Enterprise Systems Analysis (RT-161)

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Bottom Line Up Front

- Over the past several years, we have completed a series of case studies to evaluate and evolve a methodology to model enterprise systems computationally in support of policy analysis
- While the results of the case studies have been mixed, they led to substantial revisions to the modeling methodology
  - The revised methodology is designed to overcome of some the limitations of “consolidative” modeling approaches
- However, for this methodology to realize its full potential, there are several technical challenges that remain
- Addressing these challenges will require a larger community effort

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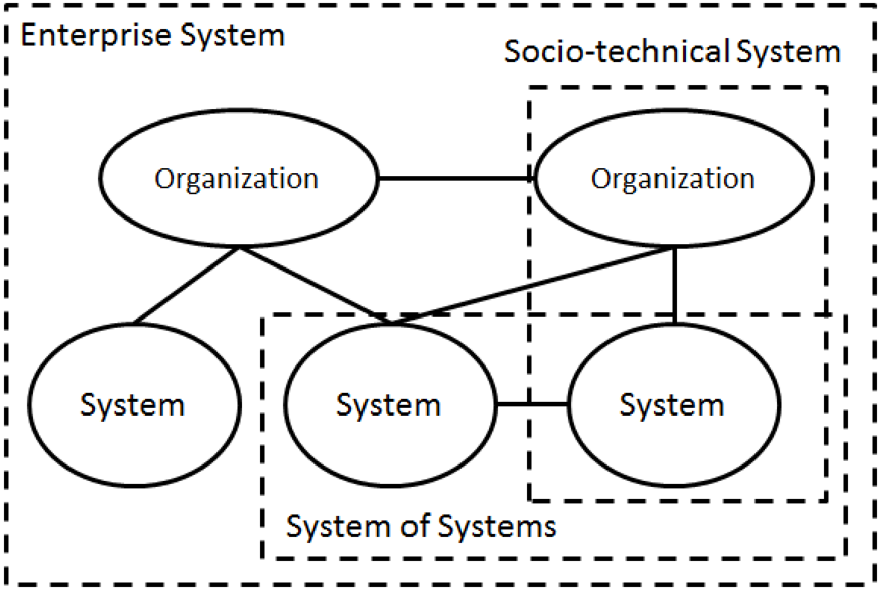
Motivation

What is an enterprise system?

- For this purpose of this presentation, an enterprise system is a collection of interacting organizations that construct and/or operate one or more technological systems to achieve a goal

- Key characteristics:
  - —No central locus of control
  - —Adaptive behavior
  - —Multiple relevant perspectives
  - —Significant interactions between social and technical phenomena



Many Contemporary Challenges are Enterprise Problems

- Many of the challenges that confront the Department of Defense (DoD) today are characterized by the intersection of complex social, political, economic, and technical phenomena
  - —Managing joint and international acquisition programs
  - —Coordinating disaster and humanitarian responses involving governments, NGOs, and US agencies
  - —Sustaining the defense supplier base in the face of declining acquisition quantities
  - —Providing healthcare to service members and their families
- Also relevant beyond DoD
  - —Evolving the US healthcare system
  - —Ensuring resilient infrastructure
  - —Understanding the impact of autonomous vehicles on cities

The Complexity of Enterprises Systems Leads to Unintended Consequences

- When faced with an “enterprise” problem, policymakers, managers, and engineers would like to have some understanding of the potential consequences of a decision before making it
- Unfortunately, the complexity of enterprise systems makes this difficult to accomplish
- No one expects to be able to make a perfect prediction of policy impacts
  - —The Law of Unintended Consequences
- However, if it were possible to identify at least of some of the higher-order or “counterintuitive” effects prior to a decision, it could be extremely valuable

Enterprise Systems are Proliferating

- Is this a new problem?
  - NO
- How was it handled in the past?
  - Expert opinion, scenario analysis, gaming exercises, custom built simulations
- What is different now?
  - The growth of communications networks have increased decentralization and increased the speed of interactions
  - Enterprise systems of today adapt and evolve faster than ever
  - Increasing numbers of autonomous systems will exacerbate this problem
  - There is not enough time or enough experts available to support every decision that needs to be made

A Rapid Way to Detect Unintended Consequences is Needed

- We need a way to rapidly analyze one or more policy options and detect potential higher-order effects
  - This is a deliberately ambitious goal
  - But for many decisions, the results of a six-month study effort will be too late to matter
- In principal, computational modeling could provide the speed, but there are several challenges:
  - How do we generate “unintended consequences” within the models?
  - How do we integrate relevant knowledge into the models quickly?
  - How do we hand the “multi-scale” nature of enterprise systems?

Framing the Problem

Four Levels of Uncertainty

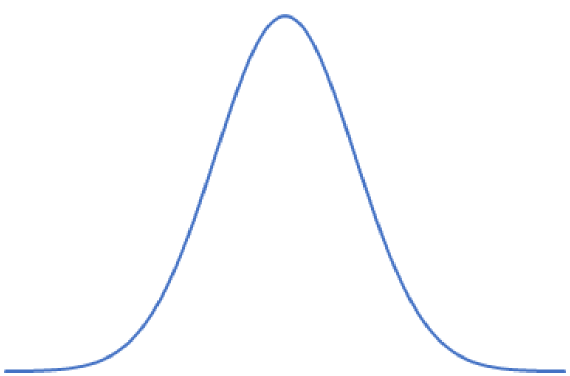
- Courtney, et al (1997) postulated four levels of uncertainty and associated strategies
  - — Courtney, H., Kirkland, J., & Viguerie, P. (1997). Strategy under uncertainty. Harvard business review, 75(6), 67-79.
- Level 1: Clear enough future
  - — Uncertainty is low enough that single forecast is sufficient
  - — Strategies: conventional planning, adapting
- Level 2: Alternative Futures
  - — Uncertainty is higher but falls into several discrete scenarios
  - — Strategies: shaping, hedging, adapting
- Level 3: Range of Futures
  - — A range of outcomes are possible but are dependent on a few variables
  - — Strategies: shaping, hedging, adapting
- Level 4: True Ambiguity
  - — Impossible identify a range of outcomes or relevant variables
  - — Strategies: Shaping

Formalize with the Posterior Distribution

- We can characterize the problem formally using a Bayesian approach

$$P(H|E) = \frac{P(E|H)}{P(E)} P(H)$$

- In essence, we are asking what the posterior distribution will look like once we consider all available information



