



# The Fourth Component of Societal-Scale CPS: Components That Can Learn

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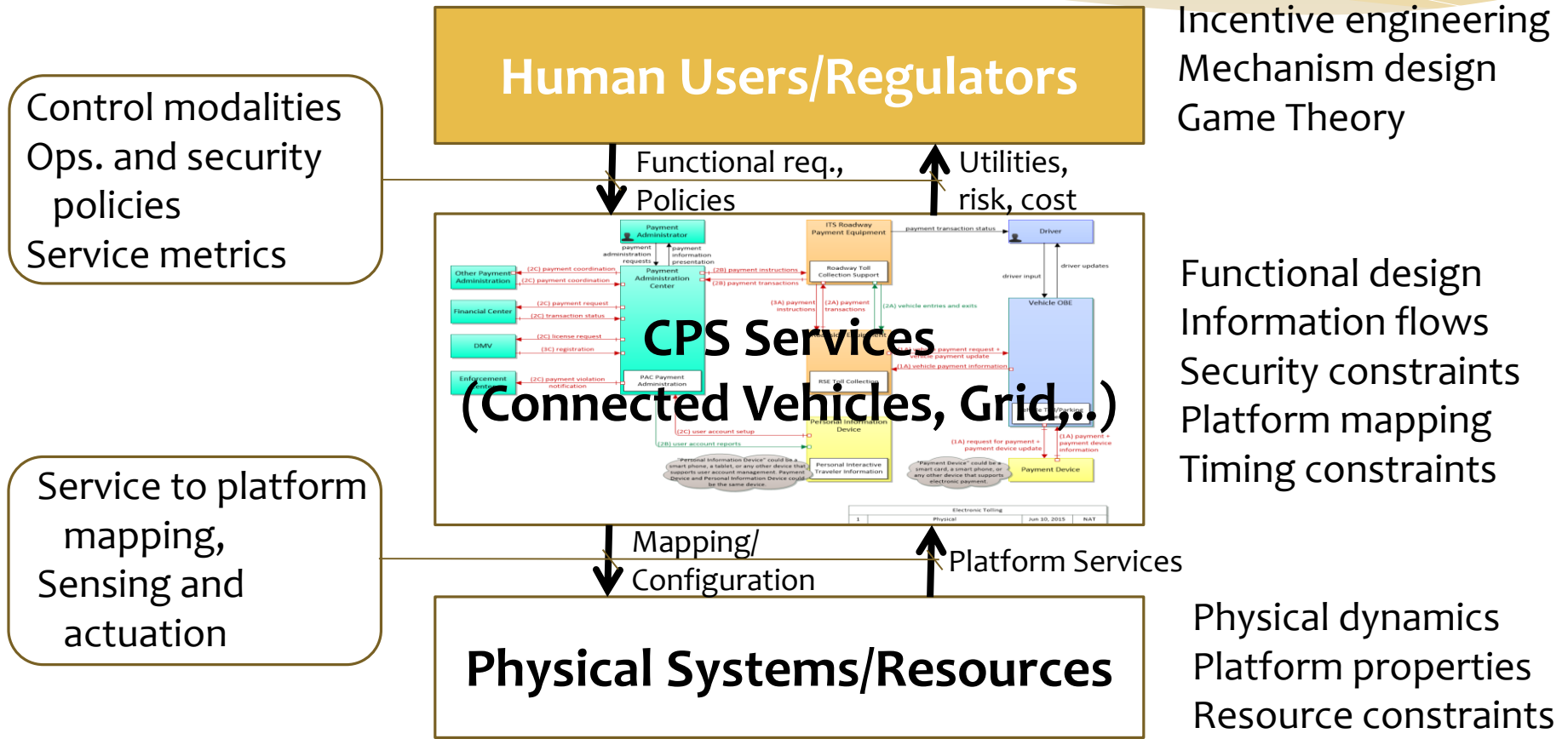
# Societal-Scale CPS

... are enabled by emerging industrial platforms in IoT, II and Fog Computing. Examples addressed by FORCES are:

- \* Transportation networks
- \* Air traffic networks
- \* Energy distribution networks
- \* Water distribution networks

