

Understanding resilience optimization architectures with an optimization problem repository

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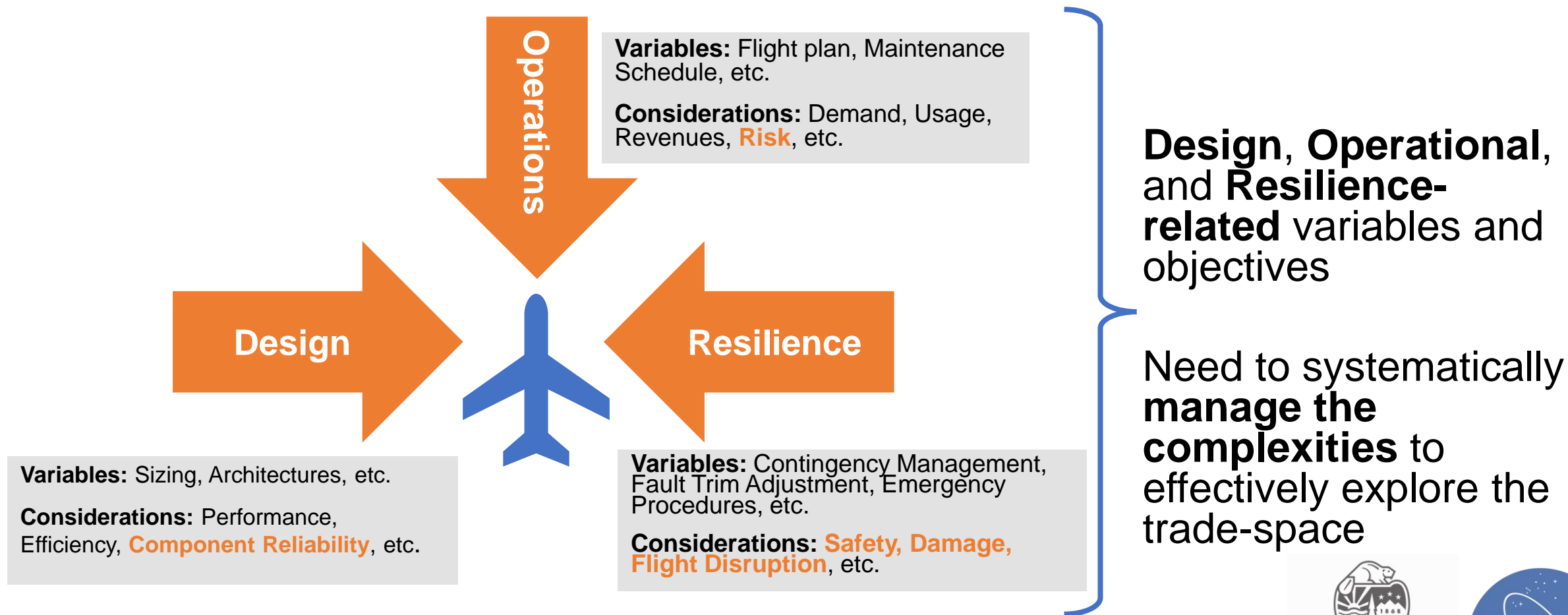
DAC-09: Design for Resilience and
Failure Recovery