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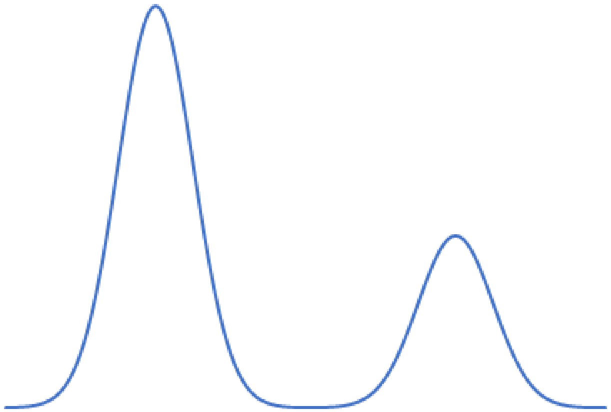
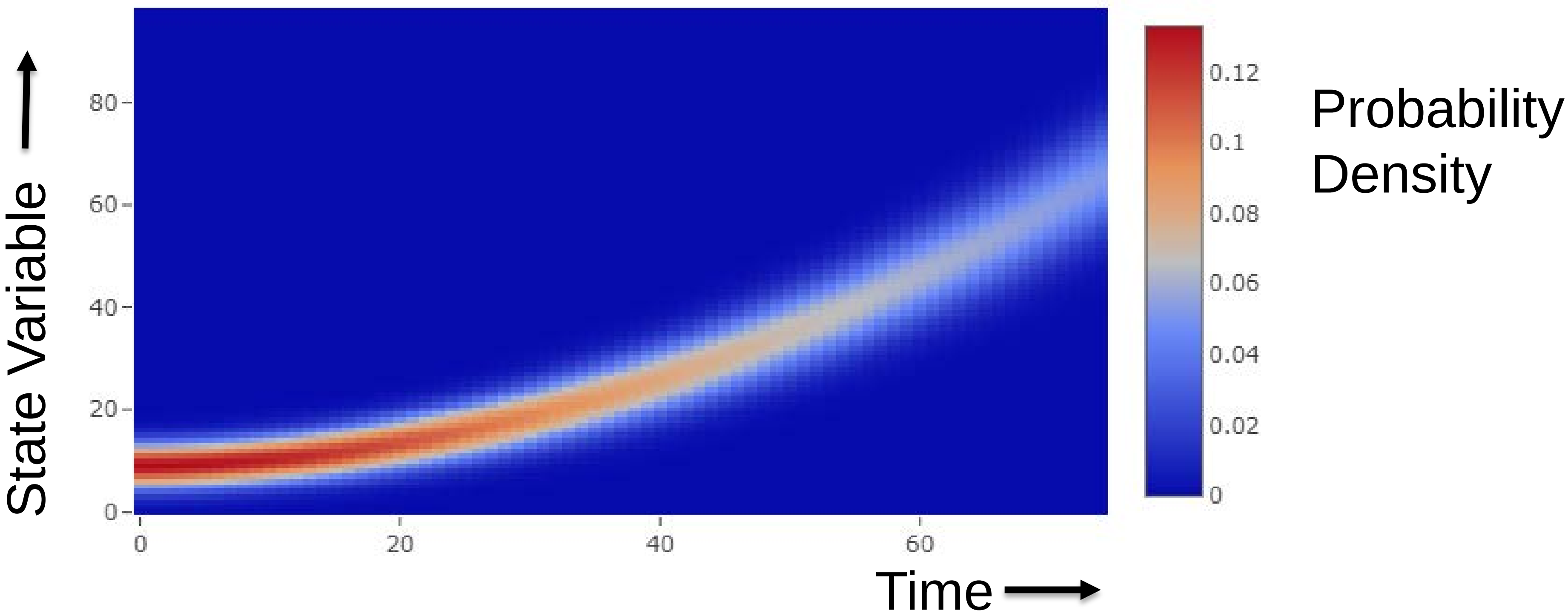


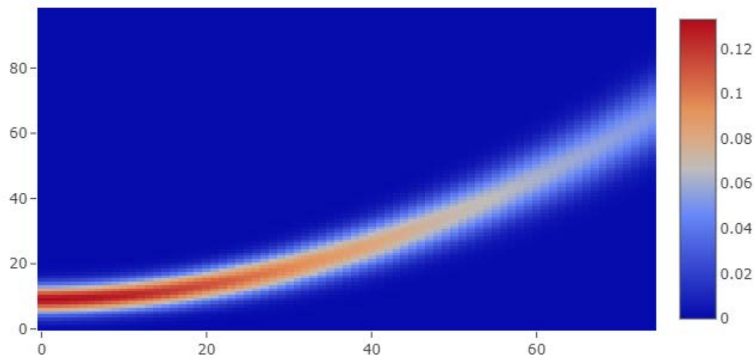
Depicting the Uncertainty

- Since we are interested in dynamic scenarios, we will use the notional heat map below to illustrate the differences in uncertainty levels

