Intelligent Contingency Management for Urban Air Mobility

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Where are we heading in Aeronautics?

Third Aviation Revolution

- Urban Air Mobility
  - Part of **Anyone, Anywhere, Anytime** Advanced Air Mobility concept
  - Largely enabled by electrification and automation
  - **Autonomous flight** to fully realize the market potential
  - **Urban Air Mobility** is the most challenging subset
  - Operation in complex environment and densely populated areas
- Driving Factors
  - Cost
  - Reliability
  - Flexibility
  - Trustworthiness for safety-critical systems
- Dynamic data driven approaches play an integral part in enabling this emerging market

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Challenges to Enable Urban Air Mobility

- Develop **assured autonomous functions** that enable safe and efficient operations in increasingly complex environments
- Driver is off-nominal conditions requiring robust **contingency management** and **graceful degradation** to unforeseen events
- Fundamental research challenges in adaptive mission management, robust autonomous decision making, explanatory intelligent systems, intelligent contingency management, and graceful performance degradation in the unique domain of **aviation safety-critical systems**
- External **degraded** information and communications
- High level of **assurance** and **safety**
- Systems designed to include understanding of human collaborators and **own capabilities and limitations**

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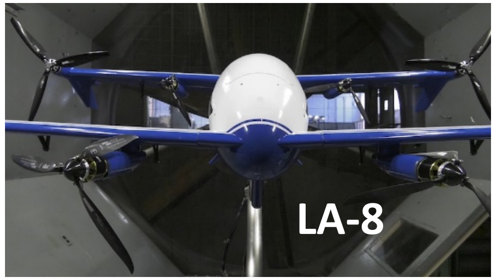
Urban Air Mobility – Technical Challenges

Air traffic management system

Vehicle mission management system

- Resilient vehicle contingency management system, highly autonomous even at early maturity levels
- Hierarchical fault tolerance & graceful degradation
  - mission level
  - vehicle
  - subsystem
- Fail-operational stability
  - If physically capable, must maintain flight
- Real-time vehicle noise management
- Real-time mission planning & trajectory generation



UAM Mission Under Study

- Vehicle mission: target final phase of autonomous flight
  - Safely fly from pt. A to pt. B following a nominal trajectory
- Environmental and operational constraints:
  - Under all vehicle-allowable weather conditions,
  - In a high-density airspace and complex urban environment,
- React appropriately to off-nominal situations and contingencies without direct human control,
- Currently contingency management is a highly prescribed, rule-based approach.
- We are interested in exploring intelligent contingency management that can appropriately handle unanticipated situations.

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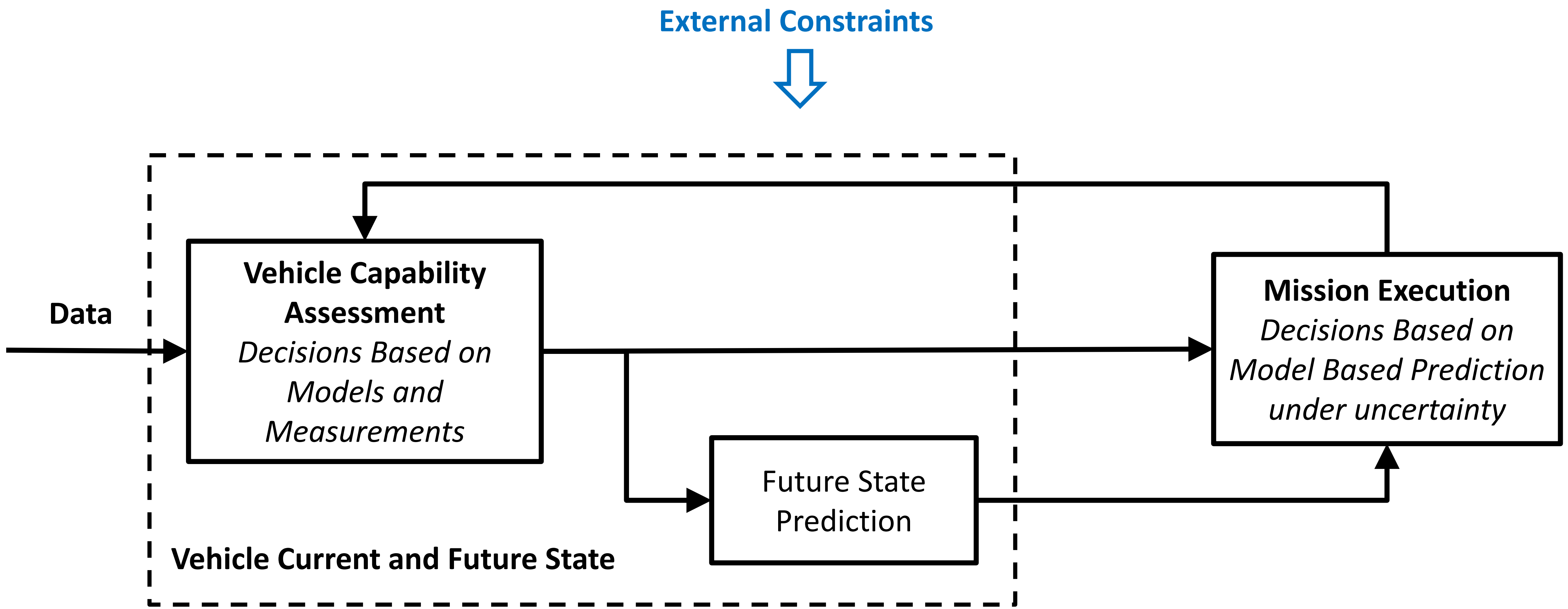
Intelligent Contingency Management – Architecture



