



Single-loop System Reliability-Based Design & Topology Optimization (SRBDO/SRBTO): A Matrix-based System Reliability (MSR) Method

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A. Deterministic Optimization

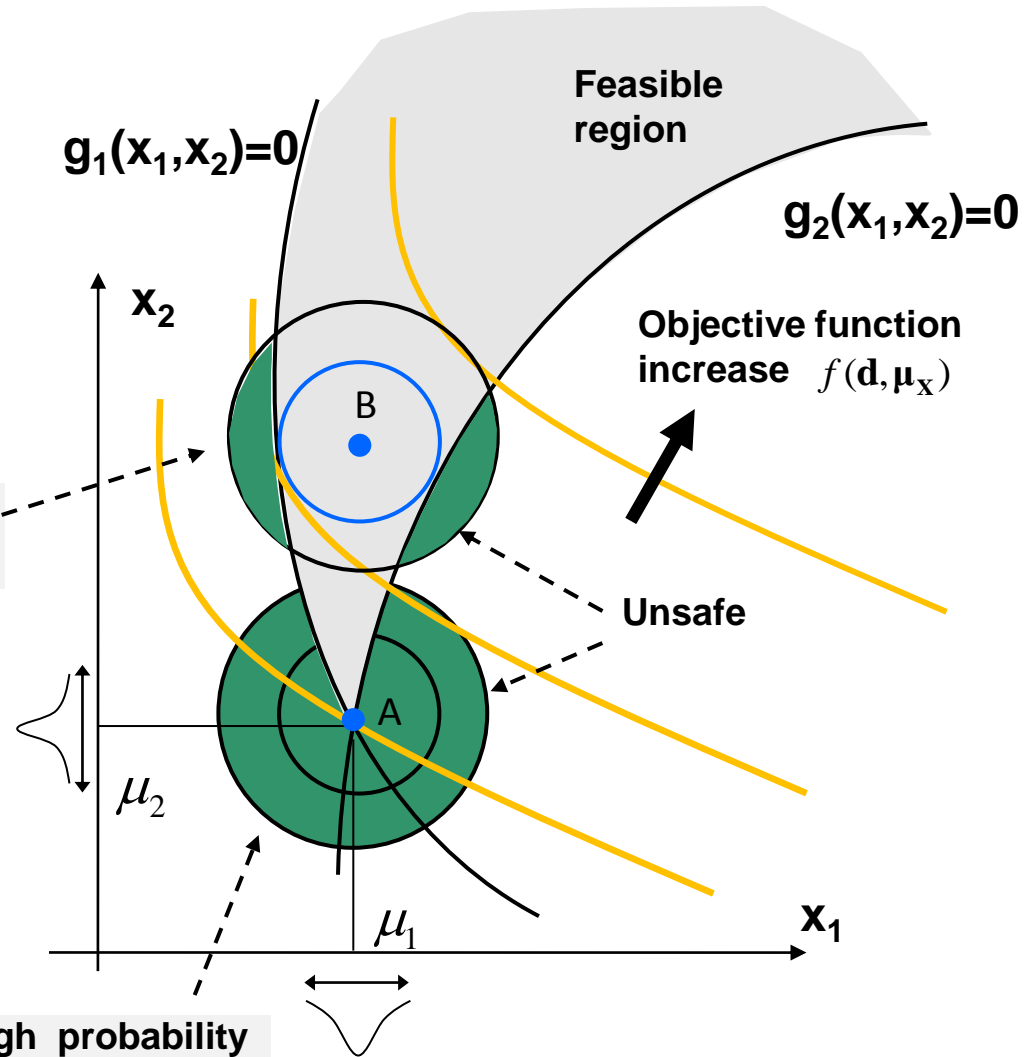
$$\begin{aligned} \min_{\mathbf{d}, \boldsymbol{\mu}_X} & f(\mathbf{d}, \boldsymbol{\mu}_X) \\ \text{s.t.} & g_i(\mathbf{d}, \mathbf{X}) \geq 0 \quad i=1, \dots, n \\ & \mathbf{d}^L \leq \mathbf{d} \leq \mathbf{d}^U, \quad \boldsymbol{\mu}_X^L \leq \boldsymbol{\mu}_X \leq \boldsymbol{\mu}_X^U \end{aligned}$$

Low probability of failure

B. Reliability-Based Design Optimization (RBDO)

$$\begin{aligned} \min_{\mathbf{d}, \boldsymbol{\mu}_X} & f(\mathbf{d}, \boldsymbol{\mu}_X) \\ \text{s.t.} & P[g_i(\mathbf{d}, \mathbf{X}) \leq 0] \leq P_i^t \quad i=1, \dots, n \\ & \mathbf{d}^L \leq \mathbf{d} \leq \mathbf{d}^U, \quad \boldsymbol{\mu}_X^L \leq \boldsymbol{\mu}_X \leq \boldsymbol{\mu}_X^U \end{aligned}$$

