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Initial Study of An Effective Fast-time Simulation Platform for Unmanned Aircraft System Traffic Management

Min Xue* and Joseph Rios†
NASA Ames Research Center, Moffett Field, CA 94035

Small unmanned aircraft systems are envisioned to play a major role in surveilling critical assets, collecting data, and delivering goods. Large scale operations are expected to happen in low altitude airspace in the near future, where many static and dynamic constraints exist. High sensitivity to wind and high maneuverability are unique characteristics of these vehicles, which bring great challenges to effective system evaluations and mandate such a simulation platform different from existing simulations that were built for manned air traffic system and large unmanned fixed-wing aircraft. NASA's Unmanned aircraft system Traffic Management (UTM) research initiative focuses on enabling fair, safe, and efficient unmanned aircraft system operations in the future. In order to help define requirements and policies for a safe and efficient UTM system to accommodate a large amount of unmanned aerial vehicle operations, it is necessary to develop a fast-time simulation platform that can effectively evaluate policies and concepts, and perform parameter studies in a close-to-reality environment. This work analyzed the impacts of some key factors and demonstrated the importance of these factors in a successful UTM fast-time simulation platform. Preliminary experiments were also conducted to show potentail applications of such a platform.

I. Introduction

The volume of small Unmanned Aircraft System(sUAS) operations is expected to increase dramatically in the near future.[1] Potential sUAS applications include, but not limited to, search and rescue, inspection and surveillance, aerial photography and video, precision agriculture, and parcel delivery. According to the marketing analysis[2] , the global small UAS market is anticipated to hit 10 billion by 2020. FAA also forecasted that over 7 million sUASs will be sold annually by 2020.[1]

The sUAS's low operational altitude, small size, and envisioned scale of operations make Unmanned aircraft system Traffic Management (UTM) quite different from conventional aviation traffic management. In the low altitude airspace, besides fast-changing wind conditions, restricted areas, manned aircraft/helicopters, and tall buildings/terrain impose many constraints in sUAS operations. The sensitive trajectory response and high maneuverability make sUAS different from manned or unmanned large-size fixed-wing aircraft and dramatically change the way traffic system operates. These characteristics and the predicted large scale operations[1] present great challenges in managing safe and efficient traffic operations in low altitude airspace.

NASA's UTM research initiative[3,4] is researching and defining requirements and policies for the UTM system to ensure fair, safe, and efficient UAS operations in the future. In order to investigate the impacts of various device parameters, traffic system rules and policies, operational schedules, and wind conditions, especially in dense operations, it is necessary to build an effective fast-time simulation platform that can incorporate different parameters, rules, and models, and evaluate them statistically in realistic environments.

This work reviewed past literature, studied key factors/requirements, and presented examples of potential applications of such a UTM fast-time simulation platform. This paper is organized as follows: Section II

*Aerospace Research Engineer, System Modeling and Optimization Branch, Aviation Systems Division. Mail Stop 210-10. AIAA senior member.
†Aerospace Research Engineer, System Modeling and Optimization Branch, Aviation Systems Division. Mail Stop 210-15. AIAA senior member

presents literature review of simulations and trajectory models. Section III analyzes the impacts of several key factors in sUAS trajectory prediction. Section IV discusses the necessity and effectiveness of the Monte Carlo method. Section V presents preliminary simulation experiments and results and Section VI draws conclusions.

