A 3D Simulation Platform for Decentralized Decision-Making in Advanced Air Mobility

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***Abstract*– This paper presents a general purpose, plug-and-play simulation platform for the use of future aviation stakeholders, such as urban airspace planners, air vehicle operators, ground operation managers, air traffic controllers and aviation researchers. The presented simulator platform is envisioned to serve as a toolkit to visualize, evaluate, and configure future advanced air mobility (AAM) operations. Highlighting features of this toolkit include a modular architecture that allows multiple smart unmanned aerial systems (UASs) to remotely connect to the simulation server and participate in decentralized decision-making scenario simulations. As an example of the decentralized decision-making scenario, an inter-agent negotiation-based conflict resolution use case is considered in this paper, where the UASs leverage the on-board/on-the-edge artificial intelligence (AI) capability to continually build situational awareness, and use this information to predict future conflicts and resolve them through machine-to-machine negotiation. As such operations are non-existent at scale currently, the presented simulation platform offers a viable and cost-effective alternative for assessing the efficacy of AAM research outcomes and challenges in future shared airspace usage. The simulation platform allows plug-n-play connectivity with AI and non-AI compute modules representing individual UAS's flight control. Each module can interact with the simulation platform independently to communicate current and desired future states, situational awareness, and conflict resolution utilization costs for inter-agent negotiation. The simulation environment orchestrates realistic operational scenarios with spatiotemporal details, dynamic events, tactical conflict-resolution methods, interfaces for customizing air traffic control parameters, and information exchange uncertainties. In the future, this can serve as a community focused cloud simulation platform, incorporating multi-stakeholder airspace constraints from regulatory, government, city, and local agencies.**

I. Introduction

Urban Air Mobility (UAM) and its more general form, Advanced Air Mobility (AAM), have gained significant popularity in recent times with the advent of aerodynamically stable small-scale aircraft, robust flight control systems, powerful edge, fog, and cloud compute platforms, and above all the demand for fast short-haul transit and package delivery in urban areas struggling with ever-increasing ground traffic congestion. Numerous research and development activities can be found in industry and academia alike to innovate the next generation unmanned aerial systems (UASs), low-altitude flight dynamics models and corresponding control systems, air vehicle tracking systems, shared airspace traffic management protocols, ubiquitous connectivity leveraging upcoming communication capabilities, and many more. When it comes to testing and validating these innovations, reliance is often put on simulation as real-world experimentation is either cost-prohibitive or logistically challenging, at least during the early stages of research. Consequently, several simulation tools, utilizing a wide variety of functionalization approaches, visualization techniques, and human machine interfaces are available in contemporary commercial [1] [2] and research [3] [4] [5] space. Specifically in the area of machine-to-human or machine-to-machine negotiation, several studies have been reported in recent time that aim to enable this feature utilizing AI prediction approaches [6] [7]. A key technological differentiation that the presented simulation platform brings in, is the utilization of collective machine intelligence and the behavior thereof, to address the shared airspace usage. This unique approach is based on the foundational idea that future aviation stakeholders, including smart autonomous vehicles, actively contribute to the global situational awareness building, and take part in the decision making.

Historically, air traffic control has not witnessed a great deal of active involvement from vehicle operators and the vehicles themselves. Rather, the traffic controllers at different control points, such as air traffic control (ATC) towers, Terminal Radar Approach Control Facilities (TRACON), and Air Route Traffic Control Centers (ARTCC), oversee and manage the airspace traffic. However, with highly diverse air vehicle types, AAM business models, and large number of AAM agents sharing the airspace with conventional air traffic, the present-day human-centric air traffic control framework is vulnerable to inefficiencies under massively increased demand in the future. Therefore, it is envisioned that decision making in the future airspace usage will be shared by AAM agents, primarily those carrying residual artificial intelligence that can be leveraged to support distributed decision making.

In our past work [8] [9], we investigated the feasibility of utilizing deep learning [10] methods to build low latency situational awareness from synthesized community data as shared by individual AAM agents, and utilizing this situational awareness to predict future conflicts. We then used these predictions of future conflict to trigger a decision engine on each AAM agent that recursively updated the utilization cost. Based on the utilization cost, which encompasses the agents' business preferences, the resolution strategy is picked from the list of approved strategies. The presented 3D simulation platform is envisioned to visualize and characterize the efficacy of such negotiation-based conflict resolution approach. Furthermore, this platform can also offer rapid verification capability to a wide range of technological innovations in the aviation research. In essence, the presented simulation platform offers two key benefits to the scientific community. First, in addition to offering an immersive 3D visualization of the airspace operations, it also helps alleviating inexplicability with modern-age artificial intelligence (AI) and machine learning (ML) techniques through demonstration of causal effects. Second, the presented tool serves as a transition platform to seamlessly pass-on the control from humans to smart machines while maintaining the human oversight and insight in an effective manner.

The rest of the paper is organized as follows: Section II describes the targeted problem statement, and provides a brief reference to our past work in the distributed decision-making area. Section III presents the simulation platform and discusses about its functional modules. In Section IV, we discuss the utilization of the simulation platform in two different use case scenarios – one in urban settings and one in non-urban settings. Section V summarizes the research and development effort. Finally, Section VI provides a discussion on the future directions.

II. Targeted Technology Space and Background Work

Anticipated rapid scaling of smart UASs, especially operating in low altitude and over short ranges, poses a significant challenge to the present-day ATC-centric decision-making framework that functions without explicit consideration of user priorities. The future aviation market is poised to witness a wide range of business demands, and catering to the multifarious operator preferences will require a much larger conventional air operation and traffic management infrastructure, if all strategic decisions are to be assessed and taken in this centralized model. A more efficient way, however, is to consider a decentralized model where smart UASs can take preferential and locally-critical decisions on their own and accept responsibility to resolve any potentially resulting conflicts through inter-UAS information sharing and collaborative negotiation.