High probability of failure





RBDO Approaches (1): RIA vs. PMA

Reliability Index Approach

Enevoldsen and Sorensen (1994)

$$\min_{\mathbf{d}, \boldsymbol{\mu}_x} f(\mathbf{d}, \boldsymbol{\mu}_x)$$

$$s.t. \quad \beta_i = -\Phi^{-1} \left[F_{G_i}(0) \right] \geq \beta_i^t$$

$$\text{where } \beta = \min \|\mathbf{U}\|$$

$$s.t. \quad G(\mathbf{U}) = 0$$

Performance Measure Approach

Tu et al (1999)

$$\min_{\mathbf{d}, \boldsymbol{\mu}_x} f(\mathbf{d}, \boldsymbol{\mu}_x)$$

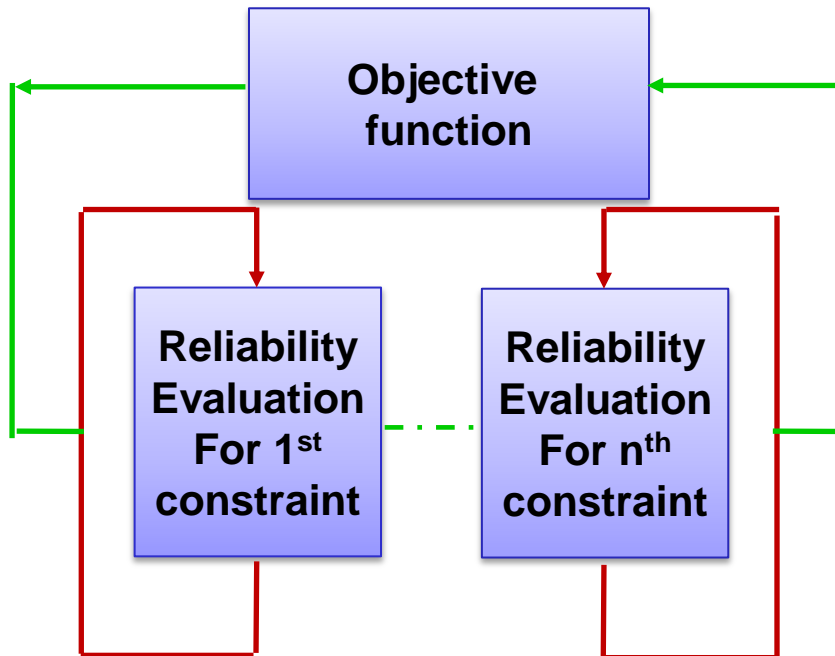
$$s.t. \quad G_{p_i} = F_{G_i}^{-1} \left[\Phi(-\beta_i^t) \right] \geq 0$$

$$\text{where } G_p = \min G(\mathbf{U})$$

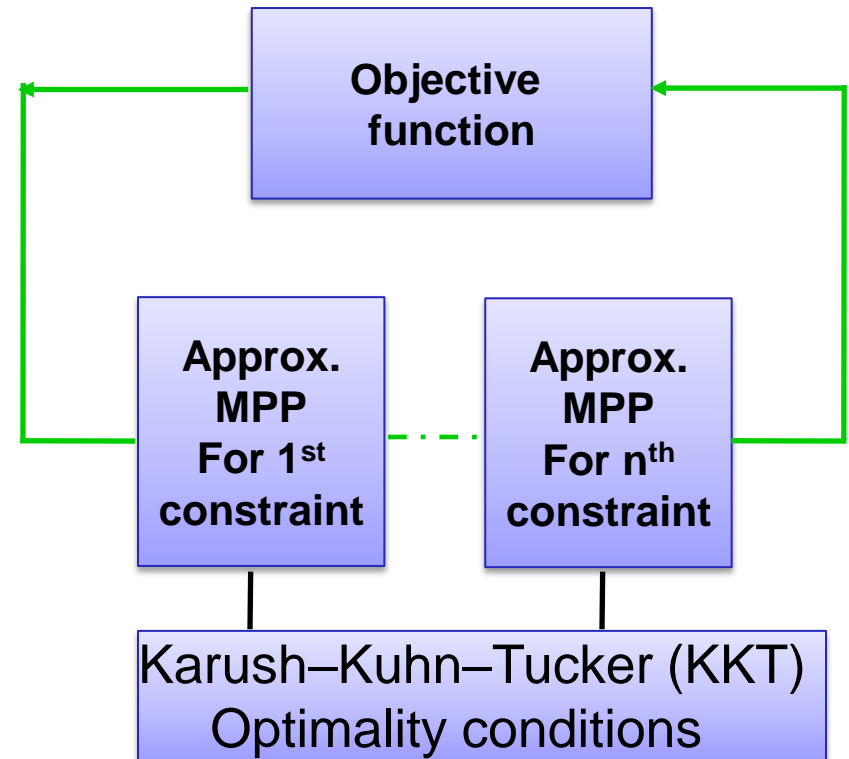
$$s.t. \quad \|\mathbf{U}\| = \beta^t$$

- If constraints are active RIA & PMA yield the same results
- PMA is generally more efficient and stable than RIA

