SoSECIE Seminar

Some Hard Problems in SoSE, and a few Potential Solutions

Sept. 20, 2022

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Purdue University – Center for Integrated Systems in Aerospace (CISA)

& DoD SERC UARC

SYSTEMS ENGINEERING RESEARCH CENTER

Priority Research Areas

AIRC ACQUISITION INNOVATION RESEARCH CENTER

Systems Engineering Research Center

Enterprises and Innovation

- *Comprehensive Enterprise/ SoS Modeling and Analysis*
- *Mission Engineering*
- *Digital Enterprise Transformation*

Models and Data

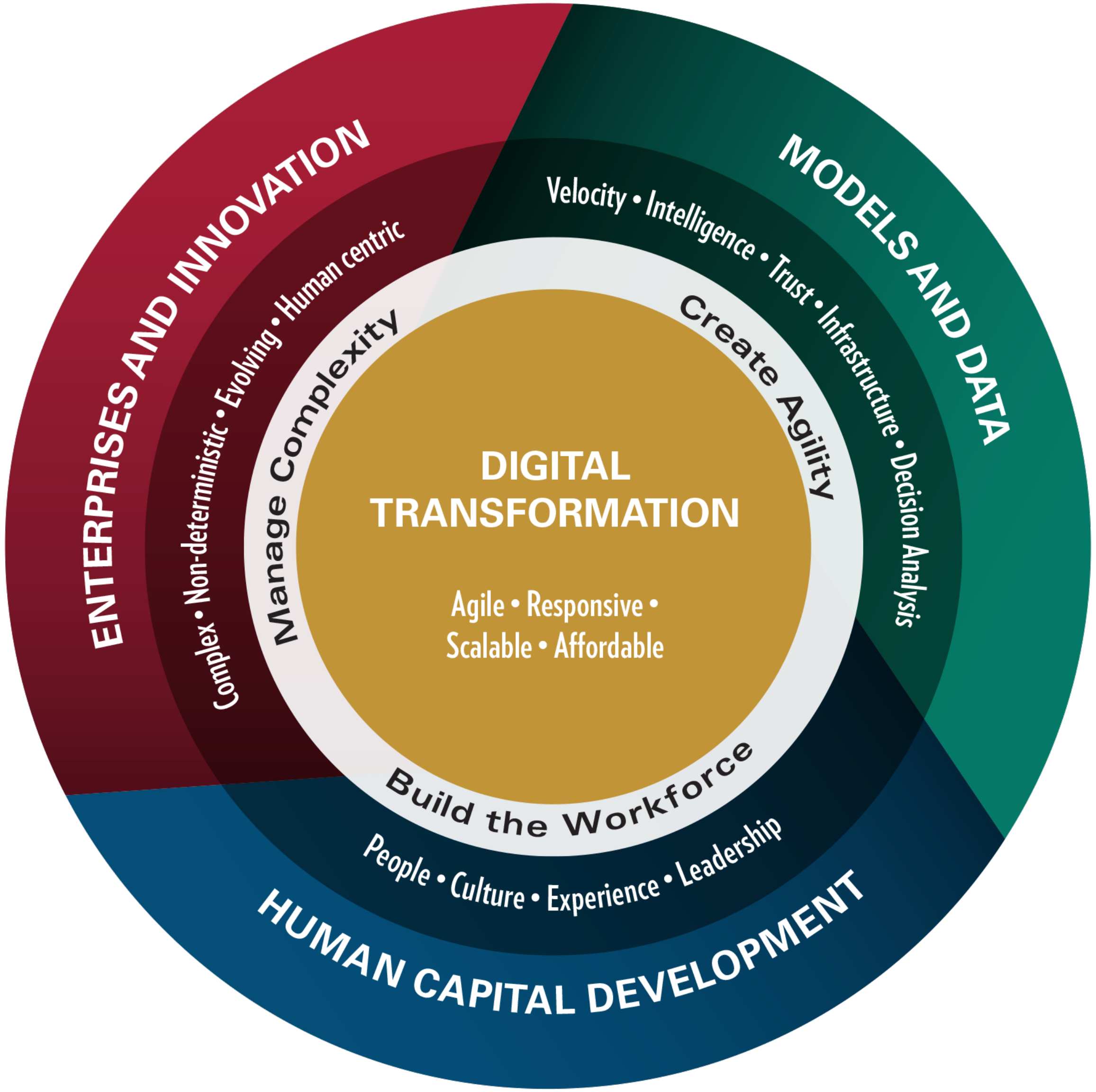
- *Systemic Security*
- *Common Architectures*

Human Capital Development

- *Evolving Body of Knowledge*
- *Digital Literacy/ Experience*
- *SE and Technical Leadership*
- *Cyber Resilience*

Digital Transformation

- *Velocity and Agility*
- *Digital Engineering*
- *SE Methods for AI and Autonomous Systems*



Acquisition Innovation Research Center

Enterprises and Innovation

- *Innovation Culture*
- *Intellectual Property*
- *Digital Enterprise Transformation*
- *Portfolio-based Acquisition*

Models and Data

- *Data Infrastructure*
- *Analytic Platform*

Human Capital Development

- *Digital Competencies*
- *Leadership & Innovation Culture*
- *Cognitive Assistants*

Digital Transformation

- *Data Management & Sharing*
- *End-to-end Lifecycles*
- *Policy Analytics*
- *Agile Program Management*

Three questions I keep hearing …

- **How do you know what is the appropriate modeling fidelity for SoS-level analysis?**
  - Multi-fidelity modeling in classic engineering systems provides some clues…but “its all physics”; in SoS, its “physics and beyond”
  - How do you discover the right questions to ask in order to determine scope, model (or data) appropriateness
  - Need benchmarks and use cases- have people exchange only models that are expressive enough for others to use them effectively
- **What kind and how much data do you need to answer a particular question, e.g. acquisition decision in a ME context?**
  - This question is perhaps recast best as an uncertainty quantification (UQ) question
  - Managerial independence – Service-level decision may satisfy local program objective but exacerbate gap in the joint portfolio
  - Approaches:? “Keep your Options Open”- Set-based design; Robust Decision-making – robust to modeled uncertainty, or missing data, for given risk tolerance
- **How to <u>model, simulate, predict, explain, learn</u> in a future multi-domain, complex (commercial or military) scenarios?**
  - **Designing future Missions** is a tough SoS problem- operational and managerial independence of the components…fast-paced multi-domain battle with unknown techs → Perhaps AI/ML and Missions as Games
  - Focus on optimizing incentives and levers - gaming, mechanism design
  - Focus on Flexibility and Adaptability- How many solutions can be obtained in relatively few changes/enhancements- Hamming distance and the flexibility /cost ratio; Far beyond today’s “War Gaming”

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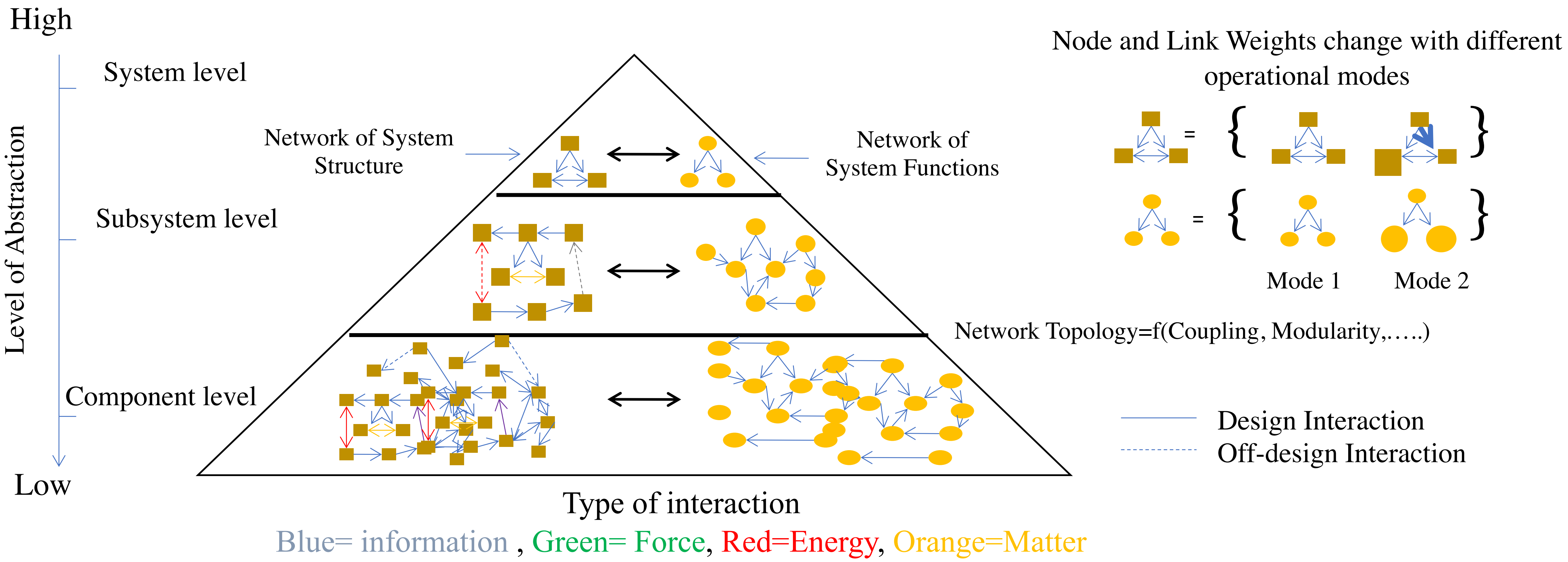
CISA pursues the Science of System Integration

Complex Systems (of Systems) exhibit integration at multiple levels of hierarchy and must be studied as such, marrying structural and functional representations of the system, addressing cross-domain interactions and seeking appropriate allocations of complexity & autonomy.



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From Definition to Abstraction:

Recognizing Complexity in Hierarchy and “Beyond Multi-Physics” in Representation

	Resources	Operations	Policy	Economics
	Laws of Physics	*Human & Machine Activities, Processes*	*Rules, Constraints & Regulations*	*Human/Org Behaviors & Incentives*

Delta ← etc →

Gamma ← Network of Networks →

Beta ← Network of Collaborating CESs and human organizations →

alpha ← Complex engineered systems (CES) and humans →

The gist is socio-technical thinking…and modeling…but in a SoSE specific manner. Aspects of complexity and its role in judicious choices in representation of a system, network, or behavior matter quite a bit.

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Mission Design and Success Prediction via
Real-time Strategy (RTS) Games + AI/ML

- Mission / SoS design problem
  - complex design spaces
  - dynamically evolving mission environments
- Simulation environments
  - AFSIM
  - Command
  - Flashpoint Campaigns
- RTS games abstract mission execution as a game played between agents.
- The L2G framework enables efficient mission design by building a surrogate model of the mission environment to assist with design tasks.