II. Literature Review

Several categories of simulations have been widely used in research related to air traffic systems. The first category of simulations is mainly built to study traffic systems that include multiple aircraft operations and rules. For example, NASA developed several high-fidelity fast-time simulation platforms for studying manned aviation, such as the Center TRACON Automation System (CTAS),[5] the Future ATM Concepts Evaluation Tool (FACET),[6] and the Airspace Concept Evaluation System (ACES).[7] Each of these platforms has different strengths in aviation simulations. Due to the similarity of trajectory models used for large-size fixed-wing UASs and manned fixed-wing aircraft, the latest ACES incorporated models of large fixed-wing UASs[8] in order to study interactions between Unmanned Aircraft Systems(UAS) and manned aircraft.[9,10] In addition to these large aircraft simulation tools, researchers often developed their own simulation tools for specific research topics. For instance, Cook et. al.[11] defined a set of conflict resolution rules and tested them in simulations with multiple sUASs. Jenie et. al.[12] proposed a method for uncoordinated avoidance maneuvers of UASs and conducted Monte Carlo simulation to verify the proposed method. The second type of simulation deals with encounter models and is usually designated as Conflict Detection and Resolution (CD&R) research. This category of simulations has a much smaller scope than the first one: It typically involves two aircraft and the flight durations are usually short since its purpose is to study encounters between two aircraft.[13,14] In recent literature, Mueller et. al.[15,16] developed a collision avoidance method and included small UASs, especially multi-rotor air vehicles. The third type of simulation is vehicle centric and is mainly developed for studying and simulating the vehicle's model and control. This type of simulator usually includes high-fidelity dynamic system and control model for a specific vehicle. For instance, the Reflection[17] included the Hanger 9 Quarter scale Cessna 172 and was used for autopilot design.

In studies of manned aircraft or large fixed-wing UASs, vehicle models usually only refer to vehicles' dynamic systems because their control systems have the capability of tightly following desired trajectories at the nautical-mile level, even in the presence of wind gust. At the cruise phase, the aircraft trajectory lateral (or cross-track) deviation caused by gust is usually ignored because the overshoots caused by wind change are negligible compared to both navigation errors and the nautical-mile separation standards. A typical approach of modeling large fixed-wing aircraft trajectories used point mass equations of motion.[18,19] In CTAS,[5] to reduce computational time, the horizontal and vertical paths were calculated separately.[20–22] Vertical profiles were calculated using flight path angles as control parameters. Whereas, horizontal paths were constructed from straight lines and turn arcs, where turn radii were decided based on bank angles and ground speeds. This simplified horizontal path calculation approach was widely used for enroute trajectory computation and prediction in aviation research. Another approach was specifically developed for CD&R studies to build aircraft encounter models.[13,14] This approach modeled trajectories by constructing a dynamic Bayesian network structure based on historical trajectory data from FAA's radar records. The typical inputs of the Bayesian network are vertical rate, airspace class, turn rate, altitude, and acceleration at the current time step and outputs are vertical rate, turn rate, and acceleration at next time step. Once this Bayesian network is constructed given the above inputs, the Bayesian network should be able to project the next state of the aircraft.

Unlike large-size fixed-wing aircraft, whose trajectory errors are dominated by navigation systems, sUAS's trajectories are more sensitive to wind, vehicle speed, and vehicle control system because of their low operational altitude, small size, and limited power, especially when separation distance requirements are at a meter level instead of a nautical-mile level. On the other hand, sUASs are highly maneuverable, which changes the conventional way of conflict resolution because their capability of hovering and flying at low speeds. These unique characteristics demand both sUASs' dynamic sytem models and controller models for an effective UTM fast-time simulation platform, such that evaluations on this platform can provide sufficient accuracy, especially for dense operations. Although recent research[11,12,15,16] started to expand vehicles' speed ranges in an attempt to represent small UASs or multi-rotor vehicles, negligence of modeling sUAS controllers will yield inaccurate trajectory predictions, especially at low altitude airspace where wind changes very often, eventually lead to invalid simulations. Therefore, besides the vehicle dynamic sysmte, vehicle's control system needs to be modeled as well.

Table 1 briefly compared the attributes of the aforementioned simulation platforms. This table is not intended to be a complete comparison as it is out of the scope of this paper. The last column of "UTM required attributes" listed the attributes that might be required by an effective sUAS traffic simulation platform. Since the wind effect is closely connected with controllers for sUAS, the UTM required attributes that are missed in many existing simulations can essentially be simplified to trajectory models with controllers and the capability of Monte Carlo simulations.