Double-loop RBDO



Single-loop RBDO



➤ Single-loop is generally more efficient than double-loop



RBDO (3): Component vs. System

■ Component RBDO

$$\min_{\mathbf{d}, \boldsymbol{\mu}_X} f(\mathbf{d}, \boldsymbol{\mu}_X)$$

$$s.t. P[g_i(\mathbf{d}, \mathbf{X}) \leq 0] \leq P_i^t \quad i=1, \dots, n$$

- n constraints on components
- Target component probabilities: pre-assigned

■ System RBDO

$$\min_{\mathbf{d}, \boldsymbol{\mu}_X} f(\mathbf{d}, \boldsymbol{\mu}_X)$$

$$s.t. P_{\text{sys}} = P \left[\bigcup_k \bigcap_{i \in C_k} g_i(\mathbf{d}, \mathbf{X}) \leq 0 \right] \leq P_{\text{sys}}^t$$

- ONE constraint on system probability
- Target system probability: pre-assigned
- Comp. Prob.: indirectly constrained

- System performance is better described by SRBDO



Existing SRBDO Methods

■ Series System

- Ba-abbad et al (2006): Sys. probability ~ sum of comp. probabilities (upper bound)

$$P_{sys} = P \left[\bigcup_{i=1}^n g_i(\mathbf{d}, \mathbf{X}) \leq 0 \right] \cong \min \left(1, \sum_{i=1}^n P_i \right)$$

- Liang et al (2007) : Sys. probability: ~ theoretical bound formulas (Ditlevsen, 1979) (upper bound)

$$P_{sys} \cong \sum_{i=1}^n P_i^t - \sum_{i=2}^n \max_{j < i} P_{ij}^t$$

- Silva et al (2009) : System reliability-based topology optimization (SRBTO) (independent component events)

■ General System (cut-set)

- MacDonald and Mahadevan (2008): Using cut-sets

$$E_{\text{system}} = (E_1 \cap E_2) \cup (E_3 \cap E_4) \cup (E_3 \cap E_5) = C_1 \cup C_2 \cup C_3 \quad P_{sys} \cong \min \left(1, \sum_{i=1}^n P_{C_i} \right) \quad (\text{upper bound})$$

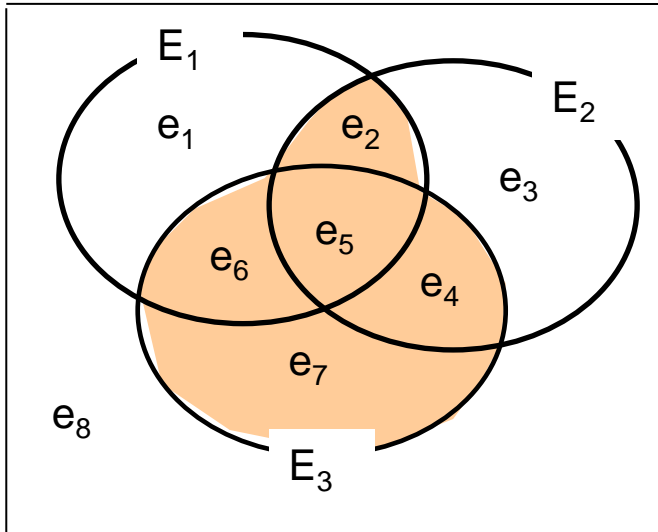
We propose using the matrix-based system reliability (MSR) method to overcome the limitations

Matrix-based formulation of system failure probability

$$P(E_{system}) = \mathbf{c}^T \mathbf{p}$$

Example

$$\begin{aligned}
 P(E_1 E_2 \cup E_3) &= p_2 + p_4 + p_5 + p_6 + p_7 \\
 &= [0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0] \\
 &\quad [p_1 \quad p_2 \quad p_3 \quad p_4 \quad p_5 \quad p_6 \quad p_7 \quad p_8]^T
 \end{aligned}$$



mutually exclusive and collectively exhaustive events (MECE)

- **c: “event” vector**
describe the system event of interest
- **p: “probability” vector**
likelihood of component joint failures

Applicable to any system event (series, parallel, general) with dependent components



Identification of Event Vector “c”

■ Construct event vector “c”

$$\mathbf{c}^{\bar{E}} = \mathbf{1} - \mathbf{c}^E$$

$$\mathbf{c}^{E_1 \dots E_n} = \mathbf{c}^{E_1} \cdot * \mathbf{c}^{E_2} \cdot * \dots * \mathbf{c}^{E_n}$$

$$\mathbf{c}^{E_1 \cup \dots \cup E_n} = \mathbf{1} - (\mathbf{1} - \mathbf{c}^{E_1}) \cdot * (\mathbf{1} - \mathbf{c}^{E_2}) \cdot * \dots * (\mathbf{1} - \mathbf{c}^{E_n})$$

- Efficient and easy to implement by matrix-based language Software (Matlab®)
- Can construct directly from event vectors of components and system events
- Can develop specific algorithms to identify event vector



Computation of Probability Vector “p”

- Iterative matrix-based procedure for statistically independent (s.i) components

$$\mathbf{p}_{[1]} = \begin{bmatrix} P_1 & \bar{P}_1 \end{bmatrix}^T$$

$$\mathbf{p}_{[i]} = \begin{bmatrix} \mathbf{p}_{[i-1]} \cdot P_i \\ \mathbf{p}_{[i-1]} \cdot \bar{P}_i \end{bmatrix}$$

