AUTOMATIC MULTIAGENT AIRCRAFT COLLISION AVOIDANCE

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

Automatic Multiagent Aircraft Collision Avoidance. (May 2015)

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In recent years, there have been incentives to move towards the Free Flight concept in aviation due to advances in technology and increasing air traffic. Free Flight proposes a distributed cooperative strategy based on direct communication between aircraft to maintain separation rather than the currently centralized manner that is handled by the air traffic controllers. Free Flight requires aircraft to be able to detect and resolve conflicts that could lead to loss of separation between multiple aircraft at any point during the flight, which proves to be a challenging task. This research seeks to find an optimized cooperative collision avoidance strategy to resolve conflicts in the horizontal and vertical planes by proposing maneuvers that involve changing the altitude or heading involving multiple aircraft. The method employed is to extend the Zeuthen strategy—an adaptation of the Monotonic Concession Protocol (MCP)—from pairwise negotiations to handle multiway conflicts. This coordinated strategy provides optimal change of trajectories through resolutions that maximize the product of agents' utilities. We show with a simulator that this distributed approach is efficient and prevents losses of separation even in a highly congested airspace. The simulator also provides an infrastructure, on which alternative algorithms can be empirically evaluated.

CHAPTER I

INTRODUCTION

Since the advent of airplanes as a viable means of transportation, air traffic control has been managed in a centralized manner by the air traffic control towers. Over time, due to advancements in radar and computer processing power, it has become more feasible for a distributed cooperative approach in aviation to be adopted. The increasing complexity of centralized control and its potential safety concerns due to dependency on a singular controller, make Free Flight a more appealing alternative to current practices [7].

TCAS (traffic collision avoidance system) is the currently mandated aircraft collision avoidance system by the International Civil Aviation Organization to be fitted to all aircraft with a maximum takeoff mass of over 5,700 kg (12,600 lb.) or authorized to carry more than 19 passengers. It independently monitors the airspace using automatic dependent surveillance-broadcast (ADS-B) transponders. ADS-B keeps track of the aircraft's position, location, and velocity using satellite navigation and periodically transmits this information on the 1090 MHz radio frequency. TCAS equipment processes these messages and communicates with other aircraft nearby to build a three-dimensional map of the surrounding airspace. It then proceeds to identify potential collisions and automatically negotiate a mutual avoidance maneuver. These maneuvers are relayed onto the flight crew through different alerts and advisories—traffic advisory (TA), resolution advisory (RA), clear of conflict [1]—which are depicted in Figure 1.

Other methods for collision avoidance have been proposed, such as trajectory optimization using linear programming [4]. This approach is an adaptation of spacecraft path-planning that reformulates collision avoidance constraints as a mixed-integer linear program. The resulting program can further be solved by commercial software packages currently available. A taxonomy of 68 different conflict detection and resolution (CDR) methods is also provided by Kuchar and Yang [3] which evaluates different methodologies based on their collision detection and resolution capabilities, ability to handle multiagent conflicts, and avoidance maneuvers involved. They enumerated a number of issues that need further attention in conflict resolution strategies such as the ability to handle multiple conflicts, coordination, computational requirements, and implementation issues, to name a few. Nevertheless, agent-based methods have not been explored in depth for this problem. Our research draws upon the idea of cooperative multiagent negotiations [9]. While conventional air traffic control provides an ample amount of separation between the aircraft, it does not scale well due to the increasing rate of airspace congestion and becomes inefficient. Other methods often tackle this problem from a worst-case scenario perspective. Although these methods provide viable solutions in the event of avoiding collision with an unresponsive aircraft (or an object flying in the aircraft's trajectory), their worst-case nature prevents their solutions from being optimal. Since aircraft most commonly fly through an uncompetitive airspace and share the common goal of transporting their goods or passengers safely to their destination, a cooperative method of analysis can reach a more efficient equilibrium solution. Furthermore, the pairwise strategies do not account for the conflicts that might arise after a commitment is made, and the outcome in these scenarios depends on the mutability of commitments.