Virtual Presentation

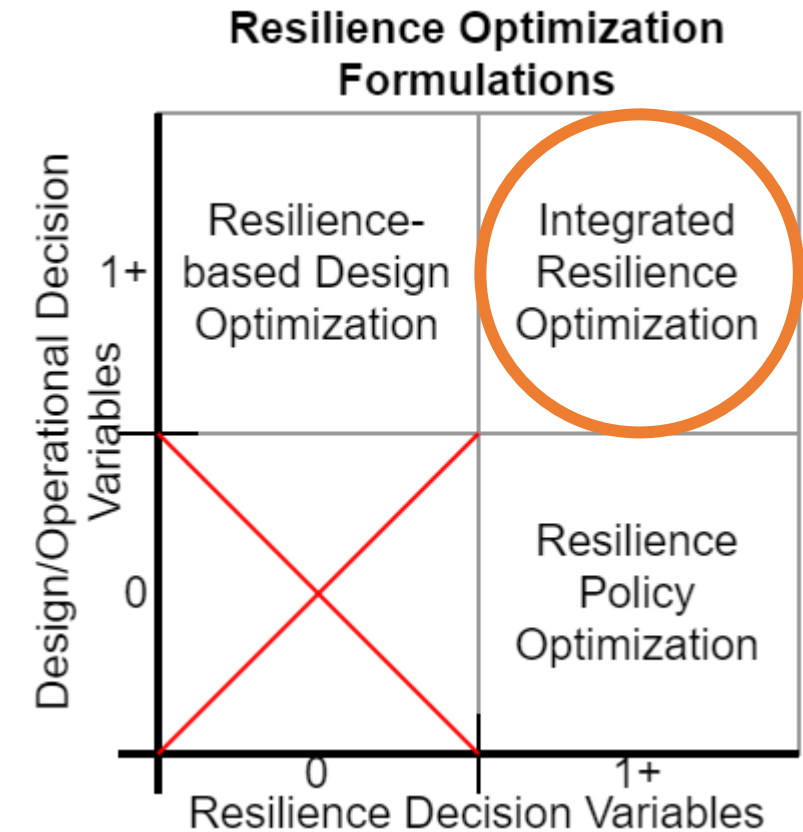
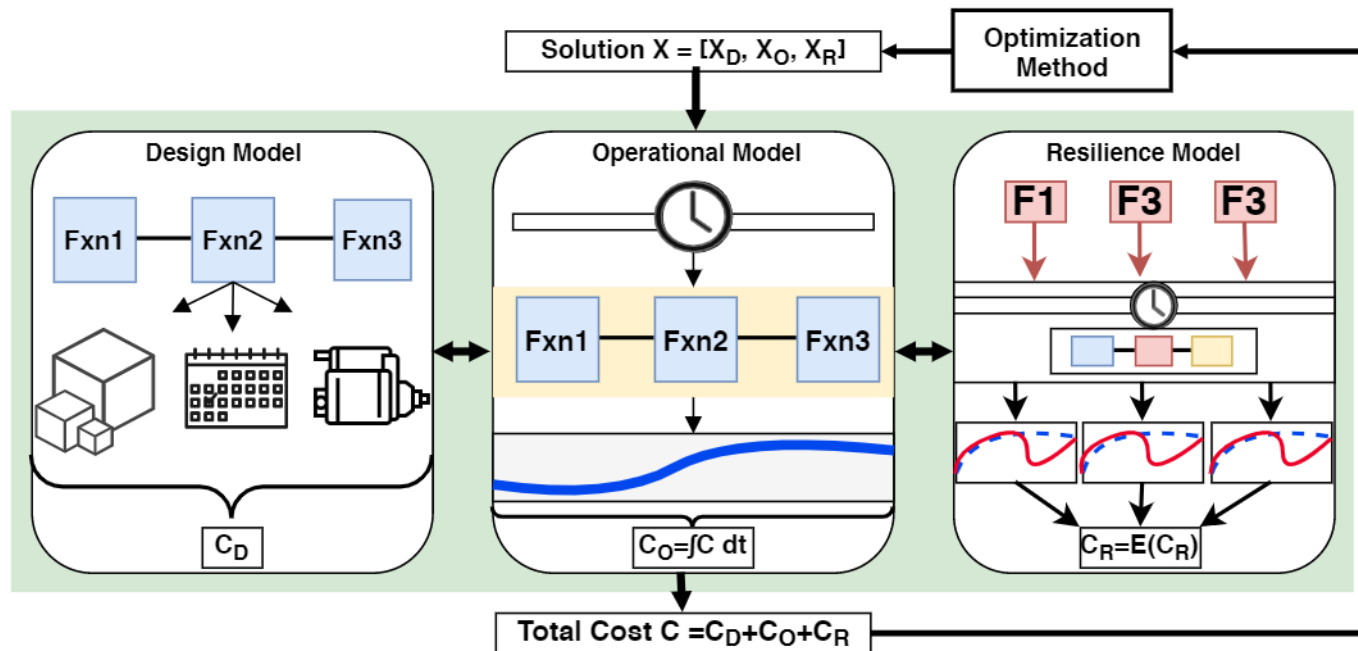
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Why Study Resilience Optimization?



