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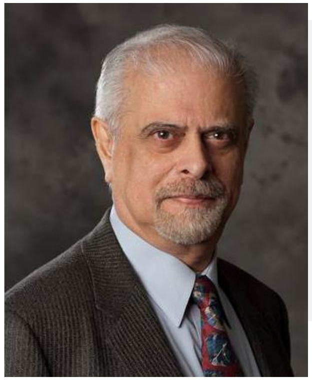

"What's Really Distributed in Distributed Autonomy?"

August 7, 2019 | 1:00 PM ET

Prof. Azad Madni, Ph.D., SERC Principal Investigator

University of Southern California

azad.madni@usc.edu

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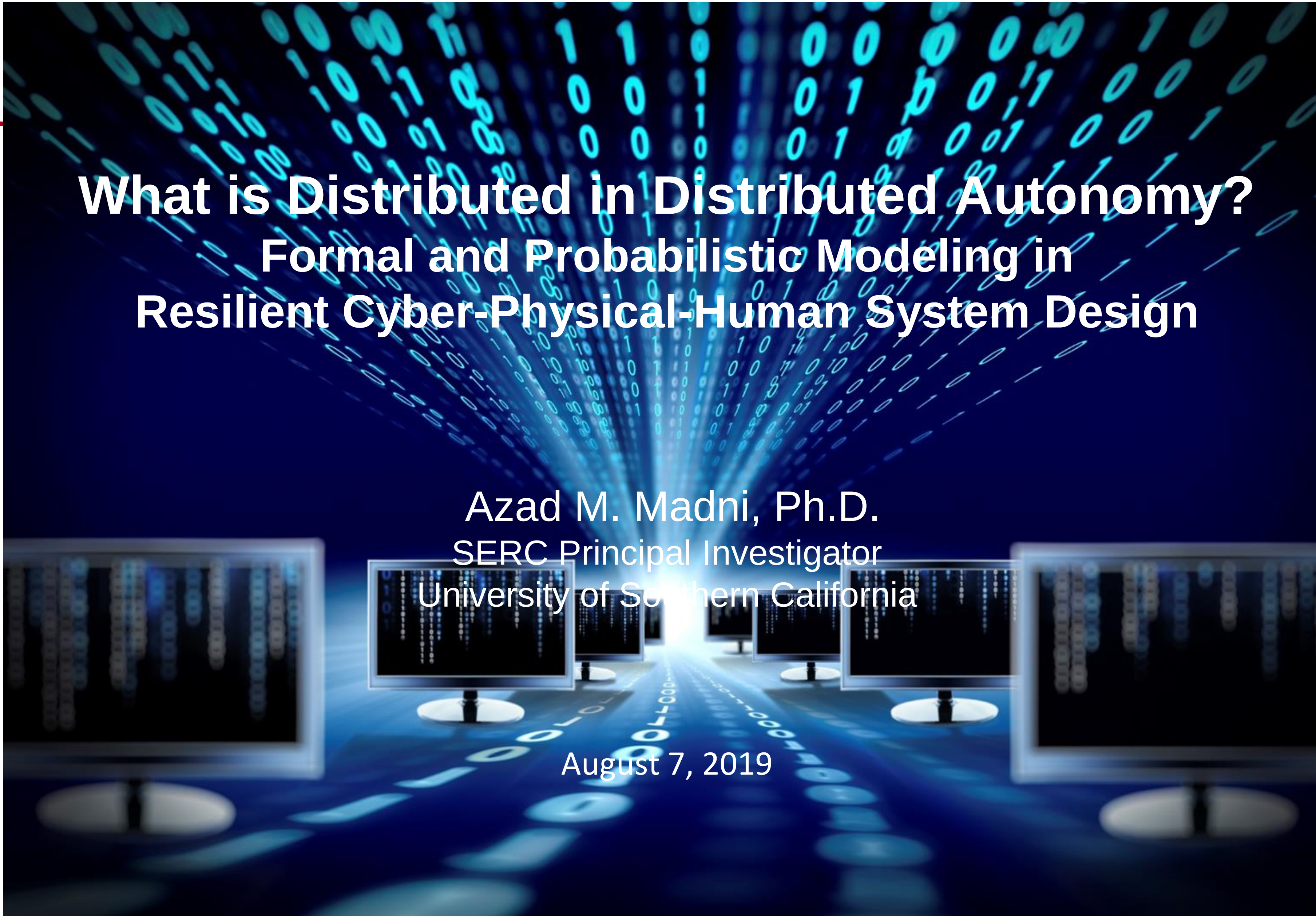


What is Distributed in Distributed Autonomy?

Formal and Probabilistic Modeling in Resilient Cyber-Physical-Human System Design

Azad M. Madni, Ph.D.

SERC Principal Investigator

University of Southern California

August 7, 2019

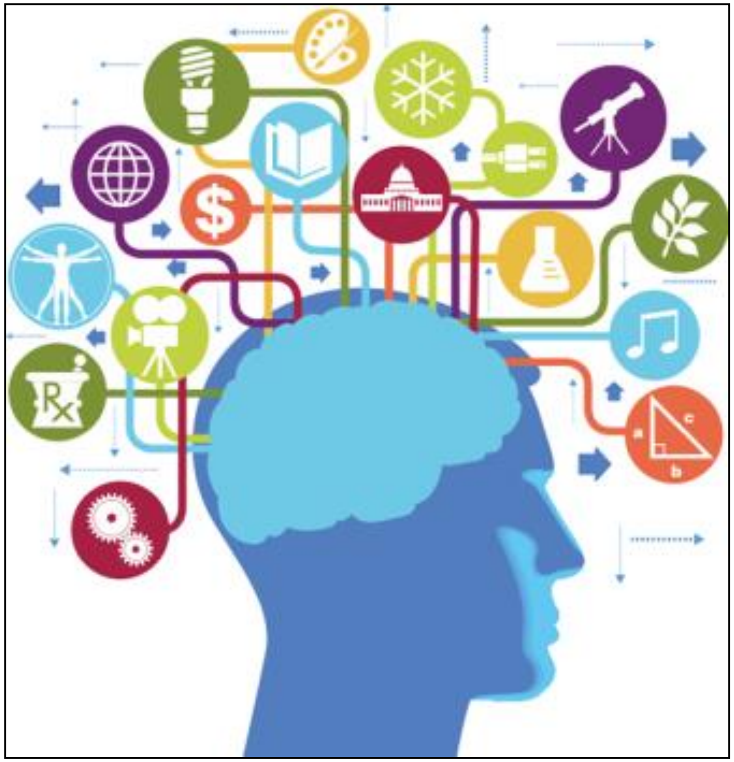
USC Viterbi

School of Engineering

Systems Architecting and Engineering

Outline

- 21st Century DoD Systems
- Distributed Autonomy Research
  - Engineered Resilience
  - Cyber-Physical-Human Systems
- Multi-Model-based Approach
- Illustrative Example
- Prototype System
- Findings To-Date
- Takeaways



21st Century DoD Systems

- High complexity (hyper-connectivity, interdependencies)
- Need to operate safely for extended periods in dynamic, uncertain environments subject to disruptions
- Long-lived (> 20 years)
- Likely to be extended / adapted over lifetime
- Stringent physical and cyber security requirements
- Adaptive and distributed autonomy

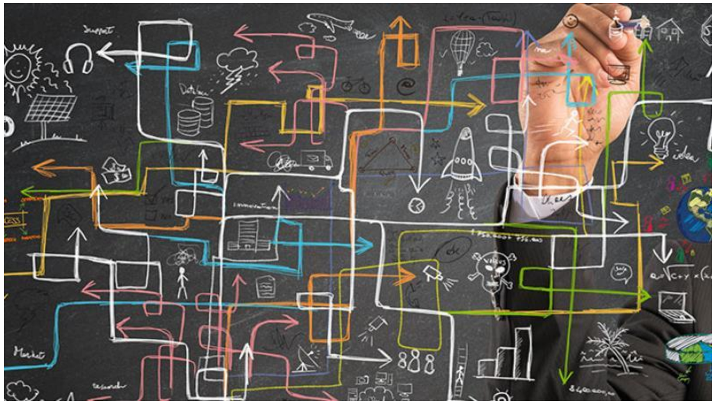
Need new modeling methods and tools

Distributed Autonomy

The extent to which a team of agents can **sense** its environment, **plan** collaboratively based on a priori and sensed knowledge about the environment, and **act** in concert upon that environment to accomplish task-specific goals assigned by an external agent (e.g., human), or created by the agent team without external intervention

Distributed Autonomy Research

- Formal and Probabilistic Modeling in Resilient System Design (sponsor: SERC)
  - **Formal** – provable correctness
  - **Probabilistic** – adapt to uncertainty
  - **Challenges** - partial observability, unexpected / unknown disruptions; noisy sensors



- Adaptive Cyber-Physical-Human Systems (sponsor: SERC)
  - **Adaptive** – respond to contingencies; learn from evidence
  - **Challenges** - incomplete initial system model; human variability; insertion of human (model) in control loop; dynamic context; changing autonomy

Engineered Resilience is A Messy Problem…Why?