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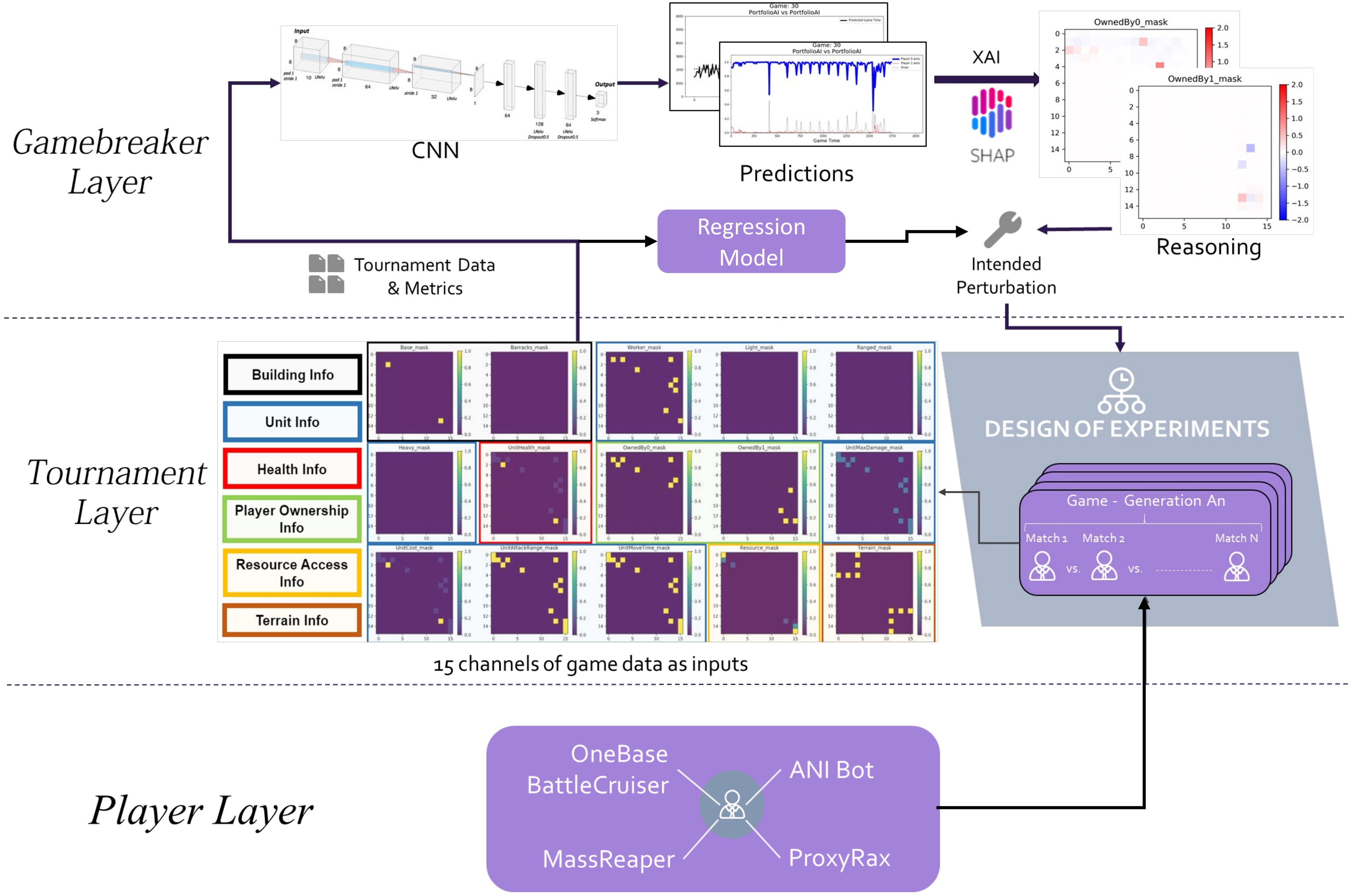
Learning to GameBreak (L2G)



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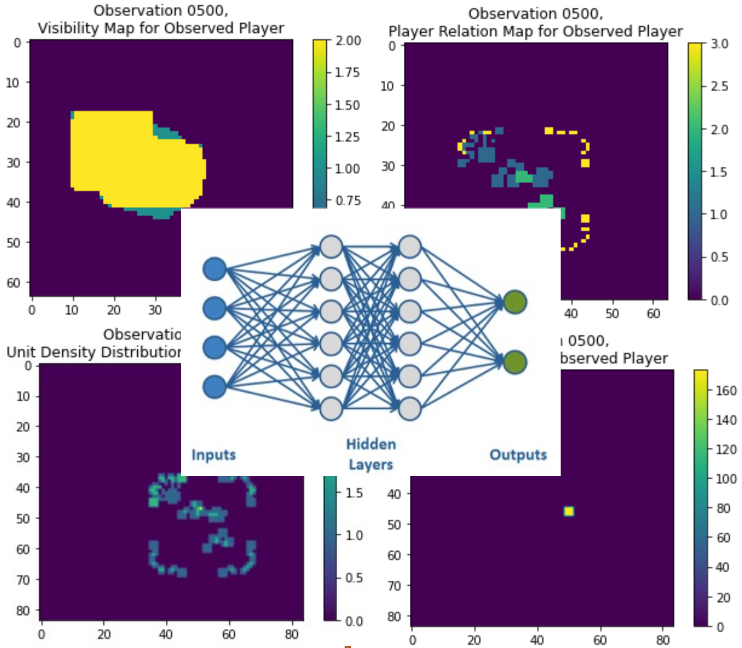
Application to StarCraft II

AI Bots
- OneBase BattleCruiser
- Mass Reaper
- Proxy Rax
- Ramp Wall
- Cyclone Push
- ANIBot

Data Collection
- 1,000 game designs, each played 10 times
- self-play games

Feature	Units	Default	Min	Max
SCV Weapon Damage	Health/Hit	5	3	7
BC ATS Damage	Health/Hit	8	5	11
BC ATA Damage	Health/Hit	5	3	7
SCV Health	Health	45	30	60
BC Health	Health	550	366	734
SCV Speed	Units/Frame	2.8125	1.8750	3.7500
BC Speed	Units/Frame	1.8750	1.2500	2.5000
SCV Build Time	Seconds	17	11	23
BC Build Time	Seconds	90	60	120

Model Building and Explaining
- Gaussian Process
- Convolutional Neural Networks
- Uncertainty quantification (MCDN)
- SHAP Explanations



Player (AI bots) **Tournament (DOE+Data)** **Game-breaking (Model+XAI)**

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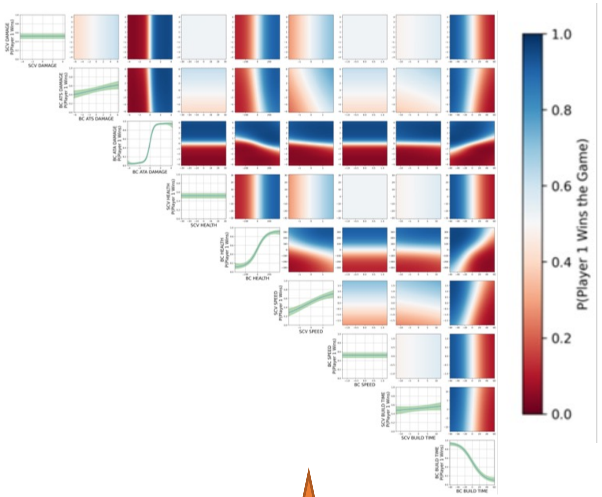
L2G Application over the Engagement Timeline

Gaussian Process Regression/NN+MCDN to predict balance points and alter initial balance.

Enables/provides:

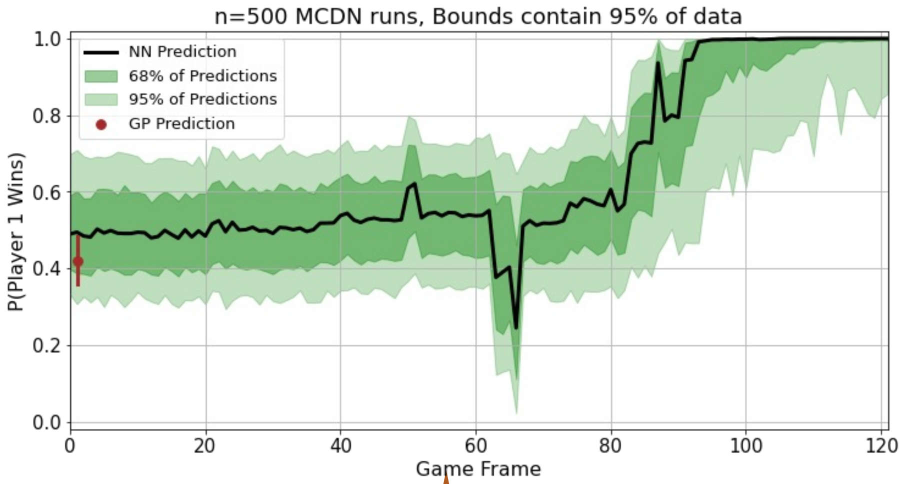
- Acquisition
- A priori analysis of engagement



Neural Network Model to predict current state of balance in engagement.

Enables/provides:

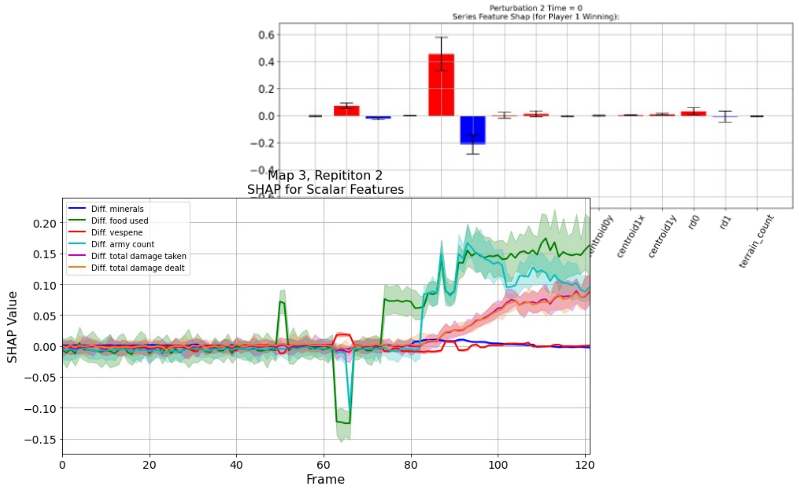
- Dynamic planning and strategizing
- Critical review of current strategy
- Real-time indication of significant events



Explainable AI for feature importance identification.

Enables/provides:

- Asset importance
- Critical and sensitive features in engagement



Pre-Mission

During Mission

Post-Mission

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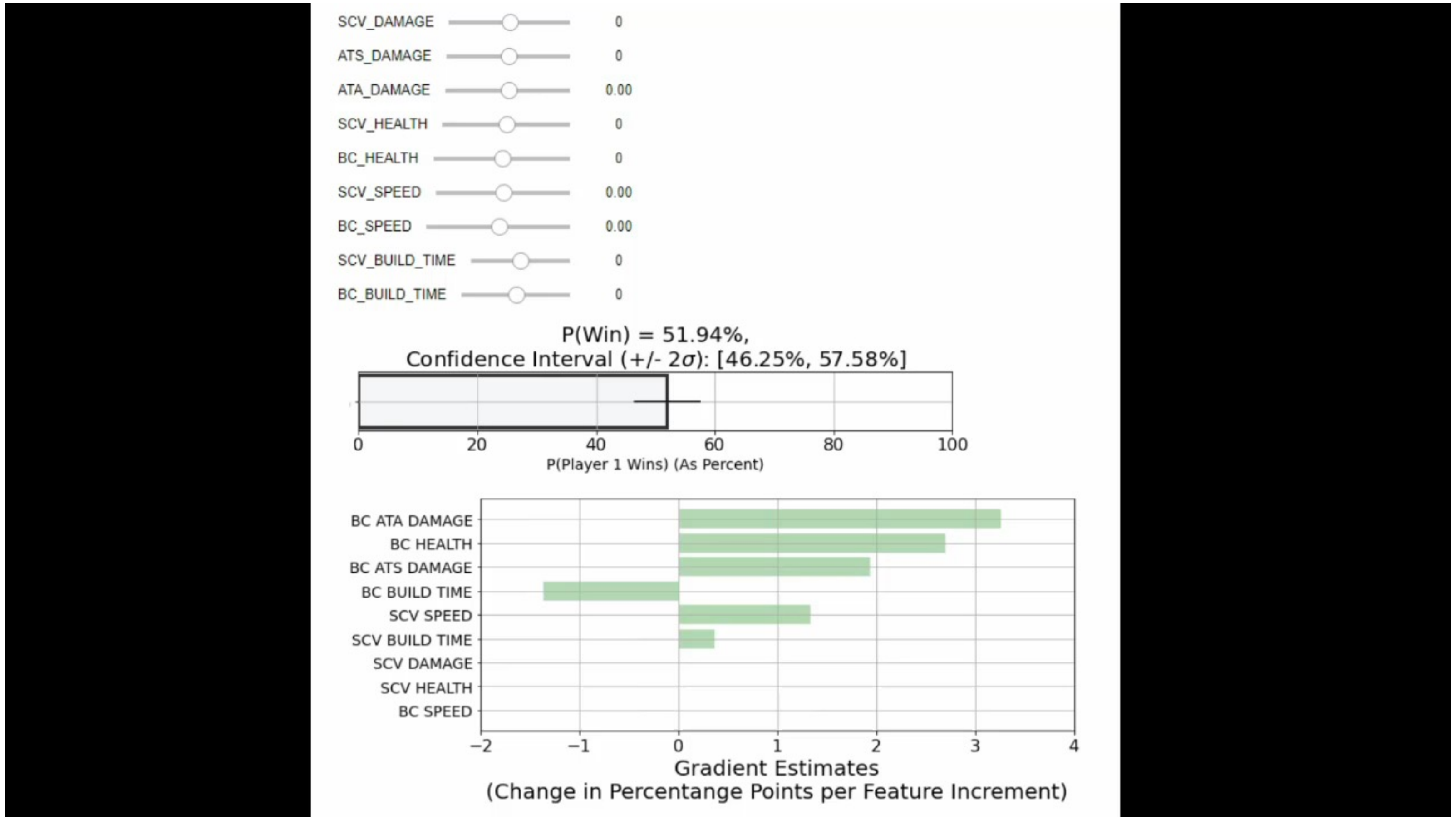
Pre-Engagement

- **Approach:** Gaussian Process Regression/NN+MCDN
- **Input:** Scenario Details
  - ➢ Enemy Strategy
  - ➢ Available Assets
  - ➢ Possible Asset Changes
- **Goal:** Determine assets to use in an engagement
  - ➢ What assets contribute to the imbalance?
  - ➢ How can we cost-effectively modify these assets to achieve optimal imbalance?