High level architecture

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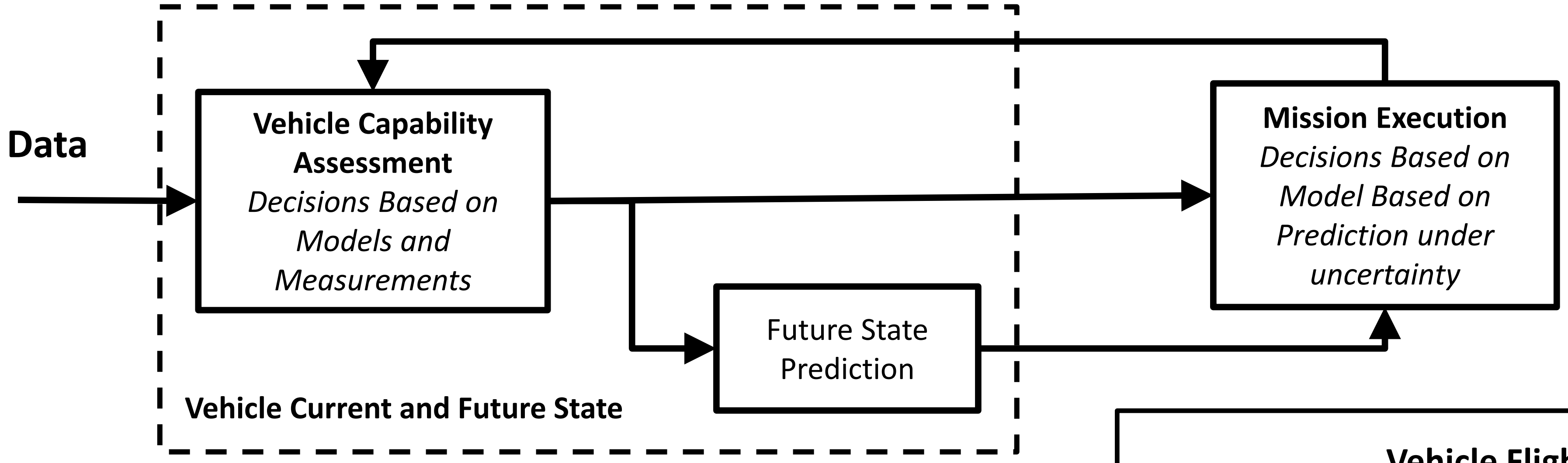
Intelligent Contingency Management – Major Component Blocks

External Constraints (Weather & Air Traffic Management)

Vehicle Model
- Model development (RAM-C)

Atmospheric Characterization
- Turbulence models for low altitude



Human Element
- Identification & Formalization of Safe Strategies

Vehicle Flight
- Trajectory planning
- Unified control – *robust adaptive control with novel allocation*

