



Strategies for Design Optimization: Lessons from Automotive Systems

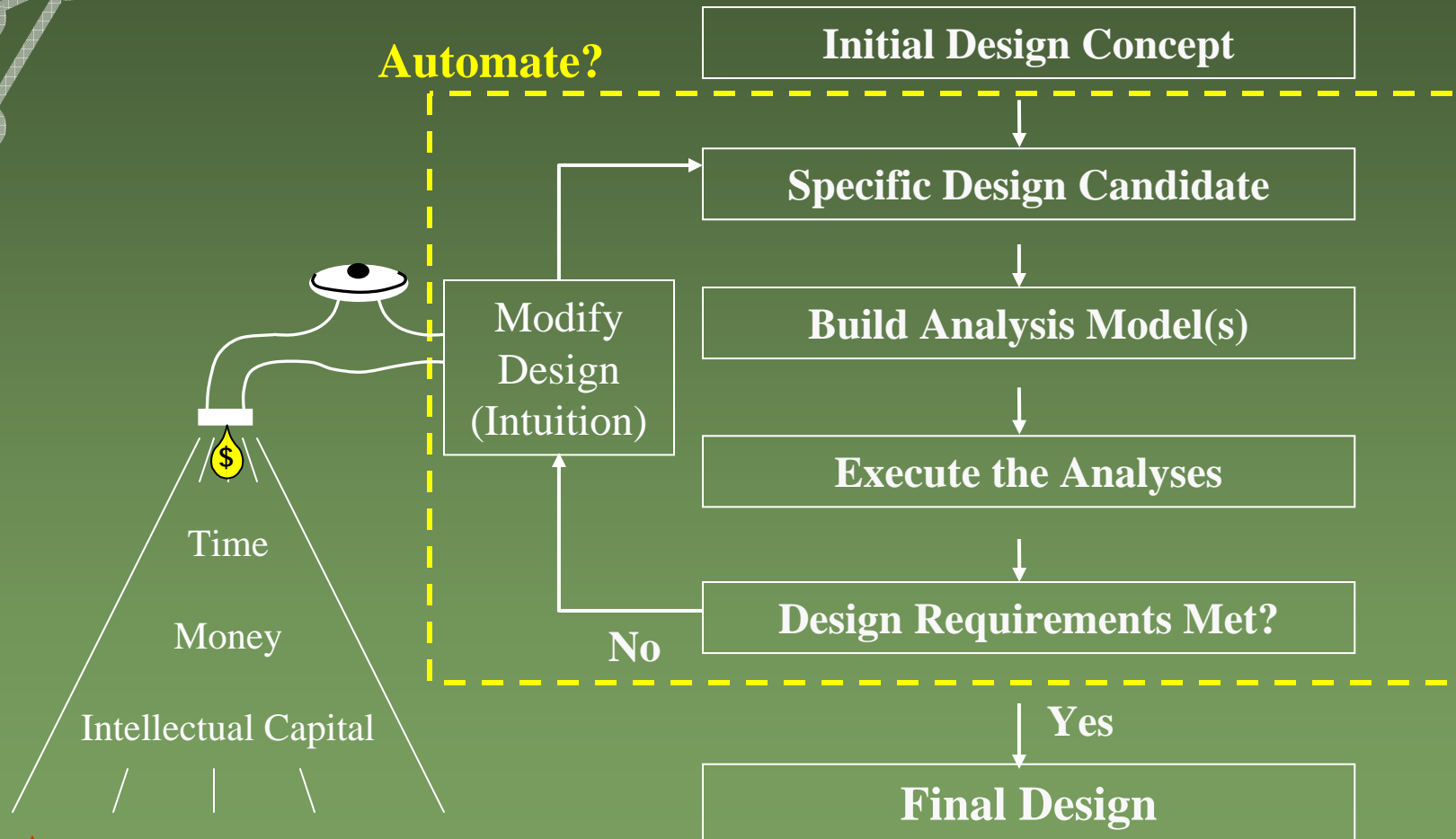
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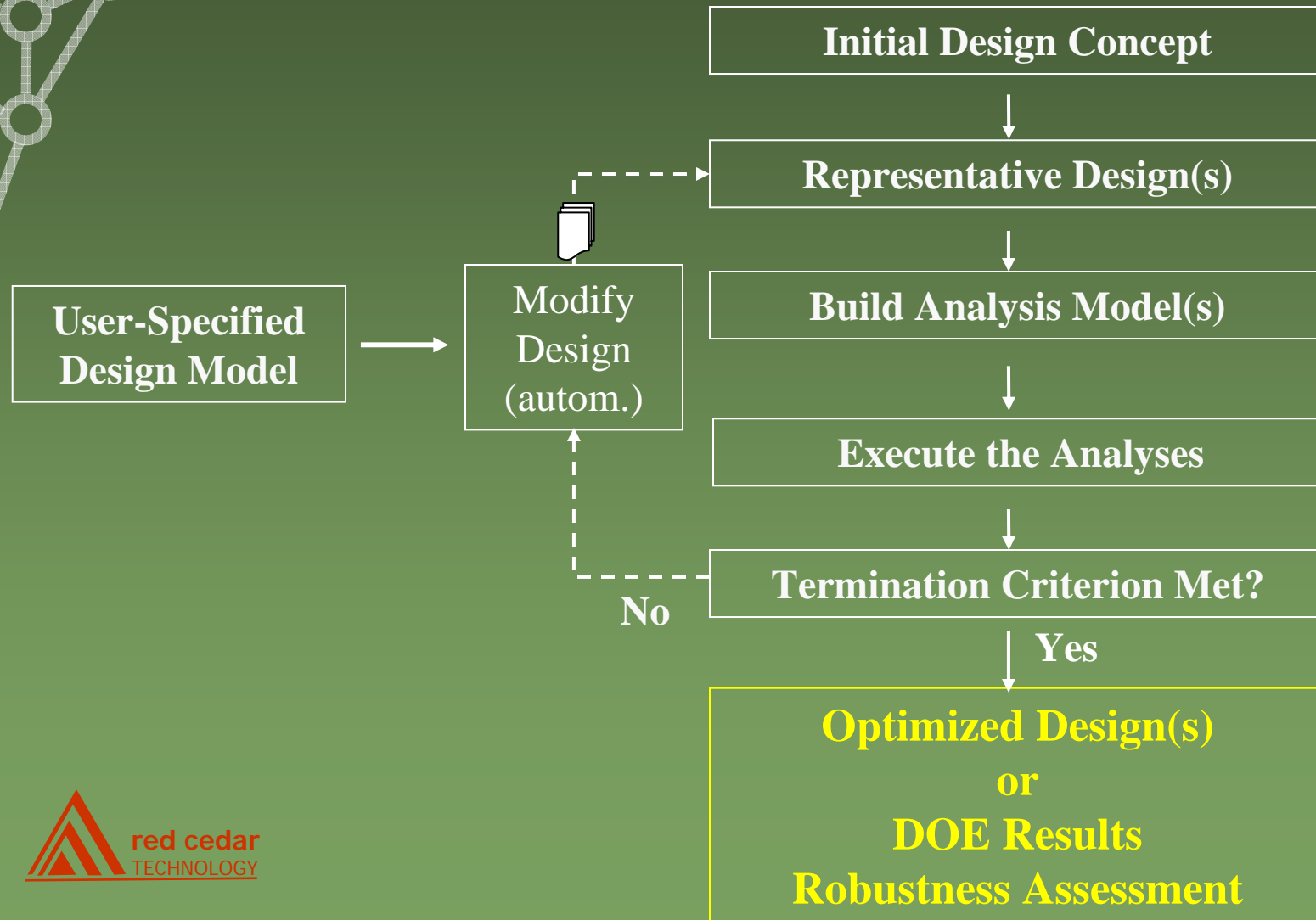
Outline

