Negotiated Decentralized Aircraft Conflict Resolution

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***Abstract*— This paper describes a sequential bargaining process that provides negotiated, decentralized aircraft conflict resolution. This process is decentralized in that it allows each aircraft to propose its own trajectories and assess their cost using its own private information. At each stage in the process, aircraft broadcast to each other proposed trajectories and then identify the response trajectories they would need to fly to avoid a conflict with the other's proposed trajectories. If the cost of any response trajectory is less than or equal to its corresponding proposed trajectory, then a resolution has been found; otherwise, the process iterates with the requirement that the next set of proposed trajectories incur greater portions of the cost of resolving the conflict. Convergence of the process and methods for describing constraints on the trajectories is examined in computational experiments. Finally, the process is demonstrated in a large-scale simulation spanning an en route air traffic control center's operations for five hours.**

***Index Terms*— Game theory, conflict resolution, air traffic control, bargaining process.**

I. Introduction and Motivation

THE current air traffic concept of operations relies on centralized, ground-based air traffic controllers to determine conflict-free trajectories. This paper proposes a method of conflict resolution with four properties. First, the conflict resolution is *distributed* such that pairs of aircraft determine their own conflict resolutions, without relying on a centralized mechanism to instead resolve the conflict for them.

Second, the magnitudes of simultaneous maneuvers by both aircraft are *negotiated* between the two aircraft so that they jointly establish a successful conflict resolution. Thus, unlike methods that only maneuver one aircraft – or that negotiate which one aircraft will maneuver – the maneuvers are coordinated between the aircraft. As this paper will demonstrate, this typically results in each aircraft's maneuver being significantly smaller than if only one aircraft maneuvers, with a corresponding reduction in total cost.

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Third, the conflict resolution is not only distributed, but also *decentralized*. While the terms distributed and decentralized are often used inter-changeably, decentralized operations are distinguished here as the further special case where the individual agents (aircraft) are allowed to maintain private information defining their views of what is feasible and optimal. In conflict resolution, such private information specifically includes the aircraft operators' cost indices (weighting the relative costs of fuel burn and delay incurred by the resolution) and other business decisions that impact performance constraints (e.g., aircraft weight, as driven by fuel tankering and freight, impacting cruise altitude). Thus, the method proposed in this paper allows aircraft to apply their own cost function and objectives, rather than having a centralized controller or other aircraft assume these, or requiring a common cost function for all aircraft.

Finally, the conflict resolution is *multi-dimensional*. At each stage of the negotiation, the aircraft propose six possible resolutions in six dimensions: up/down, right/left, and faster/slower. Each of these resolutions are negotiated such that the lowest cost dimension for resolving the conflict is selected. This formulation also accommodates constraints on maneuvering in specific dimensions due to aircraft performance constraints (e.g., limits on speed or altitude) and other constraints such as restricted airspace.

As detailed in this paper, the conflict resolution process is a sequential negotiation (bargaining) process based on game theory. At each step in the negotiation, aircraft communicate a set of *proposed trajectories* to each other, corresponding to trajectories they would prefer to fly. Then they each compute *response trajectories* representing the trajectories they would need to fly to remain conflict-free if the other aircraft flew each of its proposed trajectories. Once an aircraft prefers a response trajectory to the proposed trajectory it had just offered, the process has successfully concluded; until then, the negotiation iterates with the requirement that the next stage's proposed trajectories increase in cost in a manner that will decrease the cost of the other aircraft's response trajectories. Throughout, each aircraft need only reveal its proposed trajectories, without explicitly revealing cost indices or performance constraints.

This paper starts by reviewing decentralized, negotiated conflict resolution methods to date. It next describes the sequential bargaining process and its basis in game theory. Then, the performance of this method is explored in two ways. First, experiments are conducted across a set of pairwise conflict geometries and aircraft cost indices, and considering aircraft with the same and differing performance constraints. These experiments explore different methods for framing the cost function and performance constraints, and for maneuvering in multiple dimensions. The conflict resolution process is assessed in terms of safety (i.e., confirming resolution of the conflict) and cost (as the sum of incurred fuel and delay, weighted by a cost index), and this cost is also compared with the performance of a conflict resolution that only maneuvers one aircraft, i.e., a non-coordinated solution such as is typical in current day operations.

Finally, this paper demonstrates the bargaining process in a large scale simulation with more than a thousand aircraft flying over the Indianapolis Center, incurring more than five hundred conflicts. The traffic sets were taken from ETMS data over five hours, to represent 'real' conditions. Again, the performance is examined in terms of safety and cost, and compared with the performance of a non-coordinated solution.

II. Background: Decentralized, Negotiated Conflict Resolution

A. Defining the Aircraft Conflict Resolution Problem

A conflict between two aircraft occurs when aircraft are predicted to be closer than a given separation criteria. Current en-route air traffic control rules often define the separation criteria to be five nautical miles horizontally and one thousand feet vertically for aircraft operating in en-route airspace above 18,000 feet altitude. *Conflict detection* identifies trajectories that will lead to conflicts within a given detection time. *Conflict resolution* changes the aircraft trajectories to be conflict free for a given look-ahead time. For the conflict resolution to be effective, this look-ahead time must be greater than the detection time.

Operationally, conflict resolution is a tactical operation with a look-ahead time of several minutes. Within the broader context of aviation operations, the process of conflict resolution is described as fitting between two other related processes [1]: (1) a more strategic, longer look-ahead process that establishes effective traffic flow management and, where possible, either nominally conflict-free trajectories or at least traffic conditions within which conflict resolution is feasible; and then (2) time-critical collision avoidance such as the Traffic alerting and Collision Avoidance System (TCAS) which has a look ahead time of less than a minute and seeks to keep aircraft apart by a scant 500 feet vertically, with no horizontal separation criteria [2].

Each of these processes values different things: strategic conflict resolution generally values global metrics of an efficient traffic flow. Methods for strategic conflict resolution have, for example, examined the overall route structure to create routes that minimize conflicts, or that allow conflicts to be resolved in a manner that, in the aggregate, minimizes subsequent downstream conflicts [3], [4]. Methods for time-critical collision avoidance value miss distance measured within feet, and generally seek to provide guarantees of sufficient miss distance even if the other aircraft is not cooperative [5], [6].

