

# Towards A Computational Framework for Autonomous Decision-Making in Unmanned Aerial Vehicles

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This paper develops a computational framework to facilitate autonomous decision-making under uncertainty for safe operation for drone-like vehicles. The proposed framework is based on identifying and predicting the occurrence of various risk-factors that affect the safe operation of such vehicles, and estimating the likelihood of occurrence of these risk-factors. This analysis is then used to select trajectories for the operation of the vehicle. Feasible trajectories are classified into four different categories: “nominal and safe”, “off-nominal but safe”, “unsafe and abort the mission”, and “unsafe and ditch the vehicle”. An important challenge in the operation of drones is that there are several sources of uncertainty that affect their operation; these sources of uncertainty arise from wind conditions, imprecise future power-demands, inexact future trajectories, etc. Therefore, it is important to develop a decision-making framework that can incorporate all these sources of uncertainty and make decisions that are robust to the presence of such uncertainty. Potential risk-factors such as dynamic obstacles, battery drain, etc. are identified and the likelihood of occurrence of these risk-factors are predicted preemptively and proactively in order to facilitate risk-informed safety-assured decision-making.

## I. Introduction

Research in the topic of unmanned aerial vehicles and systems has steadily increased in the past ten to fifteen years. The Federal Aviation Administration (FAA) and the National Aeronautics and Space Administration (NASA) have shown significant interest not only in the development of technologies for unmanned aerial vehicles but also in the development of unmanned traffic management systems.

With the anticipated advent of unmanned aerial traffic and substantial increase in manned air traffic, the overall safety of the United States National Airspace System needs to be analyzed carefully. Unmanned aerial vehicles will have access to civilian air space only when the safety of the airspace, government/public/private property, and to an extent, the vehicle itself can be guaranteed.

The development of unmanned vehicles requires the simultaneous development of several technologies for sensing and data logging,<sup>1-5</sup> fault tolerant flight control,<sup>6-8</sup> simultaneous localization and mapping (SLAM),<sup>9-12</sup> obstacle detection and avoidance,<sup>13,14</sup> optimal power management,<sup>15-17</sup> path planning and trajectory design,<sup>18-21</sup> autonomous decision-making,<sup>22,23</sup> etc. Researchers around the world have been focusing on the development of each of these technologies as well as the overall system-level integration for the development and design<sup>24</sup> of the entire vehicle.

In particular, the low-altitude flight of drone-like unmanned aerial vehicles — specifically quadcopters and octocopters — in urban environments<sup>25</sup> is of specific interest. It is also important to understand that large corporations such as Google (Google Wing) and Amazon (Prime Air) are also interested in this issue. According to Koperdaker,<sup>25</sup> the near-term goal (1-5 years) is to safely enable low-altitude airspace and UAS operations while the long-term goal (10-15 years) is to safely enable massive increases in airspace density and UAS operations.

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These goals are particularly challenging because there is a significant amount of uncertainty and numerous factors that are constantly and dynamically evolving in low-altitude urban environments. As a result, developing a methodology for safe, autonomous decision-making still remains an unsolved problem.

The goal of this paper is to develop a computational framework that can aid autonomous, probabilistic decision-making for unmanned aerial vehicles, particularly in urban environments where several factors are uncertain and dynamically evolving. The presence of uncertainty implies that it is necessary to systematically quantify such uncertainty, estimate its effect on the unmanned aerial vehicle (UAV), identify risk-factors (such as obstacle collision, untimely battery drain, etc.), compute the likelihoods of occurrence of such risk-factors, estimate the risk associated with various trajectories in a dynamic manner (risk associated with an event is typically estimated as a combination of the likelihood of that particular event and the cost associated with the event), and facilitate decision-making in terms of path planning and trajectory selection.