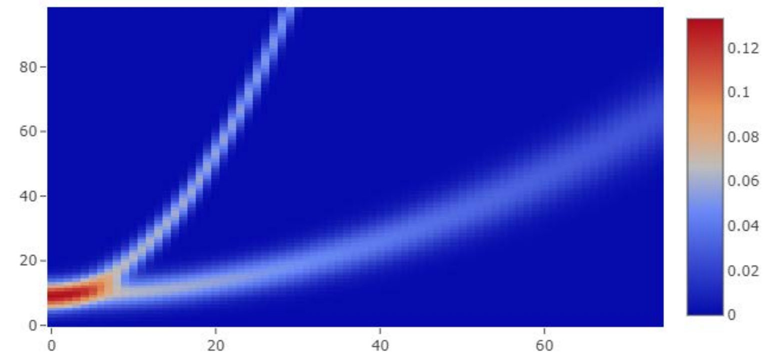


Depicting the Uncertainty Levels

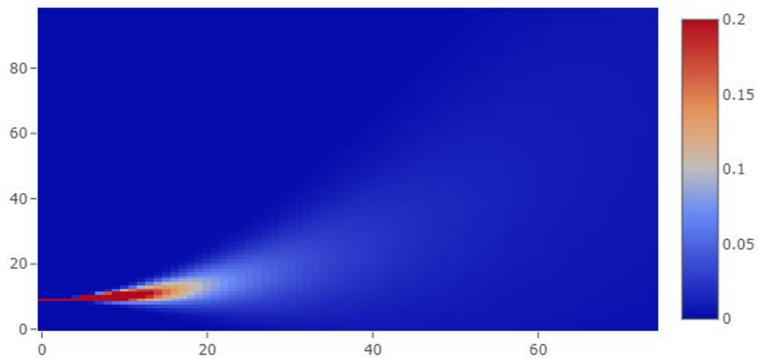
Level 1



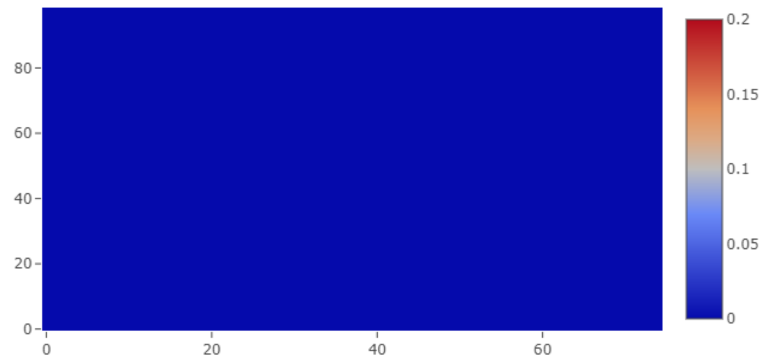
Level 2



Level 3



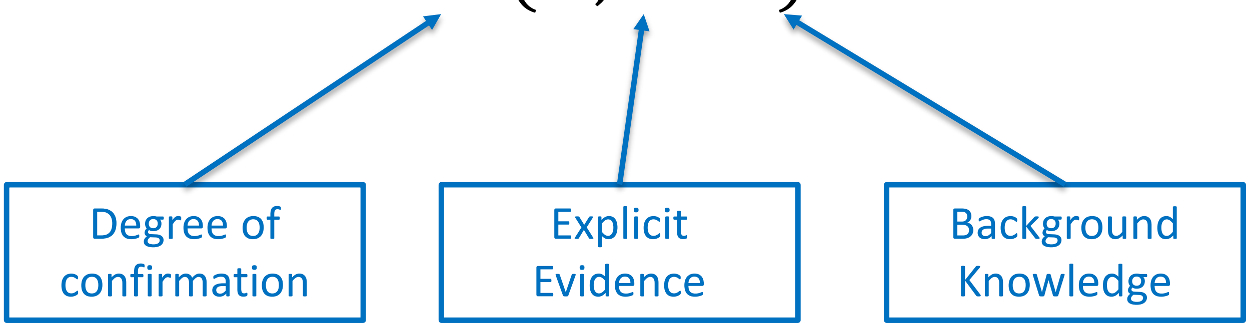
Level 4



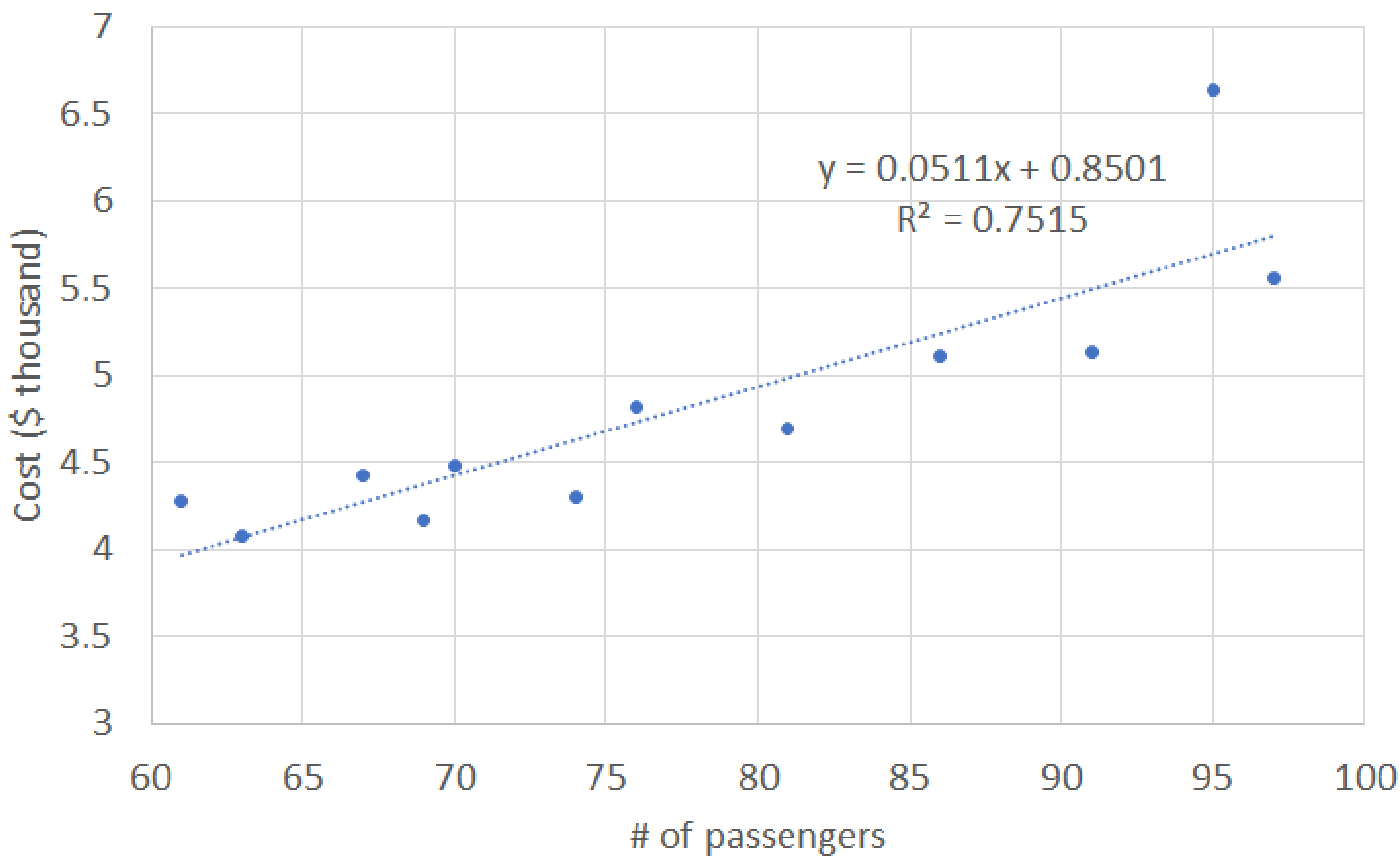
Integrating Expertise and Simulation

- Helmer and Rescher (RAND) consider how the use of simulation and expert judgement can be justified in the “inexact sciences”
  - —Helmer, O., & Rescher, N. (1959). On the epistemology of the inexact sciences. *Management science*, *6*(1), 25-52.
- Their argument is effectively Bayesian

$$dc(H, E\&K)$$

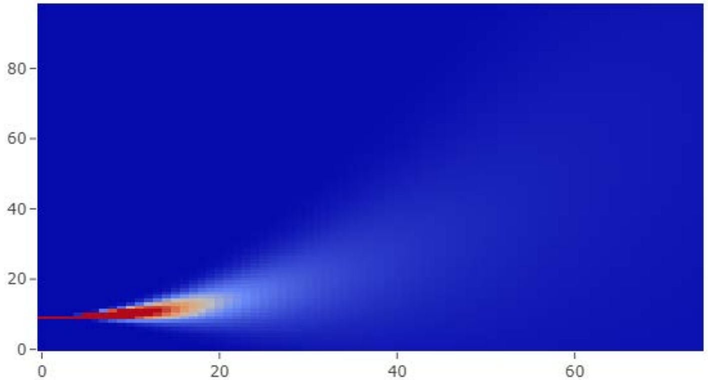


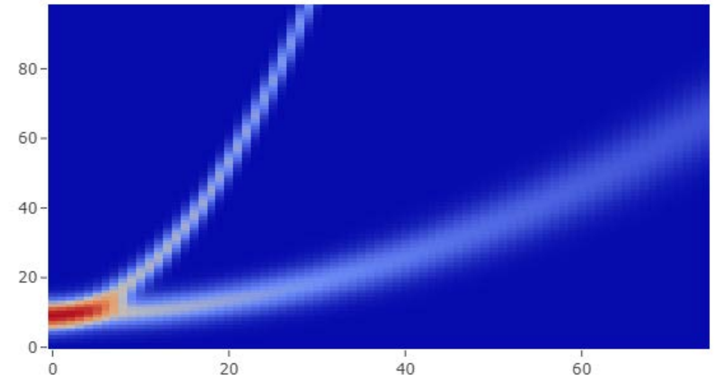
Why Background Knowledge Matters



Background Knowledge May Tighten Up the Distribution

- When used effectively, background knowledge can rule out many potential scenarios and "tighten up" the posterior distributions
- For example, it might be able to…





Turn this

Into this

Why Not Machine Learning?

