



Does Prognostics Make Maintenance Smarter?

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Prognostics

- Produces information about remaining useful life
 - Now have information that my component/system will fail in x time units
 - So, what are we going to do?
 - Repair now?
 - Repair later?
 - Change load?
 - Let it fail?
 - What we do depends on a lot of other things
 - Need to justify decision

Decisions, decisions

- Decision-making: Is it easy?
 - Yes
 - If my problem is simple
 - No
 - If my problem is not simple
 - Need to also absorb non-Prognostic information sources

Some non-prognostic information

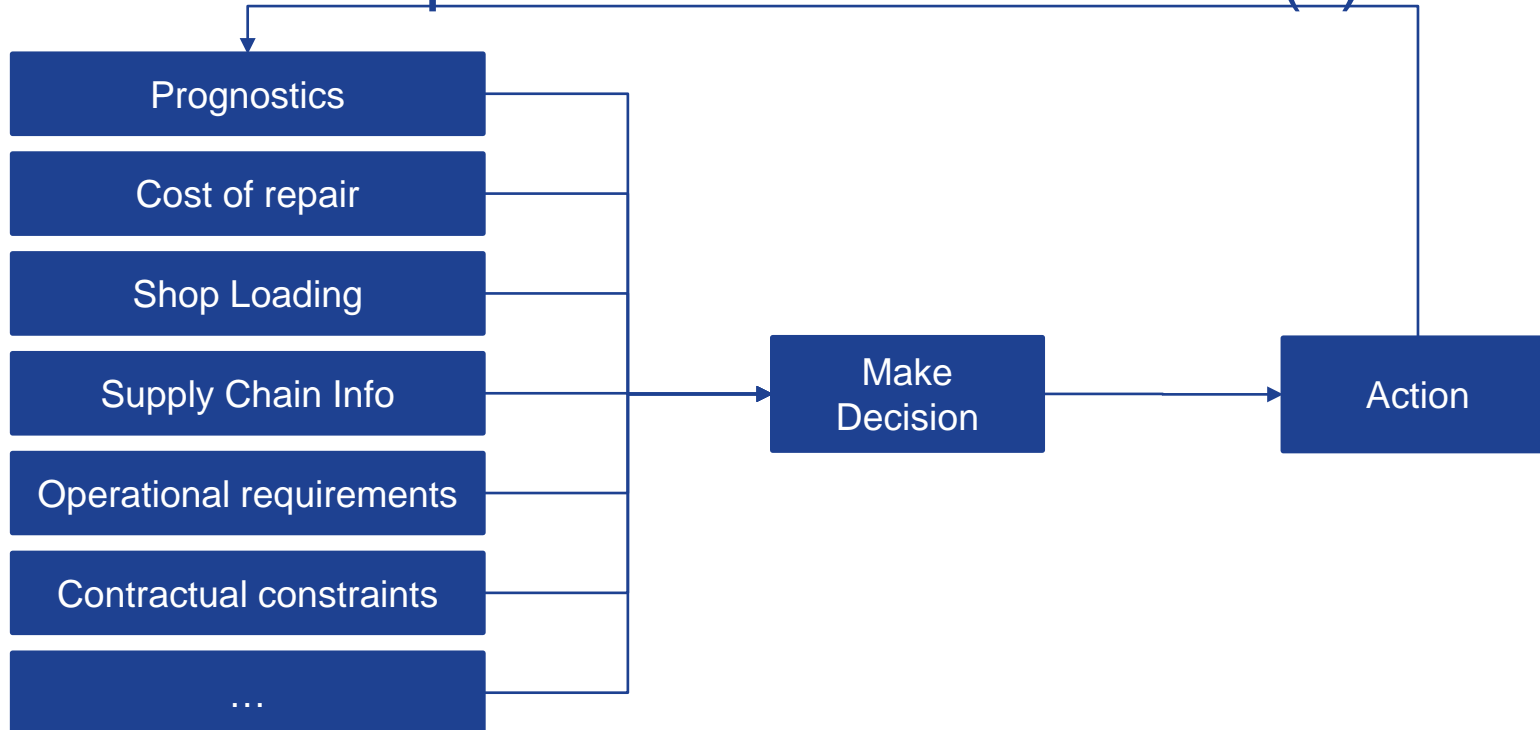
- Fleet-level considerations
 - Needs to repair other assets
- Logistics Considerations
 - Supply Chain constraints
 - Cost of repair
 - Shop loading
- Contractual obligations
 - Uptime
 - Mission completion
 - Warranties
 - Insurance
- Policies, Laws, Regulations
 - Maintenance policies
 - Regulatory mandates



Image credit: getty images

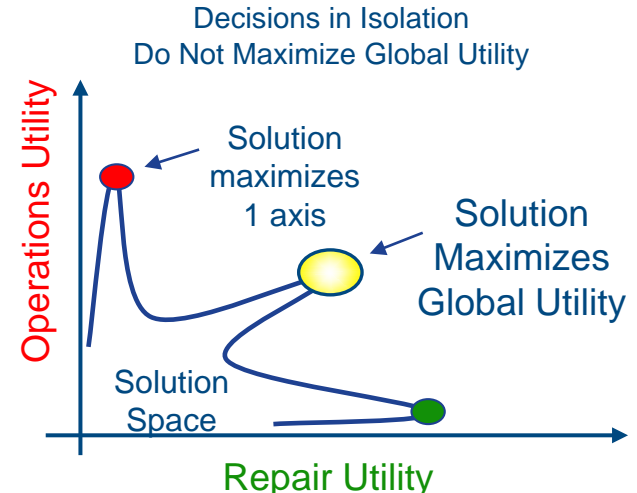
Decision Making in PHM

- HM Turns Prognostics into Action
- Take all inputs and find best answer(s)



