Deep Learning-based Negotiation Strategy Selection for Cooperative Conflict Resolution in Urban Air Mobility

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***Abstract*– This paper presents a collaborative conflict resolution technique using deep neural network-based intelligent search of the solution space. This approach offers a rapid convergence to a mutually acceptable solution for real-time conflict resolution, suitable for urban air mobility operations. Furthermore, the presented technique allows operational flexibility to the urban air mobility agents where these agents can collaboratively devise the solution via integrative negotiation, based on their local utility functions, as long as such a solution does not violate the global safety thresholds. The presented machine-to-machine negotiation method is built on our prior work on holistic assessment of the airspace and potential conflict detection implemented at-the-edge, onboard the unmanned aircraft systems. This paper extends the prior work to augment decision-making at-the-edge, thereby, promising a true distributed control architecture for urban air mobility. In this approach, each agent (a) builds a potential in-flight conflict map, (b) identifies the conflicting agents, (c) dynamically prepares a list of alternatives based on its current utility functions, (d) negotiates with the conflicting agents to pick one of these alternatives, and (e) implements the negotiated alternative to mutually resolve the conflict. Note that such an approach does not require a contingency plan to be made pre-flight, as the conflict resolution strategies are decided and negotiated in real time based on the present state of the agent. The contingency plan, if available, can serve as an input to the real-time conflict resolution strategy formulation, and also can be used as a fallback plan in case the negotiation fails and the impacted agents need to switch to a rule-based/supervisory resolution mode from the discussed distributed resolution mode. The presented collaborative negotiation-based conflict resolution technique incorporates a time-dependent reward function to catalyze collaborative resolution by incentivizing the agents with local and global rewards beneficial to their business operations.**

I. Introduction

The aviation industry is at the cusp of a technological revolution characterized by a greater diversity of businesses that bring their operations to the sky. These businesses, such as people conveyance, cargo transportation, infrastructure monitoring, surveillance, emergency services, entertainment, etc., will bring in different types of vehicles, different levels of artificial intelligence (AI) in their operations, and above all, different utility functions to create their competitive advantage in the market. Such diversities are expected to shape the airspace usage preferences of different businesses differently. In contrast to present day civil aviation, where the industry operates with only a handful of business objectives, i.e. to move people and cargo from one place to another, in the future, the industry will have many more operators with a wider set of business goals. The existing air traffic management (ATM) framework is largely centralized and human-centric, with a pre-defined and rule-based structure. Future urban air mobility (UAM) operations are anticipated to have limited onboard resources, highly non-deterministic operations, higher variability in demand for service, large vehicle population, and more limited airspace in which to operate. Merely augmenting current day systems to meet the conglomeration of business operations in the urban skies raises concerns about management latency and bandwidth, and associated airspace safety. Thus, these considerations warrant new approaches to UAM operation management that offers an optimized and commercially-friendly management model with fair tradeoffs for the UAM stakeholders, while ensuring overall airspace safety.

This paper draws its motivation from such a management model for UAM and envisions its feasibility through a distributed and intelligent control system that can support vertically isolated, latency-sensitive UAM applications by providing a ubiquitous, scalable, and robust operational management capability. In achieving the same, the research is also motivated by examining the efficacy of deep learning, which allows machines to solve complex problems even when using a data set that is very diverse, incomplete, unstructured, and inter-connected. This paper presents a concept for edge artificial intelligence (AI) decision engine for distributed conflict resolution, implemented onboard unmanned aircraft systems in urban air mobility scenarios, where the unmanned aircraft systems use deep learning-based strategy optimization for integrative negotiation.

Overall, there are four stages of the distributed and intelligent cooperative conflict resolution approach discussed in this paper. The first two stages, as published in our AIAA Aviation 2020 paper [1], entail synthesizing a multifarious data into a suitable data-frames for automated ingestion, followed by learning the collective behavior of the agents in the scenario, as represented by these data-frames, using a deep neural network that is then used for future impact assessment. The work presented in this paper focuses on the third stage of the approach that closes the loop with an AI decision engine, which selects strategies in real-time, taking into account the current utility functions of the agents, to resolve any potential conflict through pre-emptive action or active negotiation. As in the case for the impact assessment, this AI decision engine is also envisioned to be implemented in a distributed manner onboard the agents. The final stage of the approach, which will be discussed in our future work, will provide an outcome-based reinforcement to further boost the overall technology performance.

This paper is organized as follows: section II discusses the research focus, background, and motivation for this project. In section III the collaborative negotiation strategy is presented with approach for edge implementation. Section IV presents a custom simulator developed for the implementation and evaluation of the collaborative negotiation-based conflict resolution approach. Research findings are summarized in section V. Finally, section VI concludes the paper with a discussion on the future directions.

