when there is no strategic de-confliction (i.e., no schedulers are used), there is no pre-planned collision avoidance; thus, it is extremely likely that the Closer Warning threshold of 40 m and Further Warning threshold of 60 m are violated. In fact, according to Rule 1, to produce a crisp value of 80% or more (i.e., Collision Risk is Too Risky), both Closer and Further Warning thresholds within the autonomous UTM system would have to have been heavily exceeded by UAS during the simulation.

***Rule 1. If (Closer Warning is Heavy Close Collisions) and (Further Warning is Barely Clear) then (Collision Risk is Too Risky)***

We use a similar process to explain why the risk monitor assesses the inputs and outputs of the autonomous UTM system as low risk when the schedulers are used. The Stratway and GA schedulers (i.e., strategic de-confliction) decrease the amount of UAS close encounters; and thus, lessen the number of UAS that breach the closer and further thresholds. The end result is a decrease in Dynamic sNMACs. According to Rules 2 - 5, Closer Warning has the smallest fuzzy category (i.e., LCC) and Further Warning runs the gambit of categories from the smallest to the largest; however, since the overall crisp output from the FIS is low risk (the smallest fuzzy category), then rules in Rules 2 and 3 contribute more. This essentially means that within the autonomous UTM system, there are hardly any UAS breaching the closer and further warning thresholds during the simulation.

***Rule 2. If (Closer Warning is Light Close Collisions) and (Further Warning is Very Clear) then (Collision Risk is Barely Risky)***

***Rule 3. If (Closer Warning is Light Close Collisions) and (Further Warning is Mostly Clear) then (Collision Risk is Barely Risky)***

***Rule 4. If (Closer Warning is Light Close Collisions) and (Further Warning is Partially Clear) then (Collision Risk is Somewhat Risky)***

***Rule 5. If (Closer Warning is Light Close Collisions) and (Further Warning is Barely Clear) then (Collision Risk is Somewhat Risky)***

### *B. Efficiency Risk*

The results in Figure 14 suggests that Efficiency Risks are extremely high (70-80%) when either scheduler is used in the autonomous UTM system, but are extremely low (below 10%) when neither scheduler is used. This aligns well with results from [4].

Similarly, to explain the decisions made by our risk monitor for Efficiency Risk, we look into the fired fuzzy rules that produced: (1) the low risk percentage when no strategic de-confliction was used in the autonomous UTM system and (2) the extremely high risk percentage when strategic de-confliction was used for one of the runs of the Monte-Carlo simulation. Rule 6 corresponds to there being no strategic de-confliction therefore there are no modifications to distance or time, and thus there are no distance or time impacts. According to Rule 6, when the Priority input is high (we choose the highest value for all UAS) and both Distance Impact and Time Impact inputs are negligible, then this fuzzy rule yields the lowest fuzzy category and thus the lowest level of Efficiency Risk.

***Rule 6. If (Priority is Very Important) and (Distance Impact is Negligible Difference) and (Time Impact is Negligible Difference) then (Efficiency Risk is Barely Risky)***

The Efficiency Risks are high when either the Stratway or the GA schedulers are used as shown in Figure 14, because the strategic de-confliction algorithms both add temporal offsets to the launch of the UAS and distance to the mission through changes in the flight path, which extends the mission completion time. The mission completion time gets extended even further as the number of UAS increases. According to Rules 7 - 11, for any high priority UAS (which all of them were chosen to be), the Efficiency Risk will be very high whenever Distance or Time Impact inputs are reasonable high. This is the case because Rule 7 fired (even though its contribution could have been lower than the others), which yields a high risk result even when the Distance Impact is small. This makes sense, because either a delay in the start time of the UAS or an increase in the mission distance will cause an increase in the mission completion time.

***Rule 7. If (Priority is Very Important) and (Distance Impact is Negligible Difference) and (Time Impact is Major Deterioration) then (Efficiency Risk is Too Risky)***

***Rule 8. If (Priority is Very Important) and (Distance Impact is Partial Deterioration) and (Time Impact is Partial Deterioration) then (Efficiency Risk is Too Risky)***

***Rule 9. If (Priority is Very Important) and (Distance Impact is Partial Deterioration) and (Time Impact is Major Deterioration) then (Efficiency Risk is Too Risky)***

***Rule 10. If (Priority is Very Important) and (Distance Impact is Major Deterioration) and (Time Impact is Partial Deterioration) then (Efficiency Risk is Too Risky)***

***Rule 11. If (Priority is Very Important) and (Distance Impact is Major Deterioration) and (Time Impact is Major Deterioration) then (Efficiency Risk is Too Risky)***

Overall, the risk predictions of the fuzzy assurance monitor align with the expected behavior of the autonomous UTM system given specific airspace situations. Also, the fired fuzzy rules help explain the decisions made by the risk assessor.

## VI. Conclusion

In summary, this paper shows that the fuzzy monitor outputs on safety and efficiency risks align with the experimental data. The fuzzy rules are shown to reveal algorithmic characteristics in the simulation. The knowledge obtained through data analysis with the fuzzy collision and efficiency systems show the effects of using Stratway and genetic algorithm on the simulation performance and can be used for determining potential tuning. This experiment is meant to inspire confidence that these a-priori estimates can be used to gauge future performance. It also inspires confidence that explainability through fuzzy logic can bolster the quality of data analytics. In future work, we hope to be able to assess the risks of algorithms that seek to autonomously manage the uncertainty due to noisy control and navigation sensors. Also, we plan to develop realistic models with varying levels of failing autonomous algorithms to further test our fuzzy risk monitor.

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