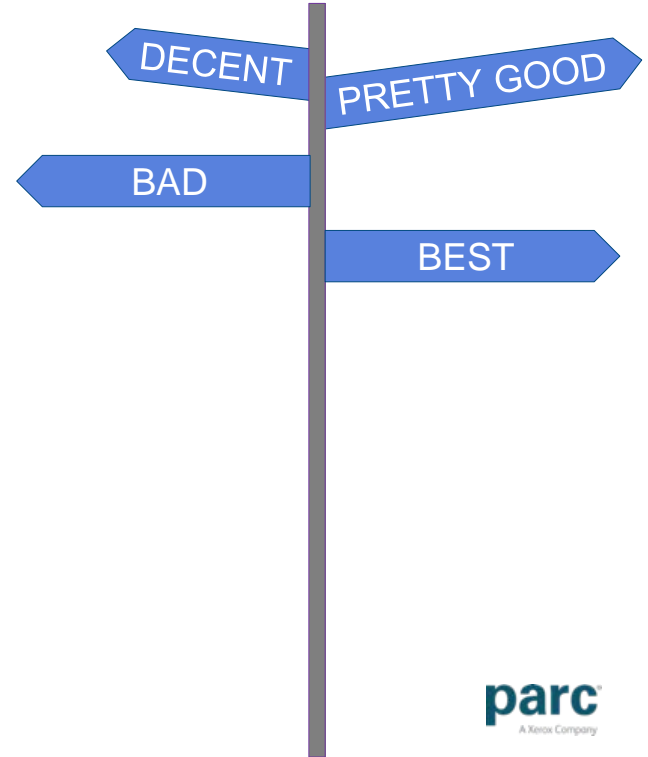
Complications

- Assimilation and interpret the information sources
- Determine best course(s) of action non-trivial task.
 - large volume of information from different sources
 - partially conflicting information
 - uncertainty associated with the pieces of information
 - large possible set of actions.
 - partially conflicting goals
 - uncertainty



What is the Best Decision?

- There are a multitude of “best” solutions
- Choose a preferred one
- Difficult to automate
 - knowledge of prevailing conditions
 - dynamic
 - situational
- Requires further refinement
 - e.g., with human insight



Complexity

Growth of number of decision solutions

- Problem complexity growth quickly
- But also increased number of satisfiable missions, mission reliability, safety, mission success rate and part availability

- Problem complexity



With 3 Missions to be Satisfied	
Max # of Asset Parts	Total # of Potential "Plans"
4	24,567
5	196,608
6	1,572,864
7	12,582,912

$$m \cdot (m-1) \cdot 2^{(m \cdot p)}$$

where m is number of missions to be satisfied;

p is number of parts per asset.

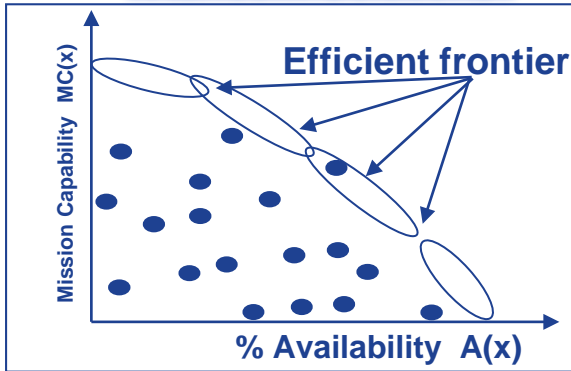
we assume there are as many assets available to satisfy the missions

Pareto Surface of Non-Dominated Solutions

Optimization Progress

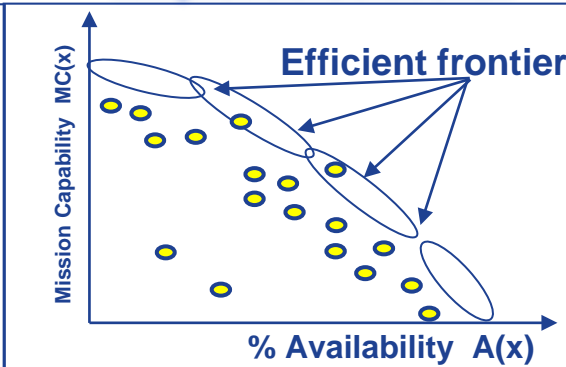


Random Solutions •



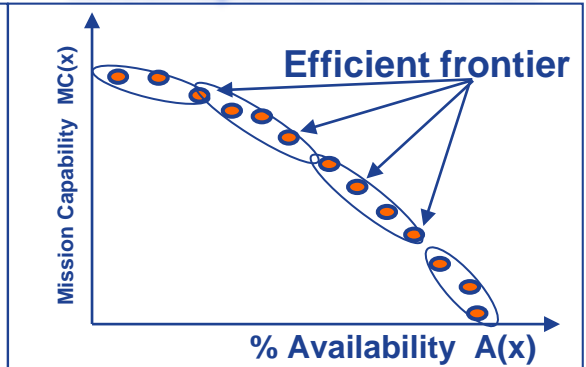
Initial population

Improved Solutions •



n^{th} generation

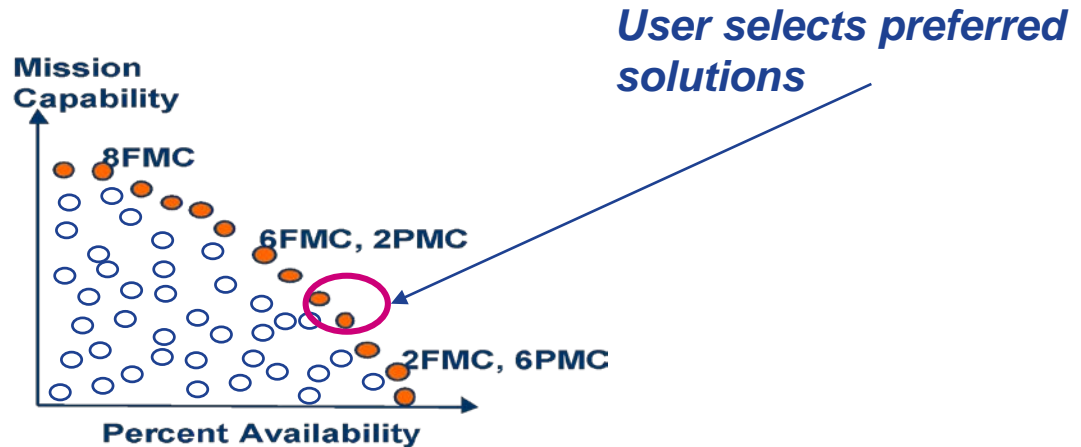
Near-optimal Solutions •



$n+m^{\text{th}}$ generation

Trade-Off Remains

- Need to achieve balance when multiple missions compete for the same resources (parts and time, man-power)
- Example: non-dominated, alternative operational plans for a group of 8 aircraft



- User indicates preferences for various tradeoffs to rank the alternatives

Needed: DSS

- Decision support system that ensures “sound” decisions
 - Overcome limited cognitive capacity in handling large quantities of information.
- Provide mechanism for discovery and evaluation of optimal decision alternatives
 - Subject to operational boundary conditions.
- Enable elicitation and application of user preferences and constraints
 - Take into account different prognostic and other information sources
 - Equipment status
 - Variables and constraints related to system logistics
 - Maintenance
 - Operations

Problem Formulation

For a time horizon T at a given instant t ,

Suppose,

$M_T(t) = \{m_1, m_2, m_3, \dots\}$ is a set of Missions to be satisfied in time horizon T where,

$m_i = (r_i, c_i, C_i)$ with,

- r_i desired Mission Reliability,
- c_i Mission Capability and
- C_i set of constraints related to the **time** within which mission m_i is to be met

$A = \{a_1, a_2, a_3, \dots\}$ is a set of available assets where,

- $a_j = \{p_{1j}, p_{2j}, p_{3j}, \dots\}$ where p_{ij} is part i in asset j

$P(t) = \{ (p_1, n_1, c_1, t_1), (p_2, n_2, c_2, t_2), (p_3, n_3, c_3, t_3), \dots \}$ is an inventory of parts available at time t for use in repair where,

(p_k, n_k, c_k, t_k) is the current inventory with n_k units of availability of the part p_k with cost of each part being c_k and repair or replacement time t_k

Problem Formulation, contd.