II. Related Work in Literature

At present air traffic management primarily relies on human intelligence to monitor the airspace, determine potential violation of the inter-aircraft separation criteria and other relevant conflicts in the near future, and provide remedial intervention to resolve such conflicts. Numerous research has been conducted to model the conflict detection and resolution (CDR) methods, as surveyed by Kuchar & Yang [2]. Almost all CDR methods use some form of trajectory propagation approach, involving nominal, worst case, or probabilistic trajectories, to identify potential conflicts and search solutions. Typically, the solution generation methods look to come up with prescribed, optimized, or force-field-based resolutions as a part of automation. Some models, on the other hand, allow the user(s) to generate their preferred solutions, otherwise known as manual solutions. Such solutions are generally more flexible as they are based on human intuition using information that may not be available to the automated compute module. Yao et. al. [3] utilized data collected and archived by the Federal Aviation Administration (FAA) regarding predicted conflict events and information about the aircraft during their flight, to demonstrate algorithms for cataloging aircraft conflict resolutions, which is then used to quantify the frequency of maneuvers used by air traffic controllers. The authors note that such automated categorization of conflicts, based on previously successful maneuvers, can help converging to potential resolutions with less cognitive burden on part of the controllers; however, such a solution-space-search can be time-consuming, and they suggest a neural network-based approach can significantly improve latency. Pham et. al. [4] later proposed a machine learning approach for conflict resolution in dense traffic scenarios with uncertainties. Their work has reported a conflict resolution success rate of over 81% using reward function and learning algorithms inspired by deep Q-learning and deep deterministic policy gradient algorithms.

Conventional automatic systems such as Automatic Dependent Surveillance-Broadcast (ADS-B) [5] and Traffic Alert and Collision Avoidance System (TCAS) [6], an FAA implementation of International Civil Aviation Organization (ICAO)'s airborne collision avoidance system (ACAS) for short-range systems, are designed to function around the distal end of the conflict detection. Assuming that the compute system onboard the smart vehicles is capable of detecting or predicting the conflict much earlier, the aforementioned conventional methods are still triggered within 1 to 3 minutes to the conflict point, as indicated via the advisory zone in Fig. 1, thereby leaving highly prescriptive resolutions as the only option to avoid the conflict. Newer conflict detection and resolution models such as the ACAS X [7] or the ACAS Xu [8], which is a variation of ACAS X for unmanned aircraft, use more sophisticated methods. For example, ACAS X implements its alerting logic based on a numeric lookup table optimized with respect to a probabilistic model of the airspace and a set of safety and operational considerations, for which ACAS X uses multiple surveillance sources such as sensors and global positioning system (GPS) measurements. ACAS Xu brings in certain special considerations such as handling of non-cooperative sensors and use of horizontal resolutions, specifically applicable to electronic vertical take-off and landing (eVTOL) vehicles. While these advancements surely enhance the efficacy of integrated airspace safety by taking into consideration a wide range of operational and environmental variabilities, there still lies a need to consider the business utility functions of the smart vehicles and their operators.

As more and more UASs are integrated to the national airspace, adding to the traffic and thereby the workload on human controllers responsible for the safety of the airspace, the demand for unsupervised or limited-supervised techniques is rapidly increasing. Interestingly, this need has been identified for quite some time now, as Eby [9] proposed a self-organizational approach for resolving air traffic conflicts, by applying simple destination-seeking rule and conflict-avoidance algorithms to each vehicle individually. The collective solution, in such case, is determined by the calculated behavior of the individual vehicles. Since this work, a lot more conflict detection and resolution approaches have been explored [10] that are specific to UASs integrated into the national airspace. Among the surveyed conflict resolution methods there are numerical optimization methods, rule-based methods, artificial potential field methods, game theory methods, geometric methods, multi-agent cooperative methods and so on.

While traditional numerical and centralized intelligent optimization methods can achieve good system level optimization, in complex environments with aircraft of different performances and objective functions, the centralized methods are susceptible to feasibility and scalability limitations. In such complex and dynamic environments, where rapid decision making is essential, distributed methods such as multi-agent collaborative approaches have garnered substantial interest from the research community. Jacolin and Stengel [11] studied an approach that allows aircraft to optimize their operations according to their own interests while traffic coordinators ensure global safety. Archibald et. al. [12] investigated a negotiation method where the agents are allowed to obtain their preferred time-slots via negotiation. [13] and [14] discuss a cooperative multiagent negotiation approach for automated conflict resolution.

The work presented in this paper studies an integrative negotiation technique for airspace conflict resolution. In this negotiation strategy the involved agents work together to find a solution that satisfies the needs and concerns of each. This process often involves holistic and creative decision making for the individual agents to suggest different ideas that jointly benefit them. Several studies on learning-based negotiation strategy formulation and implementation have been reported in literature, including a reinforcement learning-based contract negotiation method in [15], and learning-based grid scheduling in [16]. Among the emerging technologies for conflict resolution, as surveyed in [17], deep reinforcement learning, as studied in [18], have shown promising paths in conflict detection and resolution. Specifically, in [19] the authors have used conditional joint action learning to reach optimal payoffs for the agents.

The utilization of the presented AI decision engine is to facilitate a dynamic and learning-based solution search that makes the progressive offers in a negotiation not only based on the agent's own preferences but also taking into account the other agent's known and/or predicted behavior. A global reward is used to further incentivize the integrative negotiation. In summary, the proposed approach is envisioned to implement a mutually favorable solution to the negotiating agent, thereby offering a better management of their individual business objectives.

In summary, the presented approach is envisioned to deliver a lower local cost-based resolution, as opposed to lower global cost-based resolution, which is the focus of conventional human-centric, centralized, and last-minute tactical resolution approaches. Furthermore, the presented approach leverages predictive methods to effectively utilize the traditionally unused distal time window, to provide the conflict resolution at a near-strategic level as opposed to at the tactical level targeted by most contemporary resolution approaches. This is beneficial for operational conditions characterized by vehicle diversity.