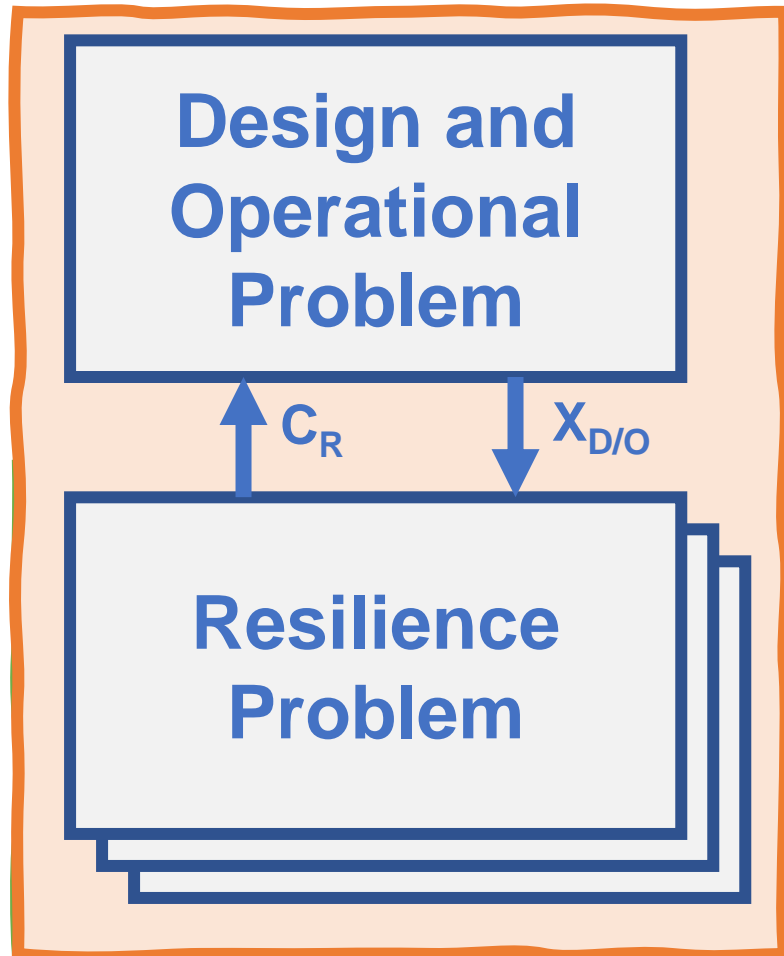
Previous Work



Previous work:

- Developed overall **Integrated Resilience Optimization** framework [1]
 - Combined optimization of Design, Operations, and Resilience variables and objectives
- Formulated different architectures and performed preliminary comparisons [1]

Previous Work: Architectures



Two types of decomposition:

- **Design/Resilience Levels**
 - All-in-one
 - Bilevel
 - Alternating
 - Sequential
- **Resilience Model Scenarios**
 - Monolithic resilience model
 - Scenario-independent resilience model
 - Grouped-Scenario Resilience model

Why Develop a Repository?

Resilience Optimization Problem

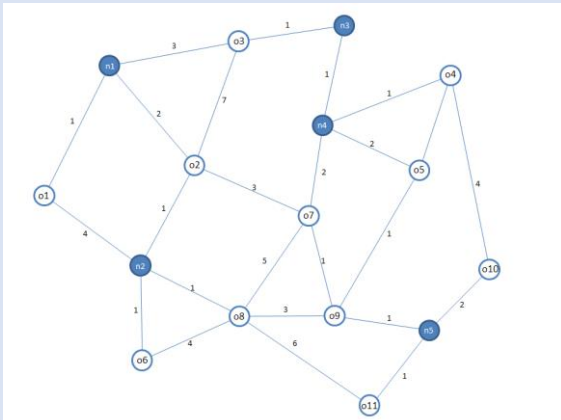
$$\min_{\mathbf{x}} C_{D/O}(\mathbf{x}) + C_R(\mathbf{x})$$

$$\text{where } C_R = \sum_{s \in S} n * r_s * C_s(\mathbf{x})$$

- Small or large **number of scenarios**
- Discrete or continuous** variables
- Analytic or simulation** models

Different problem properties and types imply **one architecture may not fit all**

Travelling Salesman Problem



Lead to the development of Ant Colony Optimization, other algorithms.