- Humans are “embedded intelligent agents”, human decision making is part of control loops: **H-CPS**
- Massive societal implications trigger conflicting societal expectations and policies: **Policy-aware system design**
- Complexity requires building systems with **Learning Enabled Components: High-confidence system design with components that can learn**

# Modeling and Analysis of Societal-Scale CPS: H-CPS Framework



Approach: Model and Component based design

# Policy-Aware System Design

Controversies created by societal-scale systems now extend to regulations, certification, insurance as side-effects of widespread adaptation. Typical conflict issues are:

- \* Autonomous and Mixed-Use H-CPS (human decision making, automation, social acceptance and liability)
- \* Privacy (utility of services, costs, personal/institutional privacy)
- \* Resilience (design complexity, cost, dependability of services)

Example: dynamic, traffic aware routing

Driver incentive: savings in travel time + fuel

Societal gain: better road utilization

Cost: neighborhoods with increased traffic

Who resolves the conflict?

Two sides of the solution approaches:

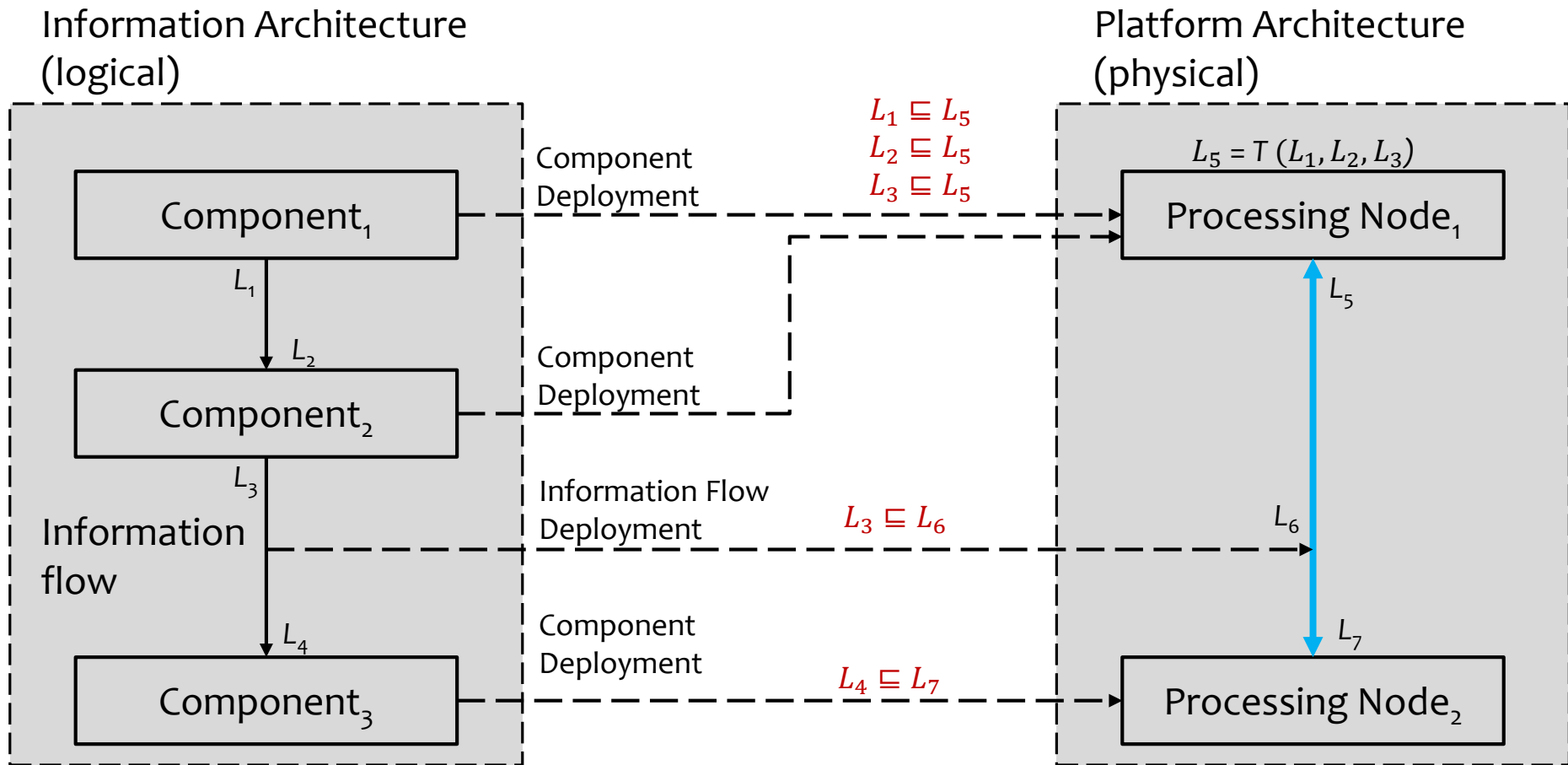
Adjusting public policy to new technology