In recent times, a neural network-based machine learning approach has emerged as a popular method in many business domains, such as financial, legal, healthcare, agriculture, and transportation, for rapid assessment of the situation and future state prediction – information that drives actionable decisions. In most of the cases, however, the machine learning module performs as a "black box," where it is not possible to explain why the AI arrived at a specific decision, nor deterministically predict its future behavior. Due to this reason, the aviation industry has remained cautiously slow in adopting AI and machine learning in mainstream air operations, where risks are much larger than other industries. A chronological and holistic visualization capability, such as for trends, patterns, and

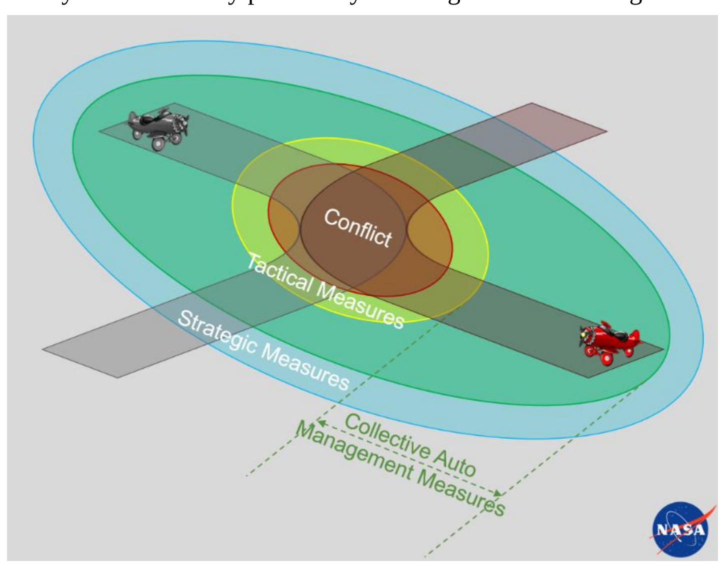


Fig. 1: Technology placement in present day air traffic management framework

agent-specific interactions, can not only offset some of the adoption risks, such as customer trust, data analysis cost, talent gap etc., for AI and machine learning in aviation operations, but also can boost the efficiency of airspace utilization planning and resource allocation efforts from AAM stakeholders. It is the goal of the presented 3D simulation platform to offer such a capability. The prototype utilization of this platform is set up to provide a comprehensive and realistic visualization of the AI-based situational awareness development and collaborative negotiation-based deconfliction in AAM operations conducted by smart UASs. A brief summary of this past research is given below.

In the current aviation operation framework, pre-flight planning takes into account the strategic deconfliction of flights. Additionally, tactical deconfliction measures (collision avoidance) are used to resolve last-minute conflicts between approaching vehicles. Typically, there is at least one level of deconfliction between pre-flight planning and last-moment collision avoidance. This is mainly done through separation assurance managed by human air-traffic controllers, and thus can be a bottleneck under high demand. Our research looks to utilize the time in between the strategic and tactical measures (tactical collision avoidance in conventional air traffic management (ATM)) as shown in Fig. 1 to offer a decentralized and automated measure for collaborative resolution of conflicts. In doing so, this research envisions to: (a) reduce human-centric management of AAM and UAM operations, (b) take into consideration the diverse business productivity metrics used by the different operators through decentralized decision making and, (c) optimize utilization of a decision window via artificial intelligence. In this approach, the presented 3D simulation platform plays two key roles. First, the positional data from each AAM agent is aggregated in the simulation environment that then serves as a snapshot of the global situational awareness. A 2D time-series of such snapshots is used as the synthetic data to compute or predict future conflicts using conventional mathematical models or deep neural net-based AI models, respectively. Second, the simulation engine also serves as a global information exchange portal that allows the AAM agents to share situational data, operational preferences, and negotiation offers.

A recursive and distributed computation framework, as shown in Fig. 2, is implemented at the backend of the decision simulation engine. A conflict detection module onboard each AAM agent identifies future potential conflicts and iteratively updates its corresponding cell in the issue table with anticipated time to conflict. One such method that uses predictive modeling to detect future conflict has been discussed in our past work [8].