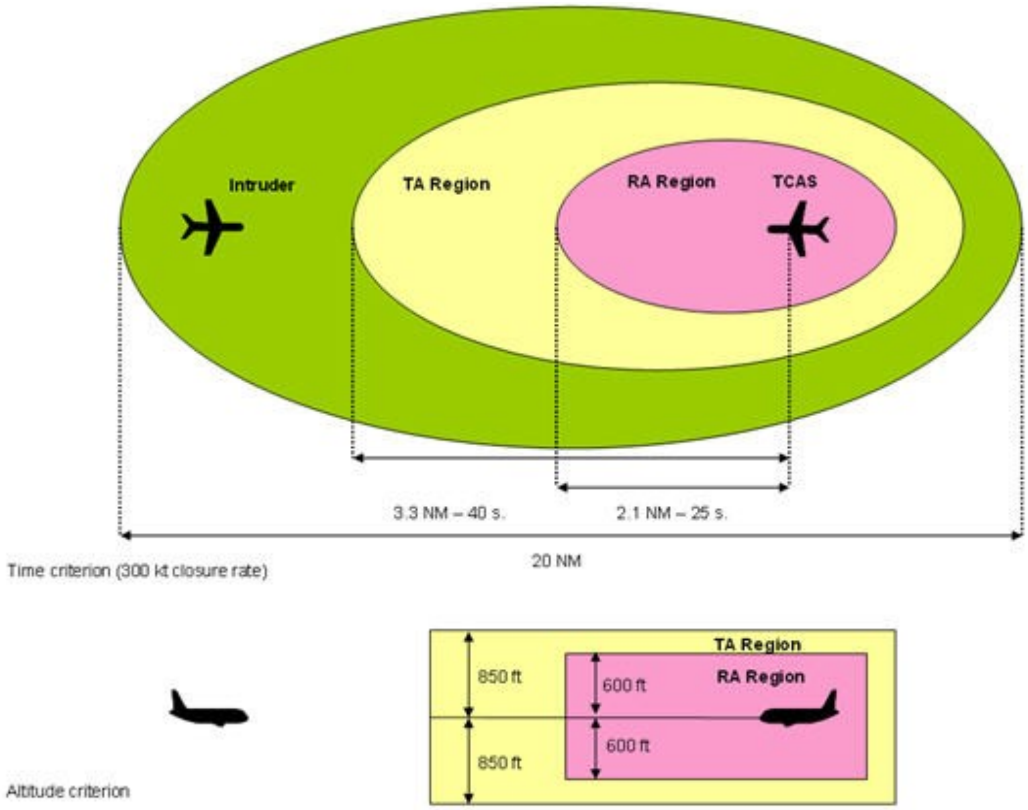

Figure 1. Example of TCAS Protection Volume between 5,000 and 10,000 feet.

Our objective is to implement the extended multiagent negotiation protocol and evaluate its impact on the efficiency of resolving complex multi-aircraft conflicts in a congested airspace simulation. In order to accomplish this, we explore how previous work in Game Theory could be applied to the air traffic coordination problem—in particular, methods of negotiation such as the Monotonic Concession Protocol (MCP) [9]. In MCP, an agent alternates with its opponent making minimal concessions until they both converge to an agreement. Since commitments are made on a pairwise basis, this approach could become problematic if one or both aircraft lose separation with another aircraft as a result of their commitment. By extending this method, our work attempts to handle multi-lateral interactions that can change dynamically over time.

We approach the solution in incremental steps; starting with a pairwise uncooperative strategy, followed by cooperative negotiation using the Zeuthen strategy, and concluding with a multiagent-adapted approach. We assume aircraft have on-board radar sensors and can communicate over a limited distance. Each aircraft will have a unique *utility function* that describes its preferences and needs, and will be used to measure an aircraft's willingness to compromise. A utility function is a function from trajectories into real numbers that quantifies desirability, and can be used to rank alternatives by preference. For example, certain flights are time-sensitive while fuel cost might be a higher priority for another aircraft. The utility function can also be used to encode the constraints on the aircraft, whether physical limitations pertaining to the mechanical aspects of the aircraft, or external limitations such as prohibited airspace or thunderstorms. Since each aircraft is assumed to know the equilibrium strategies of the other aircraft, and none of them has anything to gain by changing only their own strategy, it can be shown that adopting the Zeuthen strategy in MCP will lead the aircraft to agree upon a deal that maximizes their Nash product (product of utilities) [2]. An agent adopting the Zeuthen strategy measures its willingness to risk conflict, where it will be more willing to risk conflict if the difference in utility between its current proposal and the conflict deal is low. The conflict deal is the deal that the agents will agree to in case no concessions can be made. In our case it is simply the agents' intended trajectory since unless the agents can agree upon an alternate trajectory, there are no other trajectories available to them, and they will continue on their planned paths. As a result, reaching the conflict deal in our situation is simply regarded as a failure. In order to evaluate the Nash product of different alternatives, the deal space has to be constructed. The deal space is a finite set of all tuples of trajectories that result in no further conflict, which is computed as the Cartesian product of the discrete set of alternate trajectories available to each aircraft. For example, suppose aircraft *A* and *B* are headed towards a collision and have utility functions u_A and u_B respectively. *A* values fuel efficiency, while *B* prefers to fly at a higher altitude; therefore, we would expect these preferences to be reflected in their utility functions:

$$u_A = \frac{1}{\text{distance}}, \qquad u_B = \text{altitude} \tag{1}$$

Suppose the deal space consists of two deals:

Deal$_1$: Doubling the distance traveled by *A*, and tripling the altitude of *B*

Deal$_2$: Tripling the altitude of *A*, and doubling the distance traveled by *B*

The Nash equilibrium solution is one that maximizes the Nash Product. That is $\max_i \pi_i$ given $\pi_i = u_A(i) \times u_B(i)$ is a product of utilities for a deal in the deal space. If *a* and *b* are the utilities of the current state:

$$\begin{aligned} \pi_1 &= 0.5\, a \times 3\, b = 1.5\, a \cdot b \\ \pi_2 &= a \times b = a \cdot b \end{aligned} \tag{2}$$

Hence, the aircraft will agree on Deal$_1$. Even though *A* is not better off going through with Deal$_1$, it is an advantageous enough deal for *B* to warrant *A*'s concession. Since there exists an infinite number of deals between aircraft, we generate a discrete deal space for simplicity, consisting of actions that change the aircraft's heading or altitude in predefined increments. This allows the agents to reason about their options in a timely manner. Our methodology is described in further detail on Chapter 2.