MDO Test Suite

Table 2. Characteristics of Test Problems in MDO Test Suite

No.	Name	# of design variables (DV)	# of constraints	Notes	Status
1.1	Heart	8	8	algebraic eqs.	Done
1.2	Propane	10	10	algebraic eqs.	Done
2.1	Aircraft	10	2	empirical curve fits	Planned
2.2	Hub	many	many	parallel processing	Done
2.3	Electronic	8	3		Done
2.4	Speed	7	11	multilevel	Testing
2.5	Power	6	4		Done
2.7	Rule-based	5	5	discrete DV	Done
3.1	HSC1	44	300	GSE and database	Done
3.2	Space	163	41	Needs EAL	Done
3.4	Aerospike	15	5		Planned
3.6	Aerospike	15	5	Needs NASTRAN	Planned
3.7	FIDO 2	many	many		Planned
3.8	Damper	1507	11	integer DV	Done

Helped benchmark and develop new and existing MDO architectures.

A problem repository can help:

- **Develop** new approaches and **benchmark** existing ones
- Understand **which architecture to use** on a given new problem

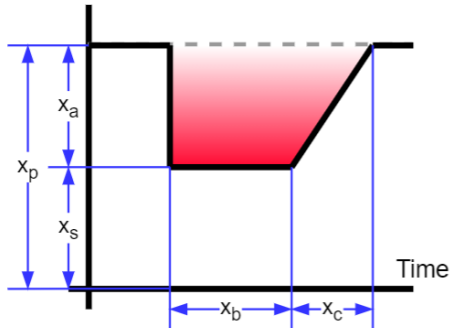
Repository Problems

Problem	Des. Vars	Res. Vars	Architecture	Decomposition	Algorithms Used	Model Type	Sim. Framework
Notional Example	4 (C)	2 (C)	AAO, Bilevel, Alt. (both)	Monolithic	Trust-Region	Equations	Stand-alone
Pandemic Management	N/A	6 (C)	AAO	Monolithic	Differential Evolution	Dynamic	Stand-alone
Cooling Tank	2 (C)	54 (D)	Bilevel, Alt. (with C_R)	Monolithic	Powell's (D)/EA (R)	Dynamic	fmdtools [51]
Drone	3 (D)	2 (D)	AAO, Bilevel, Seq. (no C_R)	Monolithic, Scenario-Set	Exhaustive Search	Dynamic	fmdtools [51]
EPS	14	N/A	AAO	Scenario-Set	Line search	Static	IBFM [52]
Monopropellant System	N/A	12 (D)	AAO	Monolithic	EA	Static	IBFM [52]

This work:

- **Collects 3 problems from previous work** (in [2])
 - **Monopropellant System:** First problem used to demonstrate resilience optimization
 - **EPS Problem:** Used to demonstrate resilience model decomposition strategy
 - **Drone Problem:** Used for initial comparison of IRO architectures in exhaustive search
- **Adds 3 new problems:**
 - **Notional Example:** Simple IRO problem not requiring a detailed simulation
 - **Pandemic Management:** Demonstrates a more complex lower-level **—(in development)**
 - **Cooling Tank:** Demonstrates a domain with different problem types at each level

Architecture Comparisons



$$\min_{\mathbf{x}} f(\mathbf{x}) = C_D(x_p, x_a, x_r, x_s) + C_R(x_r, x_a, x_b, x_c) \quad (8)$$

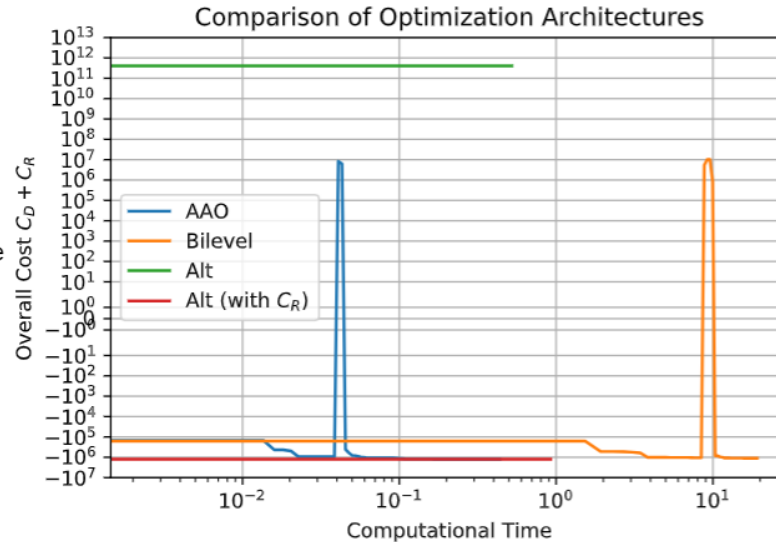
$$s.t. C_D = -a\sqrt{x_a} + 0.1 + b\sqrt{x_r} + 0.1 + c/\sqrt{x_r}$$