The key features and benefits of the proposed computational framework are as follows:

1. The proposed computational framework is preemptive and proactive in nature. Given a trajectory, this approach forecasts the future behaviour of the UAV, identifies potential risk-factors, and dynamically computes the likelihood of each risk-factor continuously as a function of future time. As a result, the framework can predict the likelihood of a risk-factor continuously as a function of future time, and therefore, can identify the future time at which there may be a potential risk-factor with a likelihood greater than a critical value.
2. The proposed framework systematically identifies the various sources of uncertainty, quantifies each uncertainty individually, estimates the overall effect of these uncertainties on the operation of the UAV, and accurately calculates the likelihood of future risk-factors in order to guide decision-making under uncertainty.
3. The proposed framework is modular and can incorporate different types of risk-factors that affect the safety of the UAV; the framework can identify prospective risk-factors in advance based on sensor data and provides a fundamental platform for information fusion where all the data from sensors can be combined with available models in order to guide decision-making.

The rest of this paper is organized as follows. Section II describes the overall approach for probabilistic decision-making under uncertainty, and Section III discusses the methodology for computing the likelihoods of risk-factors as a function of future time. Section IV presents the application of the proposed decision-making methodology to a UAV, and finally, Section V concludes the paper, with a brief summary and suggestions for future research work.

## II. Decision-Making Under Uncertainty

### A. Goal of Decision-Making: Trajectory Selection

An ideal decision-making algorithm should autonomously work in conjunction with the path planner (that generates trajectories) to identify whether a given trajectory is safe or not. In order to achieve this goal, the decision-making algorithm leverages information available from various sources as shown in Fig. 1, and identifies safe trajectories for real-time flight.

As seen from Fig. 1,<sup>26</sup> a trajectory is classified as follows:

1. Safe
  - (a) Nominally safe: The likelihoods of risk-factors are extremely low
  - (b) Off-nominal but safe: The likelihood of risk-factors are higher than the nominal scenario, but still low enough to be considered safe
2. Unsafe: The likelihood of risk-factors are considerably high.

The limits for likelihood demarcating (1) the nominally safe scenario and the off-nominally safe scenario; and (2) the safe and unsafe scenarios need to be assigned based on computing the costs/risk associated with each risk-factor.

If a trajectory is unsafe, then it is necessary to identify whether it is possible to generate a trajectory that can:

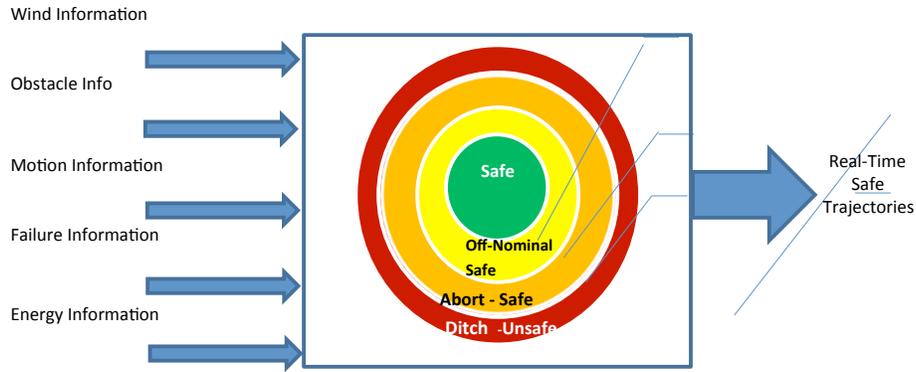


Figure 1: Goal of Decision-Making: Identify Safe Trajectory

1. Abort the mission and return the UAV safely to a landing site; (or)
2. Abort the mission and ditch the UAV without any loss of private and/or public property.

These four different types of trajectories, i.e., nominally safe, off-nominal but safe, abort and return to base, and abort and ditch, are identified in Fig. 1. Note that the scope of this paper is limited to identifying whether a given trajectory is safe or not; further classification and aspects of decision-making will be considered in future work.

