

UNIANDES-UNIFI
Secondment kickoff:
Stochastic Optimization for CPSs

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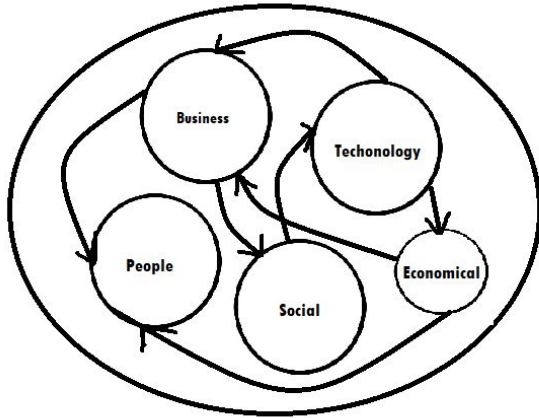
Decision Analytics Lab

Industrial Engineering at Uniandes

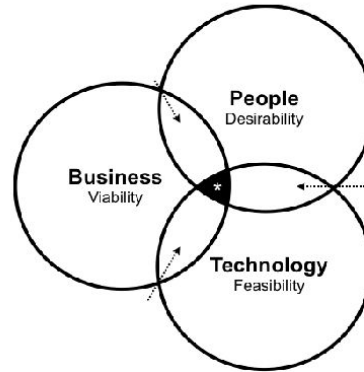


Analytics-based systems design

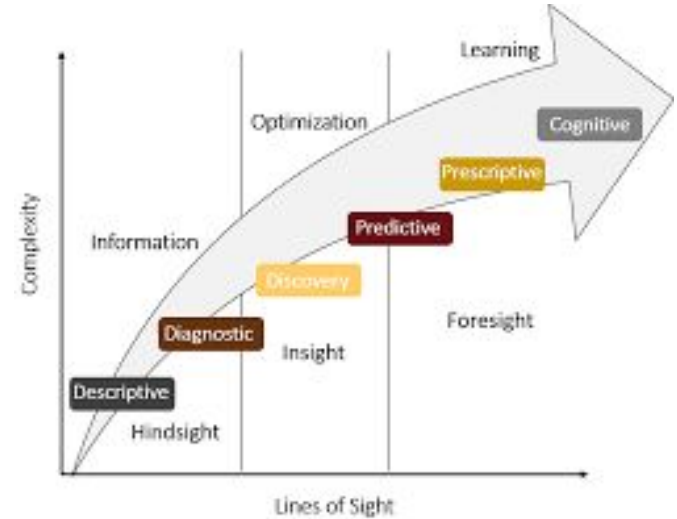
Systems Thinking



Design Thinking



Decision Analytics



COPA Research Group @ Uniandes



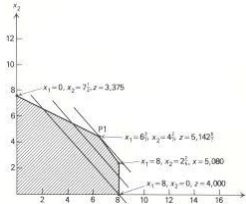
Operations Research (OR)

- Mathematical modeling

- Probabilistic
- Statistical / ML
- Simulation
- Optimization

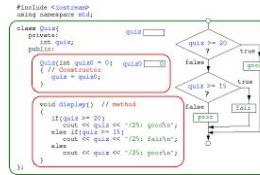
- Algorithmic design

- Decision Support Systems



- Production
- Logistical
- Infrastructure
- Energy
- Health
- Urban
- Financial

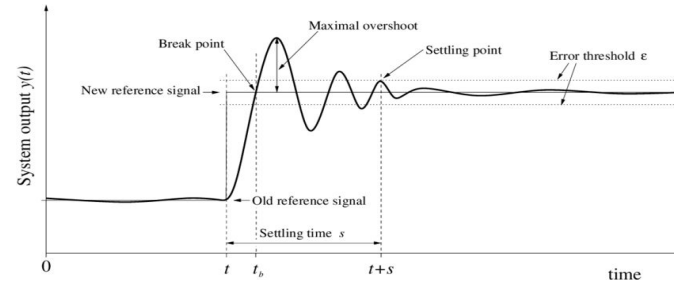
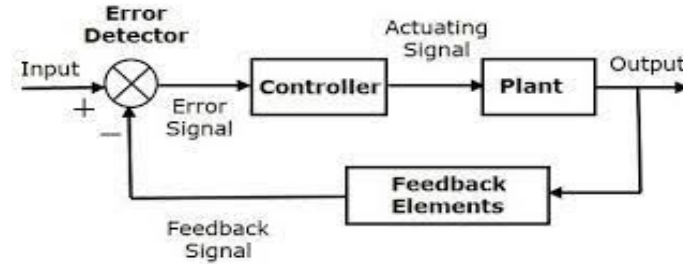
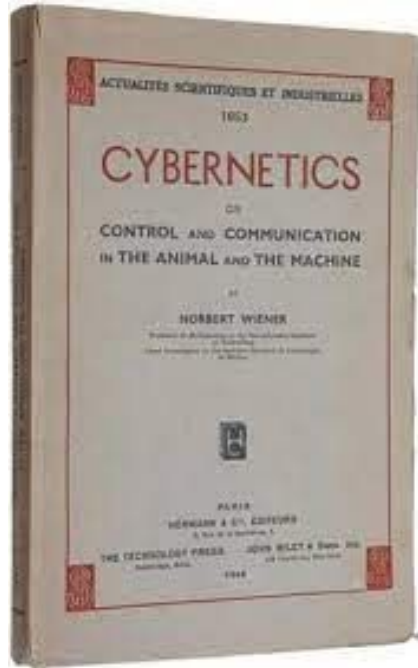
systems