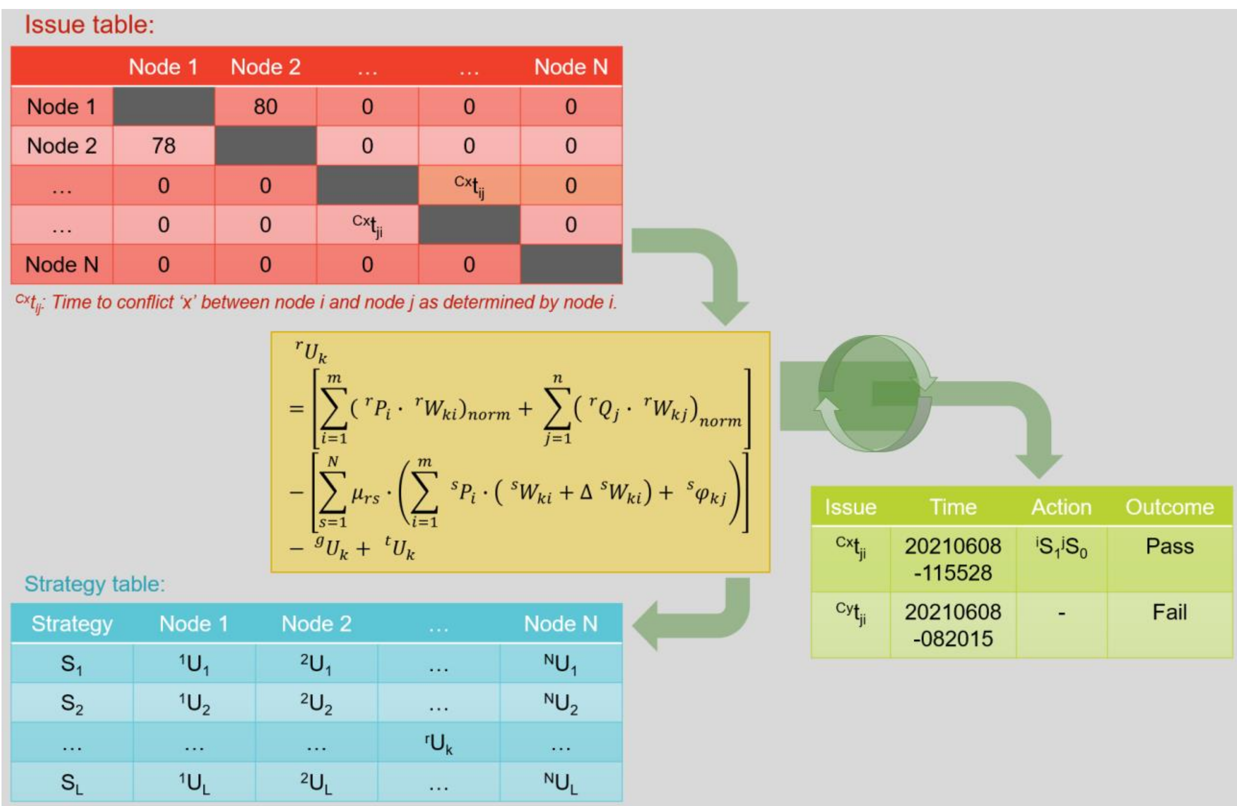


Fig. 2: Implementation plan for iterative negotiation for decentralized conflict resolution, ref. [9]

In Fig. 2 the parameters in the utilization cost ${}^{r}U_k$ determination are as follows:

$U_{1\ to\ l}$: 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)

Δ: Uncertainty in estimating other nodes' business weight preference

φ: Uncertainty in estimating other nodes' private parameters used in utilization cost

μ: Conflict status

${}^{g}U_k$: Global reward

${}^{t}U_k$: Time penalty

Non-zero values across the diagonal in the issue table trigger the respective AAM agents to negotiate. Each agent then updates its corresponding column in the strategy table with strategy utilization cost values as computed using the computation model discussed in our previous work [9] that takes into account the agents' current state, business preferences, and any other non-public parameters they include in their decision making. The decision engine analyzes pre-defined strategy pairs for deconfliction and, based on the values updated by the agents, determines if convergence is reached or not. The resolution plan is then picked by the respective agents, and they update their flight parameters accordingly.

III. Simulation Platform

The frontend 3D simulation platform is built using Unity software [11], which is a cross-platform game engine developed by Unity Technologies. Individual flight controllers of the AAM agents and the decision engine portal are built using Python programming language [12]. Web deployment of the visualization is enabled through WebGL [13].

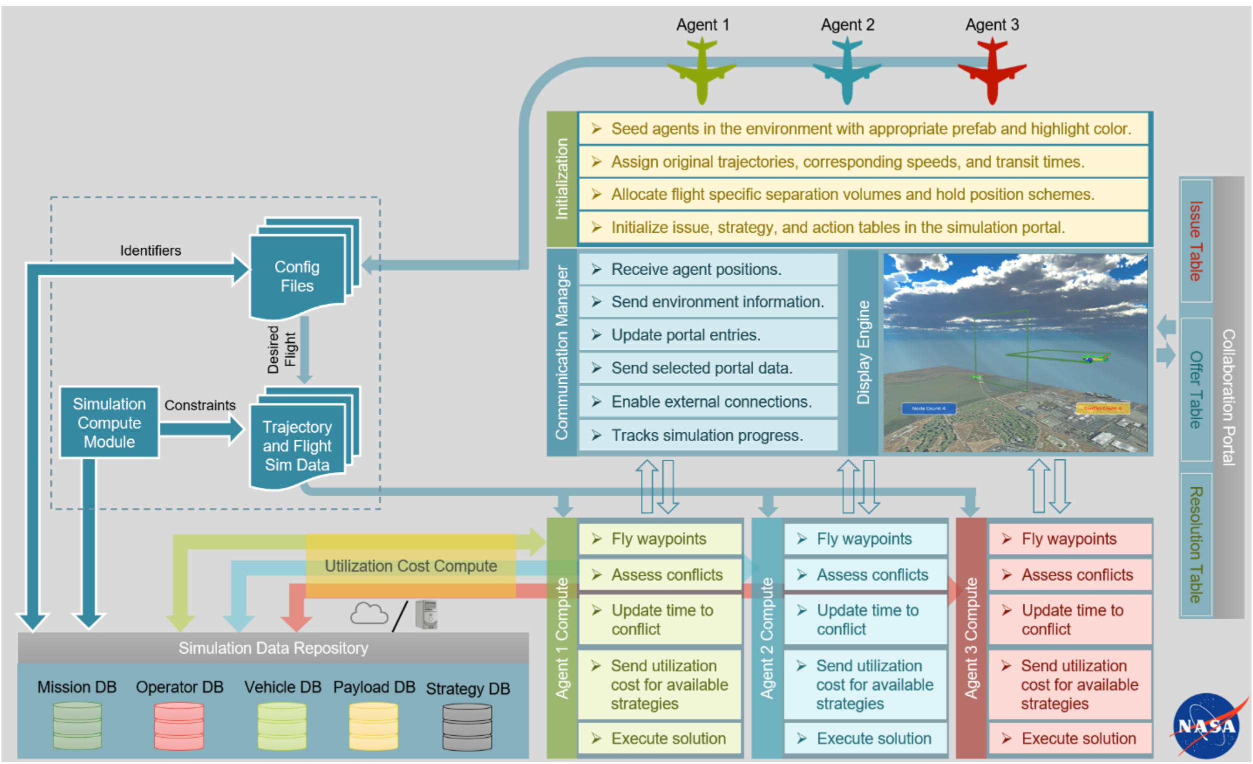
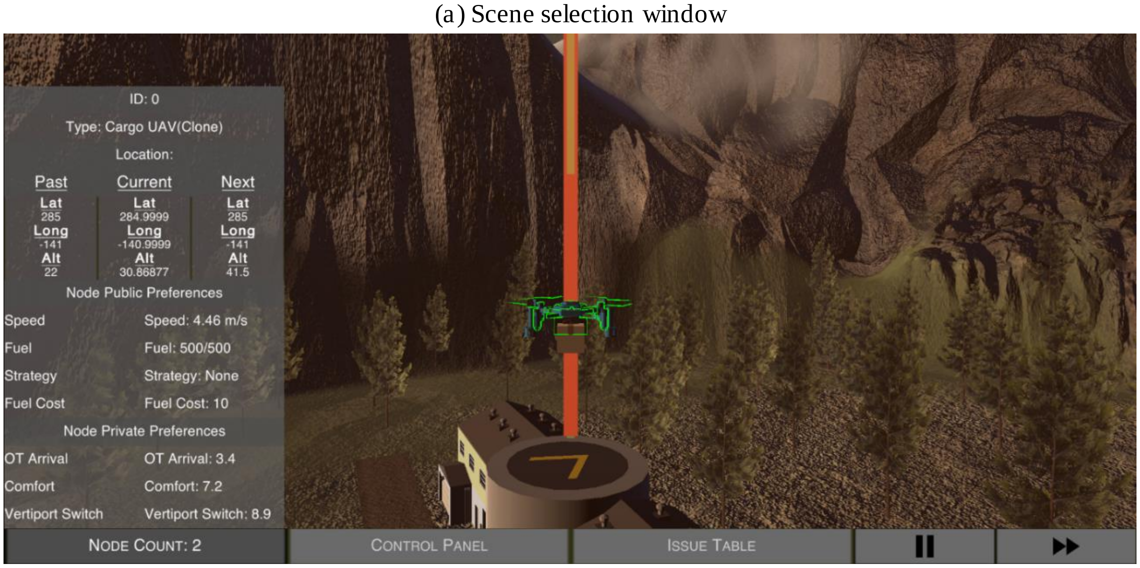