## B. Risk-Factors

While there are different types of risk-factors that are associated with flights in urban environments, they can be broadly classified into two categories, as shown in Fig. 2.<sup>26</sup>

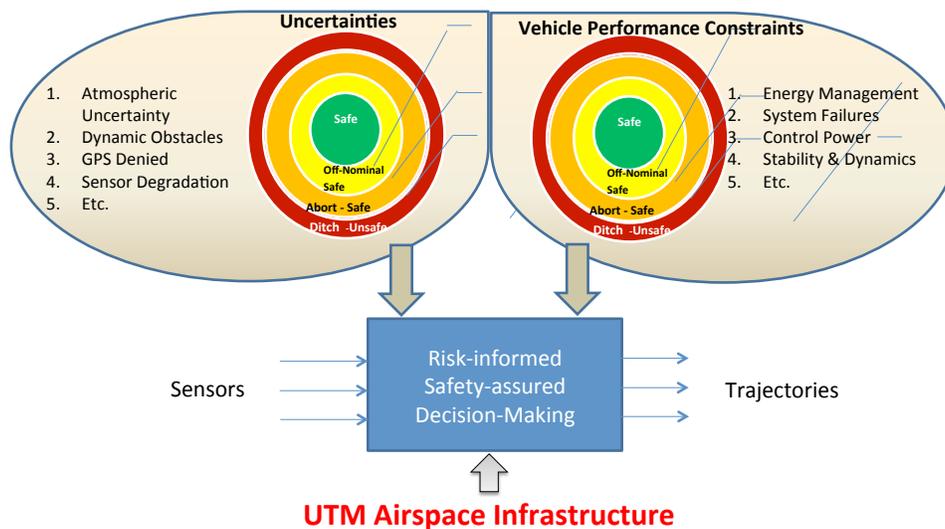


Figure 2: Risk-Factors in Low-Altitude Urban Environment Flight

As seen from Fig. 2, risk-factors may arise simply out of uncertainties (inherent variability, lack of information, etc. due to GPS Denied, degraded sensors, dynamic obstacles, etc.) or due to vehicular performance constraints (such as rapidly draining battery, lack of control, etc.) The decision-making system needs to assess all risk-factors as far as possible, assimilate information from the sensors, and select trajectories. Note that the decision-making is both risk-informed (since it calculates the likelihood of risk-factors along with

the associated risk) and safety-assured (selects only those trajectories that are considered “safe”, i.e., the likelihood of a risk-factor is far below a critical limit and hence the operation is considered safe).

### C. Decision-Making through Information Fusion

Given a trajectory, and a risk-factor, how should the determine whether the trajectory is safe? Modern reliability analysis<sup>27</sup> defines safety using the so-called limit state function, i.e., a curve of demarcation between a predefined “safe region” and an “unsafe region”.

In simple scenarios, the idea of the limit state can be viewed in terms of capabilities ( $C$ ) and requirements ( $R$ ). When capabilities of a system are more than its requirements, then the system is said to be safe; otherwise, the system is considered to be unsafe. The limit state is then represented by the equation that implies capabilities are equal to requirements  $C - R = 0$ .

In more realistic scenarios, the limit state can be represented as a generic function  $G(\mathbf{X}) = 0$ , where  $\mathbf{X}$  represents the vector of quantities that affect the limit state. In the context of this paper,  $\mathbf{X}$  may potentially include (depending on the risk-factor under consideration) wind information, obstacle information, vehicular information (including motion, dynamics, and properties), energy information, and trajectory information, as shown in Fig. 3. Without loss of generality, the region represented by the curve  $G(\mathbf{X}) > 0$  can be assumed to be the safe region, and the region represented by the curve  $G(\mathbf{X}) < 0$  can be assumed to be the unsafe region.