- **Requirements:** can be imprecise
- **Actions:** can be unclear
- **Environment:** can be unknown or partially known
- **System states:** can be ambiguous

These characteristics are incompatible with traditional modeling methods

Cyber-Physical-Human Systems
(Madni et al., 2018)

- A class of safety-critical socio-technical systems in which interactions between *physical system* and *cyber elements* that control its operation are influenced by *human agent(s)*

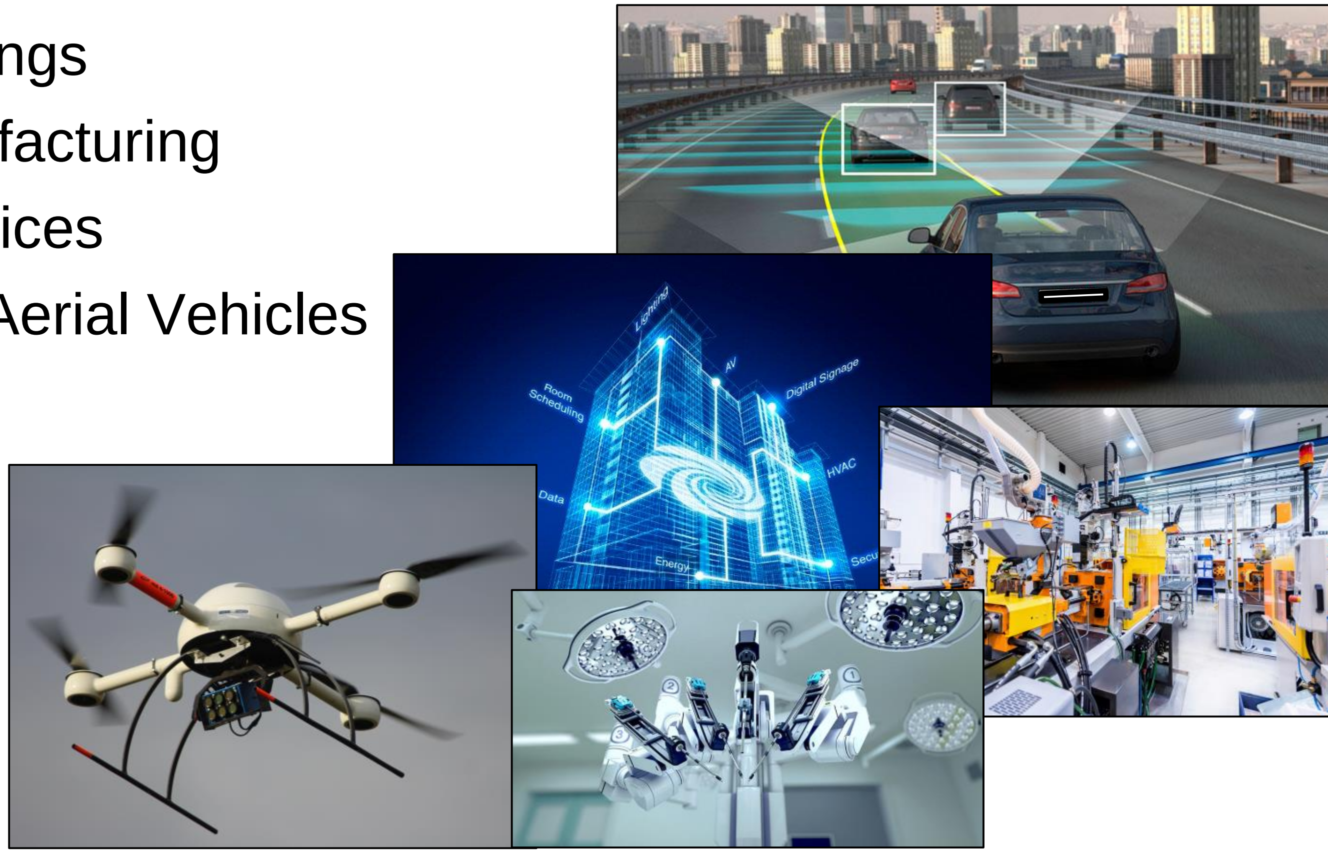
- System objectives achieved through interactions between:
  - **Physical system** (or process) to be controlled
  - **Cyber elements** (i.e., communication links and software)
  - **Human agents** who monitor and influence cyber-physical system operation

- **Distinguishing Feature:** Human (agents) intervene to:
  - redirect cyber-physical elements or supply needed information
  - …..not just to exercise manual over-ride or assume full control

Exemplar CPHS

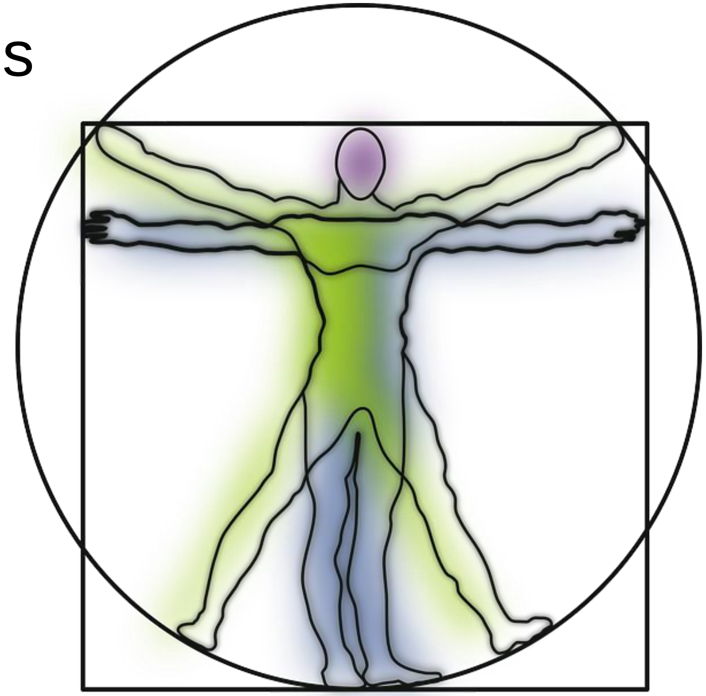
Safety-critical systems - range from a small device to SoS

- Self-Driving Vehicles
- Smart Buildings
- Smart Manufacturing
- Medical Devices
- Unmanned Aerial Vehicles



Adaptive CPHS

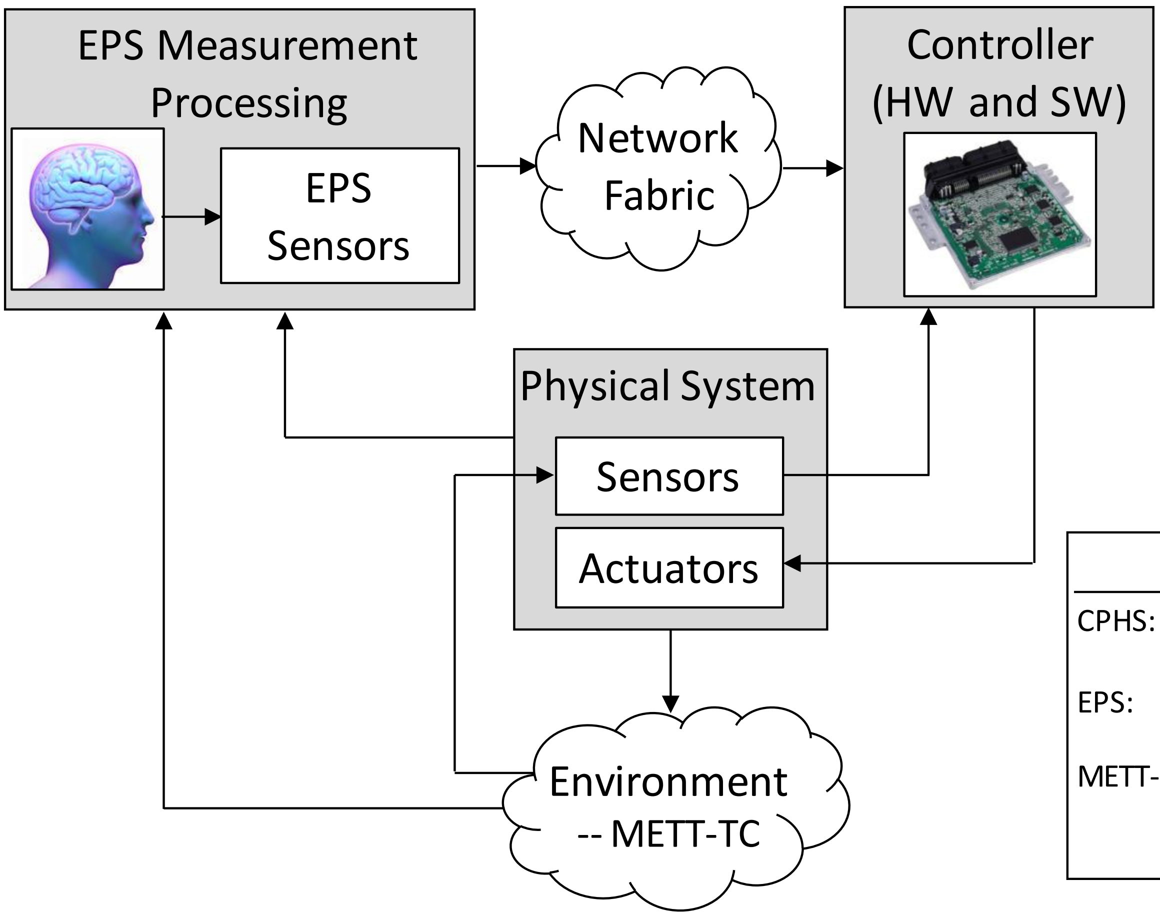
- Respond to disruptions and changes in context
- Leverage unique human capabilities
- Exploit human versatility
- Circumvent human limitations
- Exploit cyber-physical system capabilities
- Learn from experience (observations, outcomes) using ML



What Can Be Distributed in Adaptive CPHS?