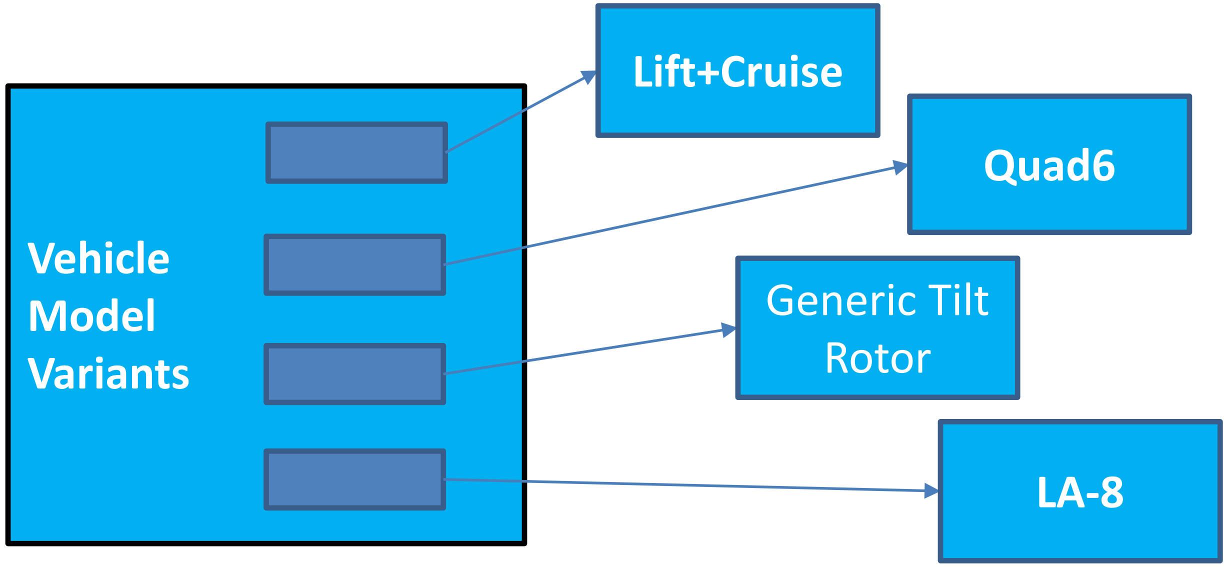
Vehicle Safety
- Safe dynamic envelope
- Collision Avoidance

ICM Architecture Simulation Environment – An Integrative Tool

MathWorks Matlab/Simulink® software

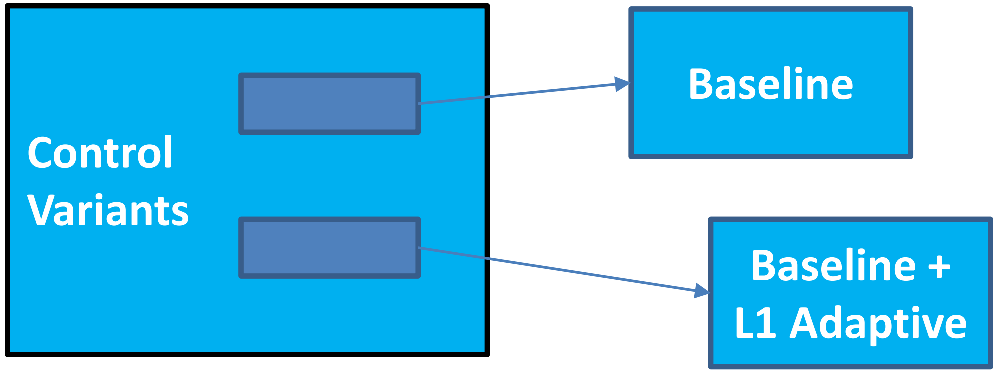
Simulation includes:

- Vehicle models
- Control systems
- Atmospheric disturbances
- Trajectory: internal and external sources



Existing vehicle types are:

- Lift+Cruise (RVLT reference) – contains multiple other variant subsystems
    - Control actuators (aerodynamic and propulsive)
    - Force & Moment computation method
    - EOM approach
    - Sensor
- LA-8
- Quad6 (RVLT reference) - 6 person capacity
- Generic Tilt Rotor – placeholder



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Aerodynamic Modeling for ICM