Table 1. Brief comparison of functionalities in simulations

Simulations	CTAS/ACES	FACET	Mueller's	Jenie's	Reflection	UTM required attributes
Maxium number of vehicles per scenario	> 100	> 100	2	> 100	1	> 100
Fidelity of vehicle models	medium	medium	low	low	high	medium+
Vehicle's controller modeled?	×	×	×	×	✓	✓
Wind effect	along-track	along-track	×	×	along-track +cross-track +vertical	along-track +cross-track +vertical
Limited flight duration?	×	×	✓	×	×	×
Capability of Monte Carlo simulations?	×	×	✓	✓	×	✓
Small UAS model included?	×	×	✓	✓	✓	✓
Collision avoidance algorithm included?	✓	×	✓	✓	×	✓

III. Trajectory Sensitivity

This section shows the importance of modeling controllers in trajectory models by discussing sensitive factors in trajectory prediction for small UASs. Although navigation system error still plays an important role in trajectory errors, it will not be considered in this work. A quadrotor is used as a representative sUAS with a predefined controller, which is described in detail in this section. In the following sections, the vehicle is required to follow a straight line with a constant speed and altitude and to fly through a cross wind field. To examine the sensitivity of the trajectory responses, the impact from various wind speeds, vehicle speeds, and controllers are explored.

A. Trajectory Model

Many types of sUASs have been designed and manufactured in past years, such as quadrotors, multirotors, fixed-wing UASs, hybrid UASs. Without loss of generality, a quadrotor dynamics model is used in this work for examination. Quadrotors may have various sizes, weights, shapes, equipment, and control mechanisms; their fundamental dynamics/plant models are the same except for different parameter values. A typical quadrotor dynamics model can be derived using Newton-Euler equations and details of derivation can be found in past literature.[23–25] After neglecting Coriolis terms and applying small angle approximations, the dynamics model can be expressed as Eqn. 1, where ϕ, θ, and ψ are roll, pitch, and yaw angles in the body frame, and p_n, p_e, and h are north position, east position, and altitude in the Earth frame. k_f and k_m are the aerodynamic force and moment coefficients for motors. J_x, J_y, and J_z are vehicle inertia and the vehicle is assumed to be symmetric. Ω_i is the angular velocity of rotor i and L is the length of the arms. w_n and w_e are the north and east components of the wind vector, where the wind effect was simplified to only affect vehicle velocities. It is also noted that drag terms are neglected in this simplified model. The parameters in the model are set as in Table 2.

$$\begin{bmatrix} \dot{p_n} \\ \ddot{p_n} \\ \dot{p_e} \\ \ddot{p_e} \\ \ddot{h} \\ \ddot{\phi} \\ \ddot{\theta} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} \dot{p_n} + w_n \\ -(\cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi)\cdot F_z/m \\ \dot{p_e} + w_e \\ (-\cos\phi\sin\theta\sin\psi + \sin\phi\cos\psi)\cdot F_z/m \\ g - \cos\phi\cos\theta \cdot F_z/m \\ \frac{1}{J_x}M_\phi \\ \frac{1}{J_y}M_\theta \\ \frac{1}{J_z}M_\psi \end{bmatrix} \tag{1}$$

Where

$$\begin{bmatrix} F_z \\ M_\phi \\ M_\theta \\ M_\psi \end{bmatrix} = \begin{bmatrix} k_f(\Omega_1^2 + \Omega_2^2 + \Omega_3^2 + \Omega_4^2) \\ (-k_f\Omega_2^2 + k_f\Omega_4^2)\cdot L \\ (k_f\Omega_1^2 - k_f\Omega_3^2))\cdot L \\ (k_m\Omega_1^2 - k_m\Omega_2^2 + k_m\Omega_3^2 - k_m\Omega_4^2))\cdot L \end{bmatrix} \tag{2}$$

Table 2. Dynamics parameters

J_x	J_y	J_z	m (kg)	k_f	k_m	L (m)
$7.5e-3$	$7.5e-3$	0.013	0.65	$3e-5$	$7.5e-7$	0.23