- Sensing
  - distributed among fixed sensors, humans, mobile robots
- Planning
  - distributed between humans and cognitive agents
- Decision Making
  - distributed between humans and cognitive agents
- Control
  - distributed between human and actuation agents
- Learning
  - distributed between machine learning agents

Adaptive CPHS System Concept



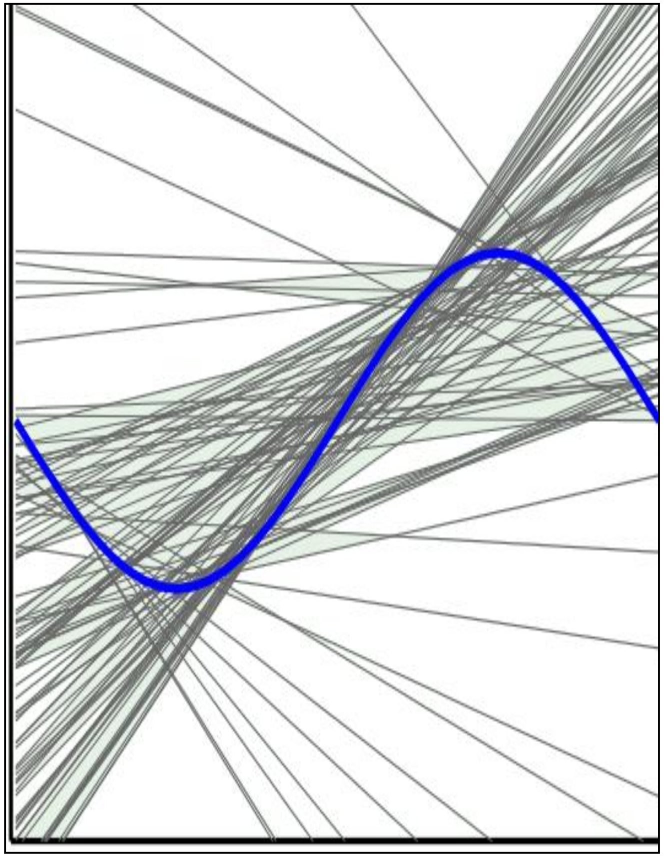
LEGEND

CPHS:	Cyber Physical Human Systems
EPS:	Electro-Physiological Sensors
METT-TC:	Mission-Enemy-Terrain (and weather)-Troops-Time-remaining-Civilian

Deficiencies in Existing Modeling Methods and Tools

- **Methods:** Ill-suited for modeling tightly-coupled, sociotechnical learning systems
  - lack semantics of time
  - lack ability to improve with use
  - lack semantics for adequately representing human behavior
  - lack flexibility to represent human behavior with variable fidelity
  - lack learning ability (offline, in-situ)
- **Tools:** reflect methodological deficiencies
  - address cyber, physical, and human elements in isolation
  - focus primarily on subsystems, not their interactions, dependencies and synchronization constraints
  - “build-time” approaches -- no provision for “run-time” learning
  - impoverished human behavior representation

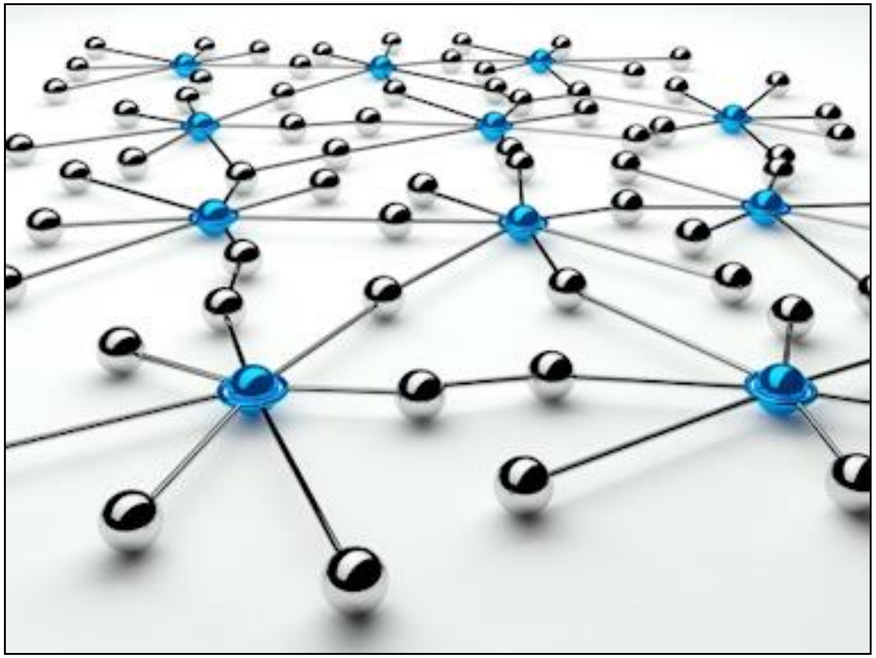
Systems Modeling



- Many different approaches – choice depends on characteristics of the system and the environment
- Different aspects of system behavior represented by different models
  - need to harmonize them
- Most serious problem results from the gap between requirements and models that need to reflect requirements
  - contributes to poor flow down of system requirements to software requirements

System Modeling Requirements

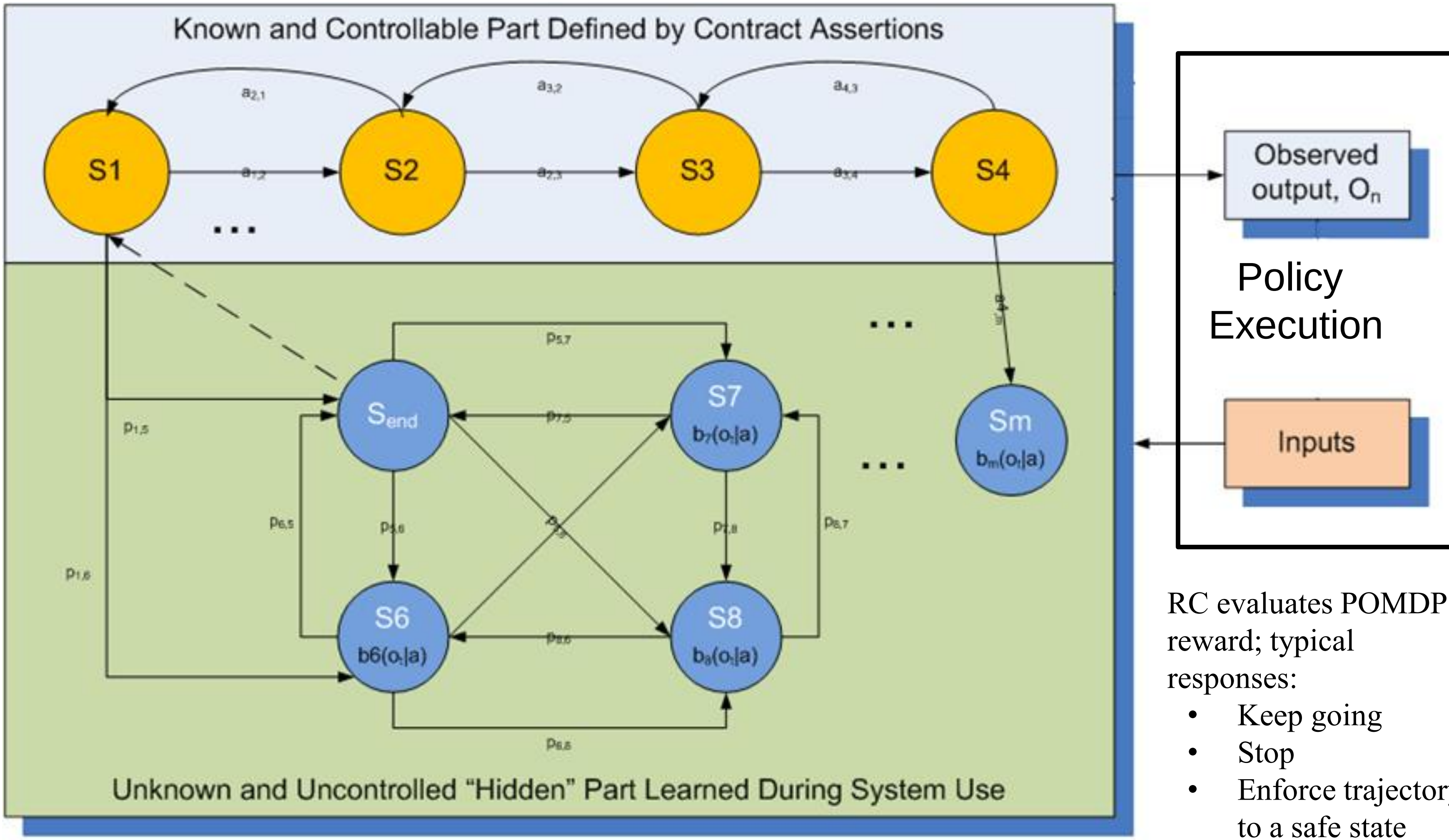
- Verifiability (provable correctness)
- Flexibility (adapt to changing conditions)
- Bidirectional reasoning support (resilient response)
- Scalability and extensibility (no. of agents, interconnections)
- Utility with partial information (not “data hungry”)
- Learn from new observations (evidence-based learning)