What is the best set of assignments from

- $P \rightarrow A$ (we refer to this as part allocation)
- $A \rightarrow M_T(t)$ (we refer to this as asset allocation)
- such that
- $M_T(t)$ is maximally satisfied

while minimizing total cost, part usage, and total time to repair?

Optimization Algorithms



Glarus; image credit: planetware.com

- Iterative (“gradient”) methods

- Walk down the mountain where the slope is the steepest
- May get stuck in local valley
- Gradient-free algorithms

- Explore new area based on heuristics

- Can “jump” over a hill
- May never get to true optimal point

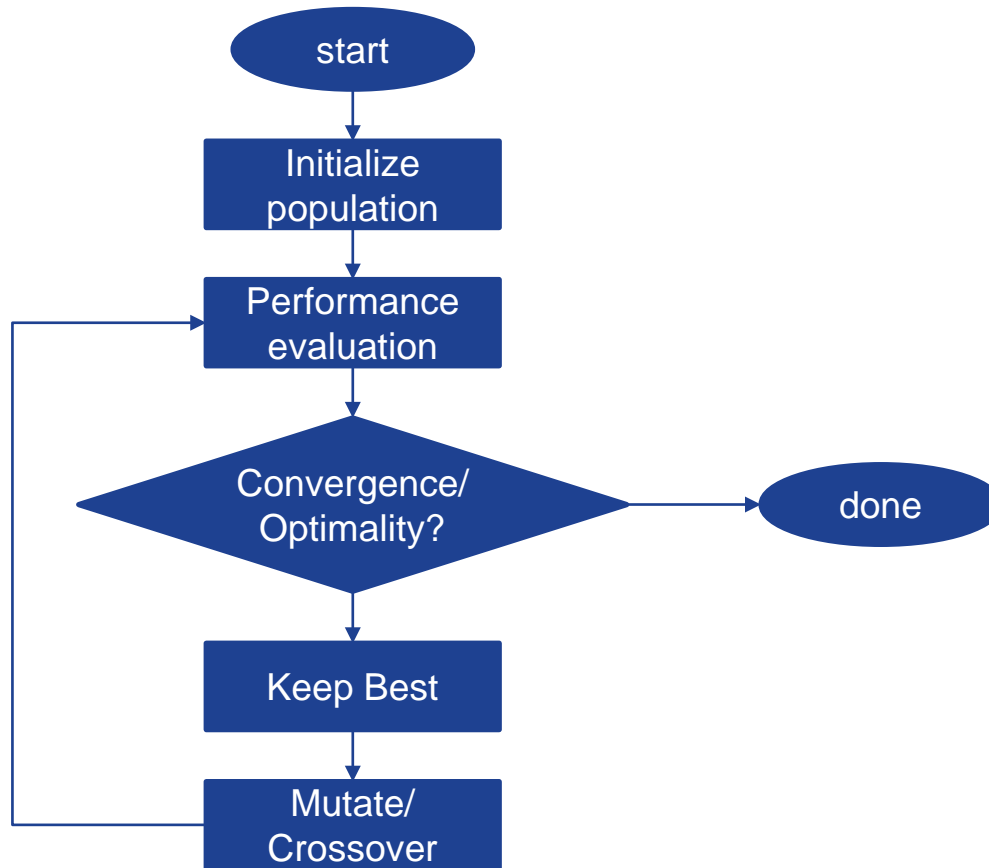
Iterative Algorithms (partial listing)

- Evaluate Hessian
 - Newton's method
 - Sequential quadratic programming
 - Interior points method
- Evaluate Gradients
 - Coordinate descent methods
 - Conjugate gradient methods
 - Gradient descent
 - Subgradient methods
 - Bundle method of descent
 - Ellipsoid method
 - Conditional gradient method (Frank–Wolfe)
 - Quasi-Newton methods
 - Simultaneous perturbation stochastic approximation

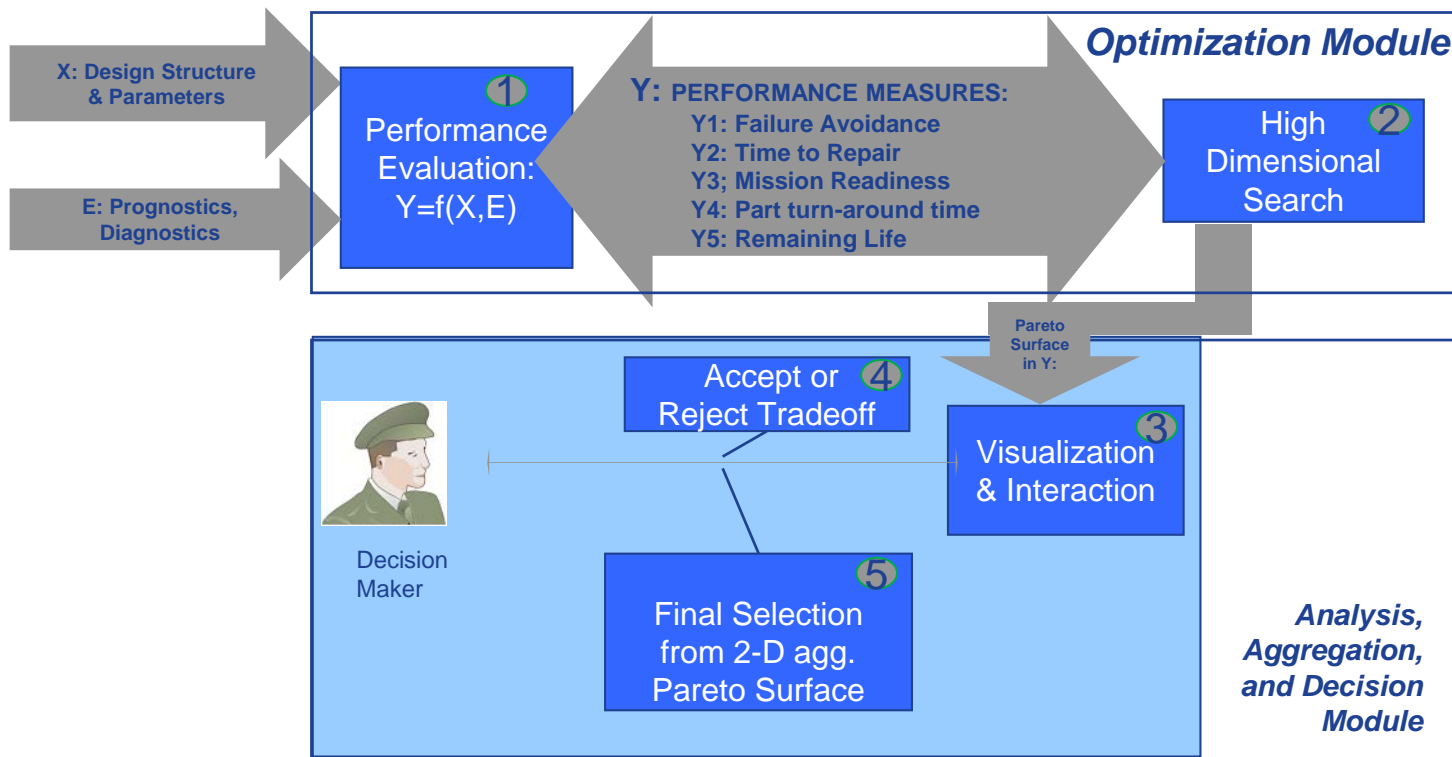
Gradient-Free Algorithms (partial listing)