III. Distributed and Collaborative Negotiation Strategy

A. Motivation

NASA, through its Advanced Air Mobility (AAM) project, is focused on helping emerging and underserved aviation markets to safely develop an air transportation system that moves people and cargo in local, regional, intraregional, and urban areas, using revolutionary new aircraft that are only just now becoming commercially viable. UAM is a part of this vision that focuses on air mobility in urban environments, with unique technological and logistical challenges due to the highly dynamic nature of the environment. Review of prior work reveals only a few helicopter-based localized implementations that are related to a transportation concept in which everything from small package delivery drones to passenger-carrying air taxis are operating above populated areas [20]. To mitigate some of these challenges, NASA laid the foundation for much of this work through the UAS traffic management (UTM) [21].

Another key factor to consider is the diversity in air vehicle types. Along with conventional fixed wing air vehicles there will be other types of vehicles such as multi-rotor vehicles and hybrid propulsion vehicles. Contrary to conventional aviation, vertical take-off and landing (VTOL) will most likely be the adopted method by the UASs for transitioning between ground and air. Furthermore, almost all such UASs will be electrically operated vehicles or eVTOL vehicles. A 2017 survey conducted by the Vertical Flight Society (VFS) lists a total of 169 different eVTOL aircraft [22]. The national air transportation association (NATA)'s report [23] on vertiport operations sheds valuable insight on design, operation, and safety considerations for vertiports that the eVTOL UASs will use. Based on different concepts of operations (conops) for people and cargo transportation, the placement of vertiports and their maintenance and accessibility metrics have been studied in [24]. With such diversity of operations, effective management of the integrated airspace becomes extremely challenging with the limited amount of resources and personnel in the current air traffic control community.

As the ever-increasing demand for smart, agile, and on-demand air mobility services for short-range transportation, package delivery, emergency response and so on continues to stretch the functional limits of human-operated and centralized air traffic control system, a distributed and collaborative management approach offers promising prospects. The challenge, however, lies in the availability of decision-making information and sharing of the same in a competitive business environment. Therefore, a more practical approach that involves negotiation-based conflict resolution is proposed in this paper that does not mandate that all agents share all information with each other. Instead, the smart agents build a set of offers/asks to be used in a negotiation setting to iteratively search the solution space.

B. Example Use Case Description and Problem Statement

Consider two smart air vehicles approaching a corridor intersection from opposite directions as shown in Fig. 1. Furthermore, let's assume that these vehicles are operated by different business operators, for example: one dealing in package delivery and the other in air taxi service. As per recent FAA regulation [25], all UASs are required to share in real-time their location and identification number on a radio frequency that can be monitored by the law enforcement agencies. Given the availability of such information, let's assume that each of the two smart UASs can query the location of nearby UASs that would reveal their positions to each other.

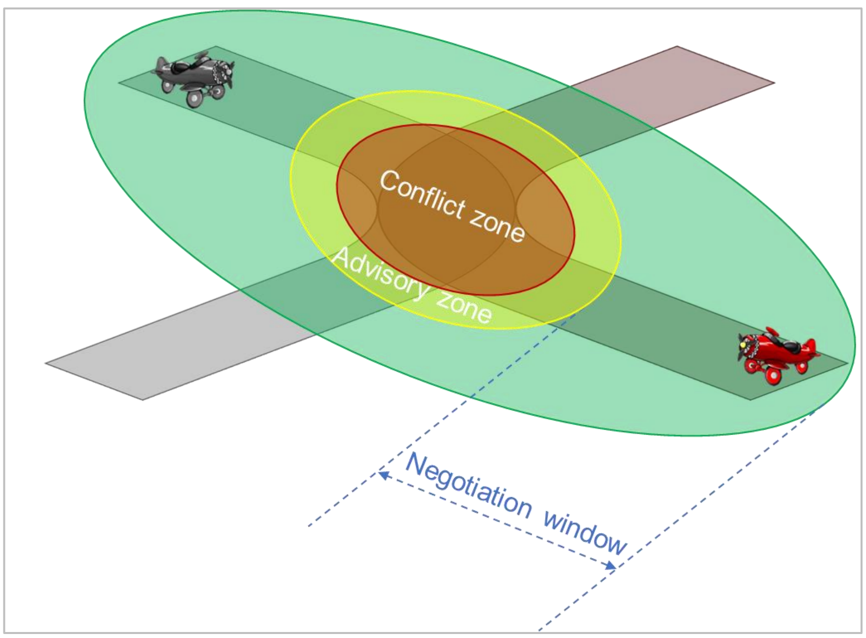


Fig. 1 Example use case rendering for negotiation-based collaborative conflict resolution

It is also assumed that the schedule of the two vehicles leading to the intersection is not deterministic due to the variability in operational demand, driven by the need to deliver a package to a specific location or transporting passengers to a particular location. Therefore, no prior information is available to one UAS regarding the other UASs' arrival at the intersection, status of its flight resources, and other operational conditions.

Therefore, the problem statement for our research is defined as follows: given the early detection/prediction (for example: 10-15 minutes to the conflict point) of potential conflicts by the smart vehicles using their onboard compute capability, can the intervention be made sooner to resolve such conflicts? Furthermore, can such interventions be self-administered by the smart vehicles, either individually or collaboratively with other conflicting smart vehicles, thereby not increasing the cognitive burden on the human/ground controller/supervisor? Lastly, can the smart vehicles leverage their specific business utility functions to implement mutually favorable resolutions?