Multi-Model Based Approach

- Modeling Constructs
  - formal modeling
  - probabilistic modeling
  - optimization (e.g., fitness functions)
  - machine learning
- Model Uses
  - planning and decision making
  - simulated/physical system control
  - human behavior modeling
  - incremental learning of system and environment states
- Model Visualization
  - context-aware dashboard with visual cueing
  - multi-perspective, multi-level

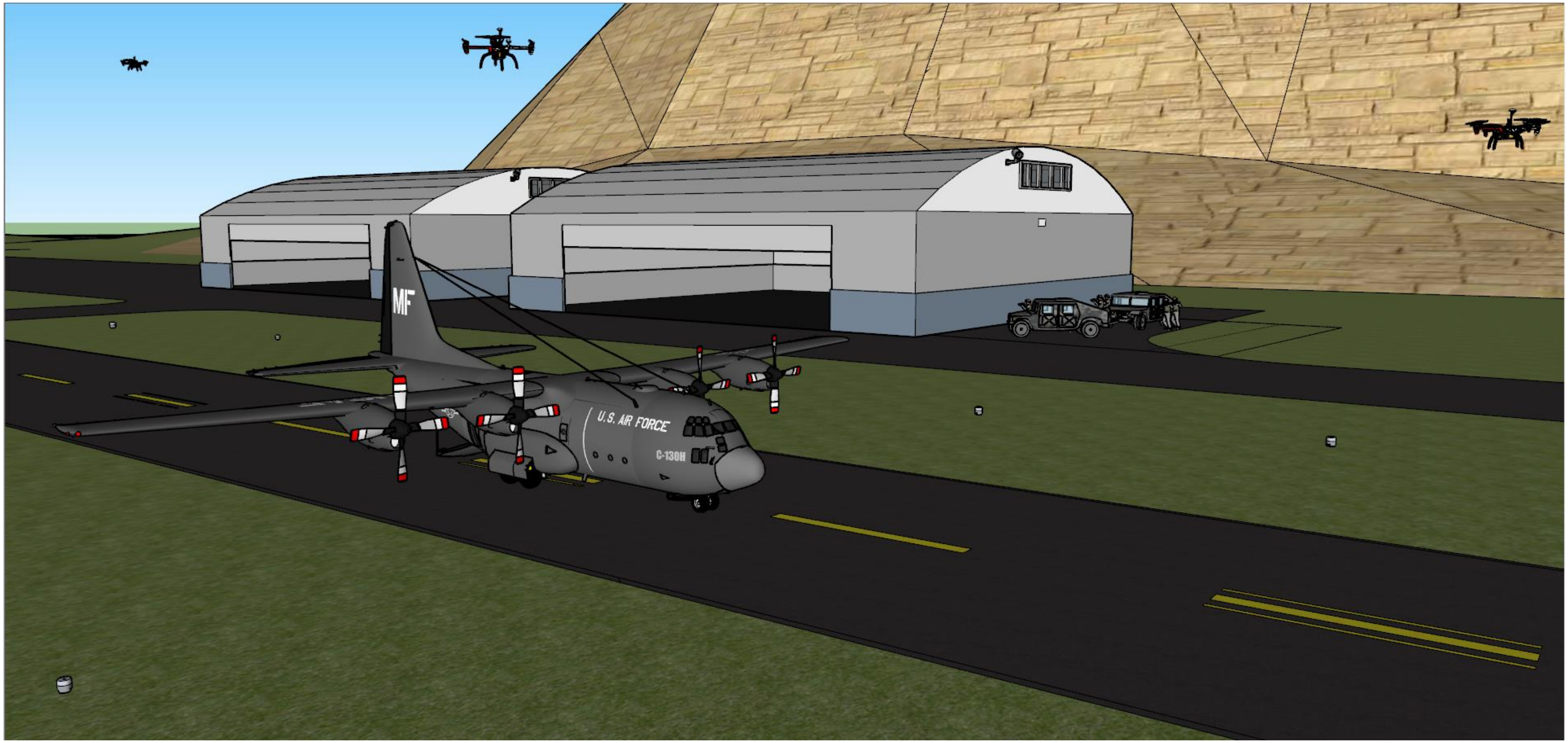
Resilience Contract (RC)



RC evaluates POMDP reward; typical responses:

- Keep going
- Stop
- Enforce trajectory to a safe state
- Notify support team

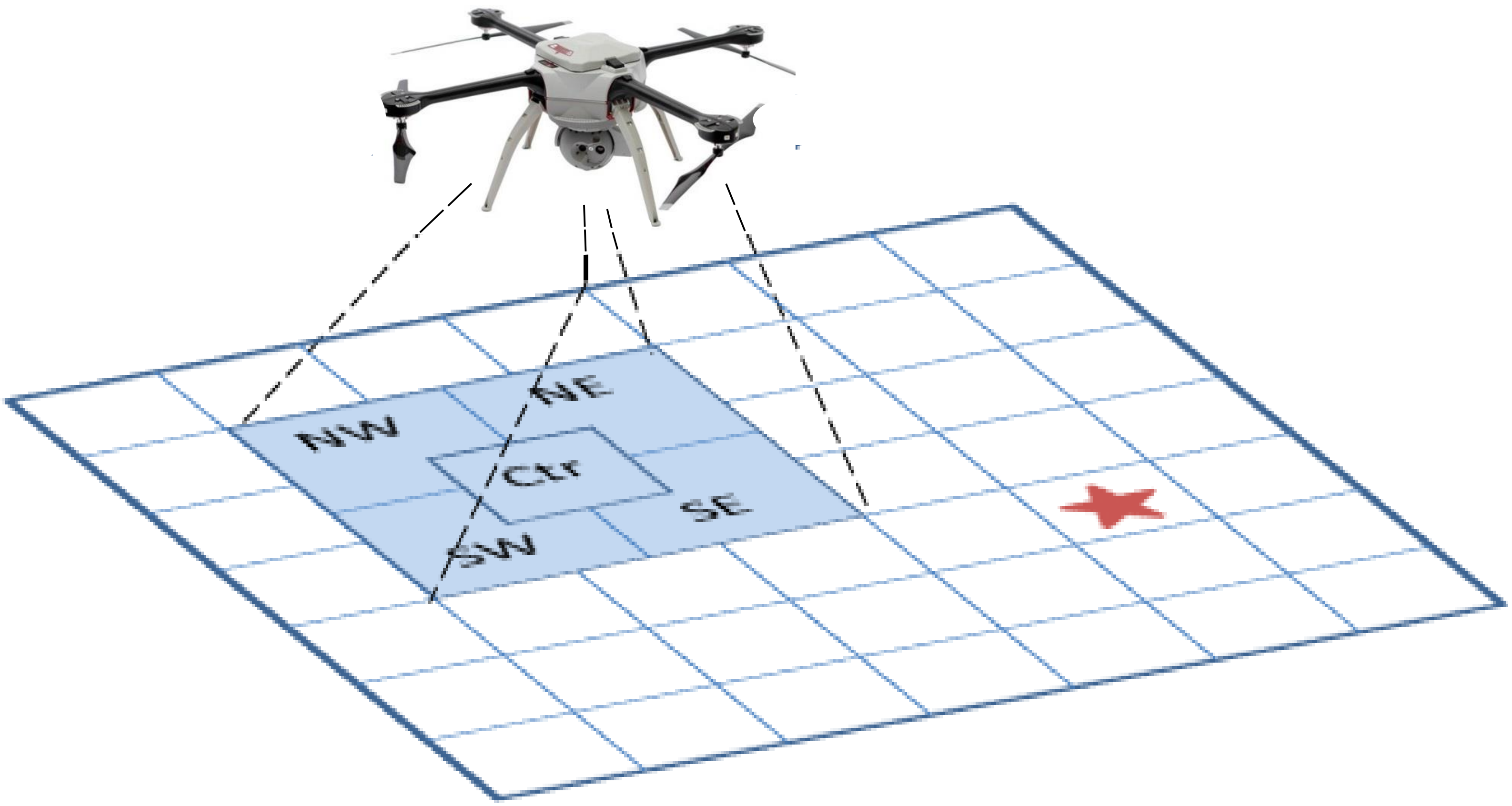
Illustrative Example:
Perimeter Security of C-130 Aircraft



Prototype Scope:
Perimeter Security of C-130 Aircraft

- Multiple QCs with downward-facing video cameras
- Building-mounted video cameras and LWIRs
- QCs hold position and altitude that maximizes a collective fitness function (FF)
  - FF reflects perimeter coverage
  - QCs can change position and altitude to maximize FF
- **Contingencies:** low battery causing QC to land; loss of QC
- **Resilience responses:** reposition remaining QCs to restore coverage; launch backup QC if repositioning does not work