- The challenge is that the background knowledge, ‘K,’ is not always framed in a way that can be easily combined with the explicit evidence, ‘E,’
  - Makes it challenging to integrate K computationally
- Question: Isn’t this what machine learning does?
- Answer: Not exactly
- Machine learning focuses on ‘E’ only. There is some evidence that with massive amounts of data, ML can emulate aspects of structure that might be called ‘K’-like.
  - If the relevant phenomena are not in the data, ML can never learn it

Accelerating Learning Using Hierarchical Bayesian Models

- Tenenbaum et al. looked at how to emulate the human ability to learn with relatively limited data
  - Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. *Science*, *331*(6022), 1279-1285.
- Using Hierarchical Bayesian Models (HBMs), they were able to "learn" abstract structure from data, emulating the accumulation of abstract knowledge
  - Their models were able to learn structures like trees, rings, and chains
- The net result is that their models were able to learn with much smaller data sets that traditional ML techniques
  - This means that the abstract structures ruled out many possibilities and allowed the algorithm to learn much more quickly

Integrating Knowledge Using Hierarchical Bayesian Models

- Work like Tenenbaum et al.'s shows that it is at least possible to emulate the human application of background knowledge computationally using a Bayesian approach
- Of course, we are not limited to learning the background knowledge from raw data
- A vast amount of background knowledge has already been accumulated over millennia of human experience
- We can already integrate this knowledge into computational models on a case-by-case basis.
- The question is how do we do it a more rapid, flexible way?

It is Necessary to Explore Different Subsets of Knowledge

- Bankes (RAND) defined the problem as one of “consolidative modeling” versus “exploratory modeling”
  - —Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations research*, *41*(3), 435-449.
  - — Consolidative models are built “by consolidating known facts into a single package and then using it as a surrogate for the actual system.”
  - — Exploratory models involve multiple “computational experiments to explore the implications of varying assumptions and hypotheses.”
- With exploratory modeling, Bankes is referring to something more than traditional sensitivity analysis.
  - — He means that in exploratory modeling, one experiments with different model structures
  - — We could view this as exploring different subsets of ‘K’

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Most Computational Modeling Artificially Restricts Knowledge

- Bankes asserts that most computational modeling is consolidative
  - Most of the time we build a model that fits the available data
  - This effectively restricts to a ‘K’ to subset
- Bankes attributes many of the problems associated with using simulations for policy analysis to the improper use of consolidative modeling when exploratory modeling would be more appropriate
  - By artificially restricting ‘K’ we miss many possibilities
  - However, throwing everything into the model at once just makes a mess
  - What is needed is a way to systematically explore subsets of ‘K’
- Bankes acknowledges that a major challenge to exploratory modeling is determining a basis of variation
  - i.e., how would your parse up and search ‘K’?

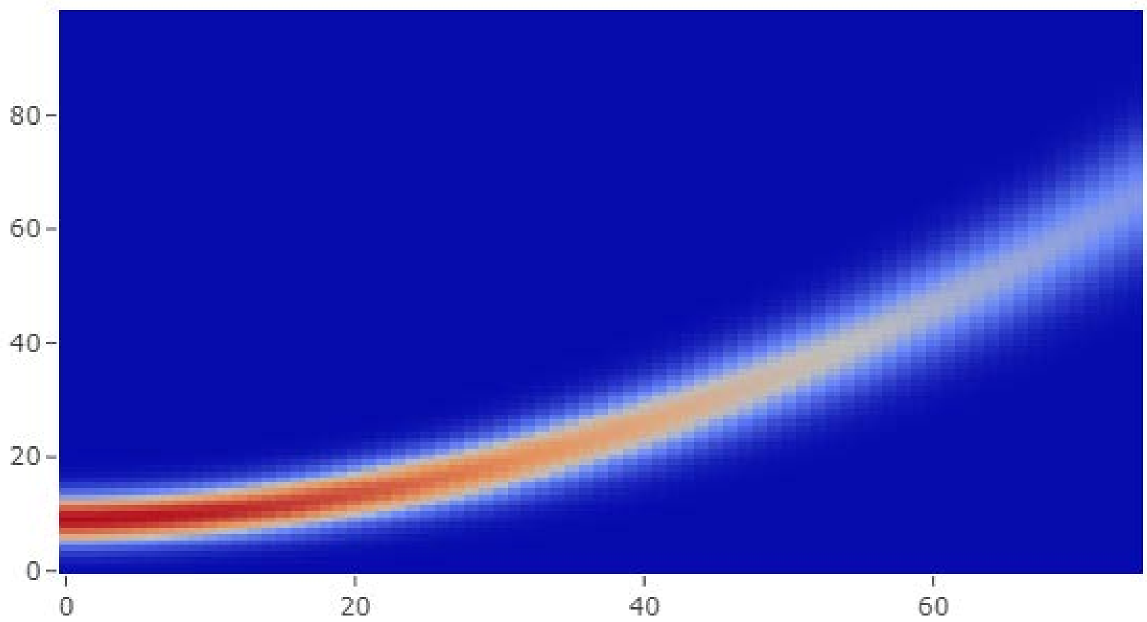
Organizing and Searching Knowledge Is Problematic

- Abbott makes comparable observations to Bankes though he emphasizes the multi-level nature of systems problems
  - —Abbott, R. (2007). Putting complex systems to work. *Complexity*, *13*(2), 30-49.
- Consequently, he deems the challenge one of building a simulation with a dynamic floor
  - — He asserts that we do not know how to do this
- We could view this as another form of searching subsets of ‘K.’
  - — We might loosely organize the elements of ‘K’ into layers of abstraction or scales, but we are still left with a challenging search and composition problem