- Example : n =3

$$\mathbf{p}_{[1]} = \begin{bmatrix} P_1 & \bar{P}_1 \end{bmatrix}^T = \begin{bmatrix} P_1 \\ \bar{P}_1 \end{bmatrix} \quad \mathbf{p}_{[2]} = \begin{bmatrix} \mathbf{p}_{[1]} \cdot P_2 \\ \mathbf{p}_{[1]} \cdot \bar{P}_2 \end{bmatrix} = \begin{bmatrix} P_1 P_2 \\ \bar{P}_1 P_2 \\ P_1 \bar{P}_2 \\ \bar{P}_1 \bar{P}_2 \end{bmatrix} \quad \mathbf{p}_{[3]} = \begin{bmatrix} \mathbf{p}_{[2]} \cdot P_3 \\ \mathbf{p}_{[2]} \cdot \bar{P}_3 \end{bmatrix} = \begin{bmatrix} P_1 P_2 P_3 \\ \bar{P}_1 P_2 P_3 \\ P_1 \bar{P}_2 P_3 \\ \bar{P}_1 \bar{P}_2 P_3 \\ P_1 P_2 \bar{P}_3 \\ \bar{P}_1 P_2 \bar{P}_3 \\ P_1 \bar{P}_2 \bar{P}_3 \\ \bar{P}_1 \bar{P}_2 \bar{P}_3 \end{bmatrix}$$



MSR for System with Dependent Components

■ System probability with dependent components

$$\begin{aligned} P(E_{sys}) &= \int_{\mathbf{s}} P(E_{sys} | \mathbf{s}) f_{\mathbf{s}}(\mathbf{s}) d\mathbf{s} \\ &= \int_{\mathbf{s}} \mathbf{c}^T \mathbf{p}(\mathbf{s}) f_{\mathbf{s}}(\mathbf{s}) d\mathbf{s} = \mathbf{c}^T \int_{\mathbf{s}} \mathbf{p}(\mathbf{s}) f_{\mathbf{s}}(\mathbf{s}) d\mathbf{s} \\ &= \mathbf{c}^T \tilde{\mathbf{p}} \end{aligned}$$

- Utilize conditional S.I of components given an outcome of random variables “s” causing component dependence, named “Common Source Random Variables” (CSRV).
- Event vector \mathbf{c} is independent of this consideration
- No need to construct probability vector for new system event

■ Approximation by Dunnett-Sobel (DS) correlation matrix

$$Z_i \square N(0, R), \rho_{ij} = \sum_{k=1}^m (r_{ik} \cdot r_{jk})$$

$$Z_i = \left(1 - \sum_{k=1}^m r_{ik}^2\right)^{0.5} U_i + \sum_{k=1}^m r_{ik} S_k$$

- $Z_i, i=1, \dots, n$ are conditional s.i given $S=s$
- Fit the given correlation matrix with DS class correlation matrix with least square error



SRBDO/MSR: Algorithm

■ Current SRBDO algorithm

- Using bound formulas (**inaccurate**)
- **NOT** applicable to general system
- **Sensitivities NOT** available.

■ MSR method

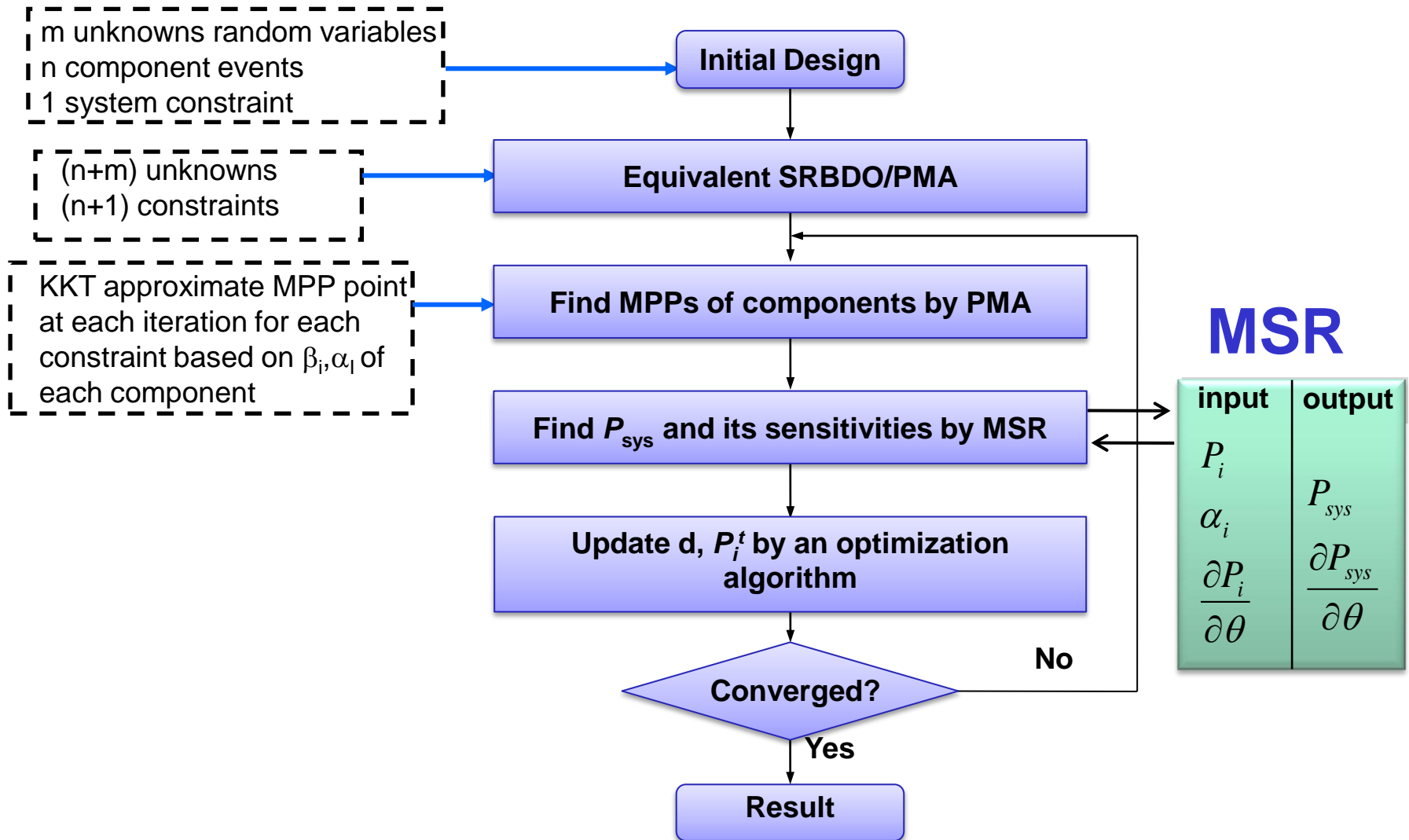
- Compute system failure probability
- Applicable to **general** system
- Independent events and **dependent** events

