The IBM Research Uncertainty Toolkit for Decision Optimization

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Project team

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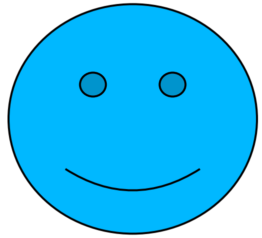
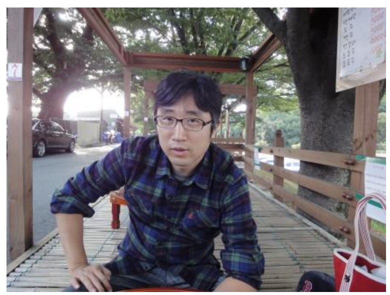


Various Decision Optimization colleagues

Ban Kawas (WRL)
Robust optimization

Ali Koc (WRL)
Stochastic optimization

Marco Laumanns (ZRL)
Robust/stochastic



Chungmok Lee (DRL)
Robust optimization

Radu Marinescu (DRL)
Stochastic CP

Martin Mevissen (DRL)
Robust optimization

Susara van den Heever (DRL / ILOG)
Project manager

Rudi Verago (DRL)
Software engineering

Nicole Taheri (DRL)
Robust optimization

Outline

- Overview of IBM Decision Optimization Center
- Industry context
- Project goals & benefits
- Uncertainty Toolkit design and architecture
- Case studies
  - Pump scheduling for energy cost minimization with uncertain energy prices
  - Pressure management for leakage reduction with uncertain water demand
  - Energy Unit Commitment with uncertain demand

IBM Decision Optimization Portfolio

Engines and Tools

CPLEX Optimization Studio

High-performance mathematical programming solvers and development tools

Solution Platform

Decision Optimization Center

Build and deploy analytical decision support applications based on optimization technology

Industry Solutions

Optimization Assets

Pre-built yet customizable industry applications

Integrated Analytics

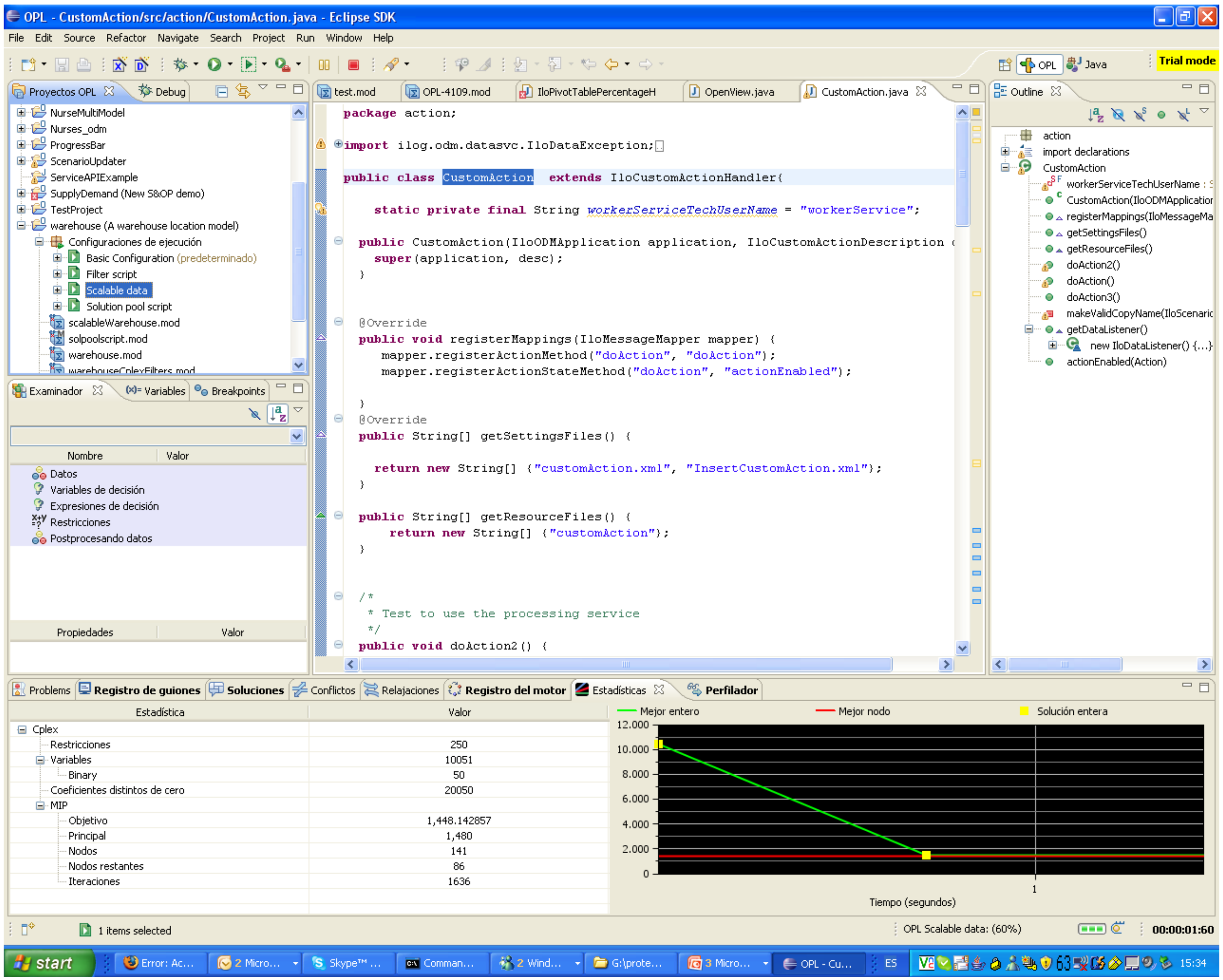
- Decision support solutions for **Supply Chain Management**
- **SPSS** predictive analytics
- **Cognos** descriptive analytics
- **Maximo** asset management

Decision Optimization Center is about Decision Support

- We support a business expert making the decision
- A Business User need
  - Manual planning in addition to Optimization
  - Recommendations
  - Explanations
  - Alternatives
  - Relaxations
  - Tradeoffs
  - Re-scheduling functionalities
  - Insight on solution sensitivity and robustness
  - “What-if” and scenario comparison