**Create technology that can be parameterized by societal context**

# FORCES: Security-Aware System-Level Synthesis

- \* How to map a logical Information Architecture (components + information flows) on a physical Platform Architecture such that
  - Functional requirements (the information architecture)
  - Performance requirements (timing)
  - Security requirements (confidentiality and integrity)are satisfied simultaneously?

# Information Architecture Deployed on a Physical Platform



# High-Confidence System Design with Learning-Enabled Components

High confidence systems require pushing the limits of “correct-by-construction” methods.

## – Model-based Technologies

Computational models that predict properties of cyber-physical systems “as designed” and “as built”.

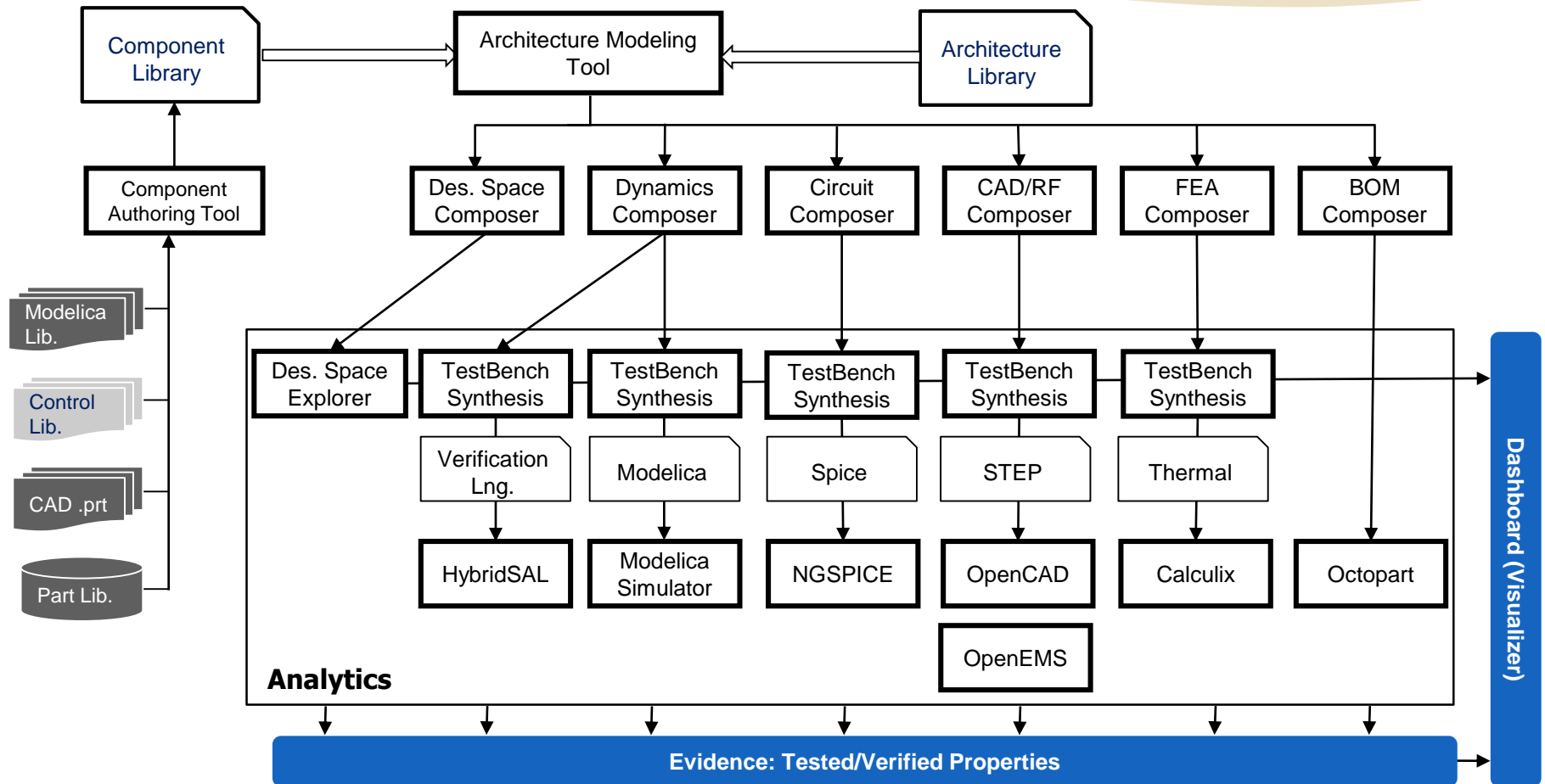
**Challenge: Develop domain-specific abstraction layers for complex CPS that are evolvable, heterogeneous, yet semantically sound and supported by tools.**