Tactical conflict resolution, fitting between the two, must meet the safety constraints given by conservative separation criteria, but also can also seek to minimize the cost of the resolution and consider other immediate constraints, such as the performance limits of the aircraft (or more conservative preferences for maneuvers) and geographic considerations such as convective weather and restricted airspace.

The strategic, tactical and time-critical processes can interact. For example, [7] noted the disruption of strategic "system stability" created by tactical conflict resolutions that create downstream conflicts requiring subsequent maneuvering. Novel methods for tactical conflict resolution may be carefully implemented within airspace operations; for example, strategic traffic flow management may build in "trajectory flexibility" to facilitate tactical conflict resolution, or decentralized conflict resolution may be delegated to appropriately-equipped aircraft in particular airspaces or in particular types of operation [8], [9]. Likewise, tactical resolutions may assume that both aircraft will execute their conflict resolution maneuver, with the assurance that, in the case of improper execution, the time-critical collision avoidance process remains engaged as an independent safety backup [5].

A relatively unique aspect of tactical conflict resolution is that it values the cost of individual maneuvers. The general form of the cost function in current-day flight management systems on air transport aircraft applies a cost index i to weigh the cost of the additional fuel $(C_f \cdot \Delta f)$ and time $(C_t \cdot \Delta t)$ incurred (by both the initial resolution and then the subsequent revised path to the next waypoint) to find the total cost c:

$$c = (1 - i) \cdot C_f \cdot \Delta f + i \cdot C_t \cdot \Delta t \tag{1}$$

While this cost function is fairly standard across air transport aircraft, the cost index i assigned to any particular flight can be purposefully varied by the aircraft operator. For example, one flight may be carrying a significant number of connecting passengers, requiring a strong weighting on delay; other flights may be operating to/from airports with high fuel costs. Thus, the cost index i reflects business decision processes that operators may consider proprietary. Similarly, tactical conflict resolution is impacted by other business decisions that drive performance constraints (e.g., aircraft weight, as driven by fuel tankering and freight).

B. Conflict Resolution Methods

A large and diverse number of conflict resolution methods have been proposed in the literature, reviewed in [9] and [10]. This paper proposes a method of conflict resolution with four important properties. First, the conflict resolution is *distributed* such that pairs of aircraft determine their conflict resolutions. This contrasts with centralized views of air traffic which seek global optimal solutions, applying methods such as mixed integer programming [11], [12]. Such distributed conflict resolution has been proposed for two reasons. The first is a concern that centralized mechanisms cannot scale to large areas and/or high-density traffic [5], [13]. The second is the proposition that distributed systems maybe more robust and reliable because they have less sensitivity to central failure modes [14].

Second, the magnitudes of simultaneous maneuvers by both aircraft are *negotiated* between the two aircraft so that they jointly establish a successful conflict resolution. This active negotiation of conflict resolutions specific to each conflict contrasts with methods applying prescribed resolution trajectories, i.e., where trajectories are either defined ahead of time, or are selected from a limited set of pre-defined maneuvers. The time-critical TCAS, for example, progressively examines a set of vertical maneuvers, selecting the one requiring the lowest-magnitude maneuver and confirming the "sense" of the maneuver (climb/descend) with the other aircraft [2]. An algorithm for tactical conflict resolution, Stratway, was purposefully developed to select resolutions according to pre-determined strategies; this modularity supports the safety verification of the system's output [15]. Similarly, protocols for resolution may apply pre-determined heuristics such as "the rules of the road" or modifications to the lateral route structure [3], [4], [16] to identify resolutions. In robotics, the negotiated maneuvers may be represented as discrete choices (e.g. waiting, dodging, retreating and turning on a grid) which are jointly selected, rather than a negotiation of continuously-valued maneuvers [17].

Likewise, other methods have coordinated some aspect of the conflict resolution. For example, [18] represented aircraft to each other as a source of coupled constraints on their trajectories, applied as each self-optimized its own trajectory.

Other proposed methods have negotiated which agent would maneuver, or which agent would determine the conflict resolution. For example, [19] established a "merit-based token passing coordination strategy" which dynamically updates the order in which agents replan; a later variant allowed one aircraft to modify both its own trajectory and that of the other aircraft to minimize total combined path cost, assuming that the aircraft valued cost the same. Similarly, [20] negotiated which agent had priority to generate their own conflict resolution; with its application to ground robots, the lower-priority agents were assumed to be able to stop and wait for the other agents to pass as part of the conflict resolution. Similarly, where problems with communication between agents has been a concern (e.g., multi-robotic systems where not every robot can talk with each other), an asynchronous method has been proposed which "elects a leader" [21].

Negotiations of the maneuver itself has been proposed by methods such as the Interactive Peer-to-Peer Collision Avoidance (IPPCA) algorithm. This searches negotiated resolutions to conflicts by examining progressively stronger maneuvers for both aircraft until a successful resolution is achieved [22], [23]. However, the method results in maneuvers that may be valued by their respective aircraft to have substantially different costs.

Likewise, two other methods have been more closely based on negotiations that account for the cost of the resolution. One viewed conflict resolution as a game in which players can condition their preferences on the preferences of others [1]. The other applied a monotonic concession protocol in which each player could, at each iteration, decide whether to concede that it would fly a higher-cost trajectory to the other aircraft to reduce the cost of the other's corresponding trajectory to resolve the conflict [24]; this protocol allows pairs of aircraft to deliberately seek resolutions at the point of mutual agreement. These negotiation protocols have the benefit that they create negotiated resolutions which 'divvy up' the cost of resolutions between the aircraft, often reducing the total cost by not relying on one more-extreme maneuver by either aircraft alone.

The third property of conflict resolution considered here is *decentralization*. While the terms distributed and decentralized are often used inter-changeably, decentralized operations are distinguished in this paper as the further special case where the individual agents (aircraft) are allowed to maintain private information defining their views of what is feasible and optimal. This contrasts, for example, with established negotiation protocols such as those described in the previous paragraph, which either assume a common cost function for all agents [24], or require aircraft to explicitly communicate their preferences [1]. Likewise, distributed conflict resolution methods have modeled aircraft as charged particles, repelling each other as they are attracted to their destinations [25]; this behavior also creates more strategic effects on the traffic flow, as it tends to spread out the aircraft so that they have some flexibility in maneuvering tactically, and its efficacy at preventing conflicts in a range of difficult, multi-agent conflict situations has been demonstrated in computational and human-in-the-loop simulations [14]. However, while the trajectories of the aircraft are effectively negotiated, the aircraft are not able to indicate preference or apply their own cost to the maneuvers.