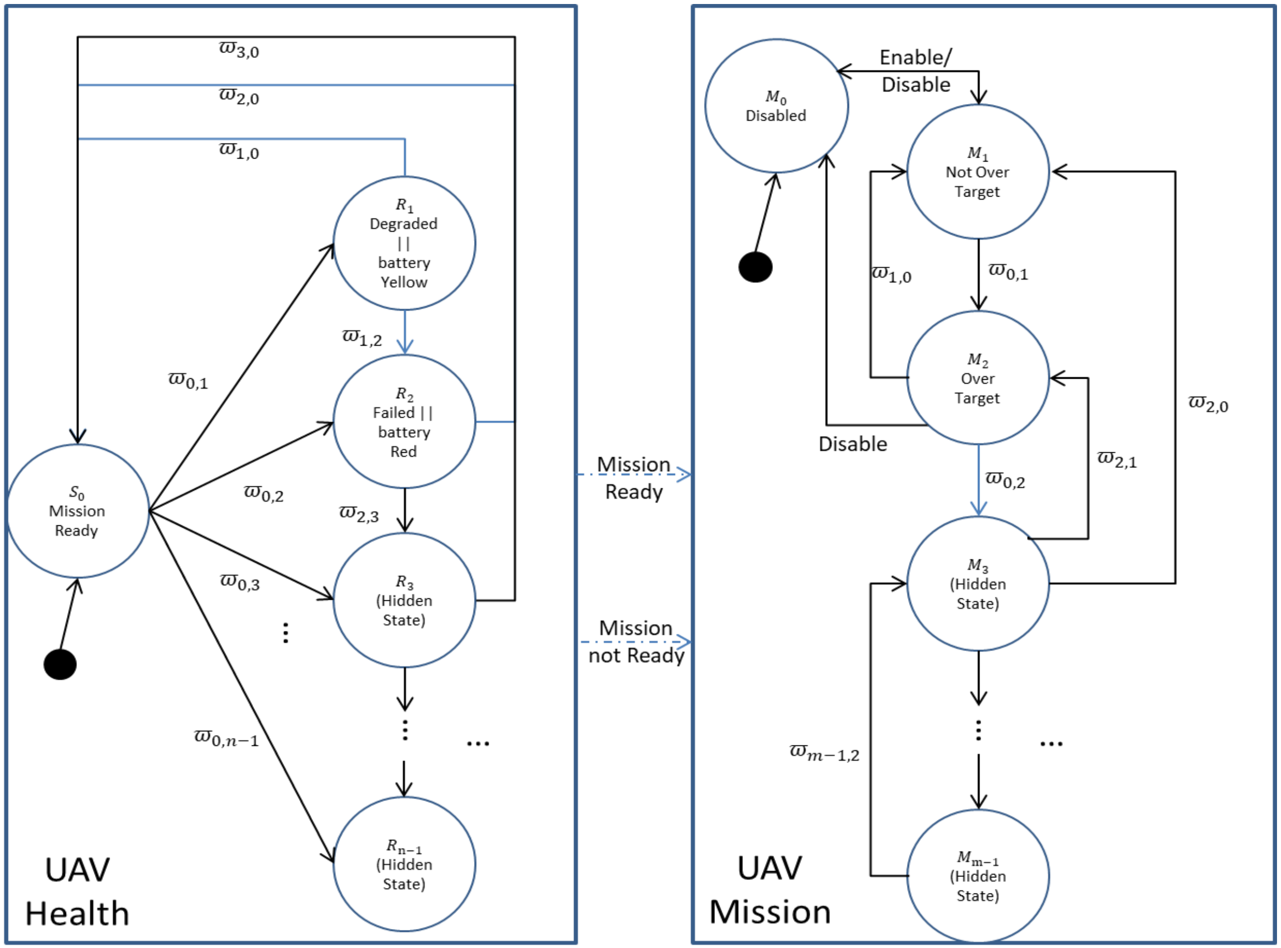
QC position relative to a reconnaissance target (red star) and FOV (blue)



Exemplar Contracts

1. ¬overTarget && healthy && batteryGreen → move_to_target
2. ¬batteryRed && degraded || batteryYellow → move_to_base
3. batteryRed || failed → land
4. unknownHealth || unknownBattery → move_to_base
5. overTarget && CTR && healthy → takeImages & hover
6. overTarget && NW && healthy → takeImages & move SE
7. overTarget && NE && healthy → takeImages & move SW
8. overTarget && SW && healthy → takeImages & move NE
9. overTarget && SE && healthy → takeImages & move NW

Simplified POMDPs: Health and Mission Models



Fitness Function to Maximize Coverage

- Discretize perimeter area into tiles
  - goal: one or two cameras observing each tile (more than two is redundant and should not be rewarded)
  - closer coverage (higher resolution of imaging) is better
- Simple approach: for each tile and each camera
  - if tile is visible from camera, sum up 1/(distance to camera)
  - cap each tile sum to avoid rewarding redundant coverage
- Future improvements to fitness function
  - reward views from widely separate camera locations to maximize available information e.g. stereo
  - account for different camera capabilities e.g. higher resolution on fixed building cameras

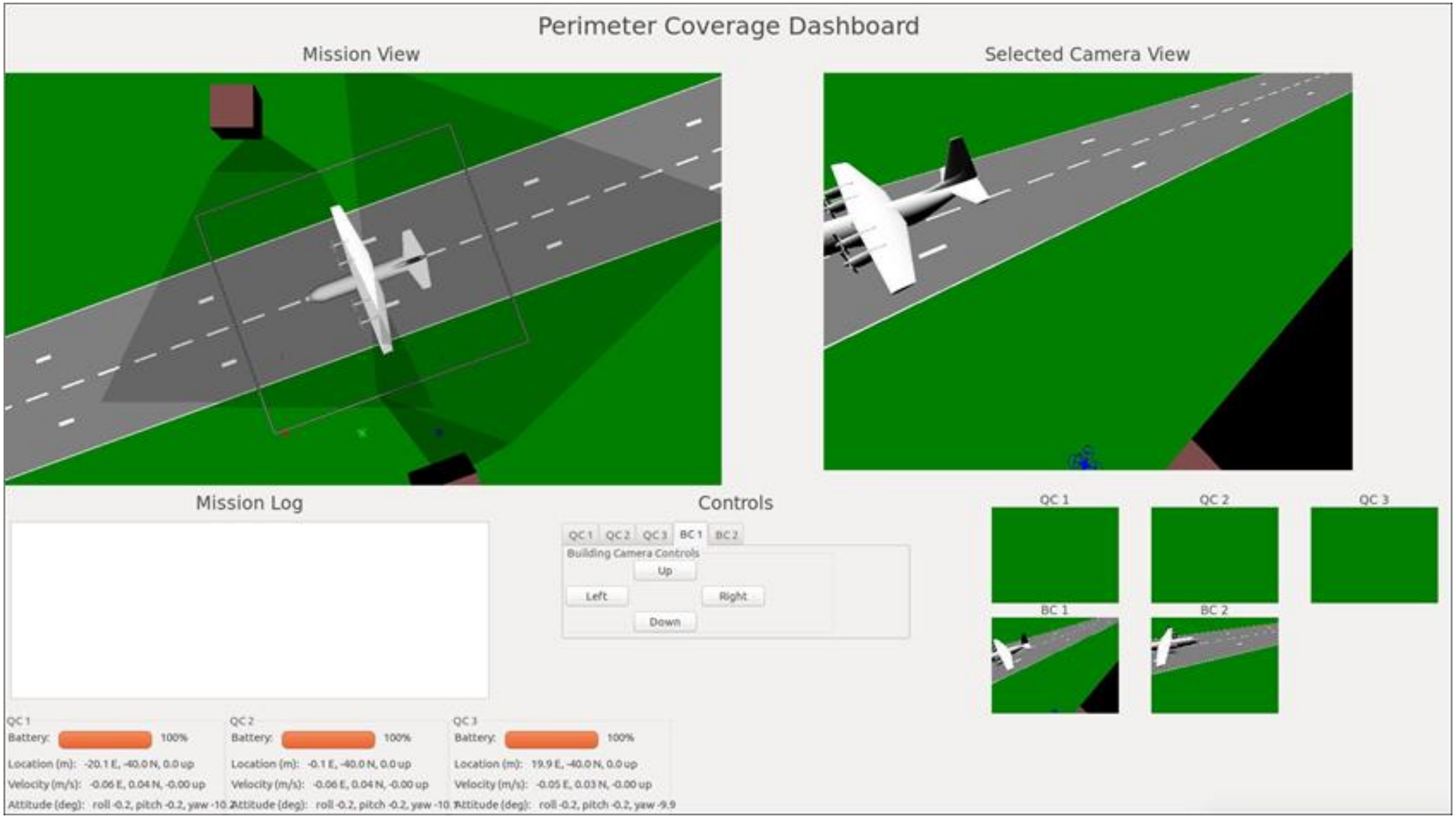
Multi-Level Coverage Algorithm

- Multi-agent control
  - multiple QCs move independently to maximize their contributions to the fitness function
  - resulting cooperative motion works to increase fitness
- Adaptation to changing circumstances
  - for example: one QC crashes or runs low on battery
  - other QCs move to adapt to the changed coverage
- Human-in-the-loop
  - if multi-agent control is insufficient to provide adequate coverage, human intervention is requested
  - at this point it is up to the human to act, e.g. launch additional QC