One of the challenges that our method attempts to solve is that an aircraft might enter the conflict zone of another aircraft after committing to a change of course. In this case, it either has to make a new commitment with the previous one in mind, or break the previous commitment and start negotiating anew with the most recent conflicting aircraft. We will introduce a new protocol based on multilateral negotiations and utilize the simulator to conduct an empirical analysis of our algorithms and evaluate their performance in these extreme or corner-case conditions. We will also use the simulation to collect data on the performance of the algorithms. Performance will include efficiency metrics, such as the amount of fuel lost due to collision avoidance maneuvers, flight delays, number of near misses, and so forth. We will examine the scalability of the system as the density of aircraft in the simulation increases. These results are presented in Chapter 3.

CHAPTER II

METHODOLOGY

The simulation of a 3D airspace is implemented using Python and the pygame graphics library using point-mass aircraft. Aircraft communication is simulated in the form of a message queue. The aircraft are assumed to change heading or instantaneously and therefore maintain constant speed while separated. Similar to TCAS, when two aircraft are within traffic advisory range of each other they exchange their speed and heading to intersect their trajectories. If *a* and *b* are the supposed aircraft and *V* and *X* are their vectors of velocity and position respectively, the time of intersection is calculated by the equation below:

$$X_{2_a} = V_a\, t + X_{1_a} \;, \qquad X_{2_b} = V_b\, t + X_{1_b}$$
$$\rightarrow \Delta X_2 = \Delta V\, t + \Delta X_1$$
$$\rightarrow |\Delta V\, t + \Delta X| \leq d \;, \qquad \textit{where d is the loss of separation distance}$$
$$\rightarrow (\Delta V\, t + \Delta X)^2 = d^2$$
$$\rightarrow (\Delta V^2)t^2 + (2\,\Delta V \cdot \Delta X)t + (\Delta X^2 - d^2) = 0 \tag{3}$$

The roots of this equation provide us the duration of the loss of separation—the time where it begins and the time where it ends if the aircraft are assumed to fly through each other. In case of imaginary or negative values, the aircraft are clear of conflict. After the possibility of collision is determined, the aircraft proceed with a collision avoidance strategy.

Pairwise Cross Product (Simple Pairwise) Strategy

This strategy is a simple attempt to resolve collisions in a non-cooperative pairwise manner. Each aircraft calculates the cross product of its own and the opposing aircraft's velocity vector. It then immediately alters its heading towards the direction of the resulting vector and continues flying until the expected end time of the potential collision. Afterwards, it changes its heading in the opposite direction of the previous plan until it reaches the original flight path. One obvious flaw in this strategy is that it is unable to prevent rear-end or head-on collisions where the velocity vectors are parallel to each other.

Pairwise Zeuthen Strategy

Utilizing the Zeuthen strategy allows the aircraft to implement a *one-step protocol* to get around the negotiation process of the MCP [2]. As described in the previous chapter, the Zeuthen strategy measures an agent’s willingness to risk conflict, where risk is the ratio of utility lost by accepting the other agent’s proposal to the utility of remaining in conflict (current trajectory). Therefore, the agent that has less to lose by accepting the other agent’s deal shall concede.

$$Risk = \begin{cases} 1 , & U_{current} = 0 \\ \dfrac{U_{current} - U_{other}}{U_{current}} , & otherwise \end{cases} \tag{4}$$

Suppose agents *A* and *B* are negotiating a conflict through the Zeuthen strategy, where $\delta_{\square}$ and δ_B are the *best* deals (of highest utility) available to *A* and *B* respectively. At any given step, agent *A* will concede if and only if: [5]

$$\begin{gathered} Risk_A < Risk_B \\ \frac{U_A(\delta_A) - U_A(\delta_B)}{U_A(\delta_A)} < \frac{U_B(\delta_B) - U_{\square}(\delta_A)}{U_B(\delta_B)} \\ U_B(\delta_B)\big(U_A(\delta_A) - U_A(\delta_B)\big) < U_A(\delta_A)\big(U_B(\delta_B) - U_B(\delta_A)\big) \\ U_A(\delta_A) \cdot U_B(\delta_A) < U_A(\delta_B) \cdot U_B(\delta_B) \end{gathered} \tag{5}$$

In the event that both agents are equally willing to take a risk, a coin is usually flipped. Therefore after each concession, the product of the utilities will never decrease. To better visualize this strategy, imagine the product of utilities for each deal in the deal space, shown in Figure 2 as a set of equipotential lines ($U_A(\delta) \cdot U_B(\delta) = k$) with respect to each agent's utility. After each concession, the current deal will either remain on the same equipotential line, or jump to one with a higher product. Since the number of deals is finite, the negotiations will converge on a deal that maximizes the Nash product. This allows us to skip the negotiation steps of the MCP and implement a one-step protocol that chooses the deal with the highest product of utilities, given both agents use the same strategy.