C. Assumptions

For the desired implementation of the presented approach, a few assumptions are made as follows:

- The operational environment under consideration is a UAM-specific environment and exhibits corresponding general characteristics, such as high temporal traffic density, low-altitude flights, short-range travel, real-time scheduling and so on. Note that in future work, the goal is to relax this assumption to include conventional air traffic to make it a true integrated air operations scenario.
- The airspace is structured with designated corridors and multiple flight levels to fly. These corridors intersect to allow transition from one route to another.
- The agents are smart, in the sense that they carry residual computation power onboard that is capable of running deep neural nets in real time.
- The smart agents, collectively describing the autonomous vehicles, operators, service suppliers etc., have network access to send and receive real-time updates from each other. For the sake of simplicity, in this paper, a simple delay in transmission is included in the simulation but not any complex model to compute latency in real time.
- While the presented approach is envisioned to be applicable for both air and ground operations, in this paper only the air operation is studied.

D. Summary of Previous Work on Conflict Prediction

In order to determine potential conflicts between smart air vehicles, in our past work [1] we demonstrated a deep learning-based approach. In this approach the vehicle's physical state along with nominal utility function information is encoded into visual features in a synthesized scenario image called "dataframes." These dataframes, representative of the collective state and behavior of the agents in the scenario, are learned by a deep neural net. The trained deep neural nets then accept new dataframes to classify the potential future state of the scenario using an AI inference process. Close to 90% accuracy was achieved in conflict prediction using this approach with very low latency (under 7 milliseconds). Furthermore, the throughput and accuracy were consistent regardless the number of agents in the scenario (scenarios with anywhere between 2 and 8 agents approaching the intersection were tested). Fig. 2 and Table 1 show the example conflict predictions on synthesized dataframes, and the accuracy and throughput metrics for the prediction, respectively. The deep neural net model training used 36,000 simulated dataframes for up to 15 epochs with a learning rate of 0.0002, and 9,000 simulated dataframes were used for testing the model inference. The ground truth for training data labeling and test data validation was collected from simulation of the scenarios in a custom simulator.

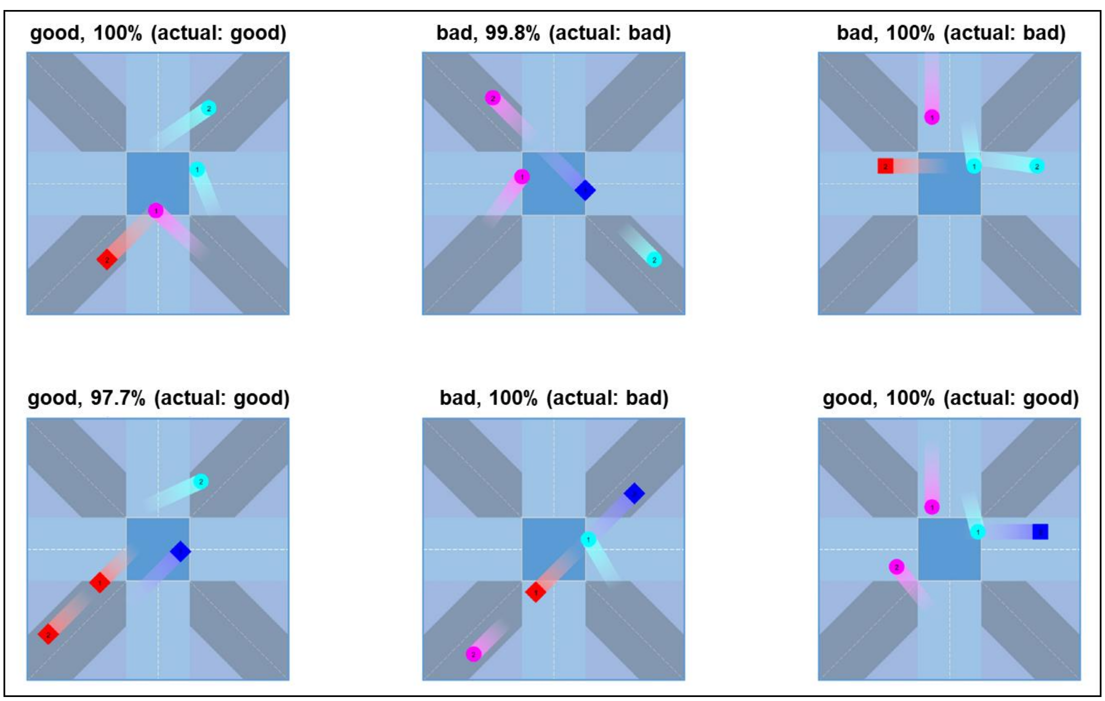


Fig. 2 Classification of new data frames by the trained model (predicted, prediction confidence, actual state)

Table 1 Accuracy and throughput of conflict prediction

Deep Neural Net Model	Training Time/Epoch	Classification Accuracy	Classification Time/Data Frame
ResNet-101	30 minutes	89.2%	3.5 milliseconds
Inception-v3	26 minutes	89.2%	6.3 milliseconds
VGG-19	8.5 minutes	89.4%	7 milliseconds

The dataframes, as shown in Fig. 2, synthesize some of the physical states of the vehicles, such as speed, three-dimensional (3D) position, and heading, with vehicle intent, such as turning at the intersection or going straight through. The information are encoded into the dataframe through the shape, size, and color of the icons representing the vehicles. Such an encoding approach is implemented to primarily take advantage of the recent advancements in deep neural net-based image classification, and also to make the prediction method edge-deployable by utilizing the next generation portable graphics processing unit (GPU) onboard the vehicle. This edge-compute capability is further envisioned to enable onboard decision making, possibly utilizing AI techniques, for distributed and collaborative conflict resolution.