- Memetic algorithm
- Differential evolution
- Evolutionary algorithms
- Dynamic relaxation
- Genetic algorithms
- Hill climbing with random restart
- Nelder-Mead simplicial heuristic: A popular heuristic for approximate minimization (without calling gradients)
- Particle swarm optimization
- Cuckoo search
- Gravitational search algorithm
- Artificial bee colony optimization
- Simulated annealing
- Stochastic tunneling
- Tabu search
- Reactive Search Optimization (RSO)[8] implemented in LIONSolver

Evolutionary Optimization



Multi-Objective Optimization

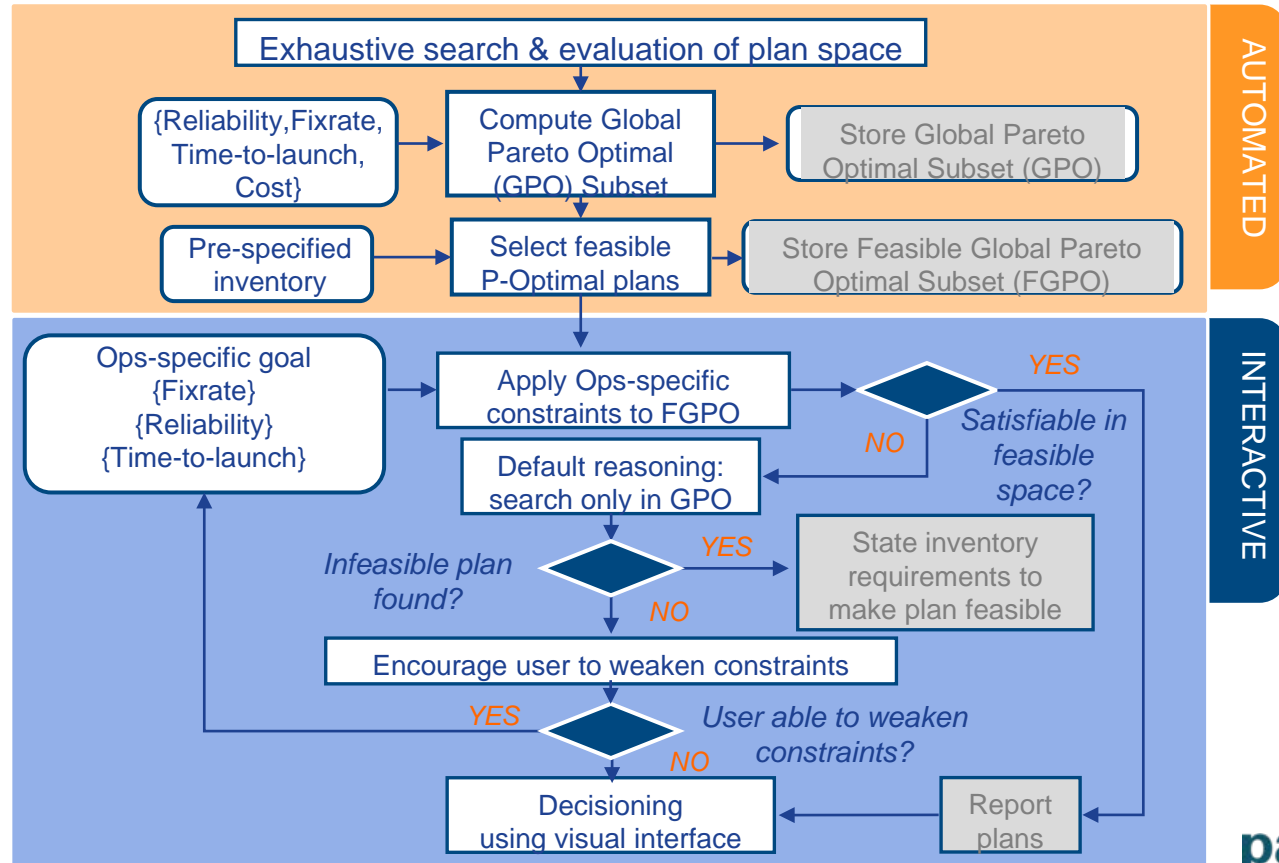


More Detail on Decision Module

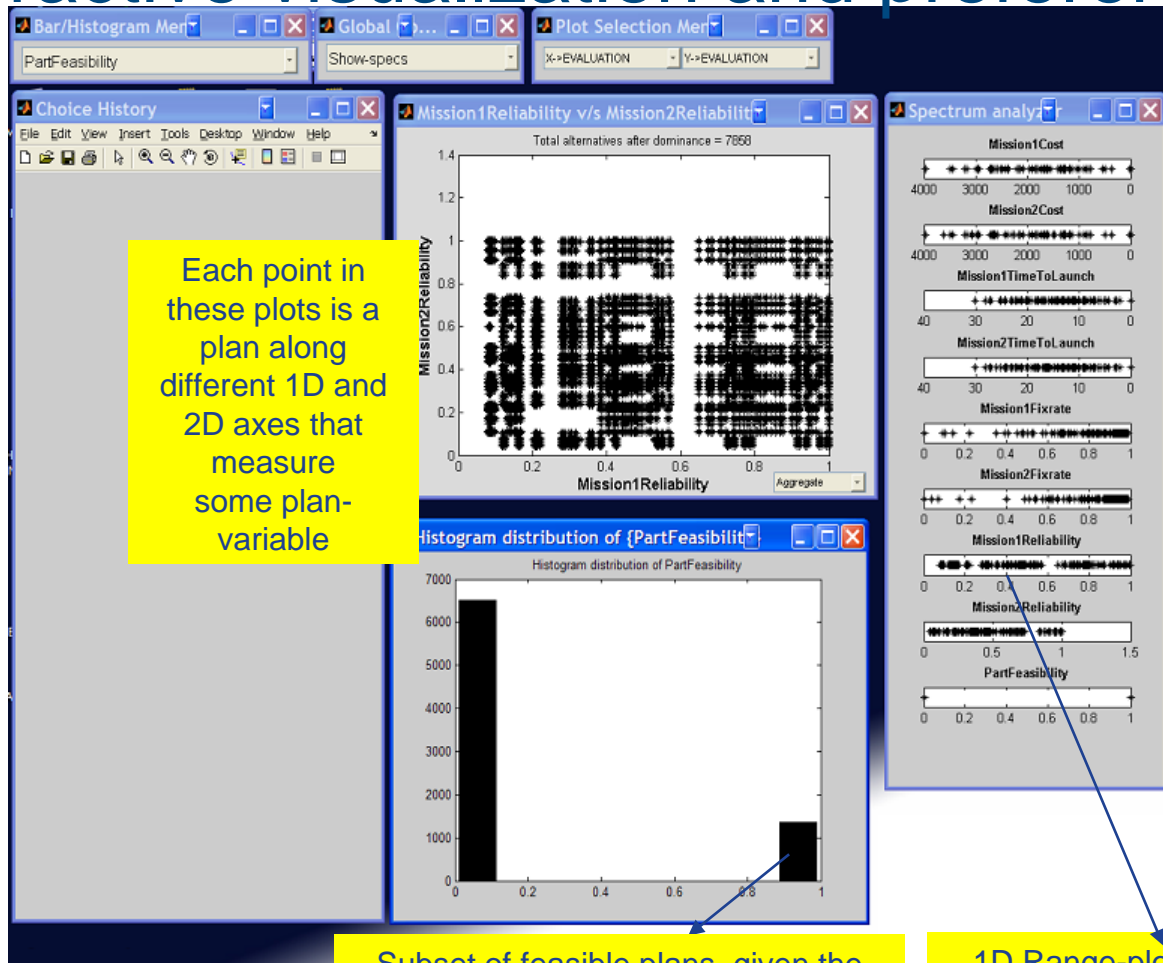
32,768
plans
7,858 plans

1,358
plans

1-5
plans



Interactive visualization and preference expression



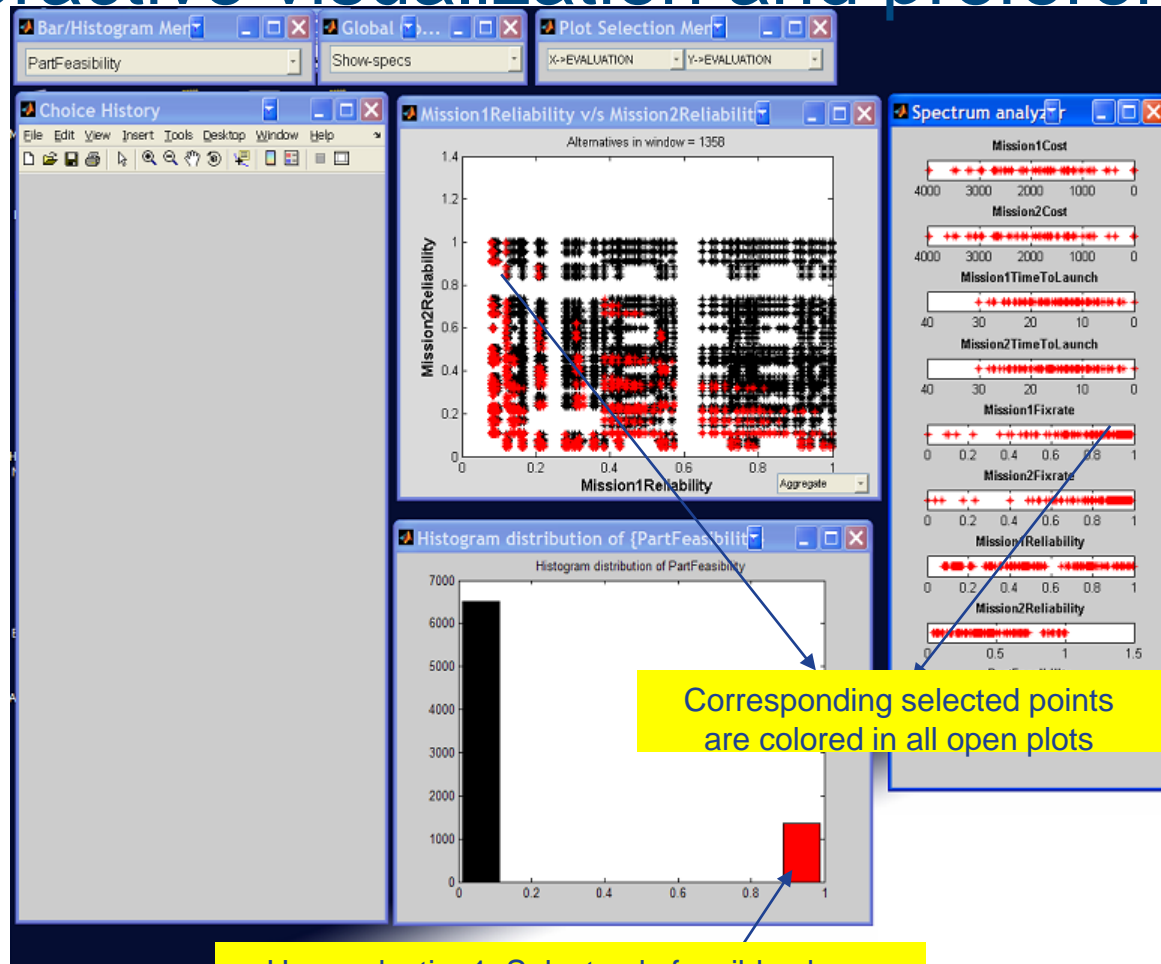
Each point in these plots is a plan along different 1D and 2D axes that measure some plan-variable