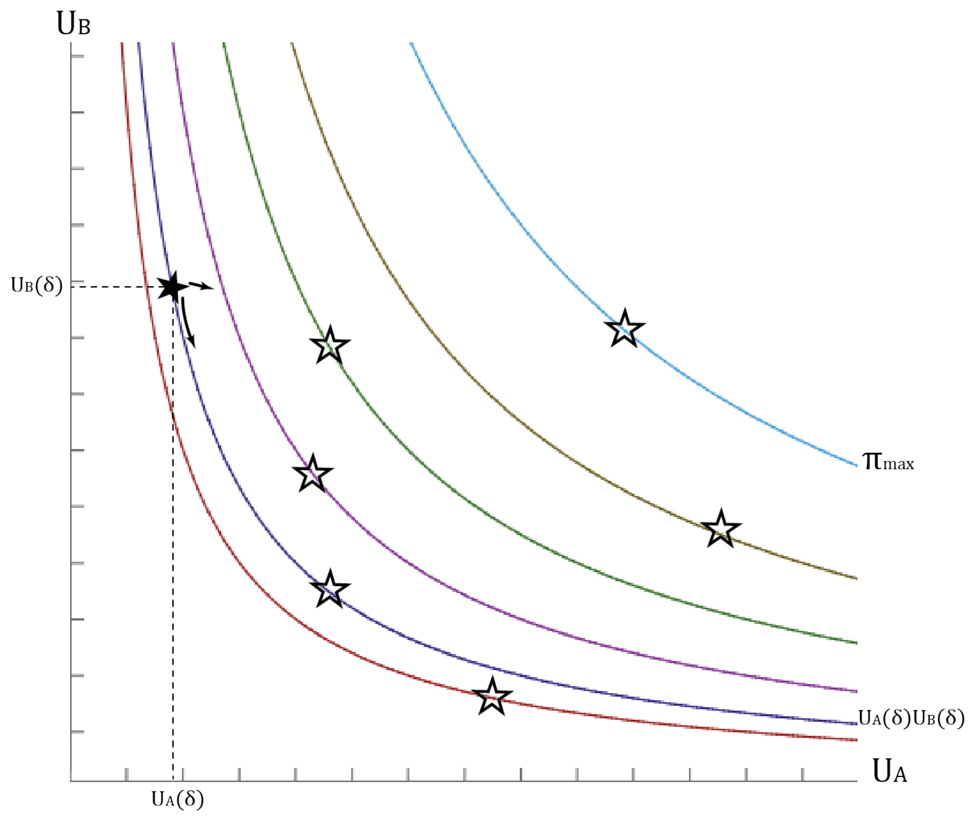

Figure 2. Visualization of the deal space in Zeuthen strategy.

Upon detection of the possibility of loss of separation, each aircraft generates a number of alternate trajectories, discards the ones that do not result in a conflict, and calculates the utility of the remaining possibilities. It then transmits this data to the opposing aircraft and creates the deal space once it has received the set of utilities from the other aircraft. Both aircraft calculate the Nash product of each deal and non-cooperatively choose the deal that maximizes this product. They construct a two-waypoint detour with the chosen deal and the conflict interval as shown in the Figure 3.

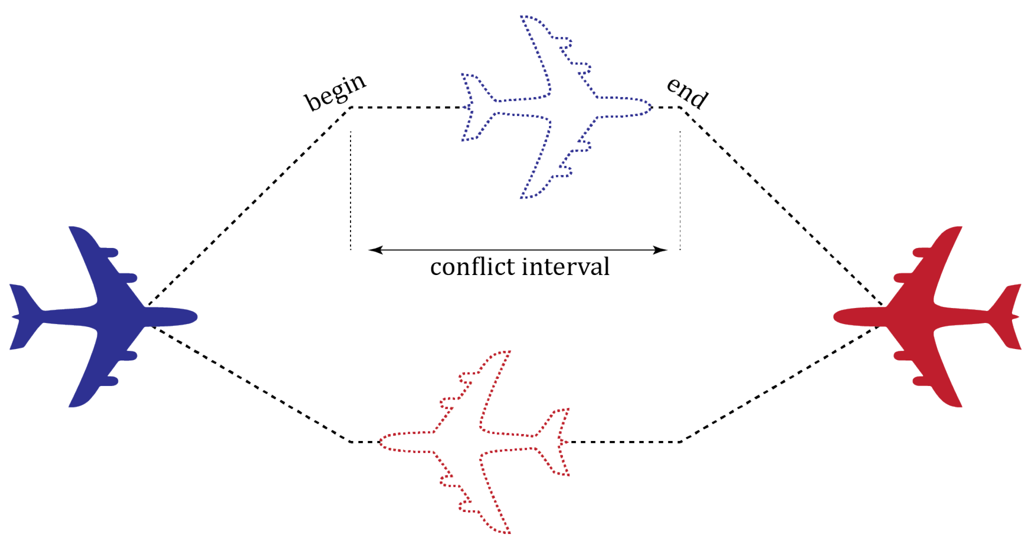

Figure 3. Two-waypoint detour and the conflict interval.

The disadvantage of this strategy is that it is unable to provide an efficient solution when multiple aircraft are headed for a collision. Furthermore, it does not account for the collisions that might arise after a commitment is made. The outcome in these scenarios depends on the mutability of commitments. For example, if a commitment is completely immutable, an agent already in a commitment facing a new collision would not be able to make any further concessions with the new party. Therefore the new party would be forced to resolve the collision on its own at the cost of efficiency. A more realistic approach, however, is employing leveled commitments by associating a penalty to decommitment. To be freed from a commitment, an agent simply pays its penalty to the other commitment parties. Sandholm and Lesser have studied this approach in further detail and provided different decommitting strategies [6]. Leveled commitments can increase the payoffs of all commitment parties when at least one of the agents faces uncertainty.