Cybernetics and complex systems background



Systems concepts behind analytical tools

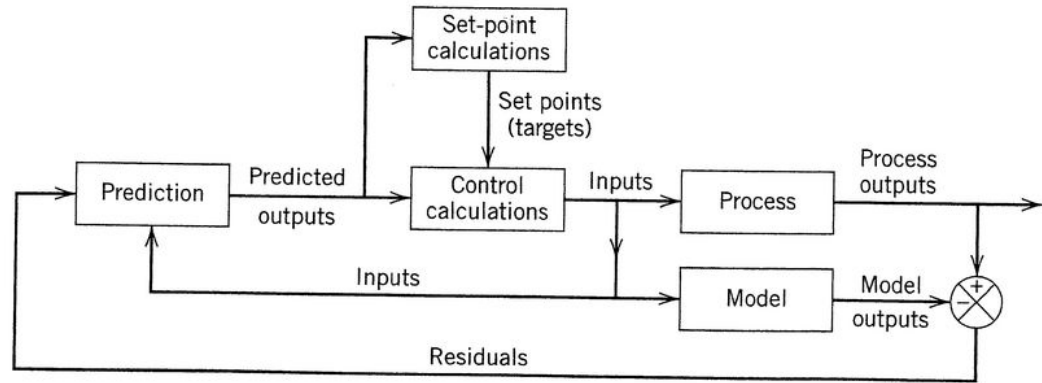


Optimization and control

A cybernetical ancestor of stochastic optimization



Anti-aircraft missile



Model Predictive Control

Research communities in Stochastic Optimization



- **Decision trees**
- Stochastic search
- Optimal stopping
- **Optimal control**
- **Markov decision processes**
- Approximate/adaptive/neuro-dynamic programming
- **Reinforcement learning**
- Online algorithms
- **Model predictive control**
- **Stochastic programming**
- **Robust optimization**
- Ranking and selection
- **Simulation optimization**
- Multiarmed bandit problems
- **Partially observable Markov decision processes.**

*How do I model and control
unknown external aspects
that can make my system go wrong?*

Powell, W. B. (2019). **A unified framework for stochastic optimization**. European Journal of Operational Research, 275(3), 795-821.

Prof. Powell's proposed unifying framework



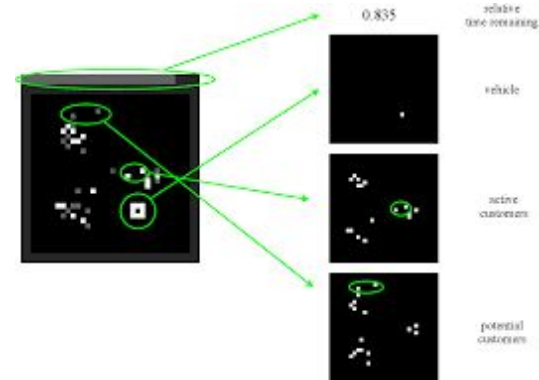
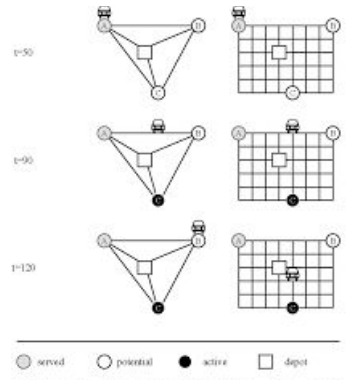
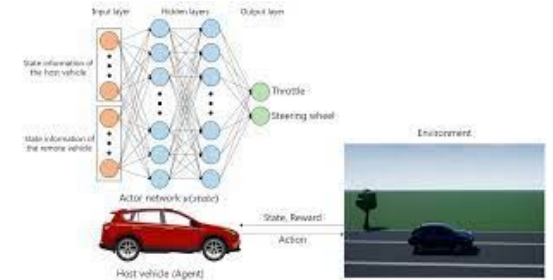
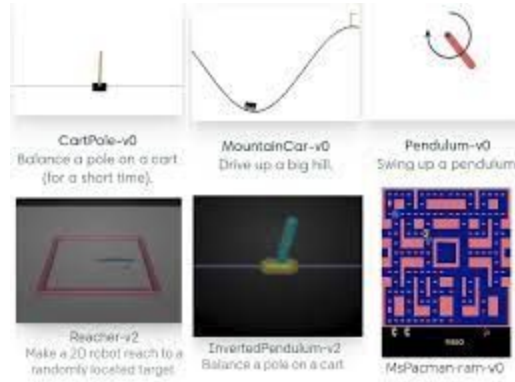
- State variables: S_t
- Decision variables: $x_t = X^\pi(S_t)$
- Exogenous info.: W_t
- Transition function: $S_{t+1} = S(S_t, x_t, W_{t+1})$
- Objective function: $C_t(S_t, X^\pi(S_t), W_{t+1})$

$$\min_{\pi} \mathbb{E}_{W_1, \dots, W_T \mid S_0} \left\{ \sum_{t=0}^T C_t(S_t, X^\pi(S_t), W_{t+1}) \mid S_0 \right\}$$