The work presented in this paper builds on the previously developed conflict prediction capability and utilizes the prediction outcome to trigger vehicle-to-vehicle negotiation for finding a mutually acceptable resolution that is determined by taking into account the business utility functions of the smart vehicles and their operators.

E. Smart Vehicle Negotiation Framework

A decision engine has been developed to streamline the iterative negotiation process. The decision engine is implemented in a distributed manner across the UAM agents where each agent operates on four categories of data:

1) Publicly shared data (such as position, speed, heading etc.)
2) Conflict assessment data (each agent's situational awareness from public data)
3) Utility functions data (each agent's business drivers and related parameters)
4) Negotiation data (each agent's offers and requirements used during negotiation)

The usage of these data is shown in Fig. 3. Each iteration of the decision engine goes through four stages. First, publicly available data about the smart vehicles are used to build the synthesized dataframe, such as shown in Fig. 2. Second, the dataframe is analyzed to build situational awareness and predict potential conflicts. The conflict assessment data is combined with utility function data to build the negotiation offer data in the third stage. Finally, in the fourth stage, the negotiation offer data is jointly analyzed by the smart agents to determine if there is a consensus. Note that the utility function data is private to the specific agents and, therefore, is not revealed to other agents.

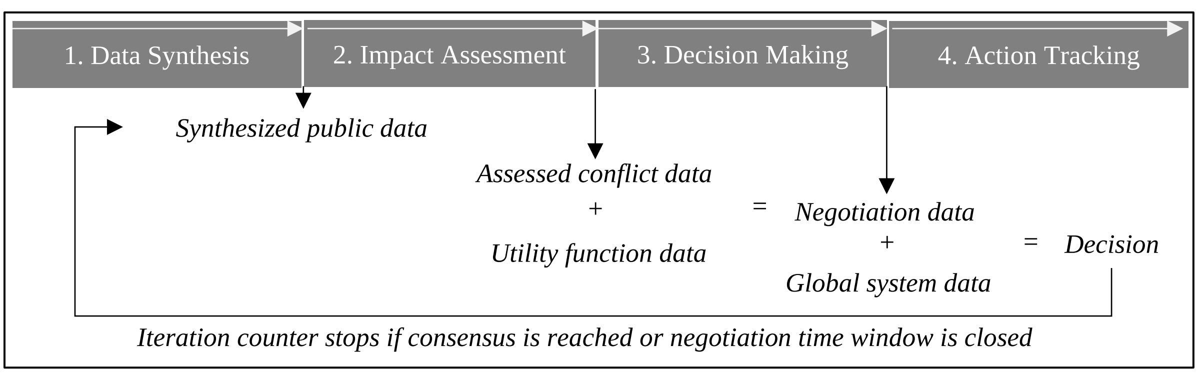


Fig. 3 Utilization of different types of data leading towards collaborative decision making

In past work [1], as summarized in Section III-C, the methods for synthesizing the public data and assessing conflict from the same has been discussed in detail. This paper will focus on the utility function data and the negotiation data for the decision making.

As mentioned earlier, the negotiation data is a joint function of the conflict assessment data and the utility function data. Assuming that the smart agents use same or similar approach for generating their conflict assessment data, it is expected that the trigger to seek resolution will be issued onboard the smart agents around the same time. From the time when *all* conflicting agents are triggered to seek resolution via negotiation, 60% of the remaining time to conflict is allocated to reach consensus. The remaining 40% of the time is reserved to switch to advisory and subsequently supervisory modes of resolution, in case the negotiation does not reach a consensus. This negotiation window, as shown in Fig. 1, is critical to ensure overall airspace safety.

Within the negotiation window there are multiple time steps. At every time step, the agents:

1) Update all four data categories
2) Check if an agreement is reached (based on the globally allowed operational thresholds)
3) Track the time to switch to a rule-based resolution strategy, in case negotiation fails

Each smart agent uses a combination of public and private sets of data to come up with its preference for a specific resolution strategy. Examples of public data include speed and heading, altitude, fuel status, emission status and so on. Examples of private data include payload details, price paid for fuel, affinity towards on-time arrival, flexibility to switch vertiports and so on. The public data is available to all agents either through sharing or on request. The private data is not shared among the agents, so the agents only know about their own private data. To keep the implementation simpler in the beginning, it is assumed that there is an approved list of strategies that the smart agents can pick from. An example list of approved strategies could include temporary speed reduction, altitude change, reroute, or hold position (for VTOLs) etc.