Multiway Zeuthen Strategy

Adapting the pairwise approach to multiple agents is not straightforward since MCP and Zeuthen strategy are only defined with respect to two agents, and it is unclear how the utility of a group as whole should be defined. First, the criteria for making a concession has to be defined, and in the case of Zeuthen strategy, the definition of risk for multiple agents. It is also crucial to evaluate whether any particular type of concession would allow us to implement a one-step multiagent protocol.

Endriss [2] has explored a number of different concessions in detail. Two concession criteria that are of particular interest to us are the *Nash concession* and the *utilitarian concession*. Nash concession aims to increase the product of the utilities of the group, while utilitarian concession aims to increase the sum. The property that especially distinguishes these concessions is deadlock-freedom. A deadlock in this case refers to a situation where no agent can make any further concessions, even though none of the terminating states of the negotiation protocol have been reached. It is important to note that this property does not hold in Nash concession if the utility functions produce negative values. We chose the Nash concession criteria to mirror our methodology in the pairwise case. A natural generalization of the Zeuthen strategy would be to evaluate risk as the ratio of the loss of utility for the agent—assuming the worst-case scenario for the agent—to the utility of remaining in conflict. Worst-case scenario is defined as the highest difference in utility between an agent's current proposal and the other agents' proposals. In other words, from the perspective of an agent: "what is the most that I can lose if one of the agents concedes?"

$$Risk = \begin{cases} 1, & U_{current} = 0 \\ \dfrac{U_{current} - \min(U_{other})}{U_{current}}, & otherwise \end{cases} \tag{6}$$

However, this strategy would not converge to a solution of maximal utility unlike the pairwise case. Worse, it is not guaranteed to be deadlock-free as shown by the example below. Suppose $Agent_i$ is currently proposing $Deal_i$. $Agent_1$ should concede, but it is not able to make a concession that affects the risk value of any of its opponents or increase its own.

	$Deal_1$	$Deal_2$	$Deal_3$	
$Agent_1$	10	6	6	$Risk_1 = 0.2$
$Agent_2$	8	10	3	$Risk_2 = 0.7$
$Agent_3$	8	3	10	$Risk_3 = 0.7$

Figure 4. An example deadlock scenario using Zeuthen concession.

As a result, a better generalization of the Zeuthen strategy is to utilize the product-increasing strategy (using Nash concession), since it converges to the solution with the highest product, which is also consistent with our pairwise approach [2]. This can be shown using an extension of Figure 2 in 3D, where the deals are positioned on equipotential surfaces in the first octant. Similarly, after each concession, the current deal will either remain on the same surface, or jump to one with a higher product. Since the number of deals is finite, the negotiations are will converge on a deal that maximizes the Nash product.

Our implementation of this strategy has a great deal in common with the pairwise method. In concept, the aircraft monitor the radar for possible losses of separation and collisions. Upon detection of a threat, the aircraft form a coalition and broadcast the utilities of alternate trajectories available to them. Each aircraft will then proceed to construct the deal space and compute a non-conflicting solution that maximizes the Nash product. In the event that any members of the coalition encounter a new conflict, they will add the new aircraft to the coalition, and broadcast this change to the members involved. This event will reinitiate the negotiation process and trigger the transmission of utilities. After each aircraft has received the updated data, it will compute and commit to a new deal. Every aircraft keeps track of its commitment and any deviations from the original flight plan to construct a corrective route that takes it back to the intended path after the commitment is fulfilled. The flowchart for this strategy is presented in Figure 5.

The ability of this strategy to produce efficient routes is directly dependent on the number of alternate trajectories available to each aircraft. For N aircraft with t alternate trajectories available to each on average, the complexity of the deal space increases exponentially by $O(t^N)$. This is the main limitation of this algorithm since past a specific N, negotiating a solution becomes temporally infeasible. In our simulations on a laptop, $N = 9$ was the practical limit given a 2 minute time out value. Fortunately, it is highly unlikely that a higher number of aircraft would cross paths in a realistic scenario; but even so, this computational limitation has to be taken into account in any practical implementation.