■ Propose: Single-loop PMA SRBDO/MSR algorithm

- Based on Single-loop SRBDO-PMA procedure
- System probability and its sensitivities by MSR



Single-loop PMA SRBDO/MSR: Algorithm



■ Parameter sensitivities $P_{\text{sys}} = \mathbf{c}^T \mathbf{p}$

$$\frac{\partial P_{\text{sys}}}{\partial \theta} = \mathbf{c}^T \frac{\partial \mathbf{p}}{\partial \theta} \quad \text{Independent}$$

$$\frac{\partial P_{\text{sys}}}{\partial \theta} = \int_{\mathbf{s}} \mathbf{c}^T \frac{\partial \mathbf{p}(\mathbf{s})}{\partial \theta} f_{\mathbf{s}}(\mathbf{s}) d\mathbf{s} \quad \text{dependent}$$

$$\frac{\partial \mathbf{p}}{\partial \theta} = \left[\mathbf{p}^{(1)} \quad \mathbf{p}^{(2)} \quad \dots \quad \mathbf{p}^{(n)} \right] \frac{\partial \mathbf{P}}{\partial \theta} = \mathbf{P} \frac{\partial \mathbf{P}}{\partial \theta}$$

$$\mathbf{P} = [P_1 \quad P_2 \quad \dots \quad P_n]^T$$

■ System probability sensitivities w.r.t component probabilities (DS class)

$$P_i(\mathbf{s}) = \Phi \left[-\frac{\beta_i - \sum_{k=1}^m r_{ik} s_k}{\left(1 - \sum_{k=1}^m r_{ik}^2\right)^{0.5}} \right]$$

$$\frac{\partial P_i(\mathbf{s})}{\partial \beta_i} = \frac{\partial P_i(\mathbf{s})}{\partial \beta_i} \cdot \frac{\partial \beta_i}{\partial P_i} = -\frac{\partial P_i(\mathbf{s})}{\partial \beta_i} \cdot \frac{1}{\varphi(-\beta_i)}$$



Example – Indeterminate Truss Structure

- **Obj. func:** Min. the weight of truss
- **Opti parameter:** bar areas: A_i
- **Constraint:** System. Prob.
- **Failure:** System fails if two members fail system event (**cut-set**)

$$\{C_k\} = \{(1,2), (1,3), (1,4), (1,5), (1,6), (2,3), (2,4), (2,5), (2,6), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6)\}$$

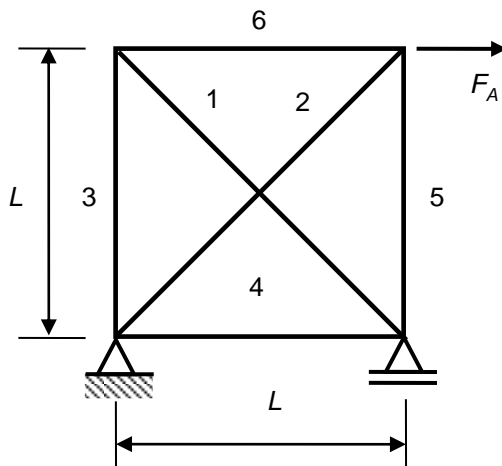
$$\min_{\mathbf{d}=\{A_1, \dots, A_6\}} f(\mathbf{d}) = \sqrt{2}(A_1 + A_2) + A_3 + A_4 + A_5 + A_6$$

$$s.t. \quad P_{\text{sys}} = P \left[\bigcup_{k=1}^{15} \bigcap_{i \in C_k} g_i(\mathbf{d}, \mathbf{X}) \leq 0 \right] \leq P_{\text{sys}}^t = 0.001$$