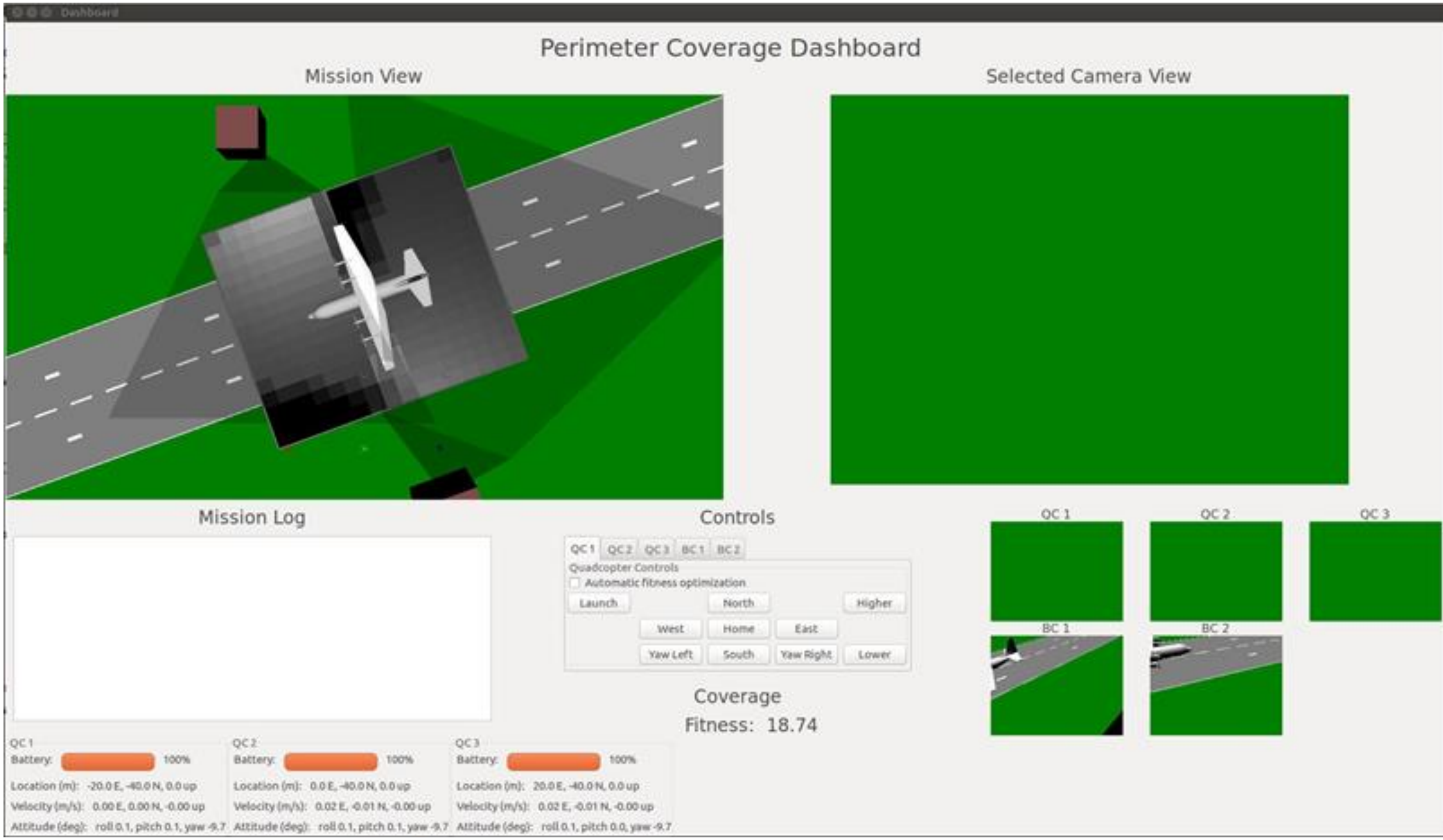
Multi-UAV Dashboard Prototype

- Purpose
  - customizable dashboard for monitoring and control of multiple simulated and physical vehicles
- Underlying technologies
  - dronekit platform with visualization facilities
  - quadcopters (hardware) and quadcopter simulation models
  - quadcopter planning and decision-making model
  - quadcopter controller
- Key capabilities
  - simulated vehicles exhibit behavior of physical vehicle
  - same commands used to control vehicle models and the physical vehicles (quadcopters)
  - can switch from simulated to physical vehicles, and vice versa