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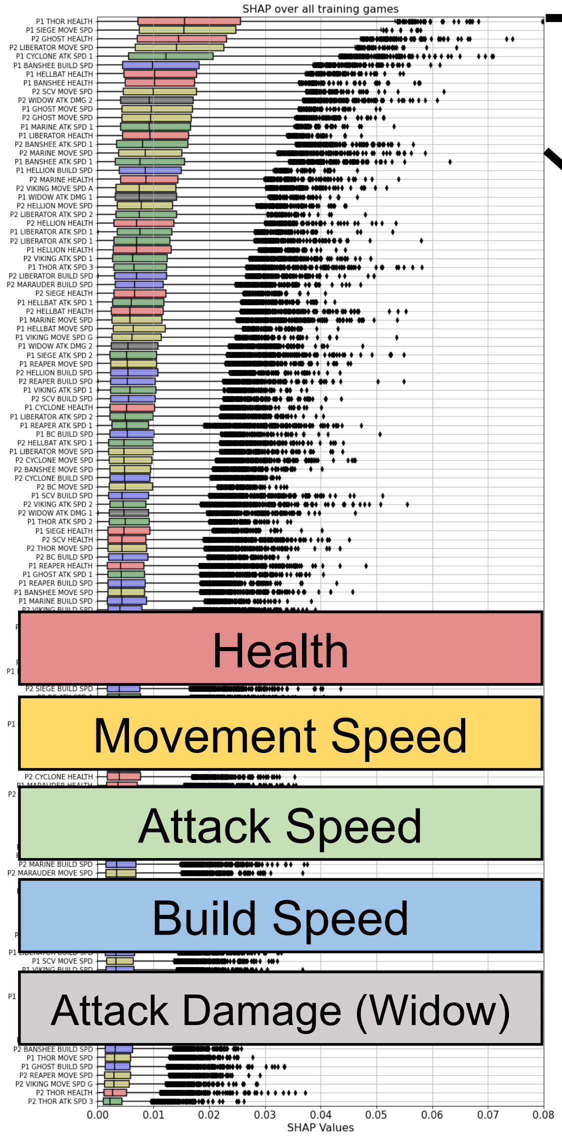
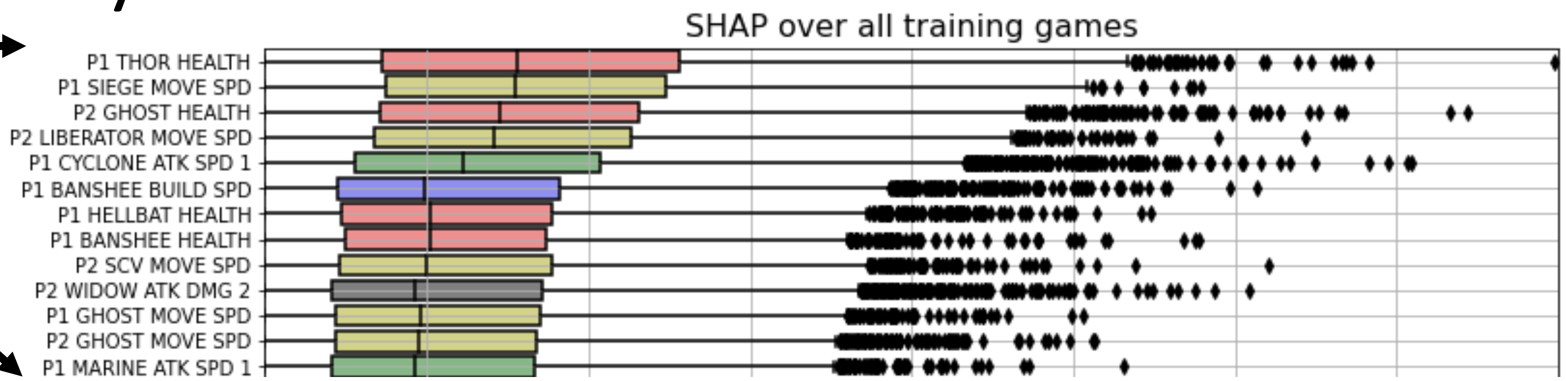
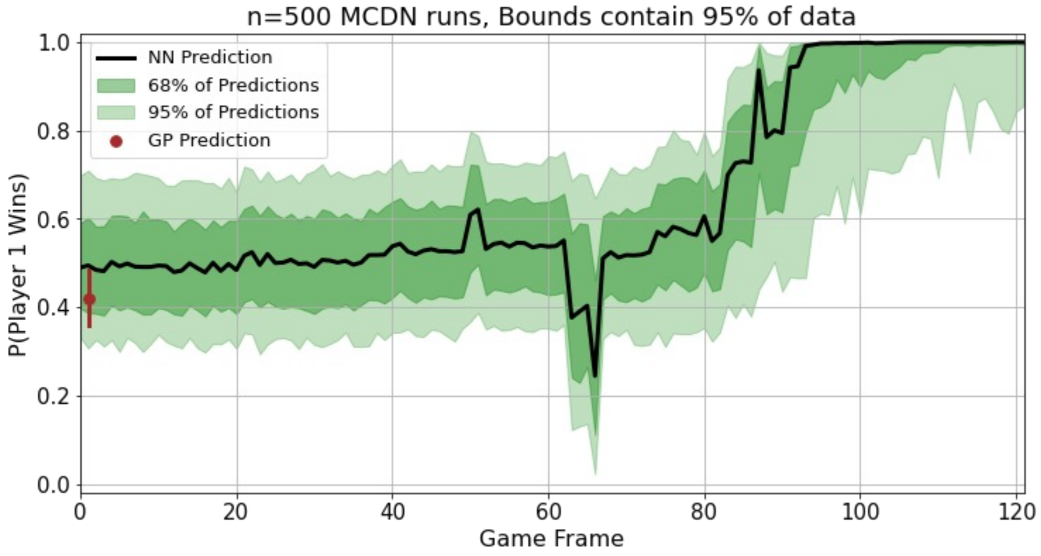
Engagement Analysis







Key Features:

- **Supply**
- **Damage Rate**

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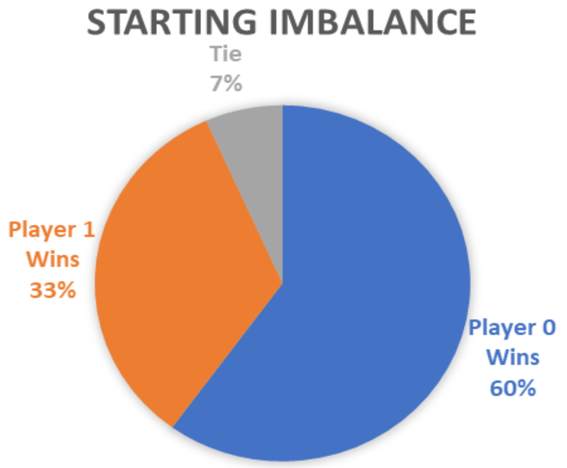
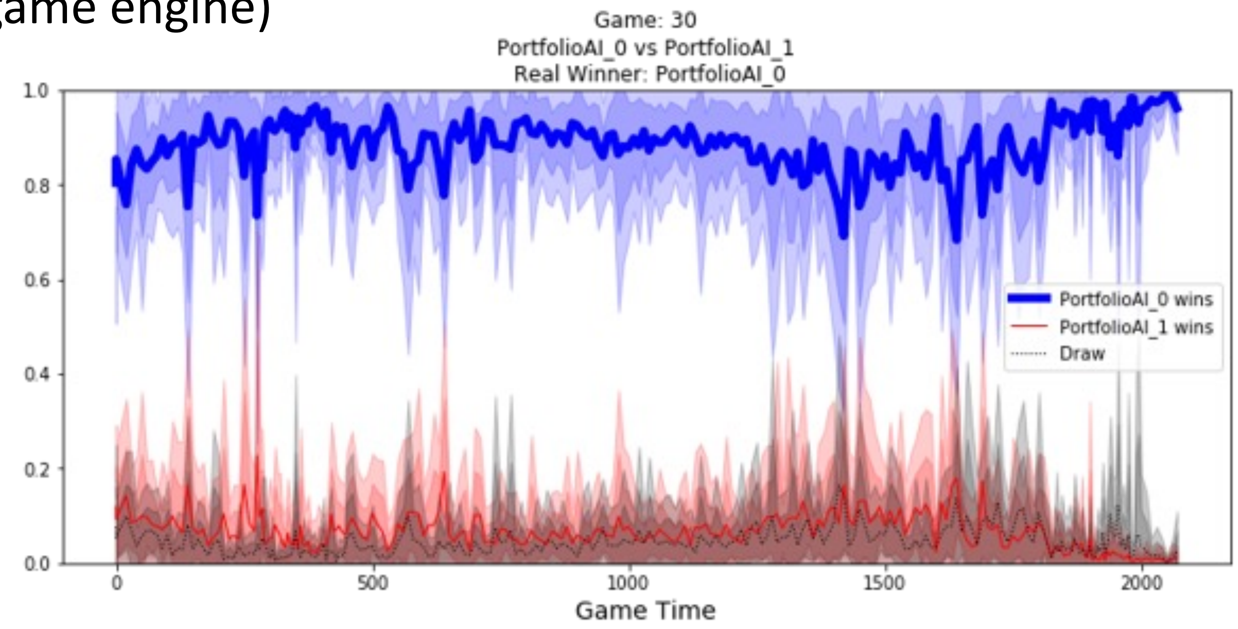
Insight: Initial Imbalance

- microRTS had an inherent imbalance due to process assumptions and handling of path planning functions.
  - ➢ Path planning algorithm unexpectedly impacted game balance
- **Lesson:** Beware of initial imbalance!
  - Unsafe to assume that any game is balanced
  - Methodology should be able to account for it.
  - Initial Imbalance was not detected in SCII (robust game engine)





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Prospects for L2G's broader application

- **Acquisition**:
  - **Key Problem**: Difficult to determine what resources/units to acquire in a MOSAIC context.
  - **L2G Relevance:** Unbiasing the Analysis of Alternatives and usage of SHAP (XAI) to identify the important levers.

- **Simulation/Characterization**:
  - **Key Problem:** Difficult to know the hidden assumptions and bias (unknown) in complex Modeling & Simulation/ Wargaming tools. Calls into question the believability of high consequence outcomes.
  - **L2G Relevance**: Detect biases and find the root cause through explainability. Leverage game balance methods to validate simulation. Generalizable Framework applicable to wide variety of problems.