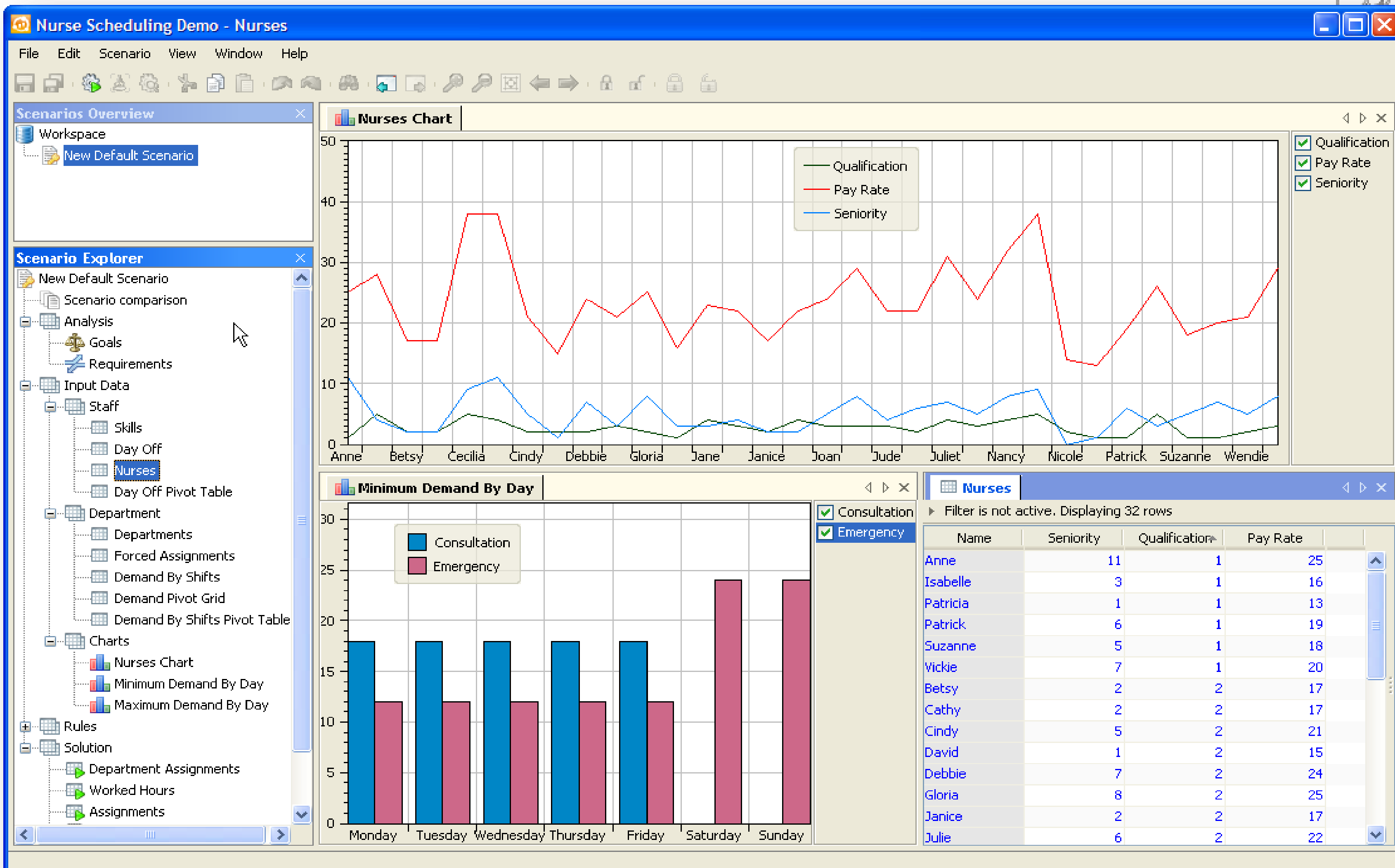
Decision Optimization Center hIDE

OPL Models Development

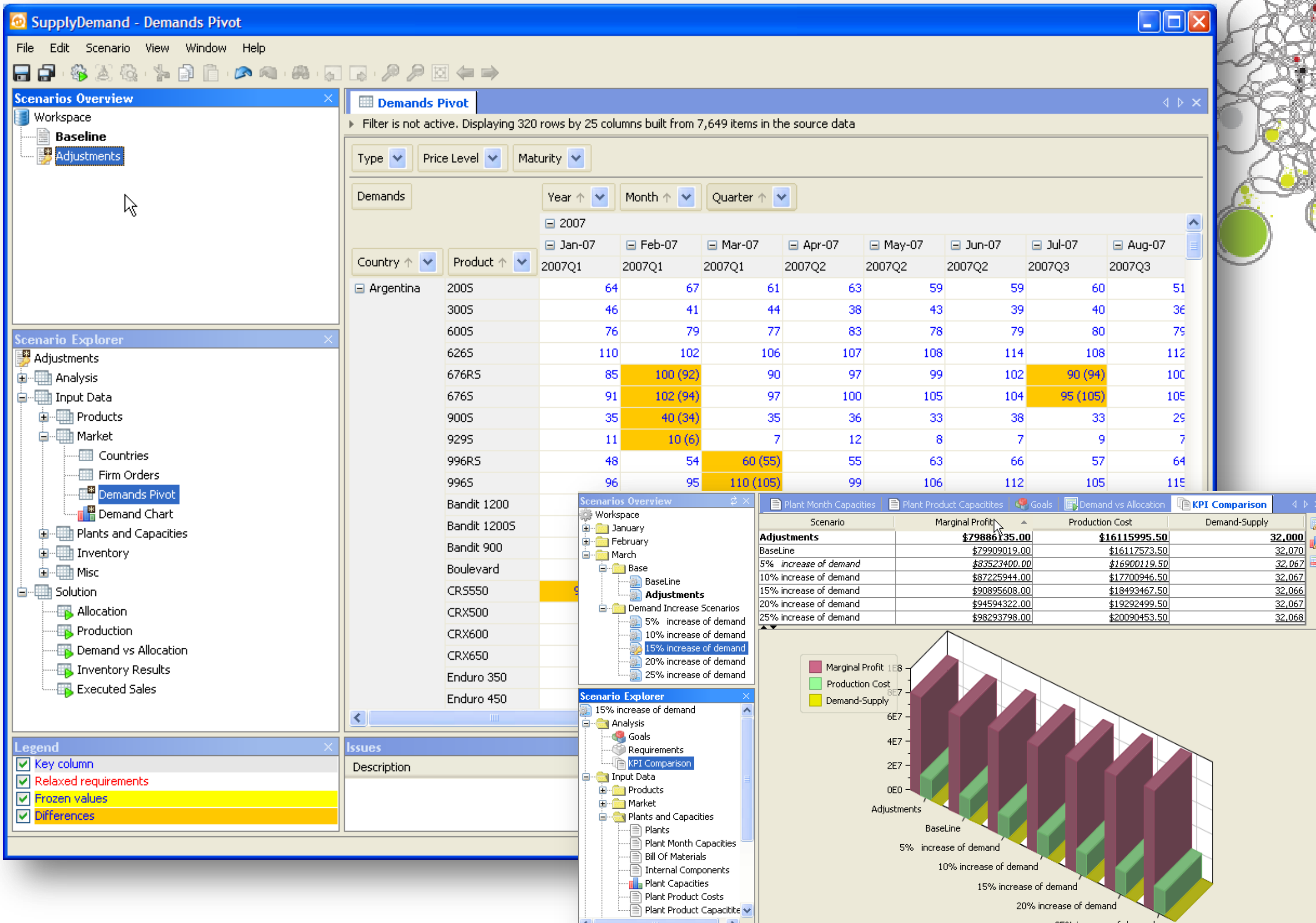


Decision Optimization

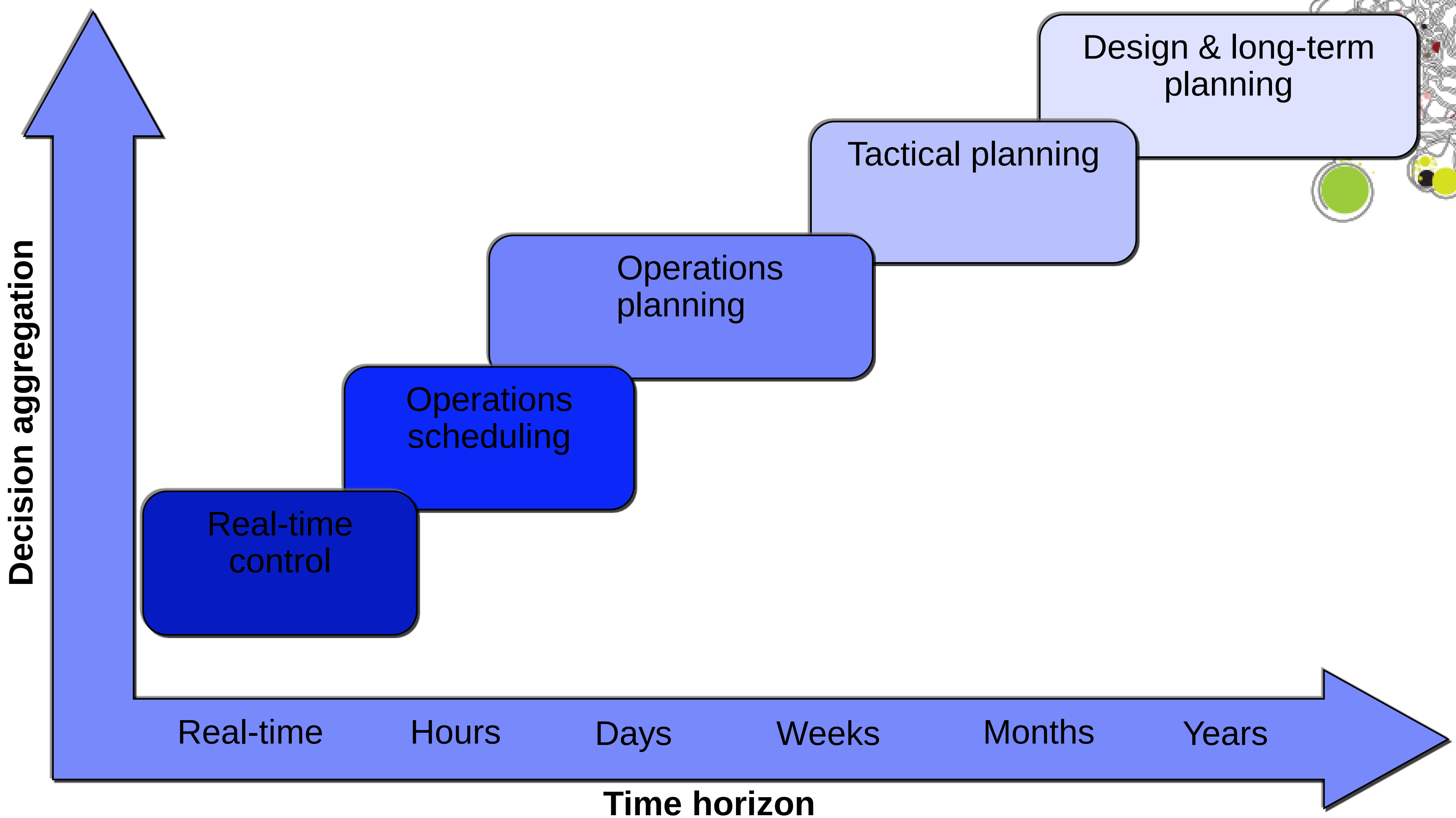
Displays using Simple Tables and Charts – out of the box



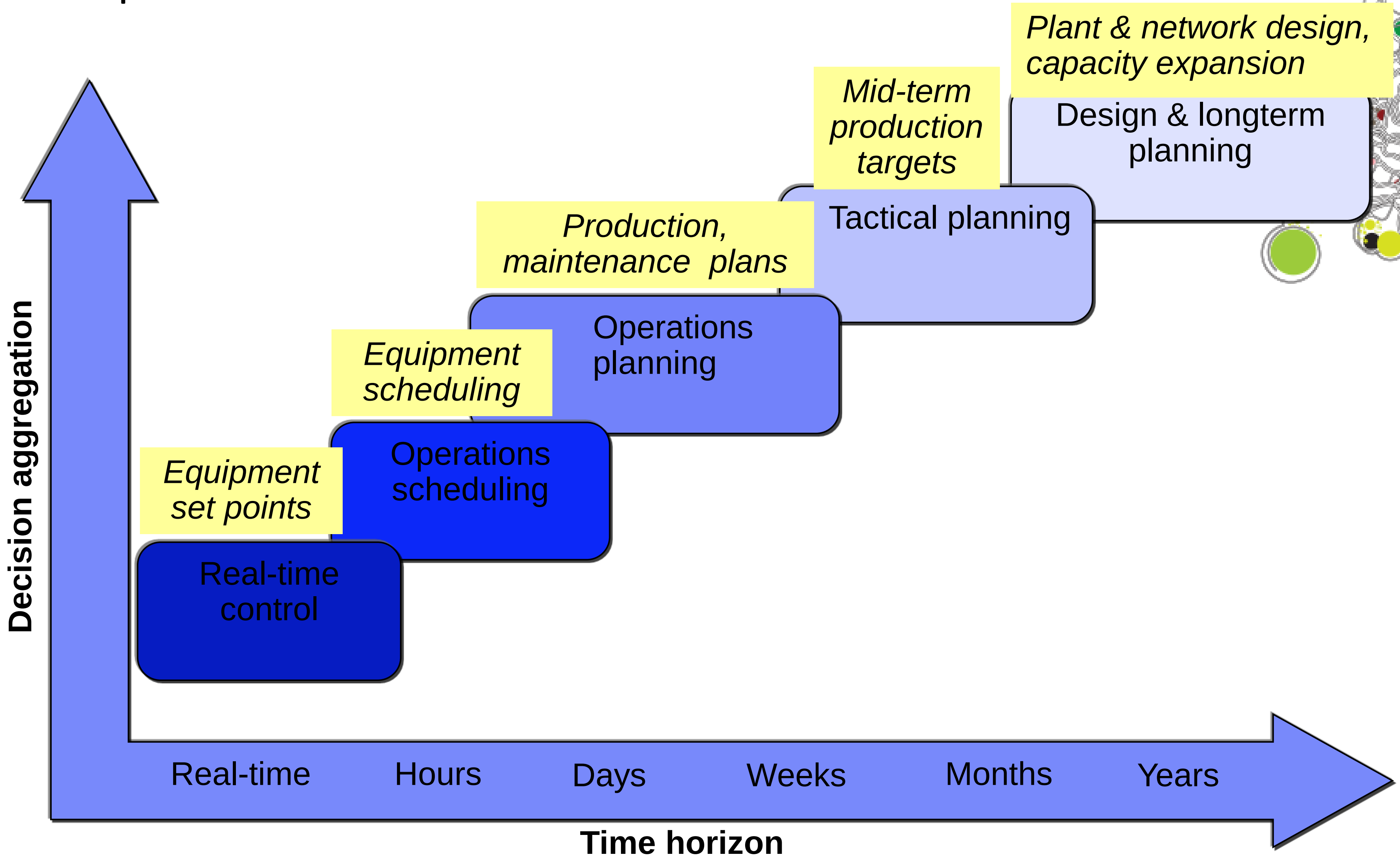
Pivot Tables and Scenario Comparison – out of the box



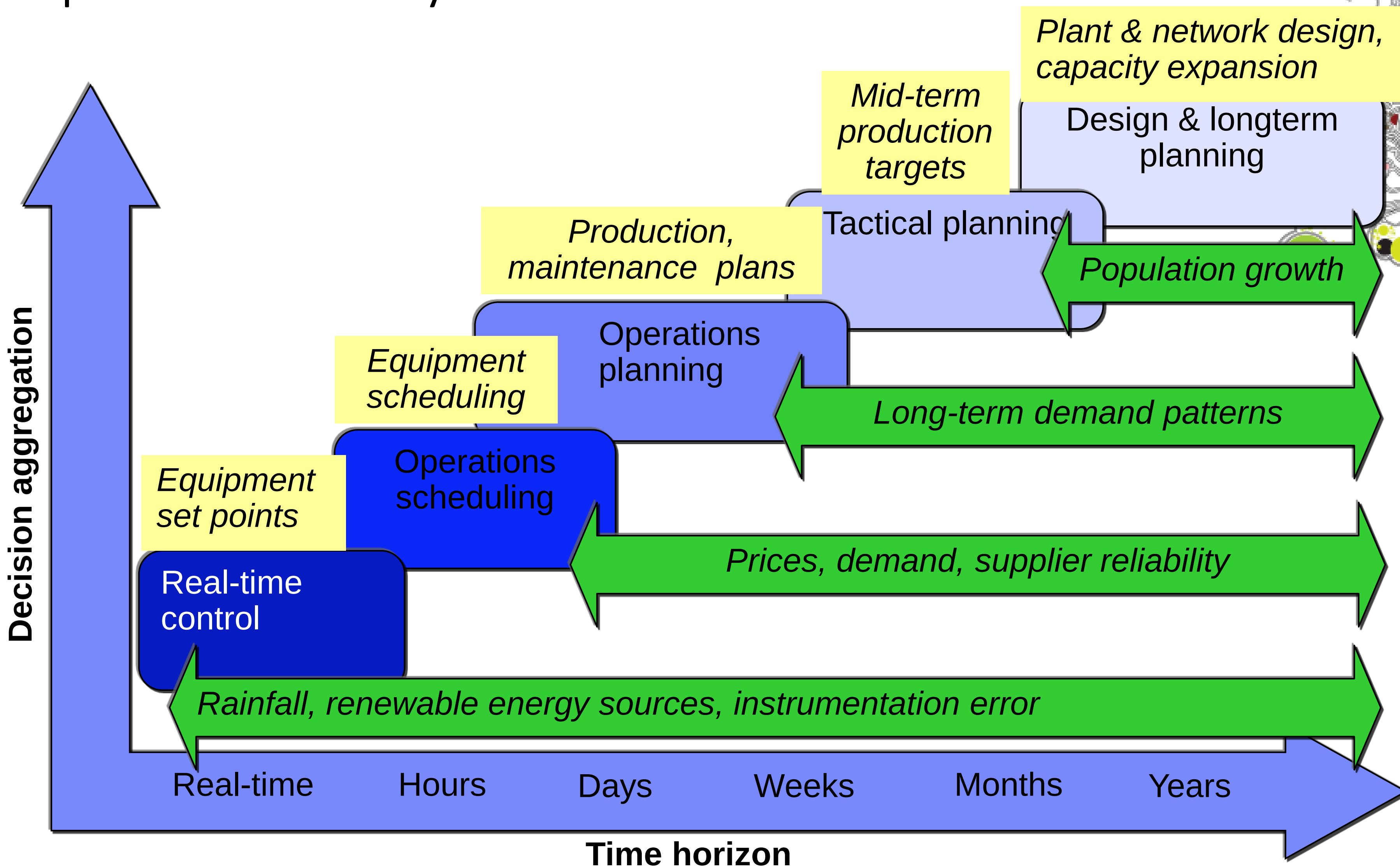
Planning levels



Examples of decisions



Impact of uncertainty



Effect of data uncertainty on decision resilience

"Resilient"
how decisions should be

re·sil·ient[1]
adjective \ri-ˈzil-yənt\
a **:** capable of withstanding shock without permanent deformation or rupture
b **:** tending to recover from or adjust easily to misfortune or change

"Veracity"
the data quality decision makers and decision software often assume

ve·rac·i·ty[1]
noun \və-ˈra-sə-tē\
: truth or accuracy

"Uncertain"
the actual data quality

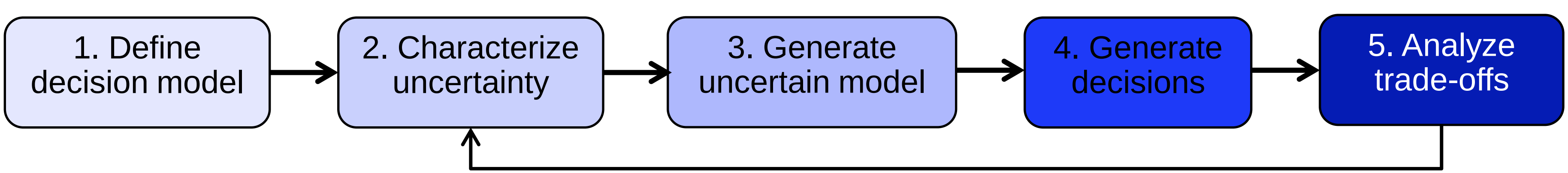
un·cer·tain[1]
adjective \ˌən-ˈsər-tᵊn\
: not exactly known or decided : not definite or fixed
: not sure : having some doubt about something

Assuming data **veracity** in the face of **uncertainty** leads to decision **instability**, as well as **distrust** in decision optimization technology.

Uncertainty Toolkit goals

- 2013 Joint Program between IBM Research and Decision Optimization
- Goals
  - Increase customer solution resilience, reliability, and stability
  - Improve trust & understanding of optimization technology
- Our approach
  - Leverage Decision Optimization & mathematical optimization to hedge against uncertainty (e.g. uncertain demand, task durations, prices, resource availability)
  - A user-friendly toolkit as plug-in to Decision Optimization Center

- *5 steps to resilient decisions in the face of uncertainty*



Stable decisions, stable profits

- Test examples
  - Supply chain planning for a motorcycle vendor

    2% increase in profits vs. deterministic optimization
  - Inventory optimization for IBM Microelectronics Division

    Greater than 7x increase in feasibility vs. deterministic optimization

- Case studies
  - Energy cost minimization for Cork County Council

    Estimated 30% value-add in cost reduction vs. deterministic optimization
  - Leakage reduction for Dublin City Council

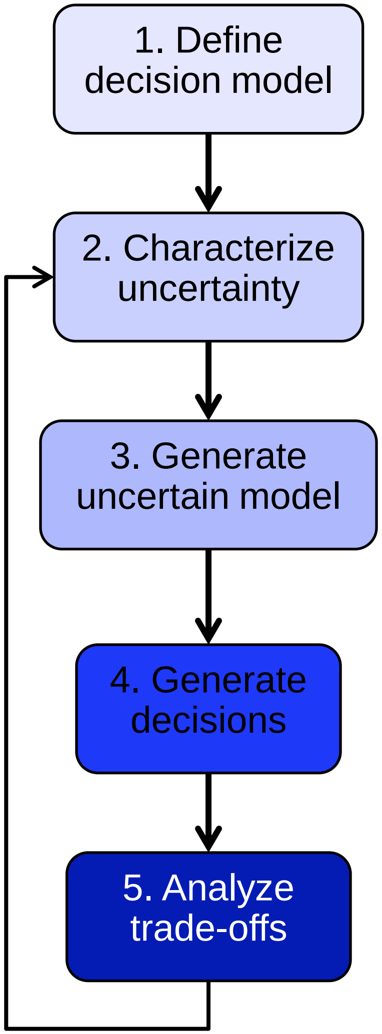
    Estimated 10 times increased stability vs. deterministic optimization

- Other benefits
  - Automated toolkit reduces dependence on PhD-level experts & statistical data
  - Visualize trade-off between multiple KPIs across multiple scenarios and plans