As an initial study, a proportional-derivative (PD) position controller is applied in this work. In order to reach a desired horizontal location (x_d, y_d), a quadrotor needs to roll and/or pitch to eliminate the deviation. Usually, a PD position controller calculates the desired accelerations $\ddot{x}_d$ and $\ddot{y}_d$ first (shown in Eqn. 3), and then desired roll and pitch angles ϕ_d and θ_d are derived using Eqn. 4 for the attitude controller to track. This process will be continued with updated states until the desired position is reached. Eqn. 5 shows the controllers for roll and pitch angles. Controller's gains are shown in Table 3, where k_p and k_d are proportional and derivative gains, respectively.

$$\begin{bmatrix} \ddot{x}_d \\ \ddot{y}_d \end{bmatrix} = \begin{bmatrix} k_p(x_d - x) + k_d(\dot{x}_d - \dot{x}) \\ k_p(y_d - y) + k_d(\dot{y}_d - \dot{y}) \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} \phi_d \\ \theta_d \end{bmatrix} = \frac{m}{U_1} \begin{bmatrix} -\sin\psi & -\cos\psi \\ \cos\psi & -\sin\psi \end{bmatrix}^{-1} \begin{bmatrix} \ddot{x}_d \\ \ddot{y}_d \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} M_\phi \\ M_\theta \end{bmatrix} = \begin{bmatrix} k_{p,\phi}(\phi_d - \phi) + k_{d,\phi}(\dot{\phi}_d - \dot{\phi}) \\ k_{p,\theta}(\theta_d - \theta) + k_{d,\theta}(\dot{\theta}_d - \dot{\theta}) \end{bmatrix} L \tag{5}$$

Table 3. PD controller gains

k_p	k_d	$k_{roll,p}$	$k_{roll,d}$	$k_{pitch,p}$	$k_{pitch,d}$
7.5	4.2	4.5	0.5	4.5	0.5

B. Wind Speed

Given the quadrotor dynamics and control model in the previous section, Fig. 1 presents the trajectory responses when different cross winds are imposed while the quadrotor was trying to follow a straight line trajectory with the speed of 5 meter per second (mps). The north wind caused trajectory deviations and the higher the wind magnitude is, the higher overshoot the vehicle has. As shown in the figure, the overshoot produced by a 5 mps wind reached 5 meters. In addition, the settling time that a vehicle needs to converge to its steady state increases when the cross wind increases. It took the vehicle over 50 meters to recover from the overshoot when it was experiencing 8.7 mps cross wind. Considering the fact that separation standards for multiple sUAS operations might be close to a meter-level precision, these deviations should not be neglected when predicting and calculating trajectories for sUASs in UTM simulations, neither should they be simplified and represented by some statistical distributions.

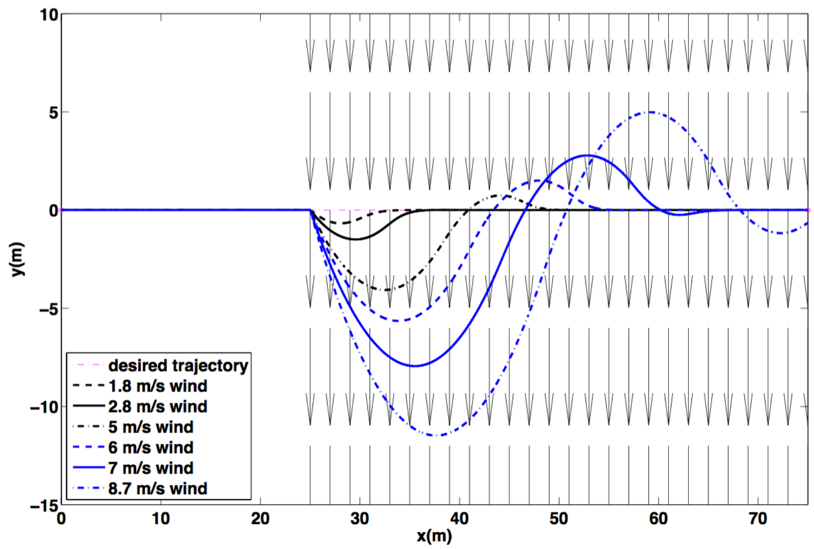

Figure 1. Trajectories at various cross wind speeds (vehicle speed = 5 m/s)