## – Component-based Technologies

Reusable units of knowledge (models) and manufactured components.

**Challenge: Go beyond interoperability; find and introduce compositional frameworks where system-level properties can be computed from the properties of components**

# Example for CPS Design Tool Suite: OpenMETA



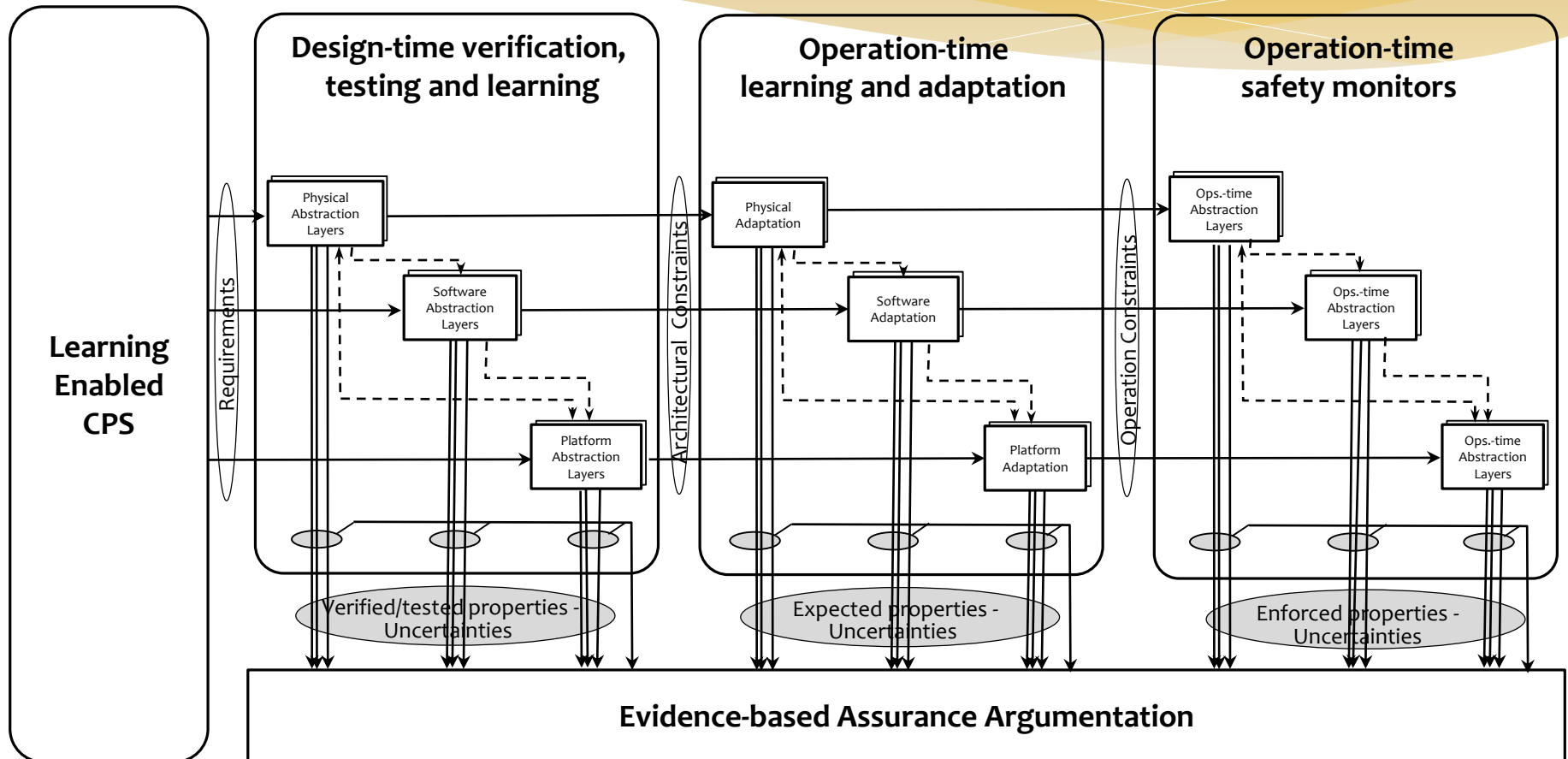


# What Are the Problems With Learning Enabled Components?

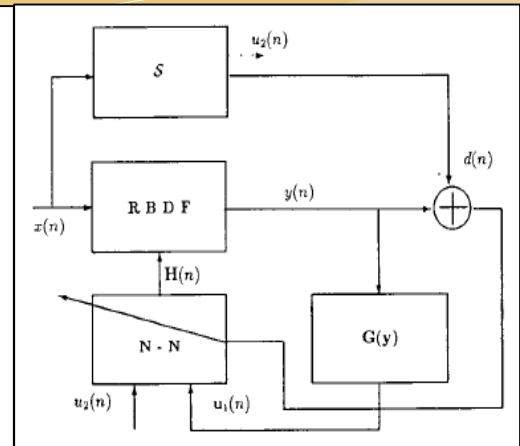
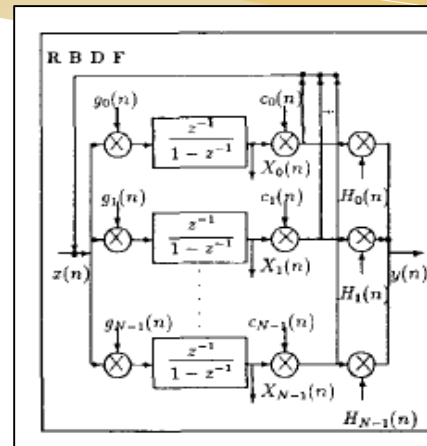