- Introduction to automated design exploration
- The REAL WORLD – and concessions to it:
 - Costly evaluations → Not your father's GA
 - Typical stepwise design process
 - Design of Experiments
 - EC/hybrid search
 - SHERPA
 - CIA
 - “The Box” and a way to escape it... sometimes
 - COMPOSE
- Example of Component Crashworthiness Optimization

Typical Design Process



Automated Design Process



Main Benefits

- *Automates* search for design alternatives with improved performance and cost
 - ★ more efficient and thorough search
- *Reduces* design time from weeks to days
 - ★ significant cost reduction
- Accelerates product and process *innovation*
 - ★ increased competitive advantage
- *Integrates and leverages* existing investment in CAD/CAE tools and hardware
 - ★ better utilization of capital
- Improves design *robustness*
 - ★ six sigma



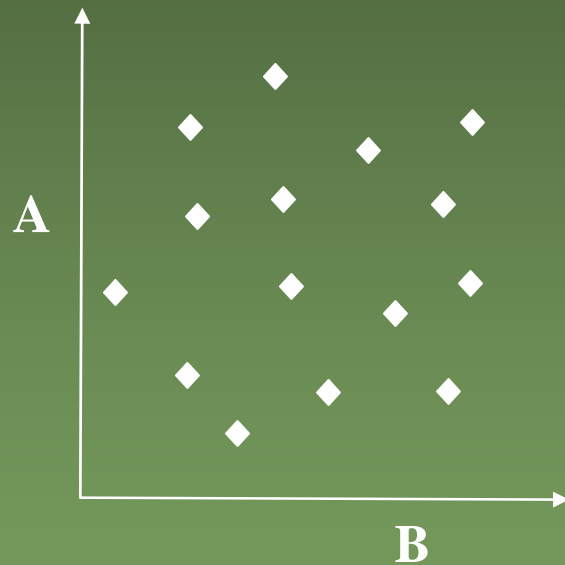
Main Ingredients Needed

- Process Integration
- Design Space Exploration
 - Design of Experiments
 - Design Optimization
 - Reliability and Robustness

Design of Experiments

Design exploration

- Design variable screening
- Sensitivity of design performance to changes in parameters
- Suggests design improvements



Local response surface

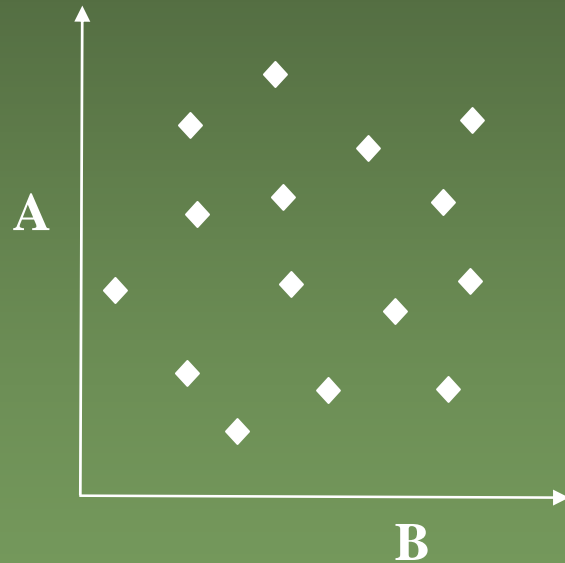
- Surrogate analysis model
- Reduces number of full evaluations

NOT a direct optimization method

Design of Experiments

Examples of Sampling Methods:

- Full factorial
- Fractional factorial
- Central composite
- Latin hypercube
- Plackett-Burman
- Taguchi orthogonal array
- D-Optimal
- User defined



Post-Processing

- ANOVA
- Pareto charts
- Main and Interaction Effects
- Response Surfaces, ...



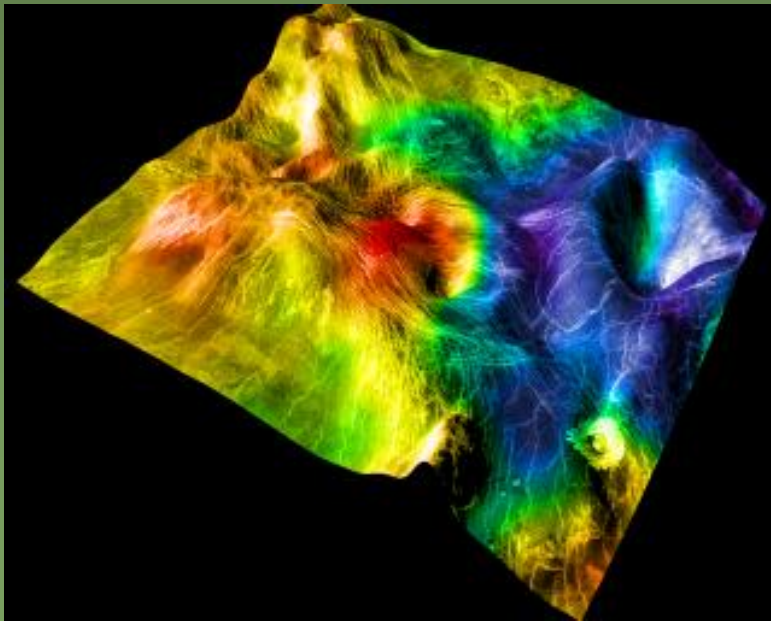
Design Optimization Scenarios

- Seek small improvements to an already good design
Local search, small variable range
- Seek best design or concept within a large design space
Global search, large variable range
- Seek design that best matches a desired performance
Minimize difference between actual and desired responses
- Modify an existing design to meet new performance targets

Parameter Optimization

Objective:

Search the performance response surface to find the highest peak or lowest valley within the feasible range



- Local searches may yield only incremental improvement
- Typically don't know the nature of the surface before search begins
- Number of parameters may be large
- Evaluations may be expensive – **CANNOT DO MANY**
- Shape optimization often involves multi-modal design spaces



Design Approaches

- Perform a DOE, fit a response surface, and search the surface

Usually valid only in local neighborhood of a given design

- Perform a DOE, select most important variables, and perform optimization over subset of variables

Lots of preparatory work to perform optimization

- Define engineering and business goals and a meaningful design space, and then search for the design that best meets those goals

Less overall time spent solving the problem

Greater potential to find better or innovative designs



How Can We Make Intractable Problems (more) Tractable?