$$g_i(\mathbf{d}, \mathbf{X}) = A_i F_i - 0.707 F_A \quad i = 1, 2$$

$$A_i F_i - 0.500 F_A \quad i = 3, \dots, 6$$

$$A_1, A_2, A_3, A_4, A_5, A_6 \geq 0$$



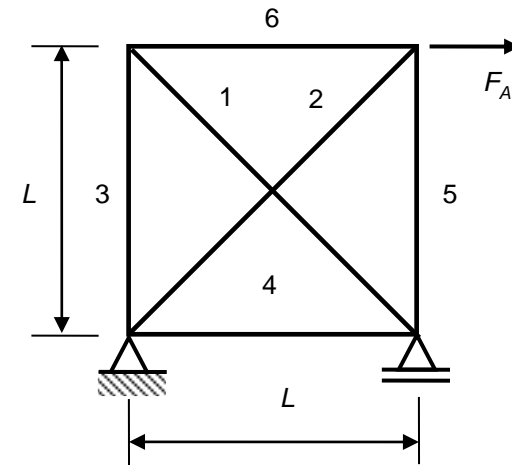
Means and Standard deviations of the random variables

<i>Random Variables</i> (Gaussian distribution)	<i>Mean</i>	<i>Std dev</i>
Member strength F_i , $i=1, \dots, 6$ (Mpa)	745	62
Applied load F_A (kN)	4450	45

Indeterminate Truss Structure

➤ MacDonald and Mahadevan (*) vs. **SRBDO/MSR**

Members	Area: A_i ($\times 10^{-3}$ mm ²)		Reliability Index: β_i	
	<i>SRBDO by (*)</i>	<i>SRBDO/MSR</i>	<i>SRBDO by (*)</i>	<i>SRBDO/MSR</i>
1	18.43	17.89	2.89	2.67
2	18.27	17.89	2.83	2.67
3	13.51	13.20	3.16	2.99
4	13.44	13.20	3.12	2.99
5	13.33	13.20	3.06	2.99
6	13.09	13.20	2.92	2.99
$f(x)$	105.24	103.36		



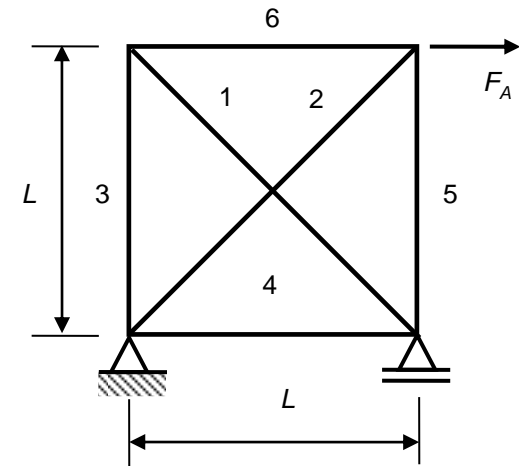
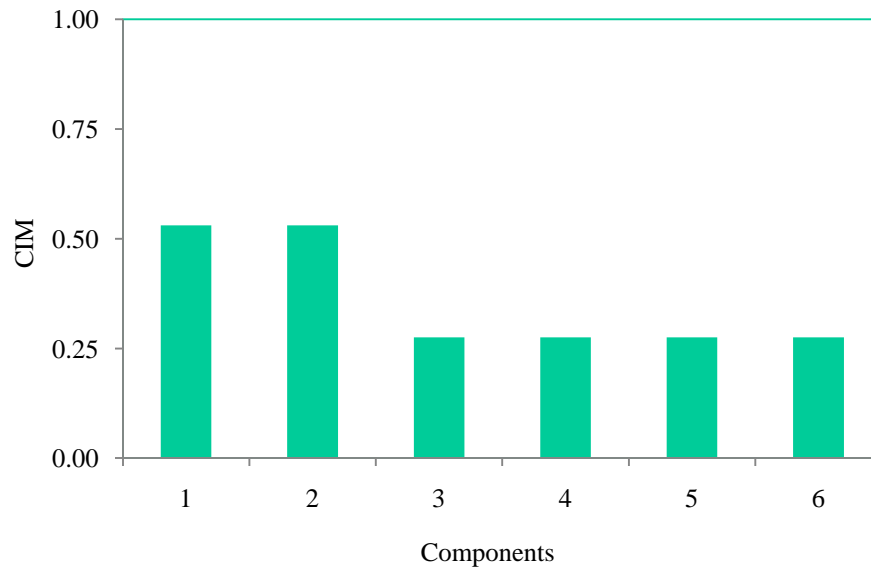
➤ **SRBDO/MSR**: better optimal design + symmetric results

➤ **MCS**: $P_{\text{sys}}=0.00107$ (10^6 times, c.o.v. = 0.03) ~ **SRBDO/MSR**: 0.001

■ Conditional probability important Measure (CIM)

$$\text{CIM}_i = P(E_i | E_{\text{sys}}) = \frac{P(E_i E_{\text{sys}})}{P(E_{\text{sys}})} = \frac{\mathbf{c}^T \mathbf{p}}{\mathbf{c}^T \mathbf{p}}$$