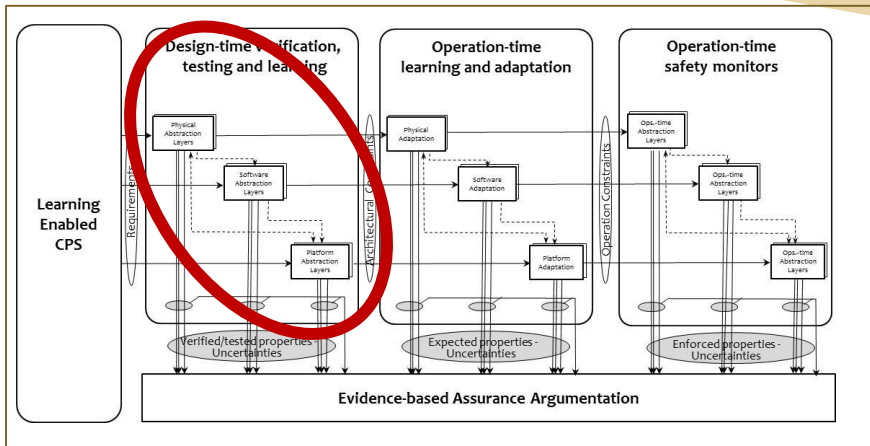
## \* Challenges:

- a. How to guarantee system-level safety/security properties?
- b. How to identify those system components/behaviors in an overall H-CPS architecture that best be implemented using learning/adaptive methods?
- c. How to make tradeoff between design-time invariant models, design-time learning/adaptation and operation-time learning/adaptation?
- d. In learning/adaptive components what is reusable across different systems?