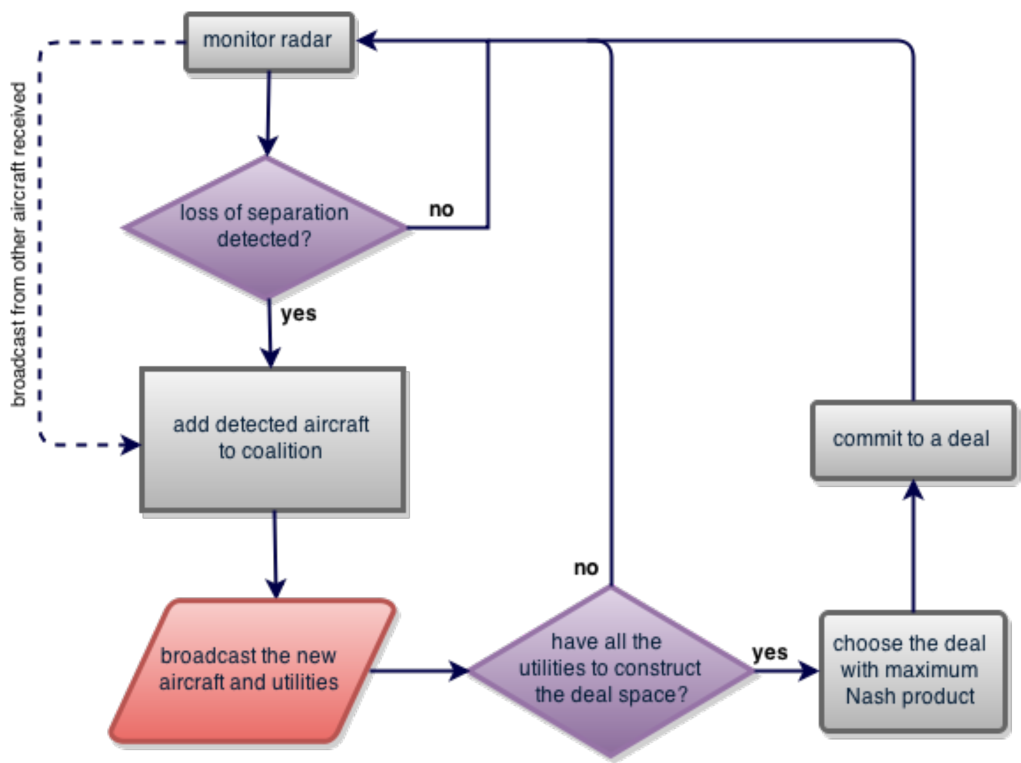

Figure 5. Negotiation protocol in multiway Zeuthen strategy.

Since in most scenarios, the conflicting aircraft span a wide portion of the airspace, it may not be necessary for all aircraft to take the preferences of every member of the coalition into account. In this case, research in agent coalition formation may be applied to partition the coalition into multiple non-conflicting groups, which can then resolve conflicts in a shorter amount of time [8]. In one of our experiments in Chapter 3, we implemented a capping mechanism to limit the size of a coalition before the agents can begin to evaluate a deal. A formal analysis of this approach is out of the scope of this paper since most efficiency metrics are entirely dependent on the random initial configuration of the aircraft's flight plans and utility functions and are hard to formalize.

Even though our results in Chapter 3 look promising, this approach would not be feasible in a practical application since it cannot guarantee deadlock-freedom as demonstrated in Figure 6.

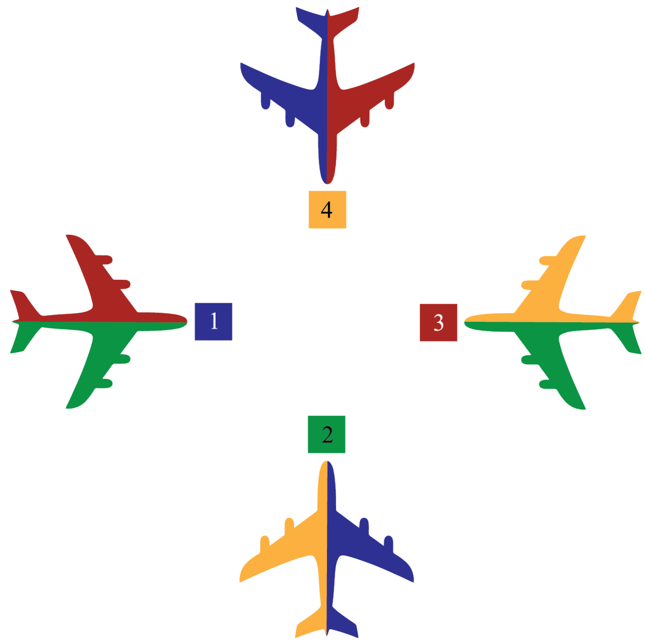

Figure 6. Deadlock scenario using the capping strategy. The cap in this example is three. The color of every aircraft is in the box in front of it. Each aircraft has formed a coalition with the aircraft that it has been colored with. None of the aircraft can complete the deal space, since they are missing the utilities from at least one other coalition member. For example, aircraft 1 (**blue**) requires the trajectories and their associated utilities from **red** and **green**, while neither has added **blue** to its coalition.

CHAPTER III

RESULTS

A series of experiments were conducted to compare the three strategies introduced in Chapter 2 based on different criteria. Each strategy will also be evaluated individually to measure its scalability and performance under varying conditions. The dimensions of the simulated airspace are 20x15x8 in terms of the average size of an airplane.