Cost to the agent for implementing a specific strategy	Parameters made public by the agent							Parameters that are private to the agent						
$U_{1\ to\ l}$: Strategy utilization cost for conflict avoidance *$P_{1\ to\ m}$: Accessible parameters that are related to the execution of the strategies* *$Q_{1\ to\ n}$: Private parameters that are related to the execution of the strategies* *W_{ij}: Business preference to alter the parameter P_i for strategy S_j* *r: Smart agent id (1 to N)*	${}^{r}P_1$: Speed & Heading	${}^{r}P_2$: Altitude	${}^{r}P_3$: Fuel	${}^{r}P_4$: Emission	${}^{r}P_i$: …	…	${}^{r}P_m$: …	${}^{r}Q_5$: Payload	${}^{r}Q_6$: Fuel Cost	${}^{r}Q_7$: On Time Arrival	${}^{r}Q_8$: Vertiport Switch	${}^{r}Q_j$: …	…	${}^{r}Q_n$: …
${}^{r}U_1$: Reduce speed by 50%														
${}^{r}U_2$: Climb up by 1000 feet														
${}^{r}U_3$: Reroute by 45°														
.														
${}^{r}U_k$: …					${}^{r}W_{ki}$							${}^{r}W_{kj}$		
.														
${}^{r}U_l$: …														

Fig. 4 Utility function computation sheet carried by each smart agent for negotiation

Each agent then assigns a utilization cost for the resolution strategies at each time step based on Eq. (1).

$$ {}^{r}U_k = \left[\sum_{i=1}^{m}\left({}^{r}P_i \cdot {}^{r}W_{ki}\right)_{norm} + \sum_{j=1}^{n}\left({}^{r}Q_j \cdot {}^{r}W_{kj}\right)_{norm}\right] - \left[\sum_{s=1}^{N}\mu_{rs} \cdot \left(\sum_{i=1}^{m} {}^{s}P_i \cdot \left({}^{s}W_{ki} + \Delta\, {}^{s}W_{ki}\right) + {}^{s}\varphi_{kj}\right)\right] - {}^{g}U_k + {}^{t}U_k \tag{1} $$

Where:

$U_{1\ to\ l}$: Strategy utilization cost for conflict avoidance
$P_{1\ to\ m}$: Accessible parameters that are related to the execution of the strategies
$Q_{1\ to\ n}$: Private parameters that are related to the execution of the strategies
W_{ij}: Business preference to alter the parameter P_i for strategy S_j
r: Smart agent id (*1* to *N*)

The expression inside the first square bracket on the right-hand side of Eq. (1) represents the agent's utilization cost based on its own private and public parameters. The expression inside the second square bracket represents the agent's estimation of the conflicting agent's utilization cost. The term 'μ_{rs}' is non-zero for all conflicting agents and zero for all non-conflicting agents. The term '${}^{s}\varphi_{kj}$' represents the uncertainty associated with such an estimation by one agent about their agents' utilization cost, as for those agents the weights *'W's* and private parameters *'Q's* are not known. The term '${}^{g}U_k$' represents global reward for successfully resolving a conflict in an unsupervised manner. Lastly, the term '${}^{t}U_k$' represents the time penalty for delaying the resolution. So as time progresses, this penalty increases gradually. In summary, the overall utilization cost goes down through better estimates about conflicting agents' utilization costs and global rewards, whereas it goes up with higher number of time steps taken to reach consensus.

IV. Custom Simulation Environment

In order to automate the decision engine as shown in Fig. 3, a custom simulator is developed in the MATLAB® App Designer environment. Fig. 5 shows an updated version of the simulator user interface.