Fig. 3: Functional block diagram of the simulation engine

Fig. 3 shows the functional block diagram of the simulation engine. Each AAM agent node is controlled independently, and each agent on its own takes the conflict resolution decisions. The simulation engine builds the real-time visualization based on status updates from individual agents. The simulation engine utilizes a set of databases to lookup different vehicle forms, operator categories, payload types, approved strategies, etc. Additionally, the simulation platform maintains a portal of current issues, negotiation offers, and resolutions. The agents can access the information on this portal to coordinate the conflict resolution among themselves in a distributed manner. In the future UTM architecture [14], such a portal can be envisioned as a (UAS Service Supplier) USS or a Flight Information Management System (FIMS) [15] [16].

The simulation platform runs on a cloud server along with the supporting communication module. Each UAS agent joins the simulation by providing a configuration dataset that contains the agent's operator identification (ID), vehicle type, flight plan, and a set of public and private parameters. Using this information, the simulation engine seeds a vehicle model in the main simulation environment. After seeding the agent in the main 3D simulation environment, control is handed back to the agent's local compute module. A node manager module controls the information accessibility for the agents. Each agent, while able to view its own operator's public and private parameters in real time, can only view the public parameters of other operators' vehicles. This essentially creates an "information fog" similar to the real world where operators/smart agents do not share all of their operational and preferential information in public to maintain competitive advantage. The agents utilize their autonomous control to fly through waypoints, assess future conflicts based on the shared information, initiate agent-to-agent negotiation to resolve these conflicts, and carry out the negotiated resolutions. To facilitate such inter-agent negotiation, an information sharing portal is made available in the simulation platform that communicates the issues, negotiation offers, and agreed-upon resolutions – all in a dashboard on the impacted agents' simulation view.

(a) Scene selection window



(b) Node view with access to the agent parameters (public and private)

Fig. 4: 3D simulation platform screenshots showing different features

A diverse set of compute capabilities, such as cloud instances, edge compute nodes, or other on-premises hardware can be utilized by the smart agents to communicate with the simulation platform. The simulation platform uses WebSocket as the communication protocol that provides a full-duplex communication channel over a single TCP connection. The WebSocket protocol was standardized by the IETF as RFC 6455 in 2011 [17], and the WebSocket API in Web IDL is being standardized by the W3C [18].

Fig. 4(a) shows the modular implementation framework that allows different concepts of operations (CONOPS) to be used in the simulation. Each simulation environment can be built and integrated as a tile in the "select scenario" window. Fig. 4(b) shows a node view in the simulation as it is seeded, based on the configuration parameters provided at the start of the simulation. In the node view mode, a pull-up window shows the node's identification and positional information along with its public and private parameters.

(a) Negotiation portal for decentralized deconfliction by smart agent

(b) Node view with access to the agent parameters (public and private)

Fig. 5: Additional features of the simulation platform

Fig. 5(a) shows a screenshot of the negotiation/inter-agent communication portal where the agents update their assessment of impending conflicts with other agents and their utilization costs for adopting particular resolution strategies from an approved list. The utilization cost is calculated by each agent independently at its respective compute module, using the computation model as shown in Fig. 2. In addition to simulating the collective behavior of the smart agents, the simulation platform also enables other impacting events, such as airspace restrictions, single-access corridors, and ground access constraints, through programmable modules in the control panel (see Fig. 5(b)). This is a subset of what could potentially be incorporated from the Federal Aviation Agency (FAA)'s Aeronautical Information Management Modernization (AIMM) initiatives [19].

IV. Example Use Cases of the Simulation Platform

Two different use cases, one in an urban setting and the other in a non-urban setting, are discussed here to provide a general overview of the presented 3D simulation platform utilization.

A. Conflict resolution negotiation in shared urban airspace

Future urban airspace will be a challenging environment for smart UAS operations due to dense UAM traffic, sharing of airspace with conventional aircrafts, and flight restrictions over numerous designated areas. Furthermore, unscheduled short-haul transit, typical in taxi and package delivery operations, will make a pre-planned traffic management structure unrealistic. In such cases, the air vehicles will often run into conflicts over access to passage. A decentralized resolution approach through inter-agent negotiation can be an effective tool in such scenarios. Fig. 6 shows a graphical representation of this approach in the presented simulation platform.