Finally, the fourth property of conflict resolution considered here is *multi-dimensional.* Most of the methods for aircraft conflict resolution described here either look at only turning maneuvers or at lateral maneuvers that may also change the longer-term trajectory and/or speed. Similar methods developed in robotics have likewise only looked at agents operating on a two dimensional plane, often selecting from a set of discrete maneuvers that including waiting or retreating maneuvers that are either infeasible or very expensive for aircraft. The charged particle models of aircraft allows for multi-dimensional maneuvers, albeit without allowing aircraft to indicate the relative cost of, or preference for, maneuvers in different dimensions.

Thus, no existing method for conflict resolution in the literature has the four properties of distributed, negotiated, decentralized and multi-dimensional. In particular, methods to date have either valued conflict resolutions based on the magnitude of the maneuver, or by assuming the same cost function for all aircraft. None allow aircraft to hold private their cost index (and other business data such as performance constraints), while also allowing aircraft to apply this private data during the negotiations.

III. A Bargaining Process for Decentralized, Negotiated Conflict Resolution

The bargaining problem is a game theory concept that seeks an equilibrium in the face of conflicts of interest arising from players having separate, conflicting objectives [26]. The equilibrium sought is a Pareto-efficient solution, i.e., one in which it is impossible to make any one player better off without making at least one other worse off. Here, conflict resolution is framed as a two-player game where, assuming

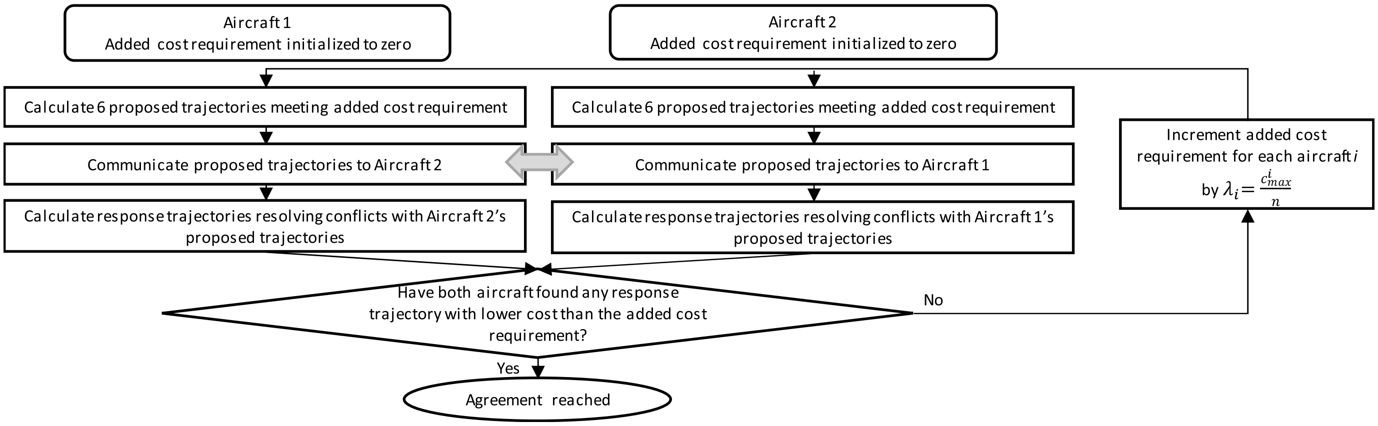

Fig. 1. Flowchart of the sequential bargaining process.

that each aircraft is already on an optimal trajectory, they would prefer that the other aircraft bear the cost, i.e., resolve the conflict through their maneuvers alone [26]–[29]. Thus, bargaining is required for the aircraft to find new trajectories that resolve the conflict and minimize total cost. At each step, the candidate set of trajectories for each aircraft implement six maneuvers (up/down, left/right, and faster/slower).

Each player (aircraft) assesses each anticipation (trajectory) using her/his cost function. Letting capital letters represent anticipations, such a cost function $f()$ is required to have the following properties [26]:

- Lower cost implies preference. Thus, if $f(I) < f(J)$ then conflict resolution maneuver I is preferred.
- The ordering of anticipations produced is transitive; i.e., if $f(I) > f(J)$ and $f(J) > f(K)$ then $f(I) > f(K)$.
- The utility and cost functions are non-unique: for example, *kf()+ c* can also serve as a cost function for $k > 0$.

Further, the bargaining process applied here assumes that the aircraft apply the same form of the cost function, i.e. using a *cost index* on the relative value of additional fuel burn and delay incurred by the trajectory, a cost function form standard in current flight path management systems. However, the cost index itself is not known outside each aircraft. This allows for different evaluations of proposed trajectories by each aircraft and establishes a truly decentralized process.

Formally, this two-agent bargaining problem consists of the set of all possible anticipations Σ (the trajectories), the feasible set of all attainable costs $F \subset \mathbb{R}^2$, and a disagreement point $d \in F$ which corresponds to the cost of each aircraft resolving the conflict alone.

Solving a bargaining problem means finding an agreement $s \in F$ viewed as better than d for both aircraft according to their personal assessment of cost. Assuming that aircraft A and B have different cost functions f_a and f_b, the set of all attainable costs associated with all possible maneuvers is:

$$F = \{(v_a, v_b) \in \mathbb{R}^2 | v_a = f_a(X), v_b = f_b(X), X \in \Sigma\} \quad (2)$$

The pair (F, d) represents a bargaining problem which identifies an agreement s. The approach to identify such bargaining functions is based on the axioms of game theory:

- *Pareto Optimality:* A bargaining solution $\varphi\ (F, d)$ is Pareto optimal if, within a set of feasible solutions Σ, there is no other solution that simultaneously provides lower costs than $\varphi\ (F, d)$ to both aircraft, i.e. for any $x \in \Sigma$, if $f_a(x) \le \varphi_a(F, d)$ then $f_b(x) \ge \varphi_b(F, d)$, or if $f_b(x) \le \varphi_b(F, d)$ then $f_a(x) \ge \varphi_a(F, d)$. This axiom reduces the space of potential bargaining solutions to those on the Pareto frontier.
- *Symmetry:* Let the function $T : \mathbb{R}^2 \to \mathbb{R}^2$ be defined by $T((x, y)) = (y, x)$. A bargaining solution $\varphi\ (F, d)$ is symmetric if, for every bargaining problem $(F, d) \in \mathcal{B}$, $\varphi(T(F), T(d)) = T(\varphi(F, d))$, i.e., preference is not given to either aircraft.
- *Invariance of Cost with Respect to Affine Transformations*: An affine transformation of the cost functions maintaining the order over the preferences should not modify the bargaining solution.
- *Monotonicity*: If (F, d) and (F', d) are bargaining problems such that $F' \subset F$, and the minimum costs for both players are the same in both problems, then $\varphi\left(F', d\right) \ge \varphi\ (F, d)$.[1]

In theory, when the Pareto frontier of the costs to all aircraft for all anticipations is known, then the agreement point s is the Kalai-Smorodinsky solution [30]. Geometrically, this corresponds to the point on the cost plan of (F, d) at the intersection the Pareto frontier and the diagonal between the disagreement point and the point at the minimum costs of each aircraft, which is usually $(0, 0)$.

However, here the Pareto frontier is not known, and the cost of each trajectory can only be valued by the aircraft that will fly it. Thus, the process must converge on trajectories representing a "fair" solution with costs on the Pareto frontier. Where the aircraft use the same cost index, the maneuvers will be symmetric, but where the costs are assessed using different cost indices the two aircraft's trajectories may deviate by a different amount even as they incur the same proportion of the cost.

The structure of this bargaining process is sequential, as represented in the flowchart in Fig. 1. Hence, each stage of the bargaining process is divided into 4 sub-steps:

[1]This axiom replaces the axiom *Independence of Irrelevant Alternatives* originally proposed by Nash [26], [30].

1. Each aircraft computes a set of six proposed trajectories (i.e., up/down, left/right and faster/slower) that it would agree to fly, represented as an immediate change in that dimension; once past the closest point of approach, the trajectory then adjusts to steer directly to the desired exit point of the airspace. Each trajectory is adjusted according to a cost requirement representing the added cost of the trajectory, as calculated by the aircraft's cost function. These cost requirements are initially 0 at the disagreement point, and then are increased with each iteration to require compromise by both aircraft in the form of subsequent proposed trajectories volunteering a greater proportion of the combined maneuvering required to resolve the conflict. Because the cost requirement is given, the magnitude of the changes in altitude (up/down), heading (left/right) and speed (faster/slower) is varied rather than following a fixed step size. Likewise, when the aircraft have different cost functions, their proposed trajectories do not have equal magnitude changes, but instead have equal cost. If each maneuver is represented as a simple 'triangular' change in trajectory (i.e., an immediate change within the maneuvering dimension, and a subsequent return to course once the conflict has passed), then trajectories can be communicated to the other aircraft as six data elements: the magnitude of each of the six proposed trajectory changes. The bargaining process can also accommodate more elaborate trajectory definitions; these would require more data elements to be communicated between the aircraft.
2. Each aircraft computes *response* trajectories, i.e. the minimum cost trajectories it would need to fly to resolve the conflict if the other aircraft flew its proposed trajectories.
3. Each aircraft compares the cost of its response trajectories computed in 2 with the cost of its proposed trajectories computed in 1.
4. If any of the response trajectories are cheaper than the proposed trajectories, then an agreement has been found in the form of proposed trajectories that effectively distribute cost between the two aircraft; else no agreement is reached and the bargaining process iterates again through these steps with an increased cost requirement on their proposed trajectories. This progression is confirmed by each aircraft communicating one bit to the other, confirming whether they have identified an agreement point.

The trajectories computed in both steps 1 and 2 must meet several constraints. First, the proposed trajectories must meet the cost requirement, which increases at each stage. Second, the response trajectories must resolve the conflict assuming the other aircraft flies its proposed trajectories. Third, constraints can be imposed to represent a broad range of phenomena, including avoiding special use airspace and terrain and, examined in detail here, aircraft performance limits. Development of this bargaining process examined three ways of representing these constraints:

1. The *clipped* method clips the feasible sets of trajectories to contain only trajectories strictly within performance limits. This guarantees that the performance limits will never be violated, but prevents a guarantee that the bargaining problem operates on a feasible set Σ containing a Pareto optimal agreement point.
2. The *infinite cost* method assigns infinite cost to trajectories that exceed constraints. In theory, this method meets the axioms noted earlier. However, it can lead to negotiation between two agents which, if both are at limits, converges on both incurring infinite cost.
3. The third *finite cost* method builds a nonlinear shaping function that adds increasingly to costs when approaching performance constraints. Thus, proximity to constraints incur finite cost penalties instead of infinite cost barriers.

Likewise, development of this bargaining process examined two different ways of examining maneuver dimensions (up/down, left/right, and faster/slower). The first method keeps every dimension separate: response trajectories are calculated as optimal responses in the same dimension as the proposed trajectories (i.e., proposed trajectories turning left and right are each solved with optimal turns for response trajectories that resolve the conflict; vertical proposed trajectories are each solved with optimal vertical response trajectories; and speed changes are each resolved with speed changes). The second method has each aircraft compute six response trajectories for each of the six proposed trajectories, generating a total set of 36 response trajectories per aircraft at each stage.

Finally, the development of this bargaining process established a mechanism for convergence in the negotiation by requiring the aircraft to honestly propose proposed trajectories at stage $i+1$ that are more expensive than previously given in stage I, and honestly report the cost of the response trajectories. After a finite given number of steps, the pair of aircraft should simultaneously be offering proposed trajectories with costs equal to the costs of the other aircraft's response trajectories to them (at least in those maneuvering dimensions where performance constraints do not asymmetrically bound the feasible set Σ or drive costs to extreme values). This is achieved using constants $\lambda_a > 0$ and $\lambda_b > 0$ such that, if a proposed trajectory has been proposed at step i by aircraft K, with a cost $f_K(t_{K_i})$, then aircraft K has to next propose a proposed trajectory at step $i+1$ such that $f_K\left(t_{K_{i+1}}\right) \geq f_K\left(t_{K_i}\right) + \lambda_K$. The cost of the disagreement point here is defined by cost c^A_{max}(i.e., the cost of the response trajectory for aircraft A to the zero-cost proposed trajectory initially offered by B) and the corresponding c^B_{max} that would be incurred by aircraft B if it were the only aircraft to maneuver. The convergence constants are then set to be $\lambda_A = \frac{c^A_{max}}{n}$ and $\lambda_B = \frac{c^B_{max}}{n}$ such that the bargaining process should converge in n iterations. Intuitively, aircraft will progressively have to deviate from their initial zero-cost proposed trajectories to solutions where the cost of the offered proposed trajectory equals the cost of the other aircraft's response trajectory, but exceptions may occur as constraints start to limit the feasible set Σ or the trajectory deviation associated with a required cost increment λ.