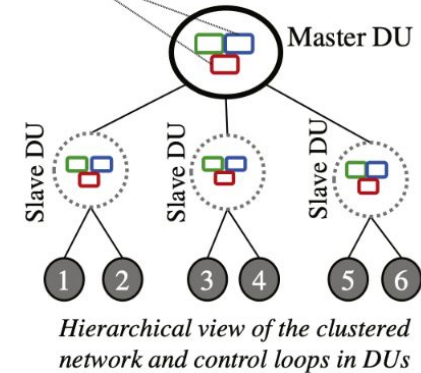
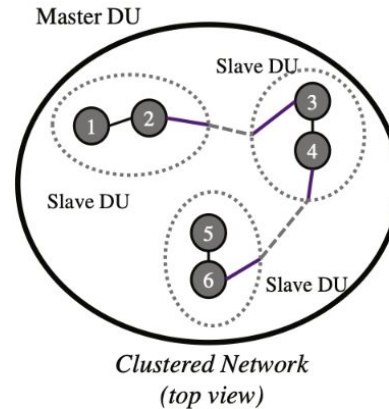
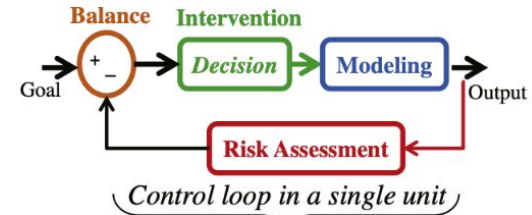
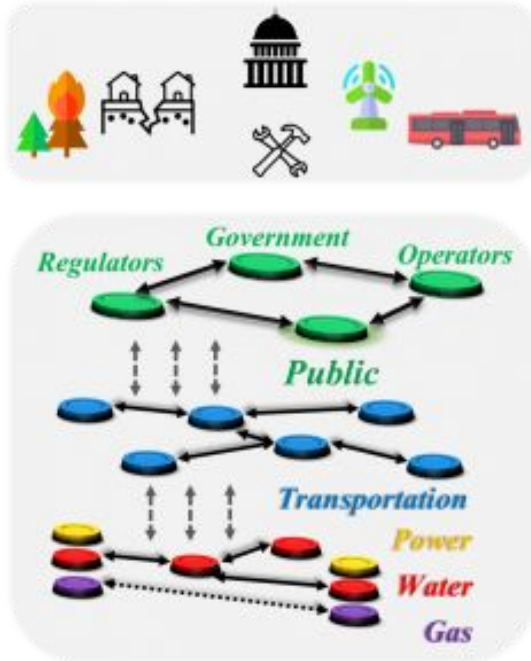
Challenges:

- Dynamics modeling
- Uncertainty modeling
- Policy Design

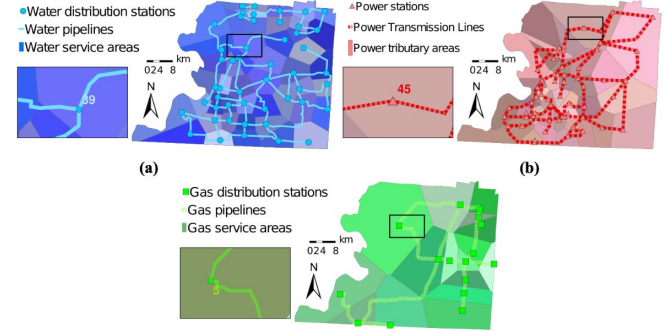
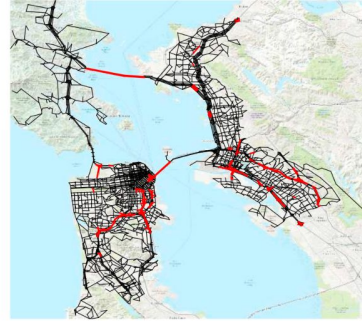
Research trends in *reinforcement learning* and ADP



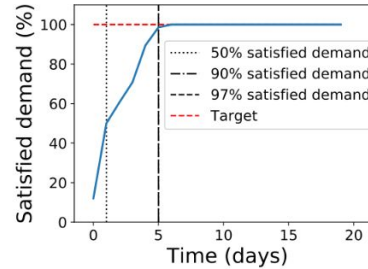
How to “control” complex Systems-of-Systems



Resilience of interdependent infrastructure networks

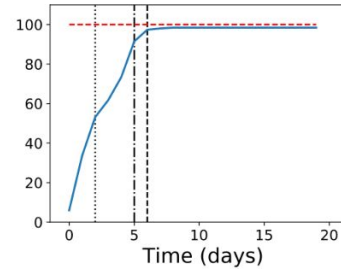


Community-driven

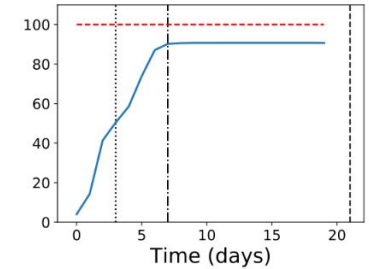


Service Recovery

Tradeoff



Operator-driven



Unrealistic central planner assumed!