Typical Simulation Approaches Work with Level 1 Uncertainty

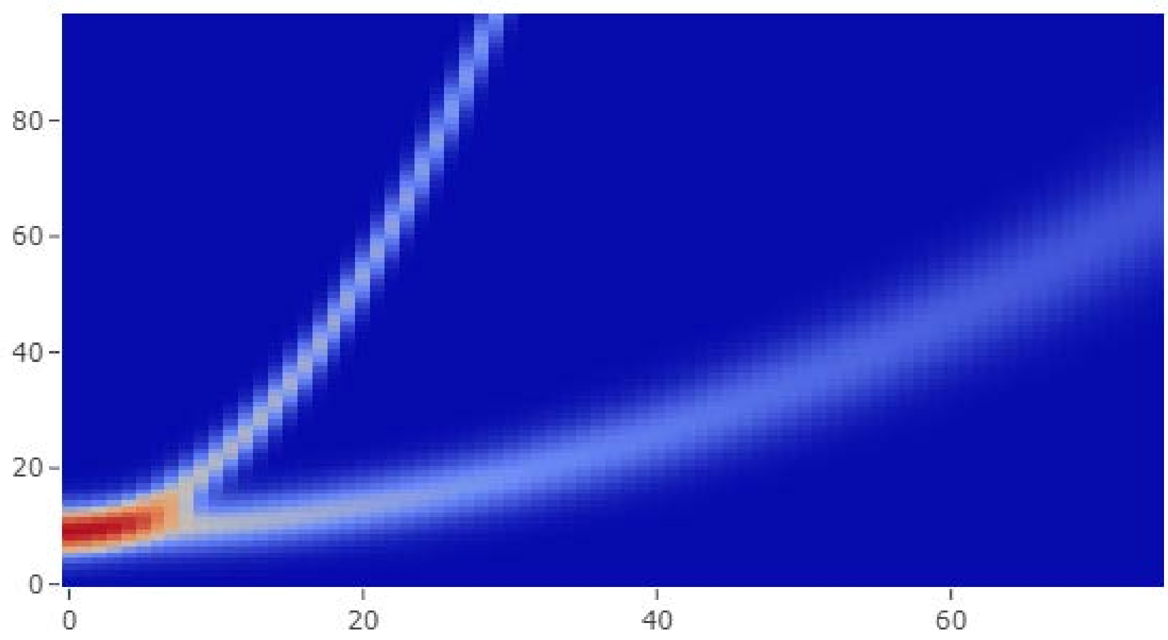
- Consolidative modeling is good for dealing with Level 1 uncertainty

- i.e., a consolidative model generates this:



Typical Simulation Approaches Would Not Work Well for Leve 2 or 3

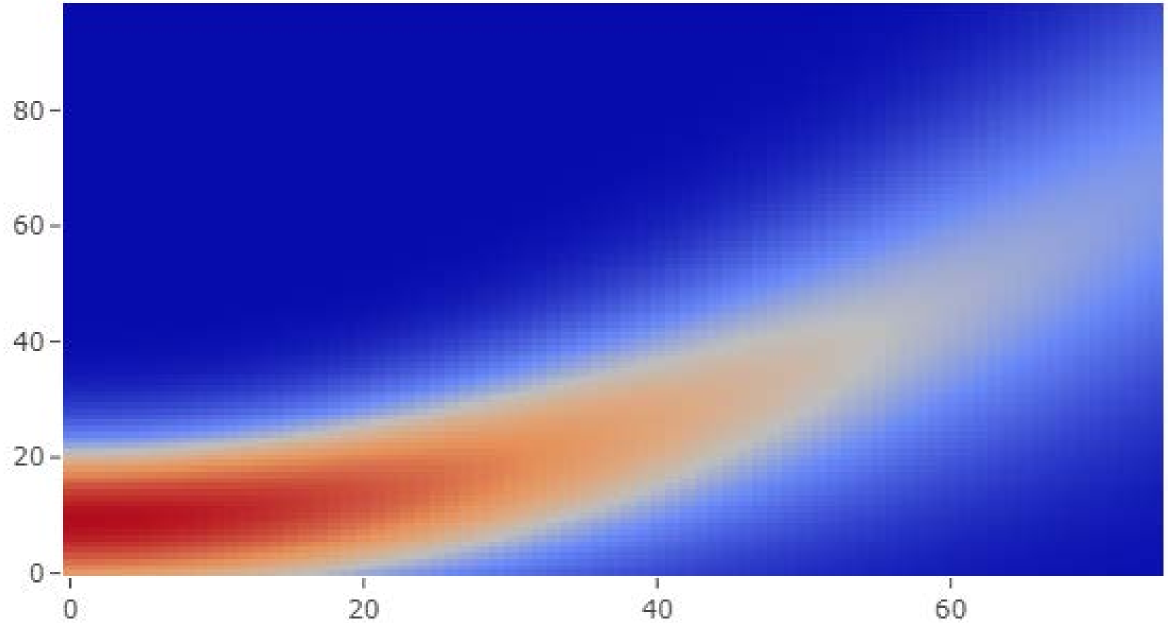
- …but it probably would not generate this



- In other words, consolidative modeling is not good at dealing with Level 2 or 3 uncertainties

Some Uncertainty Quantification Approaches Probably Make the Problem Worse

- Some uncertainty quantification approaches that just “layer on” the uncertainties, just make a mess



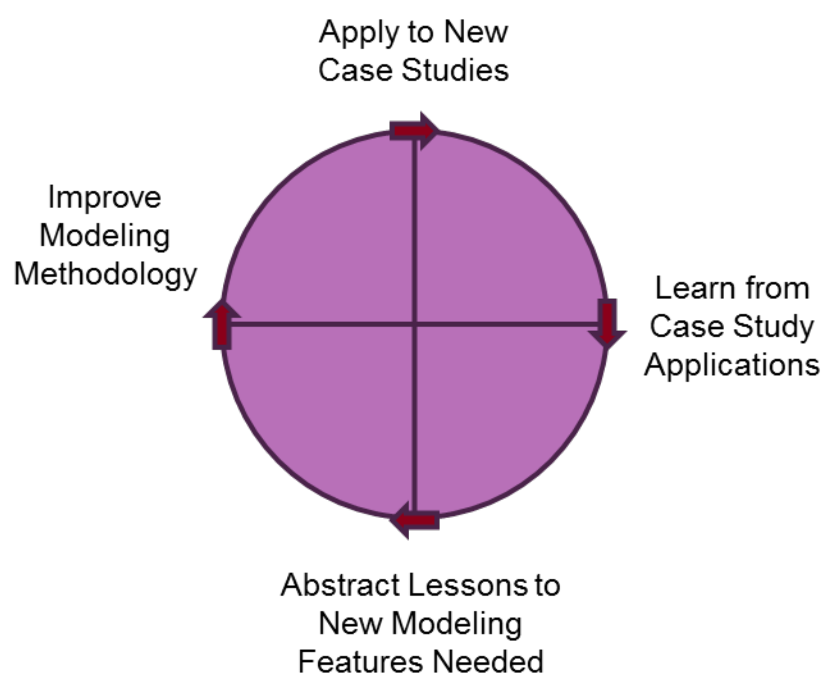
- What is required is a Bayesian approach that provides a systematic way to integrate relevant subsets of K

Progress to Date

The Research Effort has Followed an Iterative Approach

- Create methodology to model and analyze enterprises in systems engineering context
  - No locus of control
  - Adaptive behavior
  - Multiple perspectives (and thus modeling formalisms)
- Case study applications
  - Test and improve methodology
  - What perspectives and modeling approaches are useful?
  - How should they be included?