IV. Experiment in Pairwise Conflict Resolution

A. Experiment Design

The previous section noted three design variables within the bargaining process: (1) how the performance constraints are represented (clipped, infinite cost or finite cost); (2) the dimensionality of the response trajectories (six response trajectories each in the same plane as the six proffered proposed trajectories, or 36 responses trajectories resulting from six responses in all dimensions to each of the six proposed trajectories); and (3) the convergence parameters (examined here with n set to 100, 200 and 300), setting the step size in the required cost of the proposed trajectories.

A computational experiment examined these variables in pairwise conflicts. The 18 combinations of the design variables were each tested in the 9 combinations of these conditions:

- The cost indices i used by each aircraft: (1) both low, weighting fuel burn the highest ($i = 10\%$); (2) both high, weighting time delay the highest ($i = 90\%$); and different ($i = 10\%$ for one aircraft and 90% for the other). These were applied to the cost function in (1).
- The conflict geometry, creating conflicts inherently requiring different resolutions [31]. Rule A conflicts with zero miss distance between aircraft converging at 30° (resolved horizontally by eliminating closure rate); Rule B conflicts with zero miss distance between aircraft at 150° (resolved horizontally by increasing miss distance to let one aircraft cross in front of the other); and Rule C conflicts with a miss distance of 4 nm between aircraft converging at 90° (resolved horizontally by turning the aircraft into each other). All of the conflicts would result in loss of separation if not resolved; the simulation was started when the conflict was detected.

The aircraft were simulated in the Work Models that Compute (WMC) simulation framework [32]. Each aircraft was represented by a point-mass dynamics model that uses first-order controllers to directly regulate eight states to follow a given trajectory: latitude, longitude, altitude, true airspeed, thrust, roll, heading, and flight path angle. The model dynamics were integrated by a fourth order Runge-Kutta adaptive step size integration algorithm using the Cash-Karp parameters. Aircraft performance limits were calculated using Eurocontrol's BADA (Base of Aircraft Data) performance models for the Airbus A320 [33], [34].

B. Results

1) Convergence: Each of the negotiations converged in the 162 pairwise conflicts examined here (18x9), regardless of the convergence parameters (n set to 100, 200 or 300). This n value reflects the number of iterations required to drive the cost of the proposed trajectories from the disagreement point d to zero; in contrast, the cost of the agreement point s is typically greater than zero and thus the actual number of iterations is much lower than n.

2) Dimensionality of the Response Trajectories: Examining the dimensionality of the response trajectories, the negotiated solution always converged to agreement on response trajectories in the same plane as the proposed trajectories, even when response trajectories were proffered in different dimensions. Specifically, the negotiated solutions resolved conflicts at lowest cost when both aircraft contribute to the increased separation in the same dimension. In contrast, resolutions by

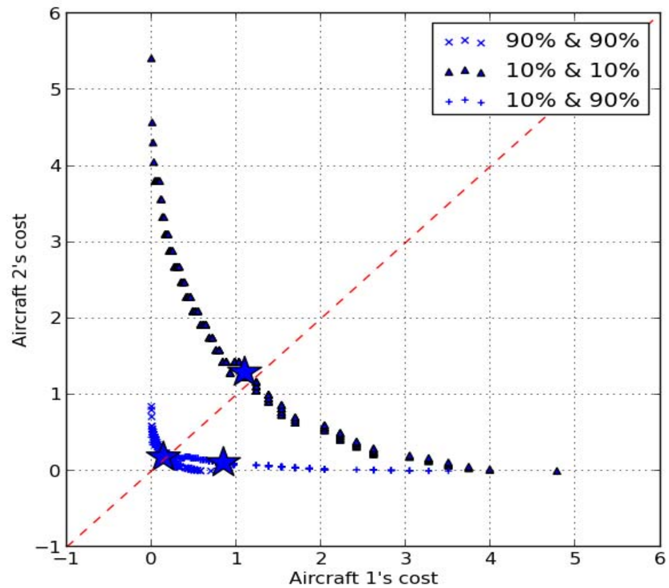

Fig. 2. Response trajectory cost plans overlaid for each pairing of cost indices. Rule C conflict geometry, infinite cost evaluation of performance constraints, n = 500. The stars indicate the agreement points for each of the costs indices pairings.

the two aircraft in different dimensions generally need to be larger than the coordinated, negotiated within-plane solutions. Thus, at least in the conflict geometries created here, resolutions were not selected with the two aircraft maneuvering in different dimensions.

3) Negotiation Not Limited by Constraints: When performance constraints do not limit the trajectories, their cost plans smoothly converge to a solution, typically in significantly fewer than n iterations. Further, when the aircraft have the same performance and have the same cost indices, the negotiations clearly follow a symmetric profile.

Consider, for example, cases identical but for the aircraft's cost indices (Fig. 2). When both aircraft have cost indices of 10%, the original disagreement point d starts with aircraft 1 perceiving a cost of roughly 4.8 to maneuver alone, and aircraft 2 perceiving a cost of roughly 5.4 to maneuver alone. As they iteratively propose trajectories of increased cost, the cost of their response trajectories traces out a smooth, roughly symmetric Pareto frontier and the agreement point (established when the cost of their response trajectories is equal-or-less than that of their proposed trajectories) represents roughly the same reduction in cost for each. A similar trend results when both aircraft have cost indices of 90%, albeit with the cost of the response trajectories consistently being valued at lower cost, starting from d at roughly (1.8, 1.8) on the cost plan.