Current research lines



Decision Support Systems in the context of:

- **Supply Chain Analytics**
- Systems-of-Systems Analytics
- Open Data Analytics

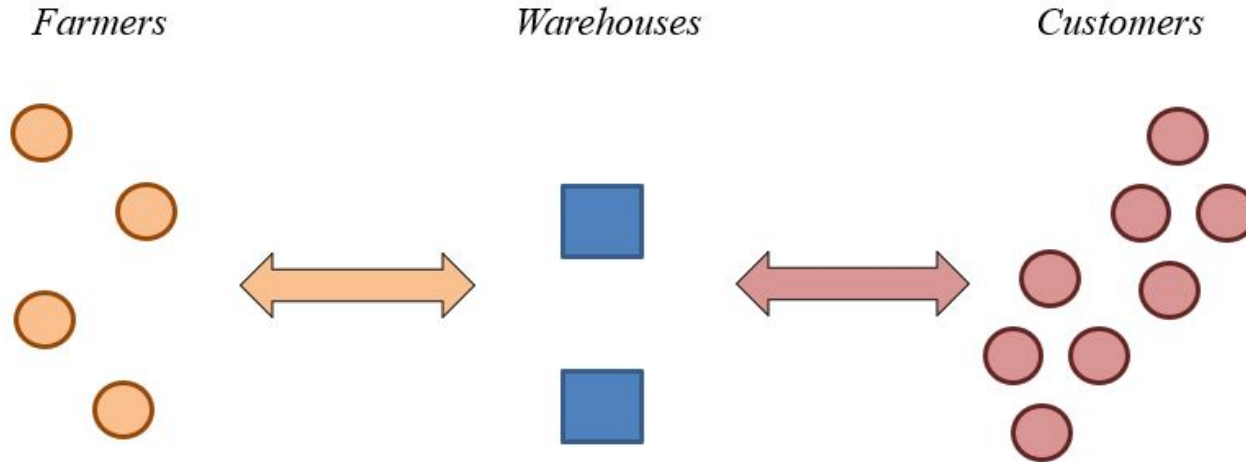
Intelligence for agri-food markets and supply chains



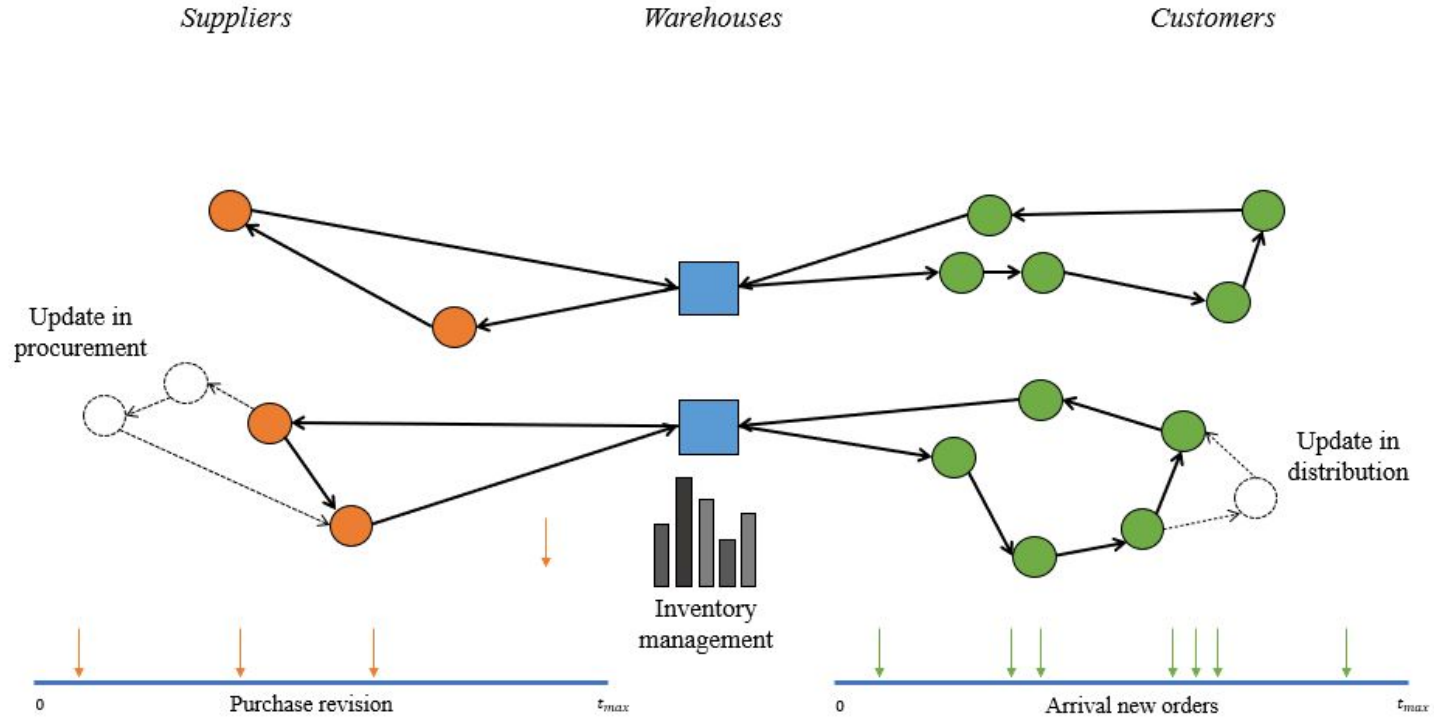
Intelligence for agri-food markets and supply chains