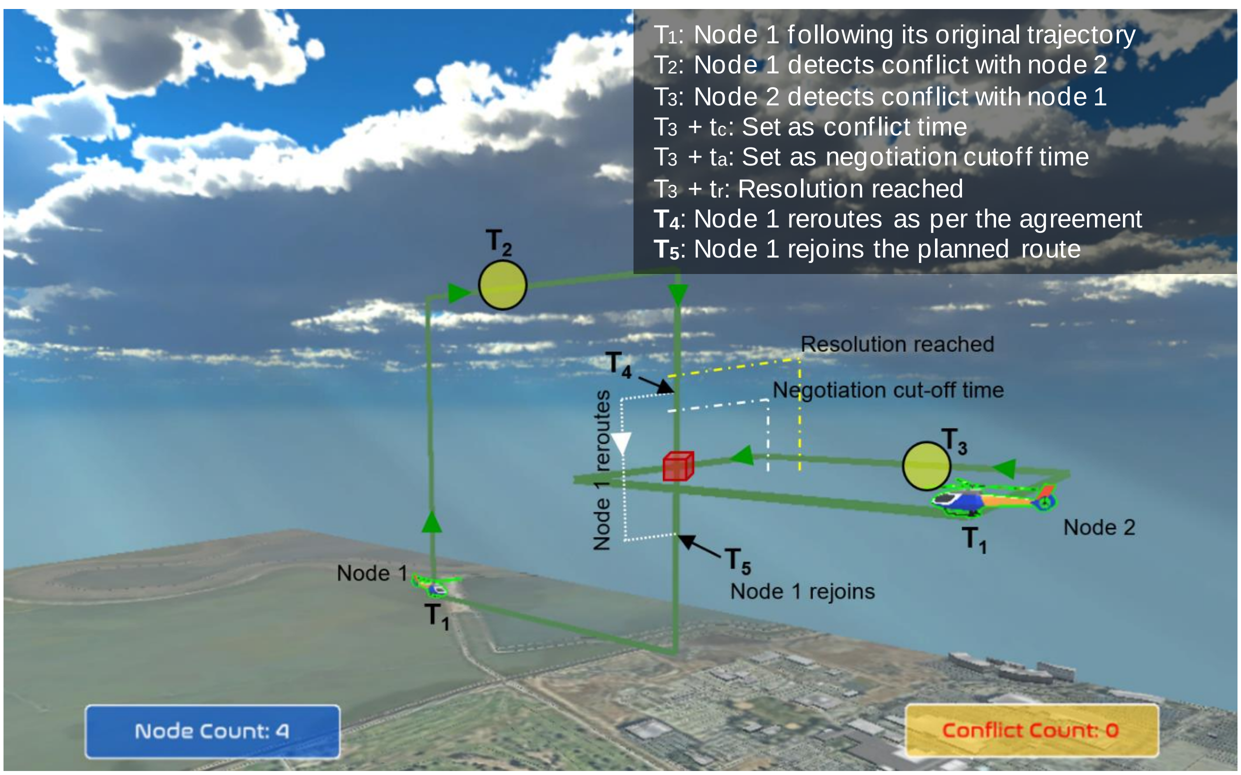


Fig. 6: Example negotiation-based conflict resolution strategy implementation in simulation

While the UASs follow their planned trajectory, they also periodically update their assessment of future conflicts based on the information collected through the simulation platform. To this effect, the simulation platform acts as a contiguous information fabric, provisioning real-time situational awareness and airspace constraints data to each agent. In the event that a particular negotiation fails to converge to agreement, the simulation engine activates tactical measures similar to ACAS Xu (Airborne Collision Avoidance System for unmanned aircraft) [20]. In such cases, the separation assurance is enforced by restricting entry to an occupied voxel or a cube-shaped volume in the airspace around the AAM agent. The resulting action often involves one or more agents rerouting from their original trajectory to avoid conflict with other agents, as shown in Fig. 7.