Gamebreaker Application Domains
Acquisition
Planning
Execution
Simulation Characterization

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OPERATIONS LIMITS FOR PASSENGER-CARRYING URBAN AIR MOBILITY MISSIONS

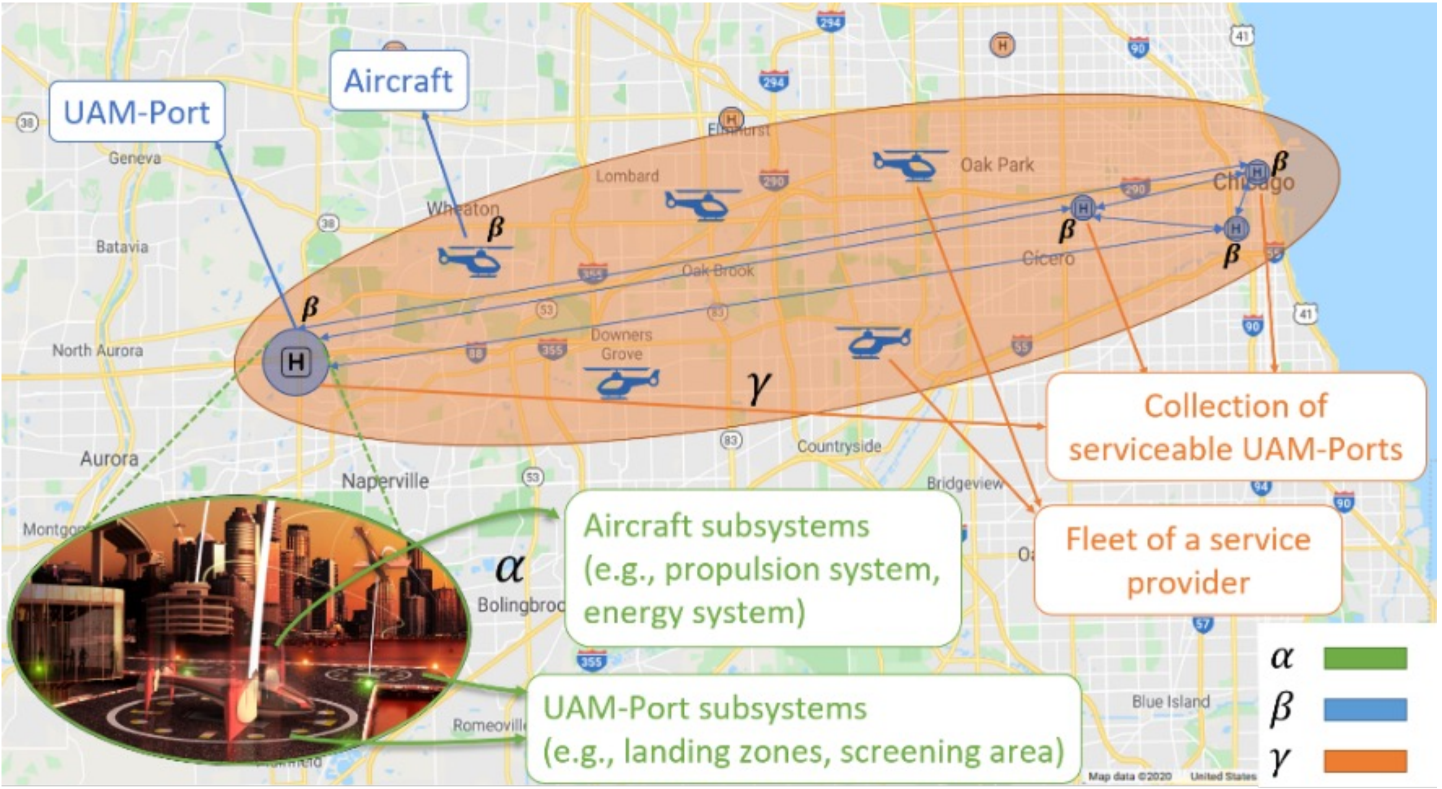
Research sponsored by NASA via National Institute for Aerospace

Presenter: Prof. Daniel DeLaurentis

(Team: Sai Mudumba, Hsun Chao, Apoorv Maheshwari, Brandon Sells, Nick Gunady, Prof. William Crossley)

Study Motivation and Overview

- Convergence of new technologies and new business models leading to emergence of new aviation markets, e.g., passenger-carrying ***Urban Air Mobility (UAM)***
- Important to assess the evolution of technology, infrastructure, societal acceptance, airspace integration, and many other factors to take us from the current state-of-the-art to the envisioned large-scale operations
- For near-term applications of passenger-carrying UAM, identify **“bottlenecks” limiting the scalability of early UAM operations (“Op Limits”)**
- Create computer model, driven by appropriate data & scenarios, to analyze significance of key Op Limits



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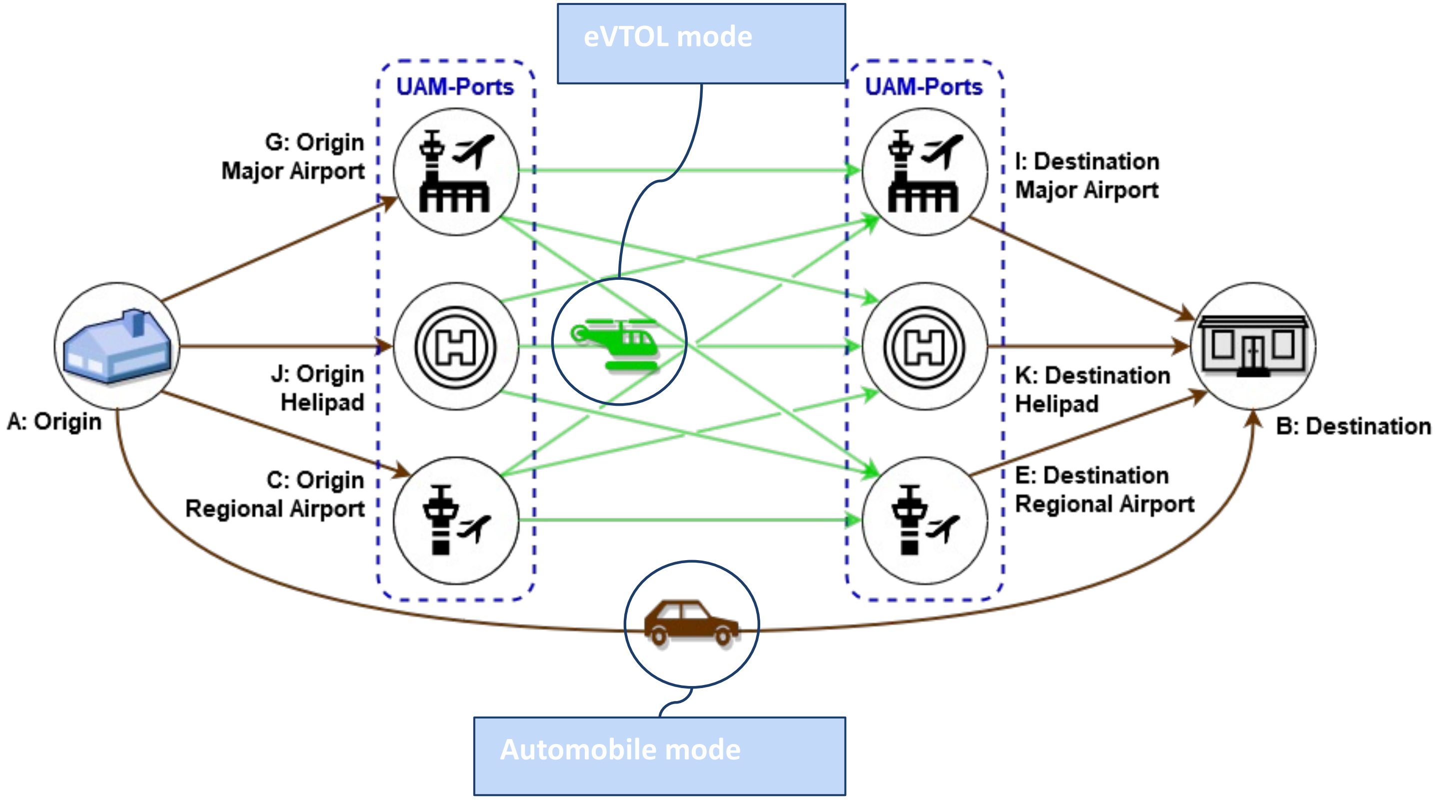
Unit of Analyses- the Urban Trip

Transportation network model composes of electric vertical takeoff and landing (eVTOL) and automobile modes

- **Green edges** are trips made by eVTOL vehicles
- **Brown edges** are trips made by automobiles
- UAM trips consist of both automobile and eVTOL modes (e.g., branch: AJKB)
- Automobile trips are conventional, ground-based trips (e.g., branch: AB)



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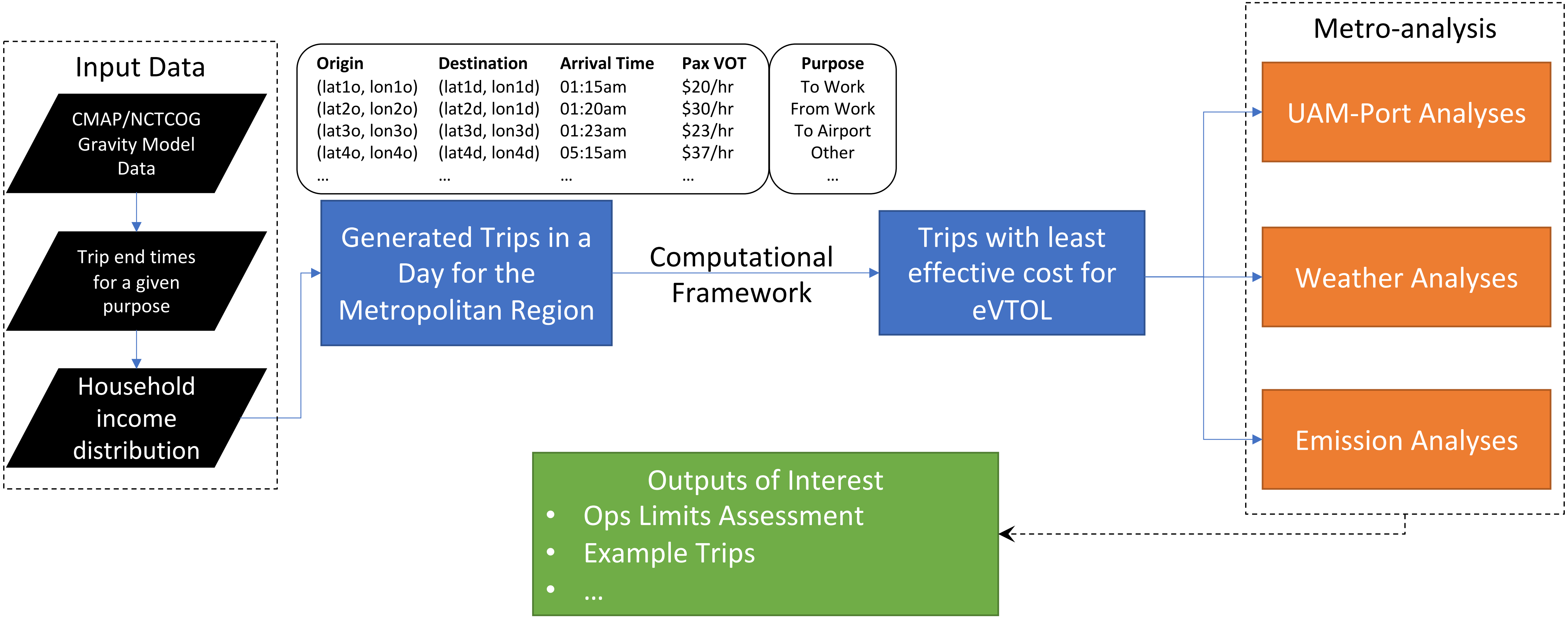
Computational Framework Analyzes Op Limits



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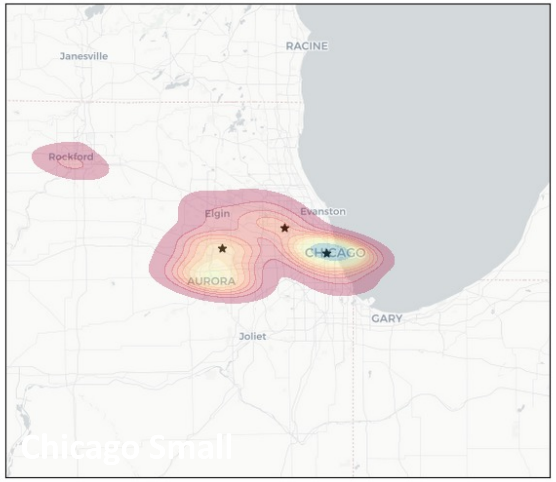
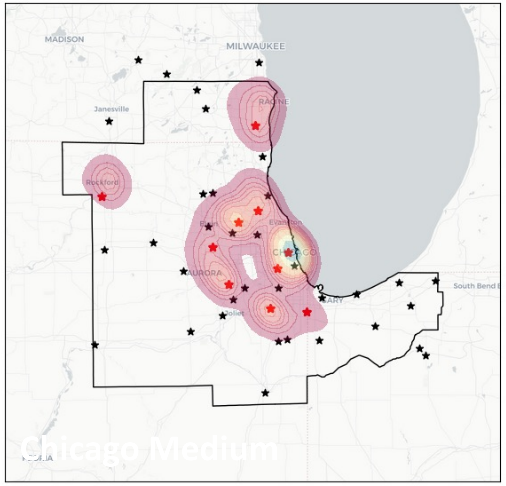
UAM Preferred Trips For Different Network Sizes (Launch)