Perimeter Coverage Scenario: Simulator Dashboard

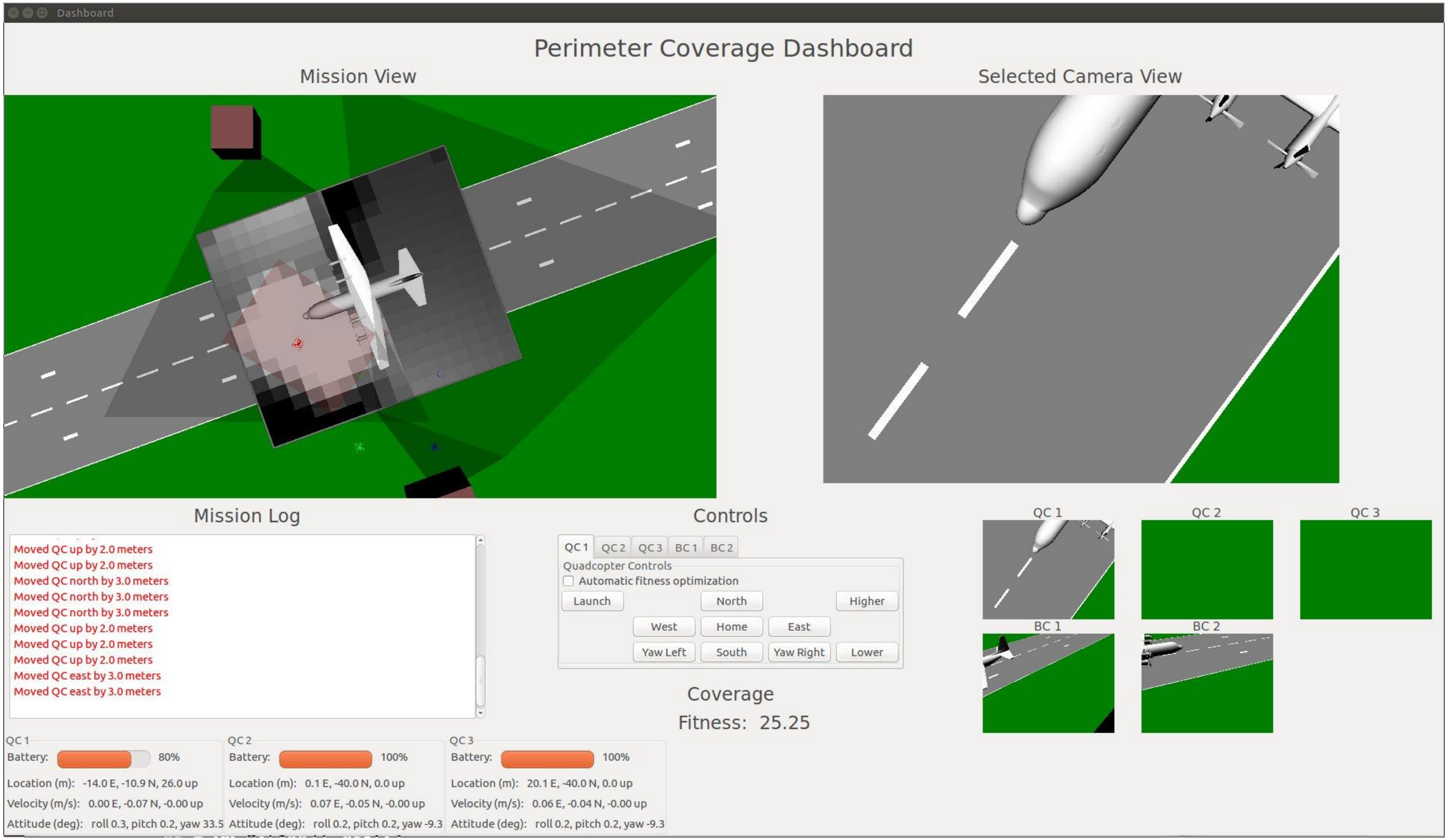


Dashboard Showing Coverage Area

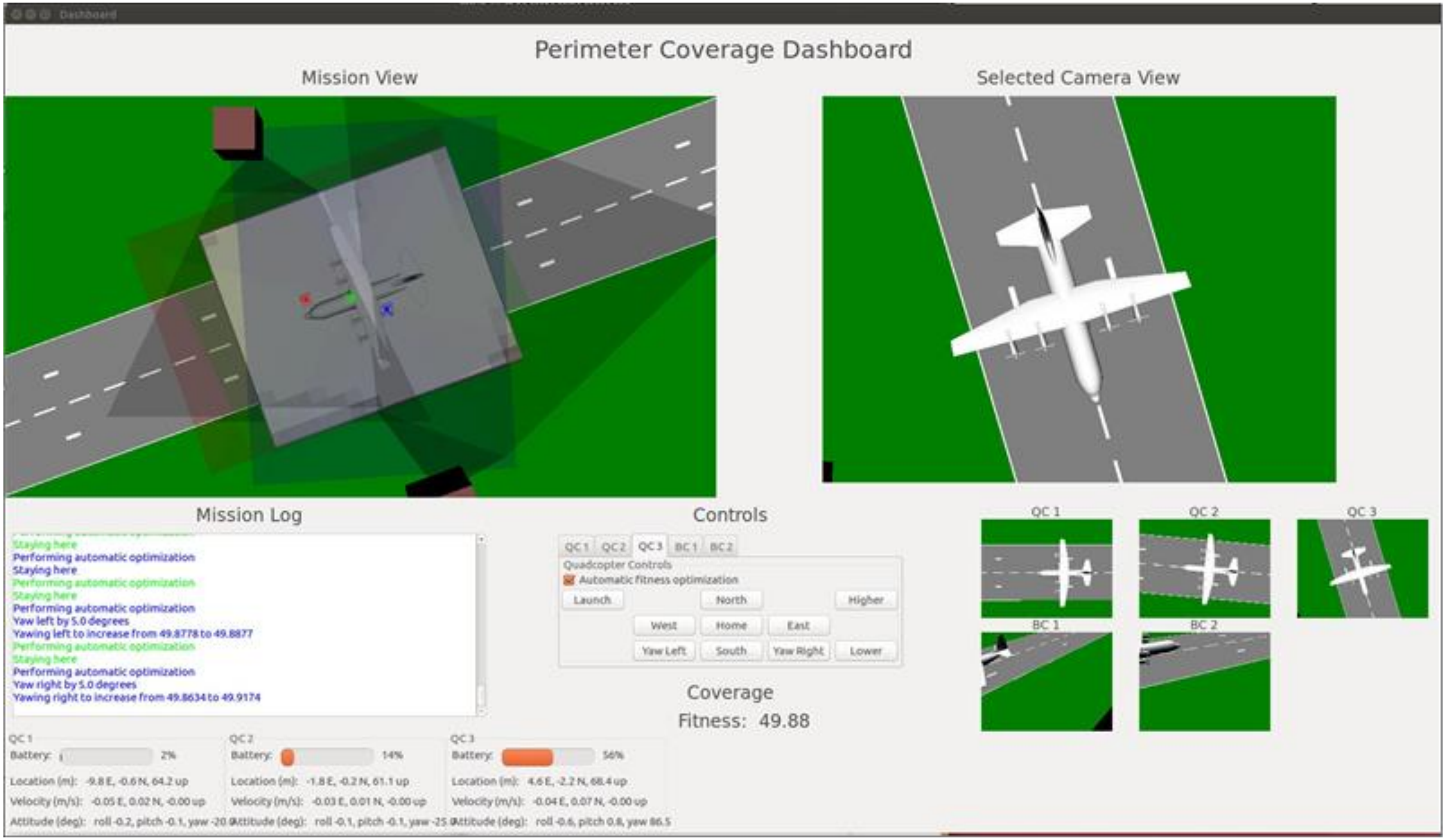


Dashboard with One QC During Optimization of Fitness Function

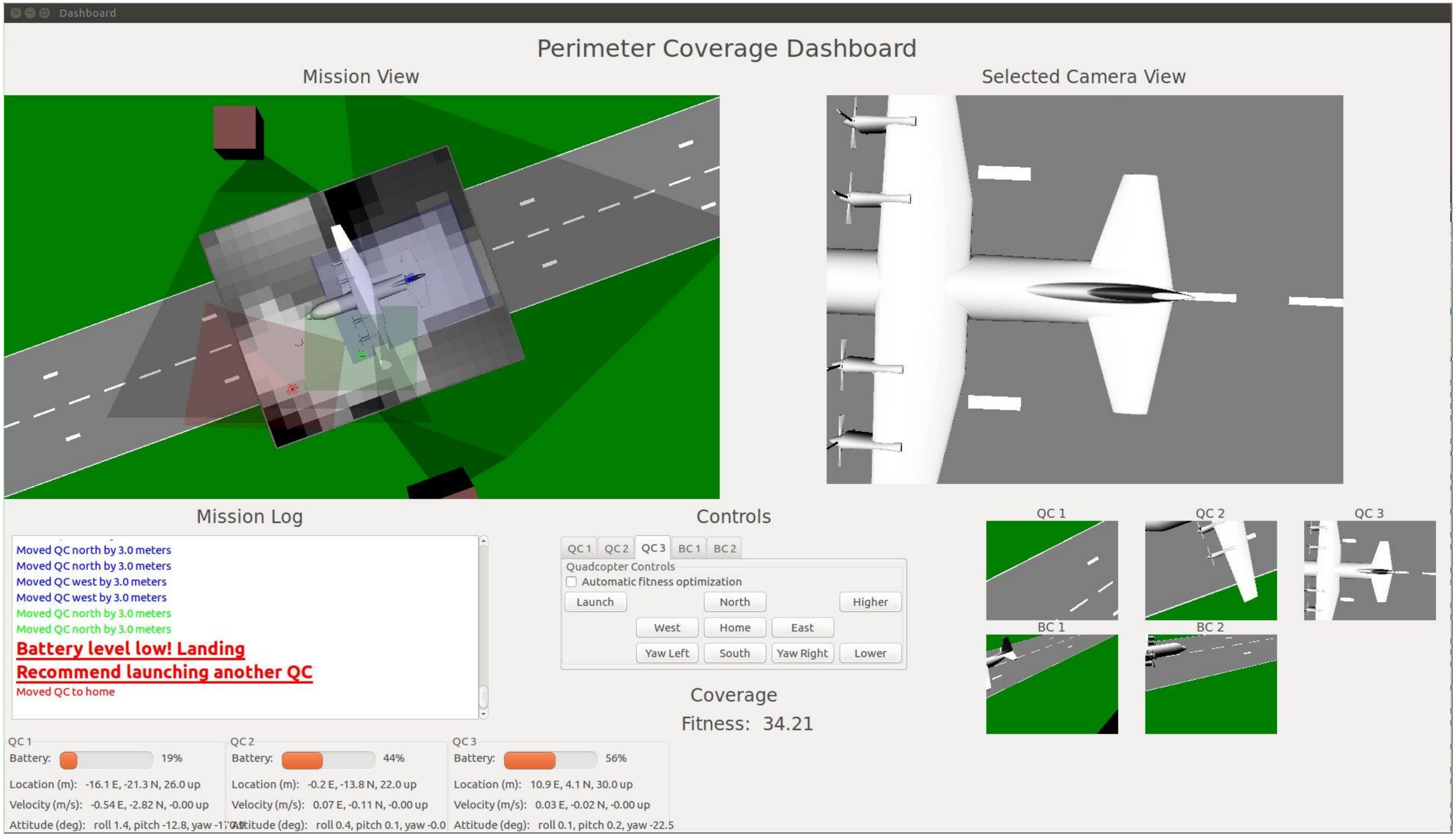
Dashboard Showing Optimal Location for a Single Quadcopter



Dashboard Showing Optimal Location for Three Quadcopters



Dashboard Showing 3 Flying QCs with One Low on Battery and Ready to Land



Human Behavior Modeling

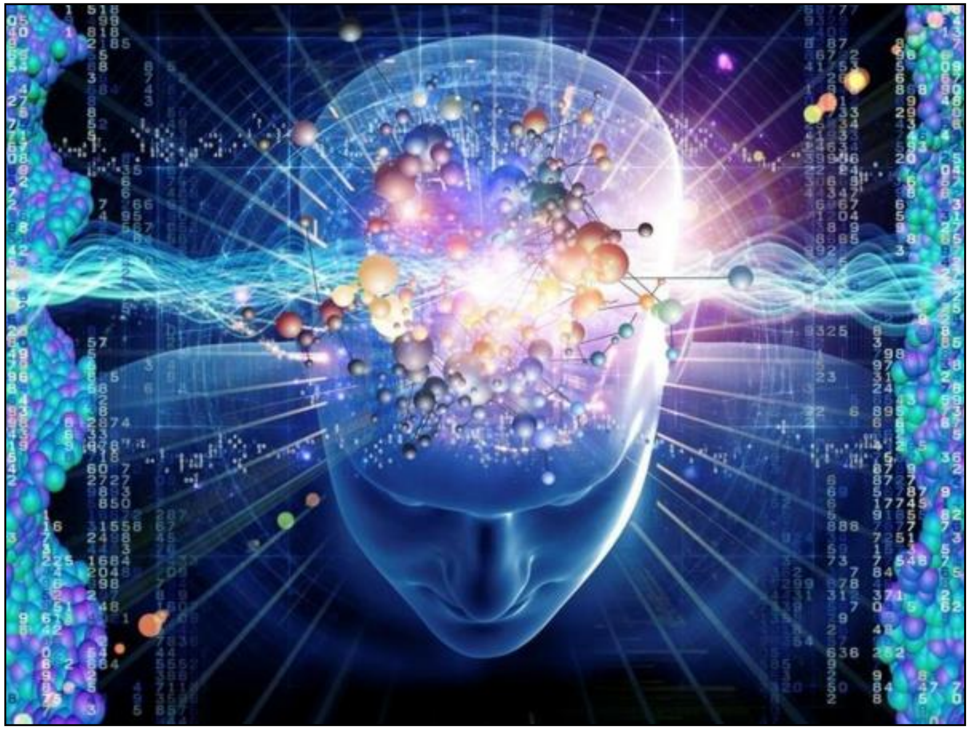
- An important aspect of gauging performance of CPHS in nominal and contingency scenarios (use cases)
  - effects of cognitive load, fatigue, and attention level on error rates
- Key research questions:
  - What aspects of humans to represent in specific problem contexts?
  - Is there a methodological basis to determine an appropriate sparse representation of a human?
  - At what level should human (model) be incorporated in CPHS feedback loop (e.g., on-the-loop, in-the-loop, inside controller, inside system model?
  - What combination of modeling approaches (e.g., math model, parametric model, probabilistic model, optimal control model) to use for a specific CPHS?