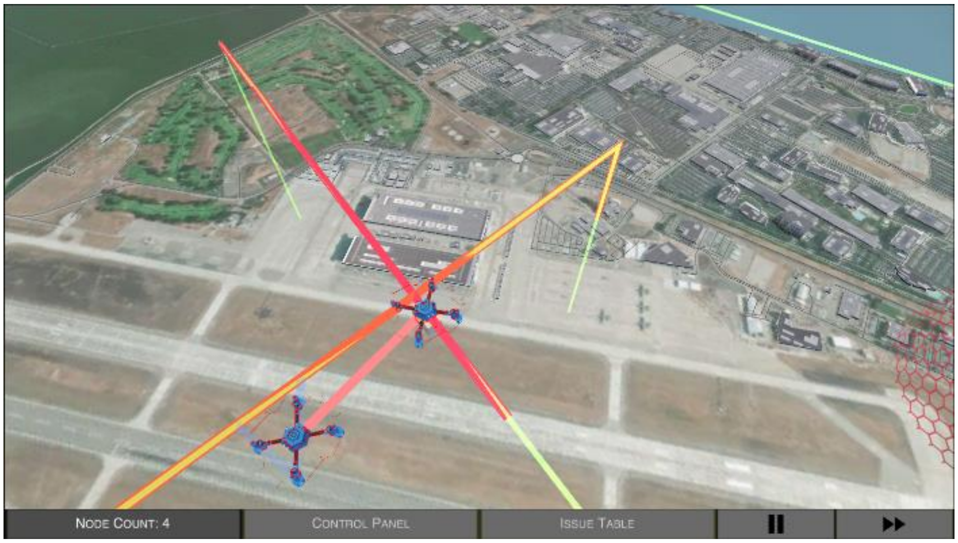
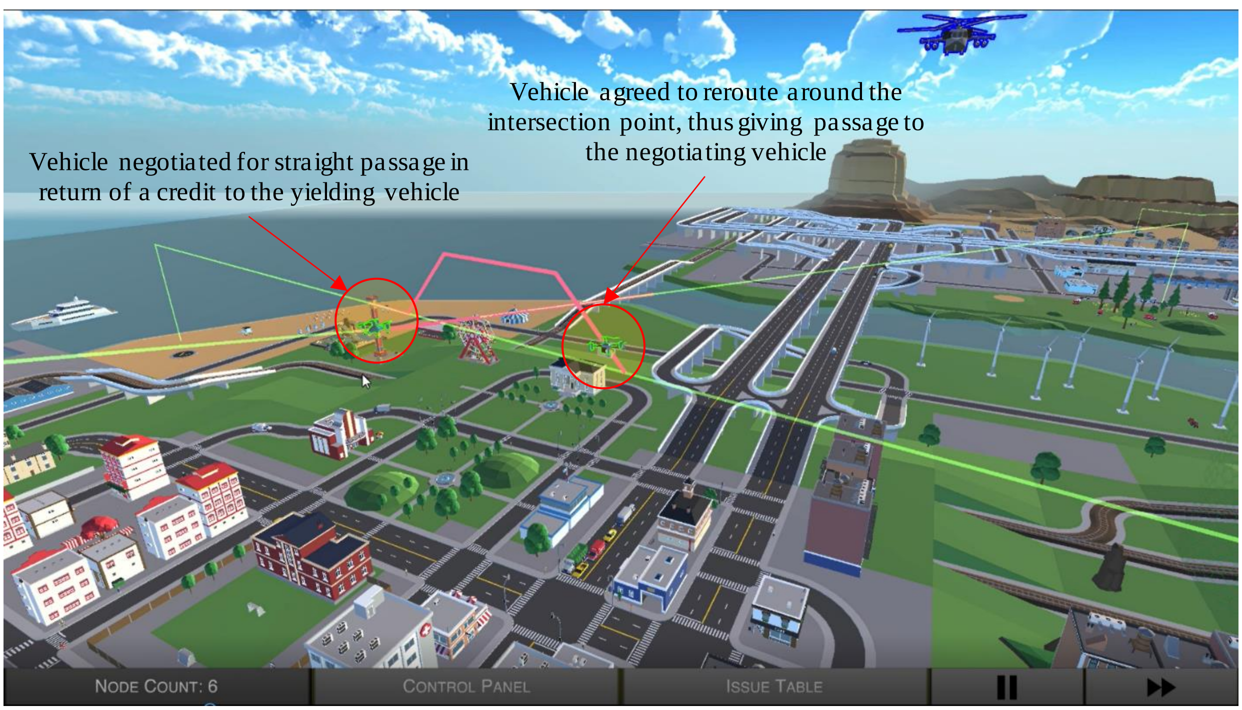


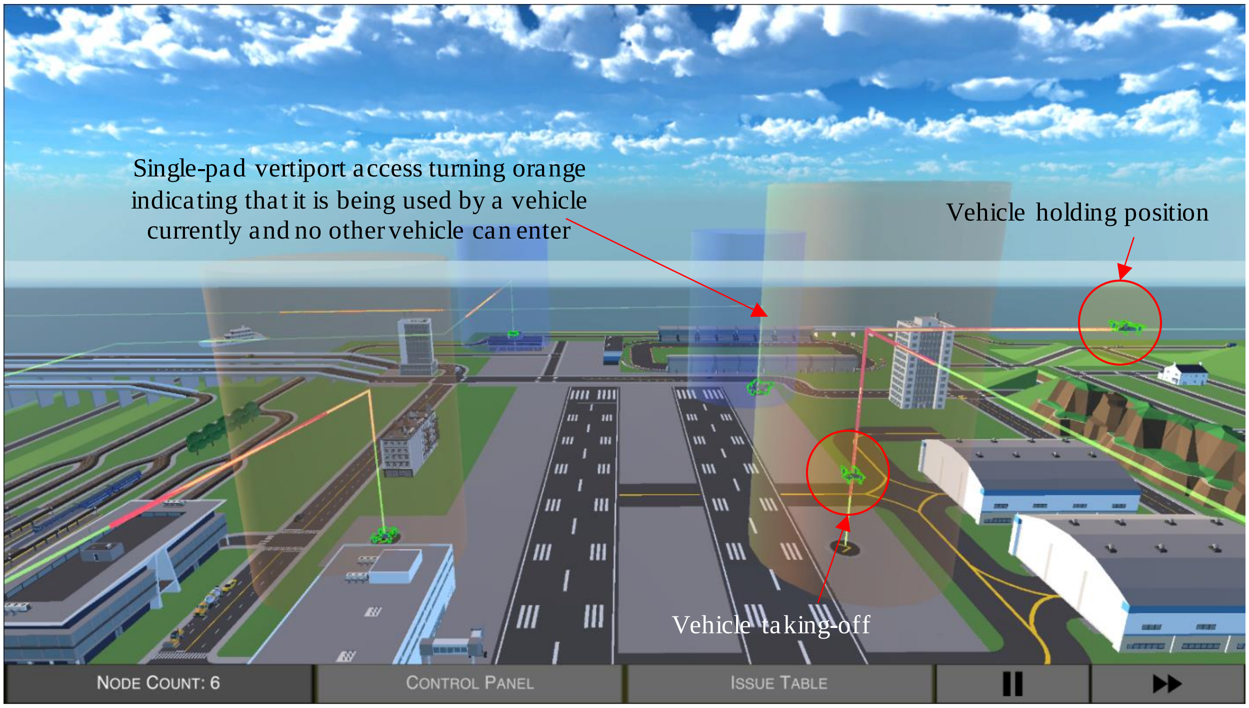
Fig. 7: Built-in tactical measure in airspace navigation

In the future, when air-traffic control can be safely handed off to smart machines, under human oversight, real-world deconfliction measures, such as separation assurance instructions would be communicated from machines to machines. This functionality could be simulated in the presented simulation platform in the form of a high-priority message, instructing a conflicting agent to override its current trajectory with the specified resolution trajectory. It is envisioned that, in real-world operations, such an override could be implemented automatically by an on-board emergency management module that would be connected to the vehicle's flight controller and deliver the tactical deconfliction solutions directly to the flight controller for quick implementation.