Enterprise Modeling Methodology and Case Study Iteration



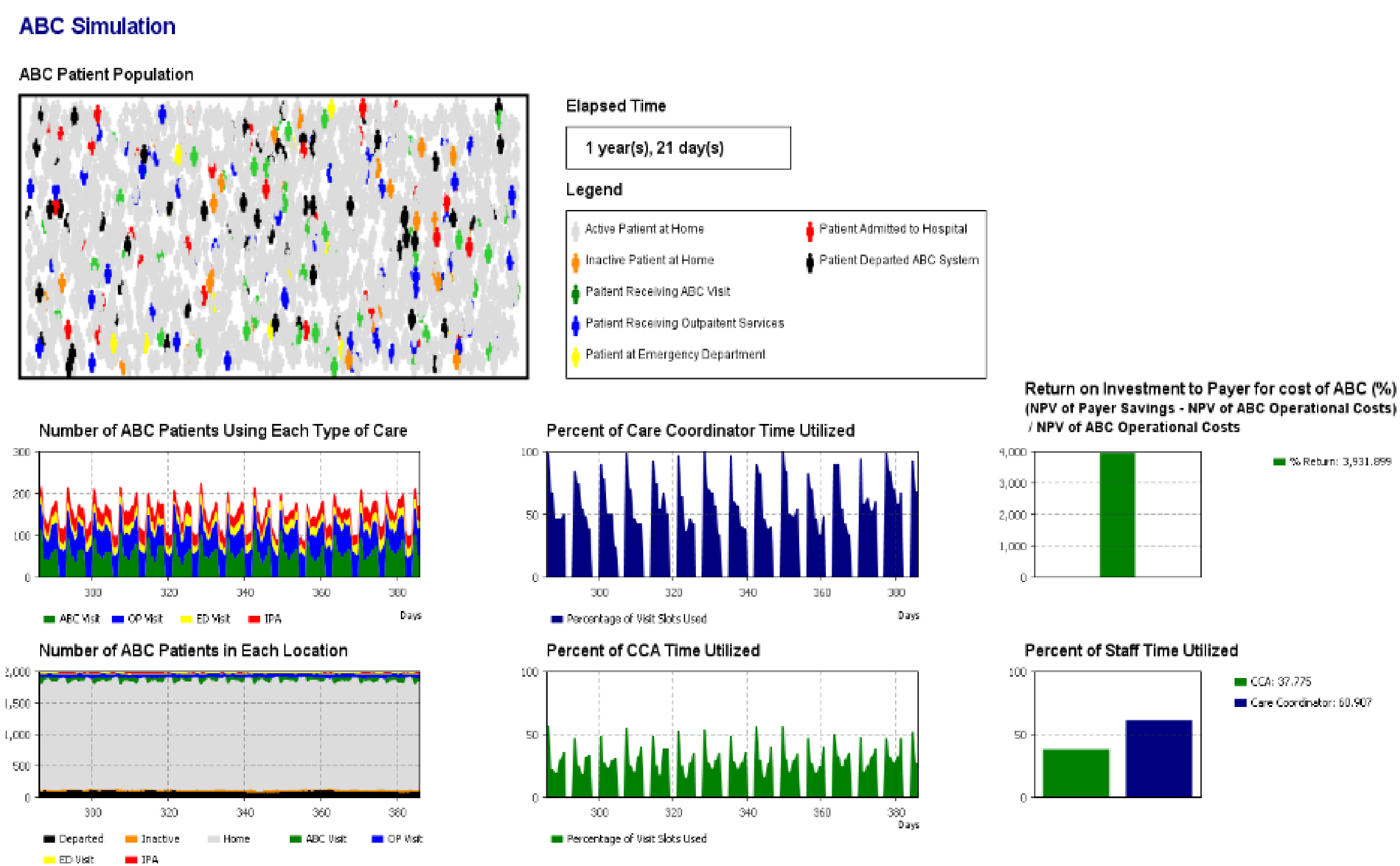
Initial Modeling Methodology

1. Decide on the central questions of interest
2. Define key phenomena underlying these questions
3. Develop one or more visualizations of relationships among phenomena
4. Determine key tradeoffs that appear to warrant deeper exploration
5. Identify alternative representations of these phenomena
6. Assess the ability to connect alternative representations
7. Determine a consistent set of assumptions
8. Identify data sets to support parameterization
9. Program and verify computational instantiations
10. Validate model predictions, at least against baseline data

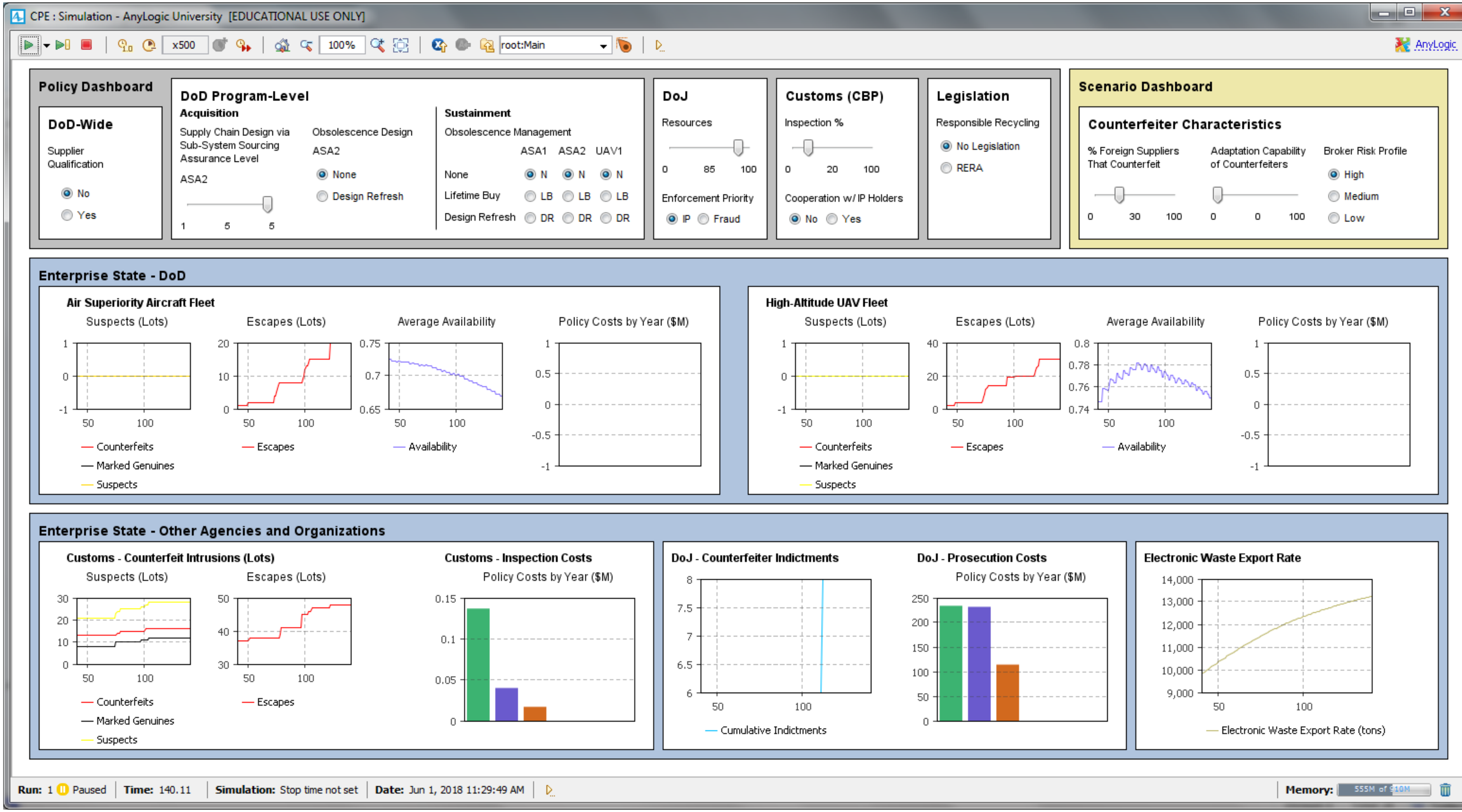
The Four Cases Led to Improving Approaches