C. Desired vehicle ground speed

In actual operations, even for the same type of sUASs, different desired vehicle ground speeds may be set up by different operators intentionally or unintentionally as long as speeds are under the maximum value. However, sUAS's trajectories are also sensitive to desired vehicle ground speeds. Fig. 2 presents trajectory responses with the same cross wind but different vehicle desired ground speed. Although lateral overshoots and deviations are similar, the resulted trajectories are quite different. The horizontal distance in the x-direction for the vehicle to recover from overshoots vary from 10 meters to over 50 meters at different vehicle speeds, which will greatly affect the 4D trajectory prediction accuracy and outcomes of collision avoidance algorithms.

D. Control mechanism

The controller might be the most sensitive source for trajectory calculation errors. The difference in the controllers can be a different control gain, a different limit on forces or rotation angles, or a different control function, such as a PD controller vs. a backstepping controller. Even a different range for capturing a waypoint causes discrepancy in trajectories as well.

As a simple example, Fig. 3 shows the comparison when different proportional gain k_p is applied. It shows that when the proportional gain increases the response time that a vehicle takes to reach the peak deviation decreases while the overshoots stay similar. However, if k_p increases too much, the vehicle oscillates around the reference trajectory and needs a long time to settle down to the desired state.

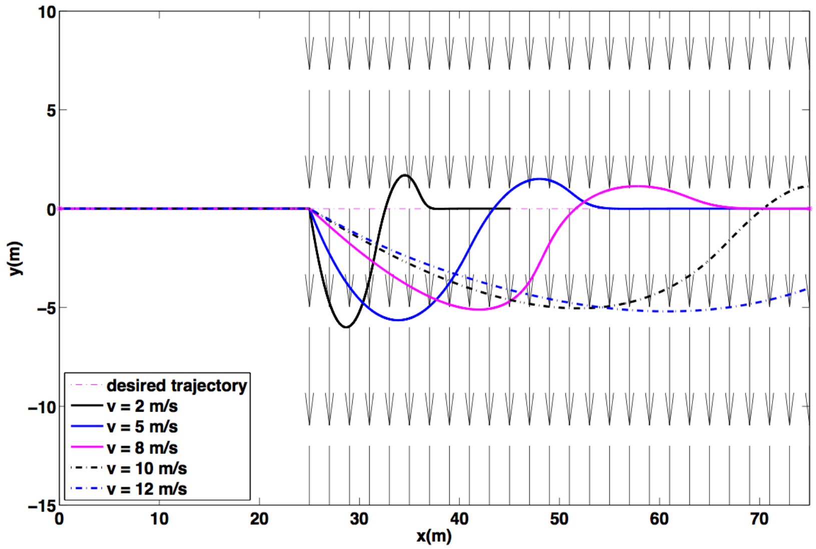

Figure 2. Trajectories at various vehicle desired ground speeds (cross wind speed = 5 m/s)

