FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Toward a Resilient and Sustainable Air Transportation System

Hamsa Balakrishnan

Joao Cavalcanti, Yashovardhan Chati & Karthik Gopalakrishnan

Berkeley UNIVERSITY OF CALIFORNIA

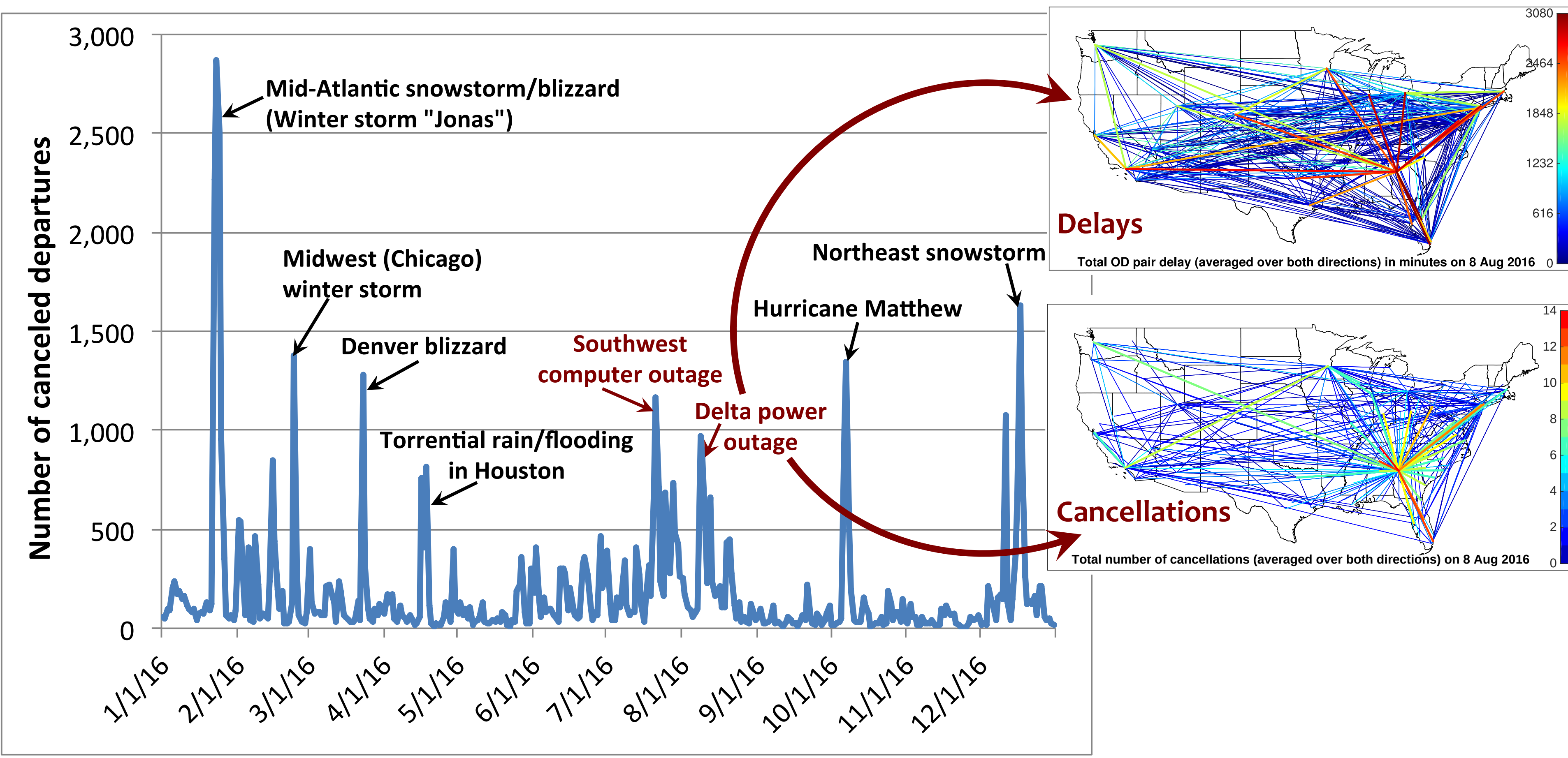
Massachusetts Institute of Technology

NSF

MICHIGAN

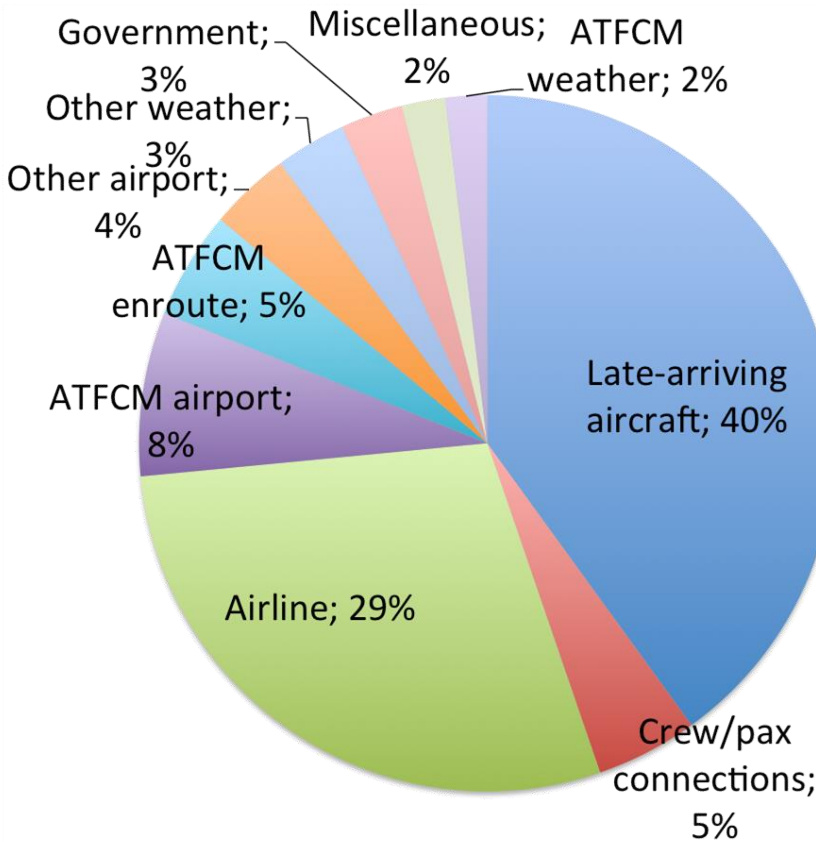
VANDERBILT UNIVERSITY

Local events have global impacts

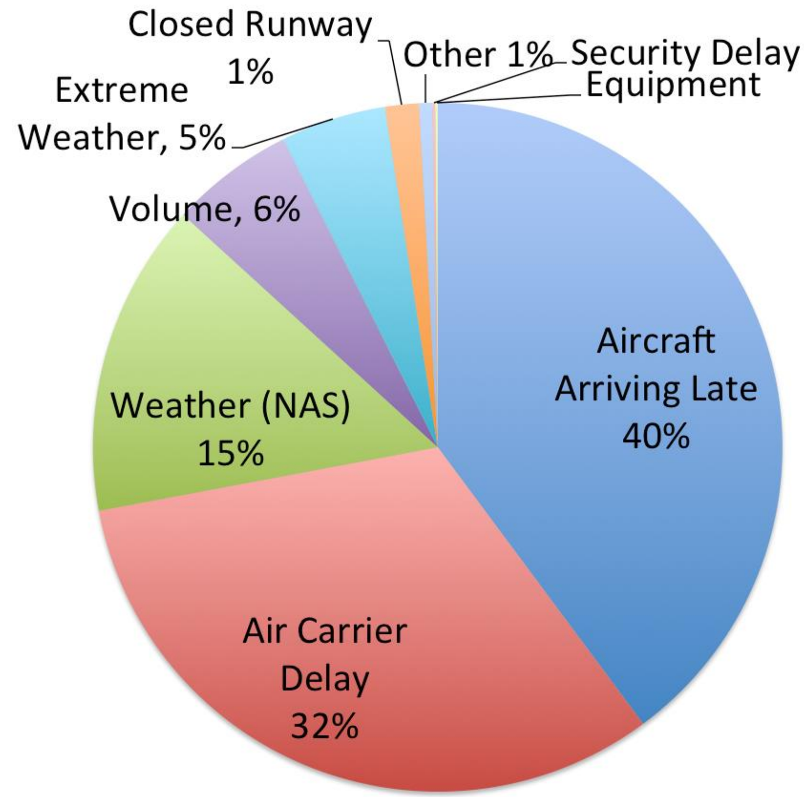


FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Flight connectivity is a big driver of delay propagation