$$C_R = x_r * n * (d * x_a * (x_b + x_c/2) + e/x_c + f/x_b)$$

$$h_{D1} = x_p - (x_r + x_a) = 0$$

$$g_{D2} = \frac{(x_p - 1)^2}{c} - x_r < 0$$

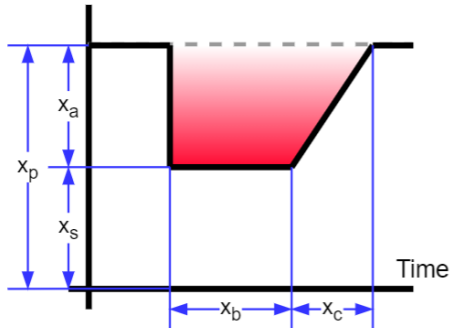
where $100 > x_p > 0, 2 > x_a > 0, 100 > x_r > 10^{-10},$
 $2 > x_b > 0, 100 > x_b > 0, 100 > x_c > 0$
 and $[a, b, c, n, d, e, f] = [1e6, 5e5, 100, 1e5, 50, 50, 20]$



Notional Example (Cont. Trust Region)

- **Bilevel:** orders of magnitude slower than AAO because each design gradient point requires a full lower-level re-optimization
- **Alternating:** most efficient but needs C_R in upper-level to be effective

Architecture Comparisons



$$\min_{\mathbf{x}} f(\mathbf{x}) = C_D(x_p, x_a, x_r, x_s) + C_R(x_r, x_a, x_b, x_c) \quad (8)$$

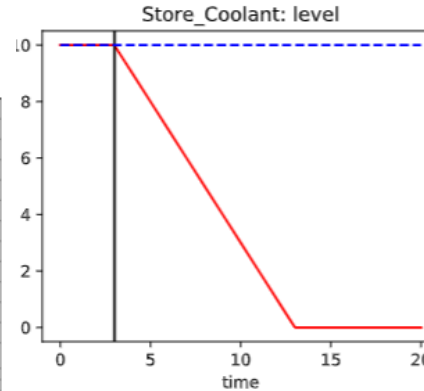
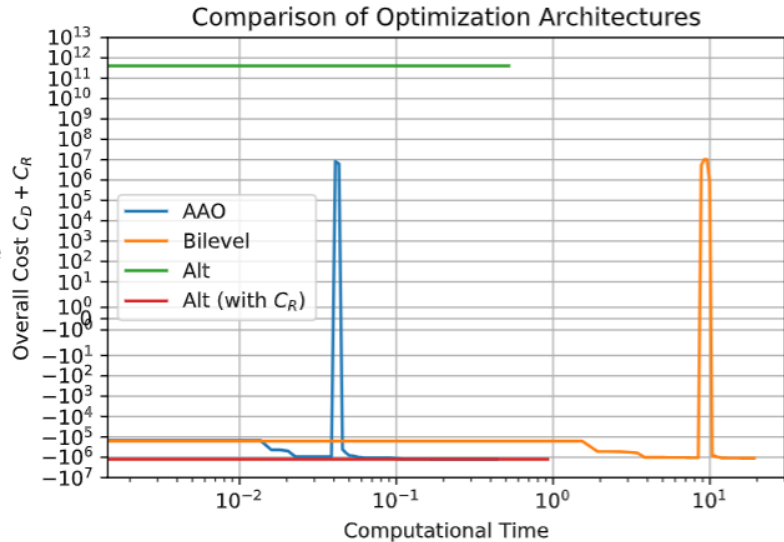
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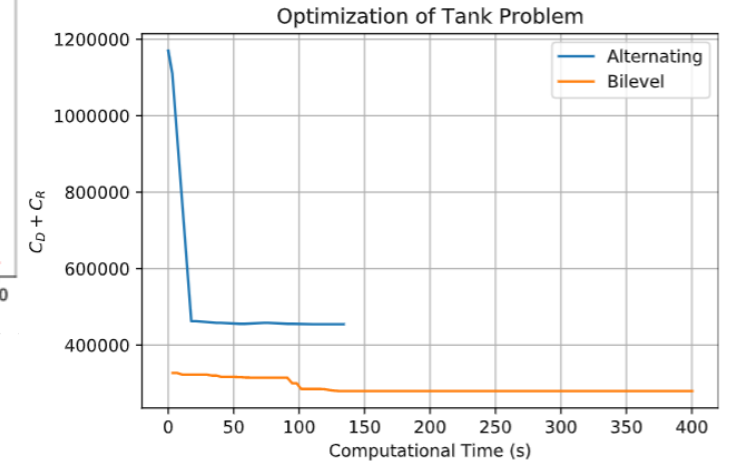