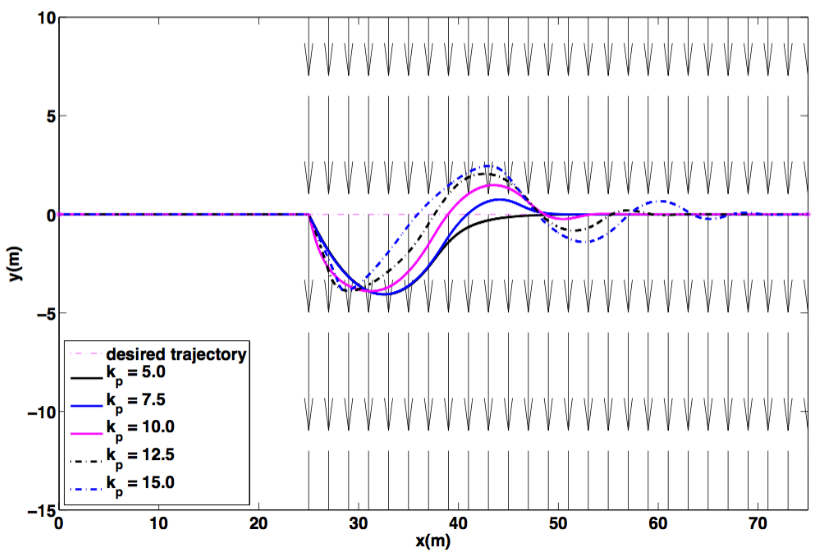

Figure 3. Trajectories with various control gains

IV. Monte Carlo Simulation

Statistical study of parameters and uncertainties is necessary to understand and evaluate the safety and efficiency of the future UTM system. The parameters and uncertainties involve many sources, such as onboard sensors, navigation and communication devices, right of way rules, collision avoidance algorithm and rules, various weather conditions, and vehicle systems. When dealing with a high dimensional problem, or high number of random variables, the Monte Carlo method/simulation[26] can be a very useful tool as it is known to be fairly independent of the problem dimension.[27,28] Monte Carlo simulation is characterized by a rate of convergence of order $O(1/\sqrt{n})$, where n is the number of simulations. The relationship between the number of simulations and the percentage error of the mean at a given confidence interval[29] can be explicitly expressed as in Eqn. 6, where z_c is the confidence coefficient. S_x and $\bar{x}$ are the sample variance and mean, respectively.

$$E = \frac{100 z_c S_x}{\bar{x}\sqrt{n}} \tag{6}$$

This property makes Monte Carlo simulation widely used in financial and engineering situations. Application exists in manned aviation as well. For instance, Gravio et. al.[30] applied Monte Carlo method to study safety performance of air traffic management system with about 1,000 simulations. In order to statistically measure the impacts of parameters and uncertainties in various models in UTM system, it is necessary for an effective fast-time simulation platform to have the capability of Monte Carlo simulations.

V. Preliminary experiments

In order to conceptually demonstrate how the fast-time simulation can be used for parameter and uncertainty studies, a prototype of a fast-time simulation platform for multiple sUAS operation was implemented for this work. Two sample experiments were conducted to demonstrate the use cases for the fast-time simulation. The experiment set-up is described in the first section.

A. Experiment set-up

In following experiments, a total of six sUASs were planned to fly cross the region. The flight plans were composed of a set of waypoints from origins and destinations with associated time[a]. For simplicity, the sUASs were assumed to be the same type. The sUASs were assumed to follow the flight plan with a desired vehicle ground speeds at 5 mps. In addition, a narrow rectangular north wind field is added to introduce errors and uncertainty into the simulations. It is assumed that the wind magnitudes in the rectangle follow a normal distribution with a mean value and standard deviation. The wind is the only uncertainty source in this experiment. As the number of Monte Carlo simulations is set to 1,000, the wind magnitude will vary across different Monte Carlo simulations. Fig. 4 shows the flight plans and wind field.