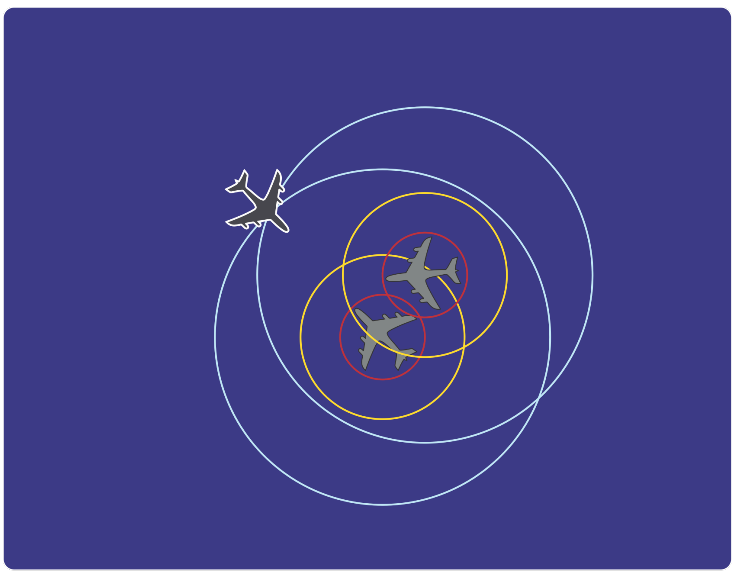

Figure 7. A screenshot of the simulations. The aircraft are colored in shades of gray, where a lighter shade signifies a higher altitude. There are three boundaries surrounding each aircraft: communication range, where the aircraft first start communicating their positions and detect collisions; loss of separation range: where the aircraft are close enough to no longer maintain proper separation; collision range, this range roughly equals the size of an aircraft, assuming it a spherical object, where collisions happen.

Each experiment is initialized with a given number of aircraft starting their flight from a random origin towards a random destination within the airspace. The initial positioning of the aircraft is validated against any losses of separation. The aircraft are all expected to reach their destination by a predetermined time, and their speed and heading is set accordingly. At the end of each simulation, the number of collisions, losses of separation, and the *efficiency* (percentage of remaining distance to destination) is reported. The number of collisions and losses of separation are averaged over multiple trials per experiment, and the mean efficiency is compared with the unpaired two-sample Student's t-test between different strategies. Each experiment consists of 30 trials per strategy. The initial configuration of the airspace is not shared between the two strategies and is randomly determined at the beginning of each trial as explained above. Each trial has been given a 2-minute timeout period.

Comparing Simple Pairwise with Multiway Zeuthen Strategy

In the case of 8 aircraft, the observed difference in the efficiency of the strategies hardly significant, but the simple pairwise strategy fails to prevent as many losses of separation (LoS) and collisions as our proposed multiway strategy. The results are shown in Table 1. As the number of aircraft increases to 12, the inability of the simple pairwise method to prevent collisions and LoS in an efficient manner becomes more apparent. Table 2 demonstrates a statistically significant difference between the two approaches. The same trend continues when scaling up to 16 aircraft. As the results show in Table 3, the simple pairwise strategy becomes unfeasible for collision avoidance in a high-density airspace.

Table 1. Comparing pairwise with multiway Zeuthen strategy in simulations of **8** aircraft.

Strategy	Avg. LoS per experiment	Avg. collisions per experiment	95% confidence interval of efficiency	T-test p-value
Simple Pairwise	1.241	0.310	86.4% - 94.1%	0.074
Multiway Zeuthen	0.103	0	92.4% - 96.2%	

Table 2. Comparing pairwise with multiway Zeuthen strategy in simulations of **12** aircraft.

Simple Pairwise	2.724	0.655	76.4% - 82.6%	$2.8 \cdot 10^{-7}$ *
Multiway Zeuthen	0.185	0	88.9% - 93.3%	

Table 3. Comparing pairwise with multiway Zeuthen strategy in simulations of **16** aircraft.

Simple Pairwise	5.276	1.276	67.5% - 73.2%	$1.0 \cdot 10^{-6}$ *
Multiway Zeuthen	2.103	0.448	80.5% - 89.6%	

Comparing Pairwise Zeuthen with Multiway Zeuthen Strategy

In the first two experiments (with 8 and 12 aircraft), both strategies performed well in preventing collisions and LoS. Although there is a real difference between the strategies, that difference is trivial. Our multiway approach prevents slightly more collisions and LoS at the expense of efficiency as presented in Tables 4 and 5. In the case of 16 aircraft however, our multiway method seems to have lost to the pairwise Zeuthen strategy. Since every trial can time out after the 2-minute timeout period (less than one-third of the trials timed out in the 16-aircraft scenario), we hypothesize that this loss of performance is due to an exponential increase in running time of the algorithm. For this reason, trials that involved conflicts of many aircraft resulted in long computation times and timed out. Alternatively, trials that failed in negotiating a deal more often than not finished in a timely manner. Therefore, the timeout value has unintentionally selected for trials that perform poorly. To test this hypothesis, we devised a capped multiway approach that limits the number of aircraft that can negotiate a deal among each other at the same time. This strategy is explained in further detail in the previous chapter. Based on the results from Table 6, the capping has provided a statistically significant increase in the efficiency of the algorithm and the number of collisions and LoS prevented, which indicates that the testing method is in fact biased against strategies with a long running time. It also shows that as the number of aircraft in a single negotiation increases, it may not be necessary for each aircraft to take all the other aircraft's preferences into account. For example, if ten aircraft are in the process of negotiating a deal and a new aircraft enters the traffic advisory range of one of them, unless all the aircraft are headed towards the same point in the airspace, they span a wide enough area of the airspace that the new aircraft would not enter a conflict with all of them, and as a consequence could omit them from its negotiation set.

Table 4. Comparing pairwise Zeuthen with multiway Zeuthen in simulations of **8** aircraft.

Strategy	Avg. LoS per experiment	Avg. collisions per experiment	95% confidence interval of efficiency	T-test p-value
Pairwise Zeuthen	0.103	0.034	99.4% - 99.9%	$7.6 \cdot 10^{-7}$ *
Multiway Zeuthen	0.103	0	92.4% - 96.2%	

Table 5. Comparing pairwise Zeuthen with multiway Zeuthen in simulations of **12** aircraft.