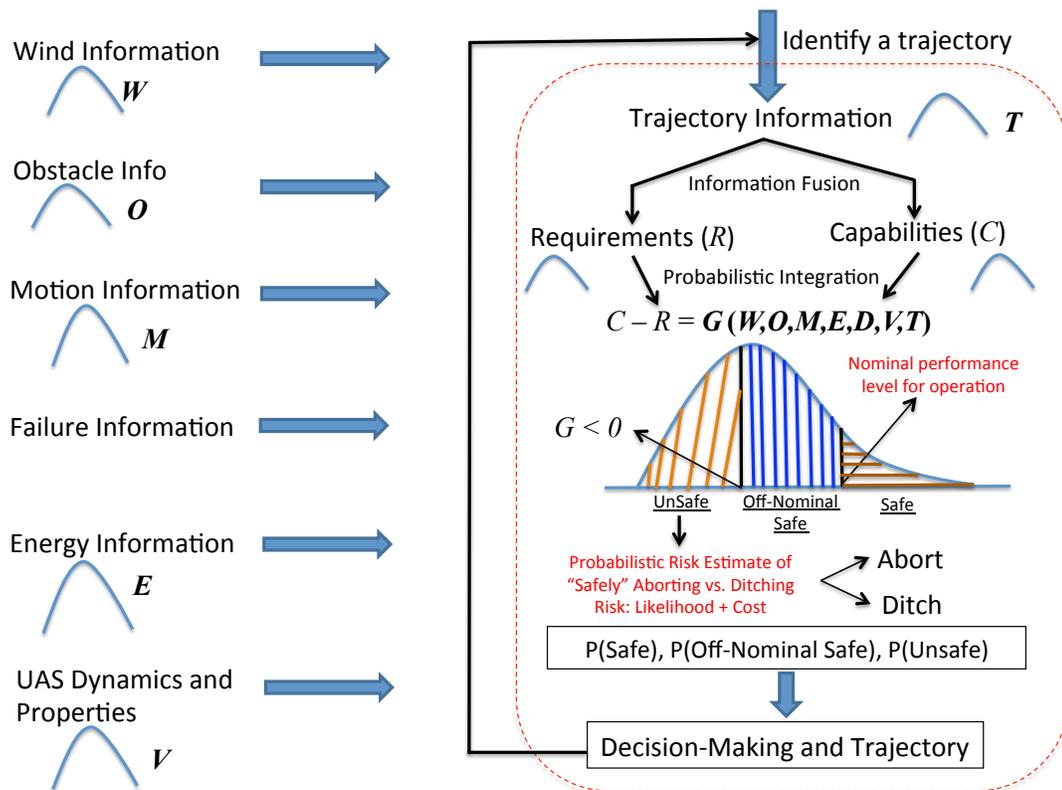


Figure 3: Framework for Decision-Making

As mentioned earlier in Section I, it is likely that elements contained in the vector  $\mathbf{X}$  are all uncertain quantities and hence, these are represented as probability distributions in Fig. 3. It is therefore necessary to compute the probability ( $P(G) < 0$ ), and this probability corresponds to the likelihood of the risk-factor under consideration. It is important to compute this likelihood continuously as a function of future time (starting with the time of prediction) until the end of the trajectory under consideration. This computation is discussed in detail in the following section.

### III. Framework for Prediction: Likelihood of Risk-Factor

Consider a given trajectory and a generic time of prediction  $t_P$  at which it is necessary to calculate the likelihood of a particular risk-factor continuously as a function of future time ( $\forall t > t_P$ ).

In order to achieve this goal, it is necessary to model the evolution of the UAV continuously as a function of time along with the evolution of external factors related to the risk-factor. For instance, in the case of a collision against a dynamic obstacle, it may be necessary to model the evolution of the position of the UAV continuously as a function of time (based on the planned trajectory), and the anticipated position of the dynamic obstacle (which is typically uncertain if the trajectory of the obstacle is unknown and can only be approximately quantified based on its position and velocity as estimated by the sensors on the UAV).

#### A. Modeling the Evolution of State With Respect to the Risk-Factor

Consider the state space model which is used to continuously predict the state of the system, as:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t)) \quad (1)$$

where  $\mathbf{x}(t) \in \mathbb{R}^{n_x}$  is the state vector,  $\boldsymbol{\theta}(t) \in \mathbb{R}^{n_\theta}$  is the parameter vector,  $\mathbf{u}(t) \in \mathbb{R}^{n_u}$  is the input vector,  $\mathbf{v}(t) \in \mathbb{R}^{n_v}$  is the process noise vector,  $\mathbf{f}$  is the state equation, and  $t$  is the continuous time variable. Note that the above state vector is not necessarily equal to the aerodynamic state of the UAV (measured in terms of position, attitude, etc.); instead, this state vector is directly related to the risk-factor under consideration. If collision against a dynamic obstacle is a risk-factor, then this state vector contains the position of the UAV. On the other hand, if battery-charge draining is a risk-factor, then this state vector contains the charge of the battery of the UAV. Note that all the quantities in Eq. 1 are uncertain in nature and need to be treated probabilistically.<sup>28</sup>