Case	Sponsor	Outcome
Expansion of Aging Brain Care Program	CMS	Effectively a consolidative model
Combating Counterfeit Parts in the Defense Supply Chain	SERC (RT-110, RT-138)	Effectively a consolidative model, but with some multi-perspective features
Adoption of the Transitional Care Model	RWJF	A step toward an exploratory modeling with two different loosely connected models at different scales
Protecting Critical Infrastructure	SERC (RT-161)	A step toward an exploratory model: threats to infrastructure were implemented as modules

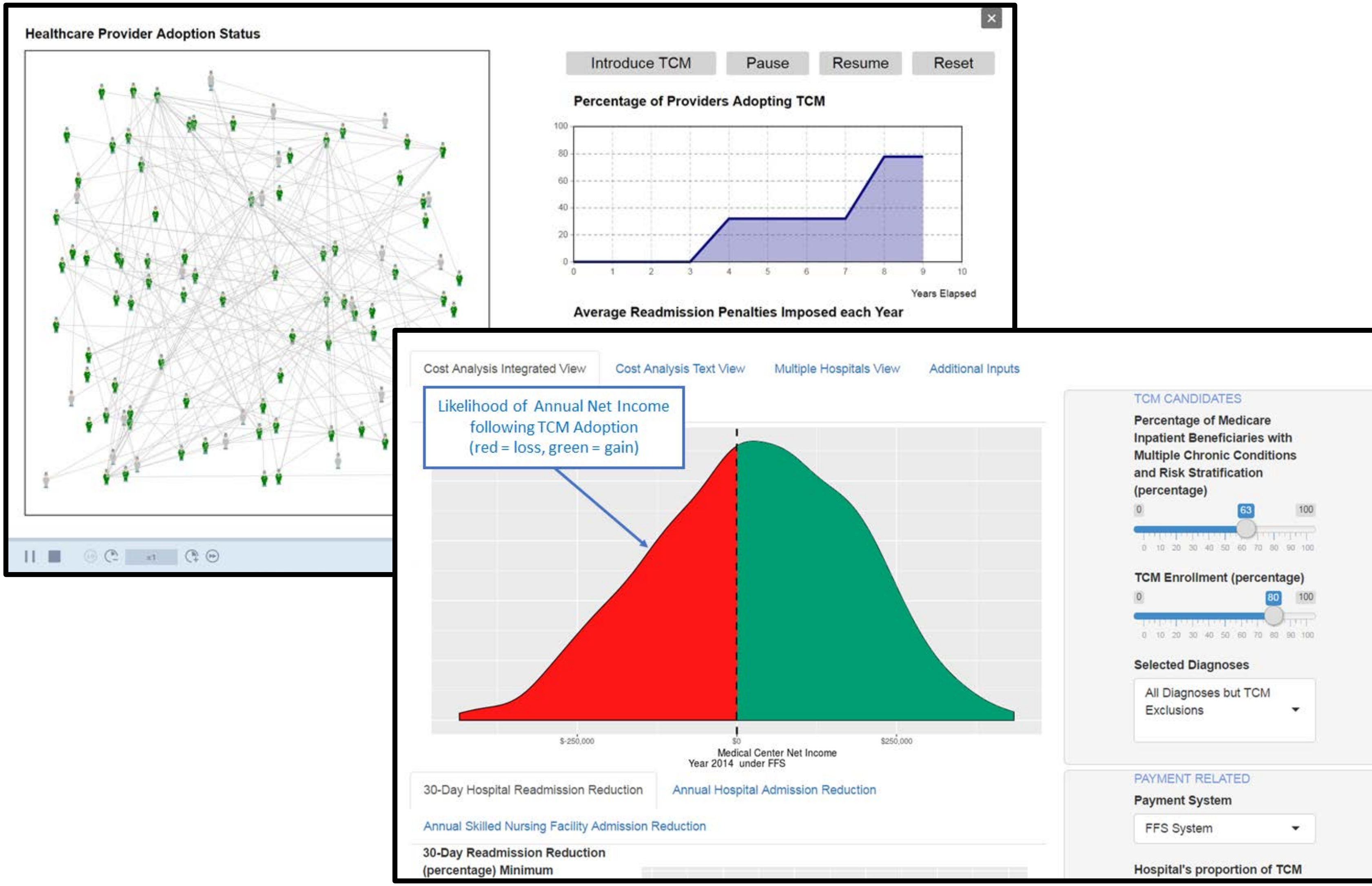
Expansion of Aging Brain Care Program



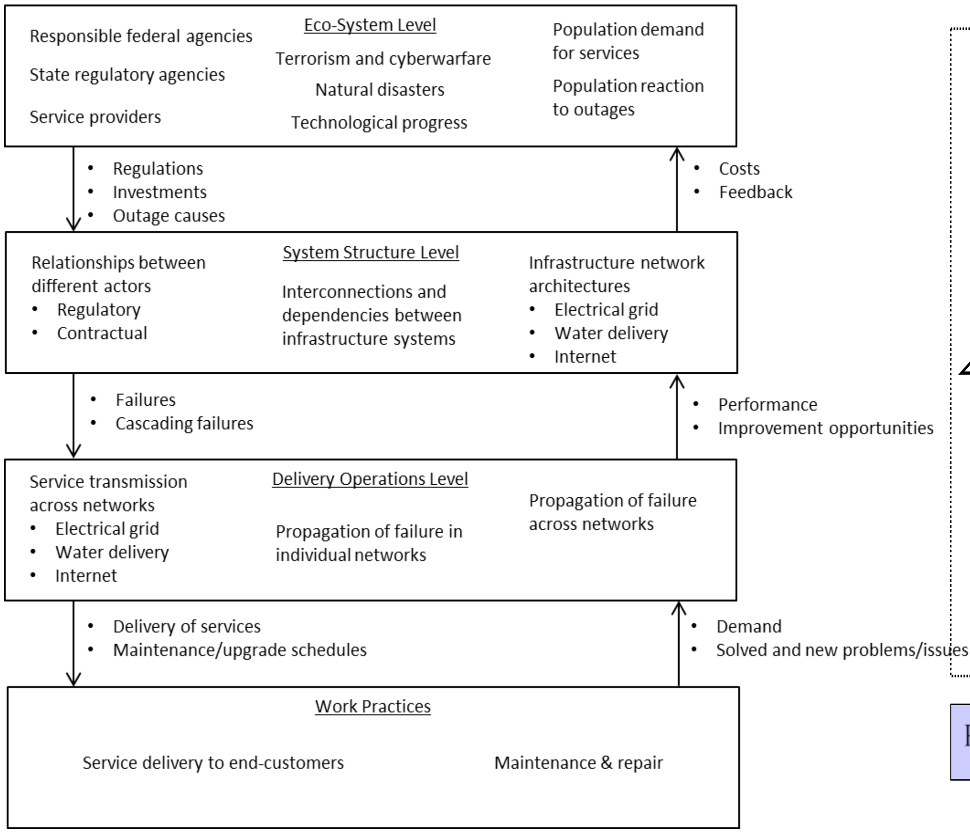
Combating Counterfeit Parts

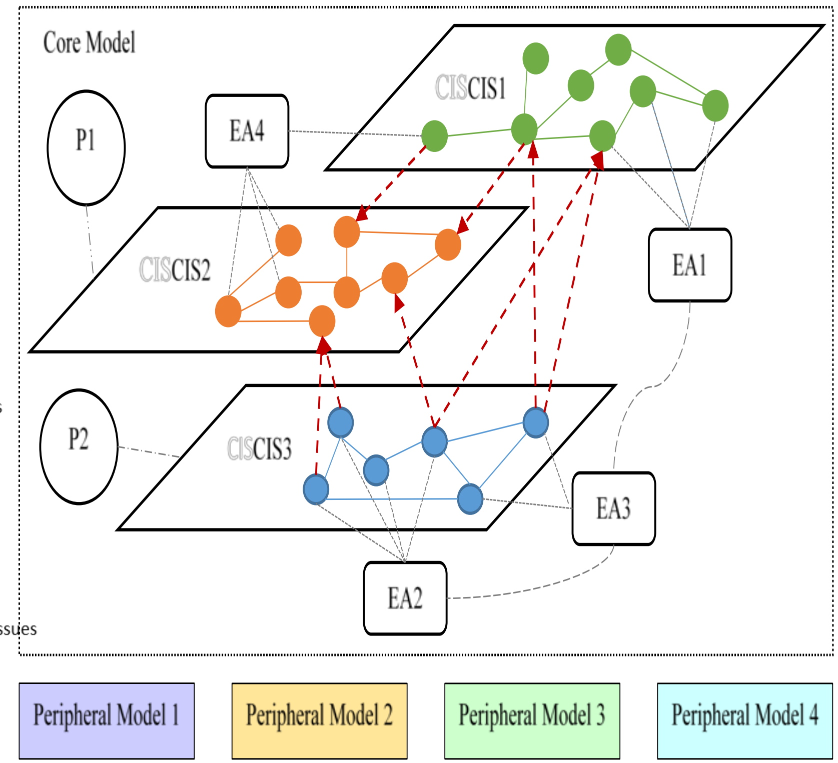


Adoption of the Transitional Care Model



Protecting Critical Infrastructure





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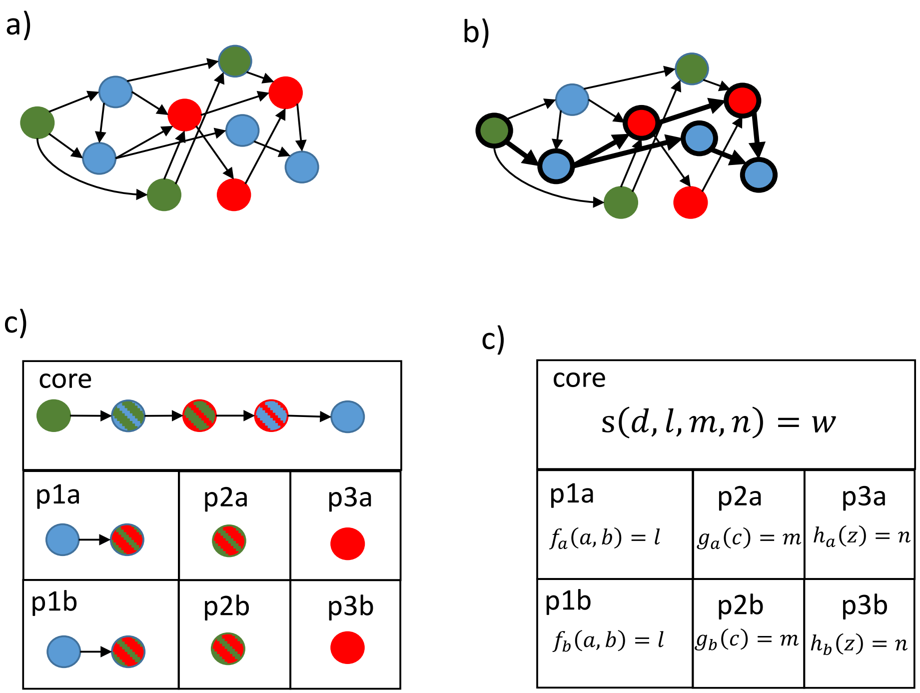
Core-Peripheral Approach

- Over the course of the case studies, we started developing a core-peripheral approach
- The core is the conventional or steady state linkage from decision variables to outcome variables.
- The peripheral models represent phenomena that disrupt the control linkage
  — Essentially peripheral models represent alternative subsets of ‘K’



Revised Methodology

- The modeling methodology was substantially revised to consist of three phases:
- Phase 1: Identify, Model, and Validate the Core Relationships
  - Ensure that the core model can represent the "as is" scenario
- Phase 2: Introduce and Model Peripheral Relationships to Generate Scenarios
  - Use a formal experimental design to generate scenarios using peripheral models
  - Screening procedures reduce the generated scenarios to a reasonable set
- Phase 3: Communicate with Stakeholders via Interactive Interface and Visualizations
  - Vet the most important scenarios and communicate them to stakeholders

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Revised Methodology

- Major goals of the revision:
  - Explicitly avoid using the same simulation to both generate and communicate scenarios
  - Lock down the core before you experiment with peripheral models to maintain credibility