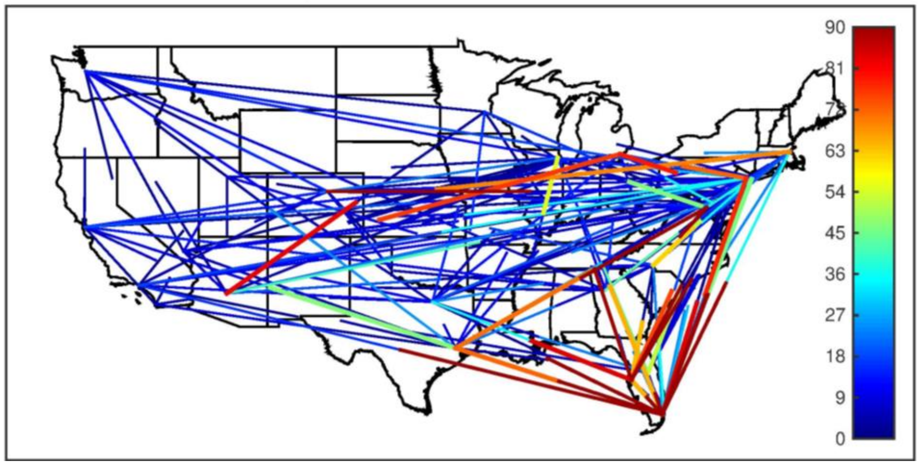
Causes of Europe delays, 2015



Causes of US delays, 2015

Bureau of Transportation Statistics, 2016; EUROCONTROL CODA, 2016

Challenges in modeling infrastructure networks



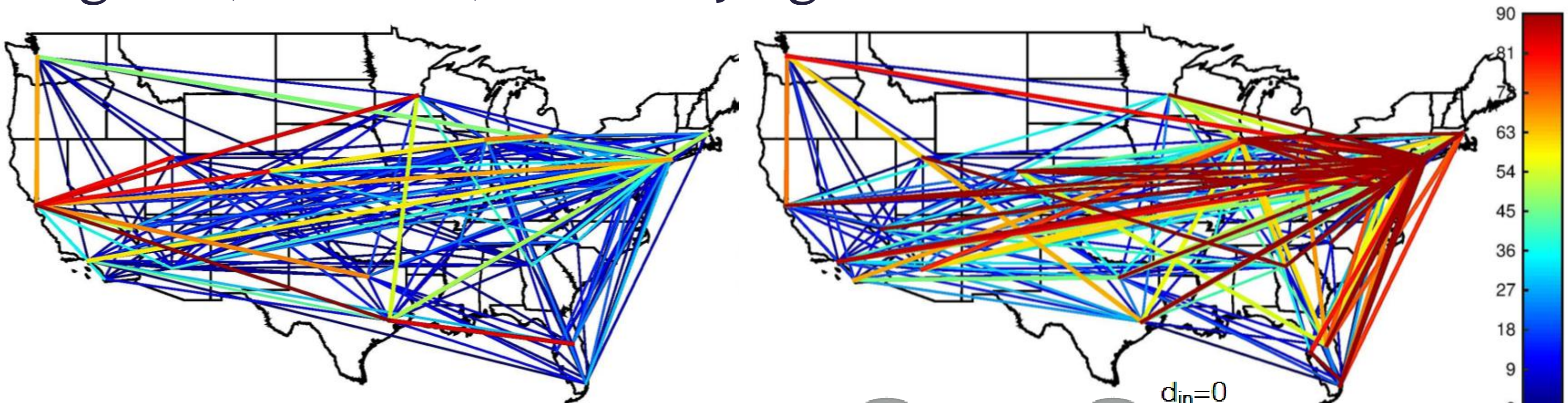
[Delay Data: Bureau of Transportation Statistics]

* Nodal and link states are best modeled as continuous variables
* Interactions are weighted and directed (asymmetric)
* Interactions (network topologies) vary with time

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

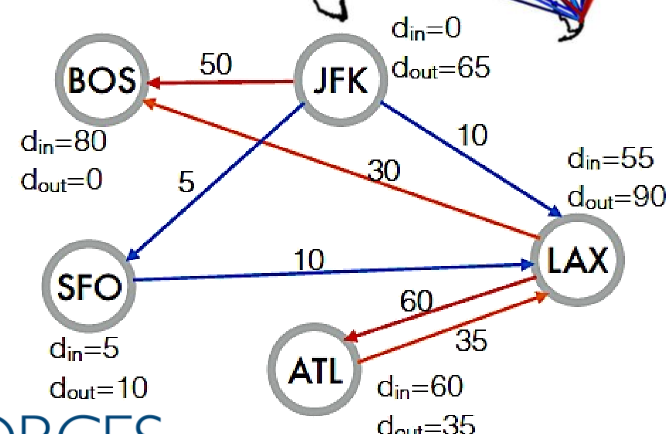
A network-centric view of air traffic delays

- For example, delay levels on edges between airports
- Weighted, directed, time-varying networks



Adjacency matrix, A:

$$a_{ij} = \begin{cases} w_{ij}, & \text{if } (i,j) \in \mathscr{E}, \\ 0, & \text{otherwise} \end{cases}$$



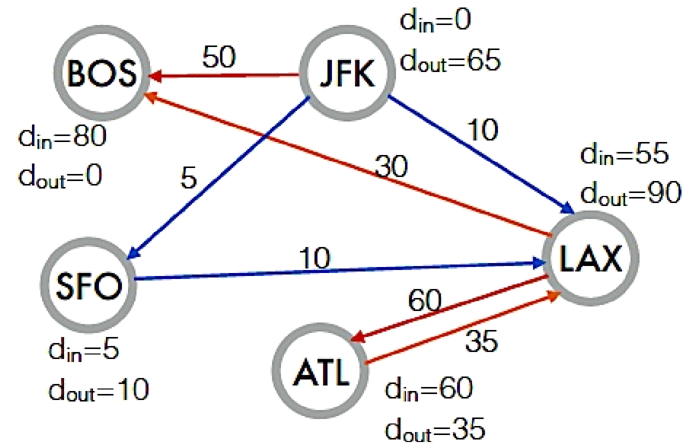
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Simplistic model of delay dynamics

* Given an adjacency matrix, $A = [a_{ij}]$

$$d^i_{in}(t+1) = \alpha^i_{in} d^i_{in}(t) + \sum_j \beta^{in}_{ji} \bar{a}_{ji}(t) d^j_{out}(t)$$

$$d^i_{out}(t+1) = \alpha^i_{out} d^i_{out}(t) + \sum_j \beta^{out}_{ij} \bar{a}_{ij}(t) d^j_{in}(t)$$



* "State" of system: $\vec{x}(t) = \begin{bmatrix} \vec{d}^{\text{out}}(t) \\ \vec{d}^{\text{in}}(t) \end{bmatrix}$

* Therefore, for given network topology: $\vec{x}(t+1) = \Gamma(t)\vec{x}(t)$

  where $\Gamma(t) = [\alpha] + [\beta] \begin{bmatrix} 0 & \bar{A}(t)^T \\ \bar{A}(t) & 0 \end{bmatrix}$

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Gopalakrishnan et al. CDC 2016]

Network topology is time-varying

* For tractability, assume that network topology belongs to a finite (known) set of possibilities
  * Results in a hybrid system
* Assume that network topology switches between different values in a Markovian manner
  * Results in a Markov Jump Linear System
* Each discrete mode has its own linear dynamics, depending on the network topology (adjacency matrix)

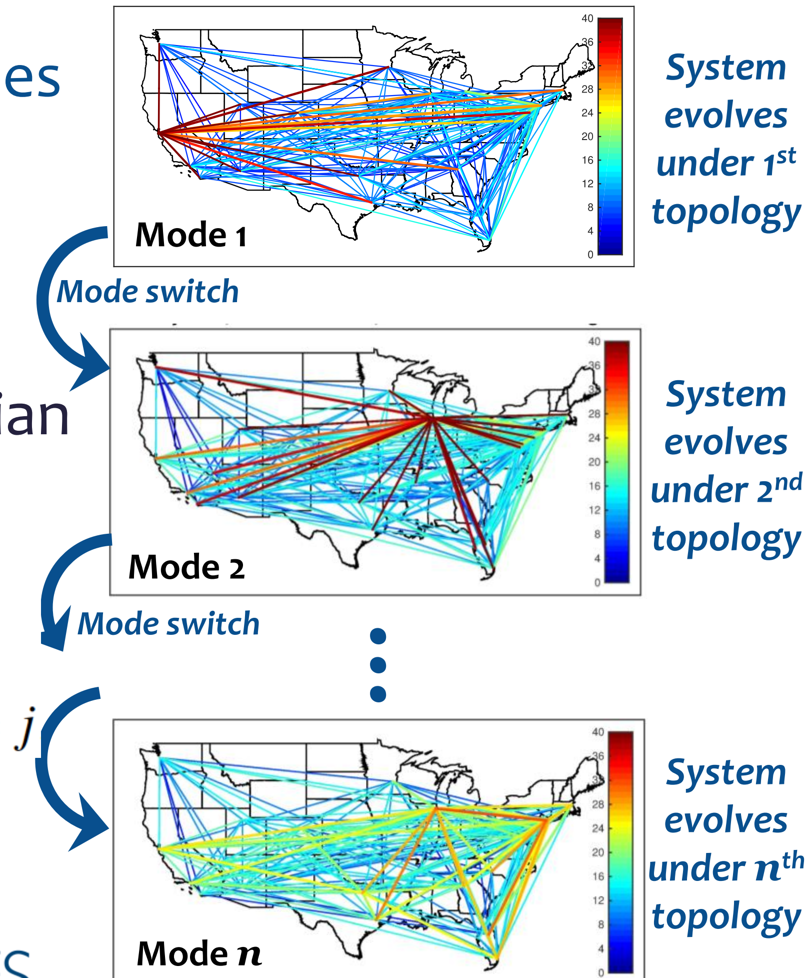
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Dynamics with switching network topologies

- Identify set of characteristic topologies ("discrete modes of operation")
- Determine linear continuous state dynamics under a fixed topology
- Switched linear system with Markovian transitions:

$$\begin{aligned}
\vec{x}(t+1) &= \Gamma_{m(t)}\vec{x}(t) \\
\pi_{ij}(t) &= \Pr[m(t+1)=j|m(t)=i] \\
\vec{x}(t+1) &= J_{ij}\Gamma_i\vec{x}(t), \text{ if } m(t)=i \text{ and } m(t+1)=j
\end{aligned}$$