- Objectives:
  - Develop **full-envelope** aerodynamic models for **UAM-class** aircraft that are suitable for **nonlinear, flight dynamics** and **controls** simulations.
  - Develop *Rapid Aero Modeling* or *RAM*, an **automated** testing and **modeling** process.
  - Research and develop **best practices** for **eVTOL** aircraft modeling and simulation development.
- Challenges:
  - In an Urban Air Mobility transportation system, aircraft may embrace many **features from both aircraft** and **rotorcraft**. These designs present **greater complexity**, aerodynamic **nonlinearity**, and a **large number** of **interacting factors**, compared to conventional aircraft.
  - **Conventional** experimental methods, in particular one-factor-at-a-time testing, **fail to capture the complexity** and numerous interactions, often resulting in costly studies in terms of time/resources and **may** still **produce** models with **deficient information**.
- Impact
  - **High-fidelity aerodynamic** model development for eVTOL vehicles enables **accurate** vehicle simulation **essential** for UAM intelligent contingency management **research**.
  - RAM improves test and modeling efficiency, in the face of greater complexity, nonlinearity, and large numbers of interacting factors associated with eVTOL vehicles.

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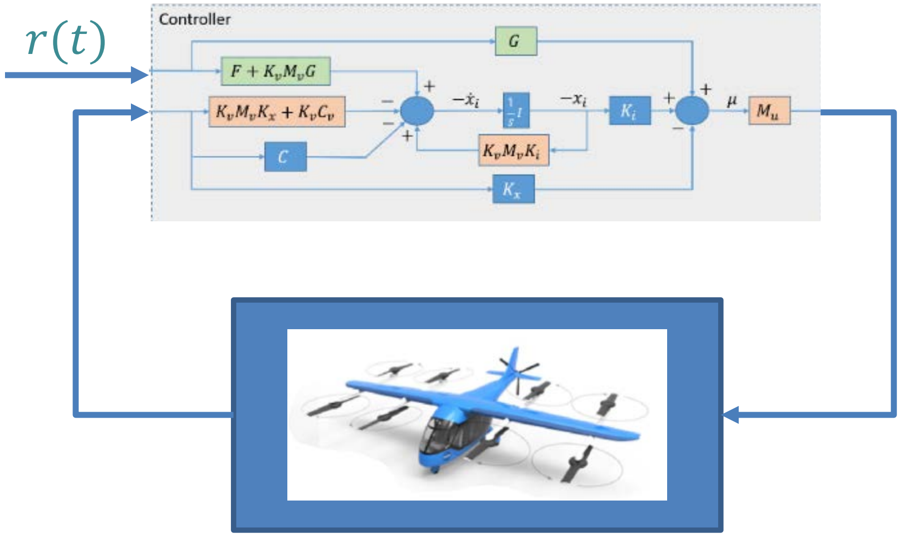
ICM – Control Overview

UAM Aircraft Control Considerations

- VTOL capable
- Modes of flight:
  - Hover, Transition and Forward Flight
  - Reflect very different ways to operate the aircraft
- Transition between modes safely and efficiently



A Robust Uniform Control Approach

- Configuration independent
- Unifies the control design across all flight modes
- Uses well known control approaches
  - Robust Servo Mechanism Linear Quadratic Regulator (RSLQR) for stability and trajectory tracking
  - Gain scheduling
- Provides a uniform set of control commands across all flight regimes
- Augmented with L1 Adaptive Control and implemented with Affine Generalized Inverse control allocation

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Trajectory Planning

A **reliably-convergent algorithm for trajectory planning with incomplete or corrupt information** to provide an **alternative** to machine learning for autonomous response to contingencies

- Establish a path to be followed by the vehicle that
  - Satisfies dynamical and air traffic constraints
  - Accommodates uncertainty in knowledge of current and future vehicle performance, environmental conditions, and traffic flow.
- Technical Approach:
  - Model:
    - Mission requirements and constraints expressed in terms of probabilistic moments.
    - Vehicle models are dispersed by random parameter values.
  - Computation
    - Vehicle command trajectory computed via constrained optimization of a collection of trajectories starting from the current state, and dispersed by random values of parameters
    - With the exception of the randomly varying parameters, the system representation is deterministic, employing Monte Carlo sampling to build up higher-level moments. Each sample trajectory is explicitly tied to a trajectory that satisfies mission requirements for the current mission moment estimate.
    - Resulting trajectory is explicitly in feedback form.