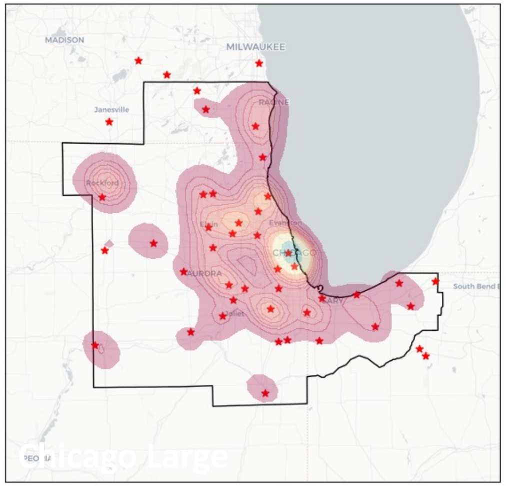
Chicago Commute Trips: 6,221,968

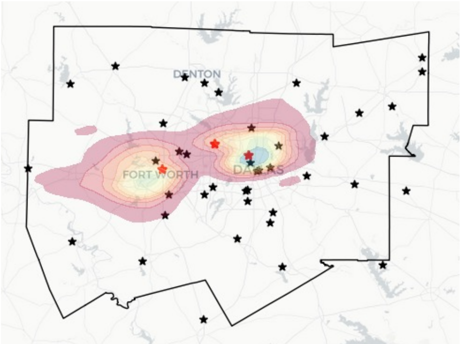
Dallas Commute Trips: 5,306,336

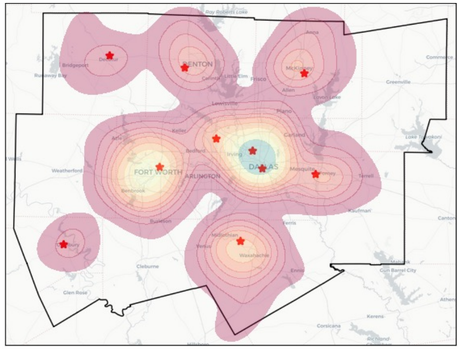
	Small (3 Vertiports)	Medium (10 Vertiports)	Large (All existing infra)
Chicago	397	3504	6305
Dallas	853	2330	6928

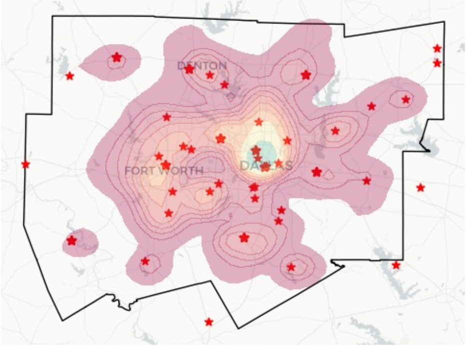












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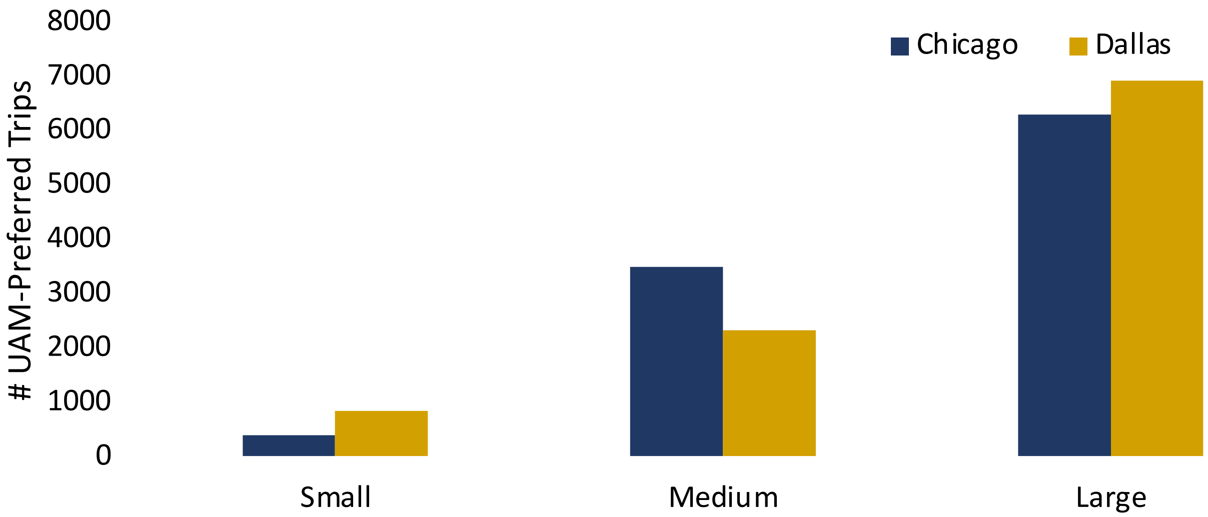
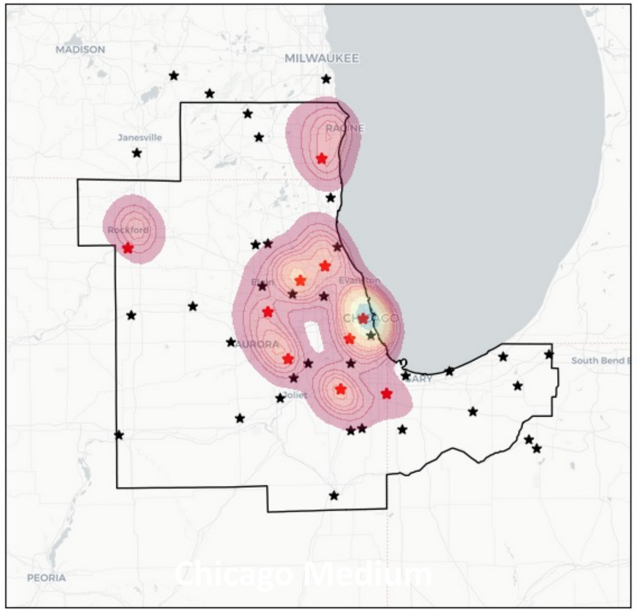
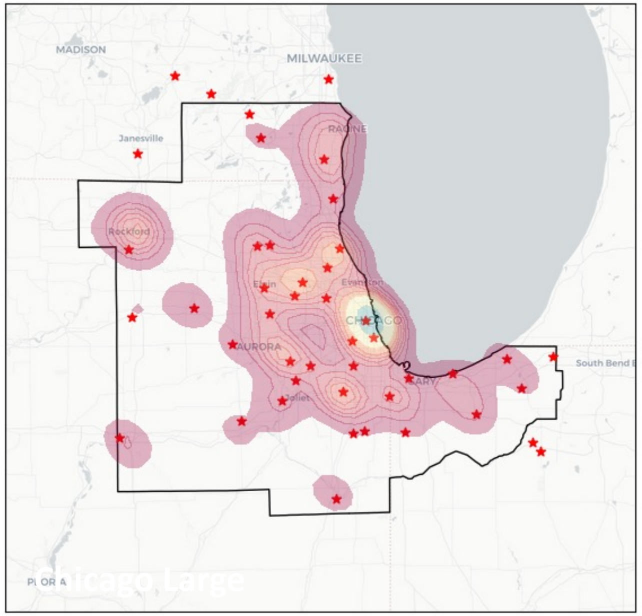
Key Observations from # UAM Preferred Trips

- #Trips increase with the number of vertiports; seems to follow a non-linear relationship
- Vertiport siting plays a significant role
  - Most trips concentrated around the vertiport locations
  - A few vertiports had quite high concentration of trips, even with high-cost launch scenario
  - Implications for congestion management







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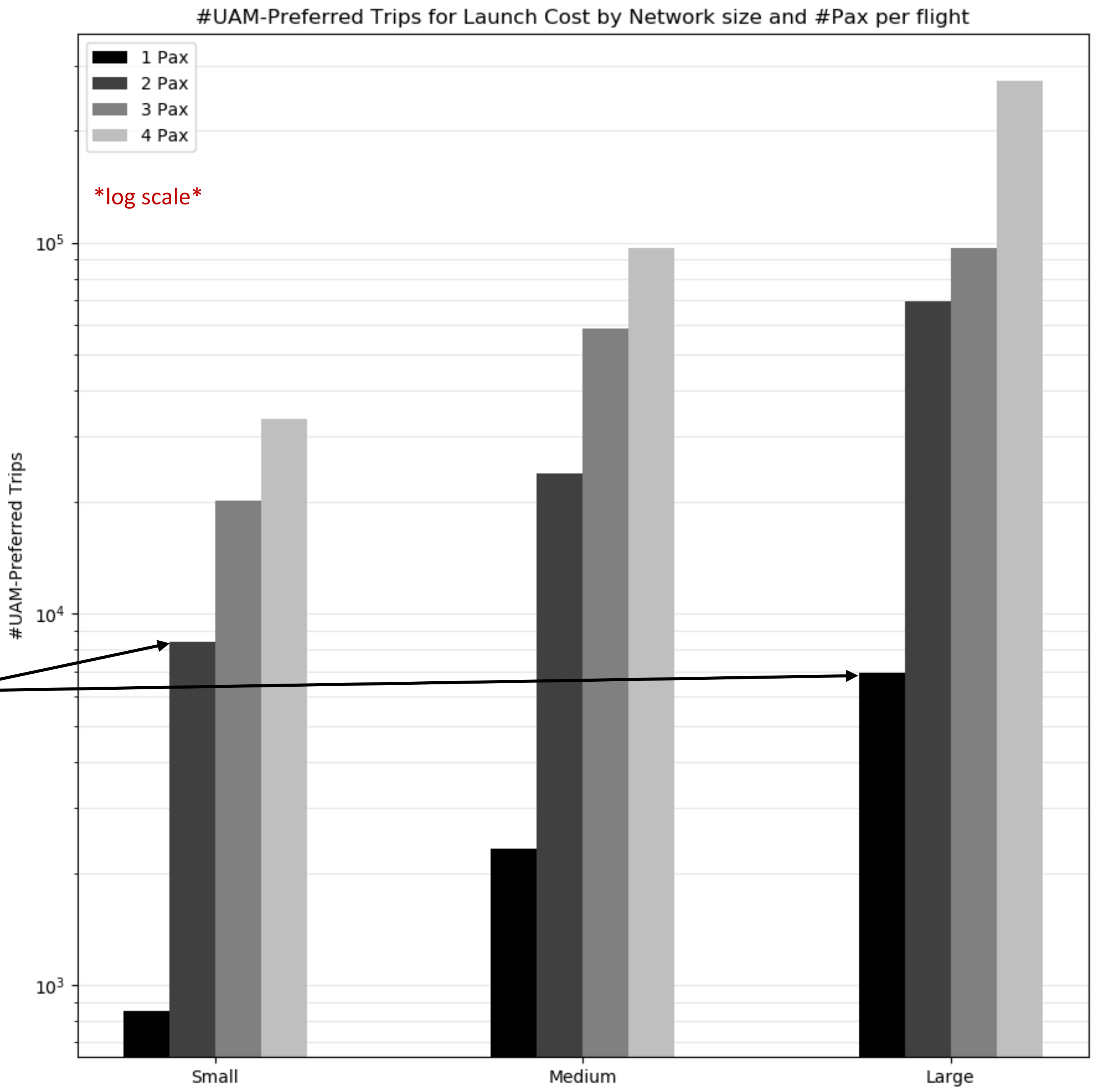
Impact of Ridesharing (DALLAS)

- Assuming the direct impact to the operating cost due to ride-sharing, #UAM-preferred trips are calculated
- For example, operating cost for
  - 1 pax $\rightarrow$ \$605/hr
  - 2 pax $\rightarrow$ \$303/hr (=605/2)
- Surprisingly, increasing the #pax per flight to 2 produces a larger impact as compared to operating at all available infrastructure locations with ridesharing not enabled!