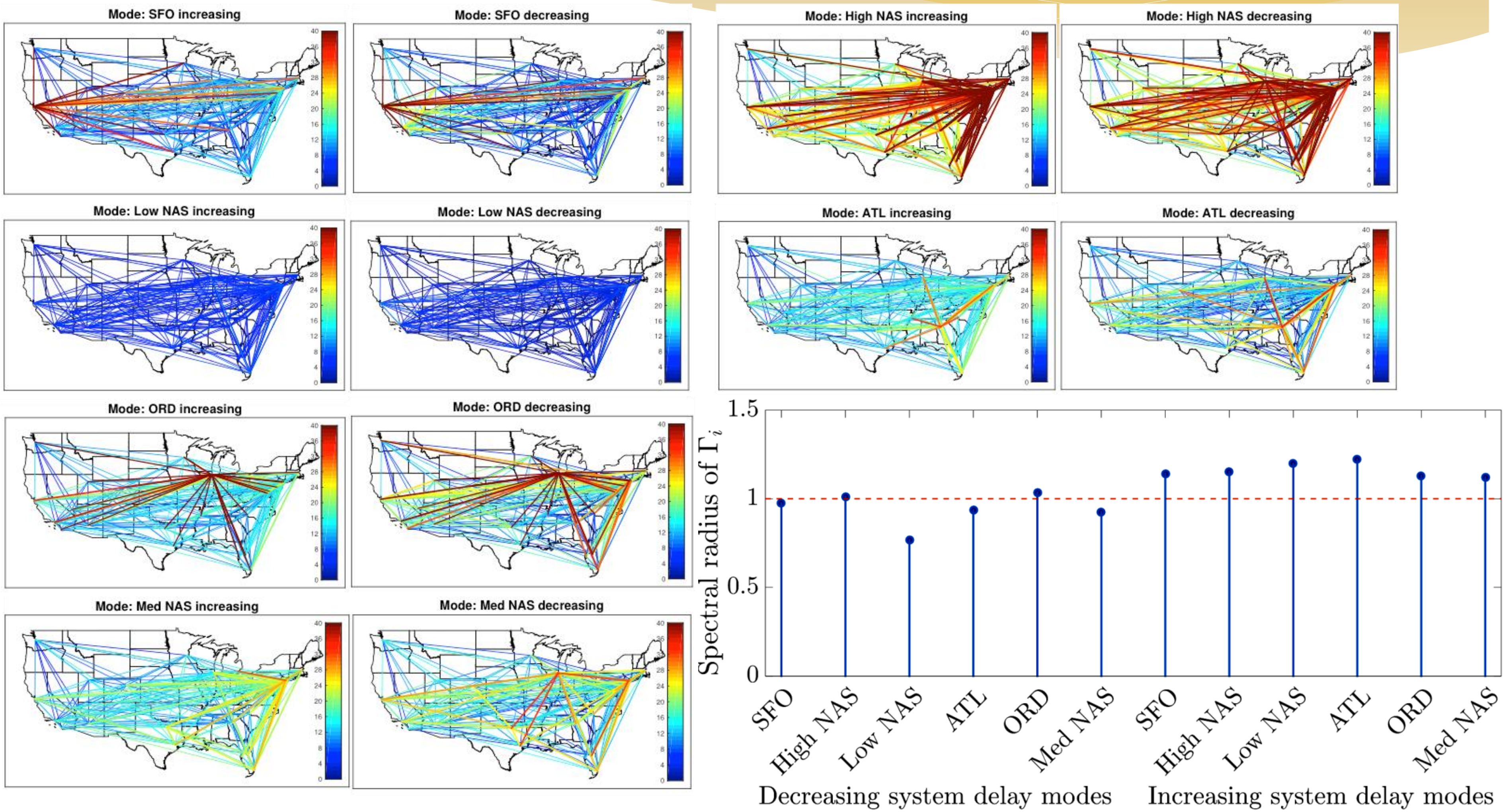
- Markov Jump Linear System (MJLS)



FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Gopalakrishnan et al. CDC 2016]

Individual discrete modes



[Gopalakrishnan et al. CDC 2016]

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Stability of MJLS model

* Consider stability of MJLS model with periodic time-varying mode transition matrices (determined by hour of day)

* Resulting MJLS model shown to be mean and almost surely stable

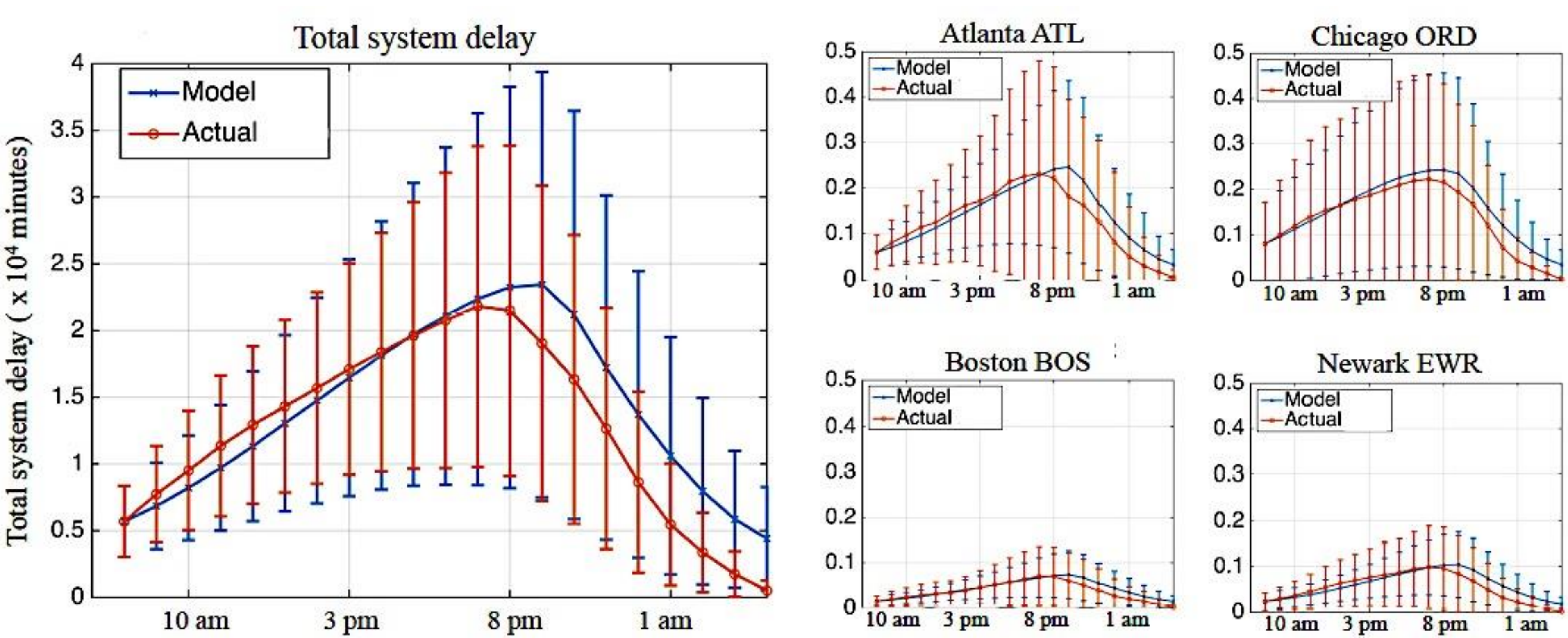
* System appears to be stabilized by the temporal variations in the mode transition matrices

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Gopalakrishnan et al. CDC 2016]

MJLS model validation

* Model learned using 2011 data; validation using 2012 data

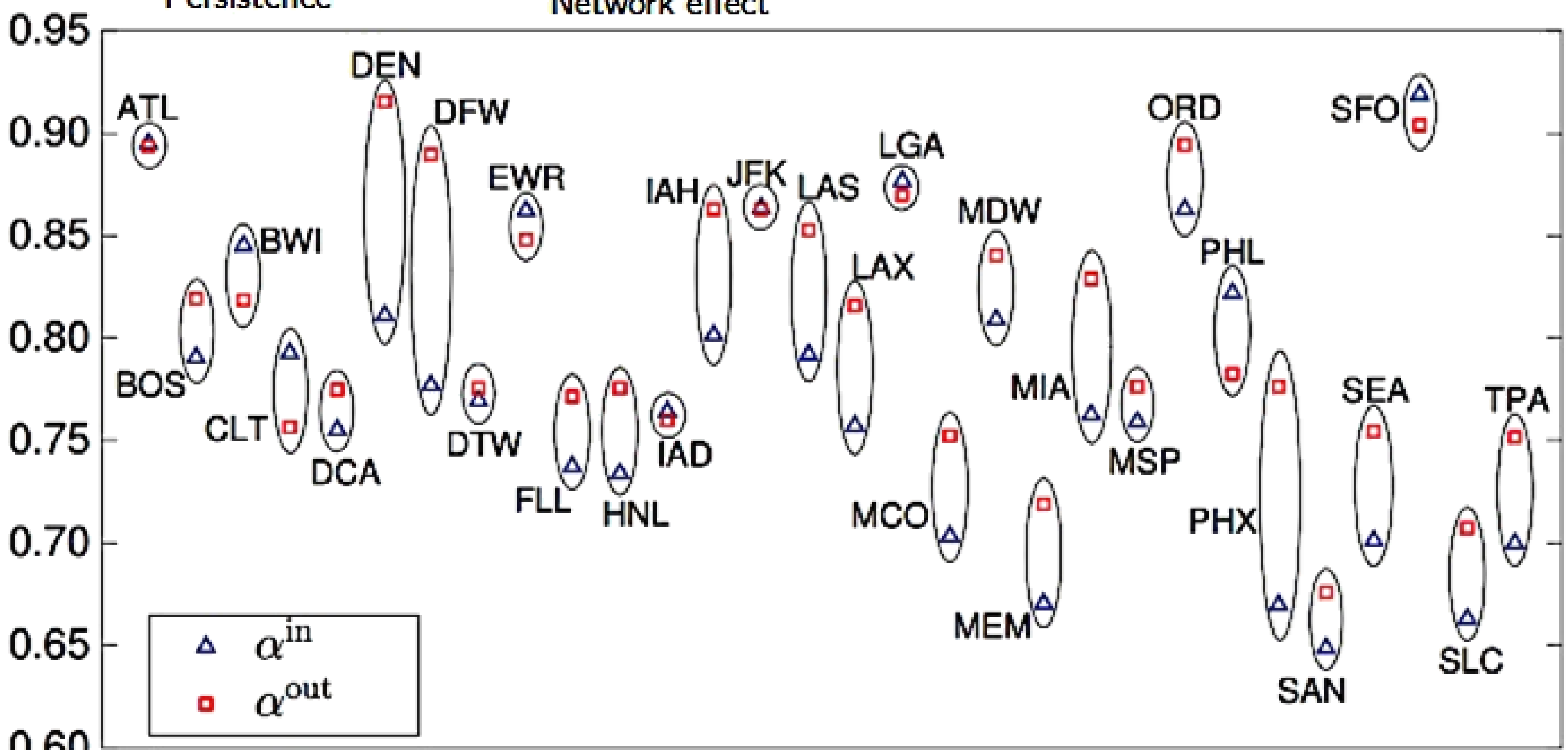


FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Measure of airport resilience: Delay persistence

$$d^i_{in}(t+1) = \underbrace{\alpha^i_{in} d^i_{in}(t)} + \sum_j \underbrace{\beta^{in}_{ji} \overline{a}_{ji}(t) d^j_{out}(t)}$$

$$d^i_{out}(t+1) = \underbrace{\alpha^i_{out} d^i_{out}(t)}_{\text{Persistence}} + \sum_j \underbrace{\beta^{out}_{ij} \overline{a}_{ij}(t) d^j_{in}(t)}_{\text{Network effect}}$$