Examples of tools that can be helpful:

- Response surfaces
- Multiple, Self-Tuning Search Methods
- Parallel/cluster/grid organization
- Multiple representations/agents – problem decomposition
- “Medicine” against convergence other than large populations
- Model decomposition – “COMPOSE”

Range of Application

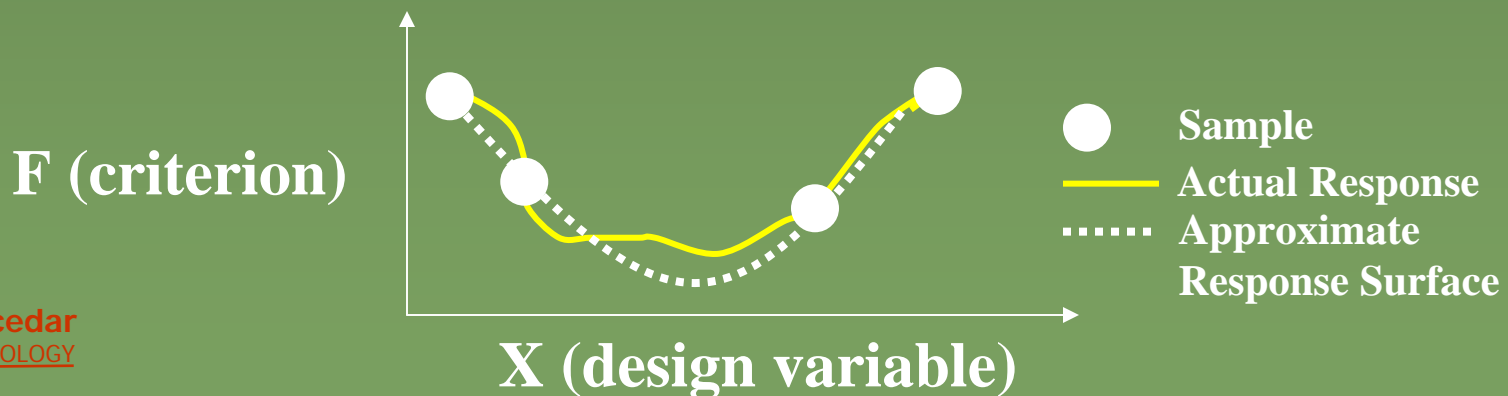
Number of
design
parameters
(evaluations)



Time needed to analyze
each proposed design

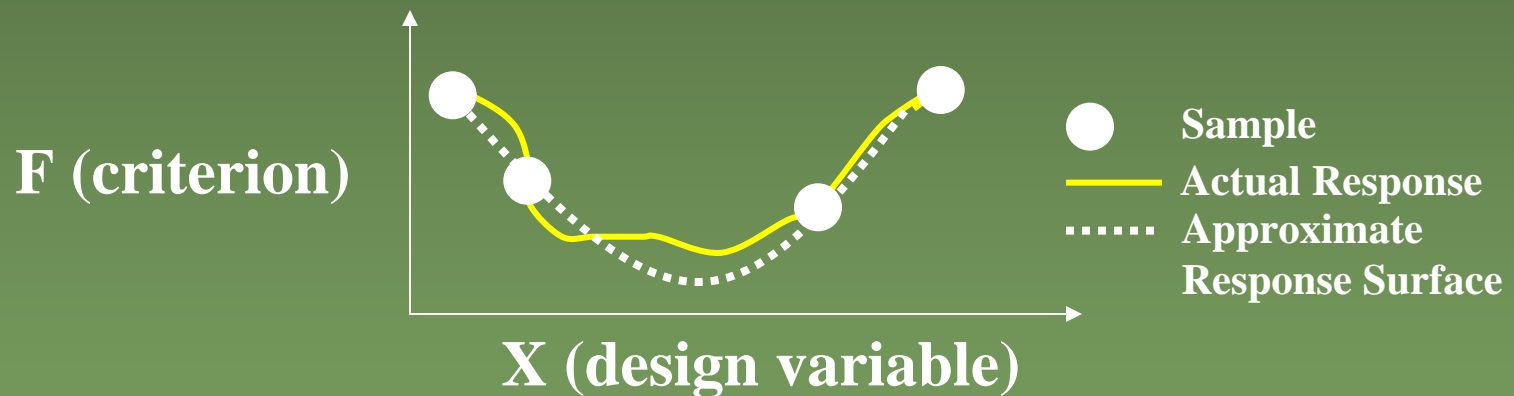
Response Surfaces

- Creates an approximate *model* of the response (a surrogate) as a function of the factors
- Low-order polynomials are often used as surrogate functions
- Typically, response surface models are “least-squares” fit to a sampling of the actual response
- This sampling may be controlled via design of experiments or using points already evaluated and saved



Response Surfaces

- Strengths
 - Eliminate many “full” performance evaluations
 - Potentially define fruitful search directions even if design criteria are not locally differentiable



- Weaknesses
 - Not designed to escape local optima
 - Design variables should be continuous in nature
 - Often works well only in local search

Choosing a Method or a Design Space?

- Design space is a function of:
 - Number, type, and range of design variables
 - Objectives and constraints
- Preferable to define design problem first, and then select search method
 - Which method to choose depends upon the design space
 - But the nature of the design space is not known, unless the problem has been solved before
- Alternative: select search method first, and then make design problem fit that method's capabilities
 - But this limits the problem scope and number of variables, and requires high level of knowledge about the method





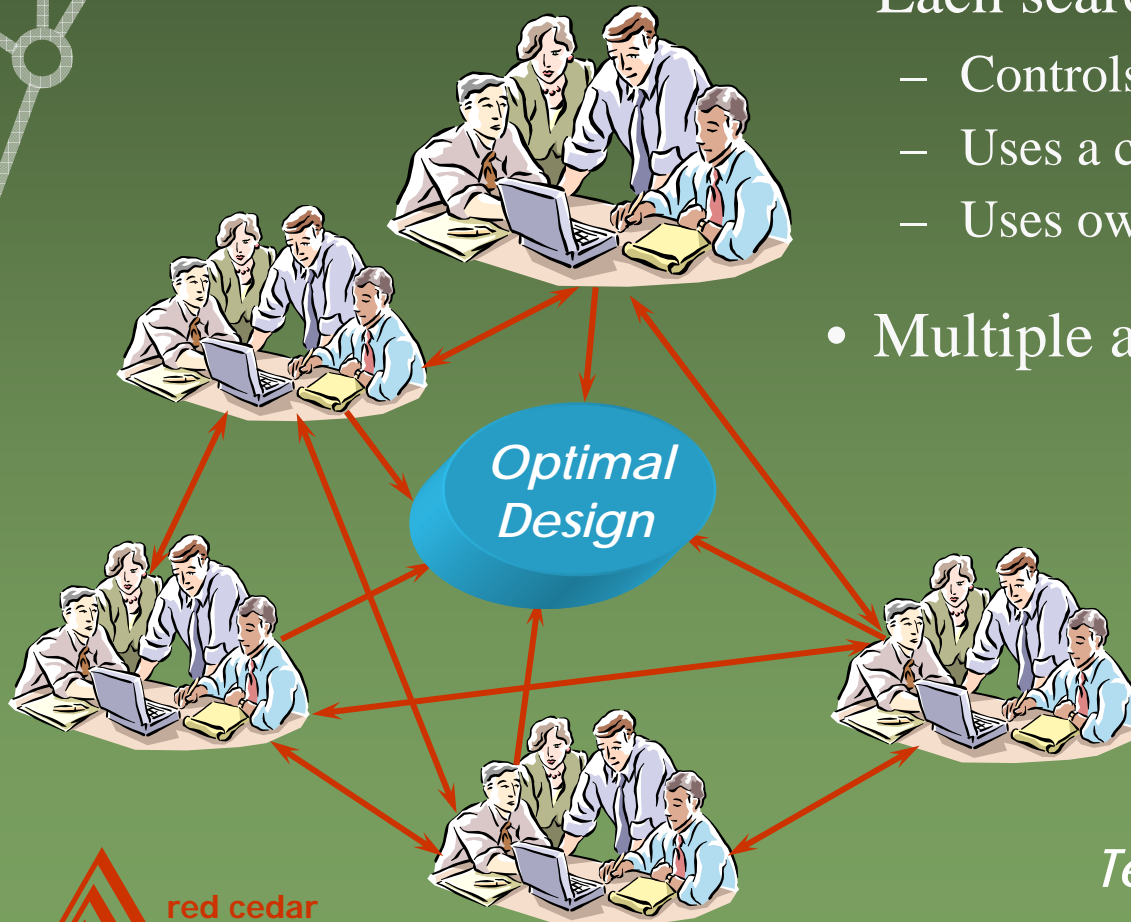
Example of Self-Tuning Search

Method: SHERPA

- Hybrid
 - Multiple methods used simultaneously, not sequentially
 - Takes advantage of best attributes of each method
 - Both global and local search techniques are used
- Adaptive
 - Each method adapts itself to the design space
 - Master controller determines which methods get used and how much
 - Tries to learn efficiently about design space and effectively search even very complicated spaces