Enabling ride sharing will be key to lowering UAM operating cost to make it a real market



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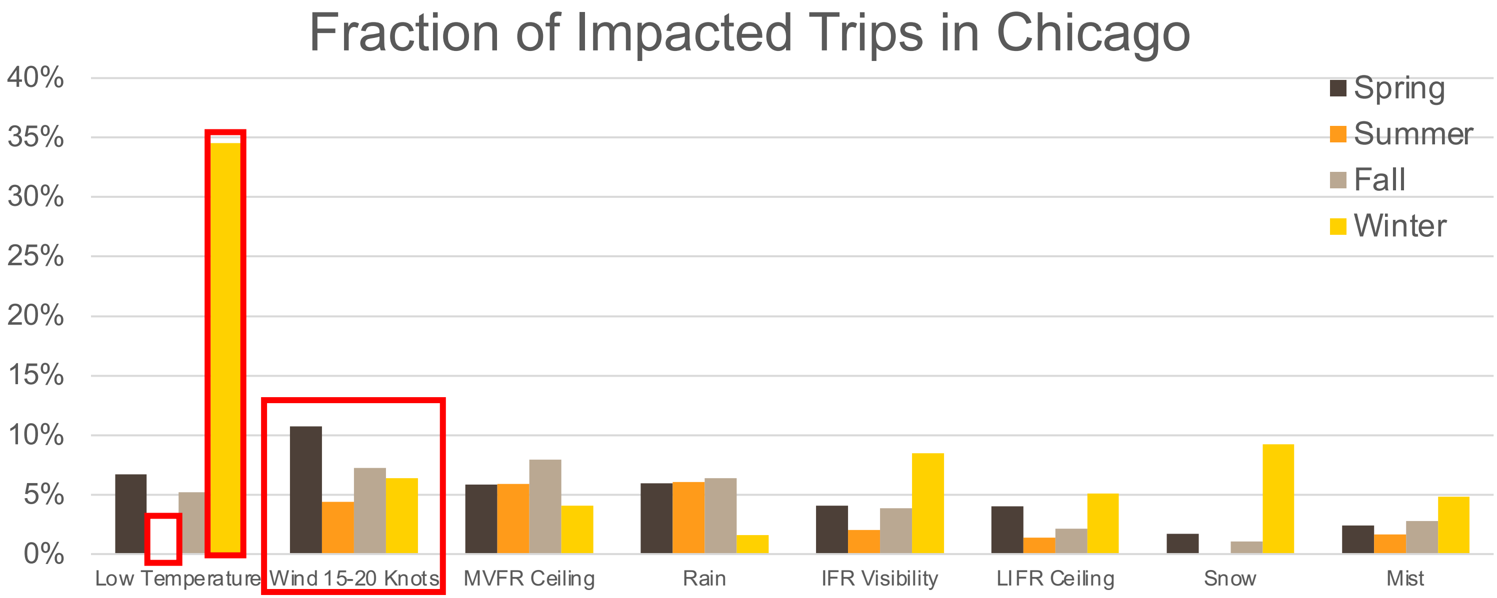
Weather Condition Ranking - Results

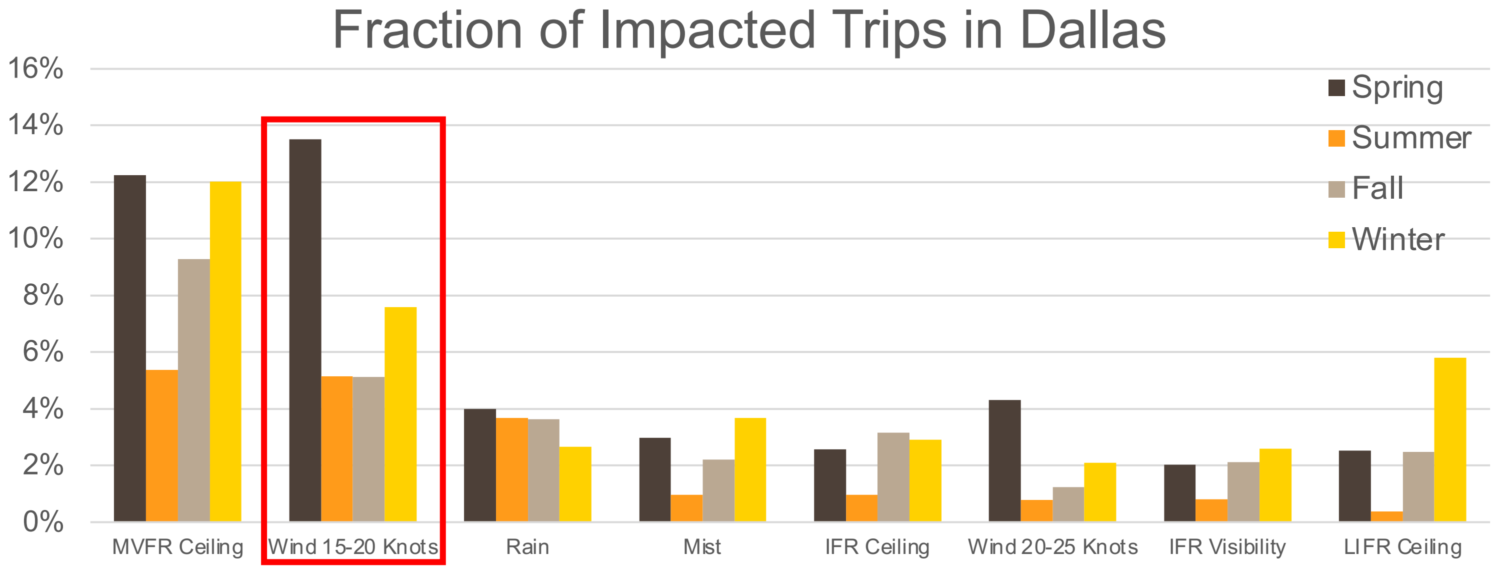
Wind 15-20 knots is the most frequently occurring weather condition in both cities

- Implies technology solution should be integrated onboard the vehicle

Low temperatures in Winter is important for Chicago

- Higher number of trips impacted in winter; 0 impacted in summer
- Modular technology solution might be suitable for this weather condition





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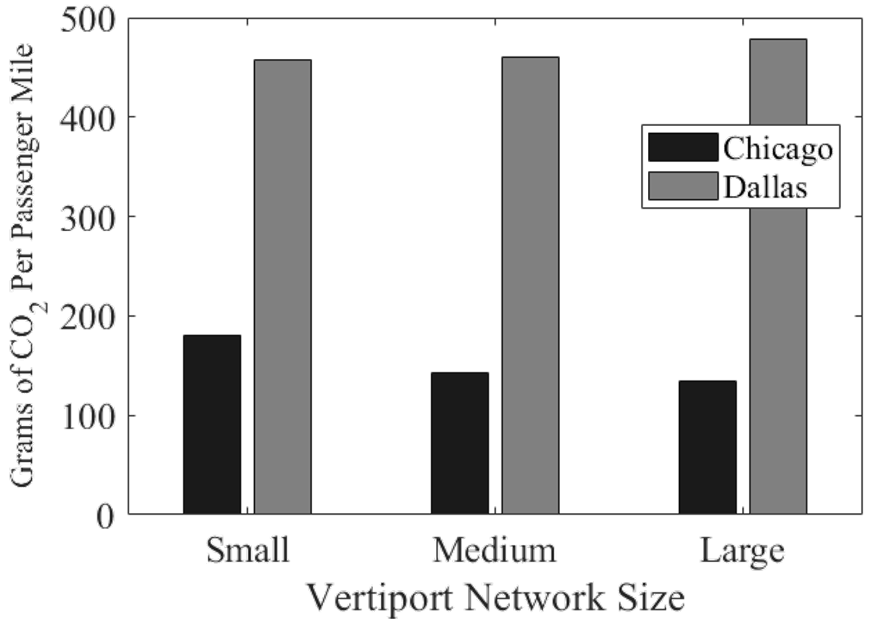
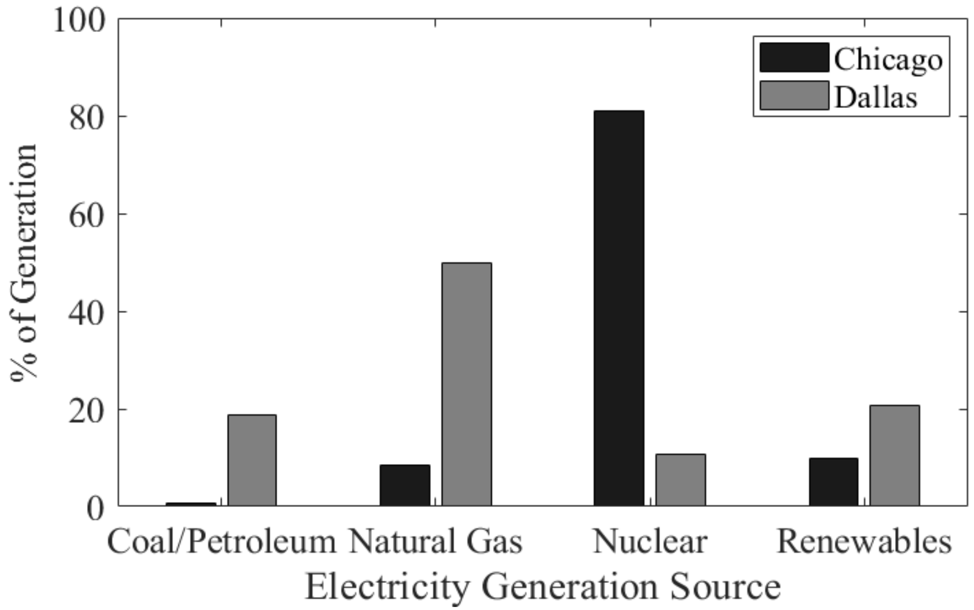
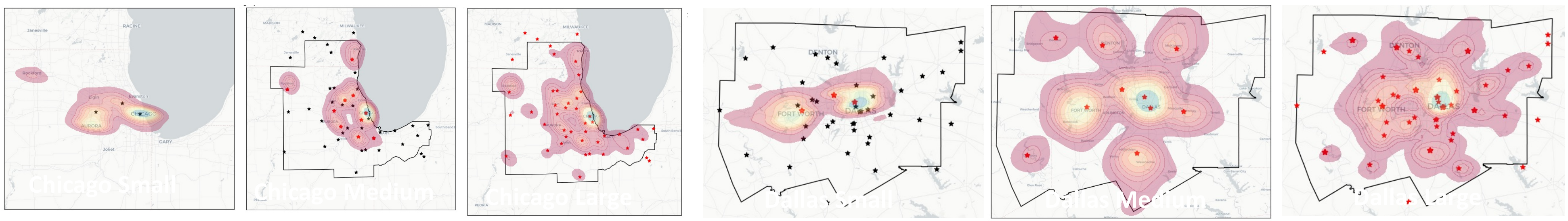
Estimates of CO2 Emissions in Dallas and Chicago

- Electricity grid makeup drives emissions from UAM operations with eVTOL + Gasoline Cars without autonomy







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Overview of Current Study Effort (Commenced Oct. 2021)

Further exploration of operations limits for Advanced Air Mobility (AAM) missions

- Identify further factors that may limit the number of AAM (e.g., Emergency medical, sUAS package delivery, etc.) operations and potential interdependencies with already identified UAM limits
- Perform case studies on additional Metro areas considering existing and potential future operational limits
- Compare and contrast results across the various Metro areas/case studies
- Recommend technology research most promising for paths to achieving scaled AAM operations

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Model-based System Engineering Approach for Realizing UAM Operations in UML-5

Hsun Chao , Edward TY Fung, Sonali Sinha Roy, Prof. DeLaurentis
Center for Integrated Systems in Aerospace, Purdue University

NASA University Leadership Initiative (ULI) S2A2 Grant led by NCA&T

Motivation

Secure and Safe Assured Autonomy (S^{2}A^2)

NASA University Leadership Initiative

- Manage UAM traffic in a dynamic airspace environment
- Operate securely and safely in high-density operation environment
- UML-5 System of Systems architecture
  - Define UAM mission requirements for ensuring safe, secured, and robust UAM operations
  - Build an abstract model to analyze and quantify UAM System performances with various technologies and concept of operations

NASA-FAA Urban Air Mobility Maturity Level (UML)[1]	
UML-1	Late-Stage Certification Testing and Operational Demonstrations in Limited Environments
UML-2	Low Density and Complexity Commercial Operations with Assistive Automation
UML-3	Low Density, Medium Complexity Operations with Comprehensive Safety Assurance Automation
UML-4	Medium Density and Complexity Operations with Collaborative and Responsible Automated Systems
UML-5	High Density and Complexity Operations with **Highly-Integrated Automated** Networks
UML-6	Ubiquitous UAM Operations with System-Wide Automated Optimization