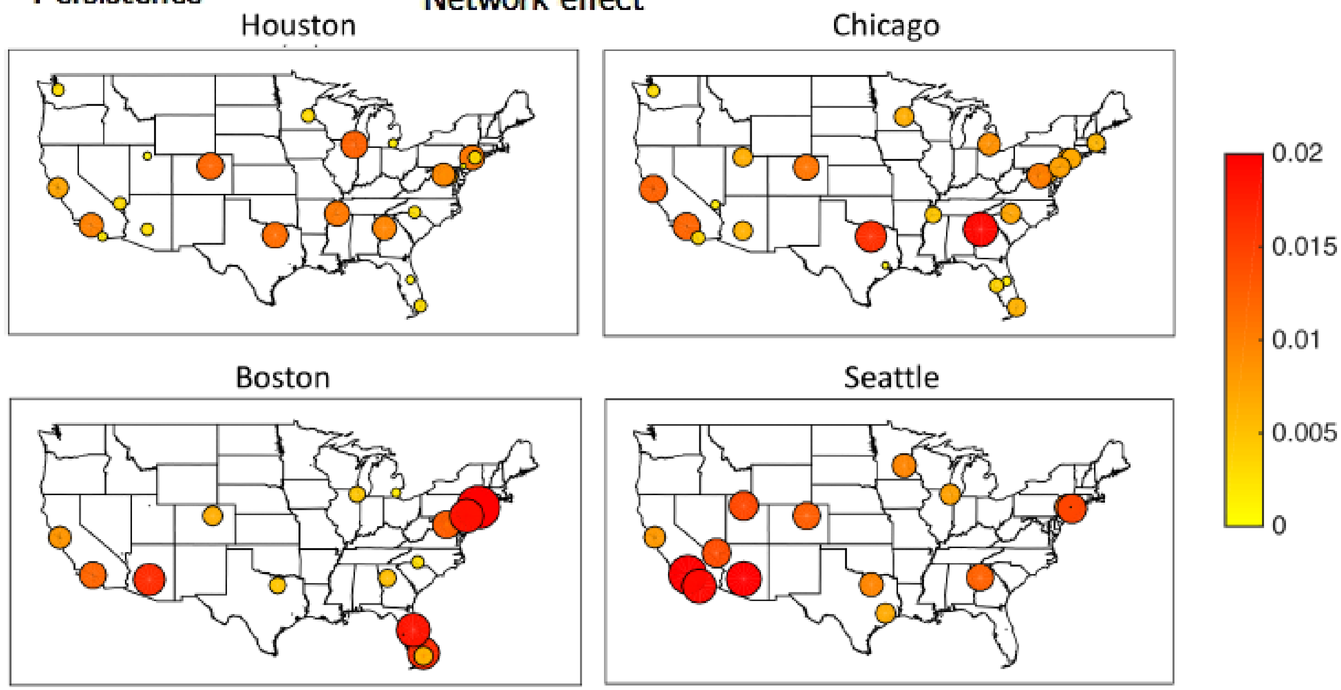
FORCES FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Gopalakrishnan et al. CDC 2016]

Measure of airport resilience: Network effects

$$d^i_{in}(t+1) = \underbrace{\alpha^i_{in} d^i_{in}(t)} + \sum_j \underbrace{\beta^{in}_{ji} \overline{a}_{ji}(t) d^j_{out}(t)}$$

$$d^i_{out}(t+1) = \underbrace{\alpha^i_{out} d^i_{out}(t)}_{\text{Persistence}} + \sum_j \underbrace{\beta^{out}_{ij} \overline{a}_{ij}(t) d^j_{in}(t)}_{\text{Network effect}}$$

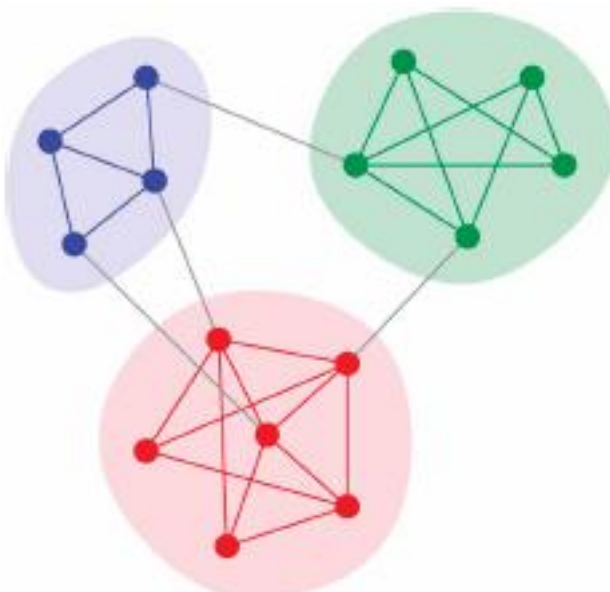


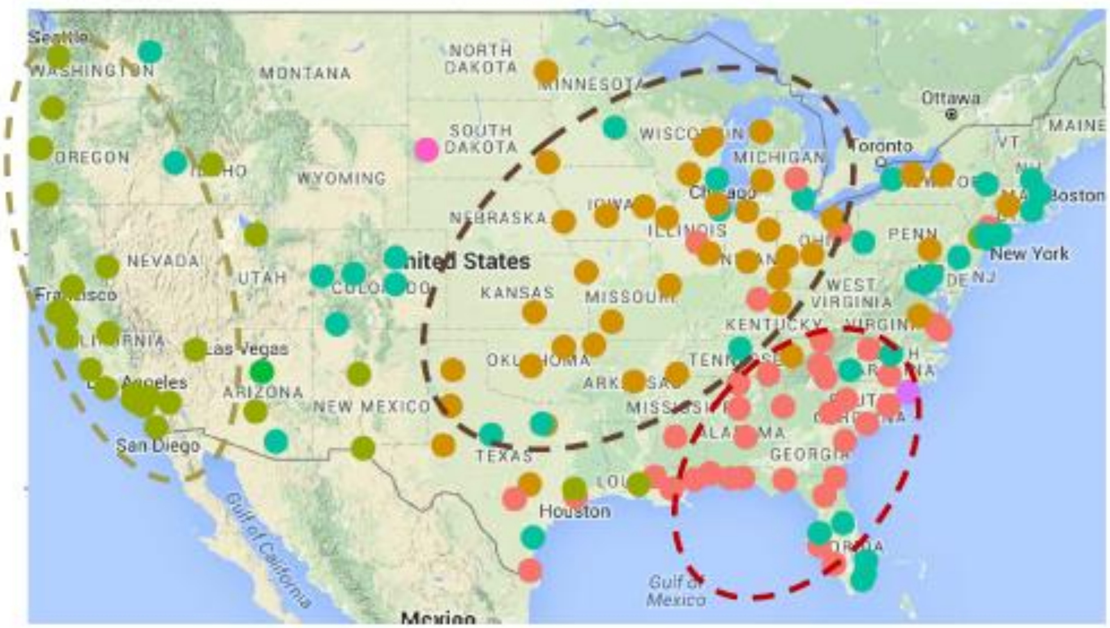
(Color and size of circle both denote induced inbound delay per unit delay at other airport)

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Delay communities

* Airports within a community have high delays between them





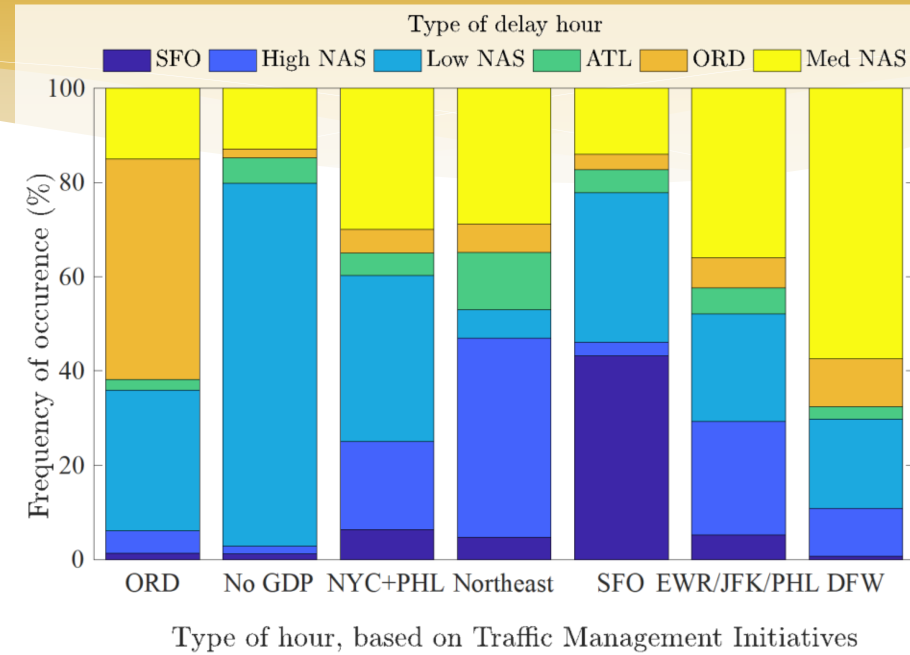
Community structure for delay network (23 March 2011)