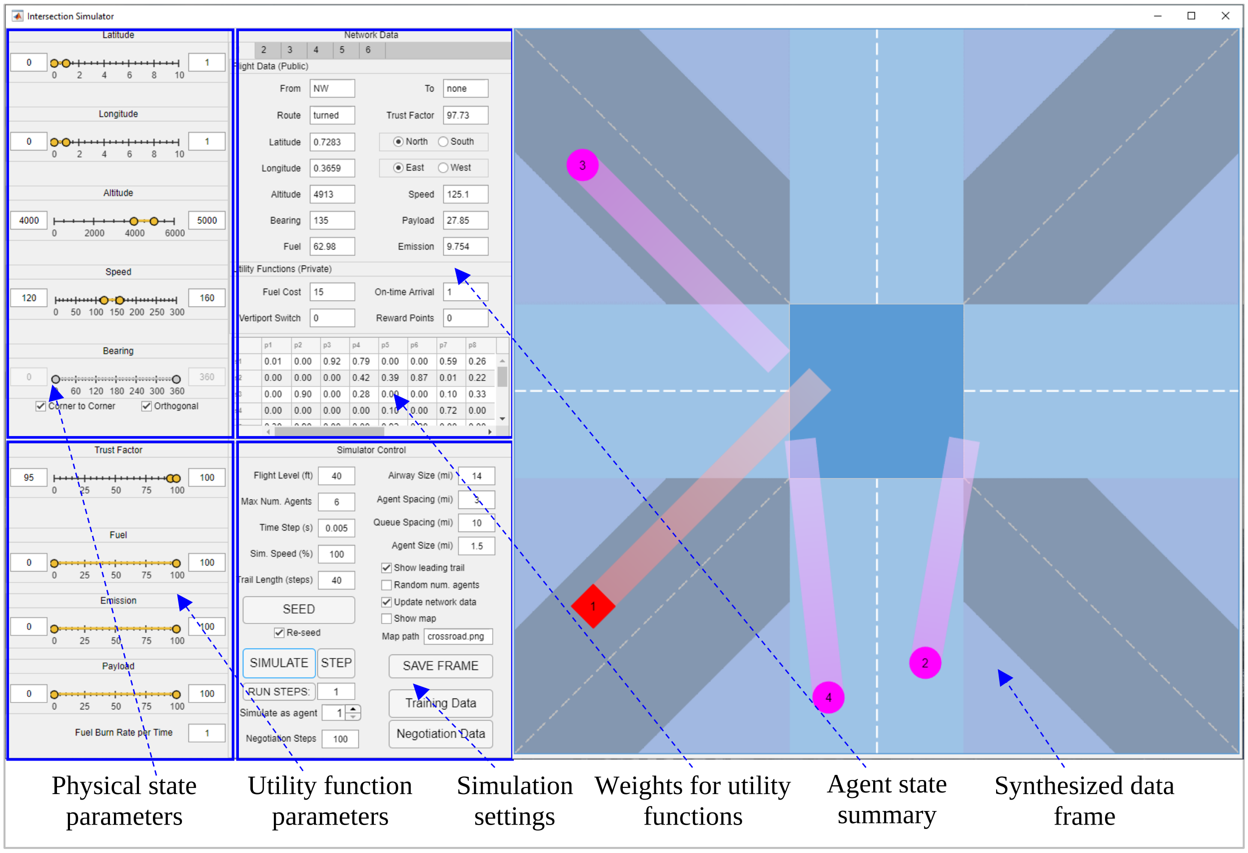


Fig. 5 Custom simulator for analyzing distributed conflict resolution

The previous version of the simulator, as presented in [1], included simulated dataframe collection and automatic labeling of ground truth via simulation for training deep neural net models. That version also incorporated model inference of new simulated dataframes to identify potential conflicts in the scenario. Note: refer to [1] for other basic functionalities of the simulator.

The updated version of the simulator, as used in the present work (see Fig. 6 for process flow), features inclusion of utility function weights *'*W_{ij}*'* for computation of utilization costs *'*U_k*'* using the real-time parameters *'Ps and Qs'* as per Eq. (1) in each simulation step following the prediction of potential conflicts by the trained neural net models.

Step 1: *Start the simulation and seed the scenario with the desired number of smart agents*

Step 2: *Load utility function computation chart for each agent*

Step 3: *Select the time horizon, i.e. the maximum number of time steps to track into the future*

Step 4: *Step forward the simulation and update the current position based on flight control parameters*

Step 5: *If no. of simulation steps > max. limit then go to Step 9*

Step 6: *Send synthesized scenario map to the deep neural net model for conflict detection*

Step 7: *Is conflict prediction confidence >90%?*
- ***Yes:*** *Are the agents within the negotiation window?*
  - ***Yes:*** *Compute resolution strategy utilization cost*
  - ***No:*** *Use rule-based conflict resolution strategy*
- ***No:*** *Go to step 4*

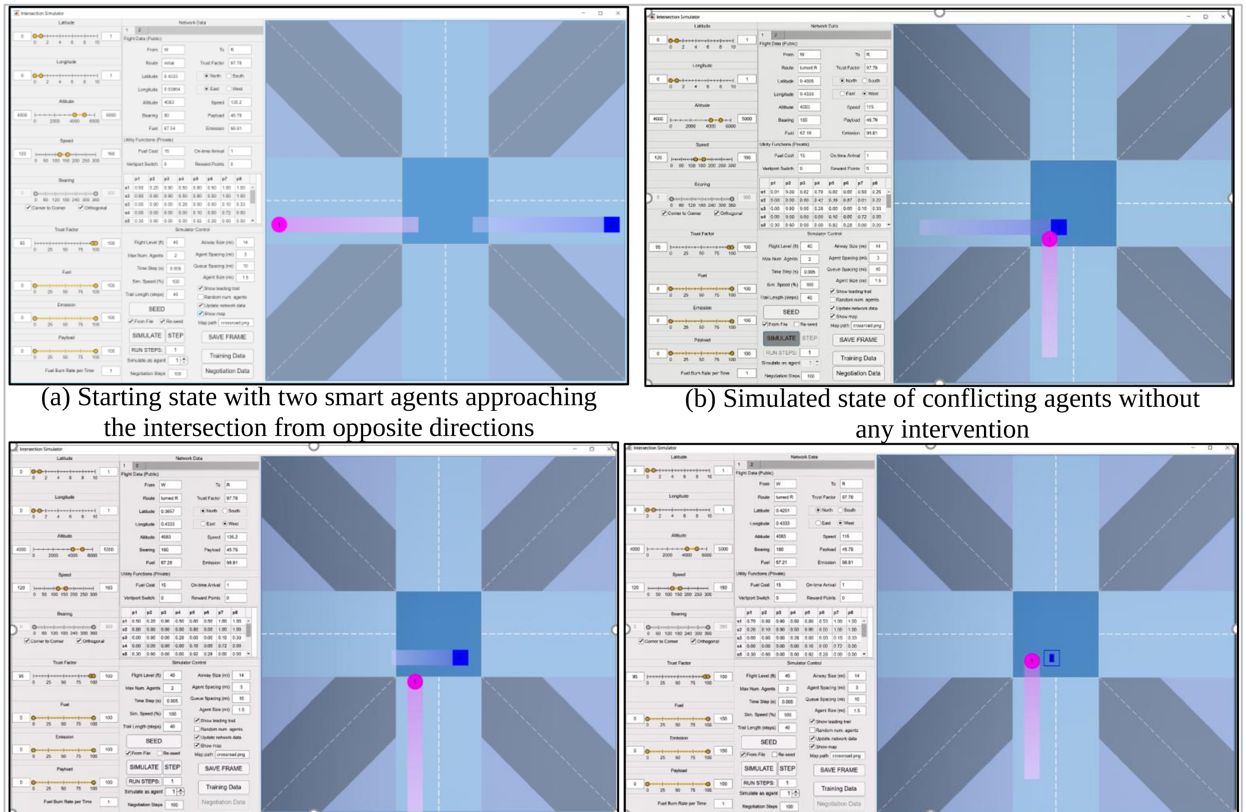
Step 8: *Are the lowest utilization costs for each agent within the consensus threshold (e.g. 20 points)?*
- ***Yes:*** *Update the flight control parameters according to the negotiation strategy*
- ***No:*** *Go to step 4*