  - Include an explicit experimental design for the use of peripheral models to avoid confounding and idiosyncratic analyses
- Each phase contains a number of detailed steps that provide additional guidance to enterprise analysts
- Added role definitions and recommended participants for each step of the methodology

Next Steps

Current State of the Research

- The revised methodology provides a process that is consistent with what is needed, but it there are several technical challenges that must be overcome to allow for rapid analysis
  - We are still custom building each simulation
- We have not fully instituted a Bayesian approach yet
  - Still generating scenarios using directly coupled models
- We do not have an approach to characterize, store, search, and compose “knowledge” in the form of a library
- Characterizing knowledge from the social sciences is still problematic

Many are Already Looking at These Challenges

- A Recent NSF workshop report discusses several of these challenges in greater depth:
  - Fujimoto, R., Bock, C., Chen, W., Page, E., & Panchal, J. H. (Eds.). (2017). *Research Challenges in Modeling and Simulation for Engineering Complex Systems*. Springer.

- For a quicker overview see:
  - Taylor, S. J., Khan, A., Morse, K. L., Tolk, A., Yilmaz, L., Zander, J., & Mosterman, P. J. (2015). Grand challenges for modeling and simulation: simulation everywhere—from cyberinfrastructure to clouds to citizens. *Simulation*, *91*(7), 648-665.

Research Needs to Rapidly Analyze Enterprise Systems

1. Theory for partitioning and refactoring models for reuse
2. An organizational scheme for refactored models
3. An algebra for combining models
4. Handshake rules for imperfect combinations of models
5. A systematic approach for exploring structural variations on models
6. A language for specifying model needs that determines the model composition and data integration scheme
7. A systematic approach to integrate qualitative social science findings with quantitative engineering models
8. Uncertainty quantification and model validation for composite models

Questions?