Multi-Agent Search: Cooperative Independent Agents (CIA)

- Each search agent
 - Controls an independent search process
 - Uses a combination of search methods
 - Uses own representation of the problem
- Multiple agents working in parallel
 - Problem decomposition
 - Diverse points of view
 - Shared discovery



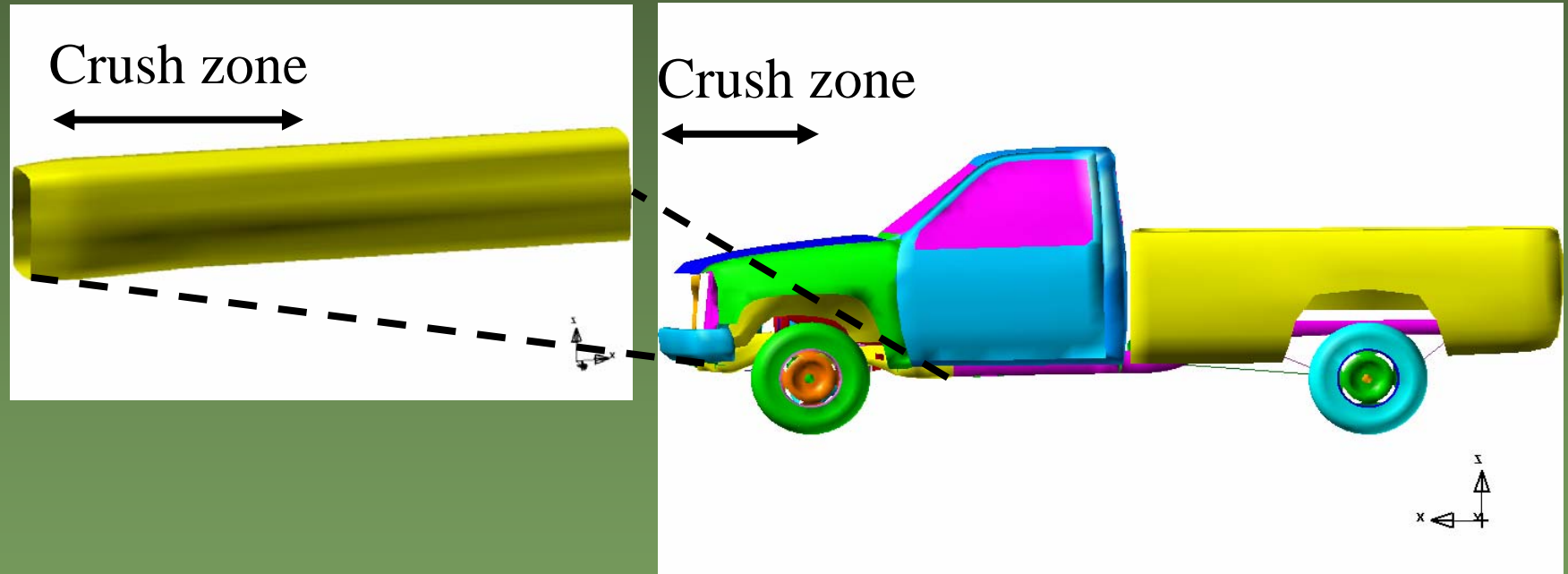


Different Agents, Different Approaches

Can decompose design space according to:

- Physical/spatial domain
- Temporal extent of simulation
- Number of design variables
- Resolution of design variables
- Stochasticity of variables
- Performance measures
- Analysis models
- Search methods
- ...

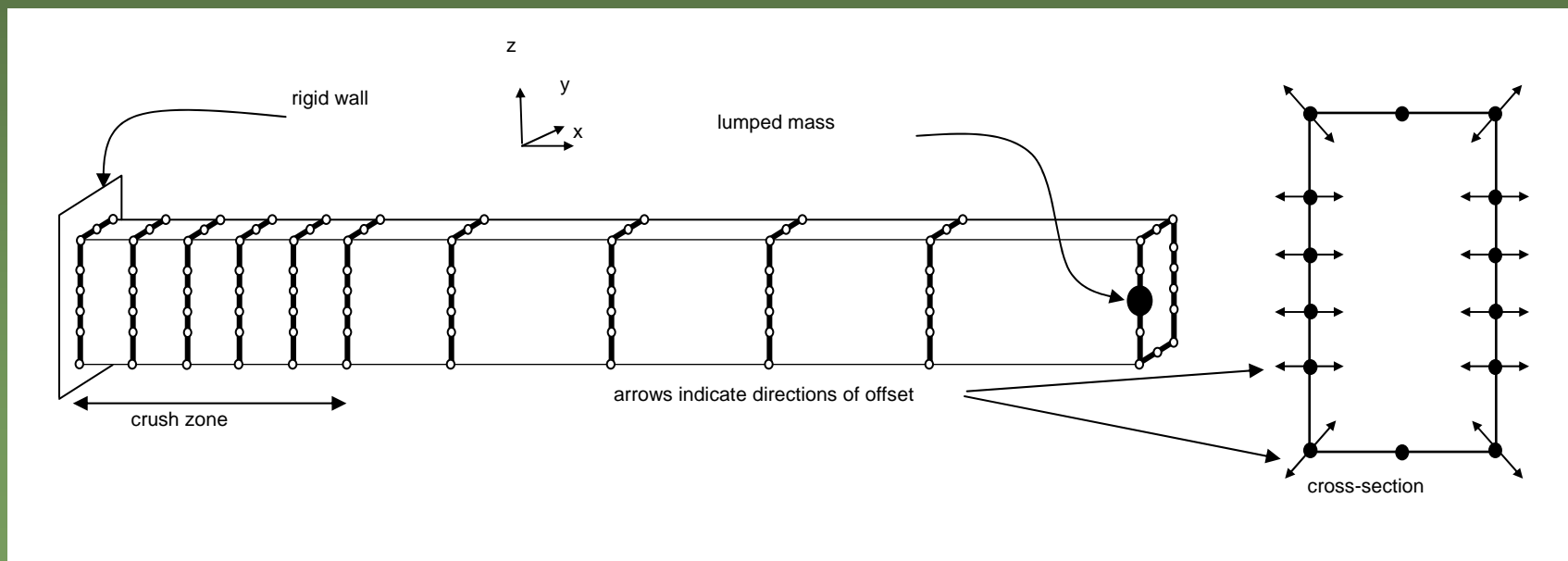
Putting It Together -- Example: Hydroformed Lower Rail



Shape Design Variables

67 design variables:

66 control points and one gage thickness





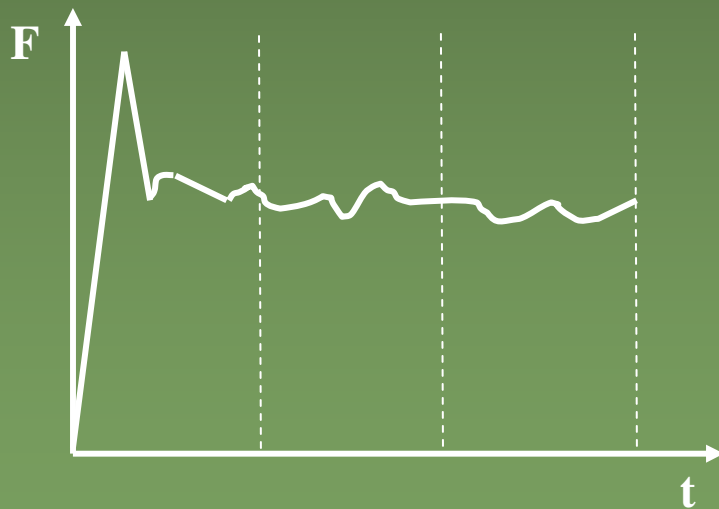
Optimization Statement

- Identify the rail shape and thickness
- Maximize energy absorbed in crush zone
- Subject to constraints on:
 - Peak force
 - Mass
 - Manufacturability

Three-Agent Topology

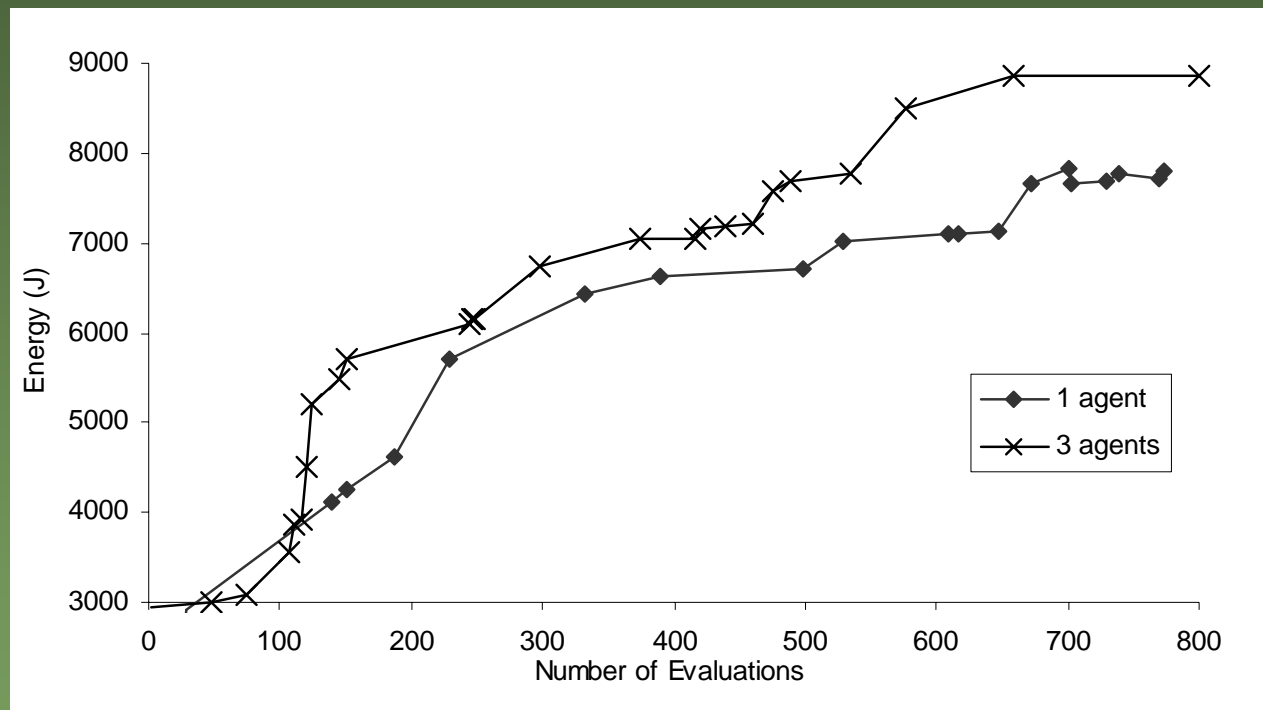
Discretize:

- crush time (reduces CPU time)
- design variables (reduces design space)

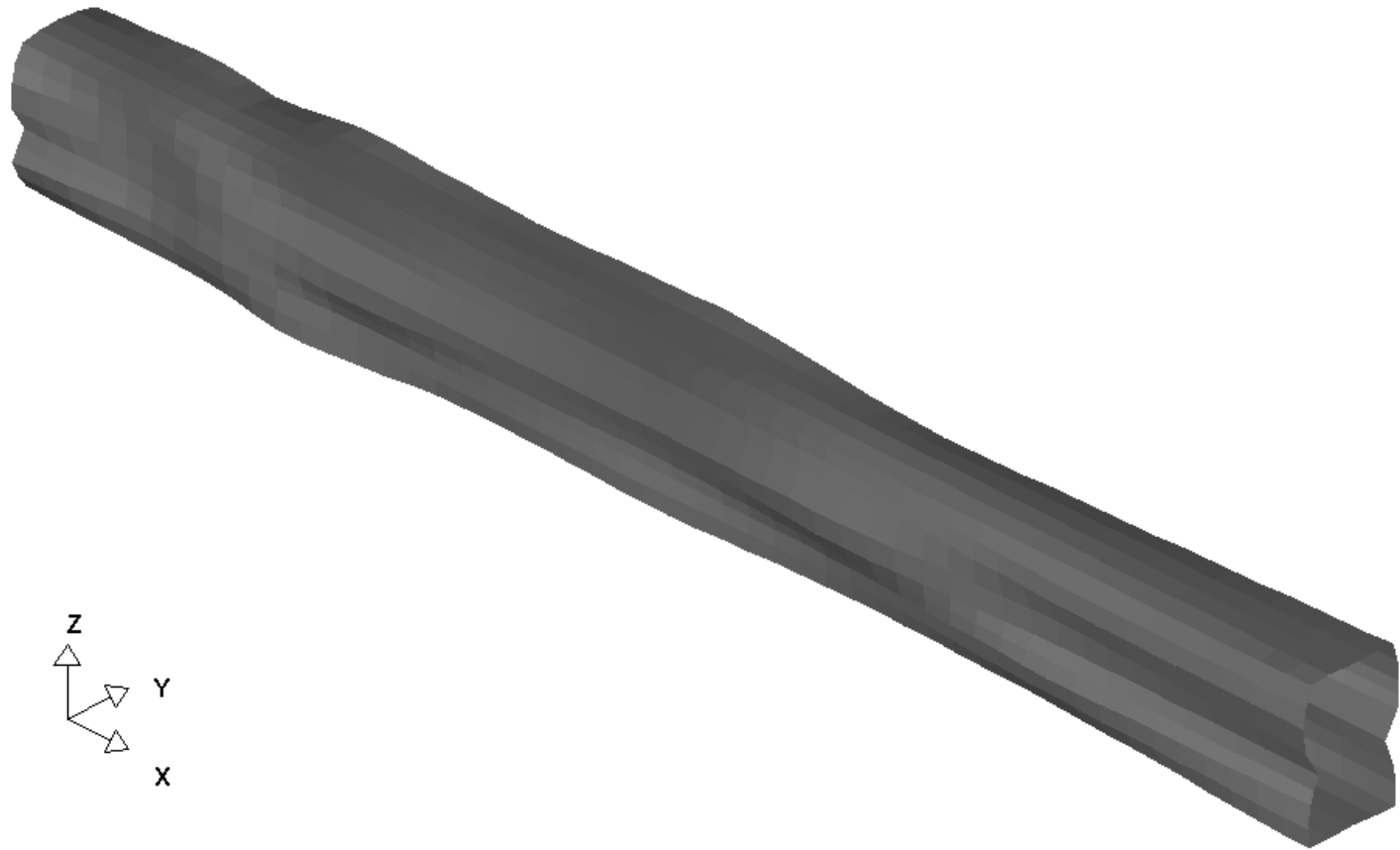


Crush Time	Agent Topology	Design Variable Discretization
t=6 ms	0	Coarse
t=10 ms	1	Medium
t=14 ms	2	Refined