Example use cases for the Uncertainty Toolkit

Industry	Typical company	Problem type
Government	Government agencies	Project portfolio management
Tourism	Hotel operators, Airlines	Revenue management
Transport	Railroads	Railroad locomotive planning
Transport	Supermarket chain, cement	Delivery / pick-up truck routing
Utilities	Electricity company	Production planning
Utilities	Water company	Tactical reservoir planning
Utilities	Water company	Water distribution network configuration
Utilities	Electricity company	Unit commitment
Utilities	Water network operators	Pump scheduling
Utilities	Water network operators	Pressure management
Utilities	Electricity company	Energy trading
Oil and gas	Oil company	Vessel scheduling
Manufacturing	Manufacturer	Operational project scheduling
Manufacturing	Car manufacturer	Manufacturing line load balancing
Manufacturing	Aircraft manufacturer	Plant assembly
Manufacturing	Car manufacturer	Sales and operations planning
Supply chain	Manufacturer	Contractor to transport leg assignment
Supply chain	Manufacturer	Product to store allocation
Supply chain	Manufacturer, oil&gas	Inventory optimization
Supply chain	Manufacturer, oil&gas	Supply chain network configuration
Supply chain	Manufacturer	Procurement planning
Supply chain	Manufacturer	Emergency operations planning
Commercial	Banks, insurance, TV	Marketing campaign optimization
Finance	Banks	Collateral allocation

5 steps to resilience with the Uncertainty Toolkit



- Create optimization model with IBM CPLEX Studio
- Some modeling skill required, or existing assets
- Embed in IBM Decision Optimization Center

"Steve" the IT expert, & "Keith" the OR consultant

- OR consultant's "wizard": 7 screens
- Defines uncertainty, scenario generation, risk measures

- Built-in automated reformulation, based on steps 1 and 2
- No modeling knowledge required
- "Robustification" (make the original model robust to change)

- Business user's "wizard"
- Automated solution generation
- Automated scenario comparison

"Anne" the business user

- Built-in visual analytics
- Analyze KPI trade-offs across multiple plans & scenarios

Uncertainty Toolkit: automated reformulations

Robust / Stochastic approach	Applicable model types	Resulting model types	Uncertainty characterization	Restrictions
Single-stage penalty approach *(Mulvey et al., 1995)*	LP	LP (or QP)	Scenarios (finite)	No uncertain data in objective function
	MILP	MILP (or MIQP)		
Two-stage penalty approach *(Mulvey et al., 1995)*	LP	LP (or QP)	Scenarios (finite)	No uncertain data in objective function
	MILP	MILP (or MIQP)		
Multistage Stochastic (e.g. *King & Wallace, 2012*)	LP	LP	Scenarios (finite)	None
	MILP	MILP		
Safety margin approach with ellipsoidal uncertainty sets (*Ben-Tal & Nemirovski, 1999*)	LP	QCP	Range	No uncertain data in standalone parameters or equality constraints
	MILP	MIQCP		
Safety margin approach with polyhedral uncertainty sets (*Bertsimas & Sim, 2004*)	LP	LP	Range	No uncertain data in standalone parameters or equality constraints
	MILP	MILP		
Extreme Scenario approach (*Lee, 2014*)	LP	LP	Range	No uncertain data in variable coefficients
	MILP	MILP		
Distributionally robust reformulation (*Mevissen et al., 2013*)	LP	LP	Scenarios	Uncertainty in standalone parameters handled as penalty term in objective
	MILP	MILP		

Uncertainty Toolkit: automated reformulations

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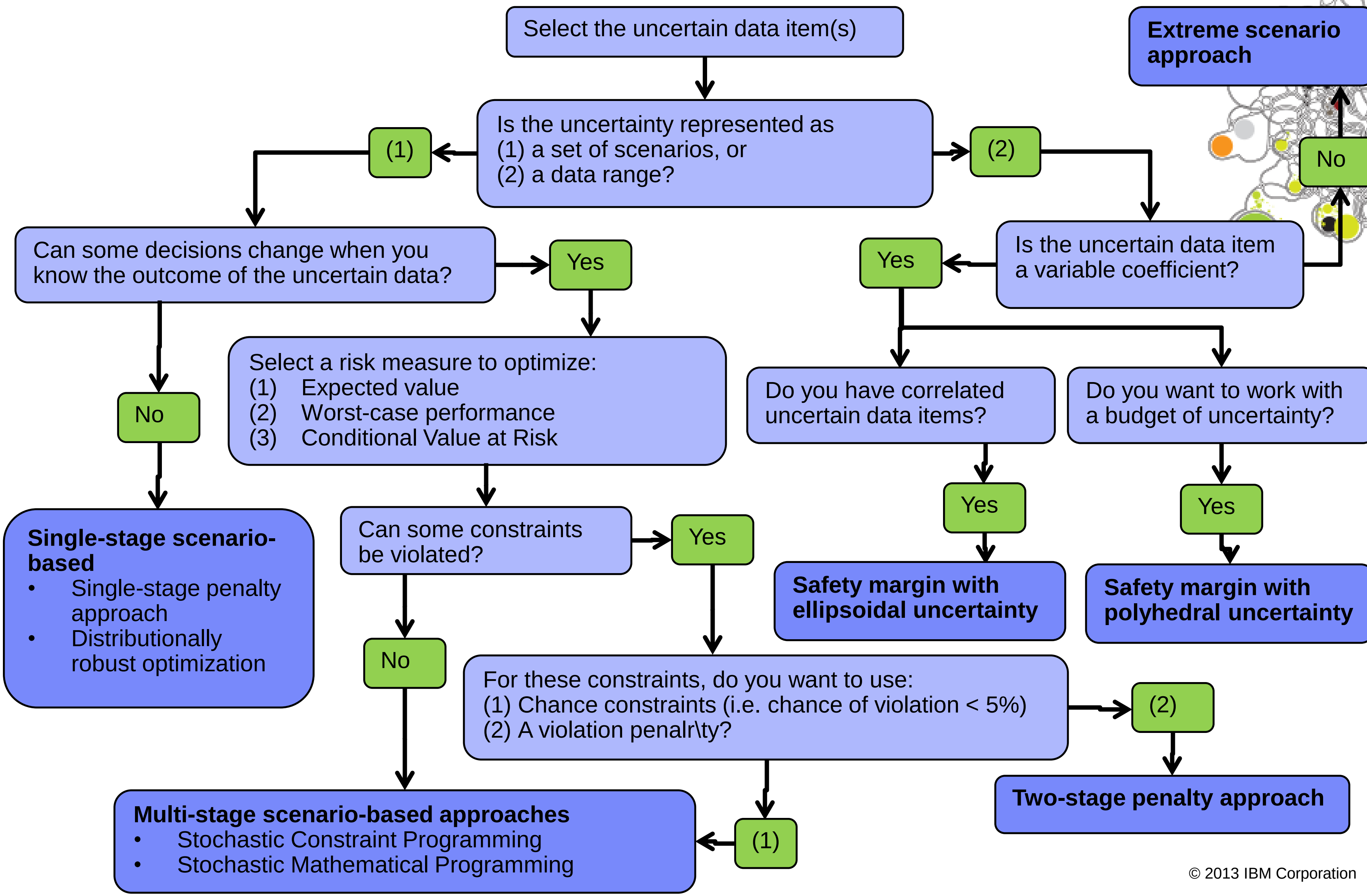
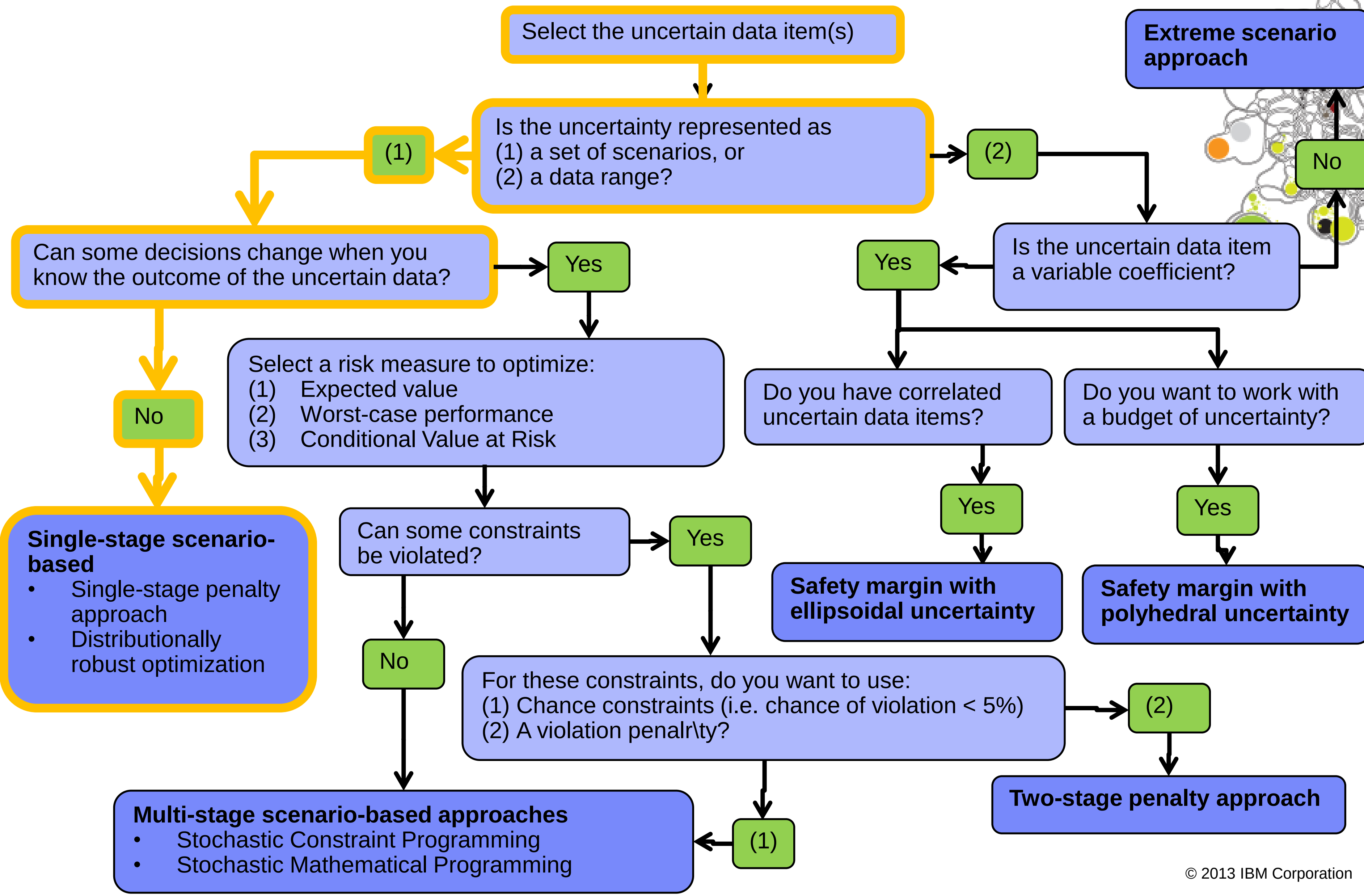
Q: How do I know which of these methods to use?

A: The Uncertainty Toolkit will decide automatically based on your input into the Consultant's Wizard

Uncertainty Toolkit Decision Tree (automated)



Uncertainty Toolkit Decision Tree (automated)



Example: Automated model reformulation for stochastic CP

```
dvar interval task[i in 1..n] size TaskDuration[i];
dvar sequence seq in task types all(i in 1..n) i;
dexpr int station[i in 1..n] = startOf(task[i]) div c;

minimize 1+max(i in 1..n) station[i];
subject to {
  noOverlap(seq, Setups);
  forall (p in Precedences)
    endBeforeStart(task[p.pred], task[p.succ]);
  forall (i in 1..n)
    station[i] == (endOf(task[i]) - 1) div c;
};
```

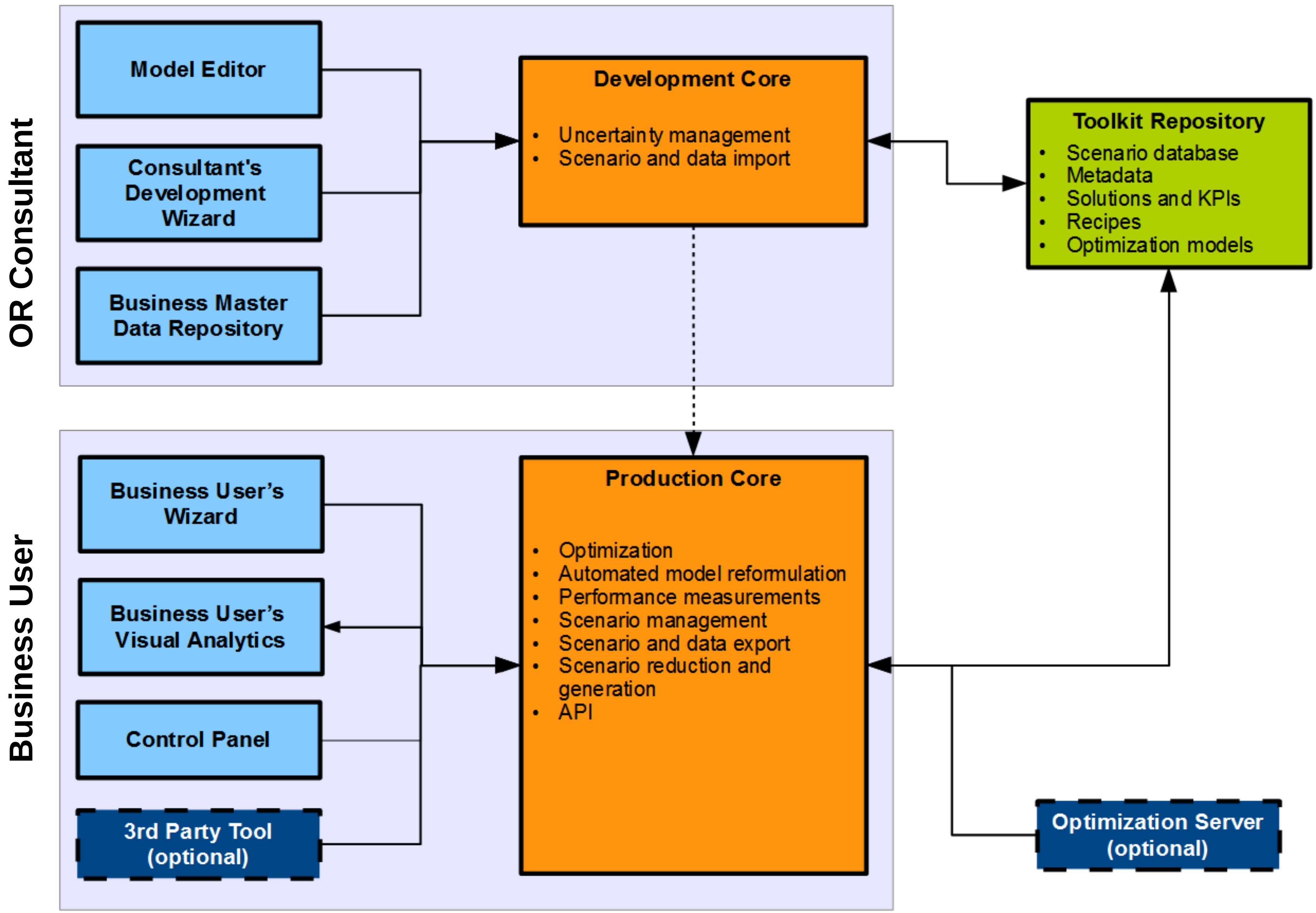
Input: Deterministic model

Automated model reformulation

Output: Stochastic model

```
dvar interval task[i in 1..n][s in Scenarios] size TaskDuration[i][s];
dvar sequence seq[s in Scenarios] in all(i in 1..n) task[i][s] types all(i in 1..n) i;

dexpr int station[i in 1..n][s in Scenarios] = startOf(task[i][s]) div c;

minimize sum(s in Scenarios) Probability[s]*(1 + max(i in 1..n) station[i][s]);
subject to {

  forall (s in Scenarios) {
    noOverlap(seq[s], Setups);
    forall (p in Precedences)
      endBeforeStart(task[p.pred][s], task[p.succ][s]);
    forall (i in 1..n)
      station[i][s] == (endOf(task[i][s]) - 1) div c;
  }

  forall (s in 1..(S-1), i in 1..n) {
    typeOfNext(seq[s], task[i][s], -1) == typeOfNext(seq[s+1], task[i][s+1], -1);
  }
};
```