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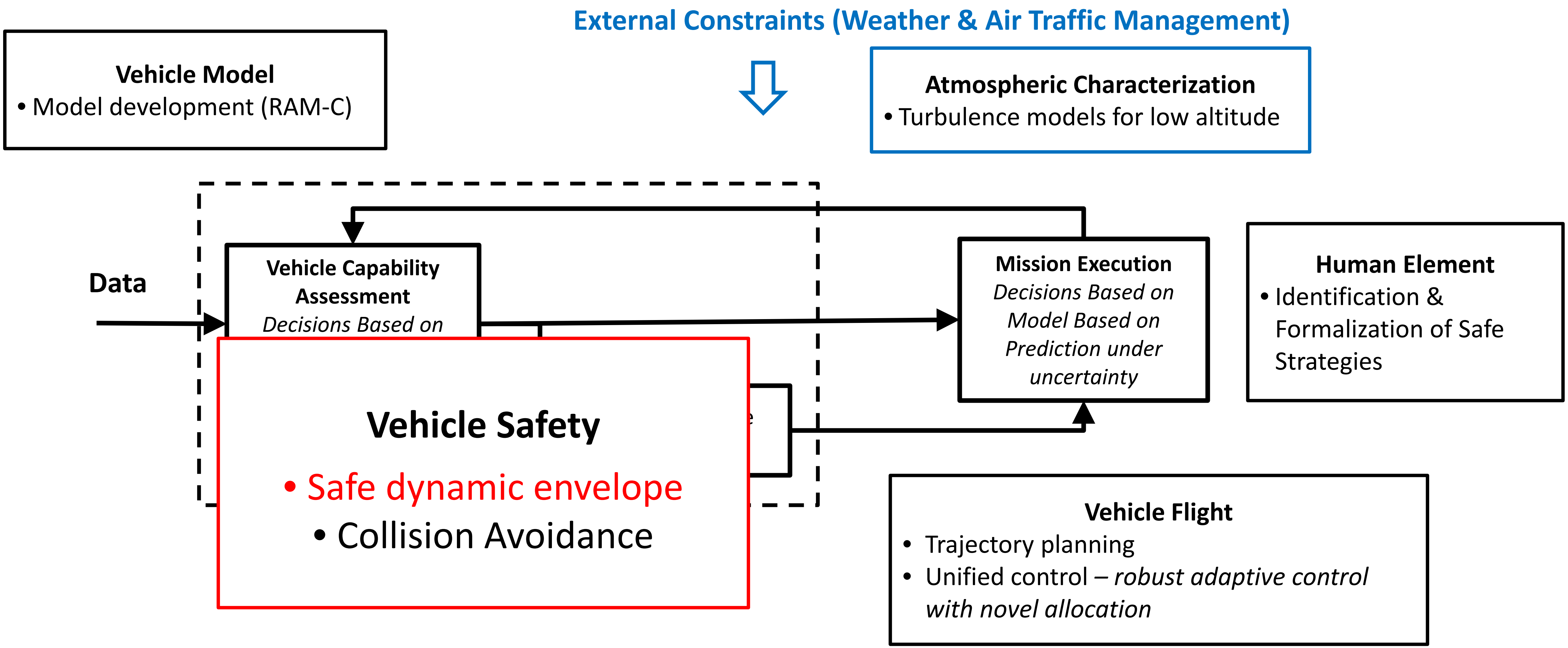
Intelligent Contingency Management – Major Component Blocks



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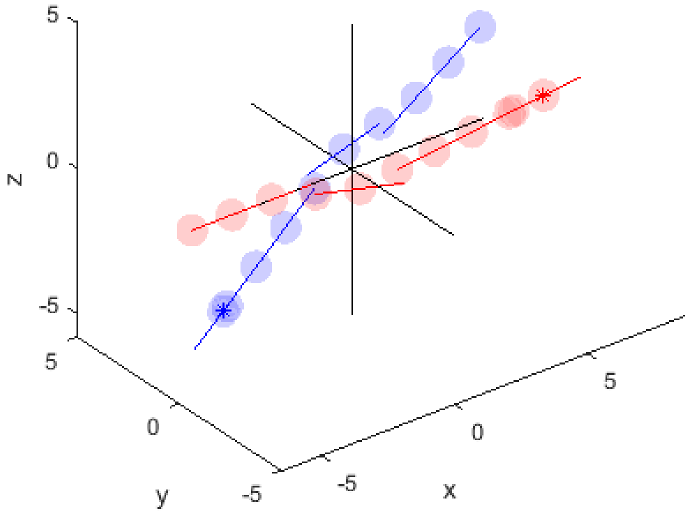
Collision Avoidance via Deep Reinforcement Learning

- Approach motivated by learning algorithms used for autonomous navigation through crowds extended to 3D urban air environment
- Challenges are similar
  - Each agent is aware of only a subset of other agent states
  - Need to anticipate interaction patterns
  - Be computationally tractable for real time implementation
- Supervisory training from a known solution provides initial baseline policy
- DRL uses an epsilon-greedy version of baseline policy to explore other options and improve it.
  - Offline learning offloads online computation for real time implementation.