$$s.t. C_D = 1000(x_T - 10)^2 + 1000(x_T - 10) + 10000x_T^2$$

$$C_R = \sum_{s \in S} n * r_s * C_s(x_{ip}, x_{op})$$

$$g_R = \sum_{f \in N} f \leq 0$$

where $x_T \in (10 - 100), x_f \in (0 - 1),$
 $x_{ip,z} \in [-1, 0, 1], x_{op,z} \in [-1, 0, 1]$



Notional Example (Cont. Trust Region)

- **Bilevel:** orders of magnitude slower than AAO because each design gradient point requires a full lower-level re-optimization
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Cooling Tank Example

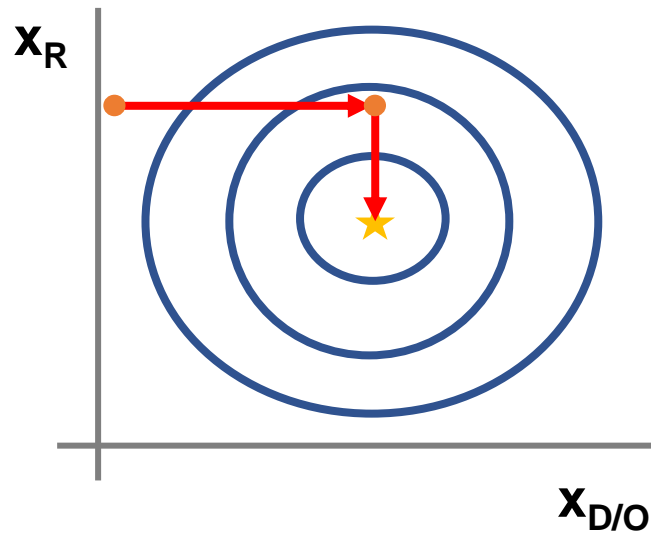
- Powell's Method in design model, evolutionary algorithm in resilience model
- Even with C_R in the upper-level, the **alternating approach is ineffective** compared to the bilevel architecture



Why do we have contrary results?

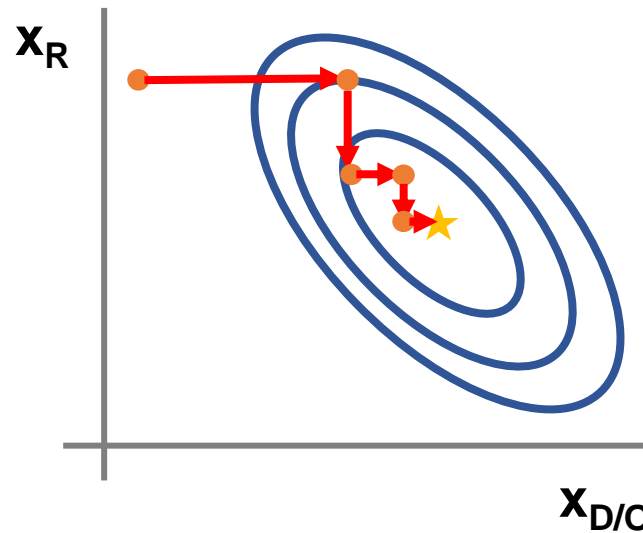
Differing levels of **Coupling**: the level to which design ($\mathbf{x}_{D/O}$) and resilience (\mathbf{x}_R) variables depend on each other.