- 7858 plans to begin
- All are optimal
- Only some are feasible

Subset of feasible plans, given the part availability (inventory)

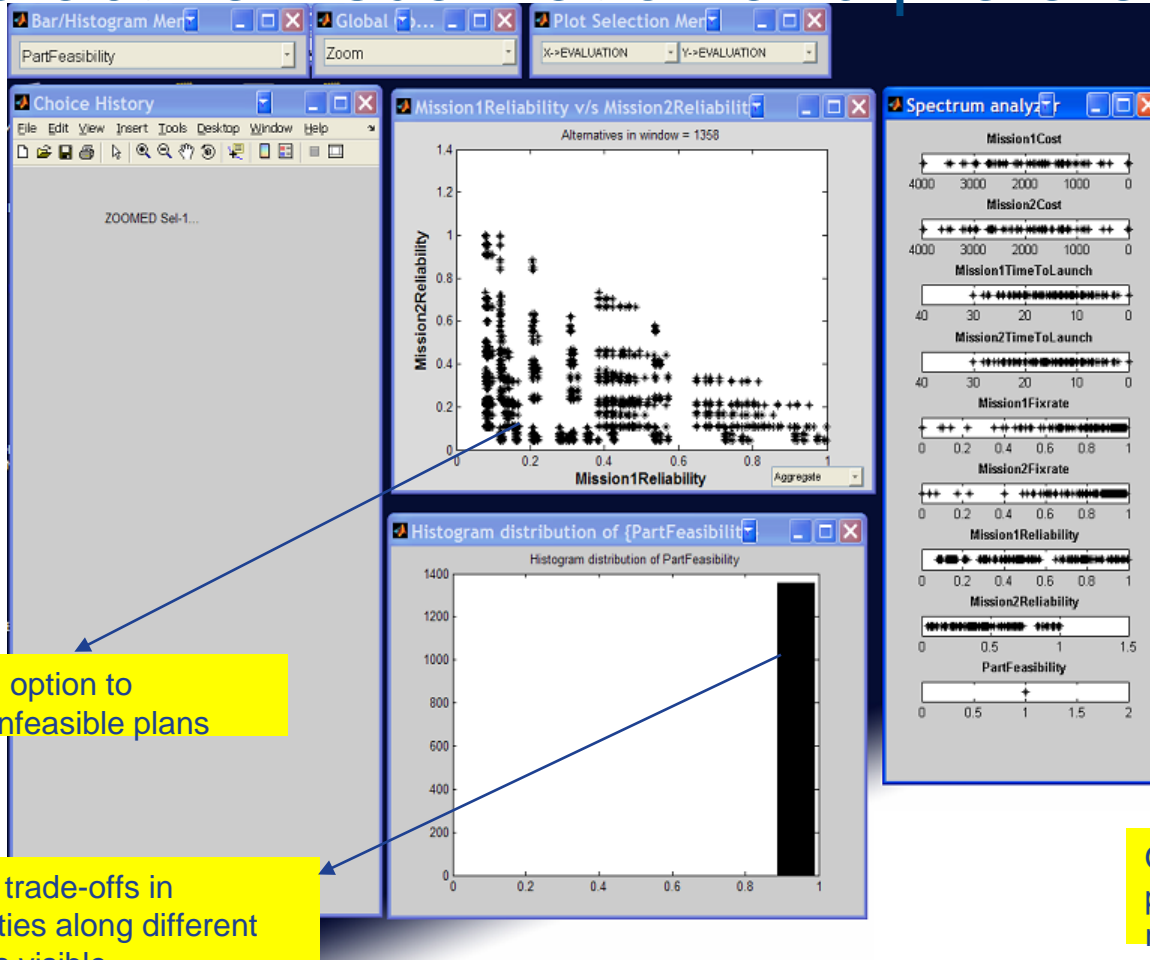
1D Range-plots of all variables of interest to user