Decision Optimization
Uncertainty Toolkit architecture

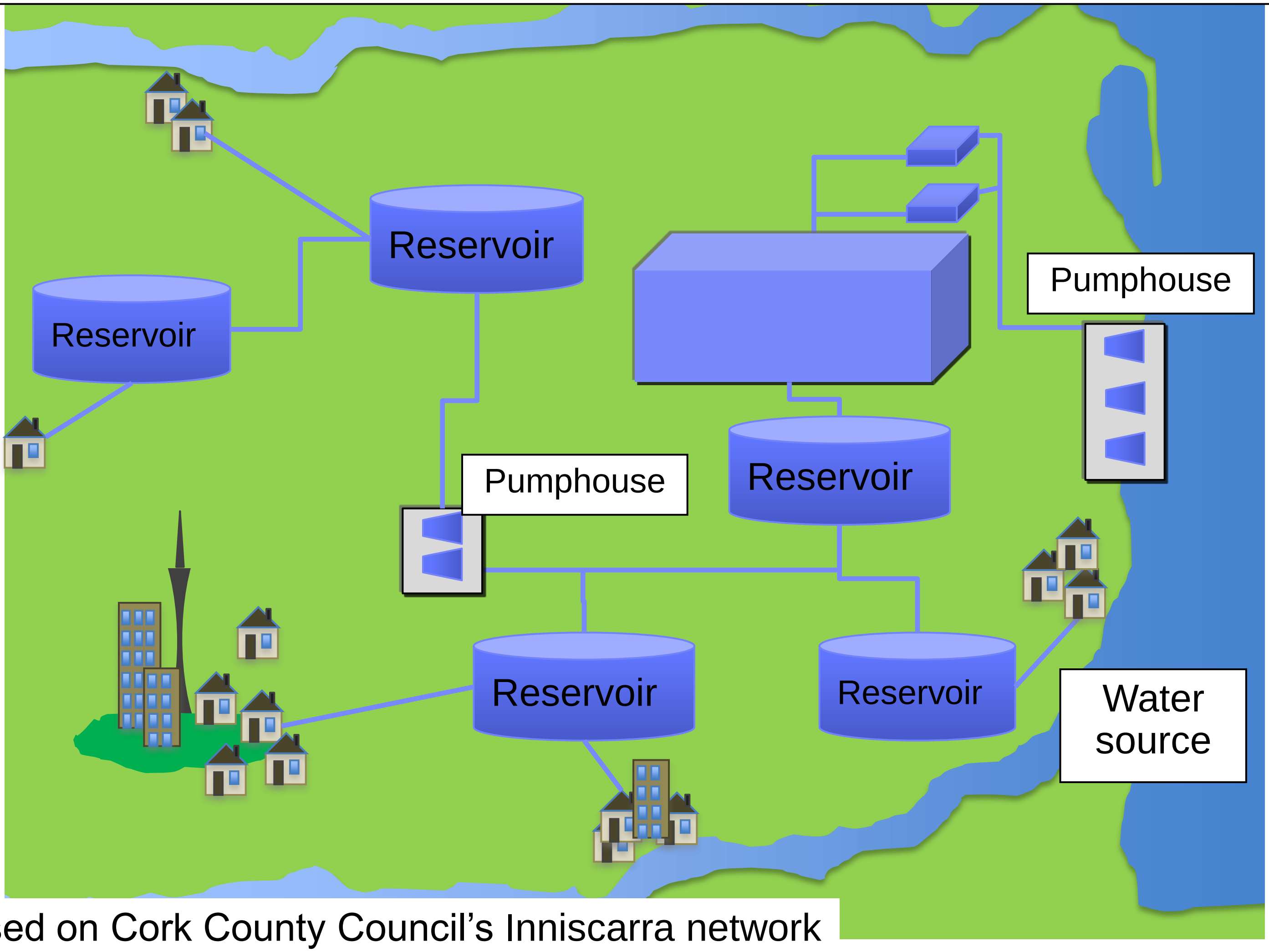


Case study: Water treatment/distribution energy cost reduction

- Big picture: Cork County Council must reduce energy consumption by 20% by 2020
- 95% of this utility's water-related energy costs due to pump operations
- New dynamic energy pricing schemes leverage renewables (wind energy)
- Trade-off: Cleaner energy at lower prices, but uncertainty in price due to
  - Wind uncertainty
  - Network outages
  - Other weather conditions
- Goal: Schedule pumps leveraging dynamic prices, while hedging against uncertainty in price prediction

Simplified network (illustration purposes)

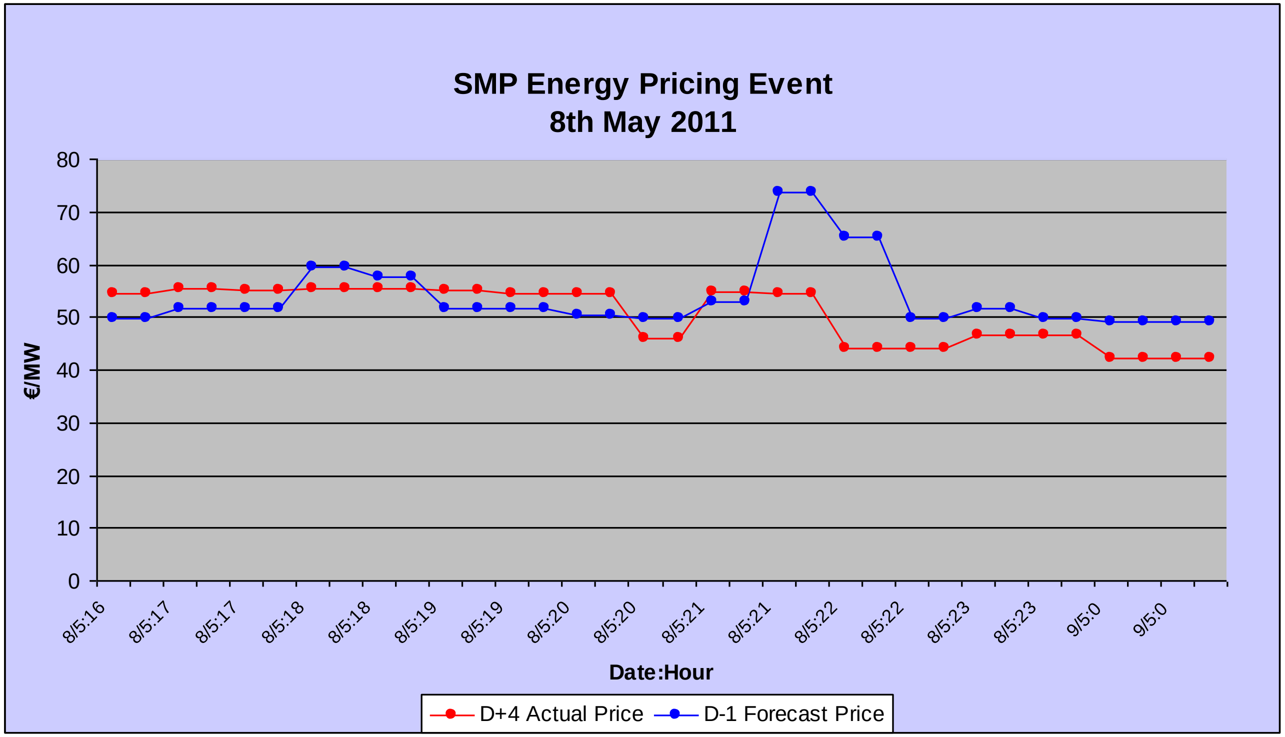
Goal: Optimize pump schedules to minimize (uncertain) energy costs while meeting demand and respecting plant and network constraints*



* Based on Cork County Council's Inniscarra network

Uncertainty in price prediction

- Forecasted (D-1) post ante price from supplier
  - Considers forecasted demand based on weather, special events, wind, etc.
- Actual (D+4) price charged 4 days after the event
  - Forecasted (D-1) and Settled price (D+4) can differ due to changes in predicted wind energy availability, weather, and unpredicted grid events



Question:
Should utility switch to a dynamic pricing scheme?

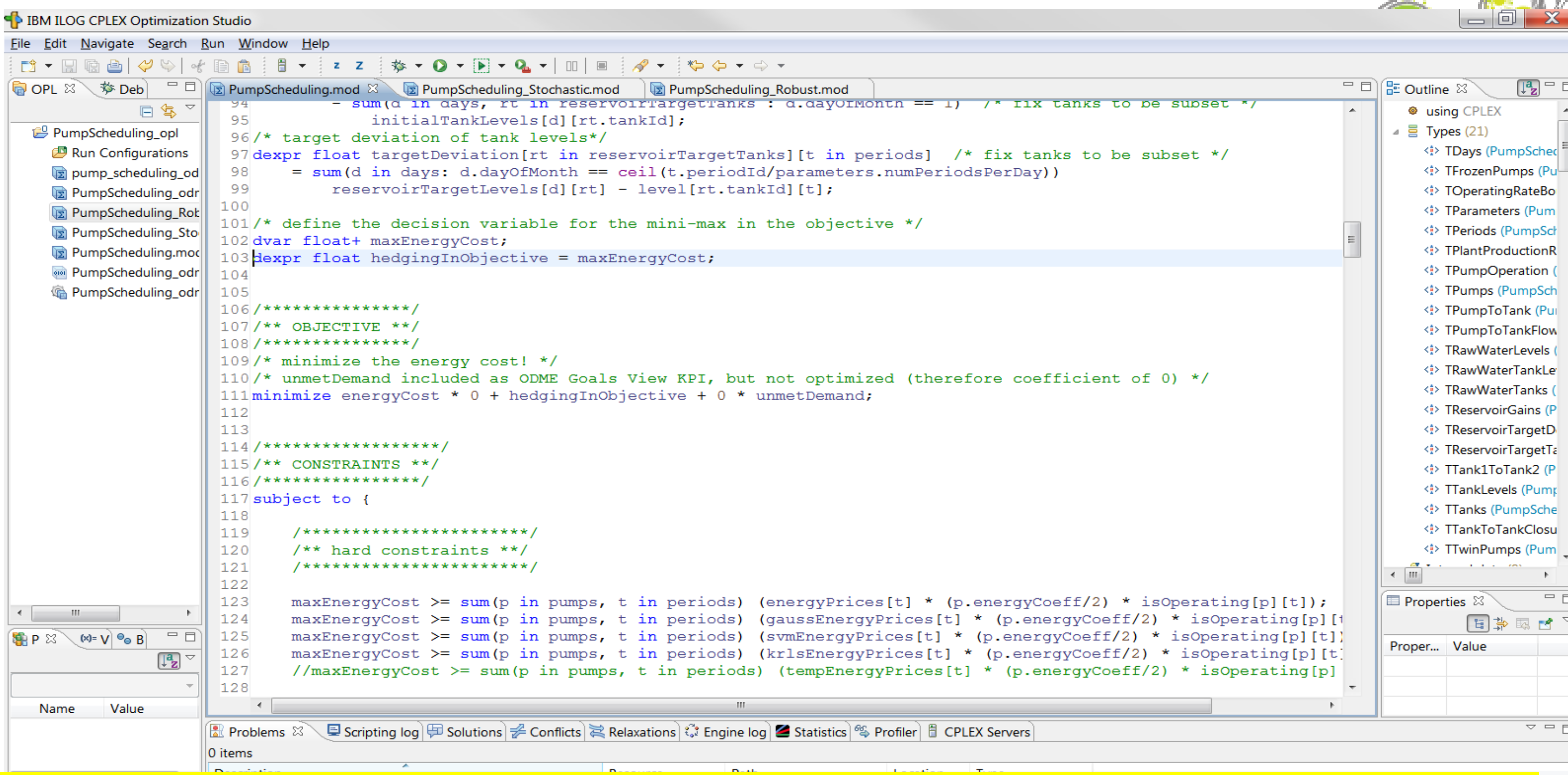
Step 1: Prove dynamic pricing benefits

Step 2: Prove optimization benefits

Step 3: Deal with uncertainty

Step 1: Define decision model

- Define objective, decisions, constraints (mathematical modeling skill required)
  - Objective: minimize energy costs from pump operations
  - Decisions: when to switch pumps on/off (decided every 30 minutes for 24 hours in advance)
  - Constraints: satisfy tank levels, pump operation rules, customer demand, network constraints
- Model using CPLEX Studio, assuming certain data ("deterministic" model)