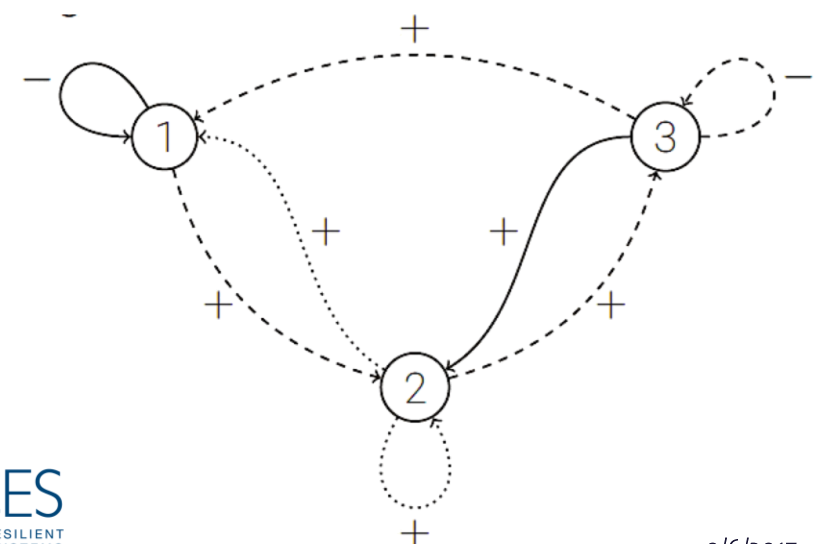
FORCES FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Gopalakrishnan et al. ACC 2016]

Ongoing research

* **Analysis of finite-time behavior** [Cavalcanti/Balakrishnan, IEEE CDC 2017]
* Triggering mode transitions
  * Weather, Traffic Management
* **Post-disruption recovery**
  * Optimal control of networks with switching
* **Prediction of future delays and delay states** [Gopalakrishnan/Balakrishnan ATM R&D Seminar 2016]
* **Multi-layer, multi-timescale networks**
  * Cancellations, **operations,** capacity [ICRAT 2016]
* **Sign-stability of networks with switching topologies**

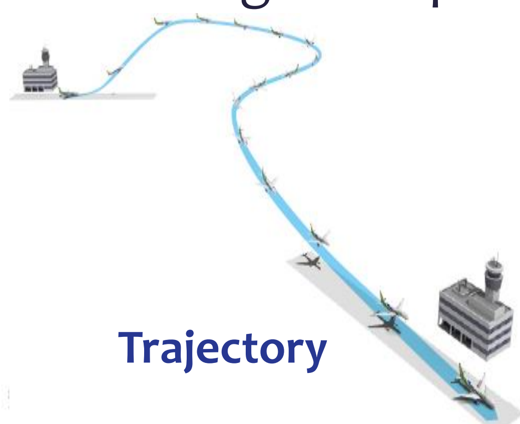




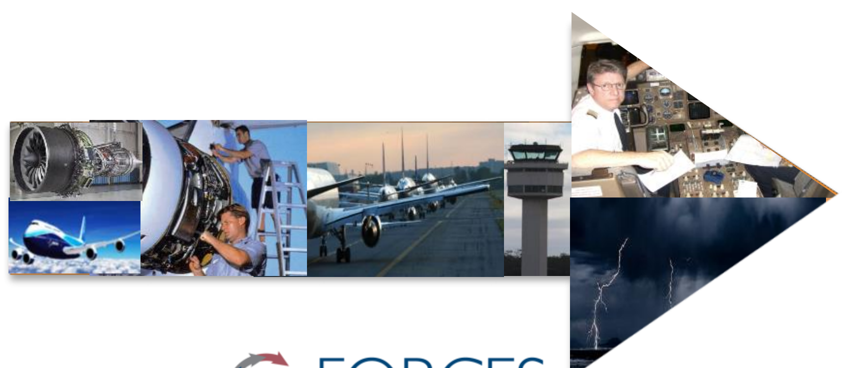
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Machine learning models of engine performance

* US airline operations consume 81 billion gallons of fuel/year (26.5% of airline expenses)
* Estimation of the fuel consumed during a flight is a long-standing challenge in air traffic management
  * Important for fuel burn and emissions inventories
  * Necessary for evaluating impact of modernization efforts and changes in operational procedures



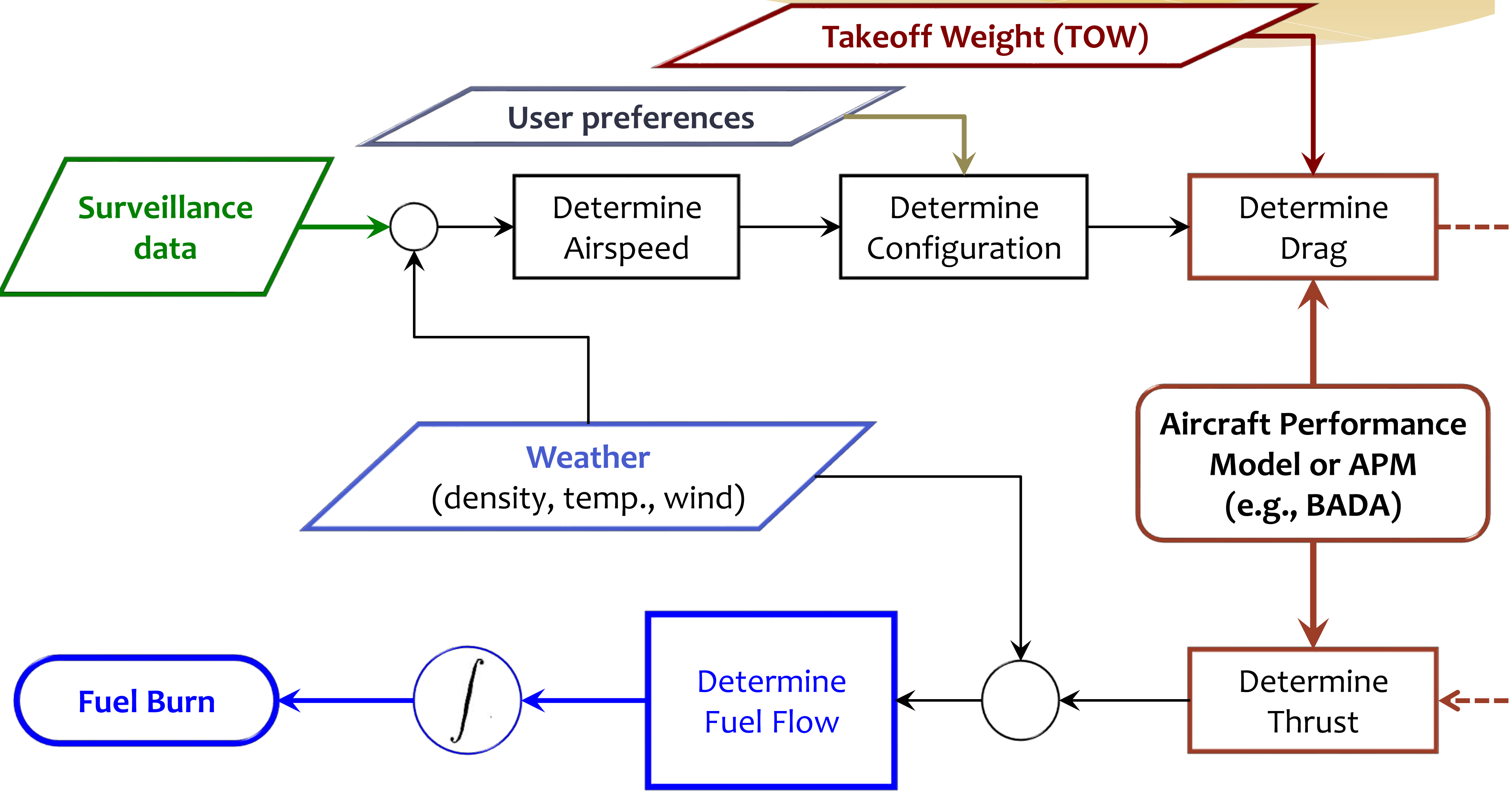
Trajectory



Fuel burn

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Traditional fuel flow model architecture



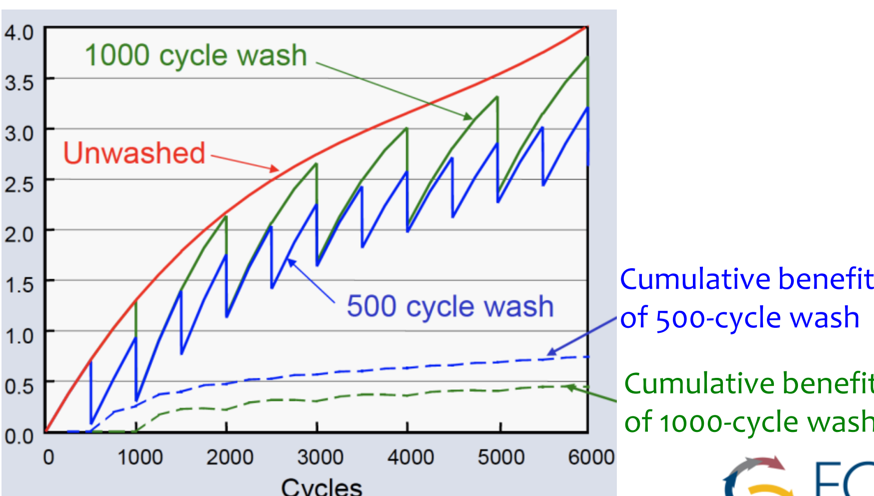
[Adapted from Enea et al. 2017]