Pairwise Zeuthen	0.241	0.103	99.0% - 99.6%	$2.5 \cdot 10^{-8}$ *
Multiway Zeuthen	0.185	0	88.9% - 93.3%	

Table 6. Comparing pairwise Zeuthen with multiway Zeuthen in simulations of **16** aircraft.

Pairwise Zeuthen	1.138	0.448	98.8% - 99.4%	$7.4 \cdot 10^{-7}$ *
Multiway Zeuthen	2.103	0.448	80.5% - 89.6%	
Capped Multiway	0.586	0	98.5% - 98.7%	$1.3 \cdot 10^{-6}$ *

The effect of aircraft density on the number of collisions and losses of separation from the previous experiments is compiled in Figure 8.

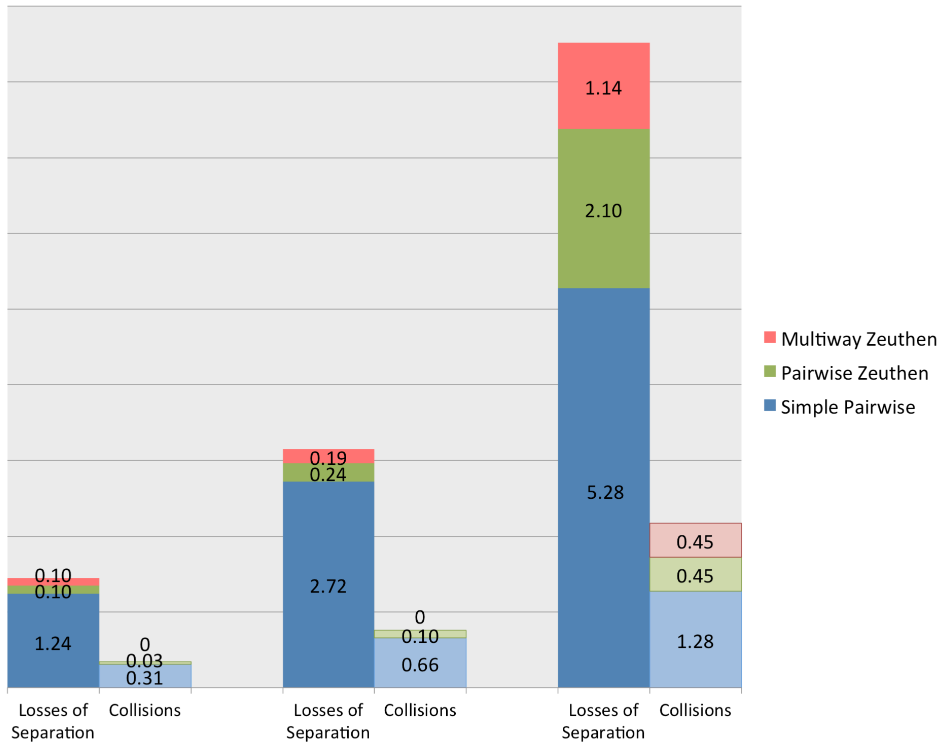

Figure 8. Effect of aircraft density on the number of collisions and losses of separation.

The Impact of Selfishness in the Multiway Zeuthen Strategy

In this experiment, half the aircraft used a more selfish utility function, where they found better alternatives exponentially more desirable while the unselfish aircraft used a linear function. Table 7 demonstrates that the selfish aircraft did not utilize statistically significant more efficient trajectories. Since greediness is not isolated to a single agent (the greediness of one agent promotes the other agents to act greedily as well), this experiment shows that the negative effects of a group of agents—as large as half of all agents—acting greedily does not significantly reduce the efficiency of the system as a whole.

Table 7. Result of simulations of **16** aircraft where half are selfish.

Characteristics	Avg. LoS per experiment	Avg. collisions per experiment	95% confidence interval of efficiency	T-test p-value
Selfish	0.172	0.034	90.9% - 92.3%	0.106
Unselfish	0.172	0.172	89.5% - 90.0%	

CONCLUSIONS

With increasing air traffic and further advancement of technology, it has become much more feasible to move towards Free Flight in aviation. As we discussed, prior work has often tackled the collision avoidance problem from a worst-case scenario approach, and agent-based cooperative strategies have not been studied in depth. Pairwise implementations of the Zeuthen strategy and the Monotonic Concession Protocol (MCP) work well in sparse environments, but degrade as airspace congestion increases as a result of the immutability of their commitments and the cost associated with utilizing leveled commitments.

We discussed the implications of adapting the MCP and the Zeuthen strategy to multilateral negotiations, and presented the product-increasing concession (Nash concession) as a natural generalization to the one-step protocol offered by the Zeuthen strategy. We further showed that it converges to the solution that maximizes the product of agents' utilities. We developed a simulator for the purposes of this research, and used it as a platform to empirically evaluate our algorithm and conduct the experiments. The results indicate that our strategy performs efficiently in congested airspace, although it scales exponentially with respect to the number of aircraft and their alternate trajectories. This limitation, however, should not present a significant problem in practice considering the limit reached in our experiments. Future work could address this limitation by exploring coalition formation in conflict resolution. Heuristically pruning the deal space could additionally provide a viable strategy.

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