E-commerce platforms as bridges between
producers and consumers



Intelligence for agri-food markets and supply chains



Modeling under the stochastic optimization framework



Core elements

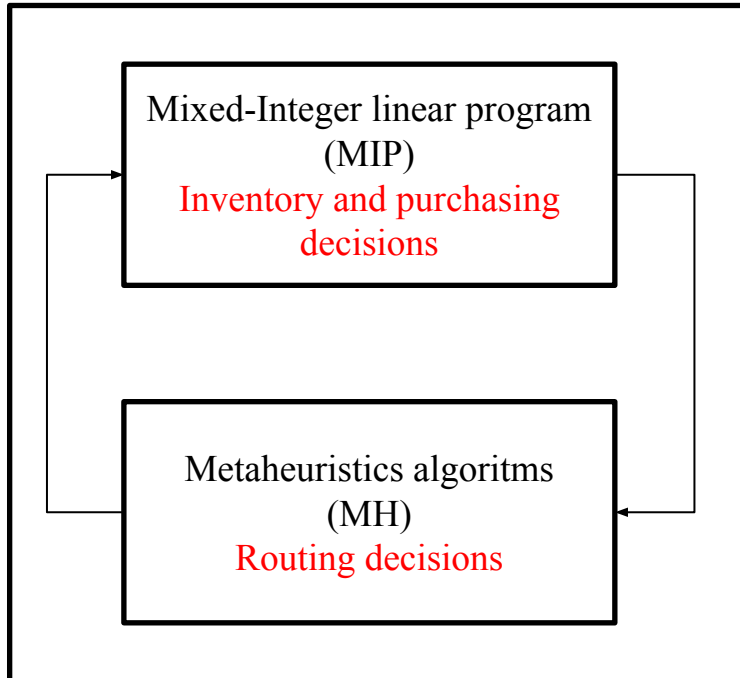
- **Metrics:** We want to minimize the total cost given by the purchasing, routing, inventory and backorders costs
 - **State (\mathbf{S}_t):** inventory level for each product at the beginning at each period t . $\mathbf{S}_t = (\mathbf{I}_{kt})$
 - **Decisions (\mathbf{x}_t):** We have to decide for each period
 - How much to replenish
 - How much to store
 - Select suppliers
 - How much to buy from each supplier
 - How to visit suppliers
- Decision variable (\mathbf{x}_t)**
- **Uncertainty sources (\mathbf{W}_{t+1}):** The demand for each product in the afternoon. (\hat{D}_{kt})

Decision Analytics in *Inventory Routing Planning*



How can we find the value of these decision variables?

Policy: $\mathbf{x}_t = \pi(\mathbf{s})$



$$\begin{array}{ll} \text{maximize} & \mathbf{c}^T \mathbf{x} \\ \text{subject to} & A\mathbf{x} + \mathbf{s} = \mathbf{b}, \\ & \mathbf{s} \geq \mathbf{0}, \\ & \mathbf{x} \geq \mathbf{0}, \\ \text{and} & \mathbf{x} \in \mathbb{Z}^n, \end{array}$$

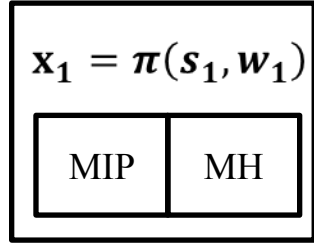
Algorithm 2 GenerateRoutes

Input: List T , M , List c_{ij} : transportation cost between nodes i and j , $z_{ikt}, w_{it}; Q$

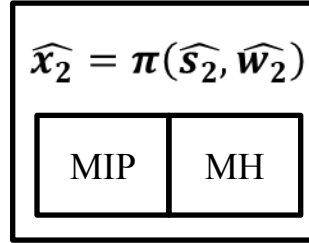
Output: Routes R : Routes of period t ;

- 1: for $t = 1$ To $|T|$ do
 - 2: $Tour \leftarrow \text{NearestNeighbourAlgorithm}(M, w_{it}, c_{ij})$
 - 3: $Graph \leftarrow \text{GenerateAugmentedGraphCVRP}(M, w_{it}, c_{ij}, Tour, Q)$
 - 4: $R_t \leftarrow \text{BellmanFordShortestPathAlgorithm}(Graph)$
 - 5: end for
 - 6: return R
-

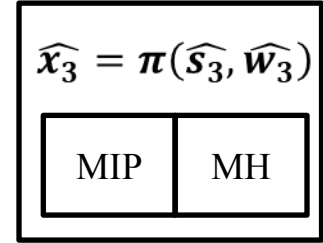
Decision Analytics in Inventory Routing Planning