➤ Only additional task is to identify the event vector of the new system



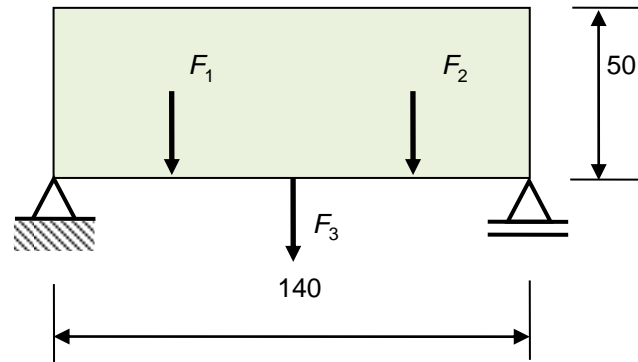
➤ Component important ranking: (1,2) -> (3,4,5,6)



Topology Optimization: DTO, CRBTO, SRBTO

$$g_i(\boldsymbol{\rho}, \mathbf{F}) = d_i^t - d_i(\boldsymbol{\rho}, \mathbf{F})$$

$$i=1,2,3$$



Random Variables

$$F_1 \sim N(100, 10)$$

$$F_2 \sim N(100, 10)$$

$$F_3 \sim N(100, 10)$$

$$\mathbf{F} = (F_1, F_2, F_3)$$

$$d_i^{\max} = 1.5$$

DTO

$$\begin{aligned} & \text{Min}_{\boldsymbol{\rho}} V(\boldsymbol{\rho}) \\ & \text{s.t.} \quad g_i(\boldsymbol{\rho}, \mathbf{F}) \leq 0, \quad i=1,2,3 \\ & g_i(\boldsymbol{\rho}, \mathbf{F}) = d_i(\boldsymbol{\rho}, \mathbf{F}) - d_i^{\max} \end{aligned}$$

1

CRBTO

$$\begin{aligned} & \text{Min}_{\boldsymbol{\rho}} V(\boldsymbol{\rho}) \\ & \text{s.t.} \quad P[g_1(\boldsymbol{\rho}, \mathbf{F}) \leq 0] \leq P_1^t \\ & \quad P[g_2(\boldsymbol{\rho}, \mathbf{F}) \leq 0] \leq P_2^t \\ & \quad P[g_3(\boldsymbol{\rho}, \mathbf{F}) \leq 0] \leq P_3^t \\ & \text{where: } P_1^t = P_2^t = P_3^t = 0.02275 \\ & g_1(\boldsymbol{\rho}, \mathbf{F}) = d_1^{\max} - d_1(\boldsymbol{\rho}, \mathbf{F}) \leq 0 \\ & g_2(\boldsymbol{\rho}, \mathbf{F}) = d_2^{\max} - d_2(\boldsymbol{\rho}, \mathbf{F}) \leq 0 \\ & g_3(\boldsymbol{\rho}, \mathbf{F}) = d_3^{\max} - d_3(\boldsymbol{\rho}, \mathbf{F}) \leq 0 \end{aligned}$$

2

SRBTO

$$\begin{aligned} & \text{Min}_{\boldsymbol{\rho}} V(\boldsymbol{\rho}) \\ & \text{s.t.} \quad P_{\text{sys}} = P[g_1(\boldsymbol{\rho}, \mathbf{F}) \cup g_2(\boldsymbol{\rho}, \mathbf{F}) \cup g_3(\boldsymbol{\rho}, \mathbf{F}) \leq 0] \leq P_{\text{sys}}^t \\ & \text{where} \\ & g_1(\boldsymbol{\rho}, \mathbf{F}) = d_1^{\max} - d_1(\boldsymbol{\rho}, \mathbf{F}) \leq 0 \\ & g_2(\boldsymbol{\rho}, \mathbf{F}) = d_2^{\max} - d_2(\boldsymbol{\rho}, \mathbf{F}) \leq 0 \\ & g_3(\boldsymbol{\rho}, \mathbf{F}) = d_3^{\max} - d_3(\boldsymbol{\rho}, \mathbf{F}) \leq 0 \end{aligned}$$

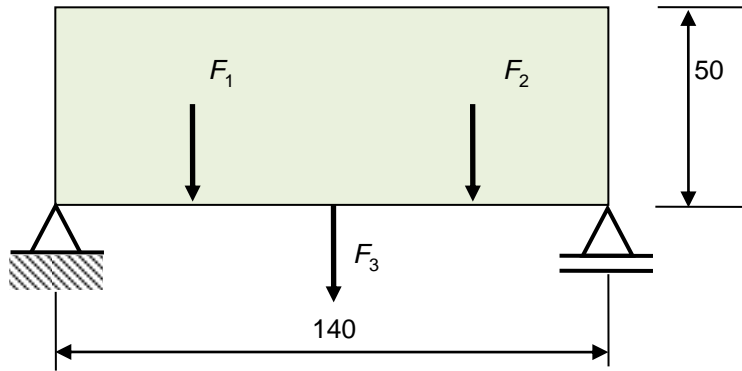
3

SRBTO/PMA+MSR

$$\begin{aligned} & \text{Min}_{\boldsymbol{\rho}, P_1^t, P_2^t, P_3^t} V(\boldsymbol{\rho}) \\ & \text{s.t.} \quad g_1(\boldsymbol{\rho}, \mathbf{F}) \geq 0 \\ & \quad g_2(\boldsymbol{\rho}, \mathbf{F}) \geq 0 \\ & \quad g_3(\boldsymbol{\rho}, \mathbf{F}) \geq 0 \\ & P_{\text{sys}} = P^{\text{MSR}}(P_1^t, P_2^t, P_3^t) \leq P_{\text{sys}}^t \end{aligned}$$