Multiple agent-to-agent engagement scenarios have been simulated in the presented simulation platform. These include: (a) deciding which agent will pass through an intersection point first based on the mission priority or willingness to compensate the yielding agent with credit, (b) accessing a single-pad vertiport for take-off or landing, (c) giving way to a public safety or emergency agent. Fig. 8 shows screenshots of such scenarios.



(a) Trajectory intersection handling scenario

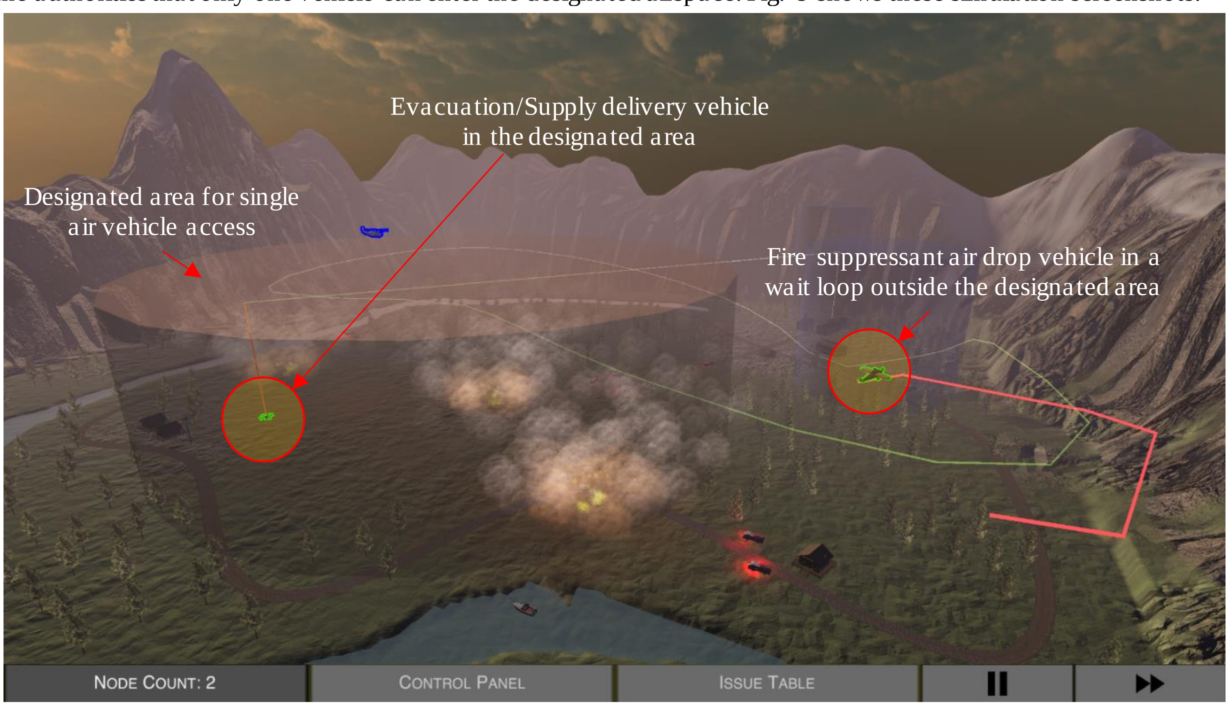


(b) Single-pad vertiport access scenario

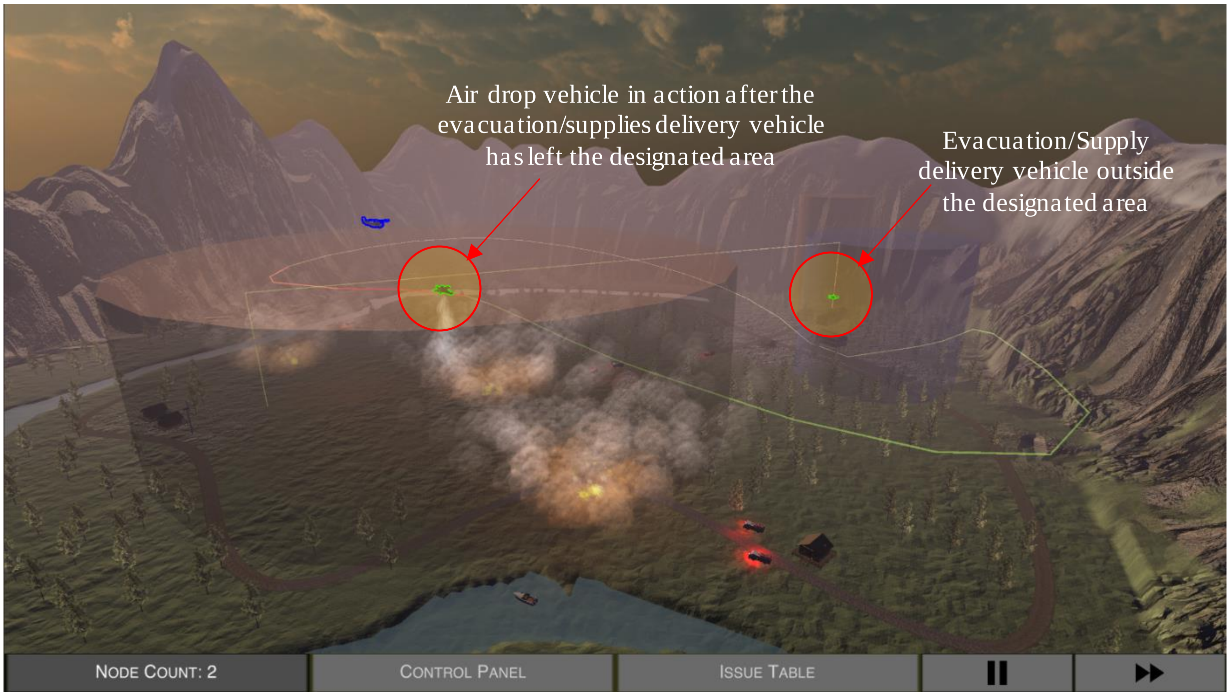
Fig. 8: Simulation of typical urban air mobility scenarios and visualization of event handling

B. Emergency response scenario in non-urban airspace

In this example, a forest fire scenario is considered that involves multiple emergency response actions, including evacuating people from the affected area, bringing in essential supplies to fire fighters on the ground, and aerial drop of fire suppressants. To facilitate a streamlined operation and avoid any air traffic congestion, it has been decided by the authorities that only one vehicle can enter the designated airspace. Fig. 9 shows these simulation screenshots.