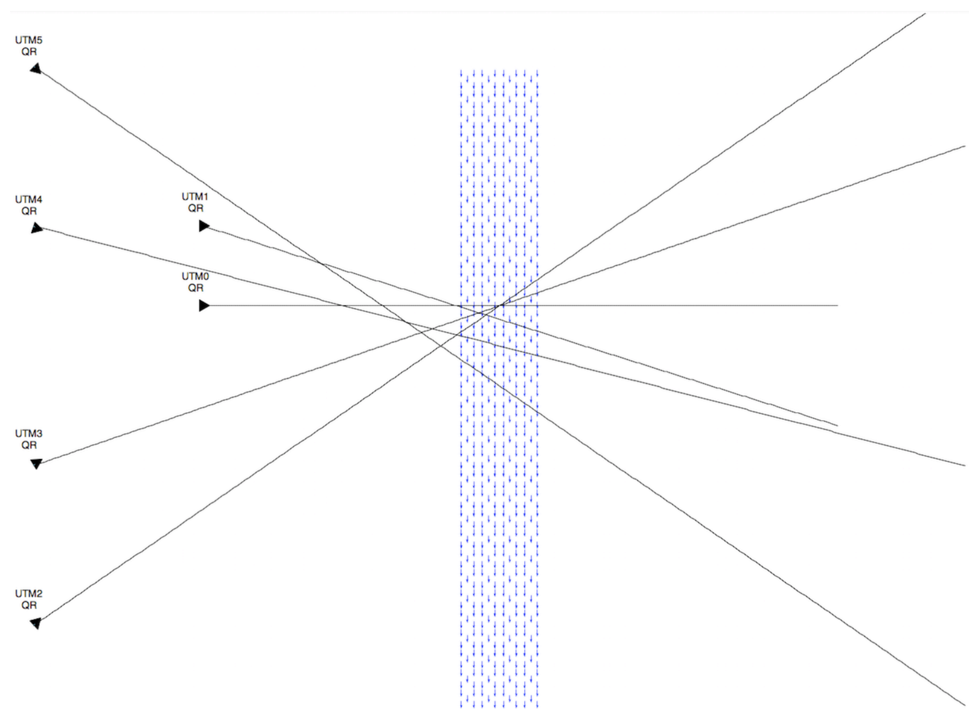

Figure 4. Flight plans and wind field setup

Besides vehicle trajectory models, traffic rules or collision avoidance rules need to be defined before any preliminary experiments can be conducted. In this prototype, conflict detection is assumed to be performed by vehicle-to-vehicle communication. Under this scheme, every sUAS is assumed to broadcast its current position and planned trajectory in future 5 second and the trajectory projection is assumed to be nominal. The detection range was arbitrarily set to 100 meters. The minimum separation requirement is also arbitrarily

[a]A flight plan with waypoints and desired ground speeds is another option.

assumed to be 10 meters for this initial study, which means if two vehicles are closer than 10 meters a loss of separation will be recorded. The minimum distance that triggers an avoidance maneuver is set to 20 meters and the minimum distance to the conflict point for an avoidance maneuver is defined to be 30 meters. A de-centralized collision avoidance algorithm is utilized here. The right of way was defined similar to ground transportation, which is that the vehicle coming from the right-hand side has the right of the way. The sUAS who doesn't have the right of way has to yield if there is any incoming conflict. Apparently, this simple rule negelects the head-on encounters as it is just used as an example for preliminary experiments. Three avoidance maneuvers were assumed: left or right turns with constant bank angles and hovering. Obviously, there are numerous parameters and options in setting up traffic rules. For instance, conflict detection can be done by onboard sensors or ground-to-vehicle communications, other than vehicle-to-vehicle communications defined in the prototype. Collision avoidance maneuvers can involve altitude changes and there also exist various methods including centralized algorithms for collision algorithms. Exploration of those parameters, options, and algorithms is out of the scope of this paper although it will be supported by the fast-time simulation architecture in future.

B. Impact of wind

In this section, the default avoidance maneuver is defined to be a right turn. Table 4 shows the statistical measurements when different wind speeds were set. Three cases are presented. There is no wind in the first case. The average wind speeds in the second and third case were 3 mps and 5 mps, respectively, and the standard deviations were 2 and 3 mps in the second and third cases, respectively. Two types of metrics are presented. Loss of separation can be a safety metric. And extra flight distance and extra flight time are metrics related to enery consumption or efficiency. Percentage errors are calculated at 99% confidence level according to Eqn. 6. For instance, an error percentage of 3.5% means that it is 99% confident that the calculated mean will not differ by more that 3.5% from the truth.

Table 4. Statistical measurements under various wind conditions

	wind speed		loss of separation			extra flight distance (m)			extra flight time (s)		
	mean	std.	mean	std.	error(%)	mean	std.	error(%)	mean	std.	error(%)
Case 1	0	0	0	0	0[b]	165.5	0.0	0.0	31.0	0.0	0.0
Case 2	3	1	0	0	0	168.8	3.6	0.17	31.0	0.03	0.01
Case 3	5	2	0.11	0.31	23.8	183.7	27.1	1.2	31.3	3.2	0.82