Most fuel burn models follow this architecture

* FAA's NextGen Office Model, Aviation Environmental Design Tool (AEDT), Aircraft Fuel Evaluation Simulation Tool (AFEST)
* GfL and Technische Universität Dresden's EJPM-based Trajectory Analysis Software (ETAS), operationally used by the German Air Navigation Service Provider (ANSP) Deutsche Flugicherung (DFS)
* Airservices Australia's Dalí
* Eurocontrol's Base of Aircraft Data (BADA) is used as the Aircraft Performance Model (APM) in all of the above
* Deterministic models

Operational variability

- Two flights of the same aircraft type, flying similar trajectories, can still have different fuel consumption
- Weather conditions (e.g., winds) can greatly influence fuel burn
- Weight
  - A 1,000 lb reduction in empty weight + payload can result in 0.6-0.7% fuel savings for a Boeing 737
  - Empty weight increases 0.1-0.2% per year due to moisture/dirt accumulation
- Maintenance activities (e.g., repetitive engine washes) can improve fuel burn

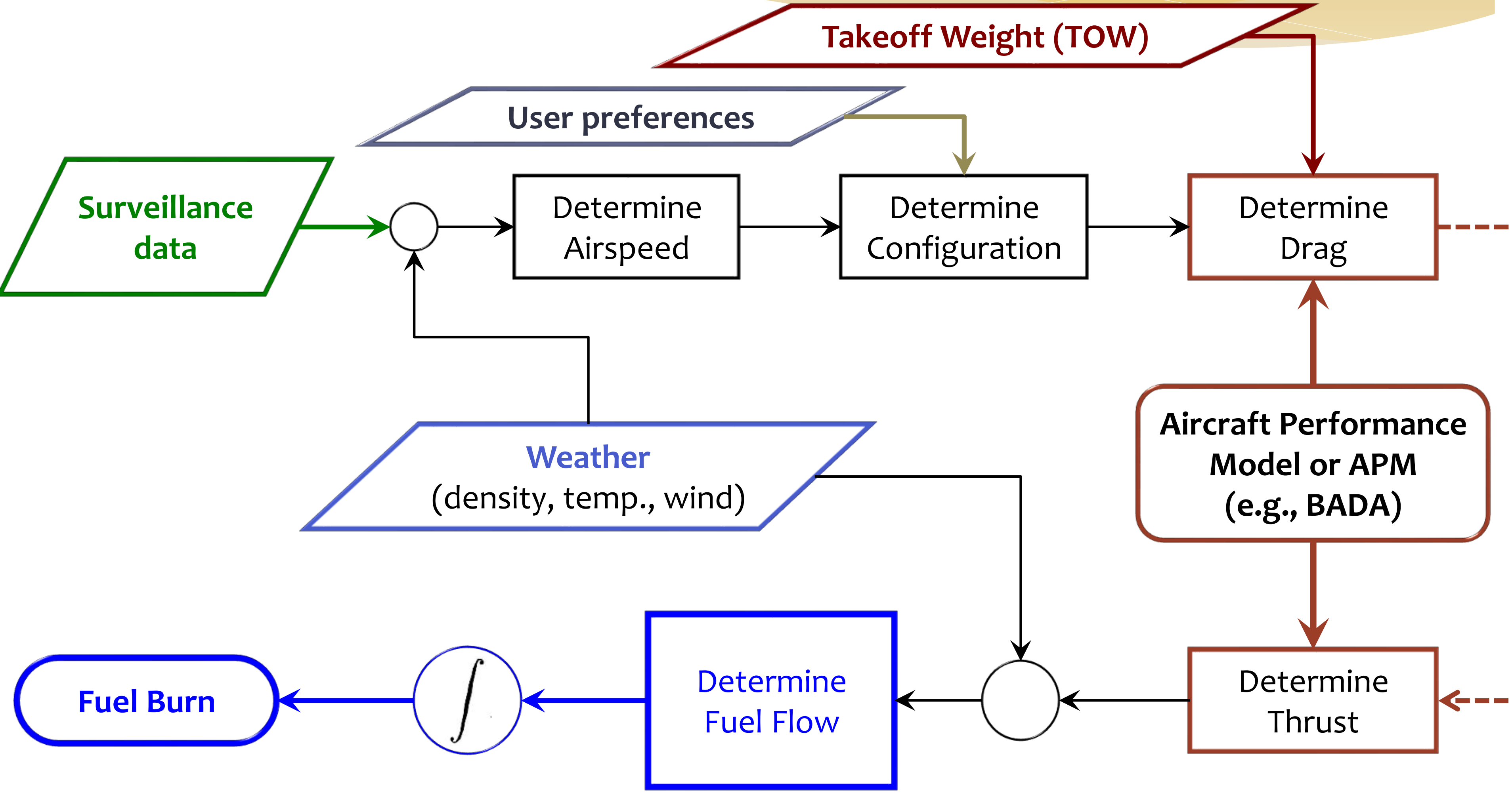


747 rough paint - lower fuselage

[Boeing, 2004]

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

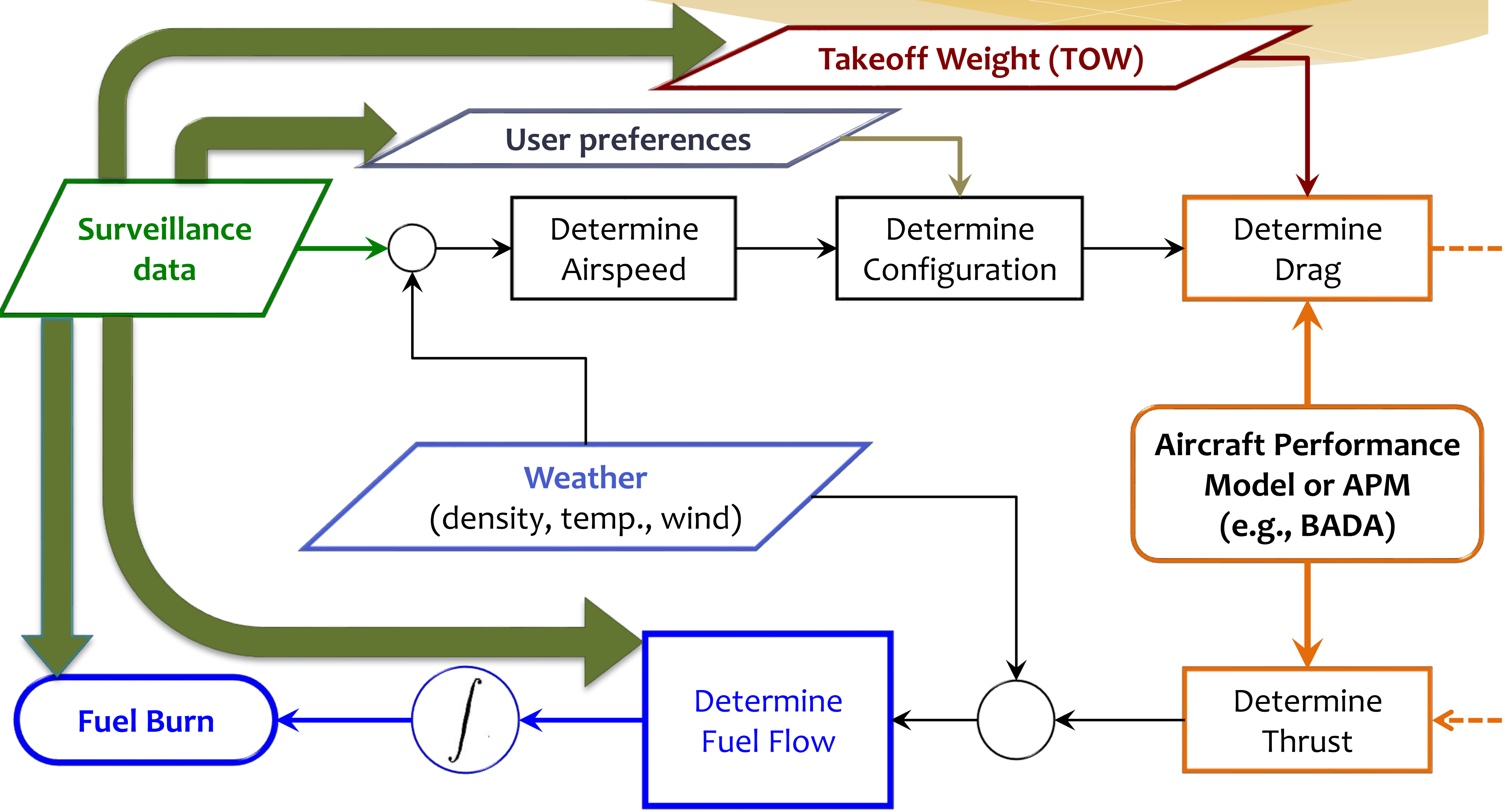
Traditional fuel flow model architecture



FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Adapted from Enea et al. 2017]

A new paradigm for fuel burn modeling



[Adapted from Enea et al. 2017]

FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Statistical modeling of aircraft fuel flow

* Use Flight Data Recorder (FDR) records from operational flights to develop statistical models
* Explicitly model uncertainty of estimates using confidence intervals
* Leverage insights from physics (e.g., for feature extraction by considering dependence on various variables)
* Predictive variables restricted to **trajectory variables**