Uncoupled: direct path from $\mathbf{x}_{D/O}^*$ to \mathbf{x}^*



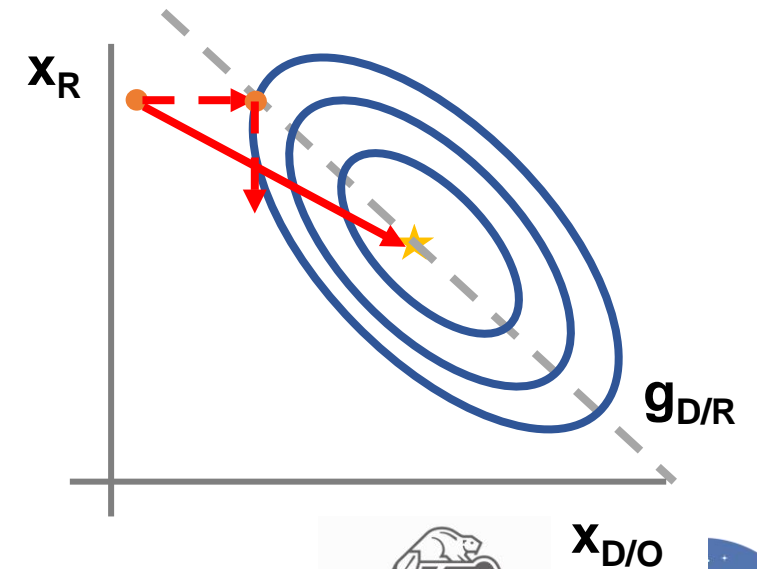
Enables **Sequential Approach**

Loosely coupled: unobstructed path that can be followed to \mathbf{x}^* in alternating directions



Enables **Alternating Approach**

Fully coupled: joint steps $d\mathbf{x}=[d\mathbf{x}_{D/O},d\mathbf{x}_R]$ must be taken to reach \mathbf{x}^*



Solvable with **Bilevel** or All-at once Approaches



Overall Repository Theory/Findings

		Appropriate Architectures	
Fully Coupled	↑	Bilevel, AAO	Bilevel, AAO
Loosely Coupled		Alternating (with C_R), Bilevel, AAO	Alternating, Bilevel, AAO
Uncoupled		Sequential (with C_R), Bilevel, AAO	Sequential, Bilevel, AAO
		← Unaligned	→ Aligned

The applicability of Design/Resilience Level Decomposition Architectures depends on **couplings** between levels

Within Alternating and Sequential architectures, the use of a C_R in the upper level depends on the **alignment** of the Design and Resilience problems.

		Resilience Problem Coupling	Appropriate Solution Approach
Independent	↑	Scenario Independence	Two-stage approach
		Independent Scenario Sets	Lower-level decomposition
Coupled		Fully Coupled Scenarios	Monolithic lower-level

The applicability of scenario-based decomposition depends on the **couplings** between scenarios (i.e., whether a resilience variables map directly to scenarios/sets or not)

Conclusions, Limitations, Future Work

Conclusions

- Developed a resilience optimization problem **repository**
- Compared optimization architectures for Integrated Resilience Optimization
- Applications help us understand **when optimization architectures apply to given problem formulations**

Limitations:

- Still developing pandemic problem
- Does not cover all **previous resilience optimization approaches/formulations** (e.g., two stage, etc...)

Future Work:

- Include and develop **more problems/formulations**
- Study other problem/architecture attributes (e.g., resilience model execution **parallelism**)



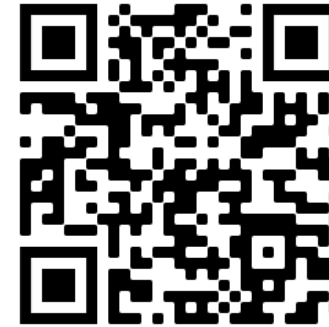
Links

Paper Link



ti.arc.nasa.gov/publications/20210010232/download

Repository Link



github.com/DesignEngrLab/resil_opt_examples

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