As shown in the table, Case 1 is an ideal case, where vehicles fly at their moderate speeds and there is no wind. Because there is no wind, no errors were introduced in Case 1. Therefore, the $1,000$ simulations are deterministic and identical simulations and standard deviations and errors are zeros. The number of loss of separation reflects how well the collision avoidance scheme works. Case 2 introduced moderate wind with moderate variation; there is still no loss of separation thanks to the conservative set up of collision avoidance scheme. However, the extra flight distance and associated errors increased, so did the variation. The percentage error of 0.17% for the extra flight distance means that there is 99% confidence that the true mean value is within 0.17% of 168.8. In Case 3, the wind's mean and variation were increased. Because the unexpected trajectory deviation increased due to the strong wind, loss of separation happened. A single loss of separation happened in 56 simulations out of a total of 1,000 simulations, which is reflected by the large error percentage of 23.8% at the 99% confidence level. This experiment showed that even with the same vehicles, equipages, and schedules, wind plays an important role on safety and energy consumption. When wind uncertainty is high, the likelihood of loss of separation increases and the required power consumption increases as well.

C. Impact of avoidance maneuver

The experiment in this section compared different avoidance maneuvers as an example of parameter studies that can be performed with this fast-time simulation capability. The purpose of this experiment is not

[b]The error percentage was set to zero based on physical meaning, because division by zero happens if following the formula.

to investigate or validate different maneuvers. The experiment is utilized to present a sample potential application that can be performed on such a fast-time simulation platform and to show the importance and effectiveness of this kind of platform for researching future UTM system. In the first case, a right turn was set as the default collision avoidance maneuver if there is any conflict. A left turn and hover were set as default maneuvers in the second and third cases, respectively. The mean and standard deviation of the wind field were defined to be 3 mps and 1 mps, respectively.

Table 5. statistical measurements with various avoidance maneuvers

	avoidance	loss of separation			extra flight distance (m)			extra flight time (s)		
	maneuver	mean	std.	error(%)	mean	std.	error(%)	mean	std.	error(%)
Case 1	right turn	0	0	0	168.8	3.6	0.17	31.0	0.03	0.01
Case 2	left turn	0.847	0.36	3.46	71.0	23.3	2.7	9.5	3.4	3.0
Case 3	hover	0.04	0.20	38.9	5.95	4.1	5.6	20.9	4.4	1.72

Table. 5 shows the statistical measurements when different avoidance maneuvers were used. Case 1 has been shown in previous section. Case 2 shows that combining left maneuver with the ground traffic right-of-way is really not a good option. It resulted in a loss of separation in 844 simulations. The percentage error shows that it is almost certain that the loss of separation will happen in any simulation. In Case 3, vehicles used hovers to avoid any detected conflicts. Loss of separation happened in 42 simulations. The extra flight distance is low[c], and the extra flight time remains at a level similar to the other two cases.

VI. Summary

This work presented key factors and requirements of an effective fast-time simulation platform for researching sUAS operations. It first briefly reviewed different capability requirements between UTM simulations where sUASs are dominant and ATM simulations where large size manned and unmanned fixed-wing aircraft are prevailing. Then a trajectory sensitivity study was conducted to demonstrate why the requirements for trajectory models are different in sUAS operations. The study showed that sUAS's trajectory was sensitive to many factors including wind gusts, vehicle speeds, and control systems. The resulted deviations are usually over several meters and should not be ignored when calculating and predicting trajectories for sUASs. The importance and effectiveness of the Monte Carlo method was discussed, which showed that Monte Carlo simulations are suited for UTM traffic problems that involve high-dimensional uncertainty/error sources. Finally, experiments were conducted to demonstrate the impact of wind on the evaluation of sUAS operations. The second experiment presented a sample application of parameter studies with different avoidance maneuvers. The proposed fast-time simulation capability can provide a comprehensive and statistical assessment for the sample parameter study.

As a follow-up step, a cloud-based fast-time simulation platform is under development by NASA UTM research teams. To evaluate safety and efficiency metrics for multiple sUAS operations at low altitude airspace, this fast-time simulation capability will address aforementioned requirements by including various sUAS trajectory models and Monte Carlo simulation capability and support studies of paramters, models, rules, and policies.

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[c] The nonzero extra flight distance in Case 3 is mainly caused by wind.

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