[1] Hill, B. P., DeCarme, D., Metcalfe, M., Griffin, C., Wiggins, S., Metts, C., Bastedo, B., Patterson, M. D., and Mendonca, N. L., "UAM Vision Concept of Operations (ConOps) UAM Maturity Level (UML) 4," 2020. [Online]

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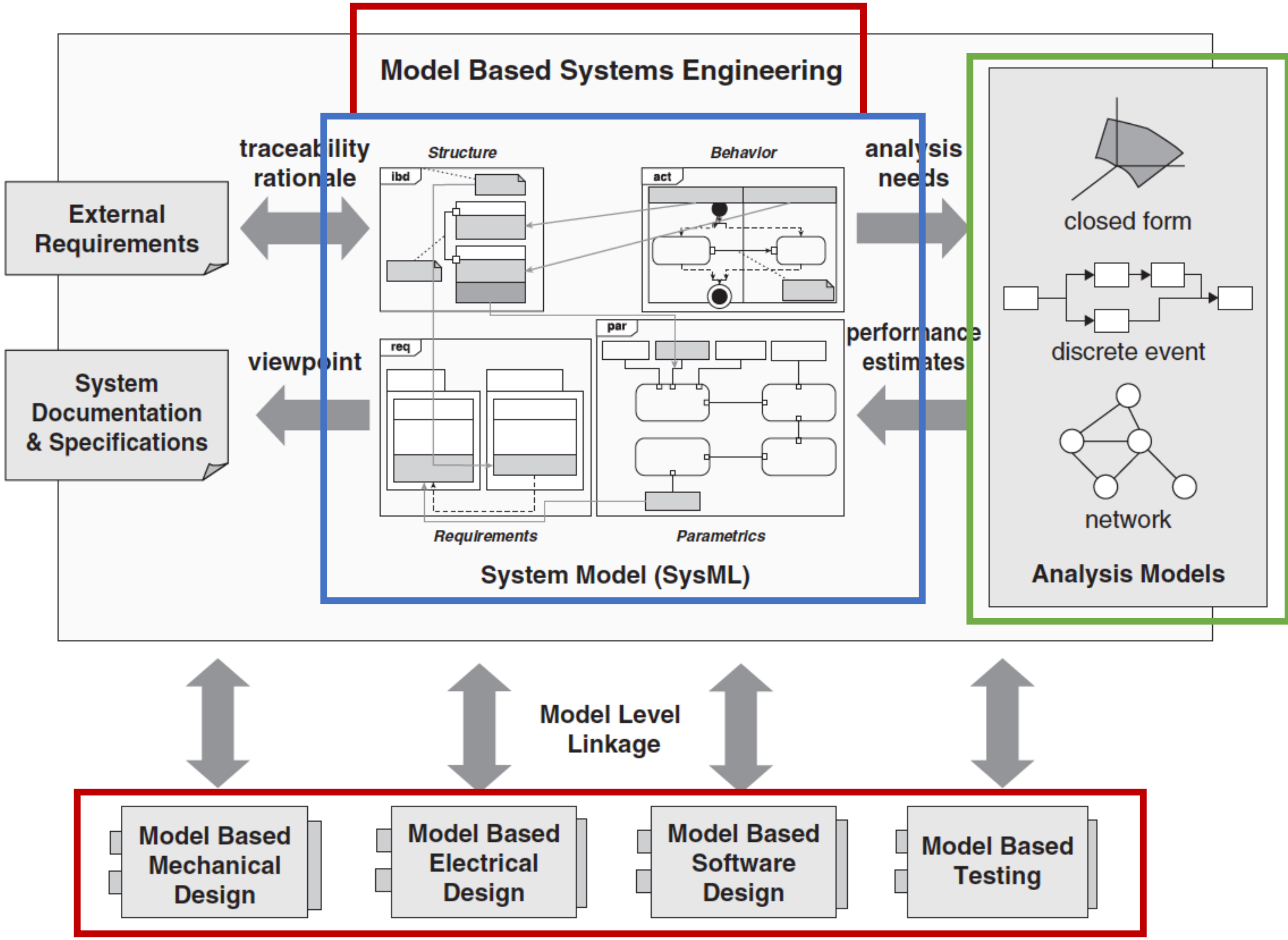
Research Methodology – Systems Engineering Models

- **Systems Engineering** models provide consistent context and input for more detailed **design and verification activities in other domains**, which can also be model-based

- In all disciplines, including Systems Engineering, there exist both **descriptive and analytical models**



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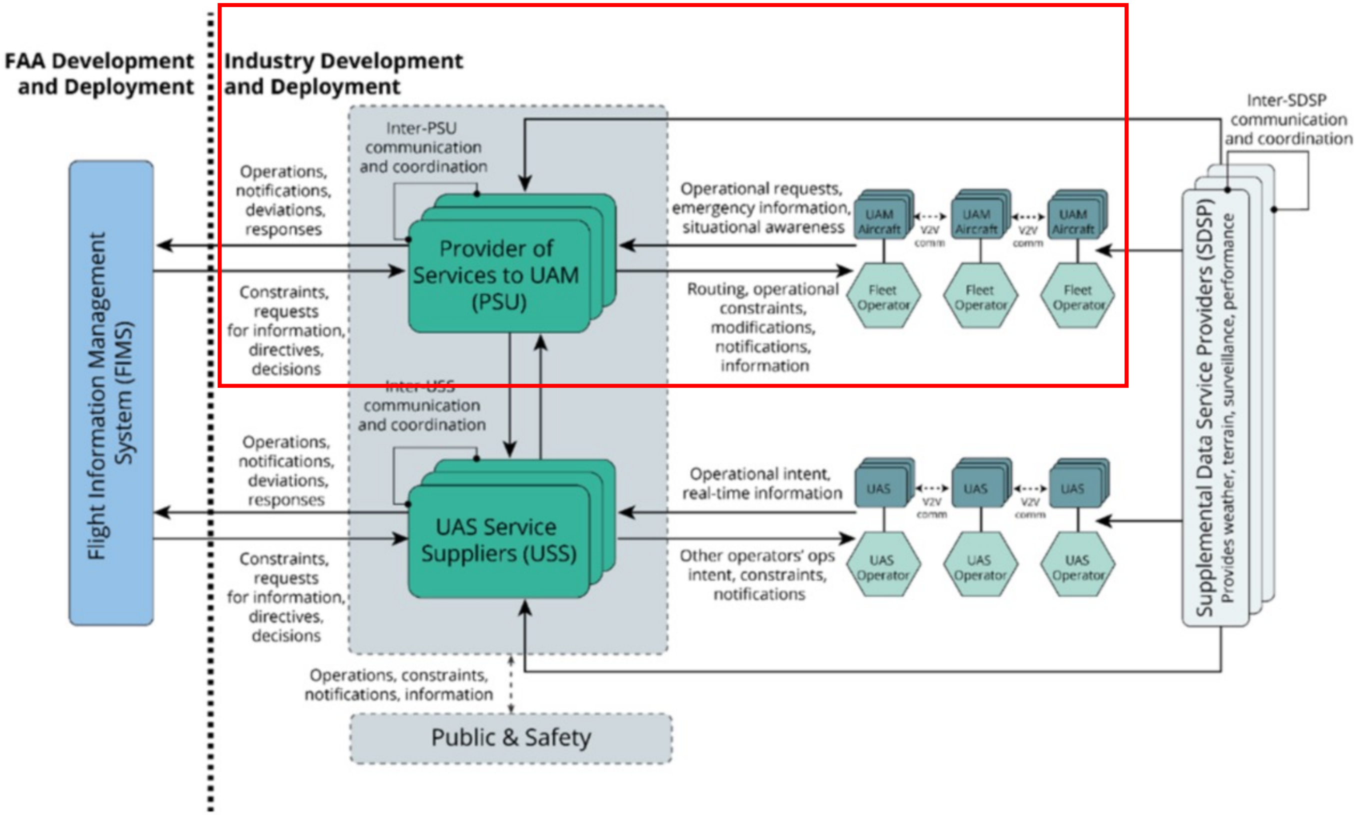
UML-5 System of Systems Architecture

System of Systems Components

- **Onboard Controller System (OC) [aircraft]**
  - Aircraft flight control, sensing, communication and navigation systems
- **Fleet Operator (FO)**
  - Responsible for UAM operation executions and regulatory compliance
  - Shares flight telemetry for safety and situational awareness, and strategic deconfliction
- **Provider of Services for UAM (PSU)**
  - Supports fleet operators to meet UAM operational requirements
  - Maintains the airspace's safety and efficiency
  - Responsible for distributing relevant data and analyzing and verifying flight intent
  - Communication with other PSU via the PSU network



UAM Communications Networks
Photo credit: NASA[1]

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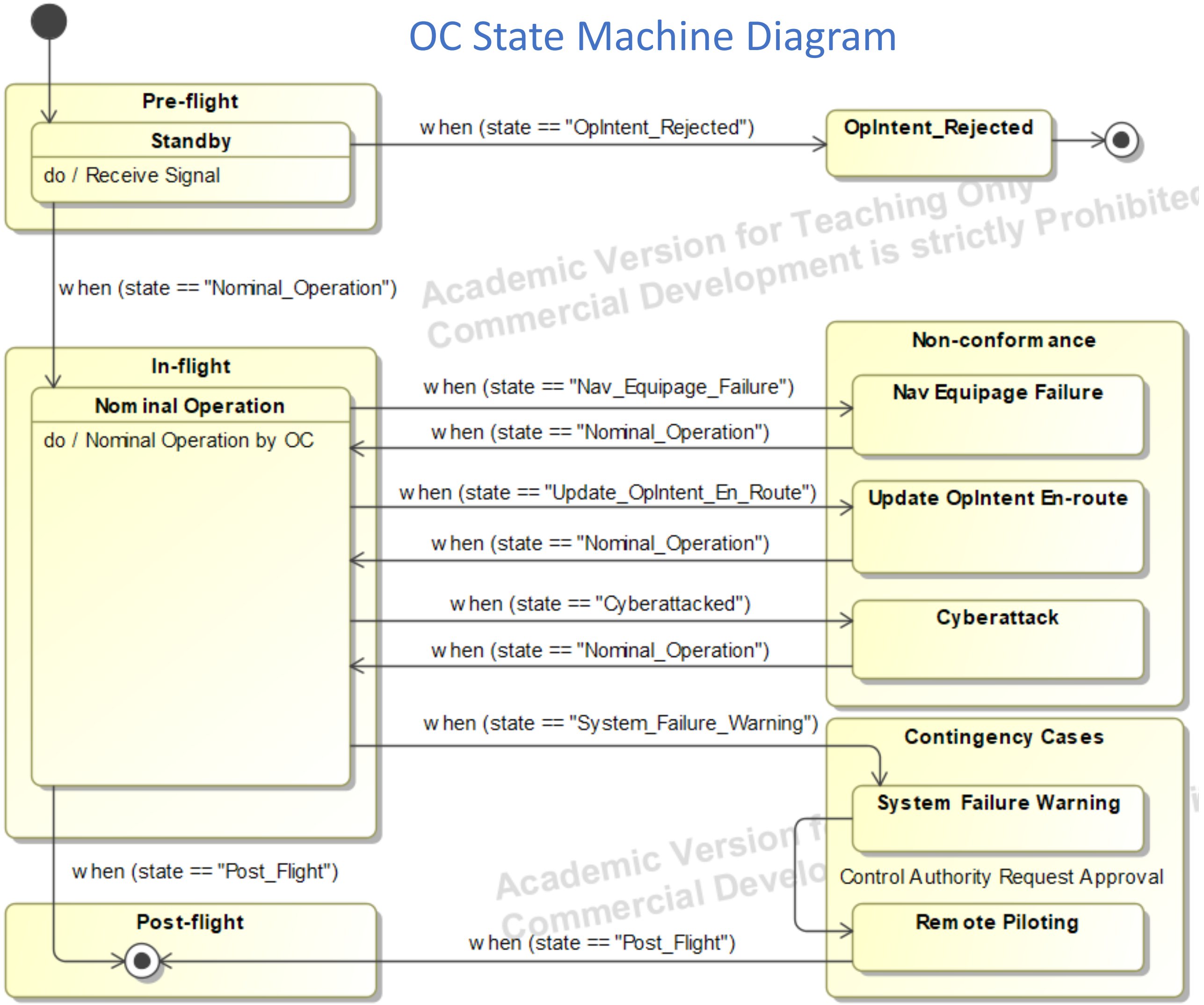
UML-5 Operational Model