(a) Vehicle in wait loop after being notified of the presence of another vehicle in the designated area



(b) Simulated coordinated response to multiple actions in emergency scenario

Fig. 9: Wildfire response air-support simulation scenario implementation

V. Summary of Work

In this paper we presented a general utility 3D simulation platform that can be used to effectively evaluate decentralized decision making in future advanced air mobility scenarios. The simulation platform is envisioned to provide a holistic visual interpretation of AI-driven actions that is not easy or possible to explain through mathematical models. Furthermore, the distributed computation framework, where each participating agent essentially handles all the assessment, decision-making, and task execution, makes the simulation platform computationally lightweight, thereby deployable through web applications with real-time performance. In addition to the photo-realistic visualization of agents and the environment, a simulation support module, running alongside the simulation engine, handles global situational awareness development, agent-to-agent communication via the conflict and negotiation portal, and the information fog that precludes an agent from accessing private parameters of other agents. In summary, the simulation closely represents real-world AAM operations. Thus, the tool can be used for planning urban airspace allocations, assessing traffic flow in general and special operating circumstances, and collecting test results in support of the feasibility and efficacy of decentralized decision making, which is yet to gain acceptance in the aviation sector.

VI. Future Directions

In the future, we intend to connect the simulation platform with physical UASs and enable the decentralized decision-making capability through the information exchange portal available in the simulation platform. In such cases, two or more smart UASs will connect to the simulation platform and share their publicly releasable flight information, conflict assessment, and utilization costs for specific resolution strategies. By utilizing this shared information from the simulation platform, the smart UASs will iteratively update their state and intent, thereby resolving potential conflicts. To participate in the simulation platform, the smart UASs can leverage their residual compute capability onboard, or use a separate portable compute module. Single board processor modules with a graphics processing unit (GPU), enabling parallel computing, are suitable for this purpose. A first-person flight feature is incorporated in the simulation platform, where the individual vehicle operators can view the simulation from a perspective by getting into the pilot's seat of a chosen smart, unmanned vehicle and manually control that vehicle around the simulated scene, interacting with other UASs and dynamic assets on the ground or in the air (see Fig. 10). Appropriate vehicle dynamics and environmental conditions will be added to the simulation platform to deliver such realistic user experience.

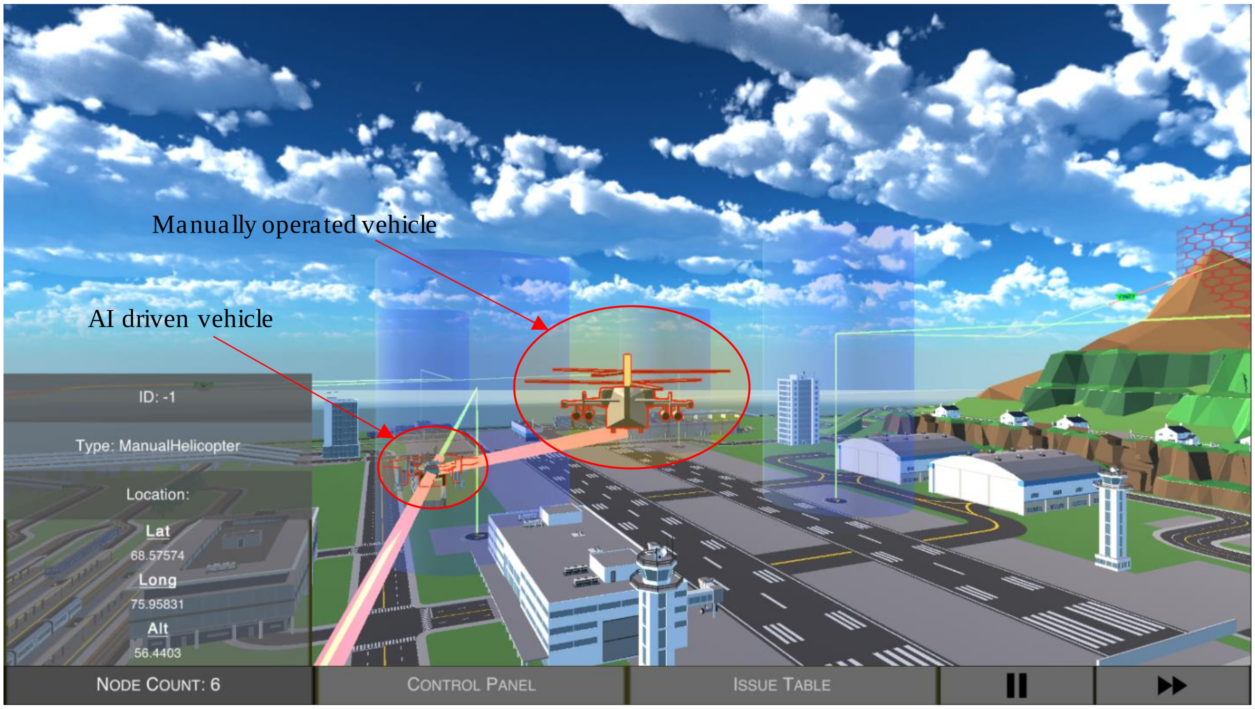


Fig. 10: Manual flight feature in the simulation platform

Additional feature development efforts will include: an in-simulation scenario editing module allowing users to customize the layout, integration with dynamic ground operations, and incorporation of more sophisticated models for vehicle and environmental dynamics and trajectory generation. The overall goal is to offer a sandbox-like toolkit for numerous research and development efforts targeting future AAM operations, where researchers can create or select a specific environment and the types of UASs and ground assets, and conduct their specific research.

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