Step 9: *End the simulation and generate detailed report of the prediction, negotiation, and simulation outcome*

Fig. 6 Simulation process flow for the negotiation-based conflict resolution

V. Summary of Results

The conflict resolution via negotiation was tested using the simulator. An example scenario is shown in Fig. 7. In this scenario two agents approach the intersection from opposite directions (Fig. 7 (a)). The entire simulation consisted 100 time-steps. At step 35 the built-in deep neural net model predicted a conflict with significant confidence which triggered the agents to get into negotiation. Furthermore, a negotiation interval was created that extended up to the 70^{th} time-step. Thus, if no resolution is agreed upon by the agents between step 35 and step 70, then the agents would switch to supervisory resolution mode at step 71, allowing sufficient time to still avoid the conflict.



(a) Starting state with two smart agents approaching the intersection from opposite directions

(b) Simulated state of conflicting agents without any intervention

(c) Simulated state of conflicting agents with negotiated resolution via speed alteration

(d) Simulated state of conflicting agents with negotiated resolution via altitude alteration

Fig. 7 Example simulated conflict resolution via collaborative negotiation between agent without external intervention. (a) Starting state, (b) Conflict due to no intervention, (c) Negotiated resolution with preference for speed maneuver, (d) Negotiated resolution with preference for altitude maneuver

The no-intervention outcome is shown in Fig. 7 (b), where the agents came into each other's space, violating the separation criteria. With the active negotiation-based conflict resolution feature on, the two agents started exchanging their individual utilization cost for resolution strategies. These utilization costs were calculated using different combinations of utility function weights. In the first case, the agents' weights for parametric preferences were lower for speed maneuvers in comparison to altitude maneuvers. Furthermore, agent 2 (represented by square icon) had a lower weight than agent 1 (represented by circular icon) in this category, indicating a higher willingness to change speed. As this offer was made by agent 2 to agent 1, within 5 time-steps a consensus was reached. Over these 5 time-steps the two agents updated their utilization costs for the list of strategies based on their current parameter values and using the weights, which came within an acceptable threshold at the 5^{th} step past the conflict detection. Thus, at step 40, agent 2 agreed to lower its speed by half for 30 time-steps allowing enough time for agent 1 to move through the intersection. The resulting outcome is shown in Fig. 7 (c). Note that the leading rectangular trace in front of agent 2 shrunk by half to represent the reduction in the agent's speed. In the second case, a different combination of weights was tried, favoring the altitude alteration over speed alteration. Consequently, at step 44 a consensus was reached by which agent 2 agreed to climb by 1000 feet. The resulting outcome is shown in Fig. 7 (d). Note that the hollow agent icon represents that the vehicle is at a different flight level.

VI. Conclusion

This paper presented a conflict resolution methodology utilizing collaborative negotiation among conflicting agents. Leveraging deep neural net based early prediction of impending conflicts, this approach makes use of the previously unutilized time leading up to the actual conflict to select and implement a mutually beneficial resolution. The results suggested that the negotiation method would allow the smart agents to weigh in their flight conditions as well as business preferences in selecting a particular resolution strategy, while keeping the information regarding their trade secrets and business strategies private. The proposed approach at present is not envisioned to replace conventional conflict resolution methods, rather it is envisioned to reduce the number of potential conflicts needing external intervention. In an integrated airspace with a diverse set of agents, especially in dense urban settings, such centralized management of conflict resolution can bear high complexity needing a great deal of resources. Even with standard automated conflict resolution methods in place, the sheer number of agents in the workspace can lead to sub-optimal results in conflict resolution, if only a smaller detection and resolution window is used, typically closer to the potential conflict point. The presented method promises better conflict management at scale by leveraging the compute capability onboard the smart vehicles to expand the CDR window and collaboratively determine the resolution strategy without needing external assistance. Note that while the paper shows the case that demonstrates that intervention can be made relatively early, the quality of the resolution still needs further investigation and also comparison with that of other CDR systems.

In its current implementation, the presented method allows the agents to select a mutually agreeable resolution strategy from an approved list of resolution strategies. However, in the future, with the help of sophisticated AI such strategies can be built in real time. Another interesting aspect of the presented approach is that longitudinal study of the negotiations taking place in the airspace can reveal non-compliant or rogue agents as well as failure modes in existing resource allocations. Future work will involve further investigation in these areas. While the presented negotiation method is not envisioned to be distributive i.e. one side wins and the other loses, there is the possibility that one side makes a higher sacrifice than the other. This mismatch is expected to be offset by the global reward, and possibly a credit system where the side making a higher sacrifice receives credits from the other side. The smart agent then can use this credit to buy out a better deal in subsequent negotiation. For this latter concept, a negotiation credit system, similar to [26], needs to be developed, which will be included in future work.

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