Onboard Controller (OC)

1. OC remains standby
2. OC receives Op Intent from FO
3. Once Op Intent is accepted, Nominal operation is initiated
4. OC sensing and navigational systems provide state vectors update to FO
5. Once aircraft landed nominally, OC notifies FO for mission completion
6. FO acknowledges mission completion
7. End of flight

OC State Machine Diagram



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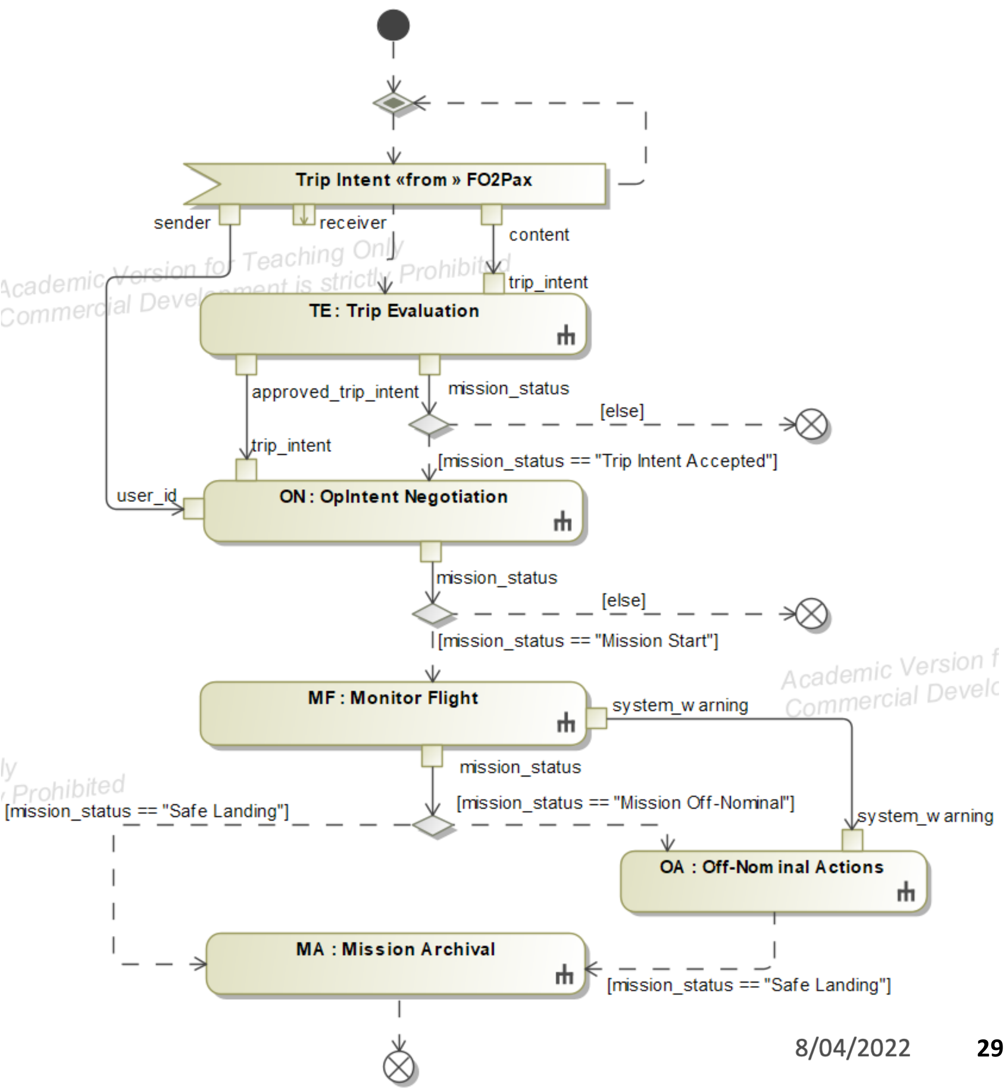
UML-5 Operational Model

Fleet Operator (FO)

1. FO standby for trip evaluation
2. FO receives Trip Intent
3. FO processes Trip Intent into Op Intent
4. FO sends Op Intent to PSU
5. PSU approves Op Intent
6. FO sends approved Op Intent to OC
7. FO monitors OC flight status and keep PSU updated
8. FO receives mission completion signal from OC
9. FO acknowledges OC completion

FO Behavior Diagram



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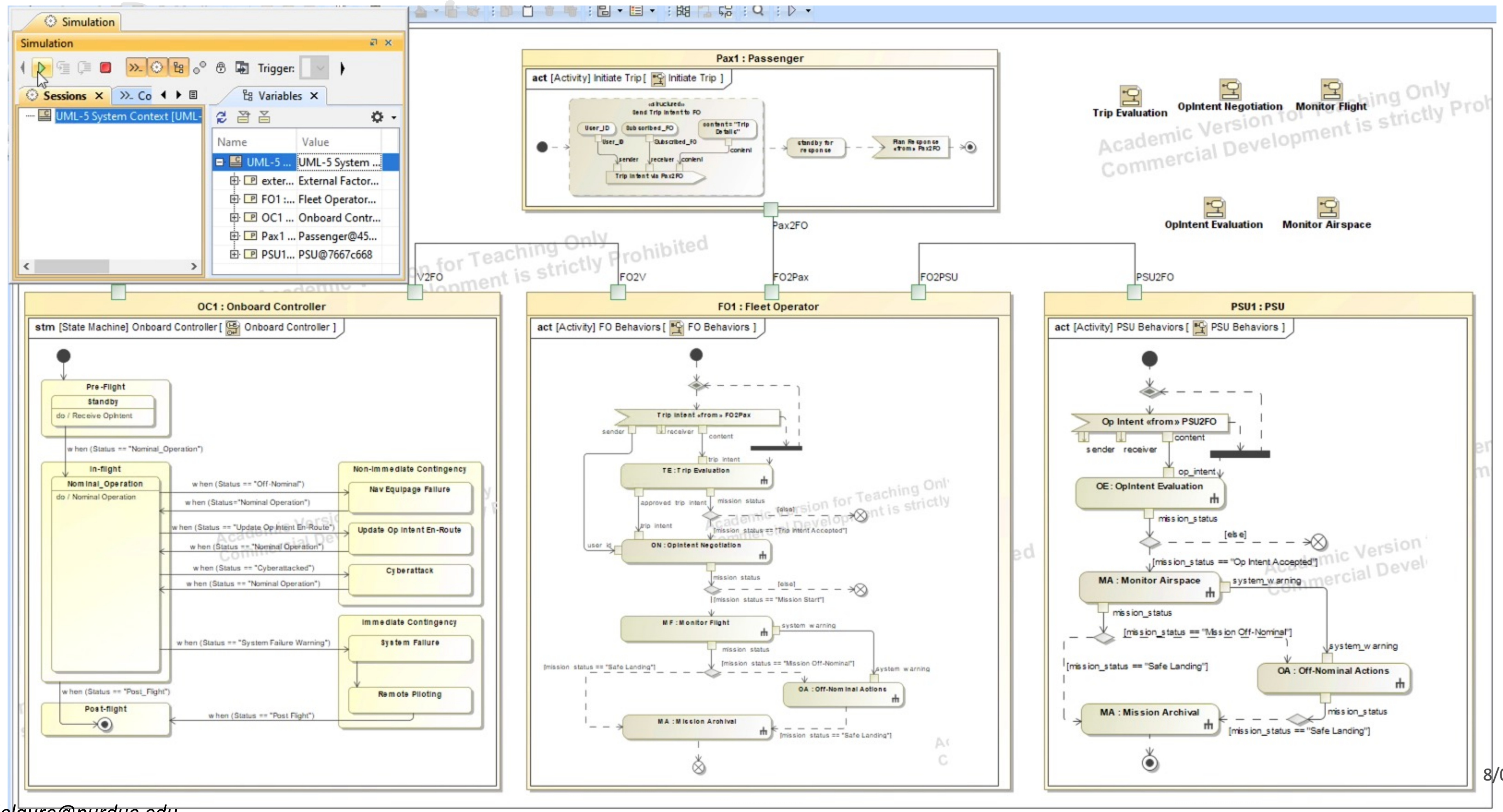
UML-5 Operational Model – Simulation



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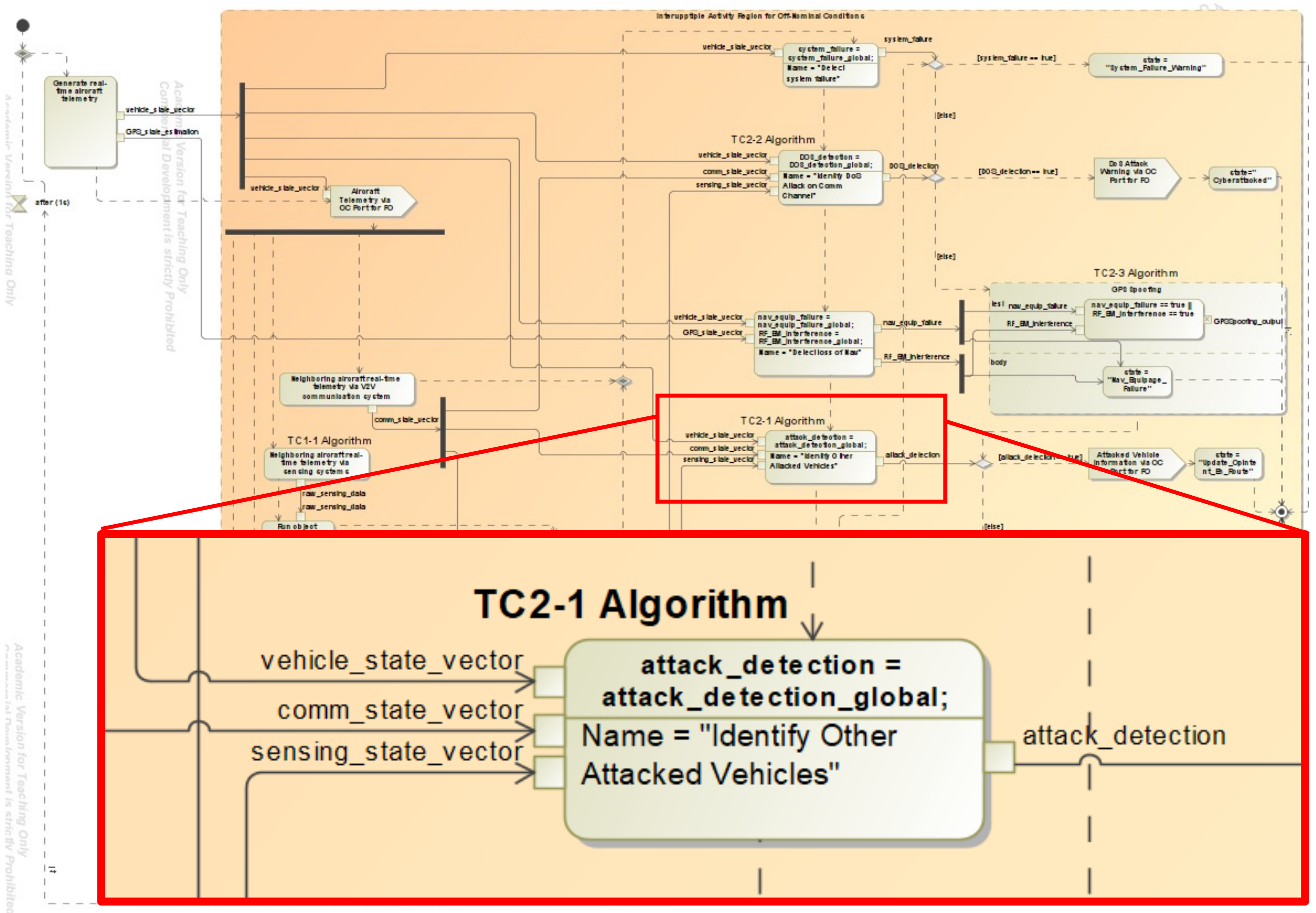
UML-5 Operational Model – Interface Identification

Demo of Integrated TC Algorithm

Onboard Controller

- TC2-1 Mathematical Modeling of UAM and Cyberattack
- TC2-2 Cyberattack Analysis, Detection, and Risk Mitigation
- TC2-3 AI-driven Cyberattack Monitoring

Onboard Controller In-Flight Nominal Operation



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What are your hard(er) SoSE problems…or better solutions??

1. ?
2. ?
3. ?