The negotiations become asymmetric (but remain monotonic) when the aircraft have different cost functions, shifting the disagreement point. For example, in Fig 2. with cost indices of 10% and 90%, d is shifted to roughly (4.8, 1.8). While the proposed trajectories are driven to have a fixed cost increment, the response trajectories are determined by the conflict geometry. Thus, the conflict may require a larger

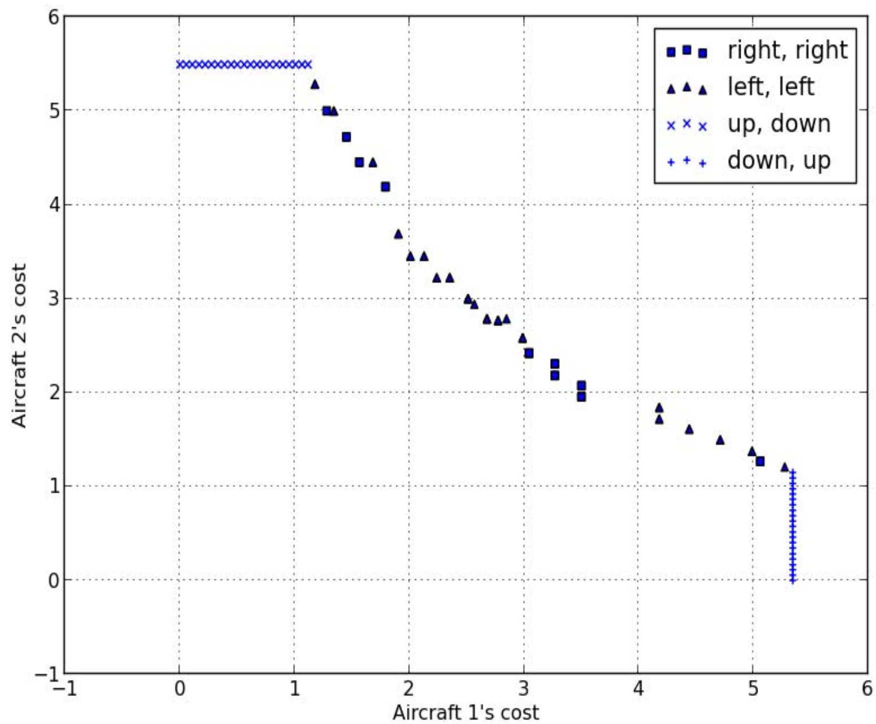

Fig. 3. Response trajectory cost plan with performance constraints requiring switches in the maneuver dimension during the negotiation. Rule B conflict geometry, cost indices 10% and 10%, infinite cost evaluation of constraints, n = 100.

response by one aircraft, skewing the shape of the response trajectory costs. The agreement point is also shifted but remains a Kalai-Smorodinsky solution.

In all cases where the trajectories selected during negotiation do not 'hit' the constraints and thus are not limited, the costs incurred by either aircraft at the agreement point are less than that of the disagreement point. This is an improvement to resolution methods that just maneuver one aircraft, or require both aircraft to conservatively maneuver as if the other may not.

4) Negotiation Limited by Constraints: In some of the conflict geometries, trajectories in some of the six dimensions were constrained. This experiment specifically examined performance constraints mirroring those on aircraft in cruise (upper altitude and upper and lower bounds on speed). However, there is no known obstacle within the method for other effects such as special use airspace, terrain avoidance, etc. also being used to identify or value constraints.

The bargaining process is impacted when these constraints limit response trajectories that have, to that point in the negotiation, been offering the lowest cost. Consider Fig. 3, for example. At the start the response trajectories offering the lowest cost are those where one aircraft maneuvers up and the other down. However, at some iteration i one aircraft cannot maneuver further up. From here, where the proposed trajectories must have cost $i\lambda$, the response trajectories using right/left turns have the lowest cost; their Pareto frontier is clearly visible and they ultimately define the agreement point.

The bargaining process is impacted differently when the agreement point involves constrained response trajectories. Here, the representation of the constraints is paramount, as shown in Fig. 4: With the clipped representation in Fig 4a, speed changes are declared infeasible shortly before agreement and the negotiation becomes driven by changes in altitude, where one aircraft is again limited. This results in asymmetric costs: one aircraft has to maneuver down more because the other aircraft can't maneuver up very far, and the agreement point needs one aircraft to incur high cost (around 2.7) while the other incurs only a cost of about 0.7, for a total of about 3.4.

Examining the same case using the infinite cost method of representing constraints (Fig. 4b) and the finite cost method (Fig. 4c), response trajectories near the constraints are not removed from the feasible set, but instead increase the total cost incurred by the two aircraft combined. In this conflict geometry, the negotiation prefers speed trajectories while they remain in the feasible set; as the speed nears its constraints the proposed trajectories offered at each stage incur increased cost λ with progressively smaller changes in speed. The solutions in both Fig. 4b and 4c correspond to the same change in speed by both aircraft, one pushing on its upper limit and the other pushing on its lower limit, with different valuing of those changes in speed. The agreement point with the infinite cost function in Fig 4b has a cost of about 1.7 for each aircraft, i.e., with the same total cost of 3.4 as before; the agreement point with the finite cost function never 'breaks' towards a different dimension and ends up valuing the agreement point at around 4.2, a higher total cost. Thus, these results demonstrate the sensitivity of the method to representing performance constraints, such that the negotiation does not converge on a