$t = 1$



$t = 2$

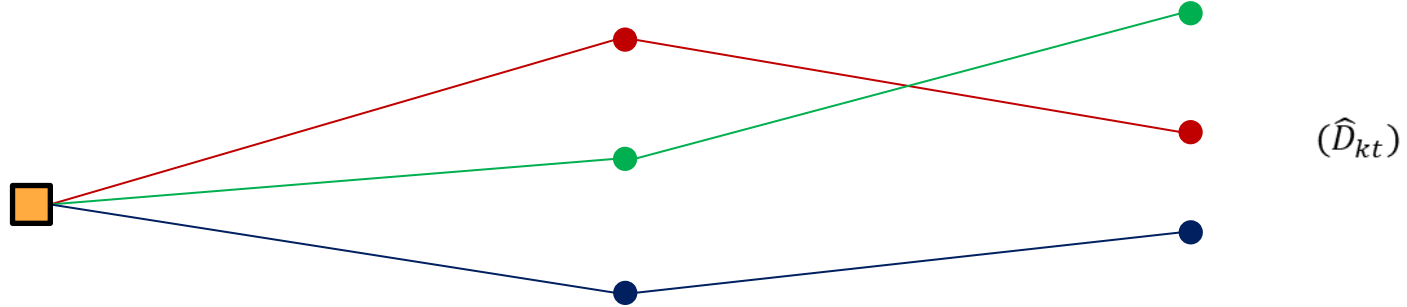


$t = 3$

Decision Analytics in *Inventory Routing Planning*

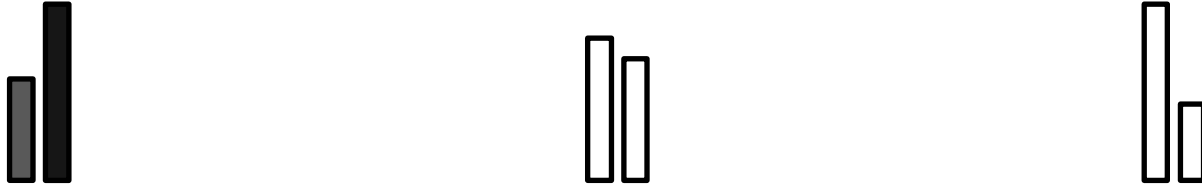


Parameters
forecast

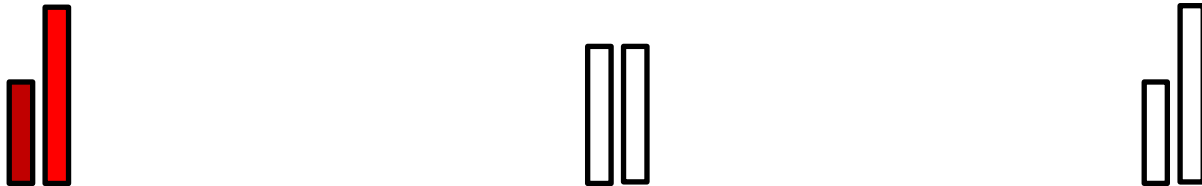


(\hat{D}_{kt})

Inventory
decisions



Purchase
decisions



Current research lines



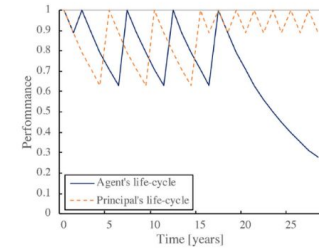
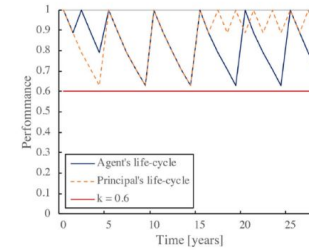
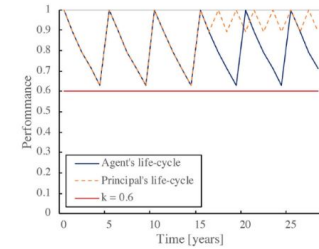
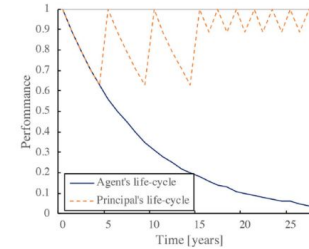
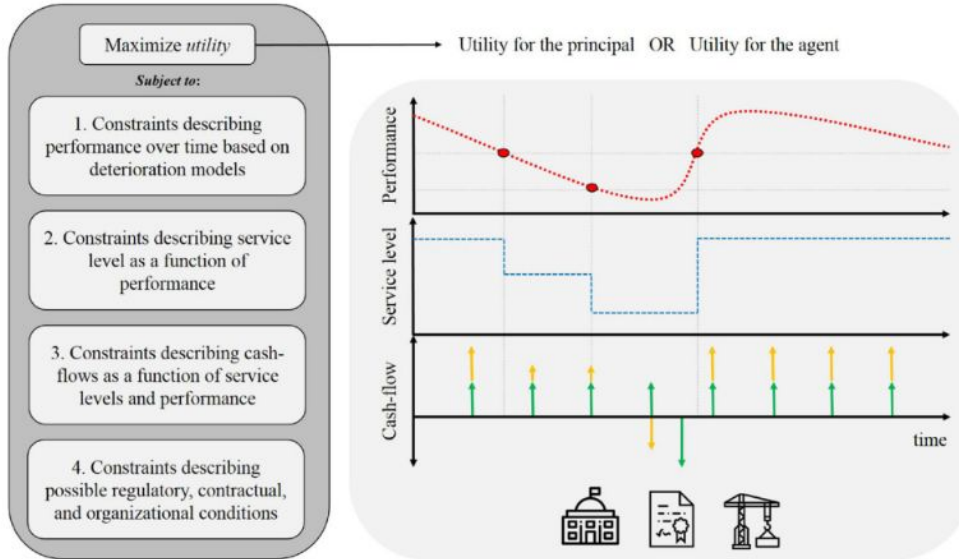
Decision Support Systems in the context of:

- Supply Chain Analytics
- **Systems-of-Systems Analytics**
- Open Data Analytics

Conflicts of interest in Systems of Systems



Public-Private Partnerships



Regulations or incentives rely on oversight: sensing and monitoring

Illustration of a bi-level optimization problem



$$\min F = 2x - 11y$$

s.t.,

$$\min f = 3y$$

s.t.,

$$x - 2y \leq 4$$

$$2x - y \leq 24$$

$$3x + 4y \leq 96$$

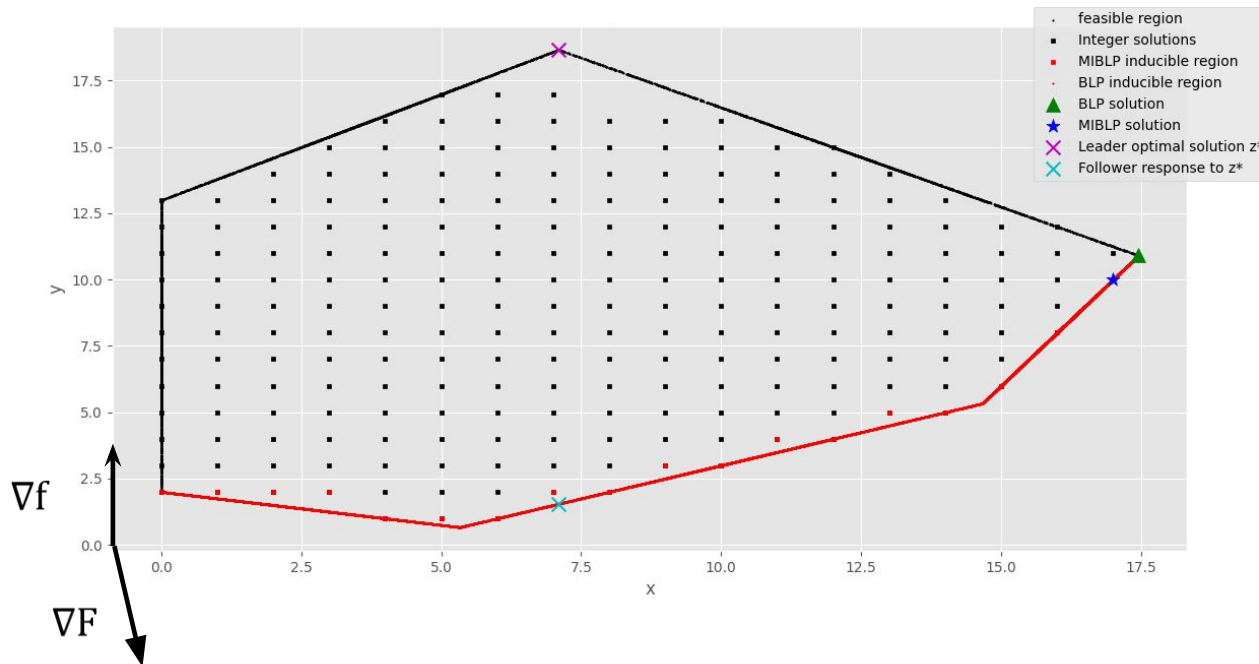
$$x + 7y \leq 126$$

$$-4x + 5y \leq 65$$

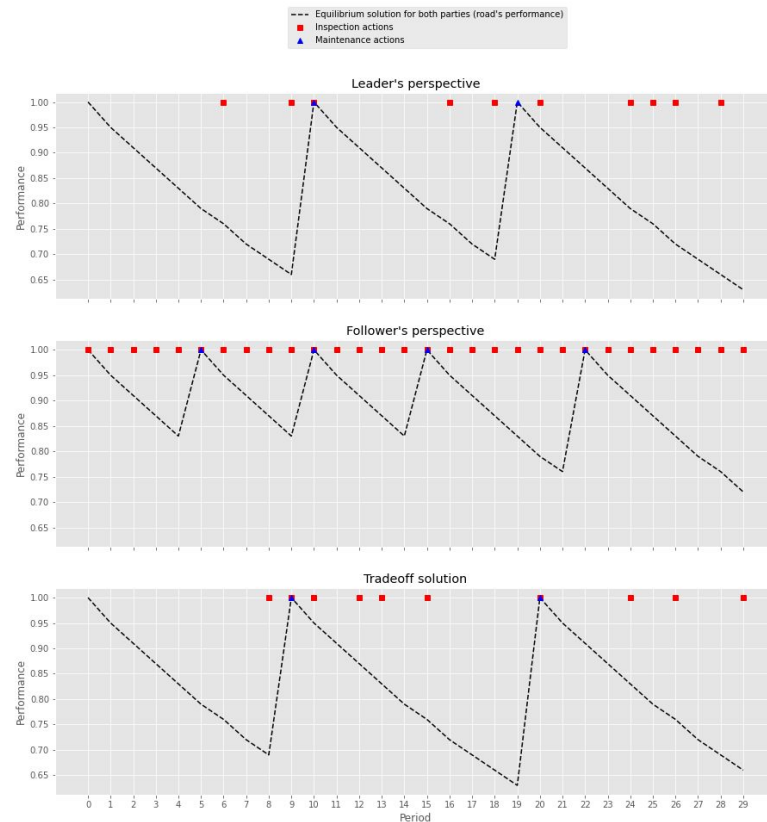
$$-x - 4y \leq -8$$

$$x \in \mathbb{Z}^{\geq 0}$$

$$y \in \mathbb{Z}^{\geq 0}$$



Agents' strategies under bi-level optimization

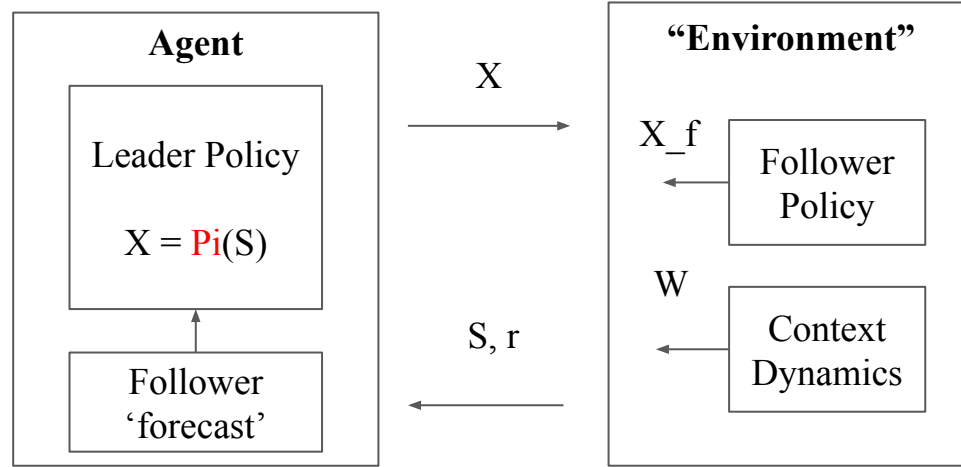


Bi-Level problem under Stochastic Optimization Framework



Wherever there is a group of interest (SoS), it's because there are things at stake;

we use Decision Analytics to get the best and fair of what's at stake



No deals?

We're out and thank you for your time!

- **Bi-level:** each party follows its own objective
Optimization: get the most out of a zero-sum game;
seek win-win solutions in non-zero sum games
- **Interdiction:** the counterpart seeks to cause the most damage
Optimization: anticipate and protect from harmful actions
(defender-attacker-defender)

In the CPS context:
Address tradeoffs between multiple stakeholders' interests (e.g., cost, safety)

Detect and prevent failure from stochastic failures or intentional attacks

Addressing V&V of CPSs under *Decision Analytics* lens



- **Modeling of CPSs under SoS and *Decision Analytics***
 - “Integrate decision making across soft and hard infrastructure in cyber-physical systems”
 - “Build consensus on common understanding, methodologies and practices for resilience assessment”
- **Test the *Sequential Decision Analytics* framework for CPSs**
 - “Model downstream effect of decisions now on (and from) from other components of the CP-SoS and the dynamic environment”
- **Exploit optimization to improve effectiveness and efficacy of V&V**