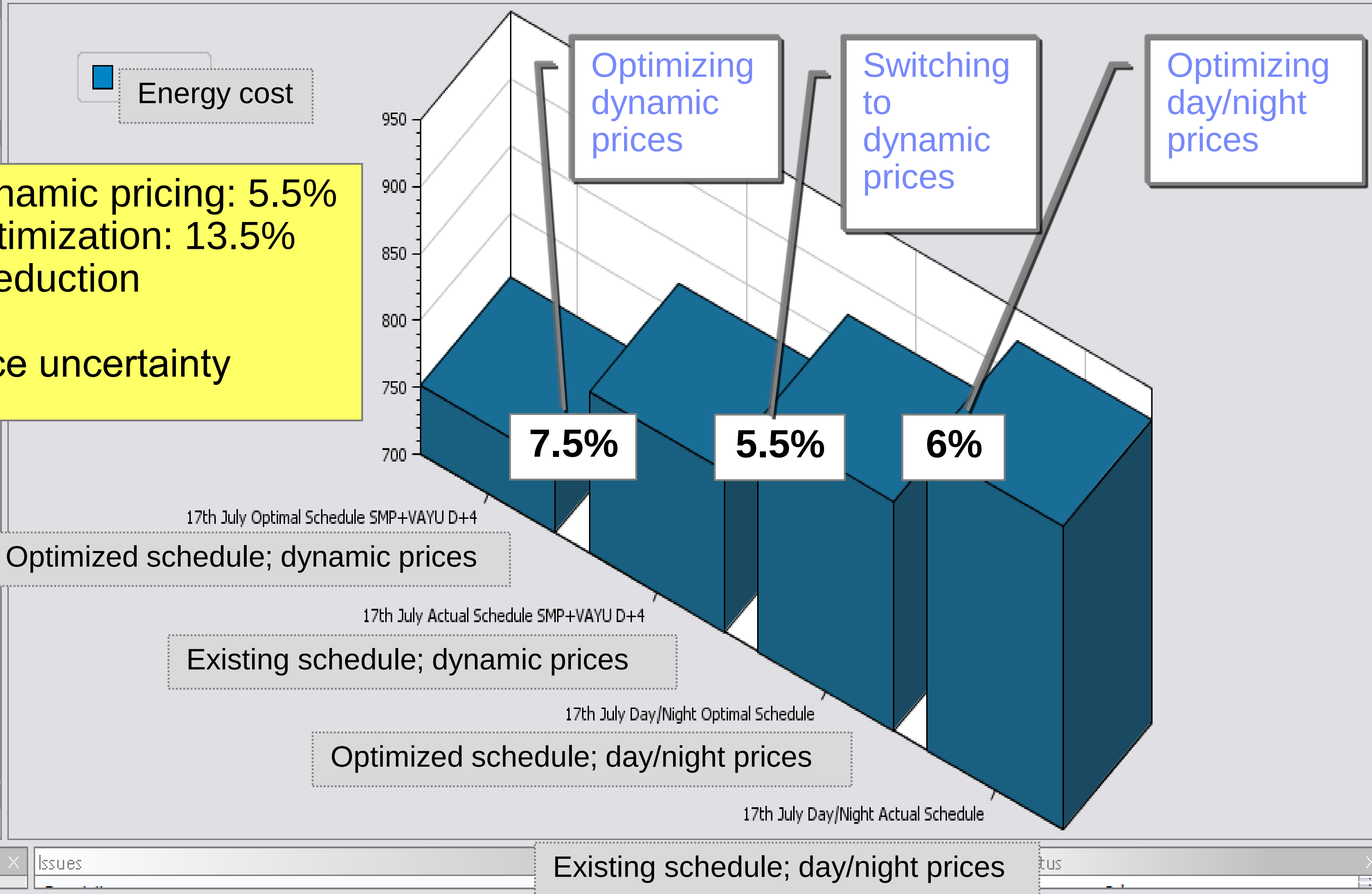
Note: When data is fairly certain, deterministic models are sufficient to provide significant benefit

Decision model in **Decision Optimization Center prototype**:
Predicted energy cost savings from pump optimization and (known) dynamic energy prices

Scenario	energyCost
17th July Optimal Schedule SMP+VAYU D+4	751.935
17th July Actual Schedule SMP+VAYU D+4	820.952
17th July Day/Night Optimal Schedule	871.883
17th July Day/Night Actual Schedule	**926.444**

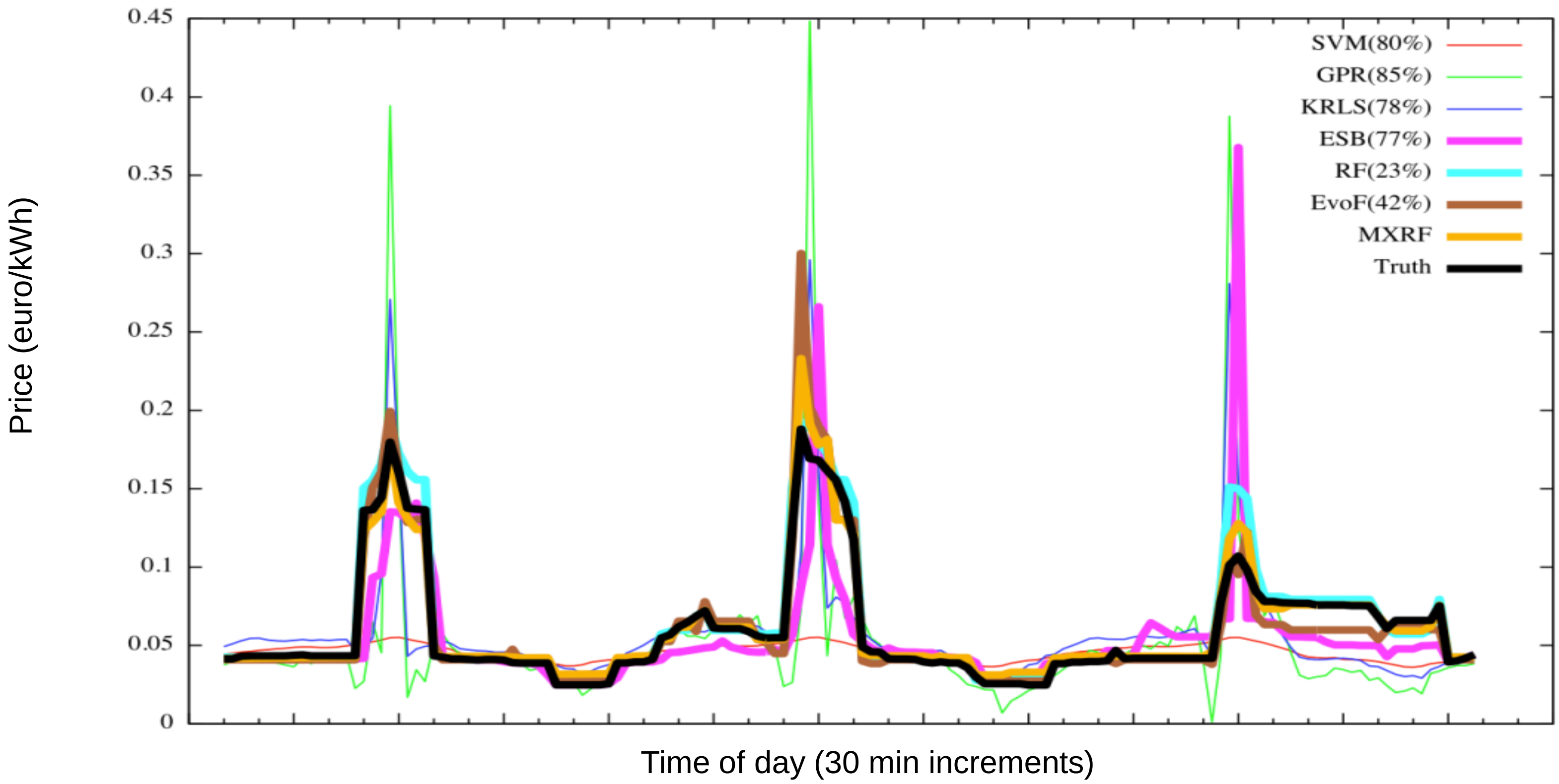
- Savings from dynamic pricing: 5.5%
- Savings from optimization: 13.5%
- Total 19% cost reduction

Next…deal with price uncertainty

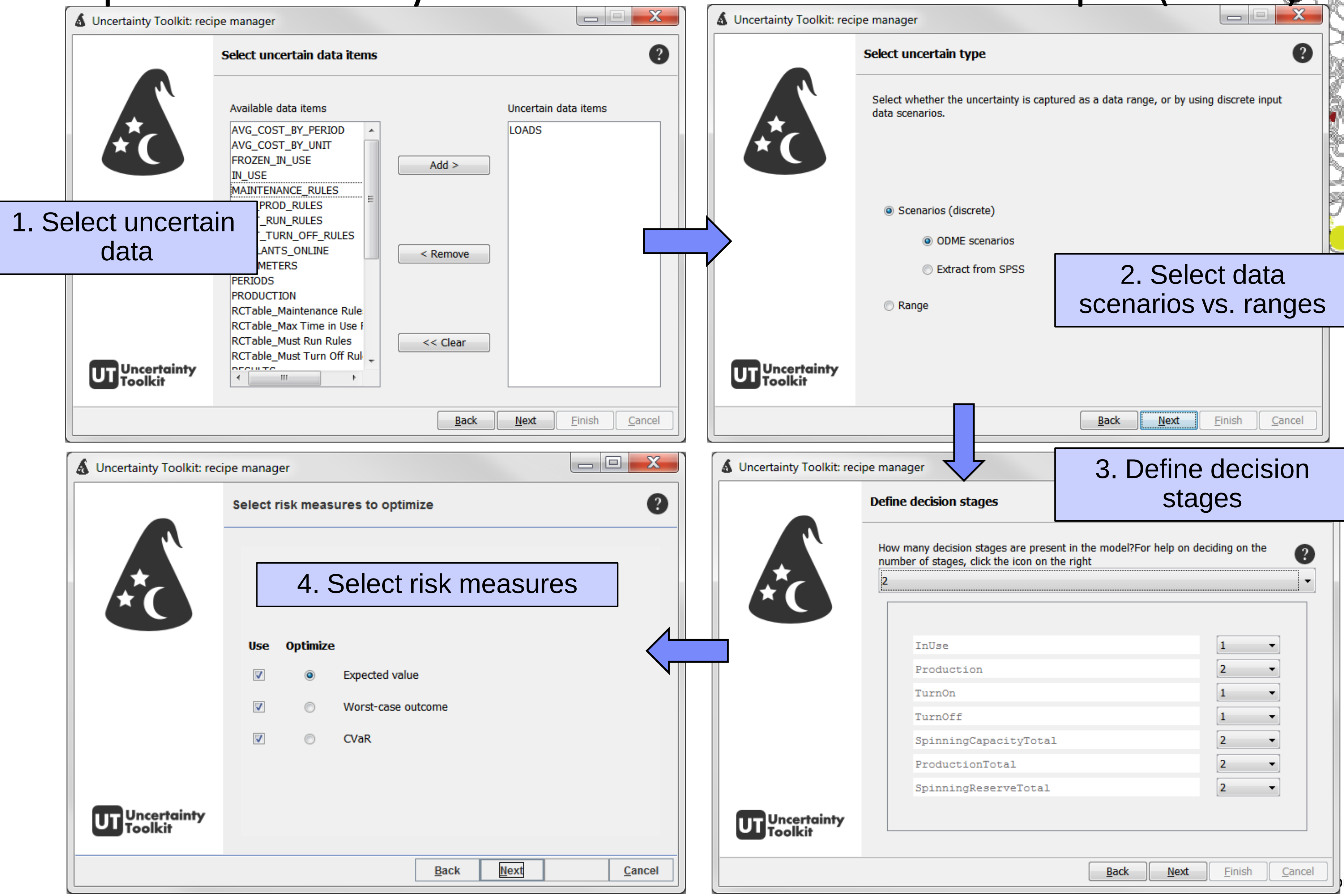


Step 2: Characterize uncertainty

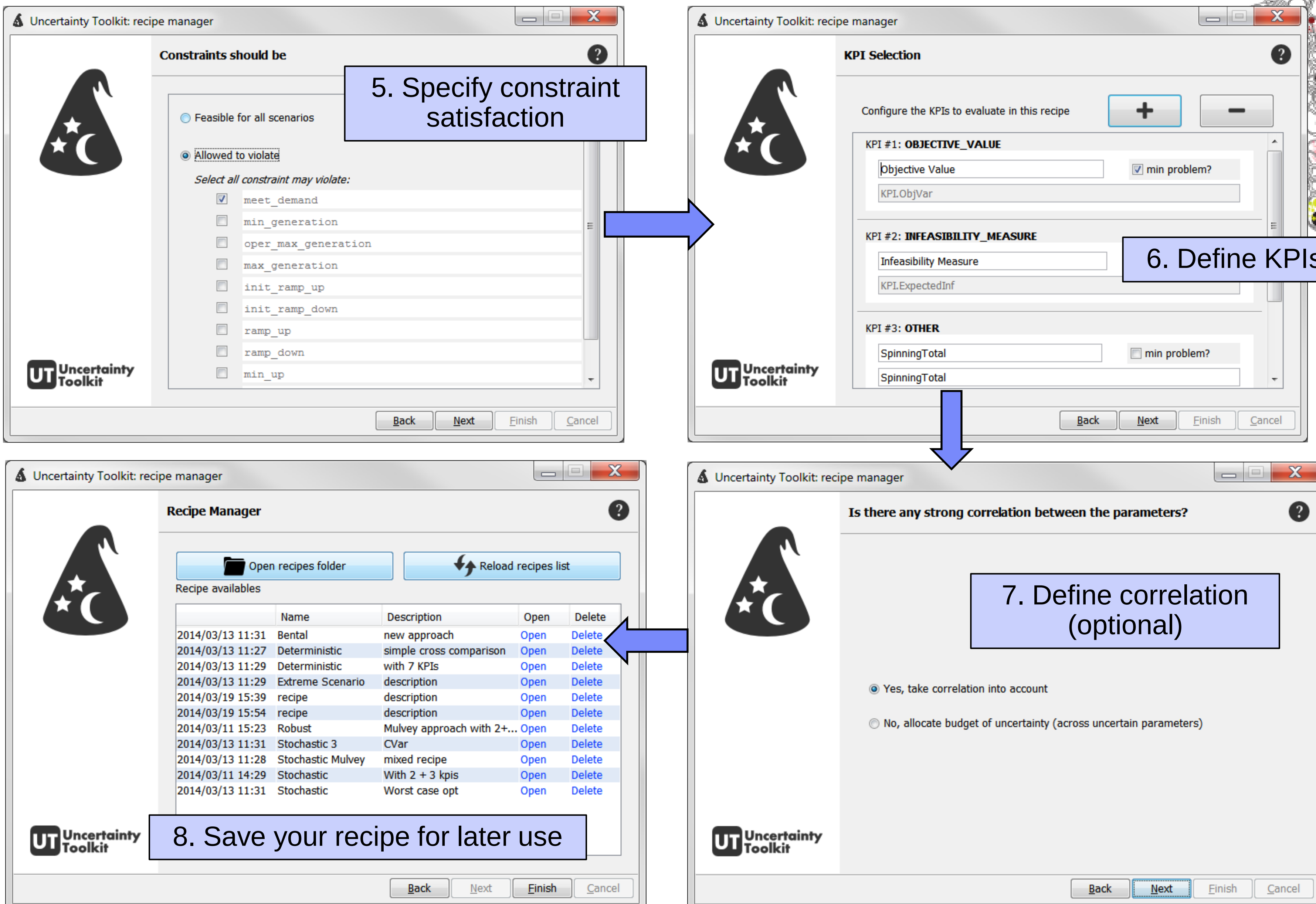
- Price scenarios, with likelihoods:
  - From energy provider
  - From IBM Research forecasts



Step 2: Uncertainty Toolkit wizard for consultant input (1 of 2)