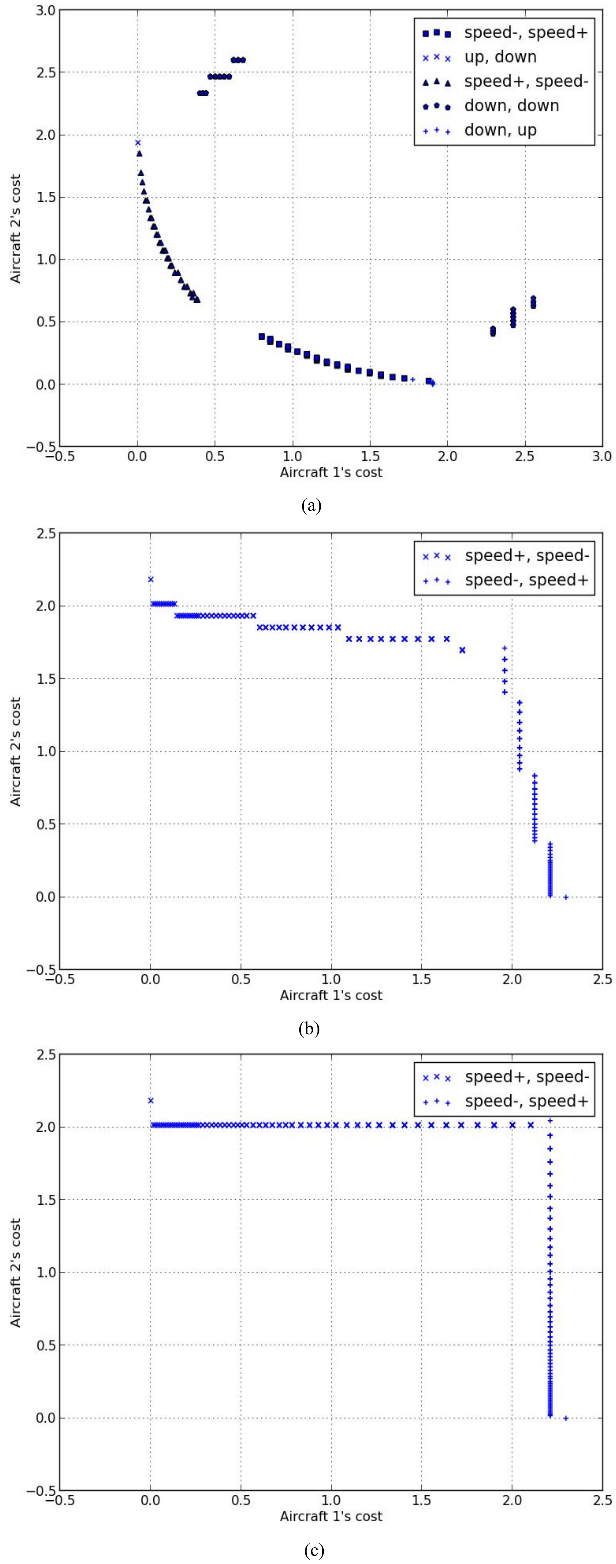

Fig. 4. Response trajectory cost plan with final agreement point close to the constraint on airspeed. Rule A conflict geometry, cost indices 90% and 90%, n = 200. (a) Clipped representation of constraints. (b) Infinite cost representation of constraints. (c) Finite cost representation of constraints.

more costly solution rather than examining other dimensions for maneuvering: in this case, the clipped representation of constraints provided the lowest cost final solutions.

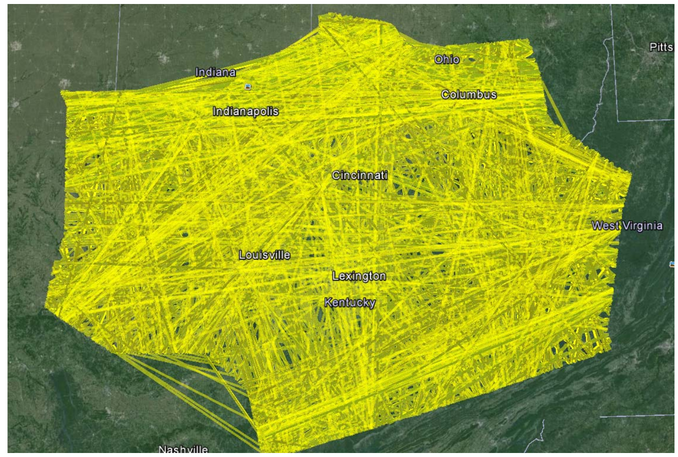

Fig. 5. Simulated flights within Indianapolis ARTCC.

V. Large-Scale Demonstration

This demonstration simulated all aircraft that progressed through the Indianapolis Area Route Traffic Control Center (ARTCC) (Fig 5). The simulated aircraft were taken from real flight data as captured from a five hour time window between 1pm and 6pm local time on a weekday in July 2005, filtering to only include the 1184 en-route aircraft that stayed above 17000’ altitude and whose entry and exit points into the airspace could be fit to an optimal, direct route through the airspace. Unlike the real flight data, the nominal trajectories for the aircraft were assumed here to be optimal routes (laterally and optimal cruise altitude) between their recorded entry and exit points into this airspace. These direct routes, not separated into different flight levels, were found to generate 538 conflicts. Of these, six conflicts were ill-conditioned for this simulation: either they entered the airspace already in conflict, or the conflict occurred just before they were required to exit the airspace at a given point and time, precluding a resolution trajectory.

The WMC framework was again used with the same aircraft dynamic models and BADA performance models as applied in the pairwise conflict experiment detailed in the previous section. Throughout the simulation, every conflict was resolved using the proposed bargaining process. Based on the results of the previous section, however, the bargaining process was configured to (1) use the clipped method of representing constraints, (2) the response trajectories were each only solved in the same dimension as the proffered proposed trajectory they resolved, and (3) the convergence parameter n was set to 100, requiring the least number of iterations within the negotiation. In the previous pairwise conflict experiment, these parameters all resulted in convergence to the lowest cost for the two aircraft combined. Conflict detection applied exact data, such that each bargaining process was triggered exactly 300 seconds before conflict; each resolution was required to be conflict free for 600 seconds. The bargaining process was assumed to take negligible time and thus the resolution was simulated as being flown immediately after detection.

Examining the resolutions of the 532 conflicts, 43% of the conflicts were resolved by turns right/left and 10% by faster/slower airspeed changes. A significantly larger