4

Topology Optimization: DTO, CRBTO, SRBTO



($P_{\text{sys}} = 0.0434$
volfrac = 0.58)

$$E_{\text{sys}} = \bigcup E_i \quad \text{Series}$$



DTO (volfrac = 0.40)



($P_{\text{sys}} = 0.005$
volfrac = 0.44)

$$E_{\text{sys}} = E_1 E_2 E_3 \quad \text{Parallel}$$



CRBTO ($P_i = 0.02275$
 $P_{\text{sys}} = 0.0434$
volfrac = 0.60)



($P_{\text{sys}} = 0.005$
volfrac = 0.47)

$$E_{\text{sys}} = \bar{E}_1 \bar{E}_2 E_3 \quad \text{General}$$

SRBTO/MSR



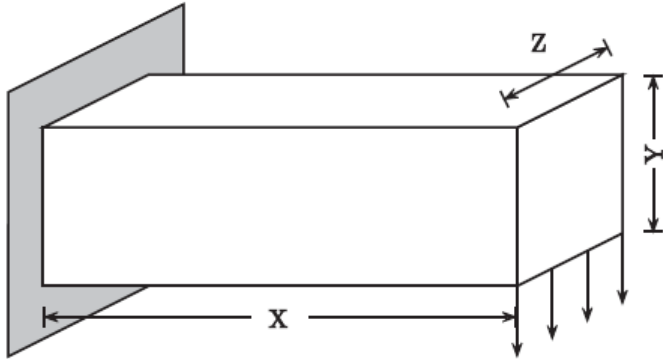
Summary & Conclusion

- Single-loop PMA **SRBDO/MSR** algorithm is proposed.
- The SRBDO/MSR is applicable to **general** system in a uniform manner.
- **Sensitivities** for gradient-based optimization
- Handle **dependence** between component events
- **Numerical examples:** SRBDO & SRBTO examples
- **Future work:** 3D topology optimization problem



Future work: Large-scale SRBTO

Problem configuration

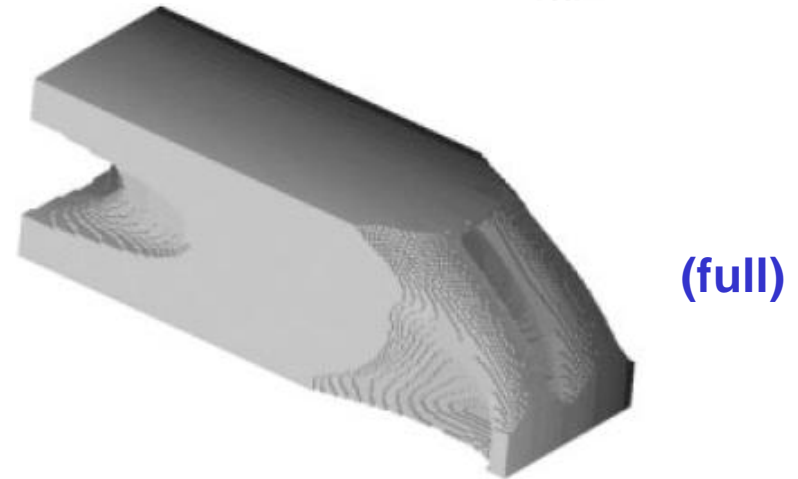
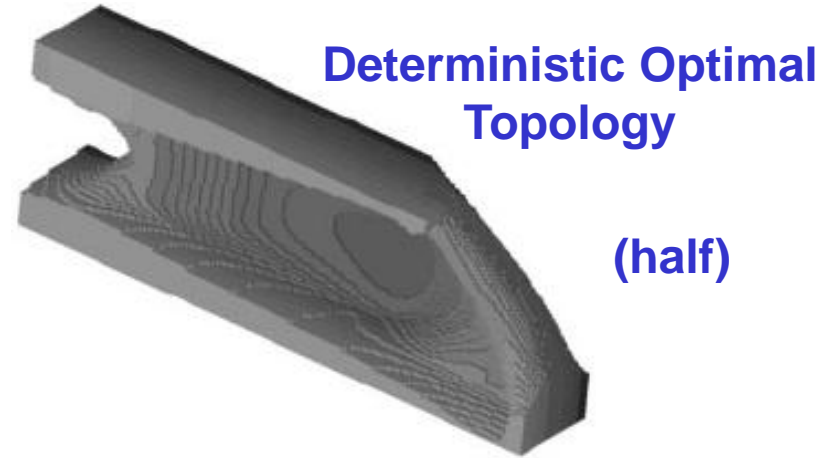


Size (full domain): 180x60x60 elements

Number of unknowns (half domain: ≈ 1.0 mil.)

Run time: ~ 45.7 hours

Filtering radius: 6 elements



High resolution SRBTO is computationally expensive