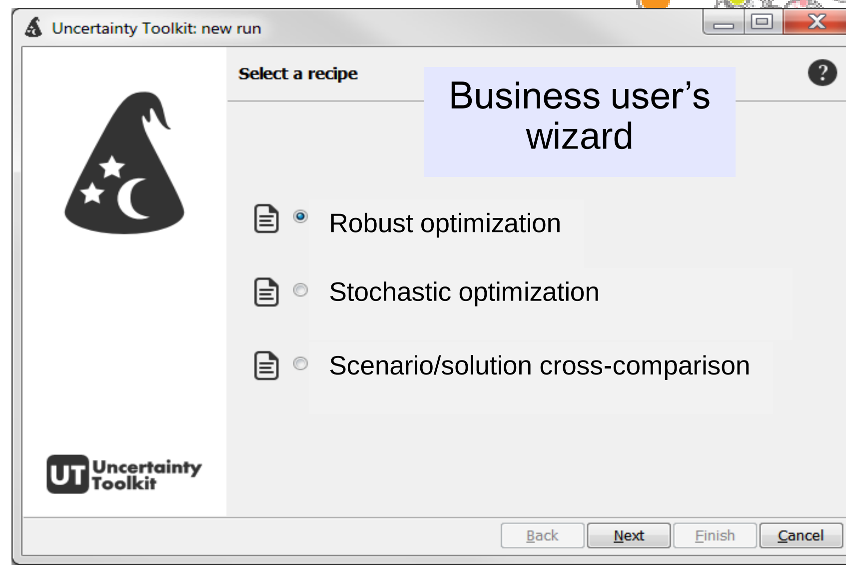
Step 2: Uncertainty Toolkit wizard for consultant input (2 of 2)



Step 3: Generate uncertain model

- Uncertainty Toolkit automatically generates the uncertain model(s) depending on choices in Steps 1 and 2

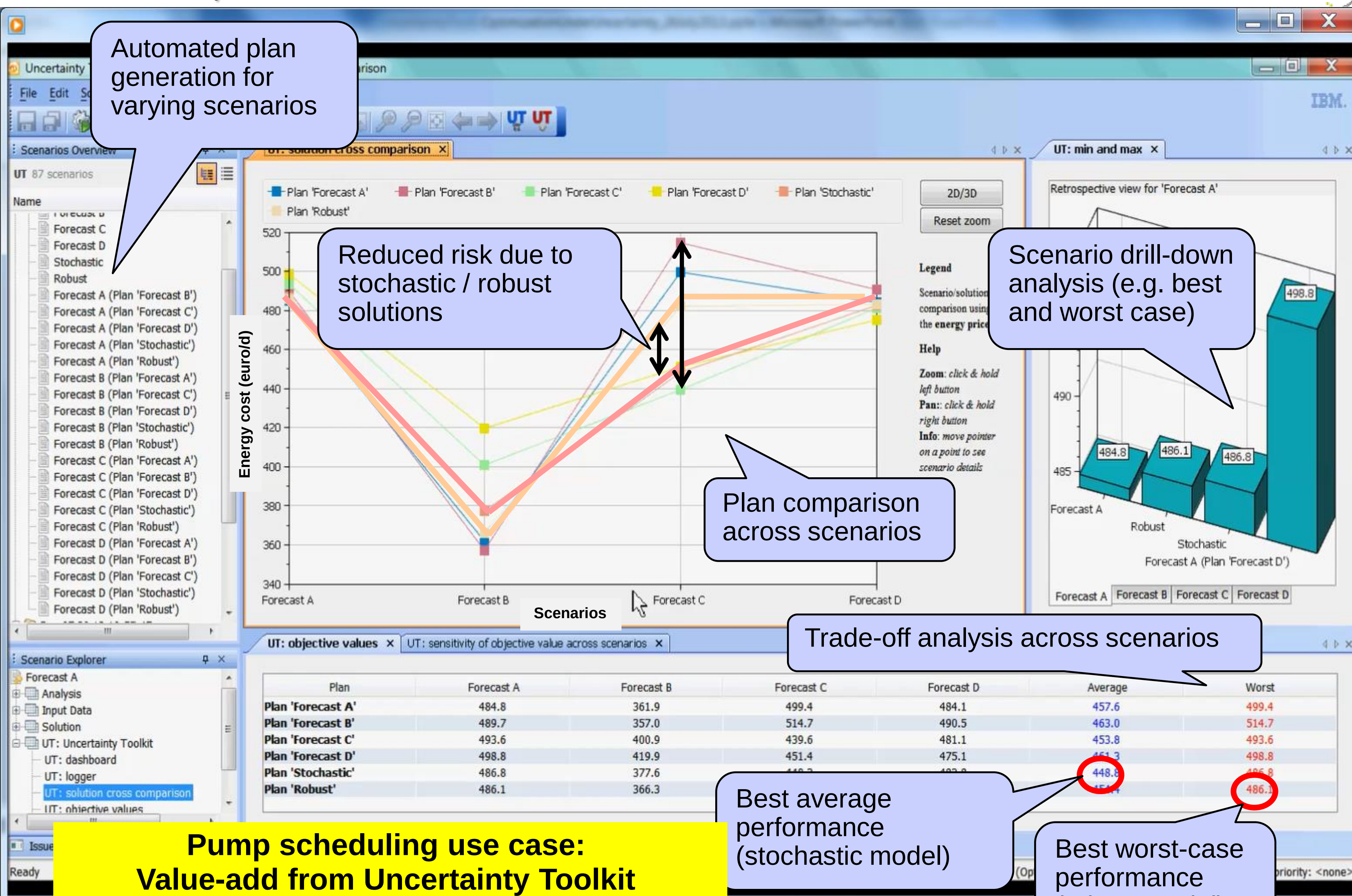
- Uncertain models are typically classified as
  – "Robust": hedging against worst case outcome(s)
  – "Stochastic": optimizing for expected outcome(s)
  – If choice unclear, use both & visualize trade-offs



Step 4: Generate plans

- Uncertainty Toolkit generates multiple solutions (deterministic, robust, stochastic)
- Uncertainty Toolkit automatically does solution-scenario cross-comparison
  – What is the impact of change on each plan

Decision Optimization



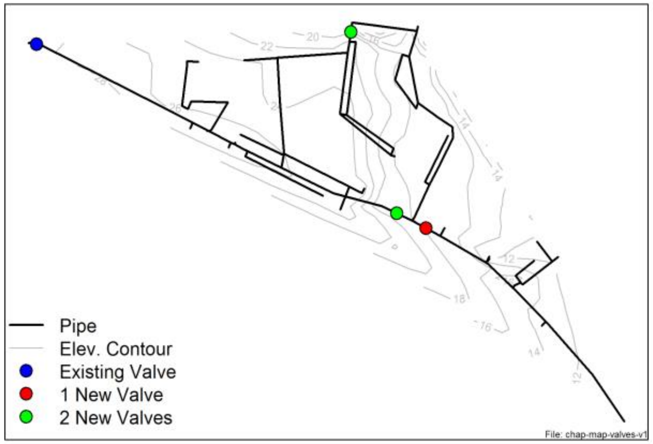
Plan	Forecast A	Forecast B	Forecast C	Forecast D	Average	Worst
Plan 'Forecast A'	484.8	361.9	499.4	484.1	457.6	499.4
Plan 'Forecast B'	489.7	357.0	514.7	490.5	463.0	514.7
Plan 'Forecast C'	493.6	400.9	439.6	481.1	453.8	493.6
Plan 'Forecast D'	498.8	419.9	451.4	475.1	[illegible]	498.8
Plan 'Stochastic'	486.8	377.6	[illegible]	[illegible]	448.8	486.8
Plan 'Robust'	486.1	366.3	[illegible]	[illegible]	[illegible]	486.1

Pump scheduling use case:
Value-add from Uncertainty Toolkit
~ 30% improvement in energy cost reduction

Example: pressure management in water distribution networks

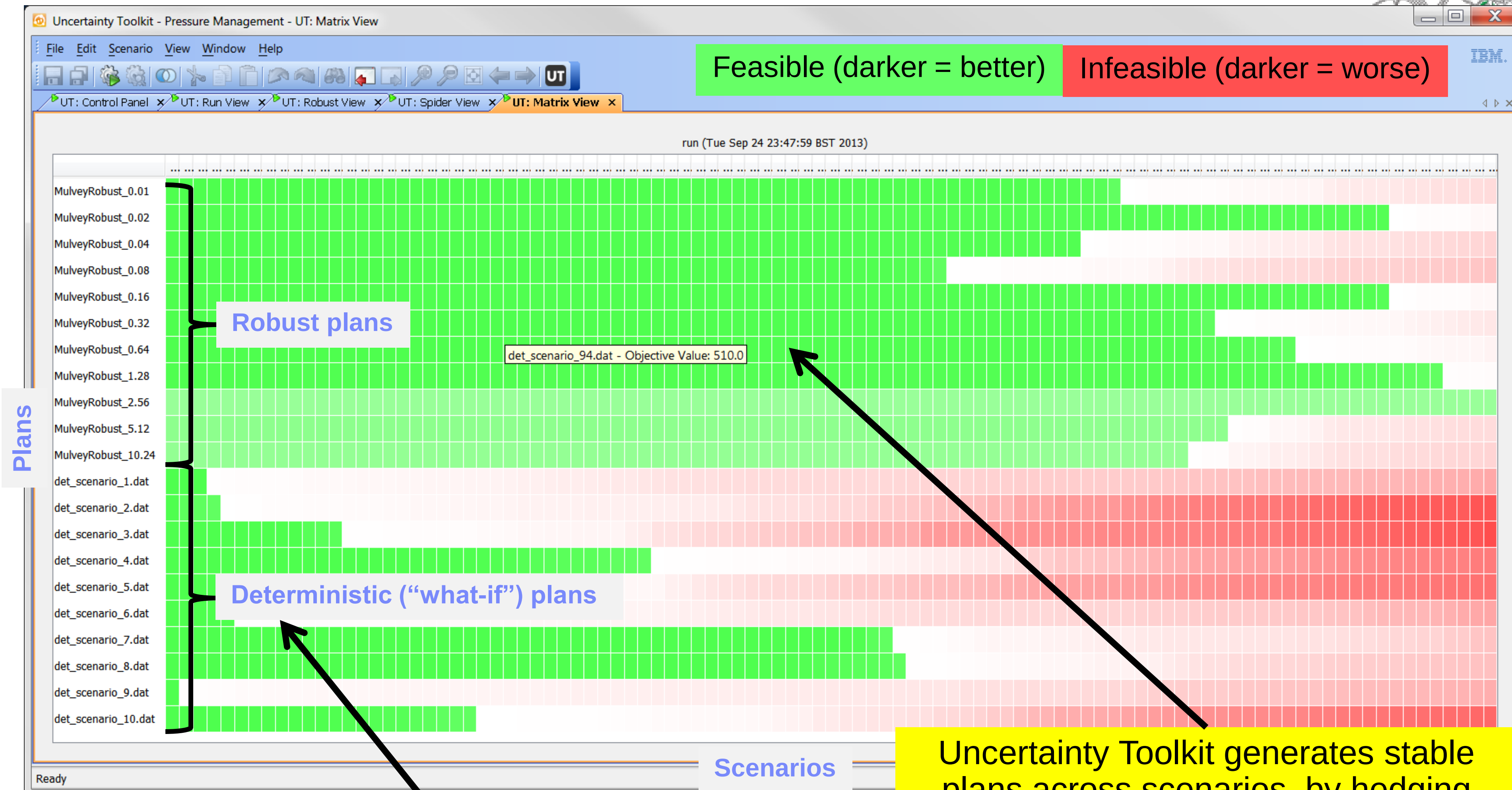
- Problem: Leakage (non-revenue water) leads to 5 – 60% of treated water lost
- Existing solution:
  - 1% pressure reduction ~ 1% leakage reduction
  - Place and set pressure reducing valves to minimize leakage for given demand pattern (deterministic plans)
- New challenge: demand uncertain
  - Unexpected short large draw-offs by industrials
  - Variations depending on time of day / week
  - Deterministic plans not robust – often infeasible & sub-optimal when demand changes
- Uncertainty Toolkit creates robust plans
  - Stable (robust) valve settings / placement (no need for frequent changes as demand changes)
  - Leakage reduction across demand scenarios

Dublin's Chapelizod network: optimal robust valve placement



Decision Optimization

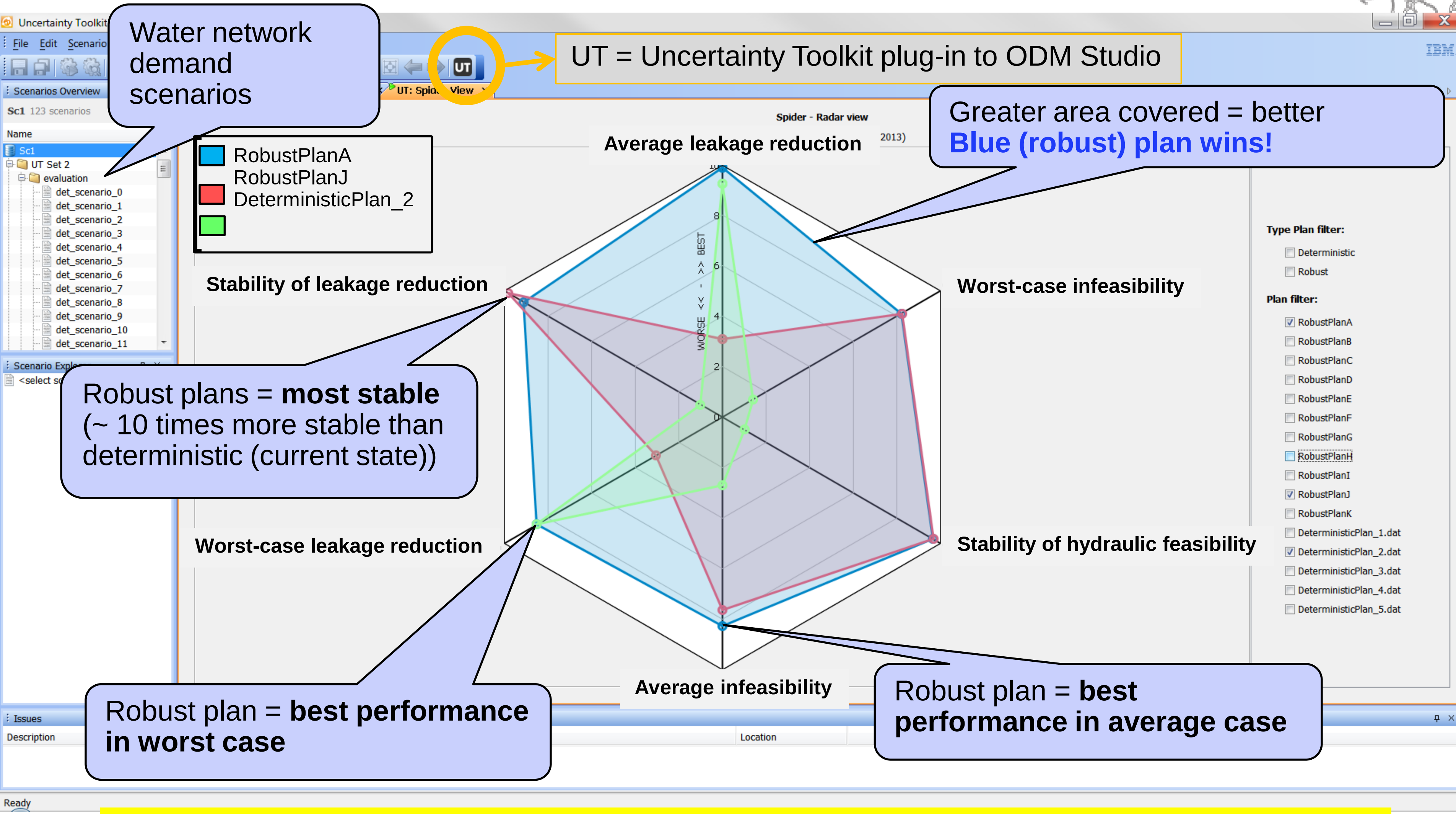
Benefits of Uncertainty Toolkit – pressure management use case



