What is an Optimizer doing at a Simulation Workshop?

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Personal Interest # 1: Stochastic Decomposition (SD)

- SD is a sampling-based Stochastic Programming algorithm
  - Stochastic linear programming data created by simulations
  - Sequential sampling of LP value function (sometimes thought of as Sampled Benders' Decomposition)
  - Allows bootstrapped stopping rule: Re-sample to evaluate approximation (function) variability.
  - Computational comparisons with IPA-based Simulation Optimization shows potential advantages of SD
- Extensions
  - Multi-stage Stochastic Programs (Sample-path creation)
  - Two-stage Binary Stochastic MIPs

Personal Interest # 2: Interfaces with Simulation

- Interplay between Simulation and Optimization
  - Many applications (e.g. revenue management) use price-based (bid-price) simulation. Stochastic programming (being based on convex analysis) provides a solid foundation for bid-price controls
  - Receding horizon (Rolling horizon) control. Learning (or approximating) appropriate planning horizon in a sequential manner: Use dual variable predictions as inputs for correcting horizon-length

Personal Interest # 3: Multi-scale Stochastic Decision Problems

- Fine Grain v Coarse Grain Stochastics
  - Simulation models often include fine grain stochastics: e.g. call-by-call resource utilization, minute-by-minute electrical dispatch (or even finer discretizations).
  - Stochastic programming works well for coarse grain stochastic where path-dependence may be important (e.g. technology evolution, public policy etc.). Typically, fine grain is used to model feasibility (e.g. power quality in electricity)
  - How do we address such multi-scale models?