# Reframing the Model-based Design Approach



# Example: Design-time Evidence for Preserving Stability



Structurally passive learning enabled dynamics

## \* Physical Architecture: Passivity-based design

- \* Method: Passivity-based design (e.g. *Proc. IEEE, Vol.100 No.1, pp. 29-44, 2012*)

Outcome: Decouples effects of time varying delays on stability caused by computation and networking effects

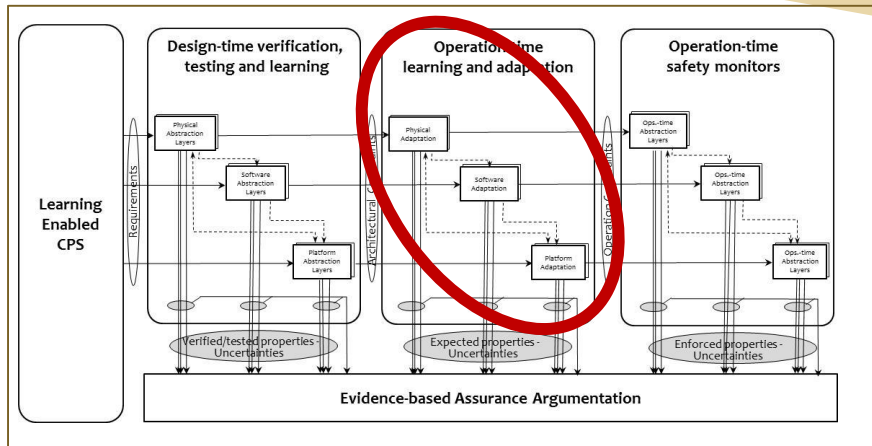
- \* Sztipanovits, J., "Dynamic Backpropagation for Neural Network Controlled Resonator-Banks," *IEEE Transactions on Circuits and Systems*, Vol. 39, No.2, pp. 99-108

## \* SW & Platform: TTA/TTP

- \* Guaranteed deadlock freeness
- \* Bounded delay

## \* Tradeoff between performance and verification complexity

# Example: Embedded Safe Learning



## \* Safe Learning

- \* Method: Learn unknown dynamics based on a Gaussian Process Model and iteratively approximate the maximal safe set Passivity-based design  
Tomlin et al: Reachability-based safe learning with Gaussian Processes. *Proc. 53<sup>rd</sup> CDC 2014*  
Chen, Fisac, Sastry, Tomlin: Safe sequential path planning via double obstacle Hamilton Jacobi Isaacs variational inequalities. *ECC 2016*  
Outcome: Safety is guaranteed during the learning process

## \* Learning approaches:

- \* Gaussian process model
- \* Deep Neural Nets

# Many Open Problems

- \* Models of learning-enabled CPS components whose behavior is bounded and composable in open CPS architectures
- \* Guarantees for Closed Loop Performance of learning-enabled CPS components
- \* Real time metrics for the performance of learning algorithms
- \* Extending model-based design methods with precise representation and utilization of partial (but bounded) models in design flows
- \* Evidence-based assurance argumentation methods that can handle both probabilistic and deterministic methods
- \* Integrated tool chain and model-based design flow that incorporates learning enabled components

# Summary

- \* Societal-scale CPS are enabled by the new platforms: IoT, II and Fog
- \* Impact of these systems requires new architecture, offer new capabilities and create new challenges:
  - H-CPS
  - Policy-aware architectures
  - H-CPS with Learning Enabled Components
- \* Achieving progress in these areas defines the next decade for CPS research