Energy Absorbed

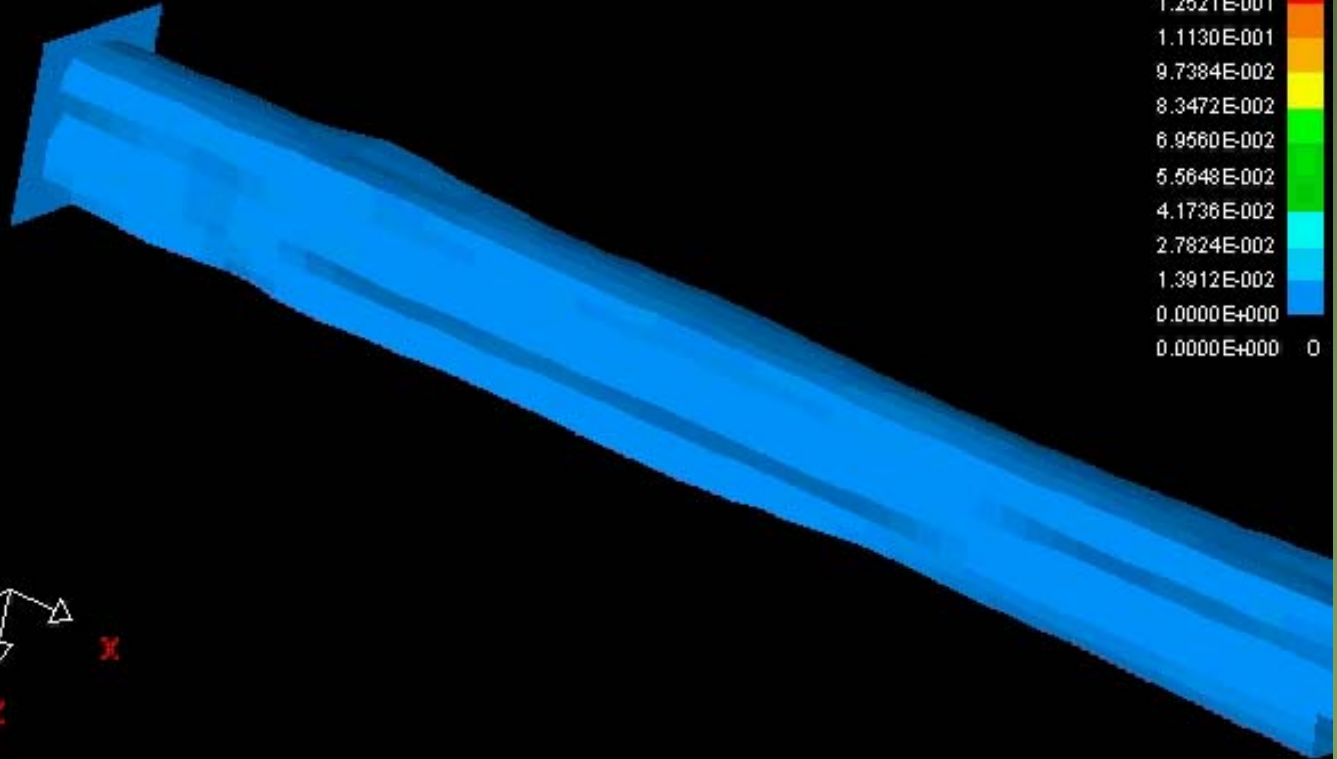


HEEDS Optimized Design



HEEDS Optimized Design

OPEN SURFACE RUN INCLUDE FILE
STEP 0 TIME = 0.0000000E+00
ENERGY



Validation





Lower Rail Benefits

- Peak force reduction by 30%
- Energy absorption increased by 100%
- Weight reduction by 20%
- Overall crash response resulted in equivalent of FIVE STAR rating



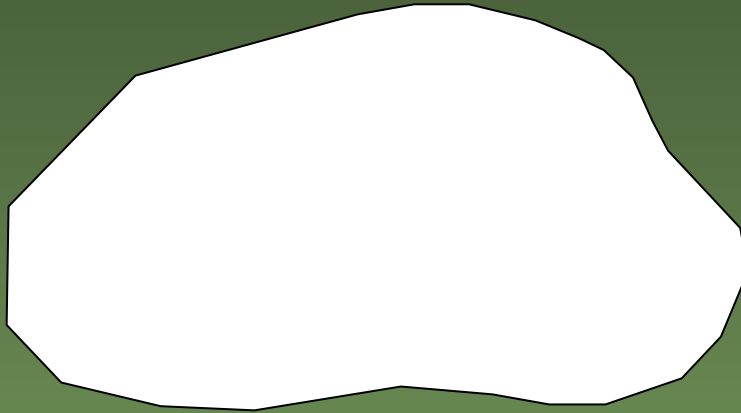
COMPOSE Breakthrough

COMPOSE –

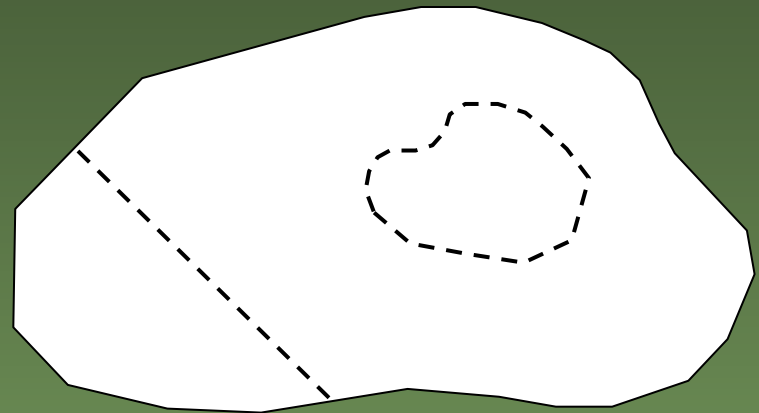
COMPonent Optimization within a System Environment:

- Pull out a component, optimize, put back in → failure
- Iterate above → failure
- COMPOSE allows subsystems (quick to simulate) to be optimized and retain their performance when reintegrated in whole system, but requires only a FEW system-level evaluations!!!
 - Reduces design time by factor of 10 – 1,000 for some problems
 - Allows search over large number of design variables
 - Makes many intractable problems practical to optimize