Interactive visualization and preference expression



User-selection1: Select only feasible plans,
using mouse-click

Interactive visualization and preference expression

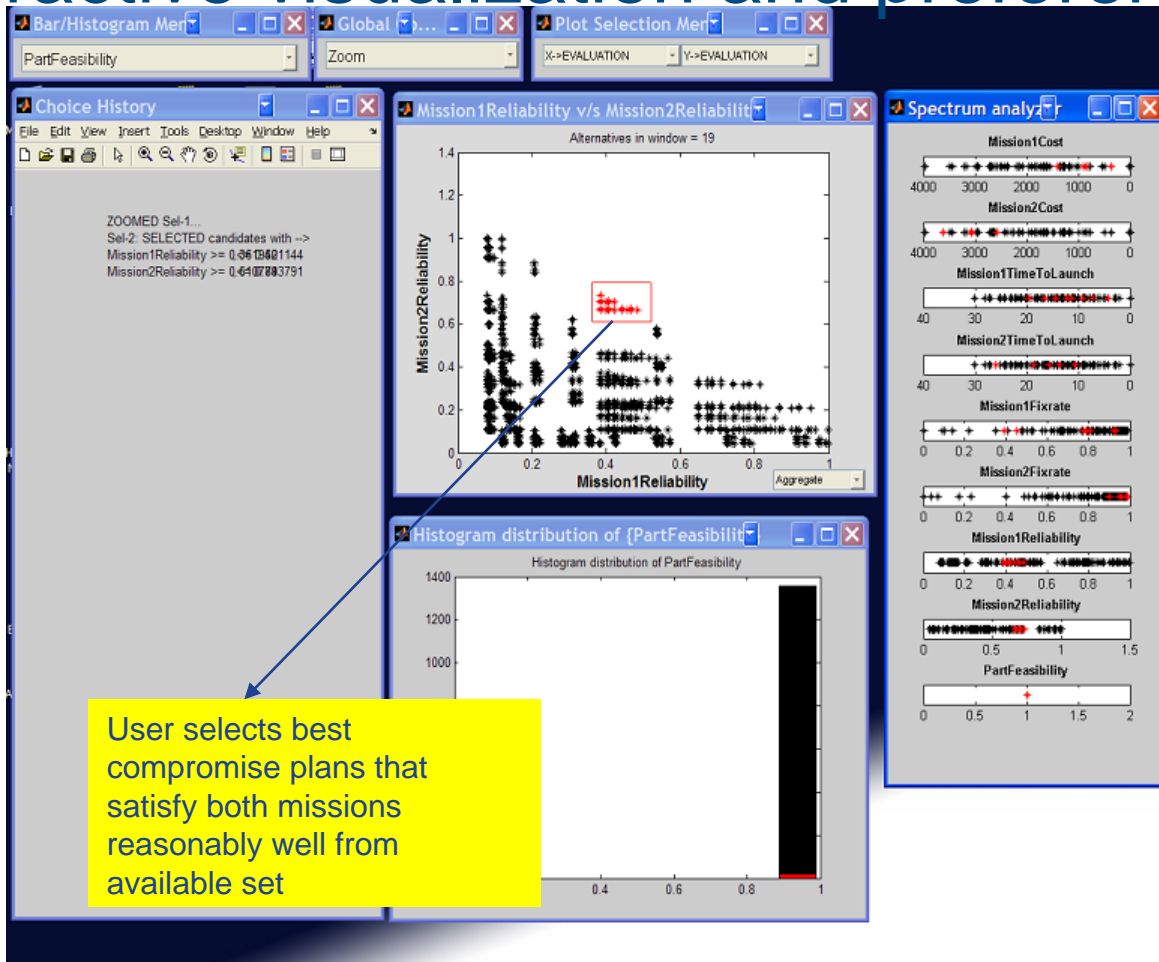


Use Zoom option to eliminate infeasible plans

Intrinsic trade-offs in Reliabilities along different missions visible

Only feasible plans from previous selection are retained in all plots

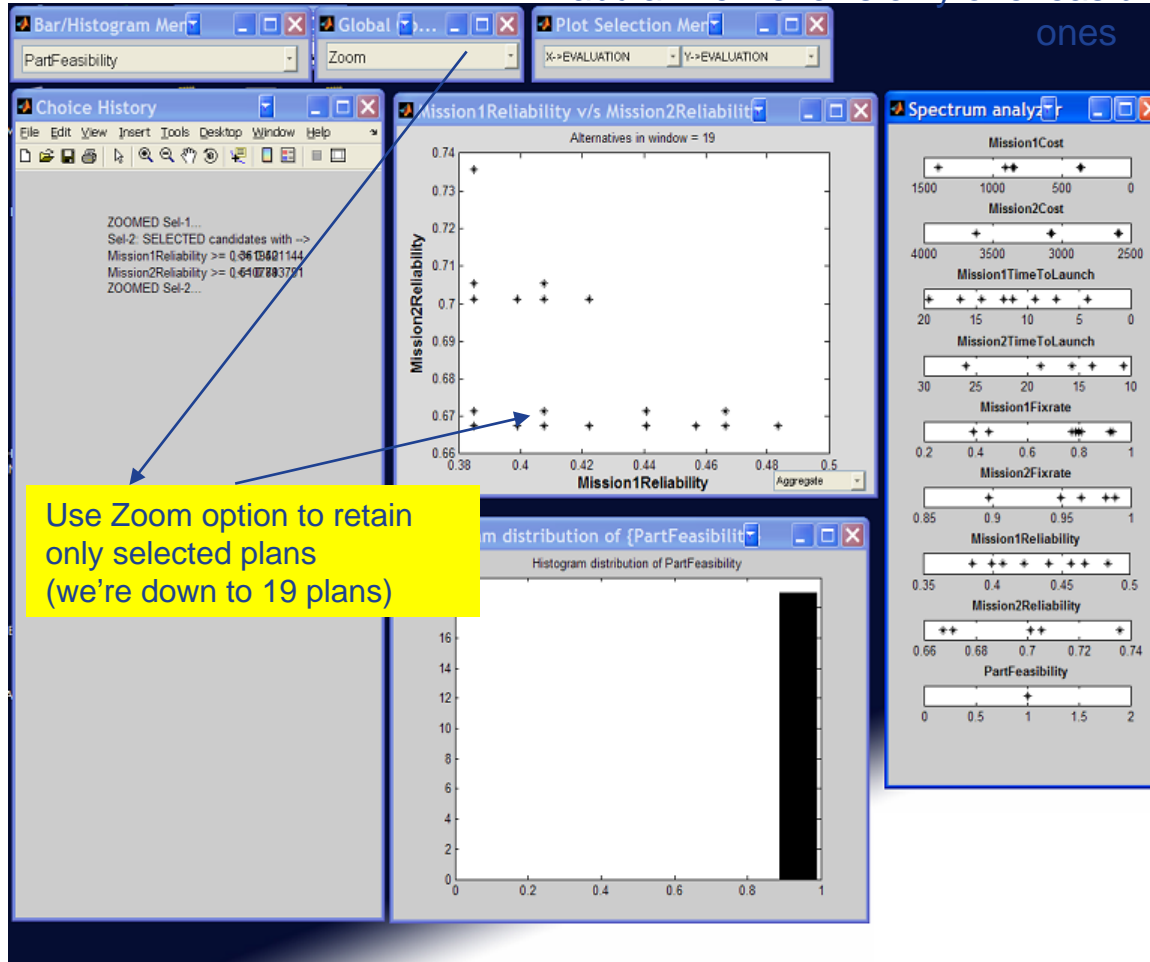
Interactive visualization and preference expression