Machine Learning

- Determine unidentified system states during system operation / use
- Determine unidentified environment states during mission execution
- Capture human priorities and preferences in different contexts in simulated operational environments

Machine Learning:
Opportunities and Complicating Factors

- Sources of learning
  - sensors
  - networks
  - people
- Complicating factors
  - partial observability
  - noisy sensors
  - disruptive events
  - hostile/deceptive actors in environment

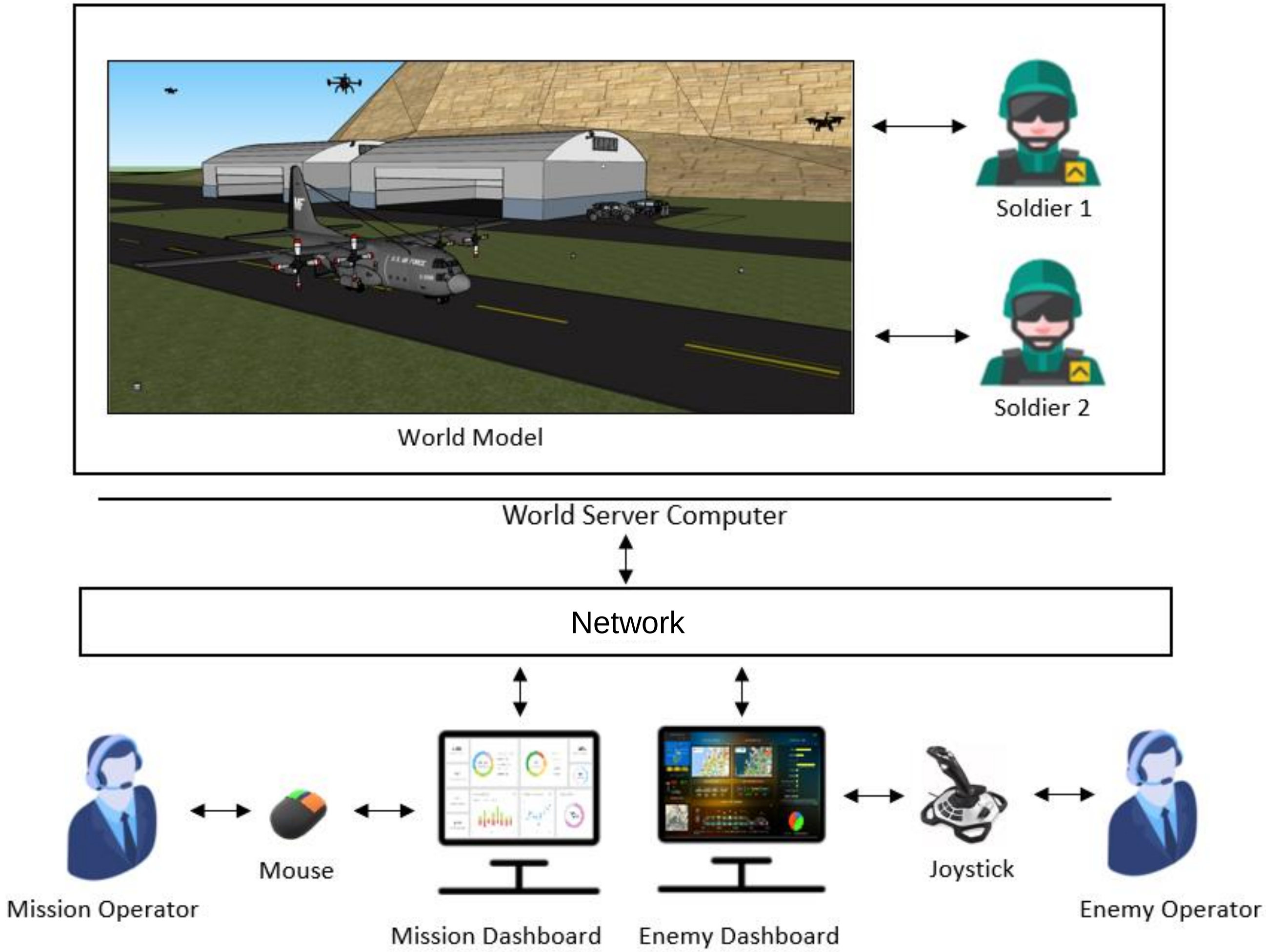


Machine Learning Methods

- Supervised Learning
  - requires labeled data
  - creates a data model with offline training
  - **application:** learn human's information seeking policies in different contexts
- Unsupervised Learning
  - creates data clusters
  - learns patterns and behaviors
  - continue learning/ training/ refining model online during execution
  - **application**: learn intrusion patterns in aircraft perimeter security
- Reinforcement Learning
  - requires real-time interaction with environment (observation)
  - makes decisions (action) based on the existing patterns (states) and real-time environmental feedback (observation)
  - **application:** progressively learn system and environmental state based on incoming sensor reports in partially observable environments

Prototype Testbed Hardware

Implementation:
Distributed Simulation Architecture



Findings To-Date

- Key problem in implementing hybrid models
  - resolving mismatch between planning & and vehicle control layer
- Mismatch resolution
  - ensure that propagated commands from planning layer to controller do not violate physical and regulatory constraints
  - propagate execution constraints from control layer to PDM layer before planning and decision-making function issues commands
  - incorporate heuristics (e.g., priorities, region of influence) to resolve conflicts and simplify computation
- Adaptive model selection
  - key heuristic: use simplest model that fits system function and environment characteristics
  - e.g., navigate to designated area with partial observability, maintain flight pattern to assure target area coverage

Findings To-Date (cont'd)

- POMDP and vehicle controller work on different time scales
  - dynamics model runs every 0.01 seconds (accuracy)
  - POMDP runs slower (high level decisions/commands)
  - waypoint navigation with goal of minimizing response time to action
  - ideal sampling period for POMDP determined experimentally
- Simultaneous creation of prototype and testbed - good strategy
  - introduced rigor in experimentation
  - current: able to switch between simulation model and physical system
  - future: incorporate operational data from physical system into simulation model to create Digital Twin
- Monitoring and execution dashboard – a key capability
  - facilitated understanding and debugging of vehicle behaviors

Next Steps

- Collaborate with David Jacques of AFIT to integrate our respective technologies
  - probabilistic system modeling
  - UAV test environments
- Expand Modeling and Simulation testbed capabilities
  - more extensive data collection
  - digital twin modeling
  - distribute computation for sensors and adversary behaviors

Takeaways

- DoD systems in 21st century need to be resilient to operate safely in uncertain, partially observable, potentially hostile environments
- Adaptive CPHS, an example of a 21st century system, poses unique modeling, analysis and distributed autonomy challenges
- System model verifiability (safety), flexibility (resilience), and machine learning (adaptation) are essential requirements
- Resilience Contract, a probabilistic model-based construct, satisfies these requirements
- Modeling today is a closed loop process spanning both build-time and run-time environments
- Model adaptation implies not only changes in model parameters but also modeling construct ("principle of proportional complexity")
- Extensible distributed simulation used to implement adaptive CPHS with distributed autonomy
- Approach successfully applied to perimeter security of military aircraft

Relevant Journal Publications

- Madni, A.M., Sievers, M. and Madni, C.C. Adaptive Cyber-Physical-Human Systems: Exploiting Cognitive Modeling and Machine Learning in the Control Loop, *INSIGHT*, 21,3, (87-93), 2018.
- Madni, A.M. and Sievers, M. "Model Based Systems Engineering: Motivation, Current Status, and Research Opportunities," *Systems Engineering*, 20th Anniversary Issue, vol. 21, issue 3, pp. 172-190, 2018.
- Madni, A.M., and Madni, C.C. Architectural Framework for Exploring Adaptive Human-Machine Teaming Options in Simulated Dynamic Environments. *Systems*. 2018; 6(4):44.
- Madni, A.M., and Madni, C.C. Lucero, S.D. Leveraging Digital Twin Technology in Model-Based Systems Engineering. *Systems*. 2019; 7(1):7.
- Madni A.M. and Purohit S. Economic Analysis of Model-Based Systems Engineering. *Systems*. 2019; 7(1):12.

Azad M. Madni

- Professor, Astronautical Engineering, University of Southern California
- Executive Director, Systems Architecting and Engineering Program
- Director, Distributed Autonomy and Intelligent Systems Laboratory
- Founder and CEO, Intelligent Systems Technology Inc.
- INCOSE Fellow, Pioneer and Founder
- Life Fellow, IEEE; Fellow, AAAS; Fellow, AIAA; Life Fellow, SDPS; Life Fellow, IETE
- Ph.D., M.S., B.S. in Engineering, UCLA; Graduate of Stanford's Executive Program
- **Research Interests**: Formal and Probabilistic System Modeling; Resilient Cyber-Physical-Human Systems; Interactive Storytelling in Virtual Worlds, Intelligent Systems Engineering
- **2019 Awards and Honors**
  - *2019 AIAA/ASEE Leland Atwood Award* for excellence in aerospace engineering
  - *2019 ASME CIE Leadership Award* for advancing use of computers in engineering
  - *2019 INCOSE Founders Award* for increasing global awareness of INCOSE
  - *2019 EC William B. Johnson International Inter-Professional Founders Award*
  - *2019 OCEC Prestigious Pioneering Educator Award*
  - *2019 Honoree for Amy King Dundon-Berchtold University Club Faculty Recognition*
- **Recent Books**
  - Madni, A.M., Boehm, B. et al. (eds.) *Disciplinary Convergence: Implications for Systems Engineering Research*, Springer, 2018.
  - Transdisciplinary Systems Engineering: Exploiting Convergence in a Hyper-Connected World (foreword by Norm Augustine) Springer, 2017
  - Tradeoff Decisions in System Design (foreword by John Slaughter), Springer, 2016
  - Madni, A.M. and Boehm, B. (eds), *"Engineered Resilient Systems: Challenges and Opportunities in the 21st Century,"* Procedia Computer Science 28 (2014), ISSN 1877-0509, Elsevier, 2014

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"What Does MBSE Reference Architecture Mean for Autonomous and Cooperative Systems?"

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Dr. Dave Jacques, Air Force Institute of Technology

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