"What-if" plans could become unstable when data changes

Uncertainty Toolkit generates stable plans across scenarios, by hedging against uncertainty

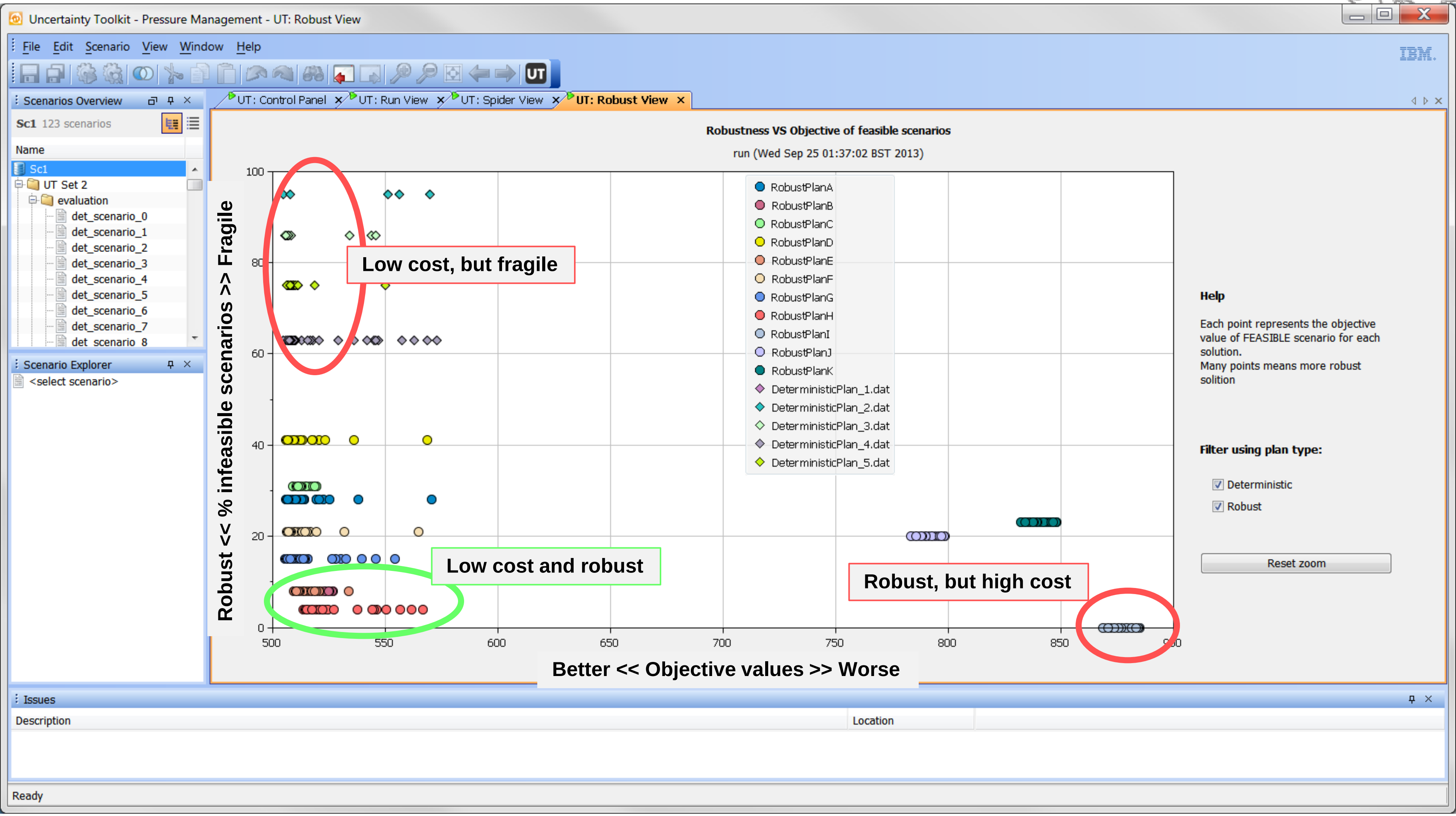
Benefits of Uncertainty Toolkit – pressure management use case



Pressure management use case:
Water network operational decisions 10 times more stable than current state, continue to perform well when data changes (i.e. “robust” plans)

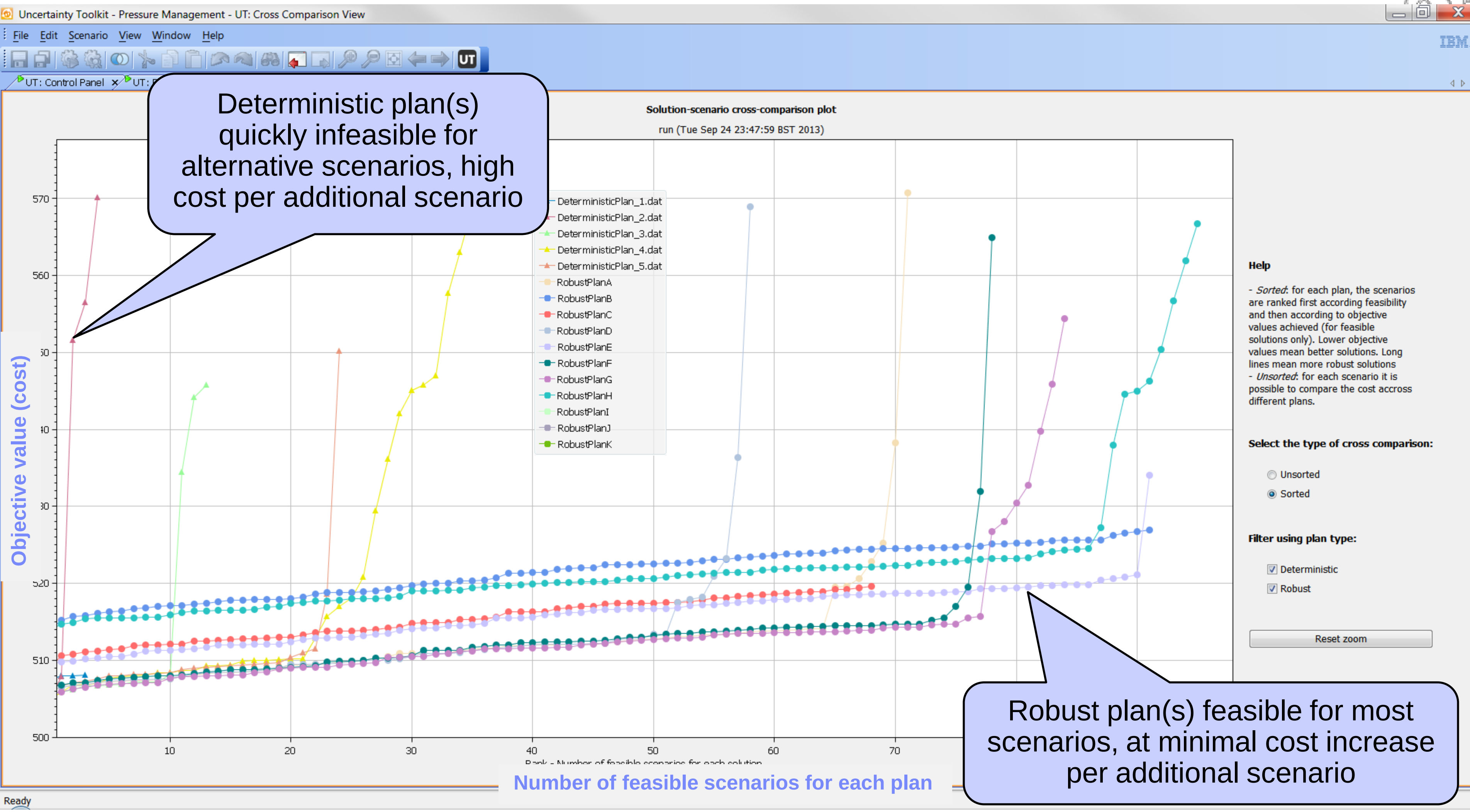
Decision Optimization

Benefits of Uncertainty Toolkit – pressure management use case



Visualization of trade-off: robustness vs. cost

Benefits of Uncertainty Toolkit – pressure management use case

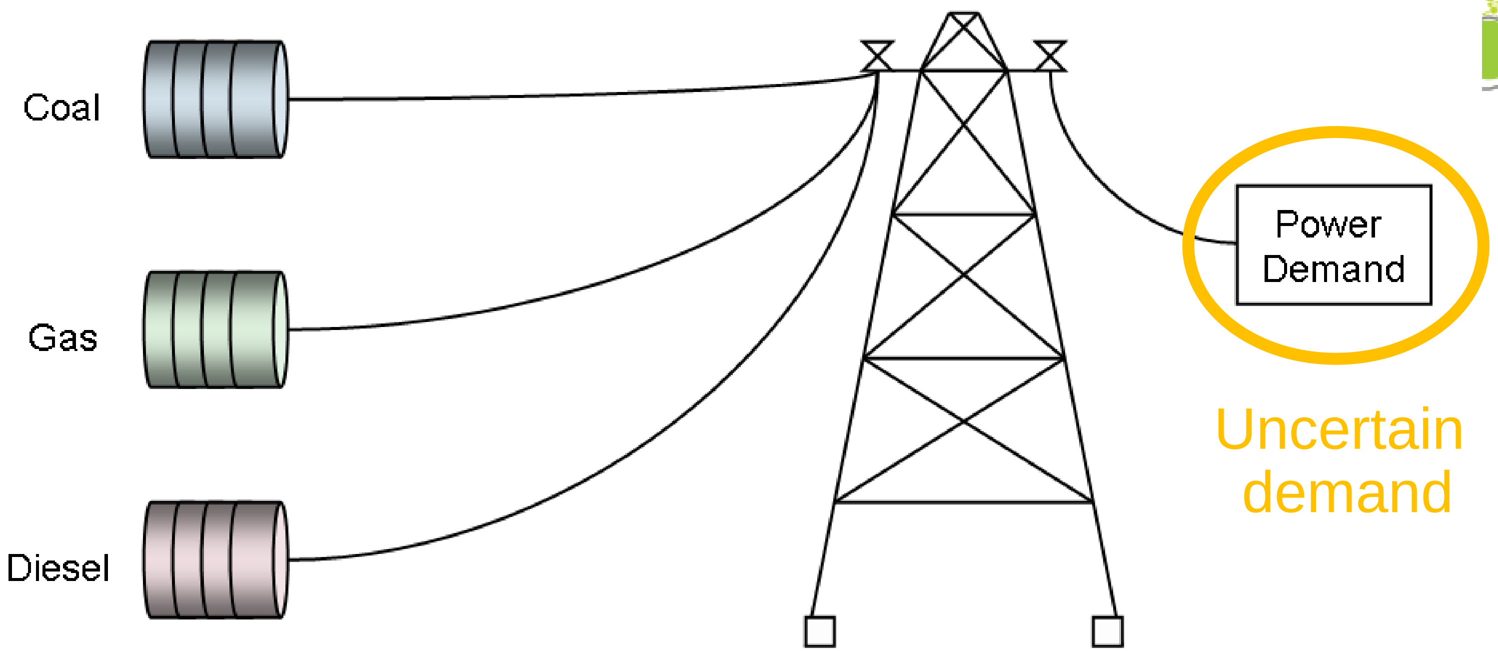


Effect on feasibility (robustness) by increasing cost

Example: Unit Commitment

The Unit Commitment Problem

3 types of power generators (units)



Business goal: Determine production schedule that minimizes startup cost + fuel cost + ecological cost (due to CO2 emissions), while satisfying demand

Unit Commitment Problem

Given

- Power generation units with
  - Costs (start-up, fuel, CO2)
  - Operational properties (capacity, ramp)
- Demand over several periods

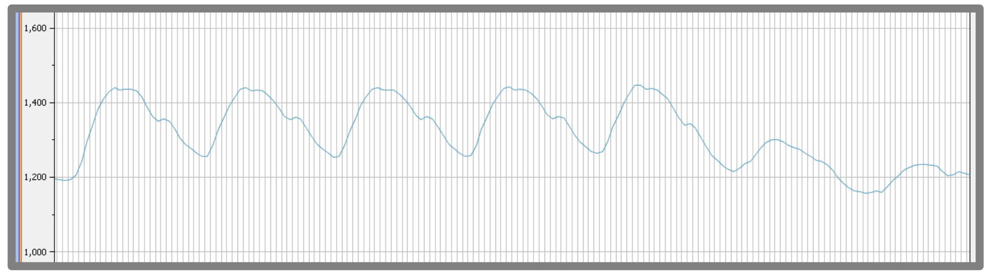
find generation plan

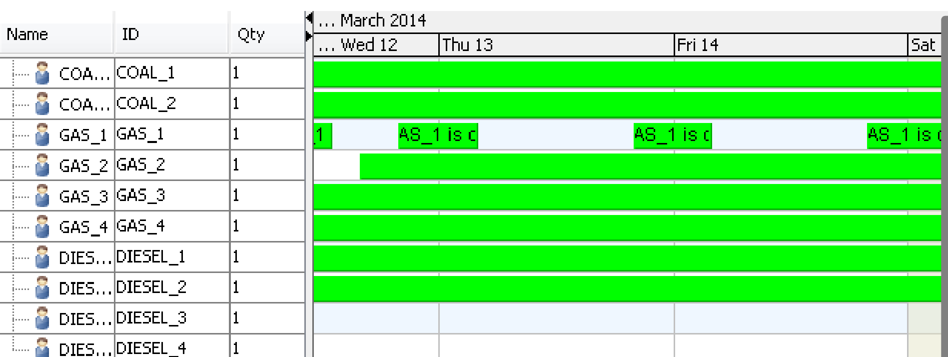
- Which units to use (unit commitment)
- How much to produce (dispatch)