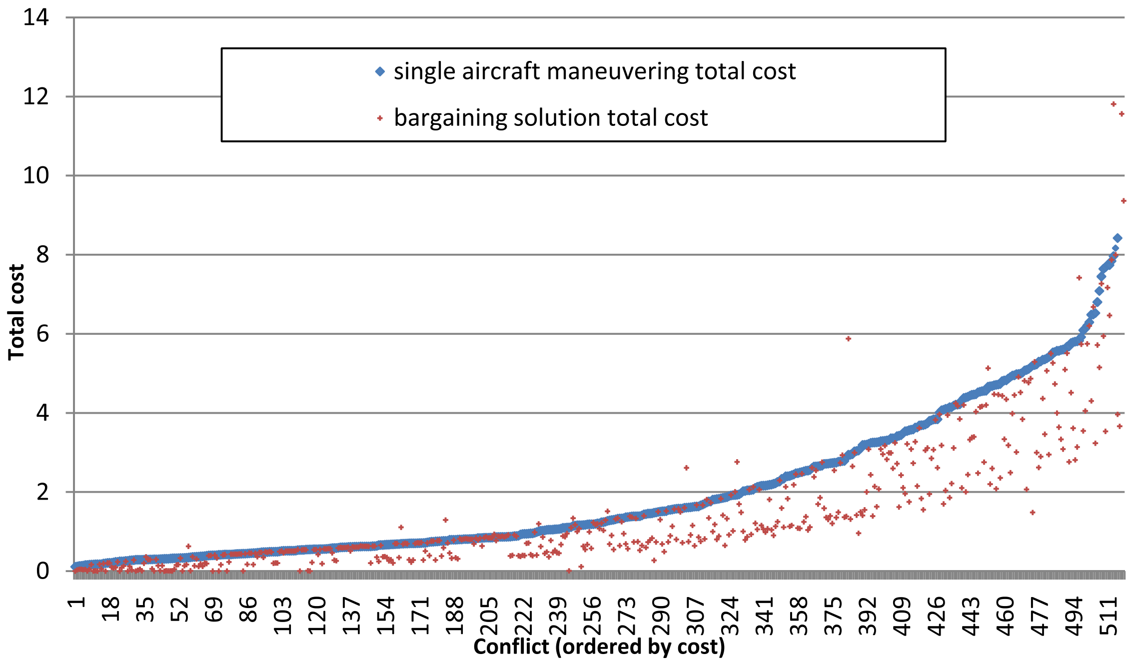

Fig. 6. Comparison of the total cost of the conflict resolution created by bargaining versus the cost of only one aircraft maneuvering to resolve the conflict alone.

percentage were resolved with altitude in this large-scale demonstration (47%) than in the previous pairwise experiment (roughly 13%), presumably because here each aircraft was flying at its optimal cruise altitude and thus the negotiation started with the aircraft already at different altitudes, which is more-easily resolved vertically. This bargaining process only resolved pairwise conflicts. Thus, to assess system stability the simulation flagged cases where a conflict resolution created a new downstream conflict: 10.1% of the conflict resolutions generated a single downstream conflict and 1.5% generated more than one downstream conflict. These results, however, are likely sensitive to a number of other factors, including traffic density [7].

Finally, the cost of conflict resolution in current-day airspace is sufficiently significant to spark a range of proposed solutions, including both better traffic flow management to reduce the number of conflicts, and better resolution methods to reduce the cost of the conflicts [1], [3], [4], [7]–[9], [11]–[14], [18], [22], [24], [25]. Figure 6 portrays the combined cost of the negotiated solution (which maneuvers both aircraft) with the cost of non-negotiated conflict resolutions (assumed to result from the lowest cost resolution incurred by maneuvering either aircraft alone). The bargaining process was more cost effective in 80% of the conflicts and on average resulted in a 29% cost reduction. The remaining 20% of the conflicts were generally in conditions with constrained resolutions; of these, 17 conflicts had more than 10% greater cost with the negotiated solutions.

VI. Discussion and Conclusions

This paper demonstrated a bargaining process that meets a strict definition of decentralized conflict resolution: aircraft only need to reveal to each other proposed trajectories meeting cost requirements and resolving the conflict, but do not otherwise need to reveal private information such as their cost function and performance constraints.

The bargaining converged in all cases examined here, and on-average resolved the conflict with a 29% lower cost than the lowest-cost resolution by either aircraft alone. However, aircraft with different cost functions evaluate the conflict asymmetrically: the bargaining follows an asymmetric cost plan and the aircraft's trajectories incur an equal share of the cost but may not by deviate the same amount.

Examining the dimensionality of the resolution, proposed trajectories were always generated in six dimensions (right/left, up/down, faster/slower), and the pairwise conflict experiment described in section IV compared calculating 6 response trajectories (each within the same plane as the proposed trajectory they resolve) or 36 (i.e., six responses to each of the six proposed trajectories). The results indicate that having the personal and response trajectories in the same plane generally resolves the conflict at lower cost, substantially reducing the computation needed within the negotiation process.

Finally, a significant factor in the negotiation is the representation of constraints on trajectories. Two representations always kept personal and response trajectories within the negotiation's feasible set, but represented proximity to constraints with significant costs; however, these methods sometimes kept negotiating in constrained dimensions, increasing the resultant cost. The third representation instead clipped those trajectories (from the set of six) that were hitting constraints, limiting the feasible set within the negotiation. This method worked well in the cases here; some safety check may be required, however, to ensure a non-null feasible set remains even should multiple dimensions become constrained.

The negotiation assumes that each aircraft reports the cost of proposed and response trajectories honestly, according to a cost function used over the duration of the flight within its flight management system. Such a capability could be automated in sealed airborne systems, similar to other government-regulated systems that are vetted for providing fair weights and measures. This would ensure that the negotiation proceeds in good faith; it does, however, preclude pilots' involvement in the negotiation; similar to the vetting pilots currently must apply to air traffic instructions resolving a conflict, they would need to confirm the safety of the negotiated maneuver.

Likewise, the negotiation time was assumed to be negligible, and the maneuver to be executed immediately. Depending on communication bandwidth, non-negligible negotiation times may need to be accommodated: Each iteration of the negotiation would require each aircraft to communicate the two altitudes, two heading changes and two speed changes corresponding to the six proposed trajectories. Similarly, on-board computing would be required to calculate the six proposed trajectories and six resolution trajectories. The delay caused by communication and/or computation could be accommodated, for example, by extending the detection time to trigger the negotiation early enough such that the resolution can be started after a time sufficient for n iterations in the negotiation. The total allowable delay is set by the requirement that the negotiation should be able to converge faster than the conflict geometry might change during the negotiation.

In this case study, the method for calculating response trajectories was simplistic in that it only sought a resolution to the immediate conflict. Thus, the same negotiation process could be envisioned with more sophisticated resolution capabilities that also prevent or mitigate downstream conflicts. This resolution of downstream conflicts would also require inter-aircraft communication, although this communication may not be as time critical since it can allow for longer detection and resolution look-ahead times. It may also flex strategic flow requirements; for example, aircraft may value response trajectories differently on whether it then has to return sharply to its original route, or can re-optimize a new route to its destination. Such a capability may also then lead to continuous refinement of strategic flow parameters.

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