Spatial Decomposition



System



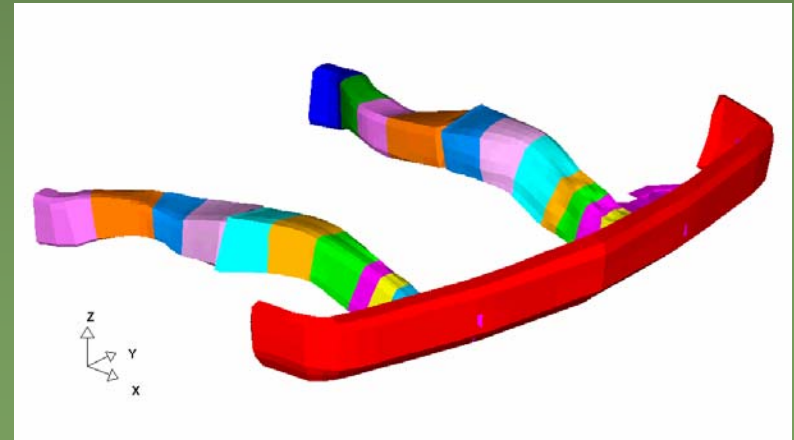
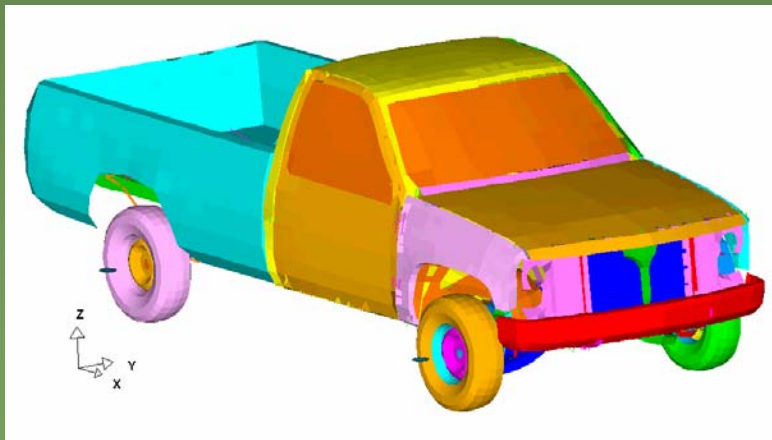
System with subsystems denoted



Subsystems

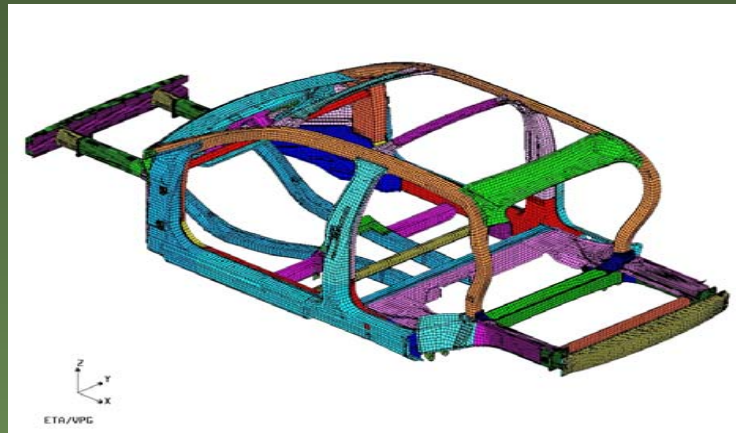
COMPOSE

- COMPOSE – COMPOnent Optimization within a System Environment
- *Enables* high fidelity design of subsystems in *highly coupled* complex systems ($10^1 - 10^3$ times speedup)



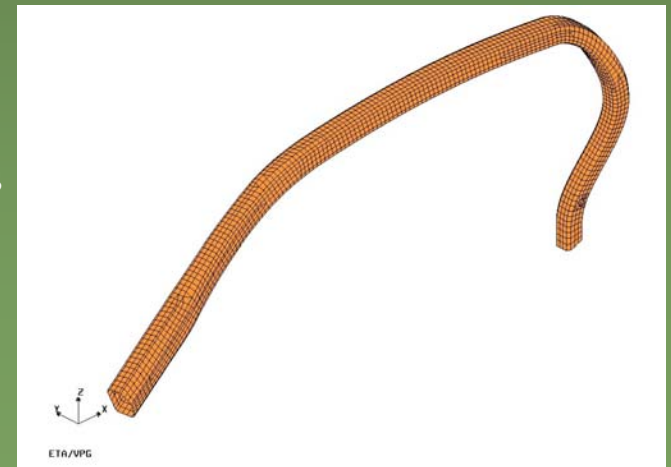
COMPOSE

- Based on decomposition
- Most CPU effort to design subsystem (component)
- Small number (3-8) of system level analyses
- Full coupling maintained between system and subsystem
- Large number of variables can be studied
- CPU time reduced by factor of 10 – 1,000



New
design
proposal

Updated
boundary
conditions



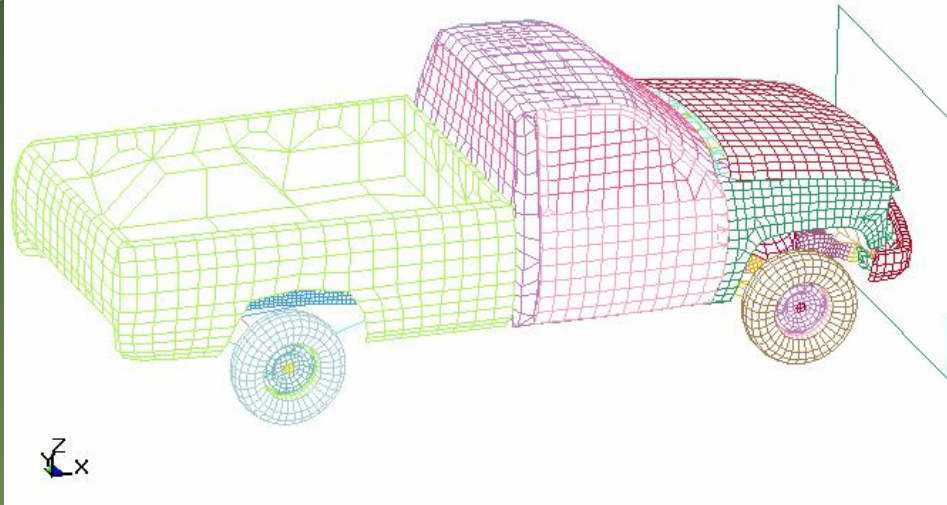


Keys to the Convergence Strategy

- Make subsystem design robust against changes in interactions (subsystem boundary conditions)
- Similar modality of response in sequential designs
 - Gradients
 - Eigenvectors
 - Etc.
- Consequence: Higher level of system robustness