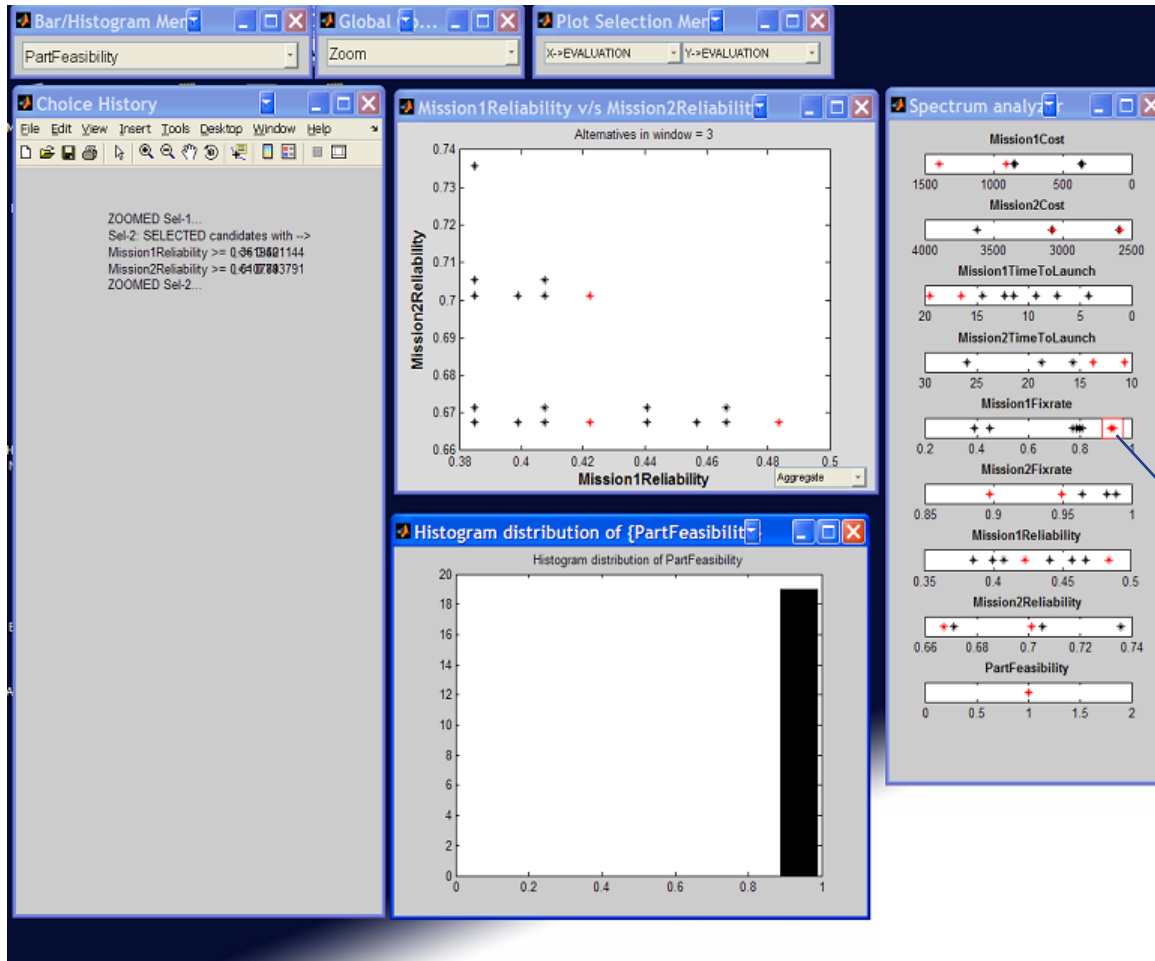


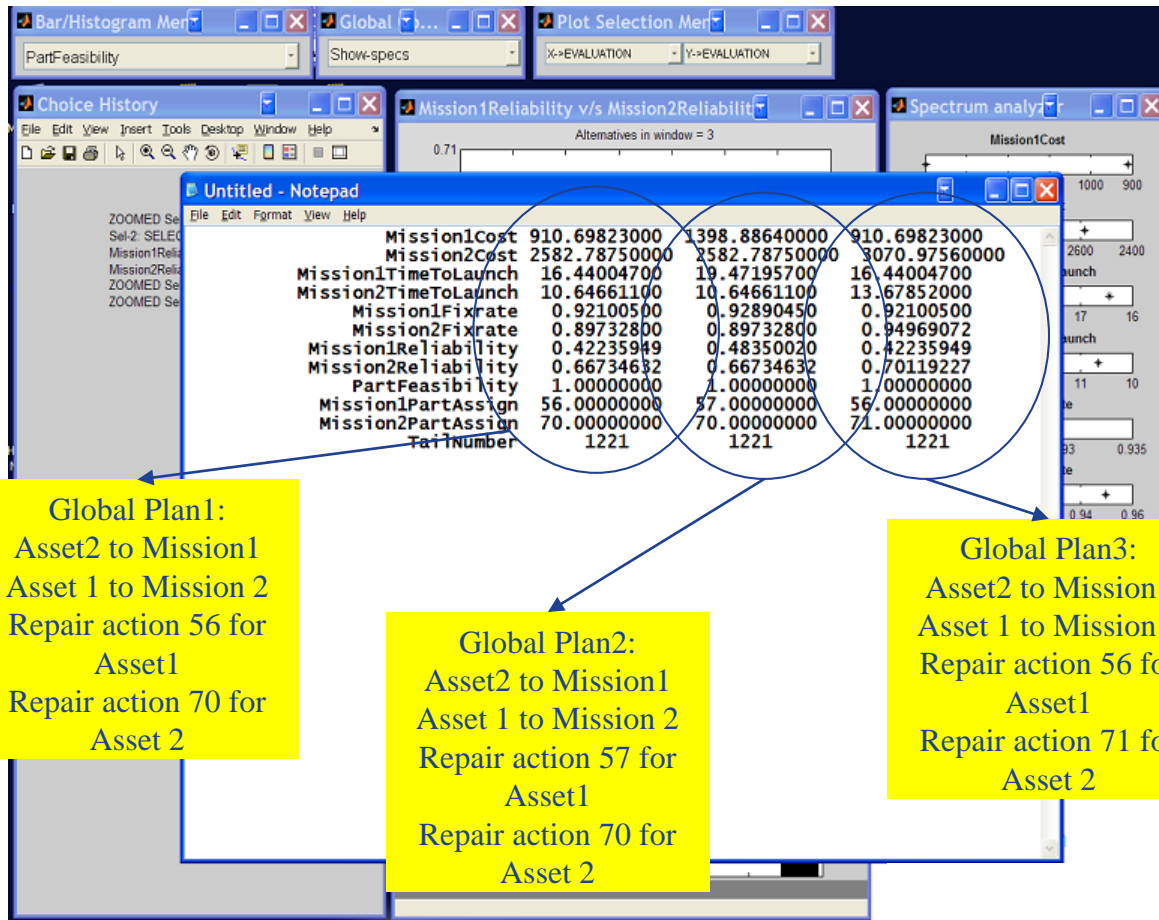
User selects best compromise plans that satisfy both missions reasonably well from available set

Tabular view shows only one feasible plan among the remaining

ones







With only 3 plans left to examine, user looks at tabular representation of the remaining plans and selects one for deployment to maintenance and operations platform

Concluding Remarks

- Prognostics can make Maintenance smarter, if:
 - Mitigation decision is made in methodical fashion
- Decision-Making can be framed as a Multi-Objective Dynamic Problem
 - Insight necessary to make right operational decisions
 - Complexity of information that needs to be processed exceeds cognitive, information processing capacity of human decision-makers
 - potential of making suboptimal decisions
 - Allow PHM user to collaborate in decision-making process
 - drive selection and eval. of operational scenarios and plans.
 - aids in discovery and eval. of optimal decision alternatives
 - subject to operational boundary conditions and user prefs.
- Overall maturity of solutions still low
- Special needs for real-time solutions for autonomous systems

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Goals and Decisions