 - “Identify cyber-physical threats affecting systems for diagnostics, protection and resilience of railway infrastructure”
 - “Define new solutions of Model-Driven Engineering for the interdependency analysis and the prevention of cascading effects”

Conclusion



- The unified stochastic optimization framework appears as an amenable modeling approach for CPS, including the modeling of the dynamics and stochasticity of complex systems, and enabling the possibility to design and evaluate decision policies.
- As a result, we can borrow OR techniques, such as stochastic and bi-level optimization, to improve decisions about a system of interest in the face of:
 - Uncertain adversity
 - Interactions with other components in a CP-SoS
 - Disruptions (“natural” or targeted)
- The current trend of research on reinforcement learning and approximate dynamic programming can lead to fresh approaches to CPS problems, calling the attention of such communities to open challenges.



Thanks!

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The popular image of a dam as a concrete wall might not be easily identified with a complex engineering system. However, the resulting engineering of the natural environment in which the dam sits becomes a complex engineering system and therefore must be treated as such. This changes completely the safety requirements of the system, from a purely structural angle to one of operation management.

The idea of static operation procedures to regulate a system in an extremely dynamic environment is a liability to the safety of the system. For such long-living systems, design-time control's effectiveness fades in time as it is dwarfed by the lifespan of the designed object.

While engineering cannot solve this fundamentally social problem, the use of common infrastructure, it can indeed help by supporting existing assets with demand management strategies, which are at the heart of systems engineering.

This could be achieved by implementing control and feedback strategies to include the users in the design and management process.

MODEL PREDICTIVE CONTROL