Vehicle Rail –Shape Optimization

C2500 PICKUP TRUCK MODEL (NCAC V8)
Time = 0

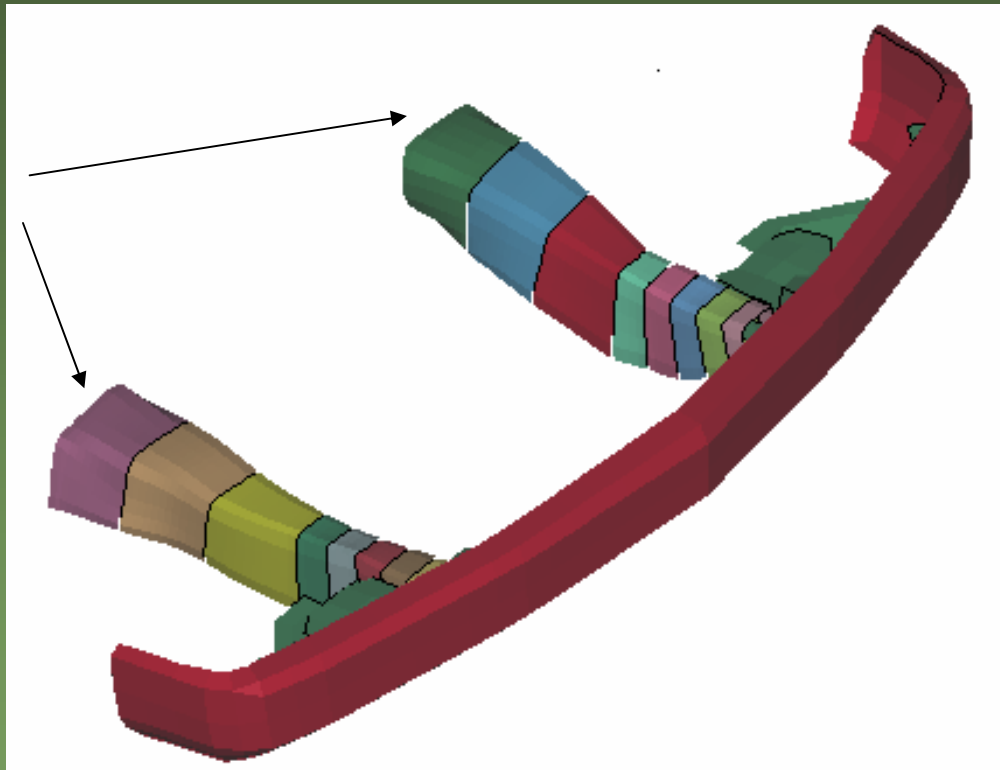


Objective : Maximize Energy Absorbed

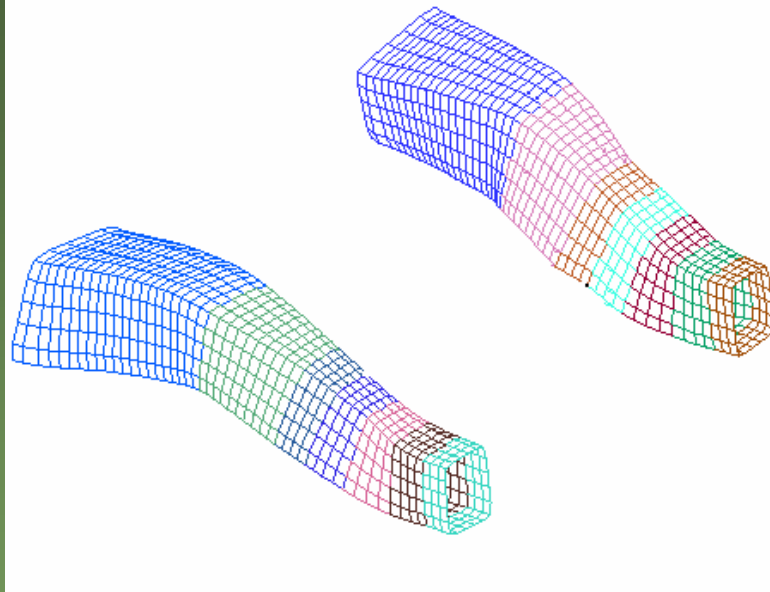
Constraint : Reaction Force

Subsystem Model

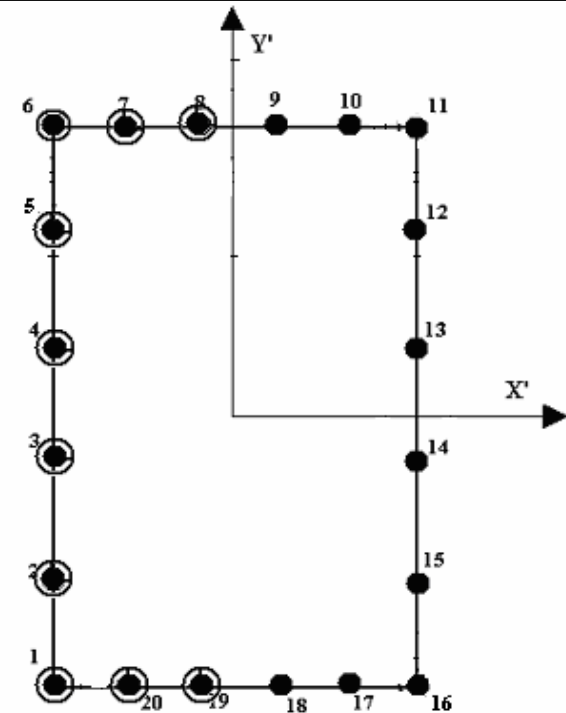
Boundary Conditions
from System Model



Subsystem Design Variables

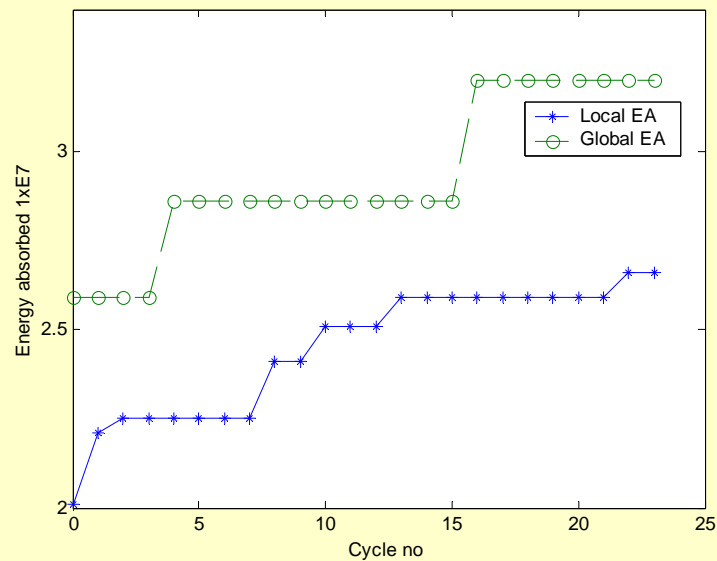


MASTER NODE
SLAVE NODE

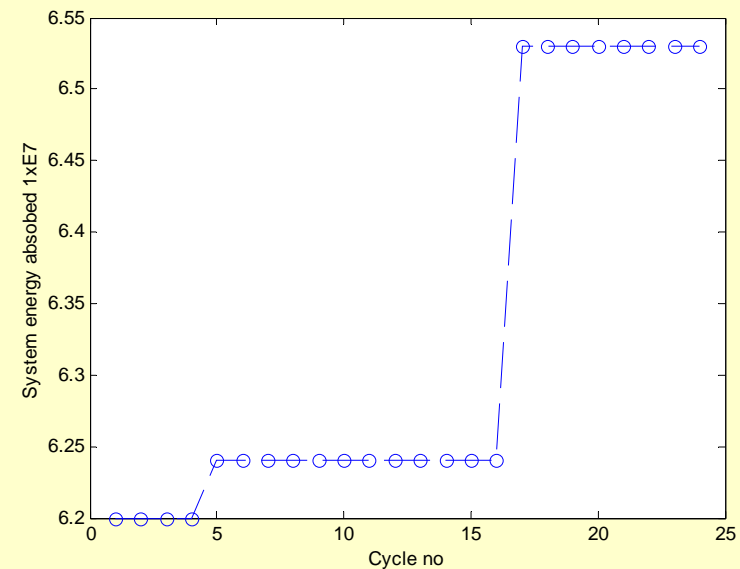


- Individually designed rails
- 7 Cross-sections on each rail
- 10 Design- master points on each cross-section
- Total of 70 shape design variables; symmetry fixes 140 values

Rail Optimization Results



Rail Energy Absorbed
(30% increase)



System Energy Absorbed
(5.5% increase)

(Optimization over 70 variables using only 6 system evaluations.)



There is no “Easy Button”

HEEDS is:

- An engineering tool
- Not “pixie dust” or an “easy button”

HEEDS requires:

- Good engineering
- Good ideas / concepts

Designing with HEEDS for Future Generation Passenger Compartment (US Auto/Steel Partnership)

- Stage 1 – Conceptual design for side impact, rollover
 - Topology optimization
 - Upper body, underbody load paths
 - Ignore fine details of the structural members
- Stage 2 – Screening
 - Design of Experiments
 - Identify members or subsystems that have greatest “effect” on performance
 - Primary factors include gage and material properties
- Stage 3 – Detailed design of cross-sections
 - Optimization of shape, gage, material to enhance performance while reducing mass