The state vector at time  $t_P$ , i.e.,  $\mathbf{x}(t)$  (and the parameters  $\boldsymbol{\theta}(t)$ , if they are unknown) is (are) estimated using output data collected until  $t_P$ . Let  $\mathbf{y}(t) \in \mathbb{R}^{n_y}$ ,  $\mathbf{n}(t) \in \mathbb{R}^{n_n}$ , and  $\mathbf{h}$  denote the output vector, measurement noise vector, and output equation respectively. Then,

$$\mathbf{y}(t) = \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t)) \quad (2)$$

Typically, filtering approaches such as Kalman filtering, particle filtering, etc. may be used for such state estimation.<sup>29</sup>

Having estimated the state at time  $t_P$ , Eq. (1) is used to predict the future states of the component/system. This differential equation can be discretized and used to predict  $\mathbf{x}(t)$  for all  $t > t_P$ .

#### B. Modeling the Risk-Factor

Risk-Factors can be expressed in terms of a binary constraint function  $c^H(\mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t)) = 1$  that maps a given point in the joint state-parameter space given the current inputs,  $(\mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t))$ , to the Boolean domain  $\mathbb{B} \triangleq [0, 1]$ . Without loss of generality,  $c^H(\mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t))$  can be written as  $c^H(t)$ ;  $c^H(t) = 1$  implies that the risk-factor is encountered at time  $t$  whereas  $c^H(t) = 0$  implies that the risk-factor is not encountered at time  $t$ .

At any generic time of prediction  $t_P$ , note that the constraint function  $c^H(t)$  associated with each risk-factor is a function of  $t$ . Therefore, the approach needs to forecast all available information until future time  $t$  in order to predict the occurrence of the risk-factor. Thus, it needs all information (states, parameters, and inputs in Eq. 1) between time  $t_P$  and  $t$ .

#### C. Likelihood of Risk-Factor and Prediction of Time of Occurrence

Typically, there are two quantities of interest, in the context of risk-factor prediction:

1. Time of Occurrence: At any time of prediction  $t_P$ , it is useful to know the future time at which the risk-factor will be encountered. Let  $T^H(t_P)$  denote this quantity. This information can be helpful in determining the amount of time remaining so that corrective action may be taken. However, due to the uncertainties involved, this quantity is a probability distribution.

2. Likelihood of Occurrence of the Risk-Factor as a function of time: At any time of prediction  $t_P$ , it is also useful to know the likelihood of the occurrence of risk-factor as a function of future time. This likelihood is denoted as  $P_t^H(t_P)$ ; note that this is a trajectory as a function of future time  $t$  and changes with the time of prediction  $t_P$ .

First, at any  $t_P$ , the time of occurrence of a risk-factor (that is, the future time at which the risk-factor will be encountered) can be written as:

$$T^H(t_P) \triangleq \inf\{t \in \mathbb{R} : t \geq t_P \wedge c^H(t) = 1\}. \quad (3)$$

It can be easily seen that  $T^H(t_P)$  depends on the state at time of prediction, future inputs/parameters, etc., which are uncertain in nature; in order to calculate the probability distribution of  $T^H(t_P)$ , it is necessary to systematically propagate the aforementioned uncertain quantities and quantify their effect on the probability distribution of  $T^H(t_P)$ . Second,  $P_t^H(t_P)$ , i.e., the likelihood of the risk-factor at future time  $t$  (predicted at time  $t_P$ ) can be expressed as  $P(c^H(t) = 1)$ .