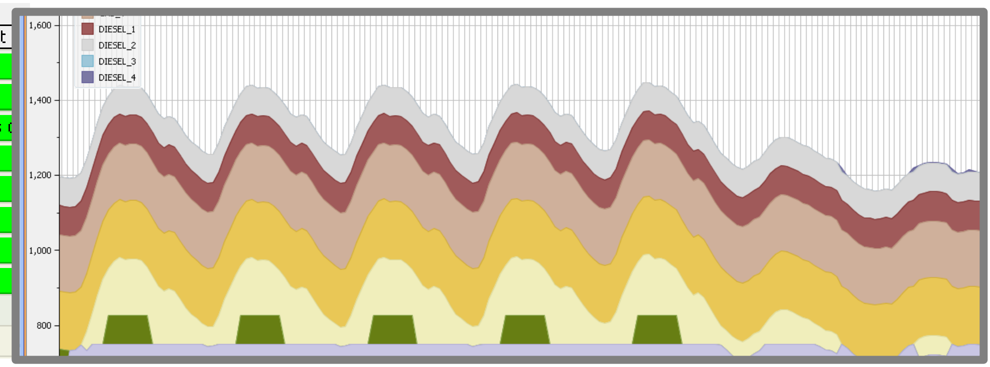
such that

- Demand is satisfied
- Operational constraints are satisfied
- Total cost is minimized

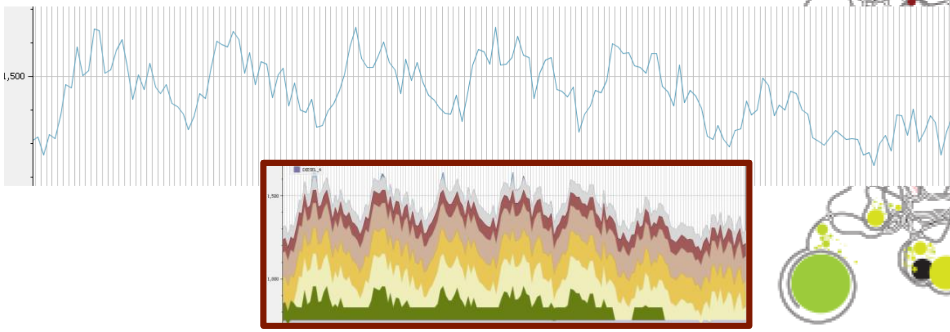
Type	Name	Linear Operations Cost	Fixed Start Up Cost	Linear Start Up Cost	CO2 Cost
Coal	COAL_1	$22.536	$5,000	$208.607	$30
	COAL_2	$31.985	$4,550	$117.372	$30
Diesel	DIESEL_1	$40.222	$560	$54.417	$15
	DIESEL_2	$40.522	$554	$54.551	$15
	DIESEL_3	$116.331	$300	$79.638	$15
	DIESEL_4	$76.642	$250	$16.259	$15
Gas	GAS_1	$70.5	$1,320	$174.117	$5
	GAS_2	$69	$1,291	$172.754	$5
	GAS_3	$32.146	$1,280	$95.353	$5
	GAS_4	$54.84	$1,105	$144.517	$5







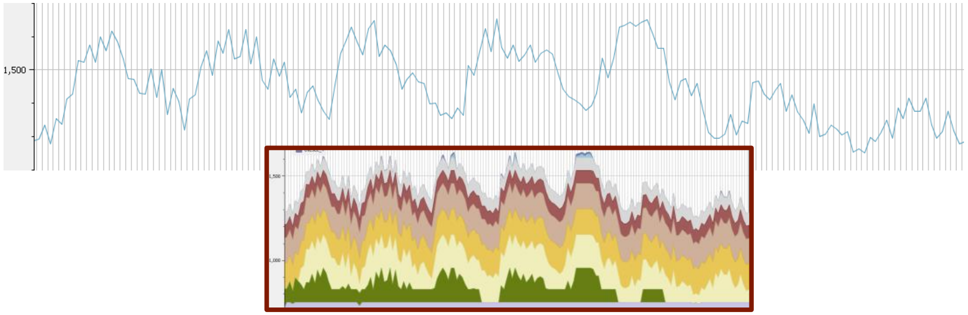
Unit Commitment Problem – Stochastic Version



Problem: How to deal with uncertain loads?

Question:

- Is the dispatch plan still feasible under a slight perturbation of the load?

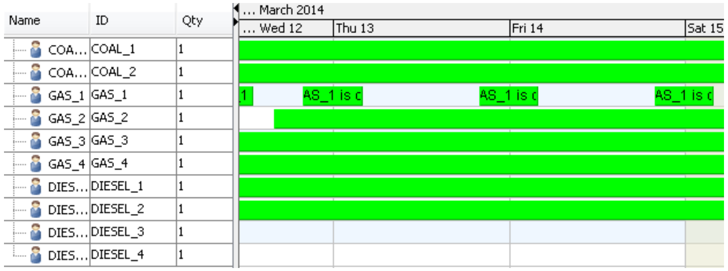


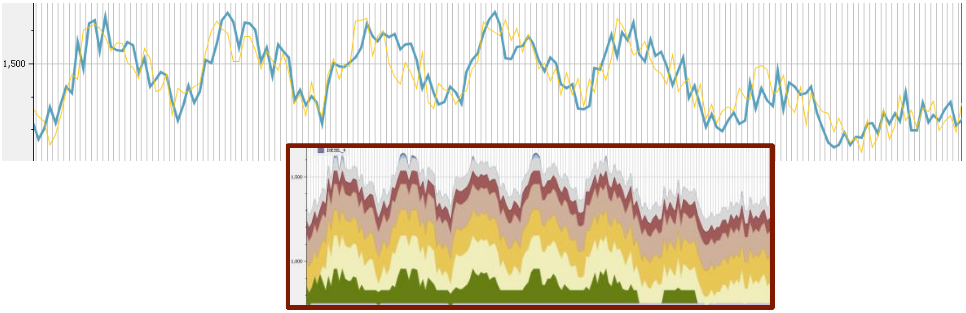
Stochastic Programming Approach

- Separate decisions into stages to be able to “react” to uncertainty

Decision Stages

- Stage 1: unit commitment
  - “Here-and-now” decisions
- Stage 2: dispatch
  - “Wait-and-see” decisions





Step 6a: Inspecting the results: Table View

UT: Control Panel | UT: Run View | **UT: Table View**

Solution-scenario cross-comparison table
anne-stochastic-8scen-random0.1 (Fri Mar 14 00:55:35 CET 2014)

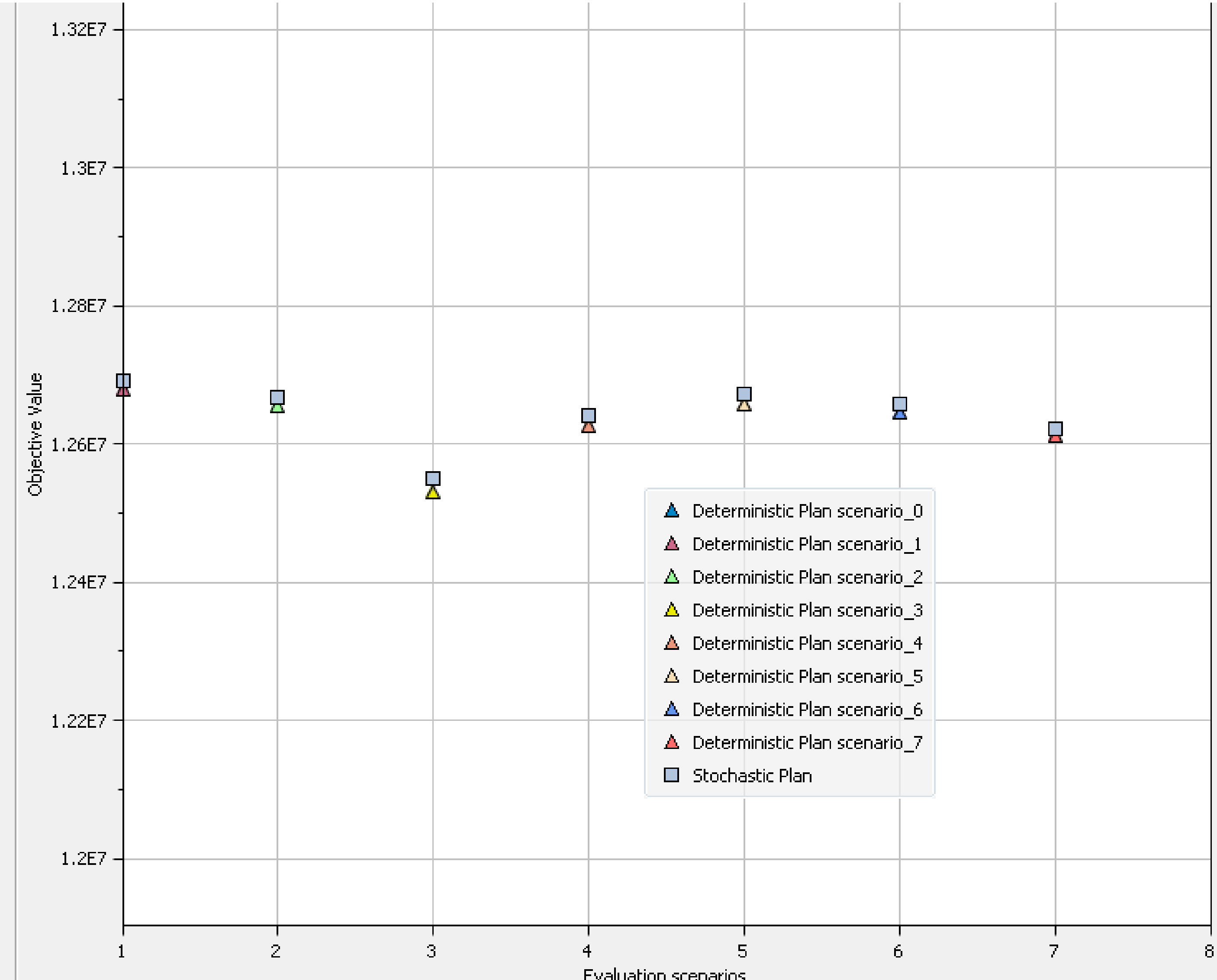
Select the KPI to show: Objective Value

Table cell width: 80

	scenario_0	scenario_1	scenario_2	scenario_3	scenario_4	scenario_5	scenario_6	scenario_7
Stochastic Plan	1.261418013E7	1.269088468E7	1.266713216E7	1.25511859E7	1.264070389E7	1.267165055E7	1.265699715E7	1.262302906E7
Deterministic Plan scenario_0	1.260033047E7							
Deterministic Plan scenario_1		1.267959751E7						
Deterministic Plan scenario_2			1.265528409E7					
Deterministic Plan scenario_3				1.253091733E7				
Deterministic Plan scenario_4					1.262720859E7			
Deterministic Plan scenario_5						1.265728358E7		
Deterministic Plan scenario_6							1.264521643E7	
Deterministic Plan scenario_7								1.261238517E7

- Stochastic Plan is feasible for all scenarios
- Deterministic plans are only feasible for “their” scenario

Step 6b: Solution-Scenario Cross-Comparison



Select KPI to display:

Objective Value

Help

Sorted: for each plan, the scenarios are ranked first according feasibility and then according to objective values achieved (for feasible solutions only). Lower objective values mean better solutions. Long lines mean more robust solutions

Unsorted: for each scenario it is possible to compare the cost accross different plans.

Type of cross comparison:

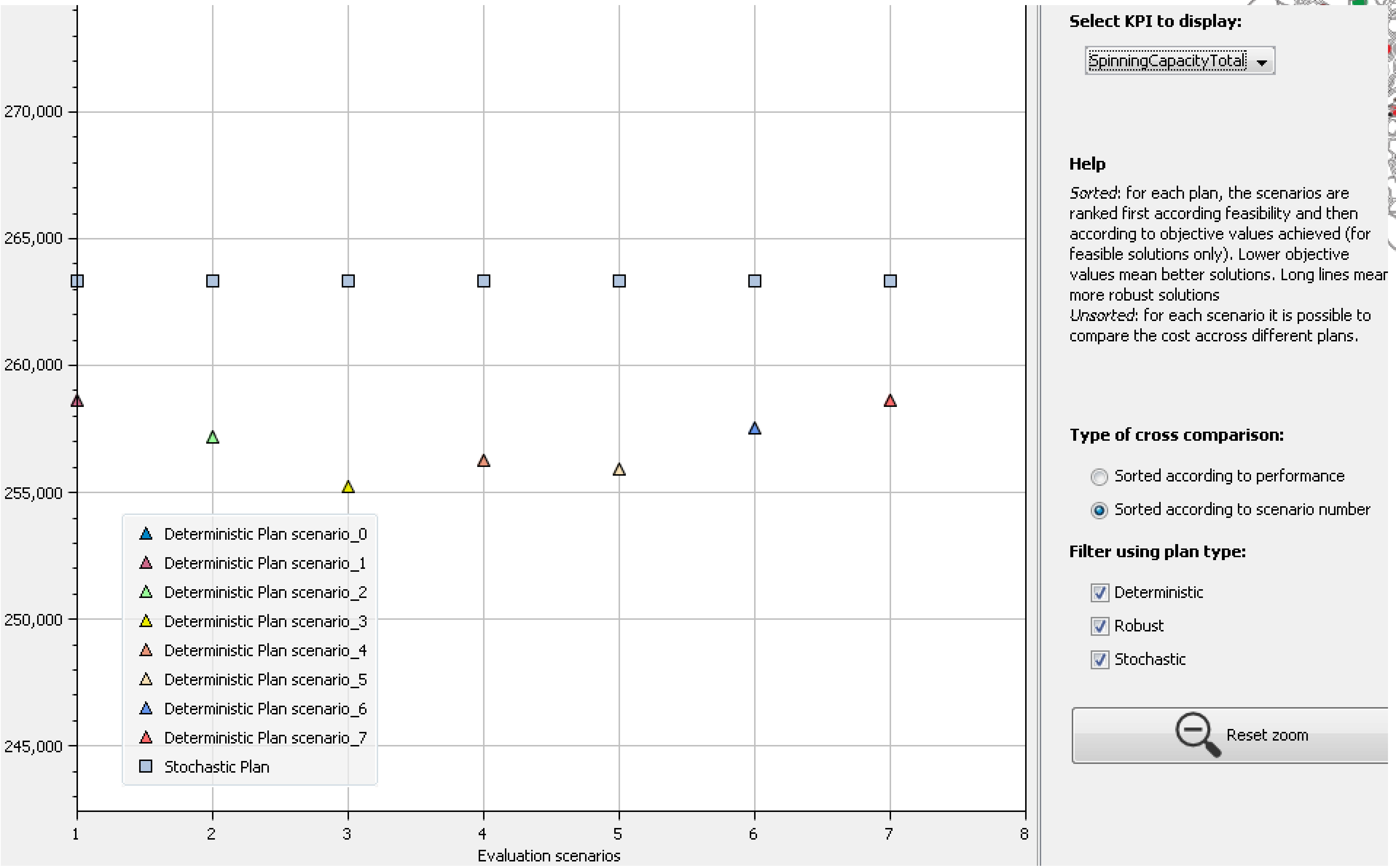
- ○ Sorted according to performance
- ◉ Sorted according to scenario number

Filter using plan type:

- ☑ Deterministic
- ☑ Robust
- ☑ Stochastic

Reset zoom

Step 6c: Cross-Comparison: Spinning Capacity



References & contact info

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