Result of baseline policy



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Resilient Performance and Safety

- Resilient performance strategies enabled development of Soar rules to facilitate novel human-machine role allocation in a safe fashion
- Soar agent's **learned behavior** was not just to avoid an undesired state, but **to adapt** its functioning to facilitate desired states enabling resilient performance
  - Resolution of impasses via learning
- Seven **requirements** were **formally verified** in UPPAAL
  - Impasse resolution requirement had verification time of 20.85 sec, and maximally observed worst case time of 23.97 seconds over 1000 runs
- Future work on evaluation of the effects of resilient strategies on **multi-agent teaming** performance (specifically human-machine teams)
- Check out the full paper!

Creating Formal Characterizations of Routine Contingency Management in Commercial Aviation

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Abstract

The identification, modelling, and analysis of root causes of accidents and incidents dominate

Session: IS-33: Enabling Autonomous Advanced Air Mobility III

I. Introduction

Traditional approaches to safety management focus on collection of data describing unwanted states (i.e., accidents and incidents) and analysis of undesired behaviors (i.e., faults and errors) that precede those states. Thus, in the traditional view, safety is both defined and measured by its absence, namely the lack of safety. In extremely high confidence systems like commercial air transport, opportunities to measure the absence of safety are relatively rare. Ironically, a critical barrier to measuring safety and the impact of mitigation strategies in commercial aviation is the lack of opportunities for measurement.

While traditional approaches to safety that focus only on minimizing undesired outcomes have proven utility, they represent an incomplete view of safety in complex sociotechnical domains such as aviation. For example, pilots and controllers successfully manage contingencies during routine, everyday operations that contribute to the safety of the national airspace system. However, events that result in successful outcomes are not systematically collected or analyzed. Characterization and measurement of routine safety-producing behaviors would create far more

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Summary

- Urban Air Mobility for the masses is a major component of user-driven, immediate and flexible air travel
- Autonomous flight for full market potential
- One of the primary challenges is responding to off-nominal events, both common and unforeseen
- Intelligent contingency management (ICM) is one of the enabling technologies
- Basic premise of vehicle ICM:
  - Vehicle aware of its internal state and external environment at all times
  - Ascertains its capability
  - Makes decisions about mission completion or modification
- Propose overall architecture incorporating deterministic and learning algorithm to
  - Assess vehicle capabilities
  - Project these into the future
  - Make decision on mission management level
- Layered approach to allow mature technologies to be incorporated into early phases of UAM

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QUESTIONS?

Related Publications at SciTech 2021

Session: IS-31, Enabling Autonomous Advanced Air Mobility II

- ***Intelligent Contingency Management for Urban Air Mobility***
  Authors: Irene M Gregory, Michael J Acheson, Barton J Bacon, Thomas C Britton, Newton H Campbell, Jacob Cook, Jon Holbrook, Daniel D Moerder, Patrick C Murphy, Natasha A Neogi, Benjamin M Simmons, John D. McMinn, and Pieter Bunning
- ***Rapid Aero Modeling for Urban Air Mobility Aircraft in Computational Experiments***
  Authors: Patrick Murphy, Benjamin Simmons, Pieter Bunning
- ***Dynamic Vehicle Assessment for Intelligent Contingency Management of Urban Air Mobility Vehicles***
  Authors: Newton Campbell, Michael Acheson, Irene Gregory
- ***Examination of Unified Control Incorporating Generalized Control Allocation***
  Authors: Michael Acheson, Jacob Cook, Irene Gregory

Session: IS-33: Enabling Autonomous Advanced Air Mobility III

- ***Creating Formal Characterizations of Routine Contingency Management in Commercial Aviation***
  Authors: Natasha Neogi, Jon Holbrook

Session: IS-24, Autonomy VI - Spacecraft, Robotics and Flight Planning

- ***Loss of Control Detection for Commercial Transport Aircraft Using Conditional Variational Autoencoders***
  Authors: Newton Campbell; Jared Grauer; Irene Gregory

Session: ACD-15/TF-09: Design/Analysis of Urban and Regional Air Mobility Vehicles

- ***A Strip Theory Approach to Dynamic Modeling of eVTOL Aircraft***
  Author: Jacob Cook

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