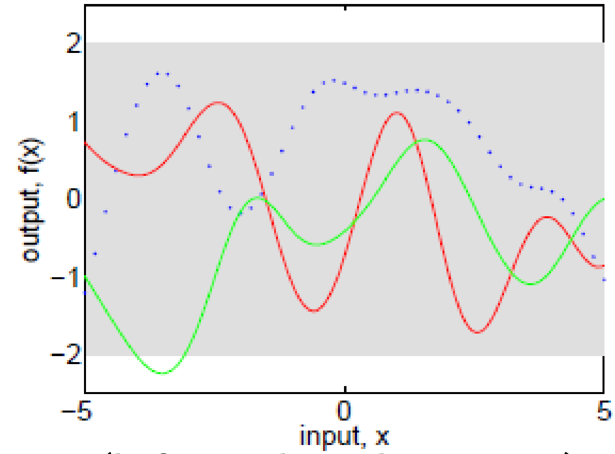
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Gaussian Process Regression models

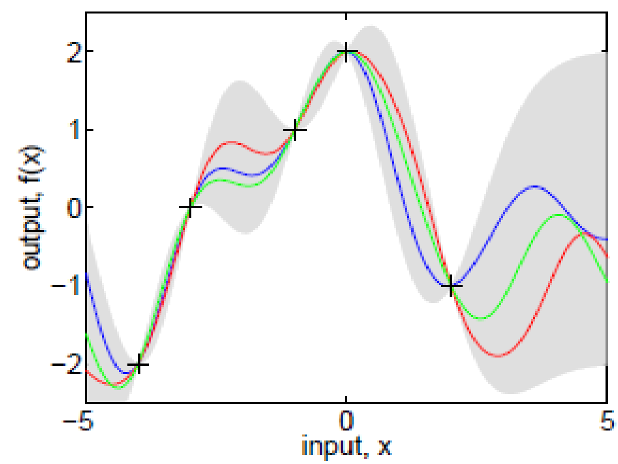
* Gaussian Process Regression
  * Nonparametric, probabilistic method

$$
\begin{aligned}
y &= f(\mathbf{x}) + \epsilon,\ \epsilon \sim \mathcal{N}(0, \sigma_n^2) \\
f &\sim \mathcal{GP}(0, k(\mathbf{x_p}, \mathbf{x_q}))
\end{aligned}
$$

  * A function is said to be drawn from a Gaussian Process when any finite set of function values follows a joint Gaussian distribution
* Advantages
  * No need to choose basis functions
  * Fast estimation of predictive distributions
* Disadvantages
  * Computationally expensive due to matrix inversion



(before making observations)



(after making observations)

Rasmussen et al., 2006.

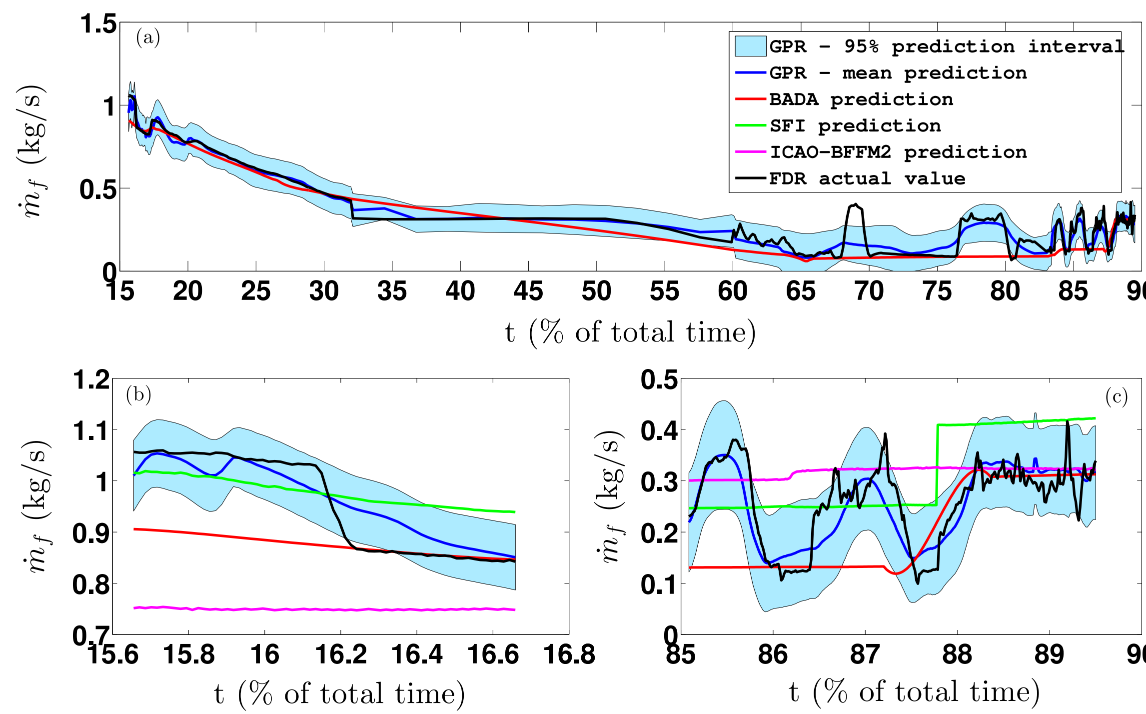
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[1] Airborne fuel burn prediction

Mean prediction error (%):

A321-111	GPR	BADA	SFI	ICAO
Ascent	0.4	7.5	N/A	N/A
Climb Out	-0.2	-0.6	6.7	1.5
Cruise	0.5	17.9	N/A	N/A
Descent	1.5	-40.6	N/A	N/A
Approach	2.4	-12.3	30.6	45.8

[Chati & Balakrishnan
Transp. Research Record 2018]

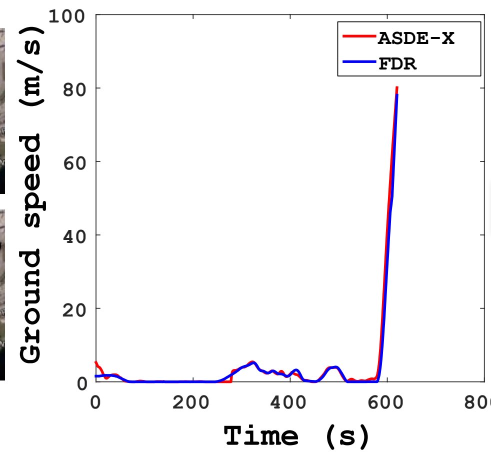


FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[Chati, ACRP Graduate Research Award]

[2] Takeoff weight prediction

* Inferring takeoff weight of a flight from its takeoff roll trajectory



WEIGHT

* Initial mass (a.k.a. Takeoff Weight, or TOW) is an essential input for trajectory prediction, as well as fuel burn and emissions estimation
* TOW of a flight is considered proprietary, and generally not shared or known

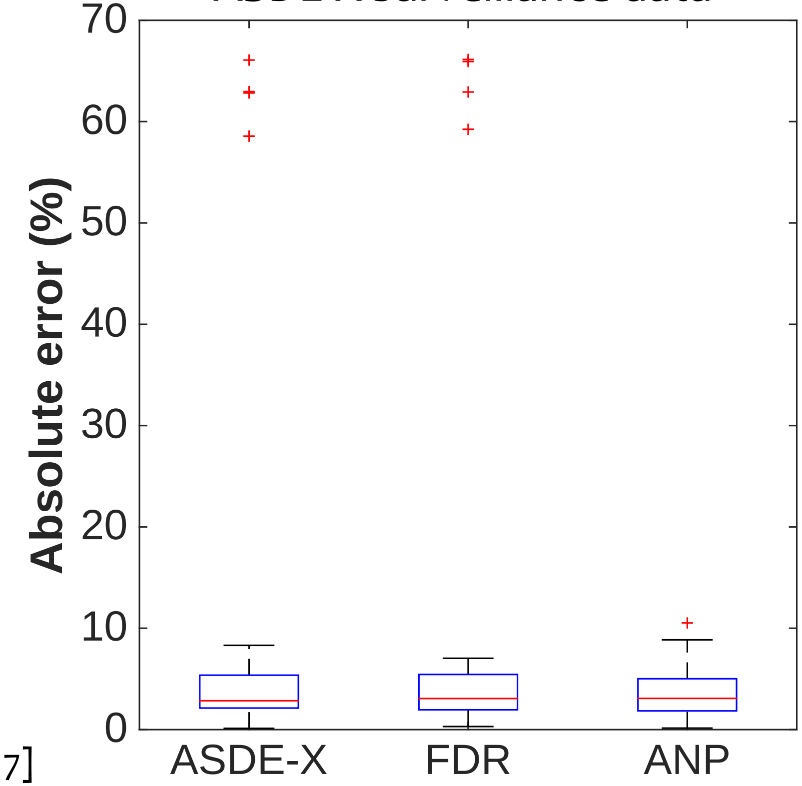
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Predictive performance: [2] TOW

Aircraft Type	GPR			BADA/ANP		
Error (%)	***ME***	***RMSE***	***PC***	***ME***	***RMSE***	***PC***
A319-112	4.6	2.0	96	5.5	7.9	--
A320-214	3.6	1.4	100	4.7	2.8	--
A321-111	6.3	1.8	96	6.7	1.9e14	--
A330-202	2.2	0.4	100	6.0	2.3	--
A330-243	1.9	0.3	95	3.6	0.9	--
A340-541	1.7	0.3	100	4.6	0.8	--
B767-300	1.9	0.3	100	8.3	2.7	--
B777-300(ER)	2.0	0.4	96	5.5	1.0	--

[Chati & Balakrishnan ATM R&D Seminar 2017]