The computation of both the probability distribution of  $T^H(t_P)$  and the probability  $P(c^H(t) = 1)$  can be accomplished using Monte Carlo sampling-based techniques, analytical techniques based on first-order and second-order reliability methods, or hybrid methods involving machine learning approaches.<sup>28,30</sup>

The next section explains the application of these methods to the operation of a small unmanned aerial vehicle, by focusing on two risk-factors: battery discharging and collision prediction. For each risk-factor, the likelihood of occurrence of risk-factor is computed using constituent models.

## IV. Illustration: Application to a Small UAV

Consider a small octocopter, operating in an urban environment. This vehicle is powered by lithium-polymer batteries and has a flying time of around 15 minutes. Such a duration is ideal for missions such as package delivery, inspection (including taking pictures), or even for monitoring the surrounding environment. While different possible trajectories can be generated in order to complete the mission at hand, it is important for the decision-making algorithms to select trajectories that satisfy the various vehicular constraints and ensure safe operation of the UAV.

There are several possible risk-factors such as battery discharging, collision against obstacles, extreme wind conditions, presence of system-level faults, loss of control, etc., that affect the flight of the octocopter. Two risk-factors have been selected for illustration in this section; it is straightforward to extend the proposed approach to any risk-factor by selecting appropriate models for the risk-factor and identifying mathematical conditions that define the occurrence of such risk-factor.

### A. Risk-Factor Example: Battery Discharging

The octocopter under consideration is powered by a Lithium Polymer battery that is discharging continuously as a function of time. Based on the planned trajectory, it is necessary to predict future power requirements and estimate if there is sufficient charge remaining to execute the planned trajectory.

The flowchart for decision-making in terms of battery discharging is indicated in Fig. 4. The fundamental idea is to continuously evaluate at every time-instant of prediction whether a given trajectory will completely discharge the battery before the end of the trajectory. If discharging is complete prior to the end of the planned trajectory, then the trajectory needs to be rejected right away (being proactive and preemptive) at the time-instant of prediction rather than waiting for the discharging to actually happen. This is accomplished by computing the probability that “the battery would have fully discharged” as a continuous function of future time, and this analysis is repeated at every time-instant of prediction. Such a continuous function for a practical operational scenario is indicated in Fig. 5.

As seen from Fig. 5, the probability is initially close to zero, and then steadily increases as the battery is gradually discharging. At a future time of approximately 800 seconds, this probability rises above 80%. Hence, it would be “risky” to approve any trajectory that lasts longer than 800 seconds.

### B. Risk-Factor Example: Collision Against Dynamic Obstacles

Dynamic obstacles cannot be planned for, during the trajectory generation stage since they cannot be anticipated in advance; they need to be detected and accounted for during flight. The decision-making

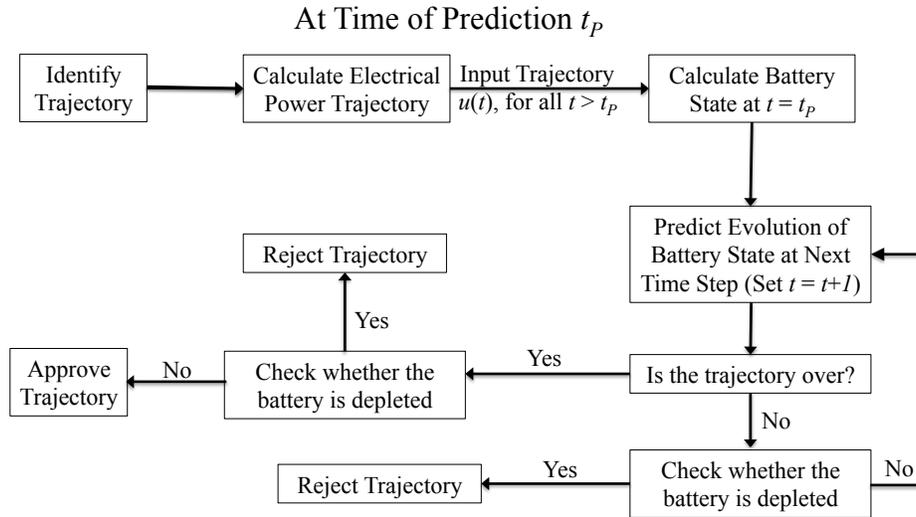


Figure 4: Decision-Making: Battery Discharging

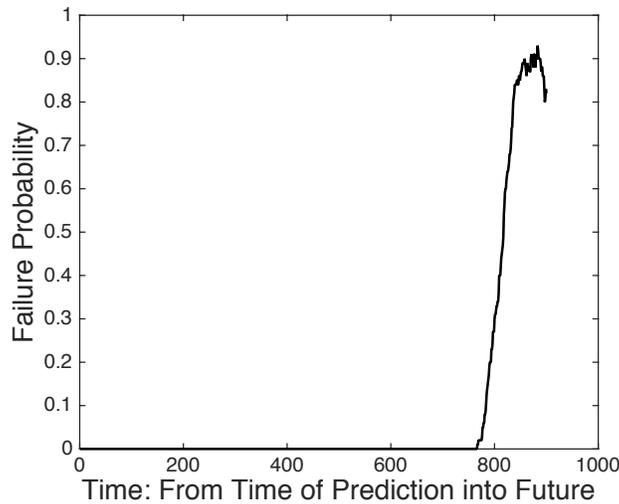


Figure 5: Probability that the Battery is Fully Discharged at Future Time

algorithm needs to approve or reject trajectories that would lead to an eventual collision between the UAV and such obstacles.

When dynamic obstacles are present in the environment, collision against such obstacles is inherently a risk-factor; therefore, a mathematical condition that determines the occurrence of such a risk-factor can be expressed as “when the separation distance between the UAV and the obstacle is less than an acceptable threshold”. The flowchart for decision-making in terms of collision prediction is indicated in Fig. 6.

Note that the algorithm uses information regarding the current position of the obstacle to estimate the velocity and the trajectory of the obstacle. If more information were available to compute the trajectory of the obstacle (for instance, if the obstacle were another UAV, then the trajectory of that other UAV could be fully known, where unmanned air/drone traffic is coordinated), such information would be more useful in practical scenarios. Based on whether the planned trajectory of the UAV would come into close proximity with the obstacle in the future, the decision-making algorithm approves or rejects the trajectory. This is accomplished by computing the probability that “separation distance between the UAV and a dynamic

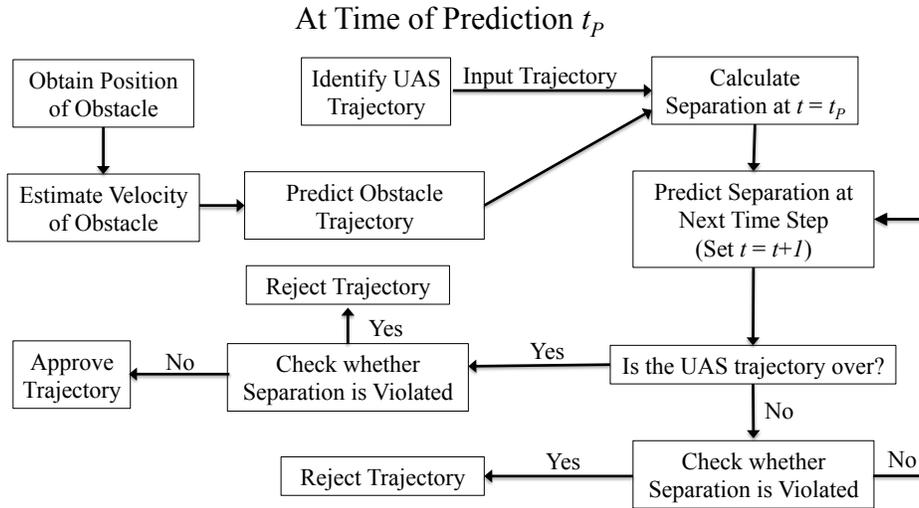


Figure 6: Decision-Making: Collision Against Dynamic Obstacles

obstacle is less than a predetermined critical minimum” as a continuous function of future time, and this analysis is repeated at every time-instant of prediction. Such a continuous function for a practical operational scenario is indicated in Fig. 7.

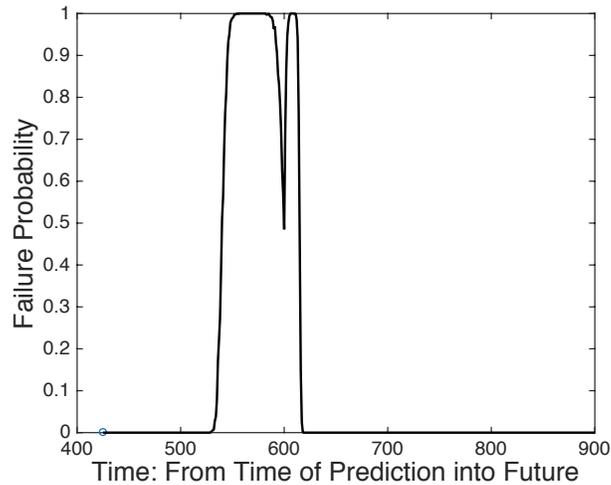


Figure 7: Probability that Separation Distance is Less Than An Acceptable Minimum

As seen from Fig. 7, the probability is initially close to zero, and then increases as the UAV is nearing the obstacle. At a future time of approximately 520 seconds, this probability rises above 80%. Hence, this approach gives a measure of the amount of time available (approximately, 100 seconds in this case) to alter the ongoing trajectory in order to avert an impending collision. (The decrease in the probability happens here because the UAV’s intended trajectory moves away from the obstacle’s estimated trajectory but later, the UAV turns and as a result, comes closer to the obstacle again leading to an increase in the probability.)

## V. Conclusion

This paper presented a computational framework for decision-making under uncertainty, to facilitate the autonomous, safe operation of small drone-like unmanned aerial vehicles. This predictive framework was based on the identification of risk-factors that affect the safe operation of such vehicles, and predicts the occurrence of events related to such risk-factors during the operation of the vehicle. By analyzing various risk-factors, the framework classified possible trajectories into four categories: “nominal and safe”, “off-nominal but safe”, “unsafe and abort the mission”, and “unsafe and ditch the vehicle”. This facilitated the optimal selection of trajectories that can achieve the mission objectives while guaranteeing minimum safety during operation. In order to achieve this goal, the likelihood of occurrence of risk-factors was systematically computed and predicted during the course of operation; the proposed framework was preemptive because it can predict the likelihood of a risk-factor continuously as a function of future operational time, and therefore, identify the future time at which a potential risk-factor may be encountered. Such computation of likelihood also required a systematic integration of the various sources of uncertainty that affect the operation of these unmanned aerial vehicles; this inclusion of uncertainty is particularly important when the focus is on preemptively predicting the future operation (future operations are significantly affected by uncertainty regarding the future conditions) and making changes to a predetermined trajectory.

While this paper presented a computational framework for decision-making, there are several directions for future research work. It is necessary to develop methods to select trajectories for aborting the mission or ditching the octocopter when safe trajectories or not possible. It is also necessary to account for faults that may occur in the system and incorporate diagnostic information into the decision-making procedure. It is necessary to include multiple risk-factors into the proposed framework and expand the computation of likelihoods; it is also important to incorporate risk measures into the proposed framework. While the present version of implementation focuses on simply predicting when future risk-factors will be encountered, ongoing research is focusing on seamlessly integrating this framework into the trajectory selection/generation procedure. Finally, it is important to transform the proposed framework into onboard technology that can be mounted as hardware used on unmanned aerial vehicles, to guide onboard autonomous, safe, operational decision-making.

## Acknowledgment

This work was supported by the NASA Ames SAFE50 Center Innovation Fund (CIF) project and the UAS Traffic Management (UTM) Sub-project, under the NASA's Safe Autonomous Systems Operations (SASO) Project. This research was also partly funded by a NASA-DHS inter-agency agreement. This support is gratefully acknowledged. The authors also thank all members of the SAFE50 team for engaging in many hours of discussions on various topics discussed in this paper.

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