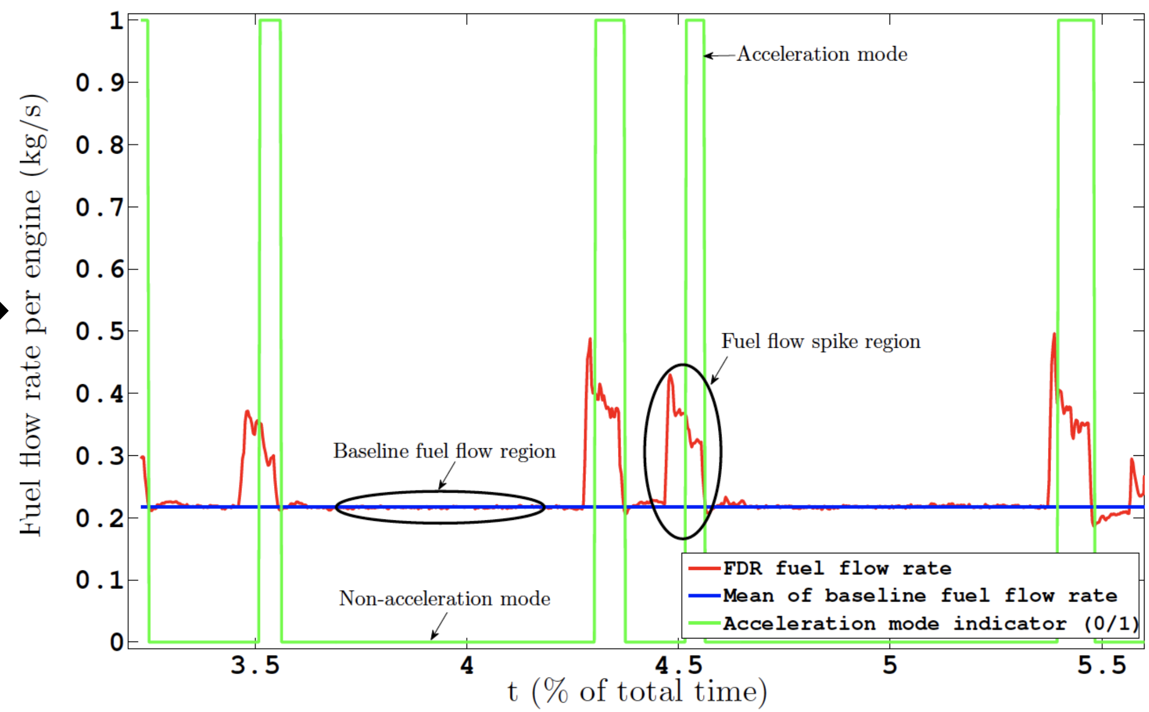
A330-300, applied to ASDE-X surveillance data



FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

[3] Developing a surface model for FAA's AEDT

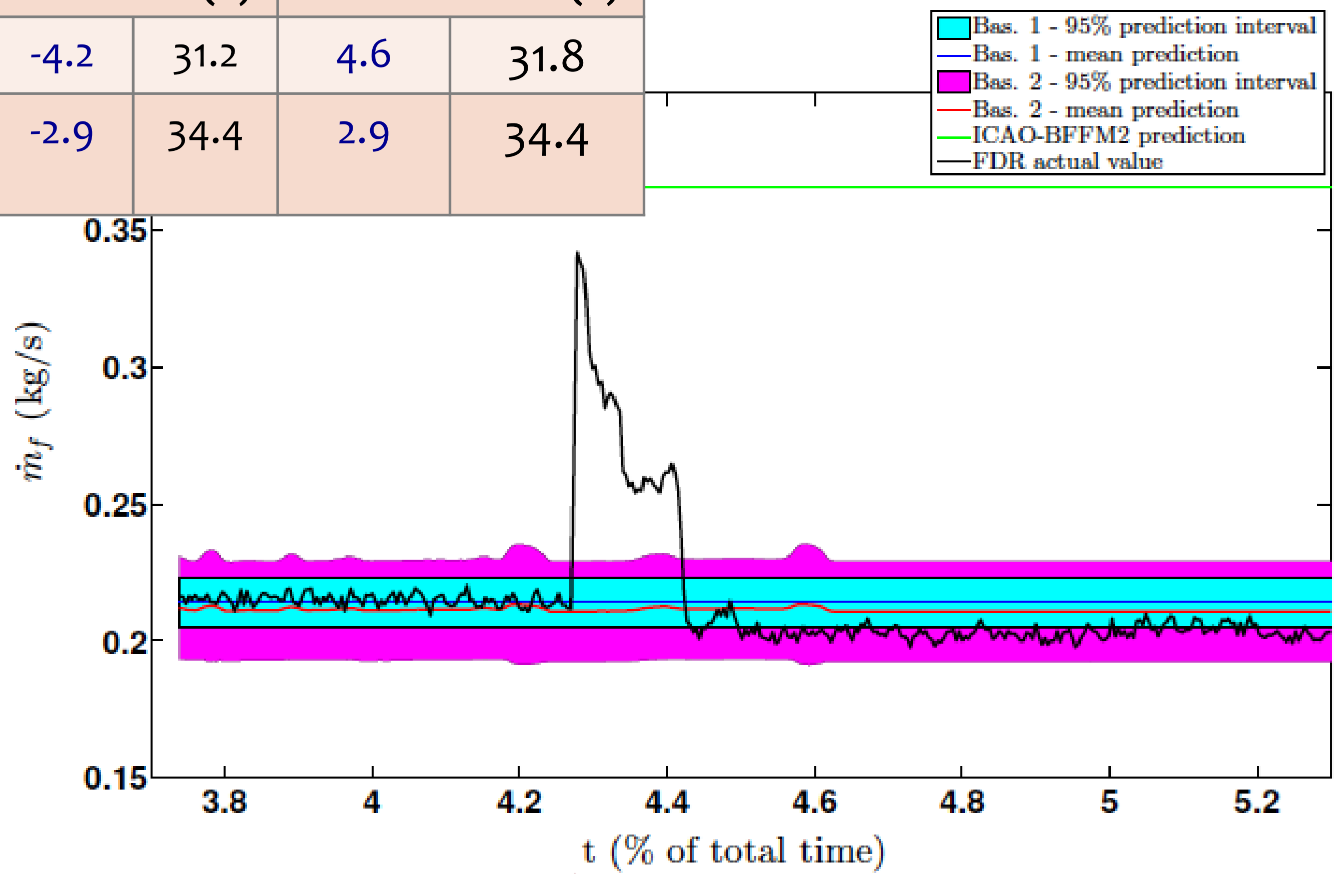
* Improve the surface aircraft performance model to predict taxi fuel burn



FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Predictive performance: [3] Taxi fuel burn

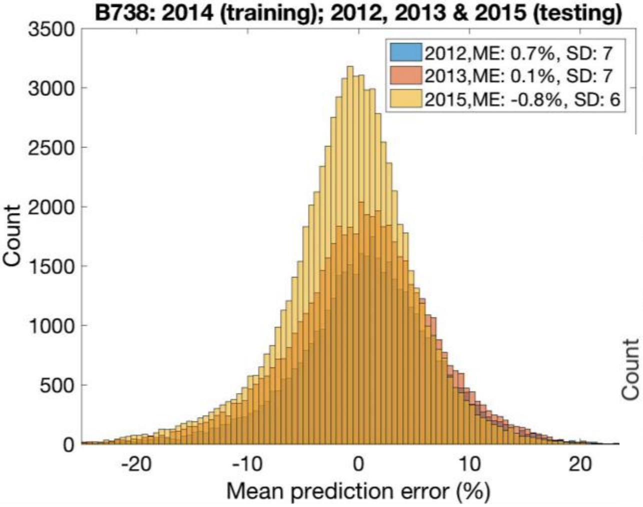
	GPR	ICAO	GPR	ICAO
	Mean err. (%)		Mean abs. err. (%)	
A330-343	-4.2	31.2	4.6	31.8
B777-300ER	-2.9	34.4	2.9	34.4

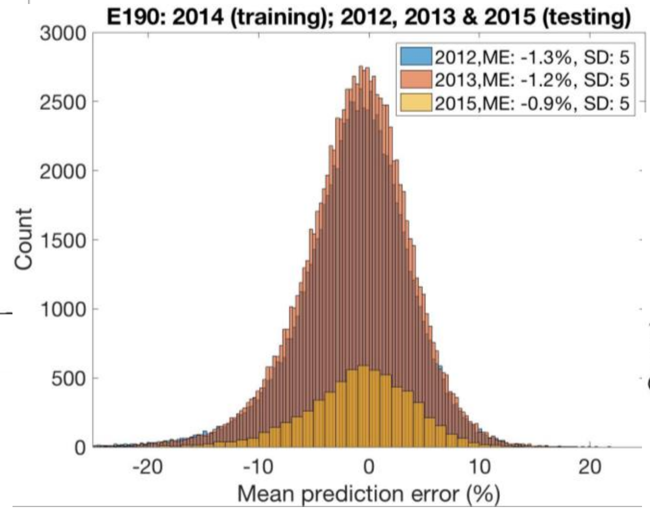


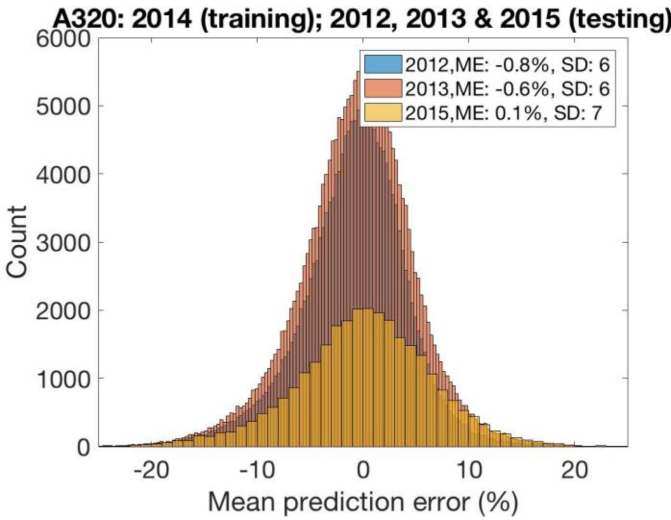
FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Ongoing work

* Fuel burn models for fleet-wide assessment for inventories
* Estimation of components (surface, air) given aggregate fuel burn







FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS