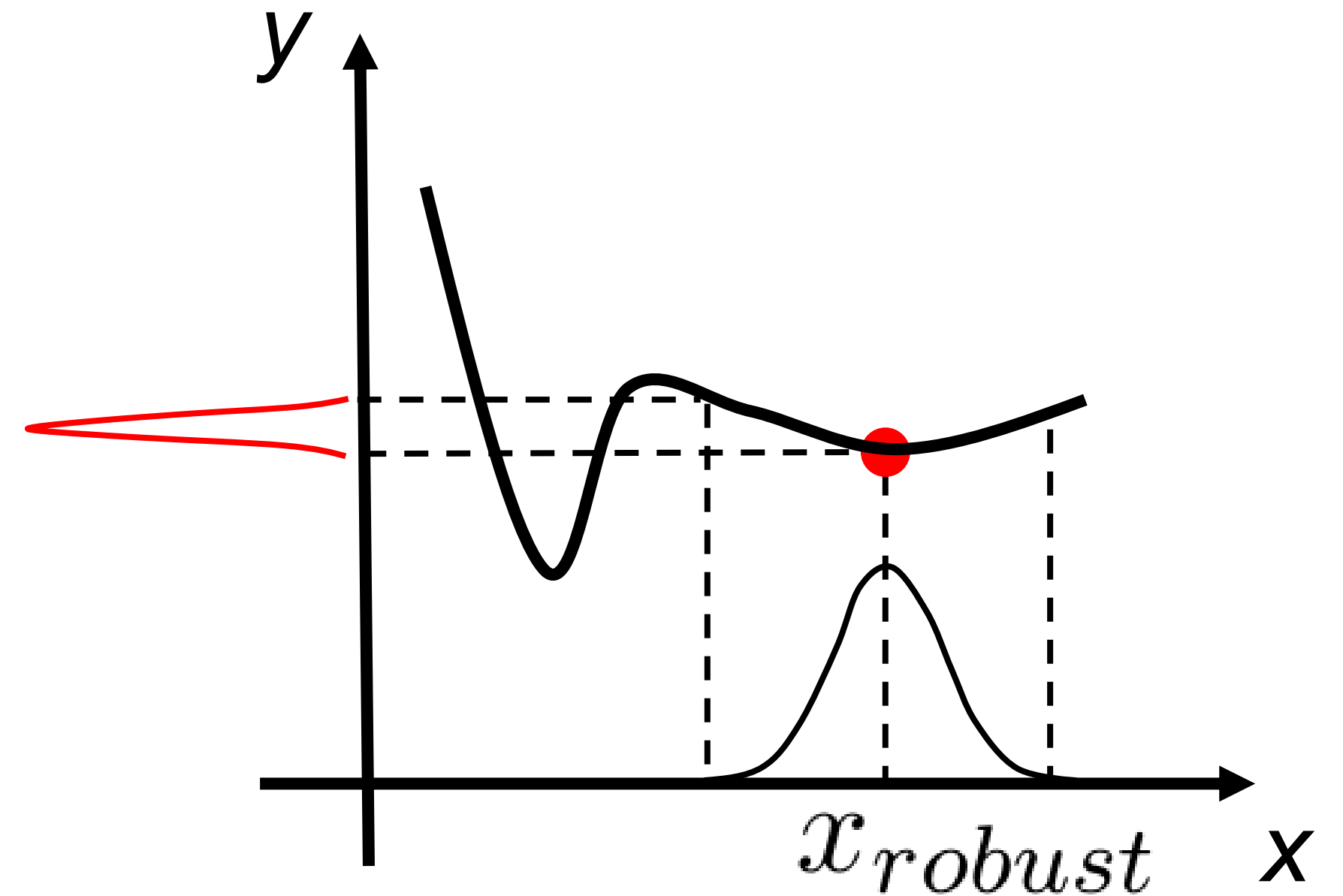


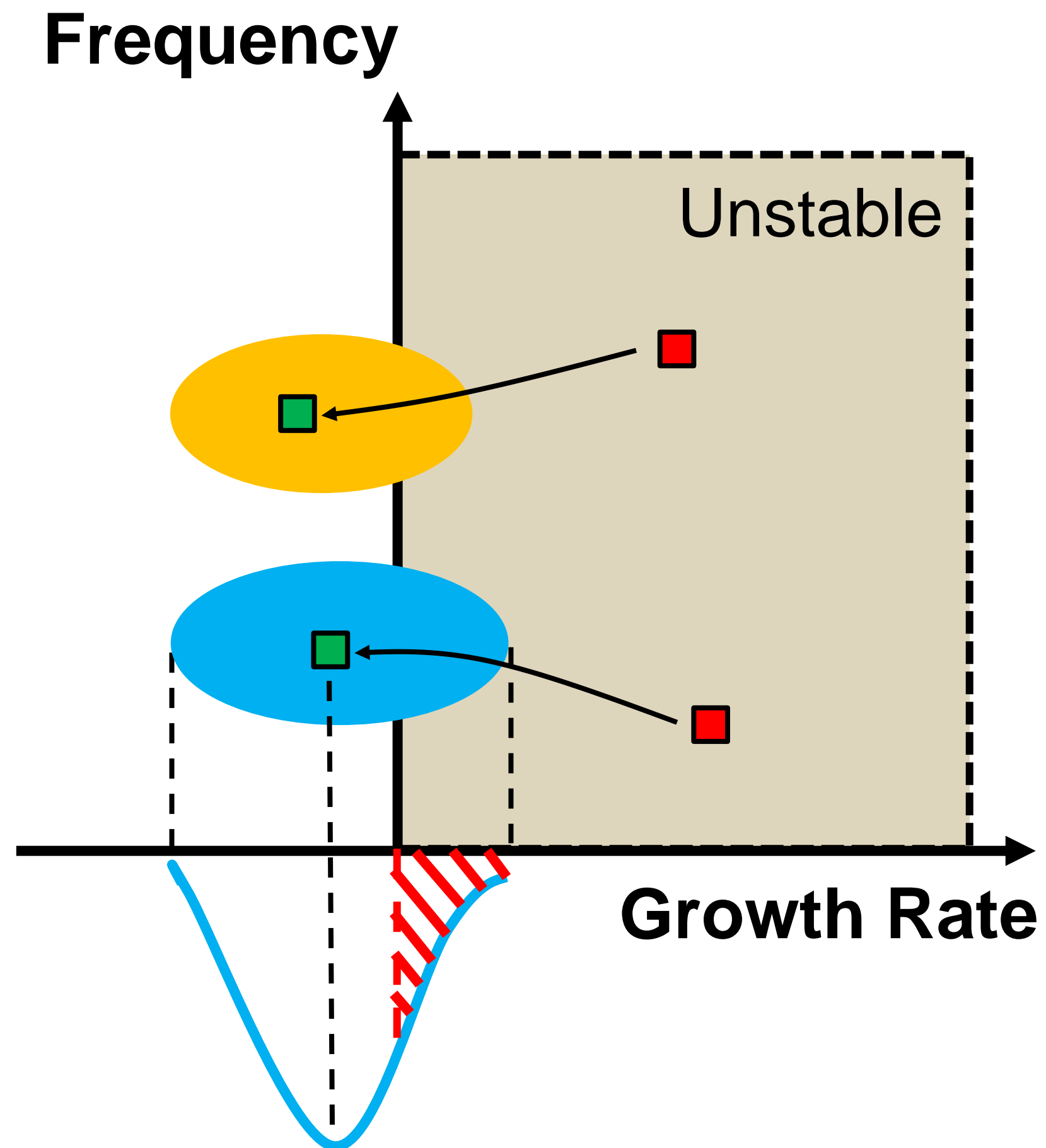
Efficient Robust Design for Thermoacoustic Instability Analysis: A Gaussian Process Approach

S. Guo, C. F. Silva, W. Polifke

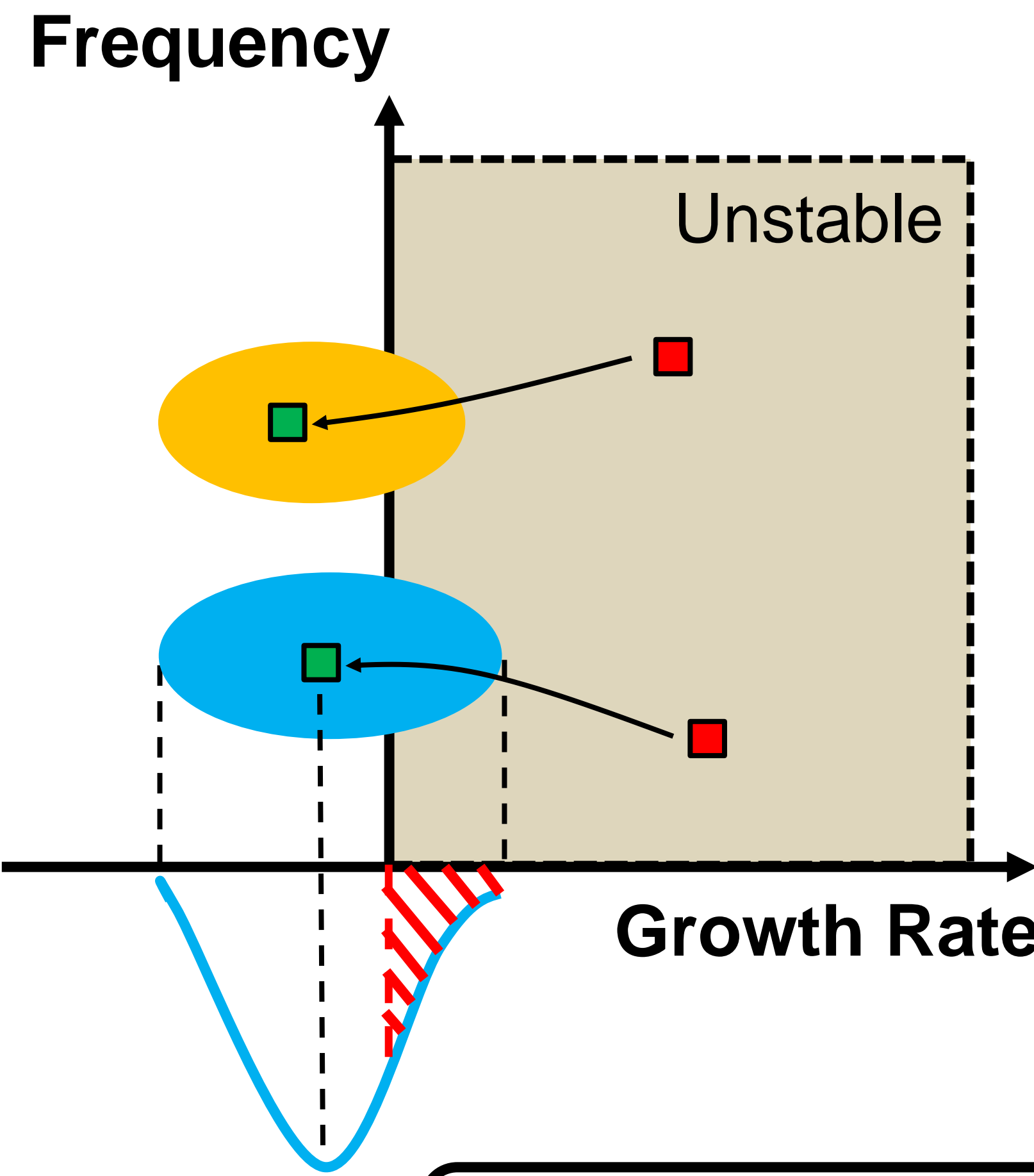


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GT2019-90732

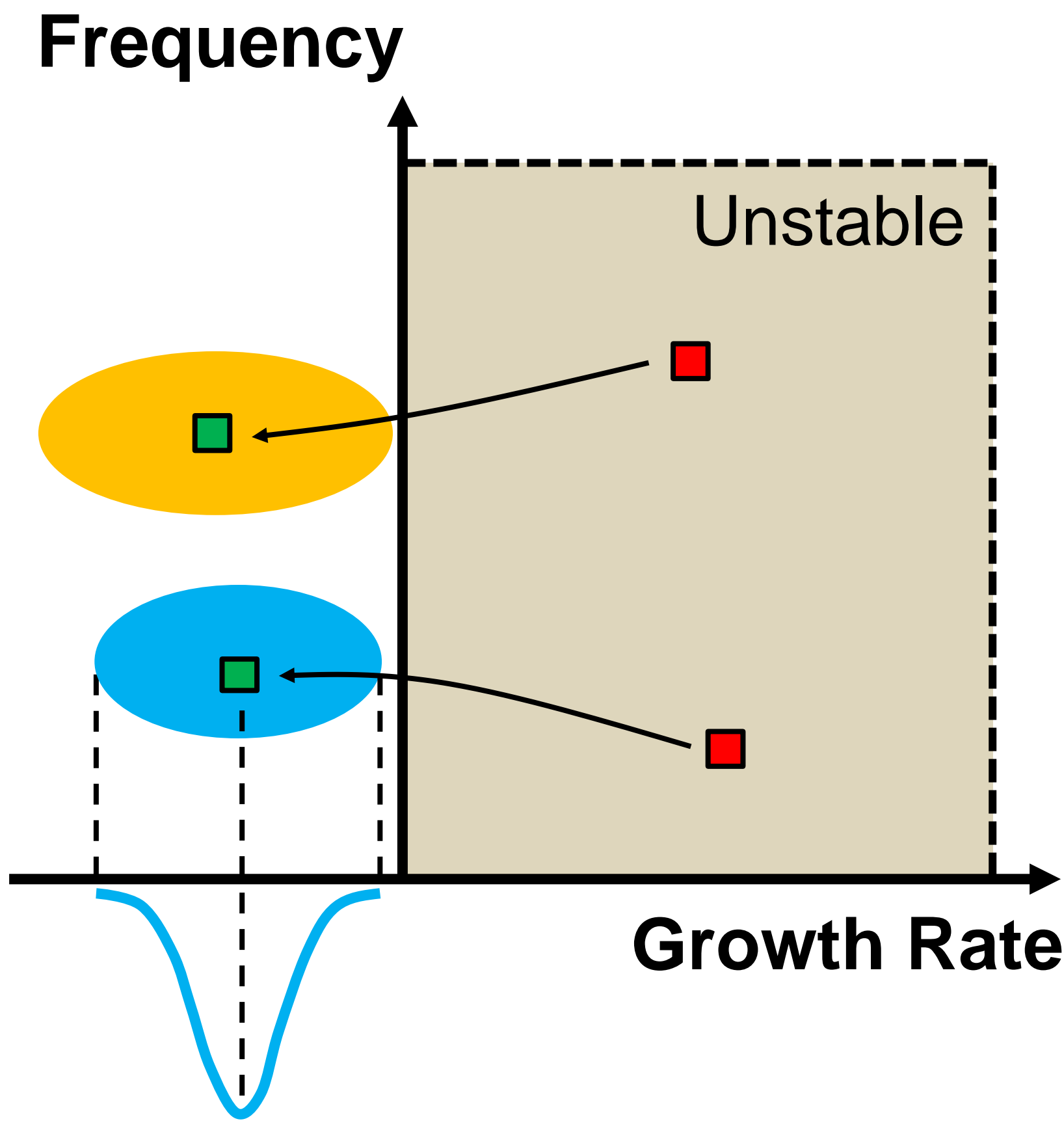
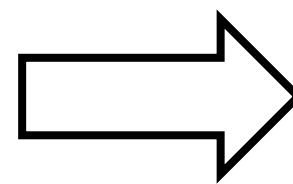
Robust analysis takes into account input uncertainties to realize risk-free thermoacoustic design



Robust analysis takes into account input uncertainties to realize risk-free thermoacoustic design



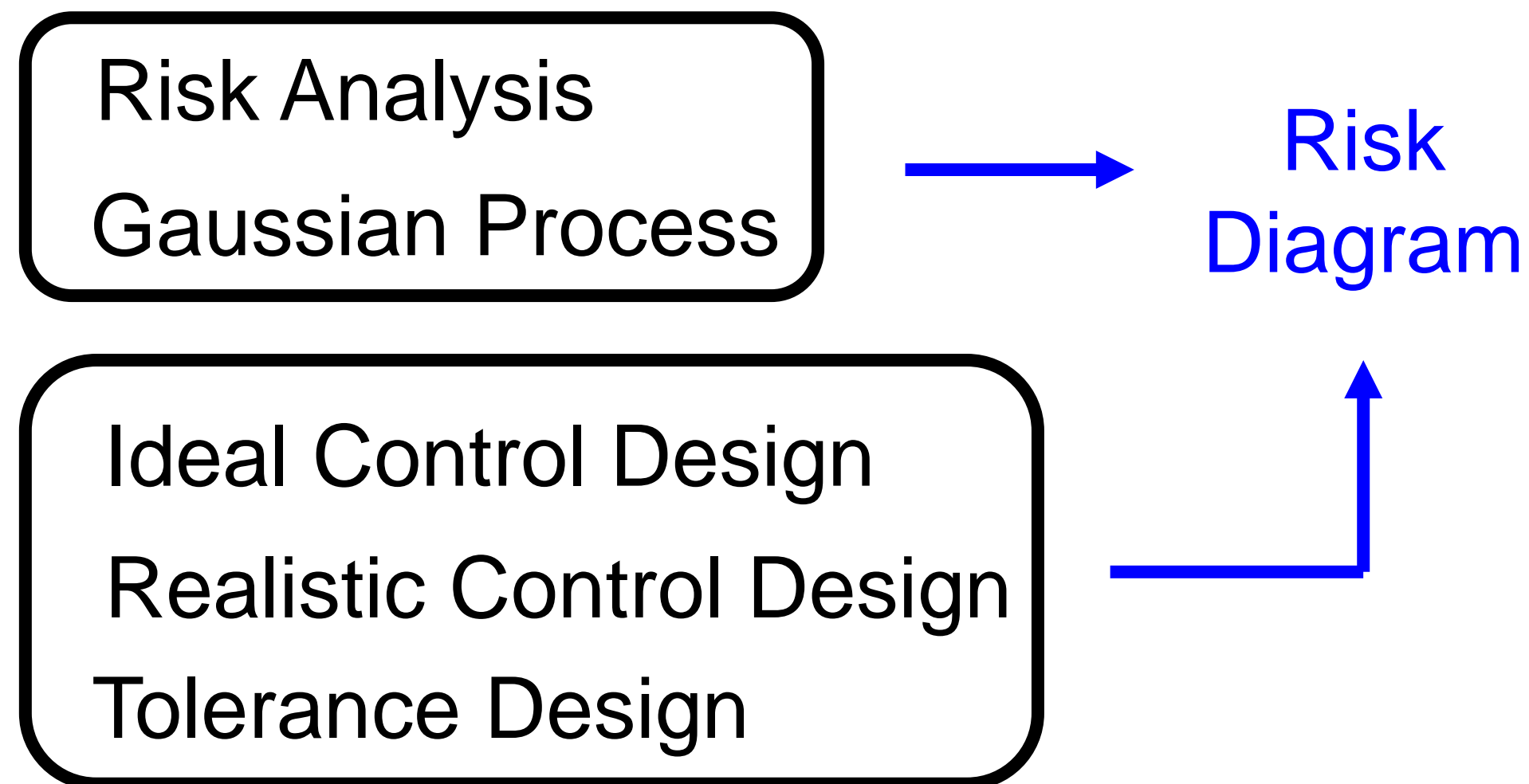
Traditional Design



Robust Design

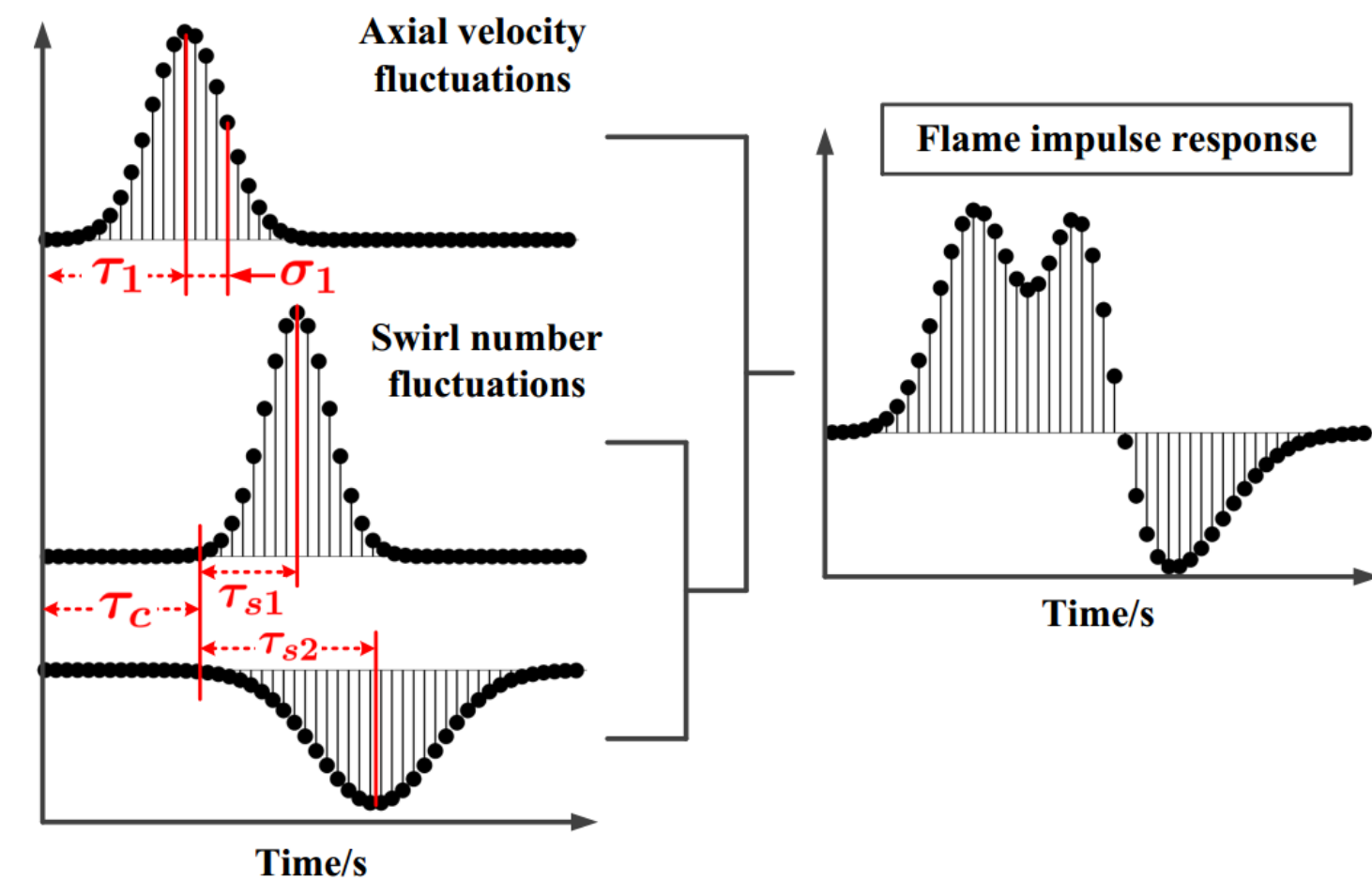
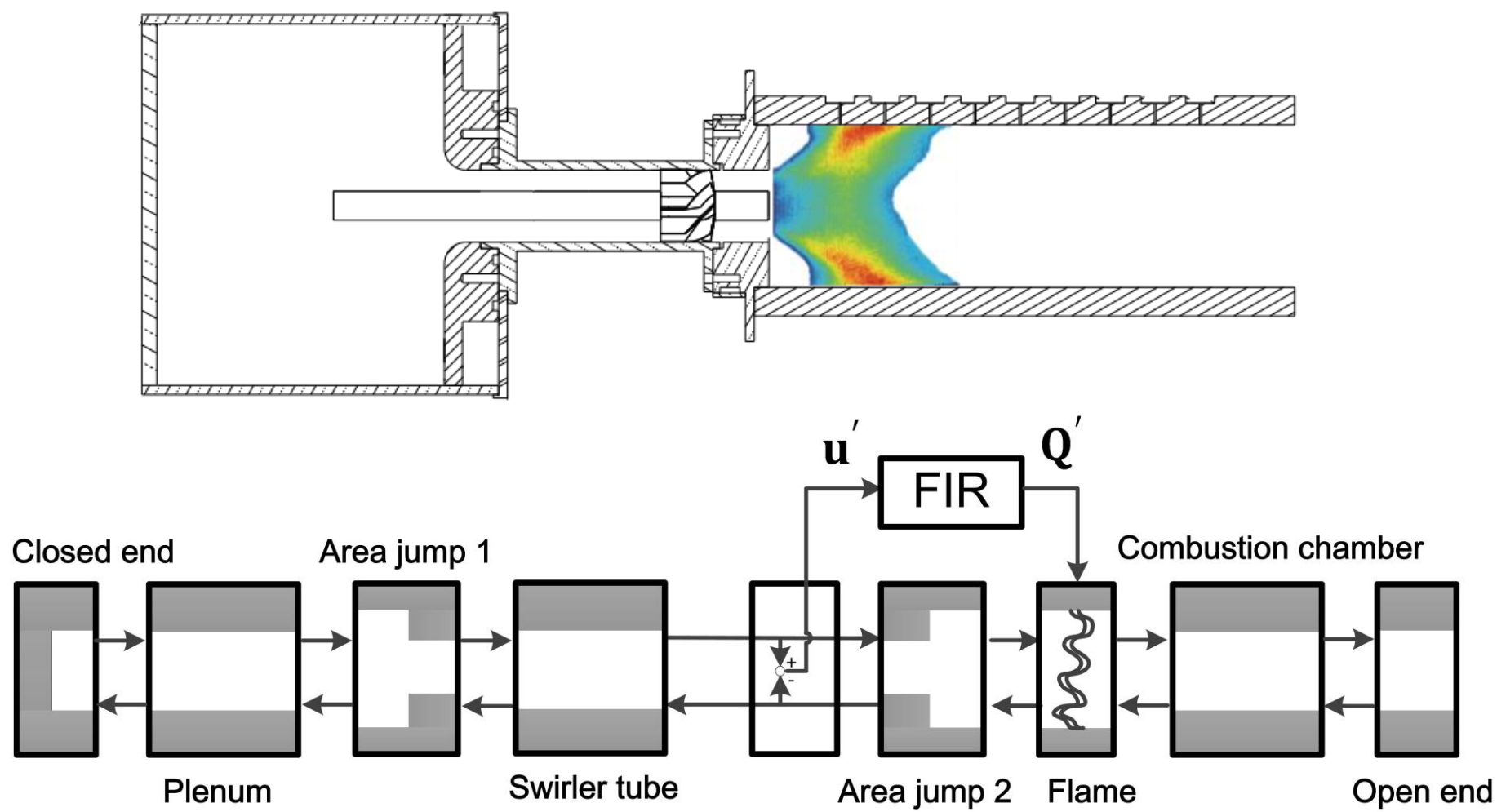
Presentation overview

- Motivation
- Thermoacoustic problem settings
- Robust design tasks



- Conclusions

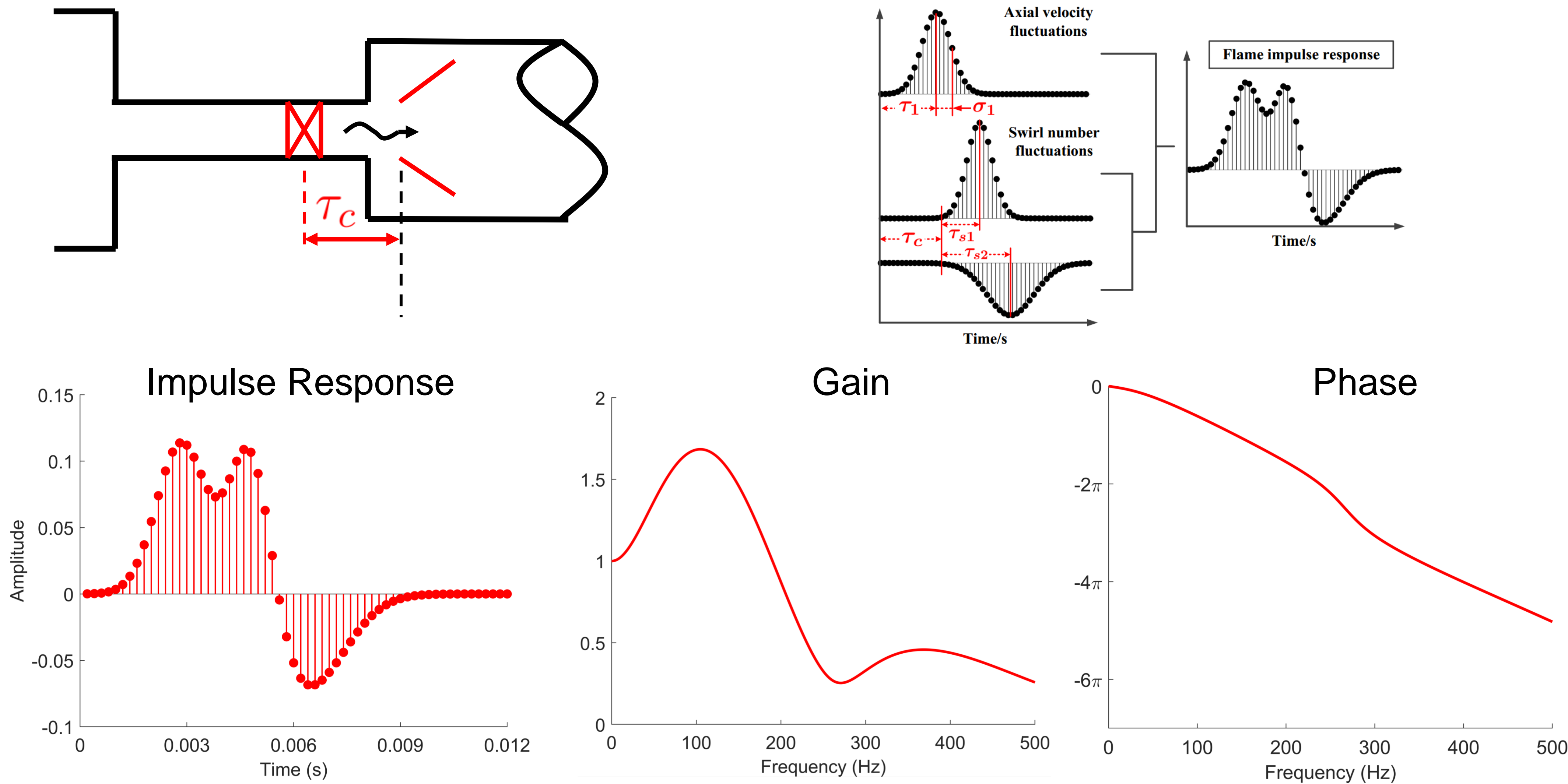
Thermoacoustic settings: solver, flame model, mode specification



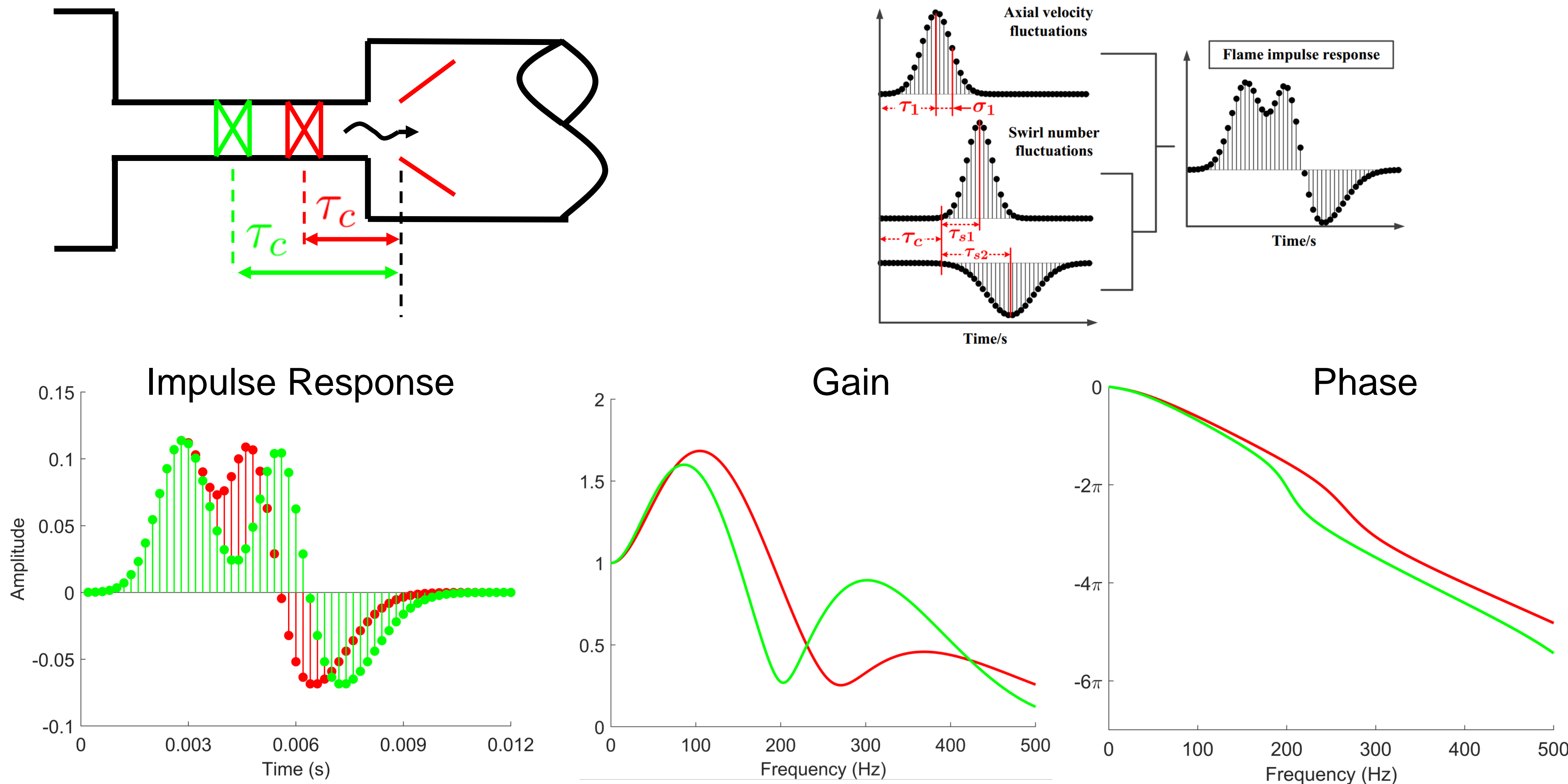
Distributed Time Lag Model [1]

[1] Komarek, T., Polifke, W., 2010, *J Eng Gas Turbines Power*.

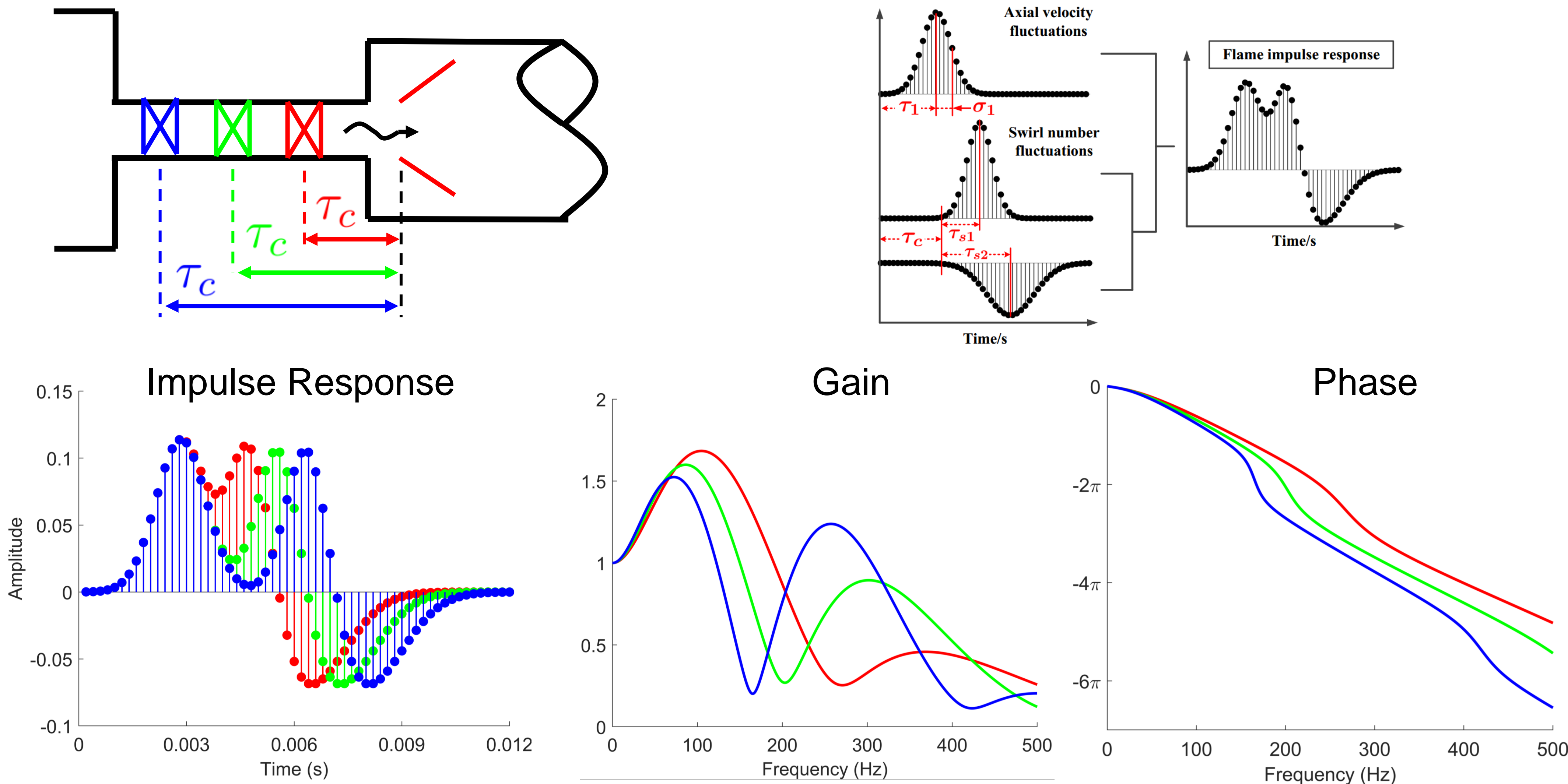
Thermoacoustic settings: solver, flame model, mode specification



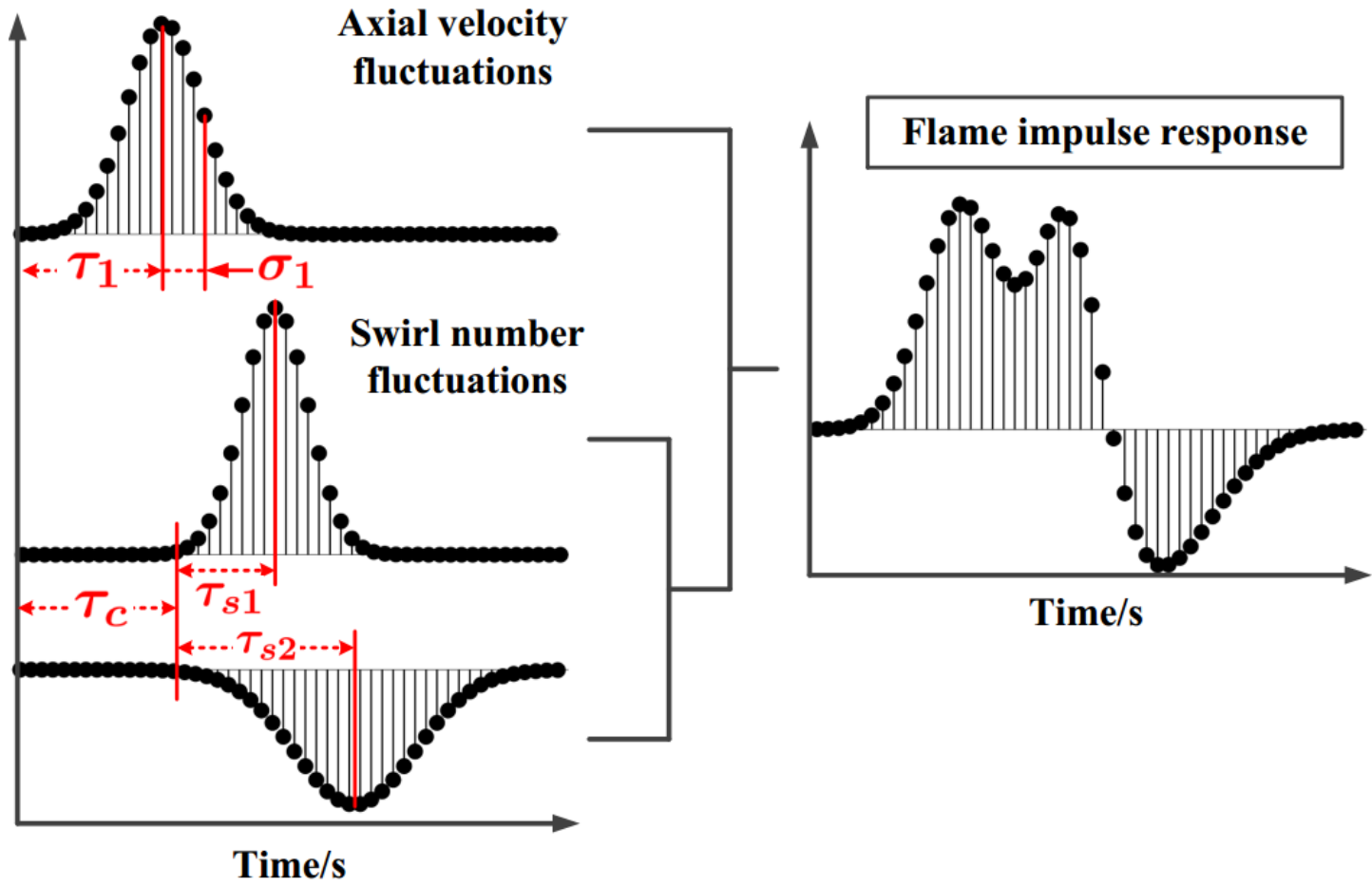
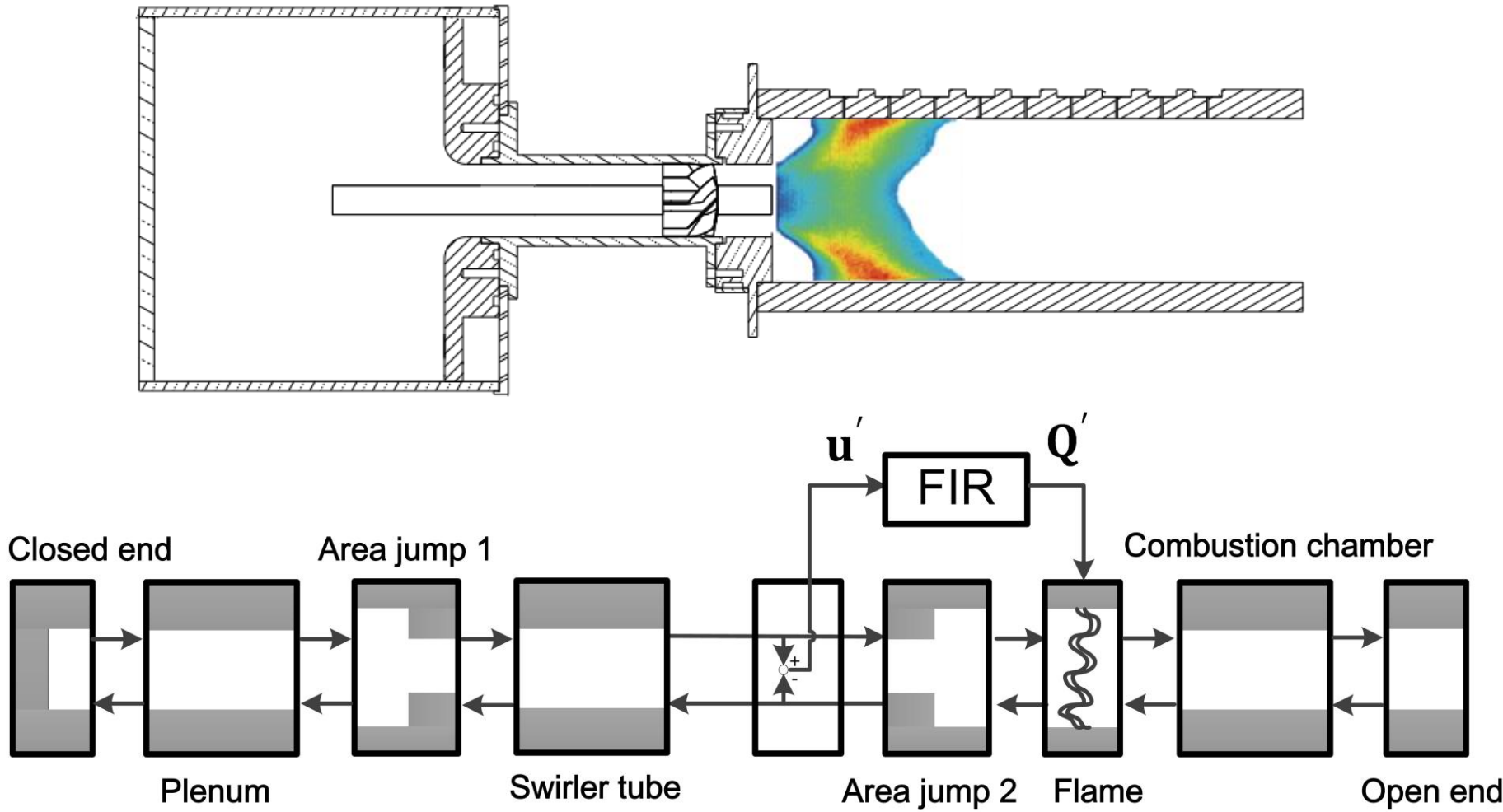
Thermoacoustic settings: solver, flame model, mode specification



Thermoacoustic settings: solver, flame model, mode specification



Thermoacoustic settings: solver, flame model, mode specification

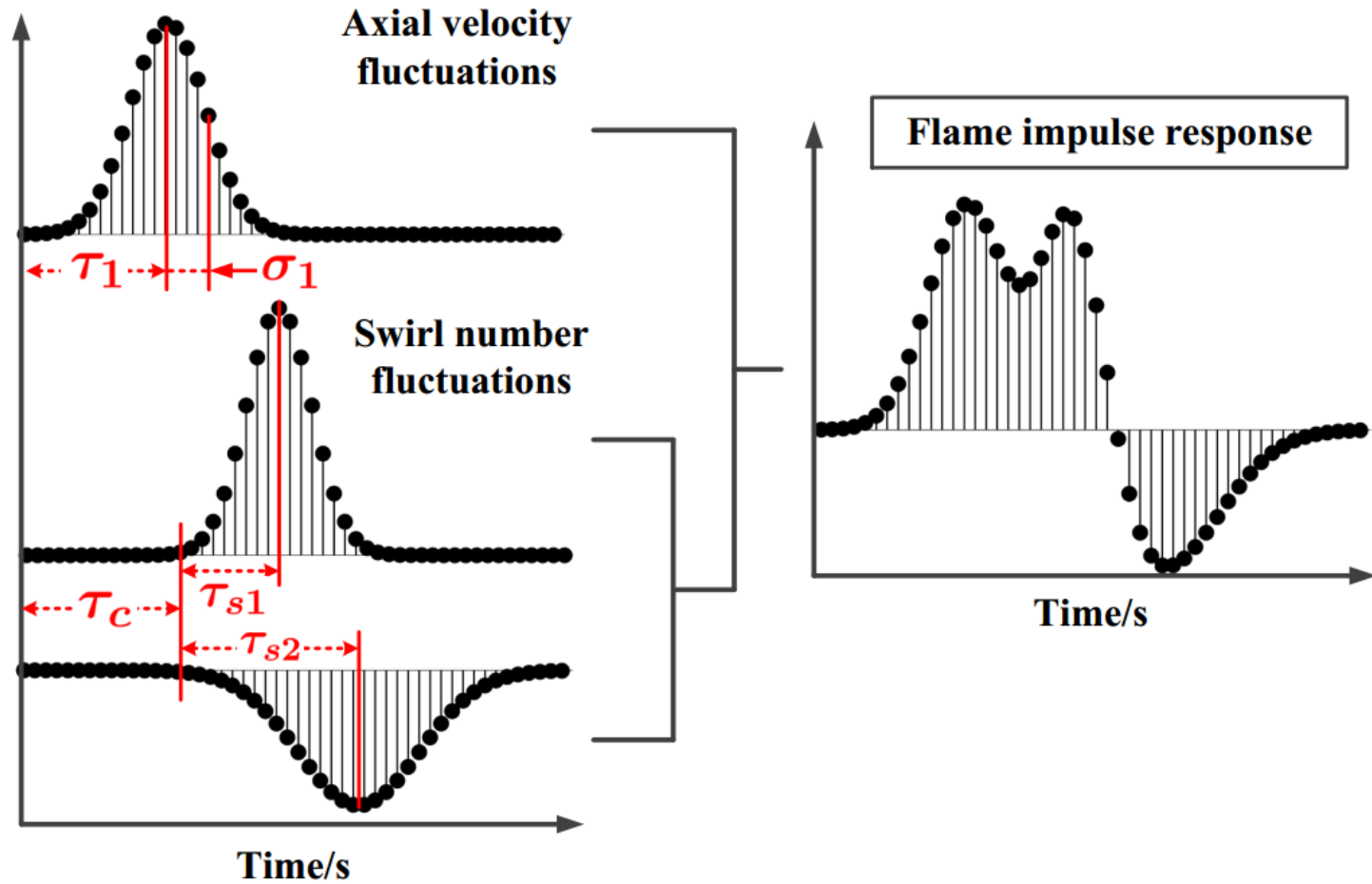
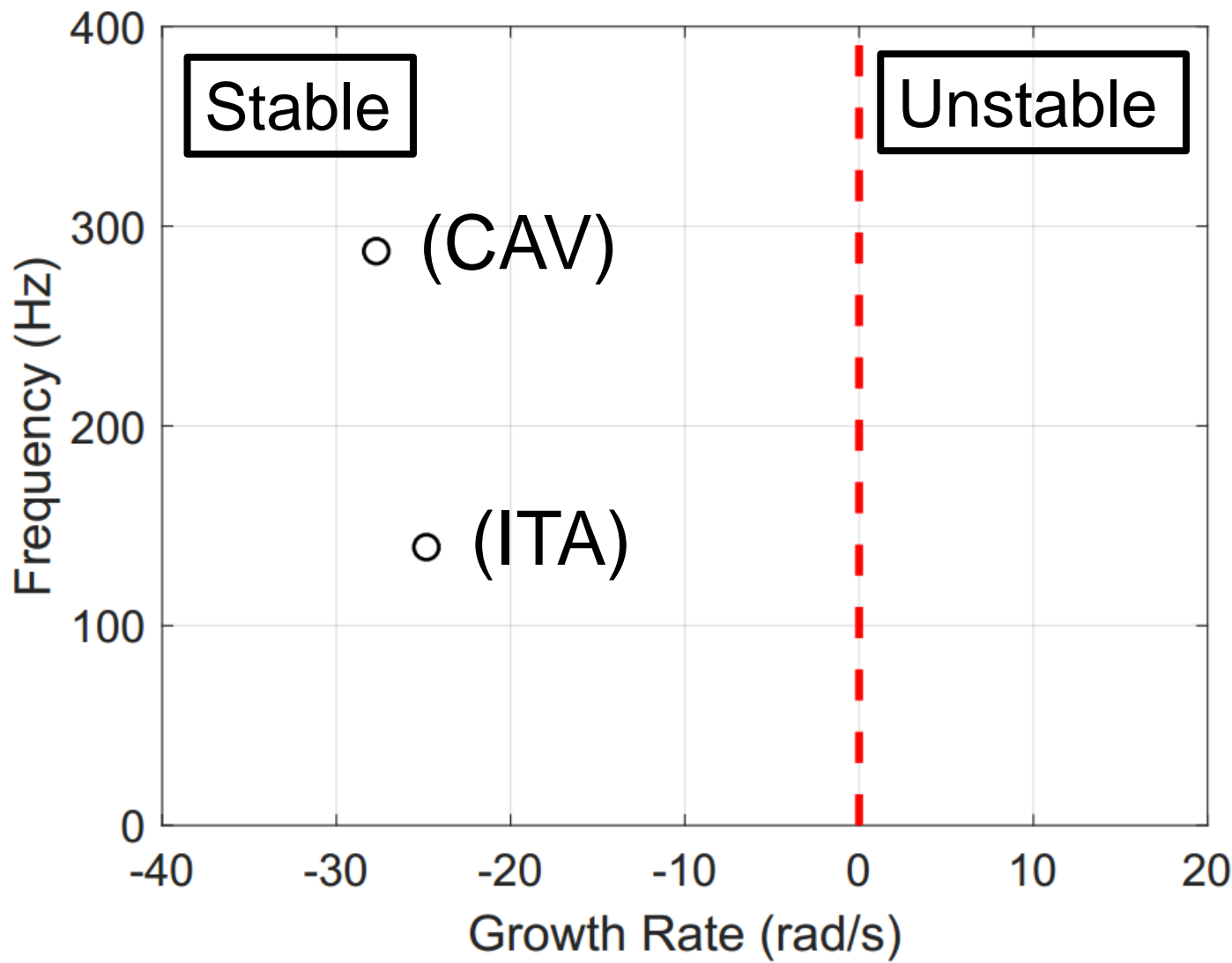
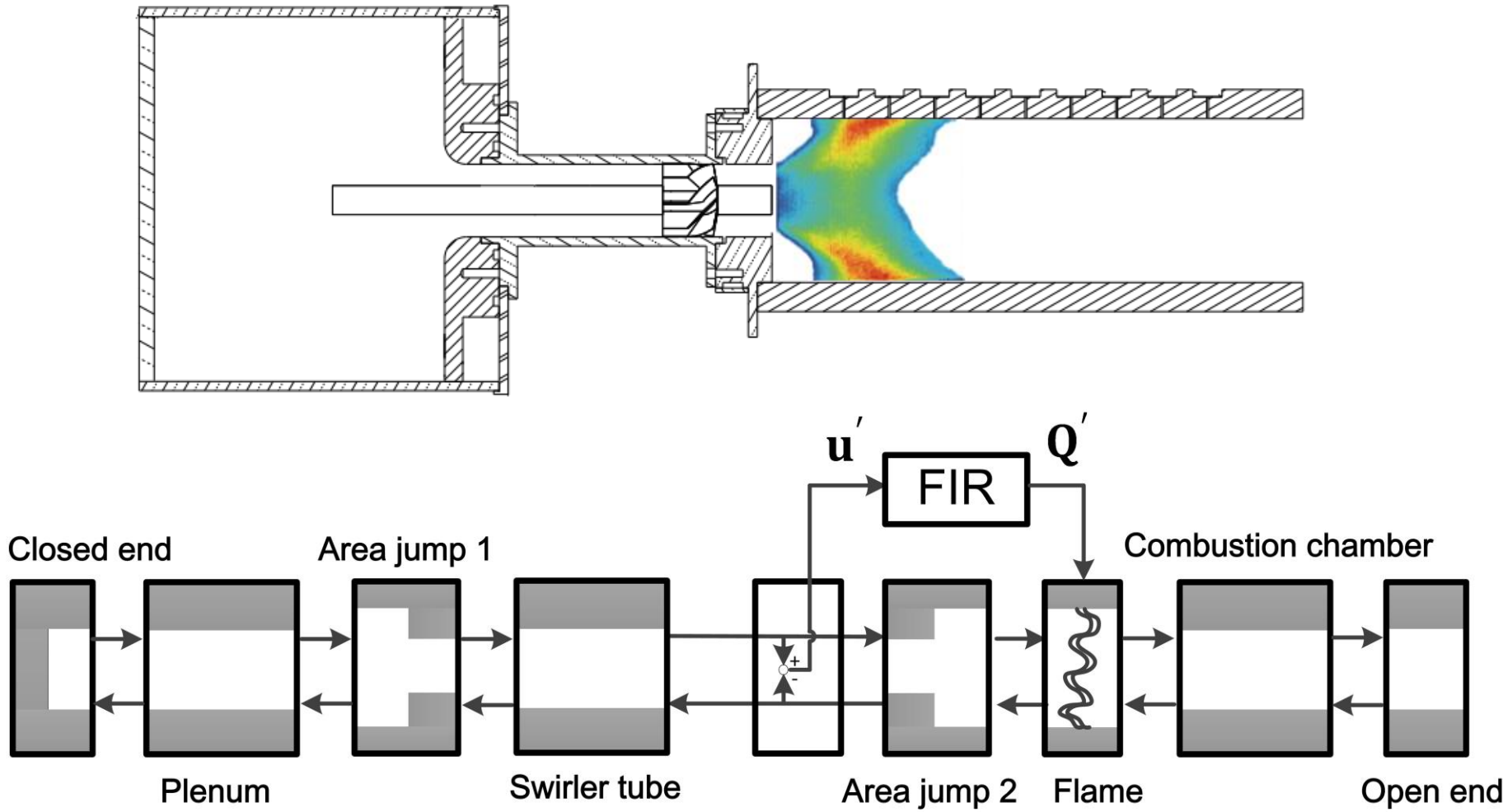


Distributed Time Lag Model [1]

Parameters		Nominal	Range
Flame (units: ms)	τ_1	$\tau_1^0 = 2.85$	$0.9\tau_1^0 \sim 1.1\tau_1^0$
	σ_1	$\sigma_1^0 = 0.7$	$0.9\sigma_1^0 \sim 1.1\sigma_1^0$
	τ_{s1}	$\tau_{s1}^0 = 1.8$	$0.9\tau_{s1}^0 \sim 1.1\tau_{s1}^0$
	τ_{s2}	$\tau_{s2}^0 = 3.3$	$0.9\tau_{s2}^0 \sim 1.1\tau_{s2}^0$

[1] Komarek, T., Polifke, W., 2010, *J Eng Gas Turbines Power*.

Thermoacoustic settings: solver, flame model, mode specification



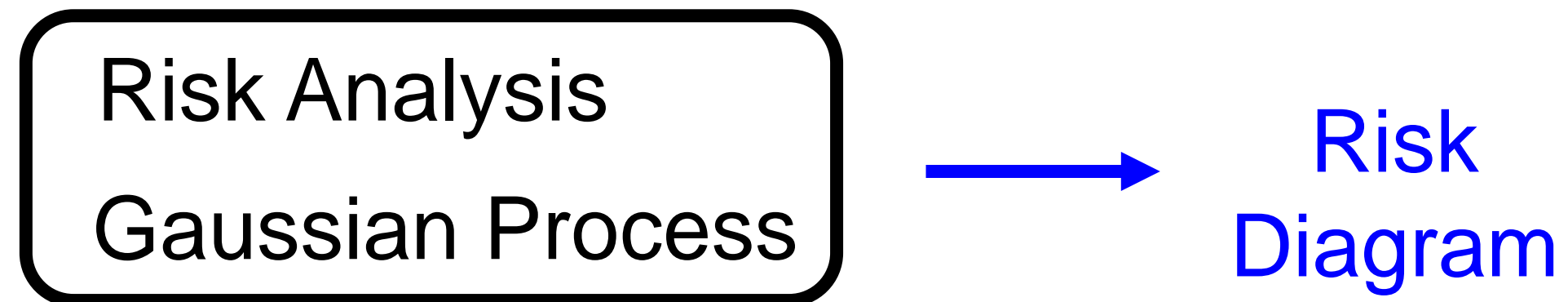
Distributed Time Lag Model [1]

Parameters		Nominal	Range
Flame (units: ms)	τ_1	$\tau_1^0 = 2.85$	$0.9\tau_1^0 \sim 1.1\tau_1^0$
	σ_1	$\sigma_1^0 = 0.7$	$0.9\sigma_1^0 \sim 1.1\sigma_1^0$
	τ_c	$\tau_c^0 = 3$	$2 \sim 4.8$
	τ_{s1}	$\tau_{s1}^0 = 1.8$	$0.9\tau_{s1}^0 \sim 1.1\tau_{s1}^0$
	τ_{s2}	$\tau_{s2}^0 = 3.3$	$0.9\tau_{s2}^0 \sim 1.1\tau_{s2}^0$
Acoustic BC	$ R_{out} $	$ R_{out} ^0 = 0.9$	$0.6 \sim 1$

[1] Komarek, T., Polifke, W., 2010, *J Eng Gas Turbines Power*.

Presentation overview

- Motivation
- Thermoacoustic problem settings
- Robust design tasks



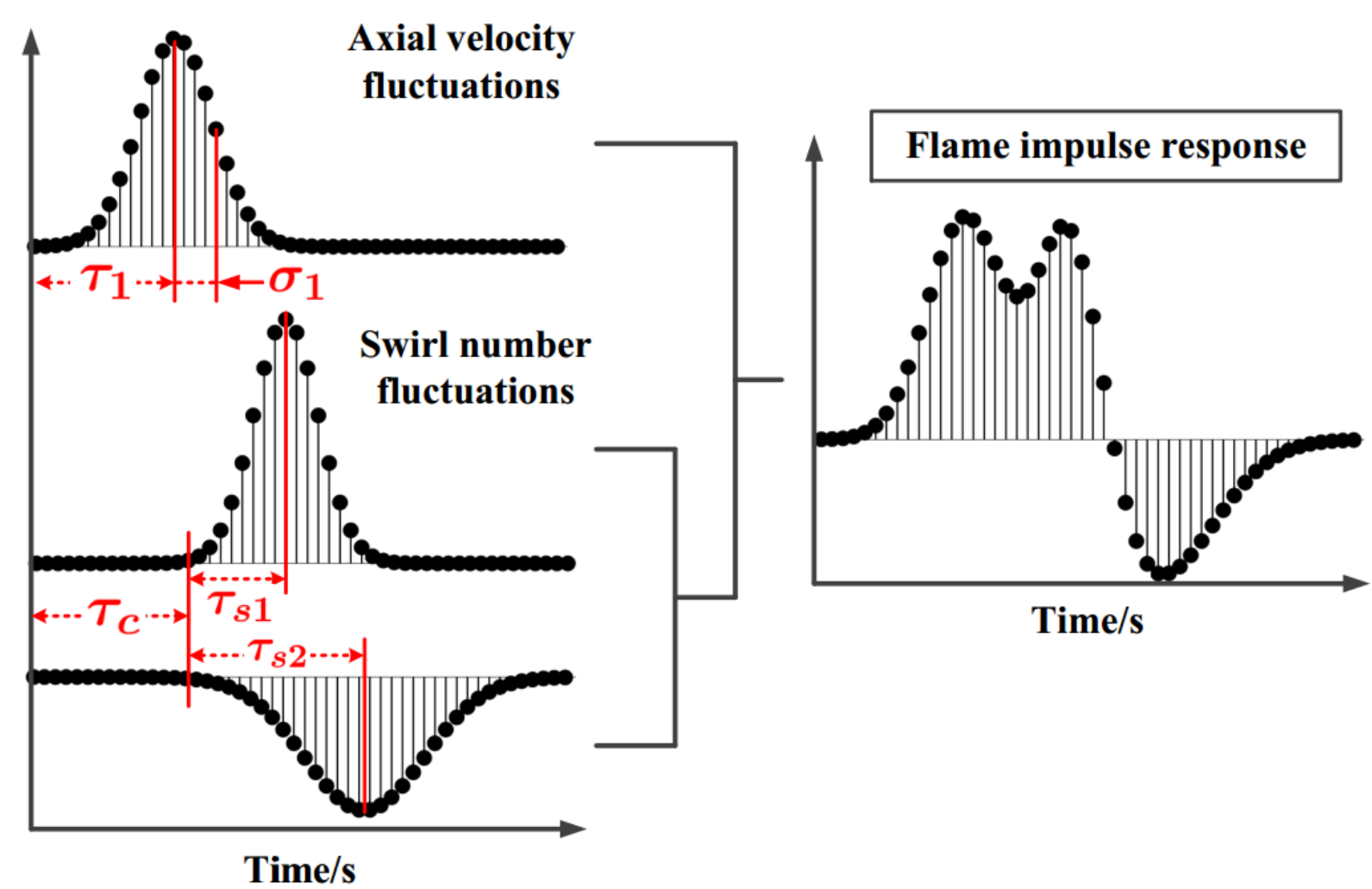
Presentation overview

- Motivation
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Risk analysis: setting the stage for the subsequent robust design analysis

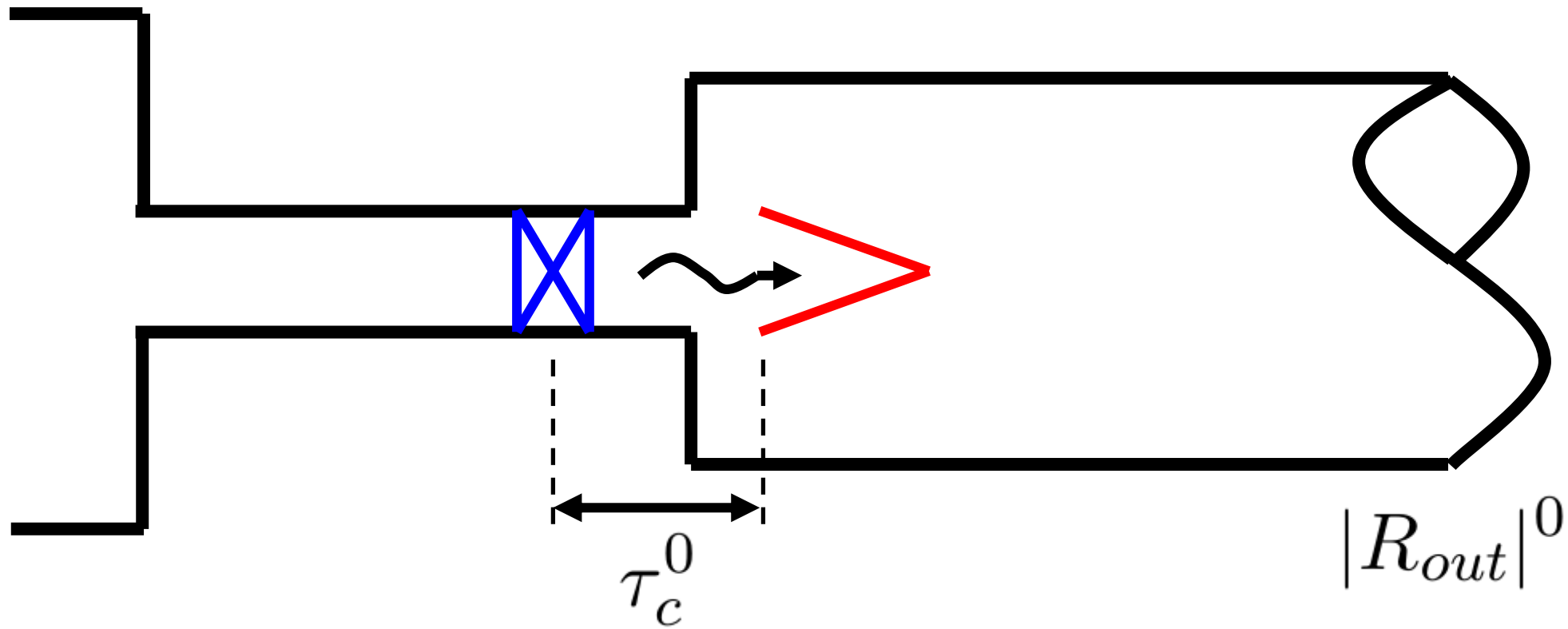
Flame model



Parameters	Nominal	Range
Flame (units: ms)	τ_1	$0.9\tau_1^0 \sim 1.1\tau_1^0$
	σ_1	$0.9\sigma_1^0 \sim 1.1\sigma_1^0$
	τ_c	
	τ_{s1}	$0.9\tau_{s1}^0 \sim 1.1\tau_{s1}^0$
	τ_{s2}	$0.9\tau_{s2}^0 \sim 1.1\tau_{s2}^0$
Acoustic BC	$ R_{out} $	

“Q1: what is the risk factor of the system when uncertainties are presented in the flame parameter τ_1 , σ_1 , τ_{s1} and τ_{s2} ?”

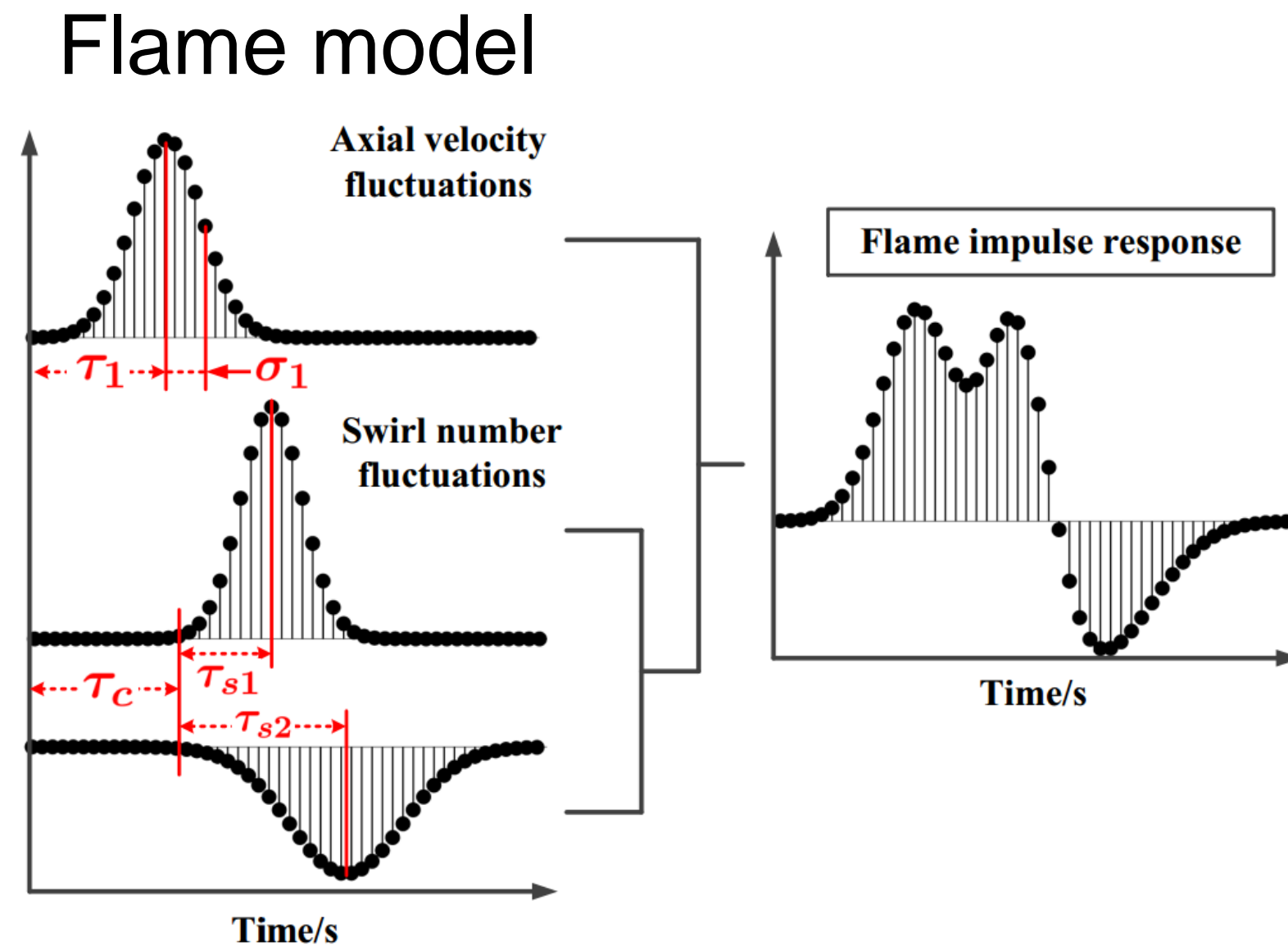
→ Risk Analysis



Known: $\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$
 $\tau_c = \tau_c^*, |R_{out}| = |R_{out}|^*$

Solve: $P_f^I = \int_0^\infty PDF(\alpha)d\alpha = ?$
 $P_f^C = \int_0^\infty PDF(\alpha)d\alpha = ?$

Applying Monte Carlo directly on acoustic solvers is very expensive



Known: $\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$

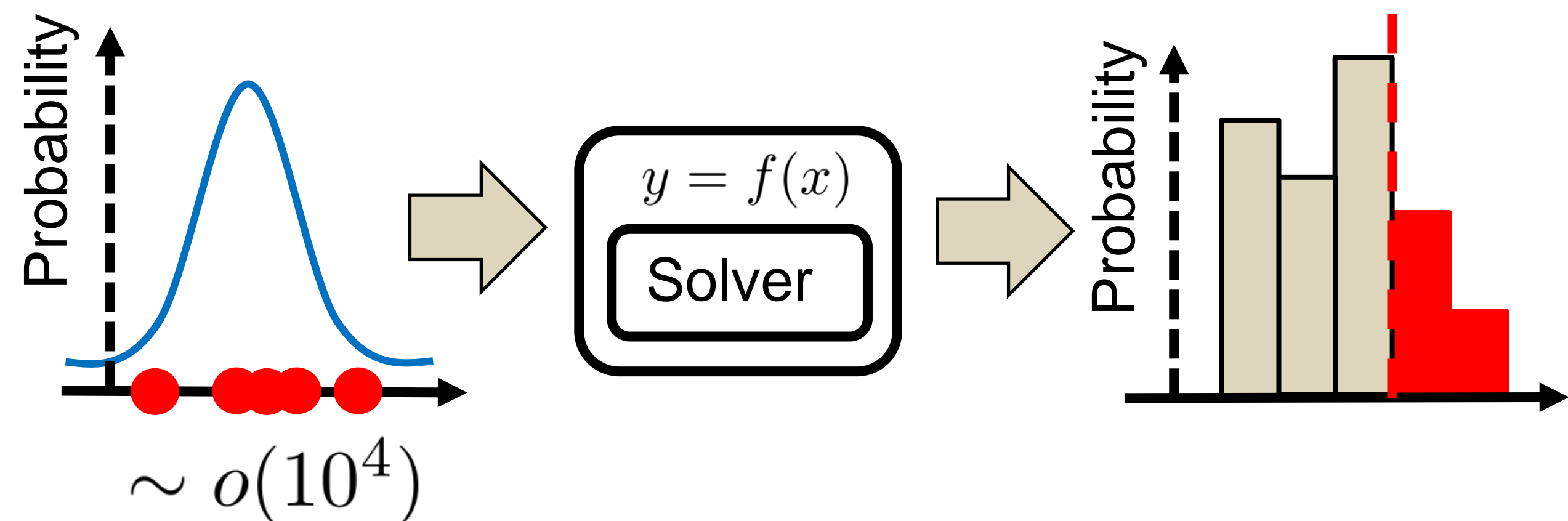
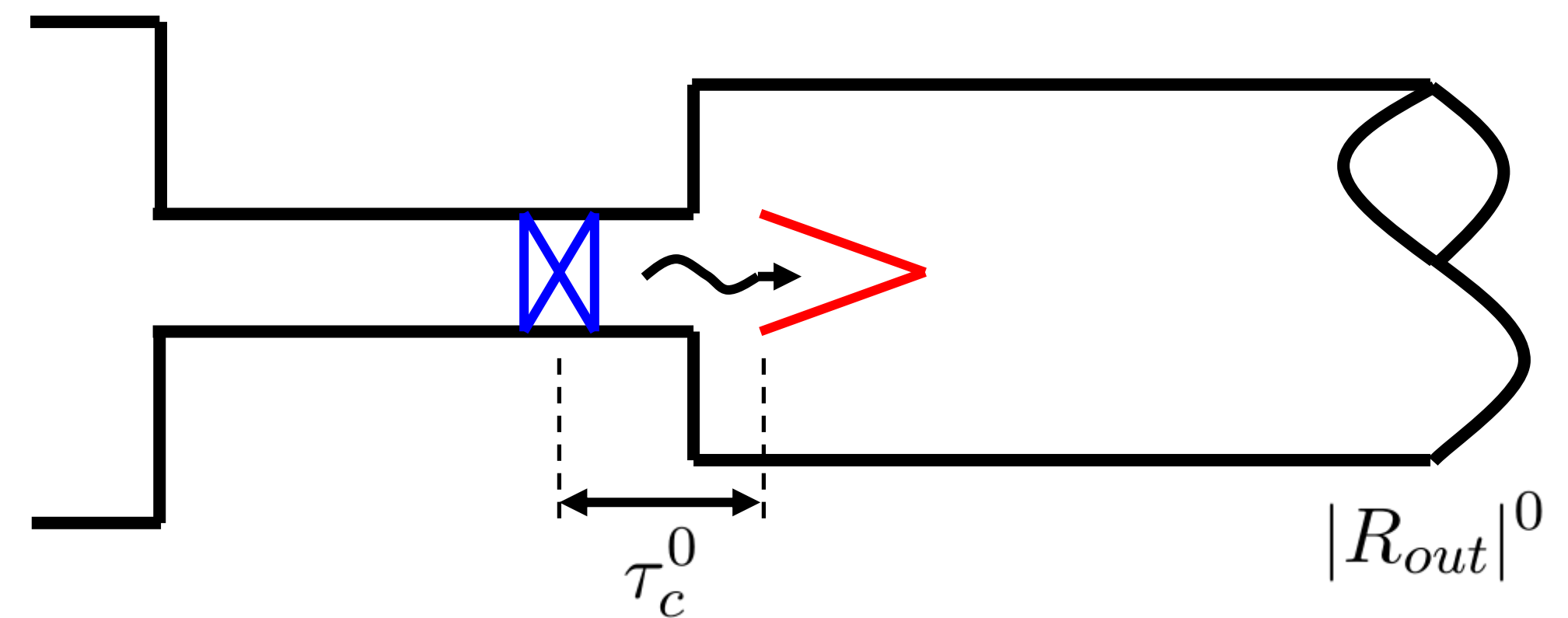
$\tau_c = \tau_c^*, |R_{out}| = |R_{out}|^*$

Solve: $P_f^I = \int_0^\infty PDF(\alpha) d\alpha = ?$

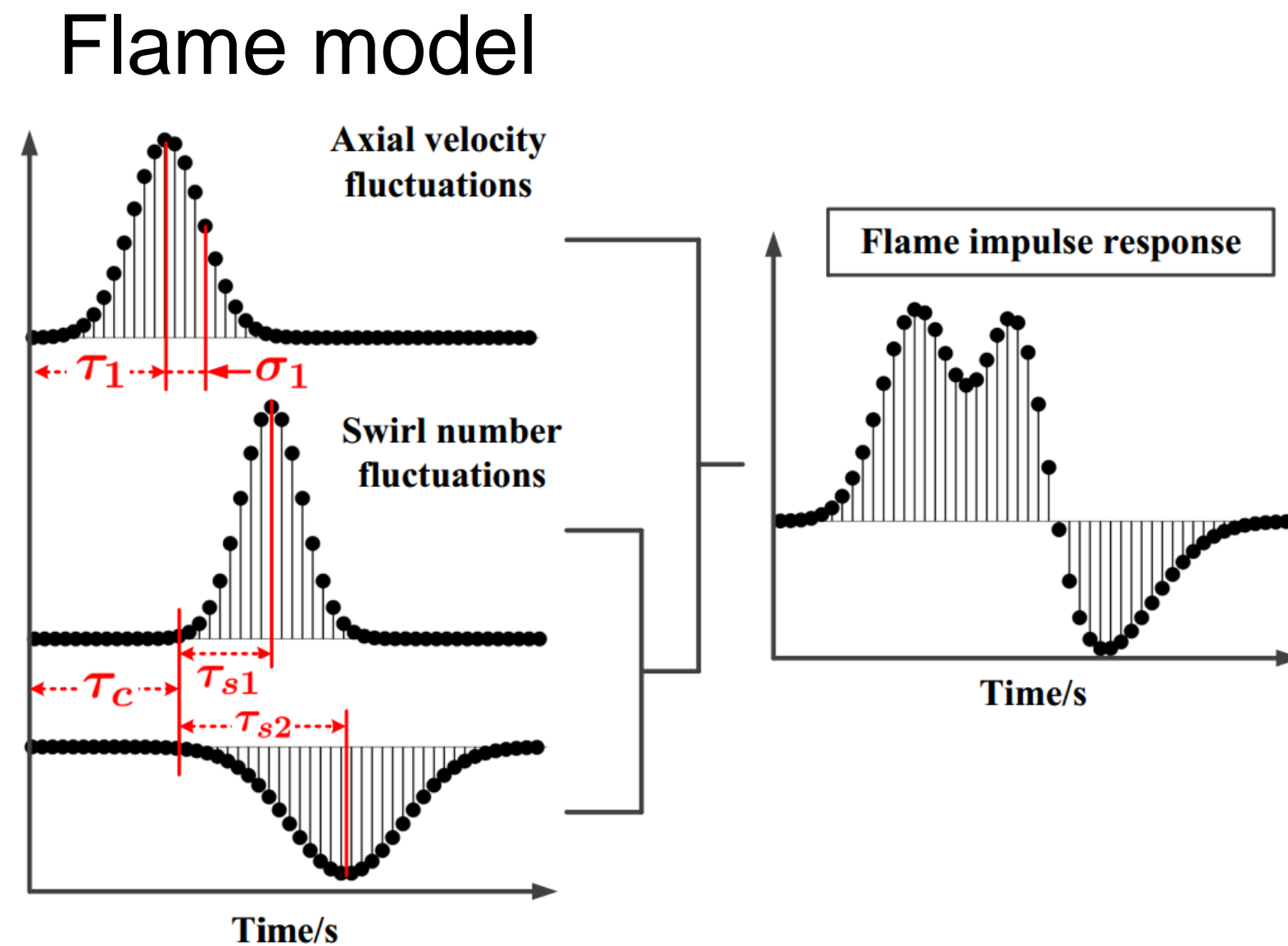
$P_f^C = \int_0^\infty PDF(\alpha) d\alpha = ?$

“Q1: what is the risk factor of the system when uncertainties are presented in the flame parameter τ_1 , σ_1 , τ_{s1} and τ_{s2} ?”

→ Risk Analysis



Surrogate modeling technique can significantly improve the efficiency of risk analysis

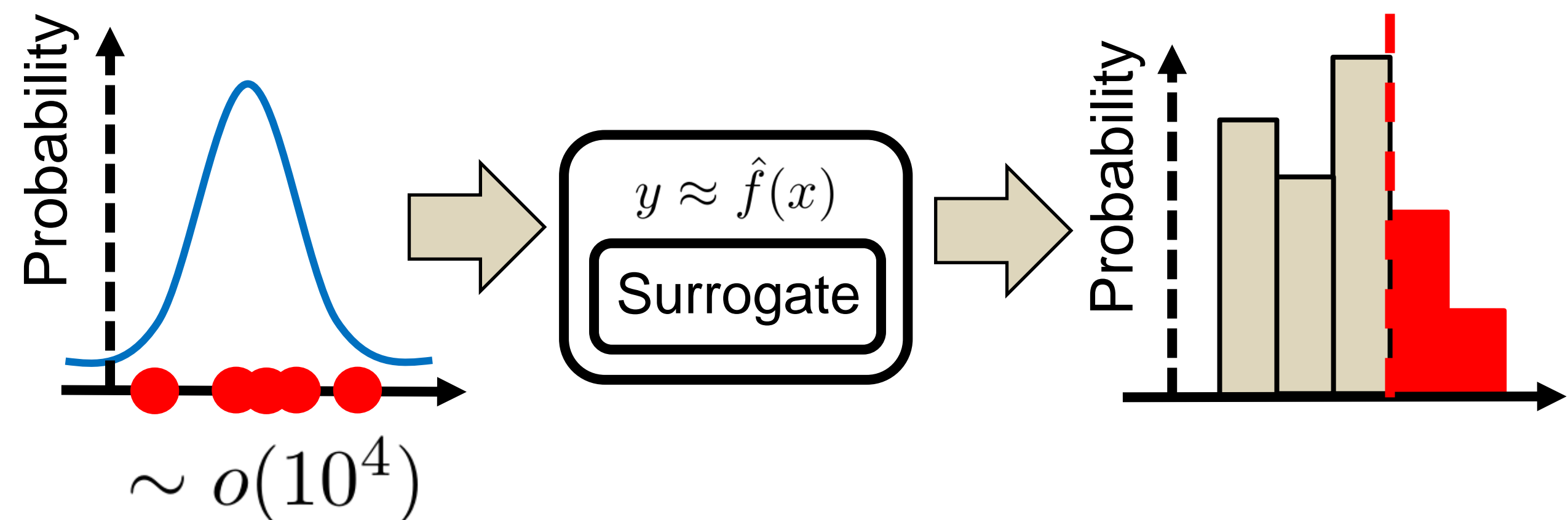
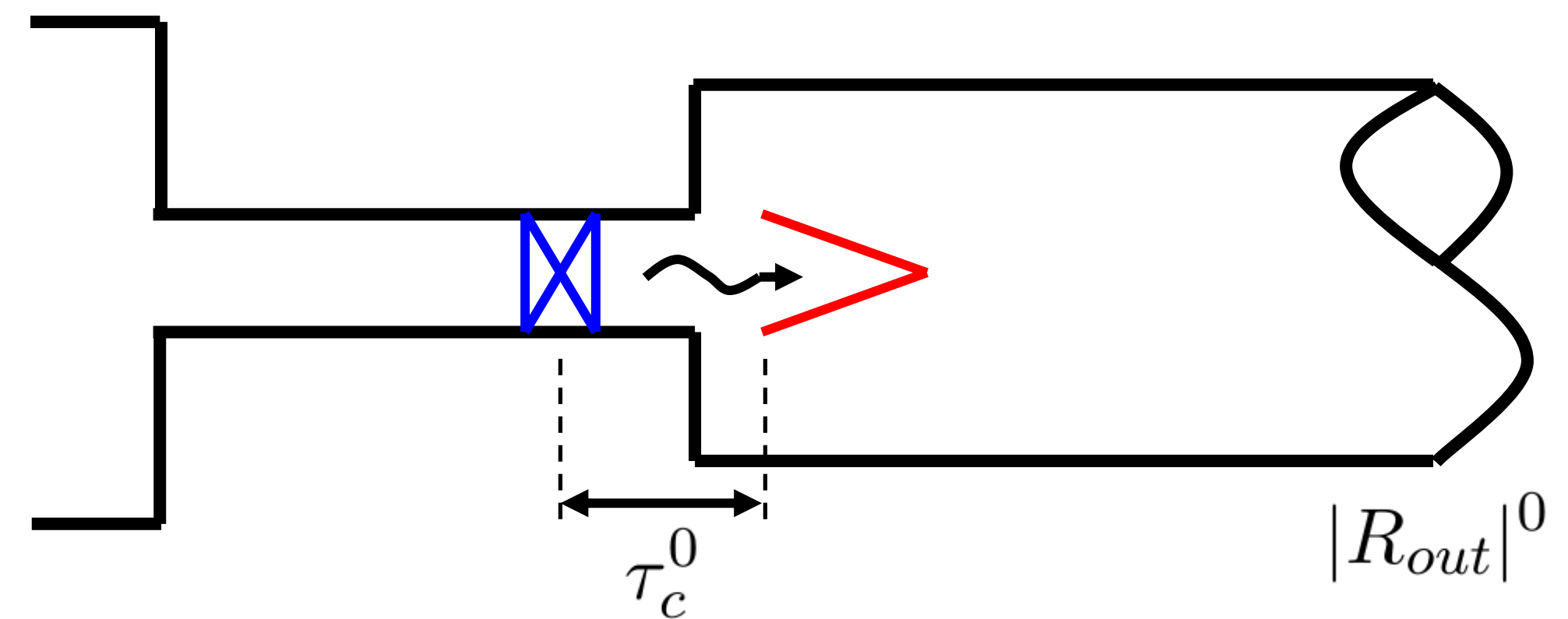


Known: $\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$
 $\tau_c = \tau_c^*, |R_{out}| = |R_{out}|^*$

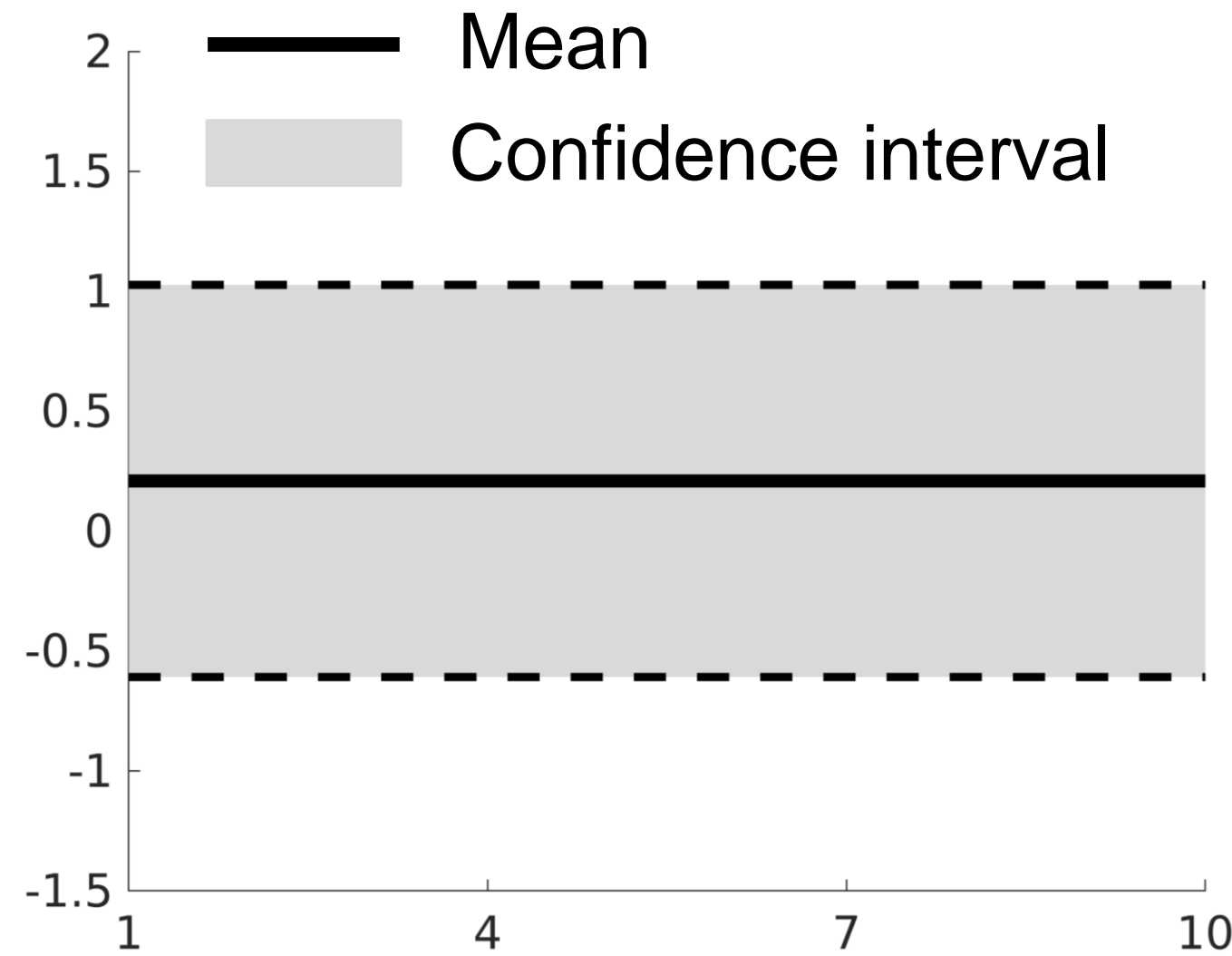
Solve: $P_f^I = \int_0^\infty PDF(\alpha) d\alpha = ?$
 $P_f^C = \int_0^\infty PDF(\alpha) d\alpha = ?$

“Q1: what is the risk factor of the system when uncertainties are presented in the flame parameter $\tau_1, \sigma_1, \tau_{s1}$ and τ_{s2} ?”

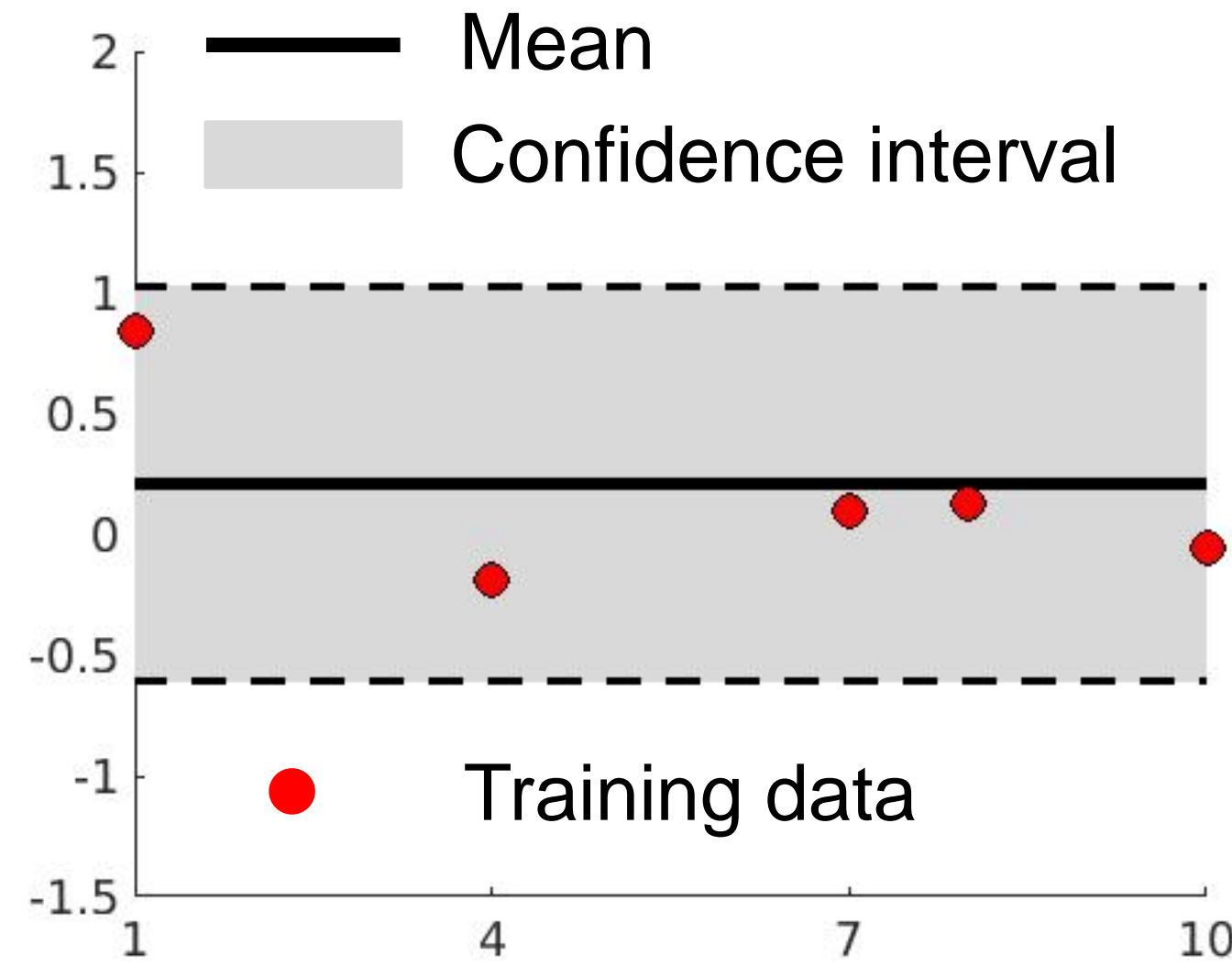
→ Risk Analysis



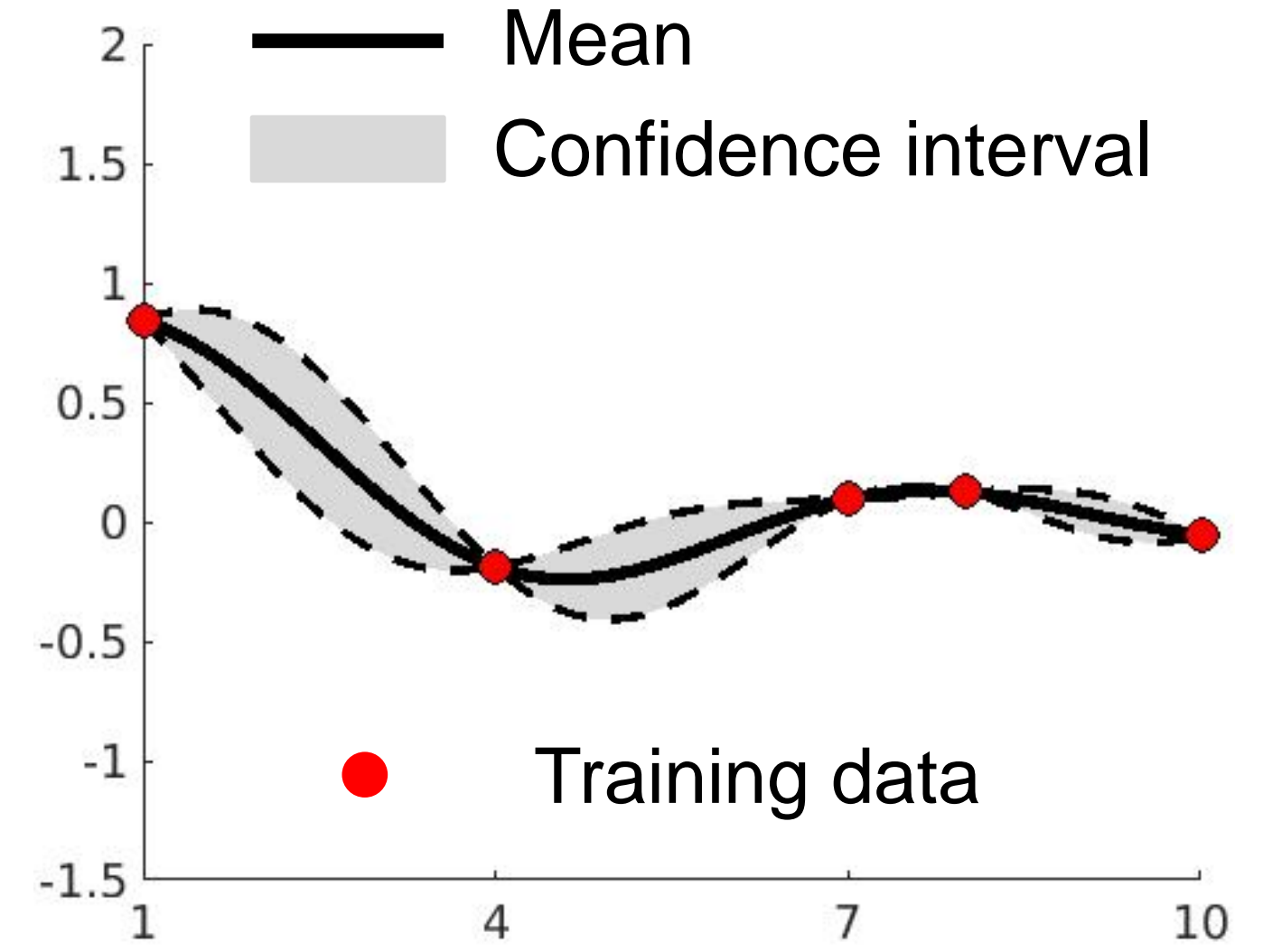
Gaussian Process is employed as the surrogate model in our study



Prior



Data



Posterior

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

$m(x)$: Polynomial

$k(x, x') = \sigma^2 \exp(-\theta |x - x'|^2)$: Kernel



$$f^*(x) \sim \mathcal{GP}(m^*(x), k^*(x, x'))$$

Gaussian Process is employed as the surrogate model in our study

Goal

$$\alpha^I \approx GP^I(\tau_1, \sigma_1, \tau_c, \tau_{s1}, \tau_{s2}, |R_{out}|)$$

$$\alpha^C \approx GP^C(\tau_1, \sigma_1, \tau_c, \tau_{s1}, \tau_{s2}, |R_{out}|)$$

Training

- A total of 102 samples are used
- Reuse for all design tasks

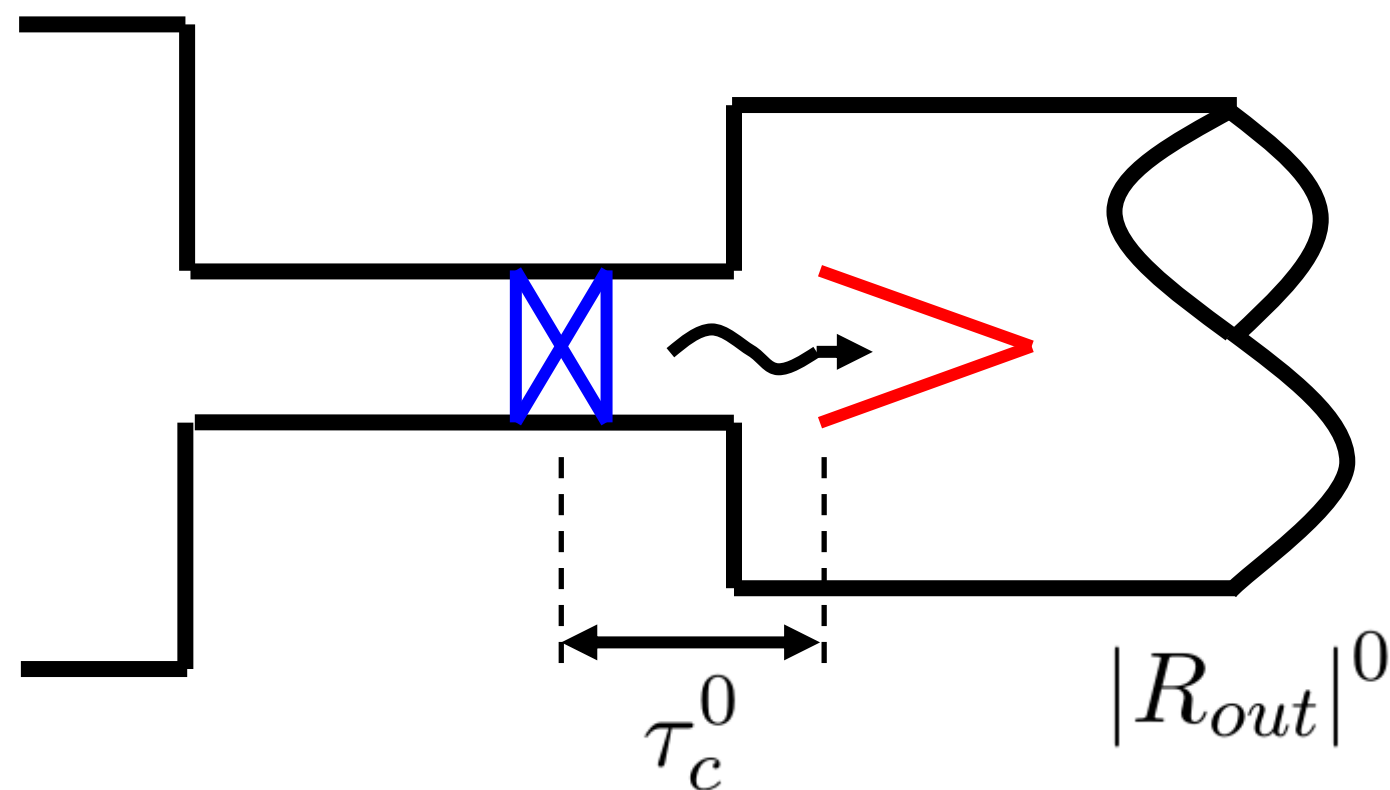
Gaussian Process models have delivered highly accurate risk analysis

Q1: Risk Analysis

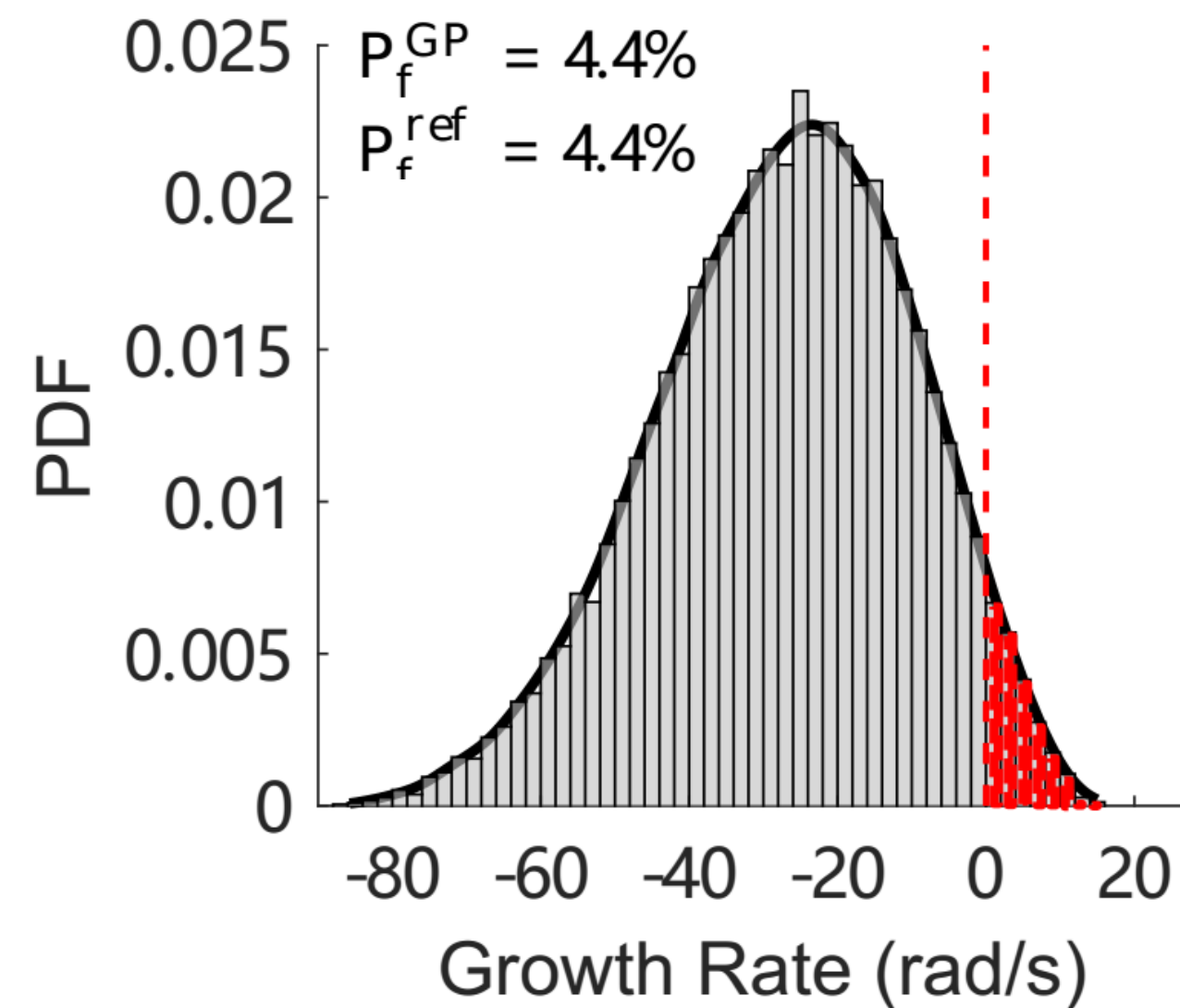
Known: $\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$
 $\tau_c = \tau_c^0, |R_{out}| = |R_{out}|^0$

Solve: $P_f^I = \int_0^\infty PDF(\alpha) d\alpha = ?$

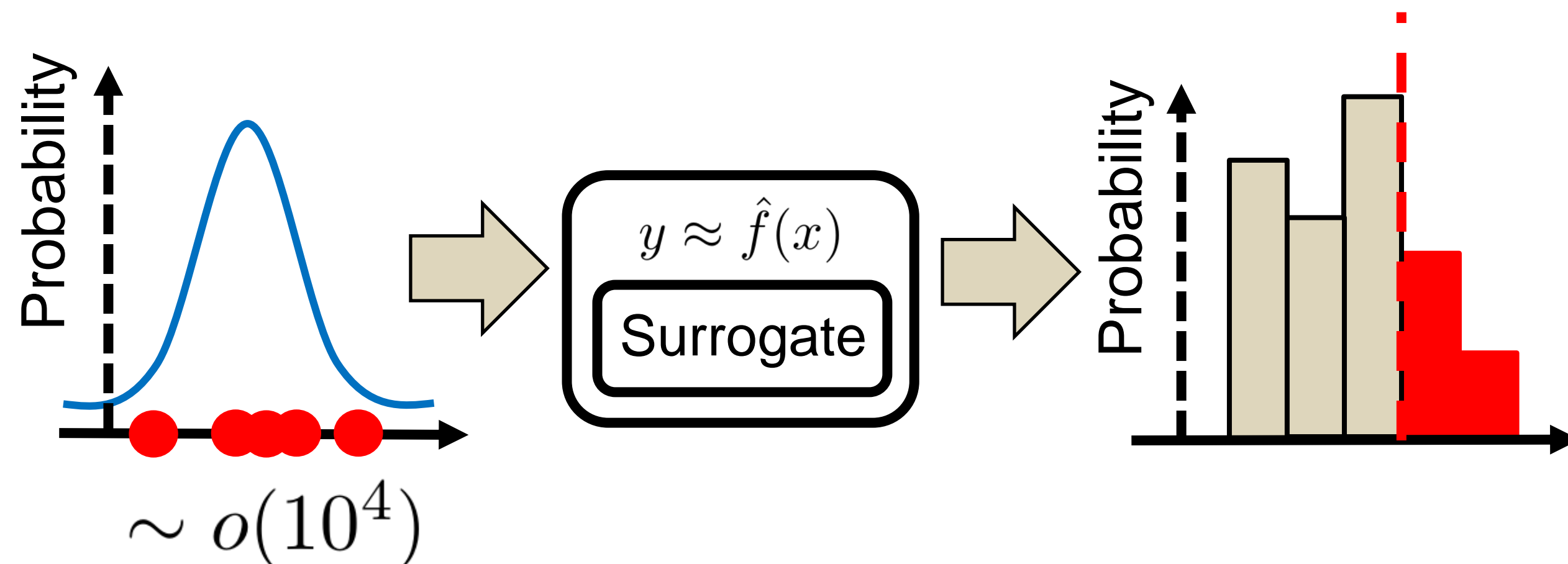
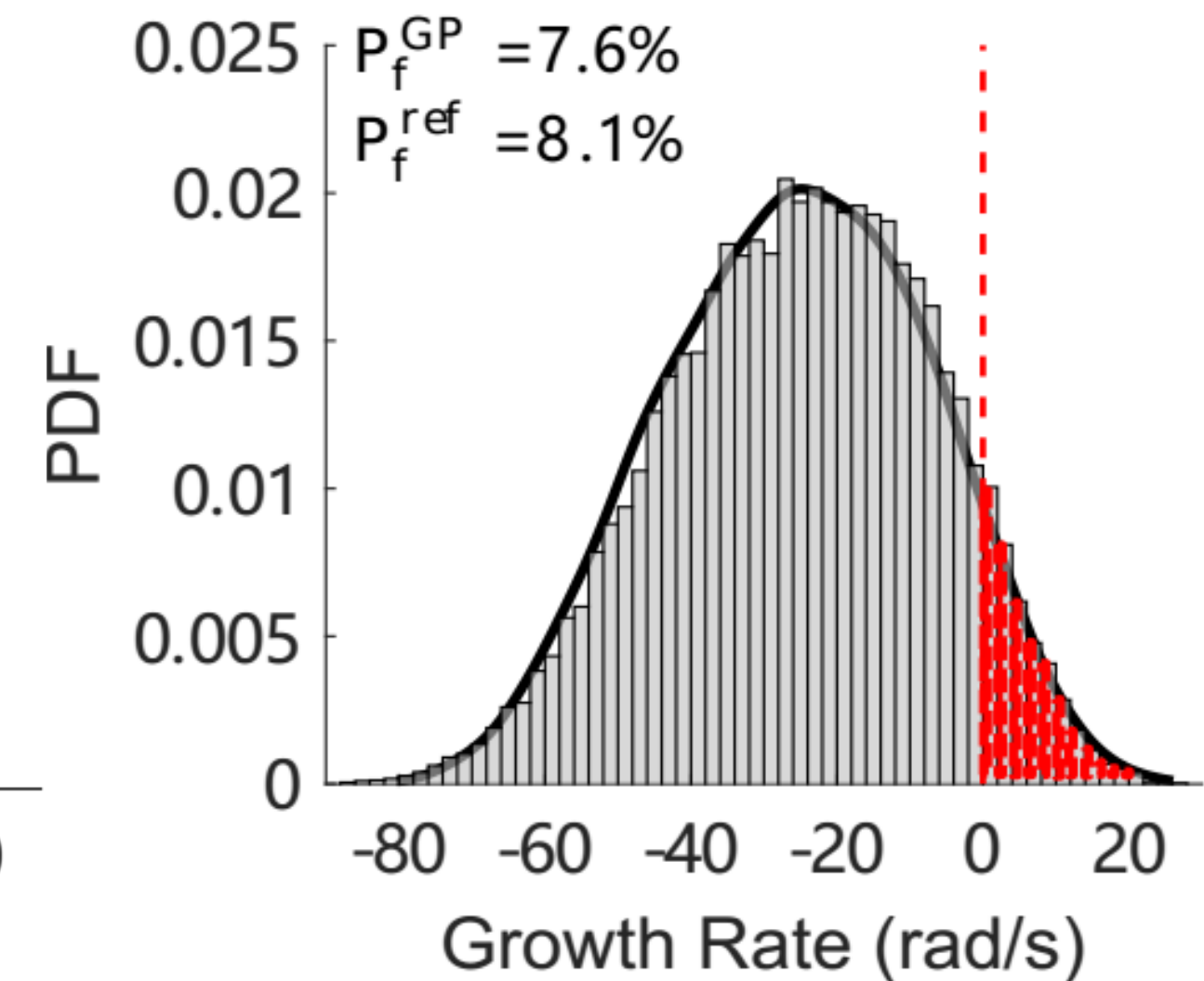
$P_f^C = \int_0^\infty PDF(\alpha) d\alpha = ?$



ITA Mode

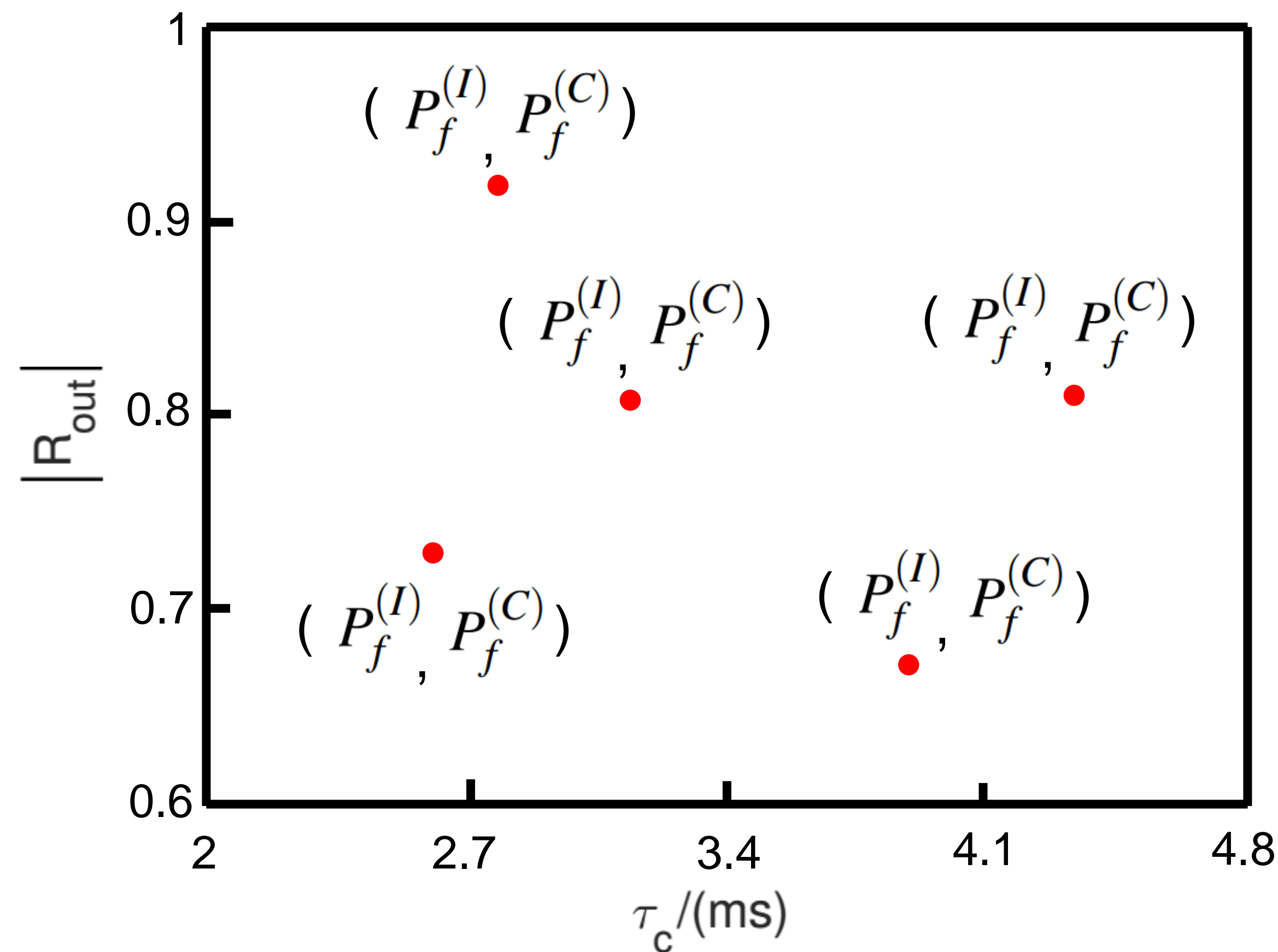


Cavity Mode



Risk diagram visualizes the risk pattern over the entire parameter space

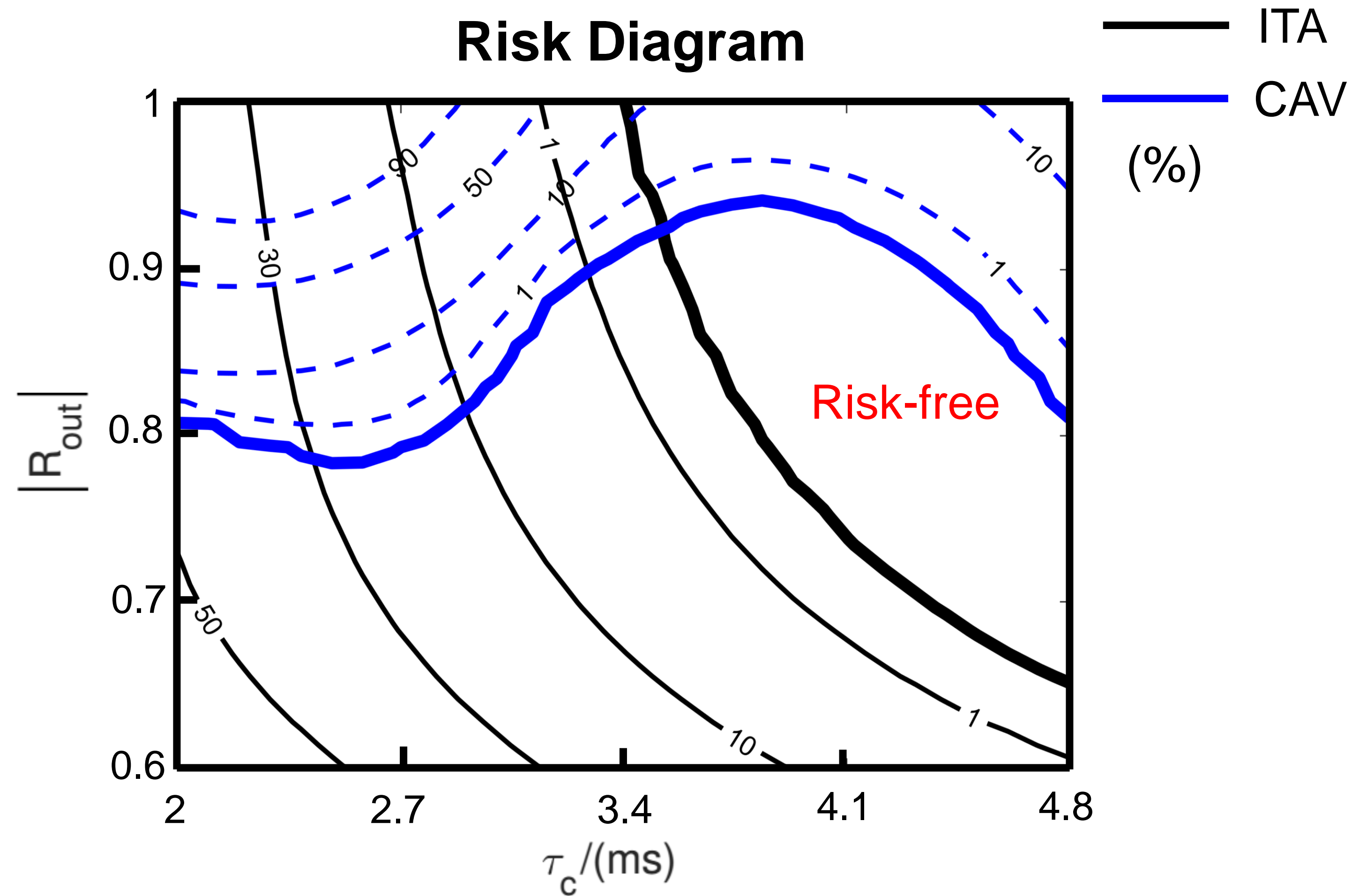
Risk Diagram



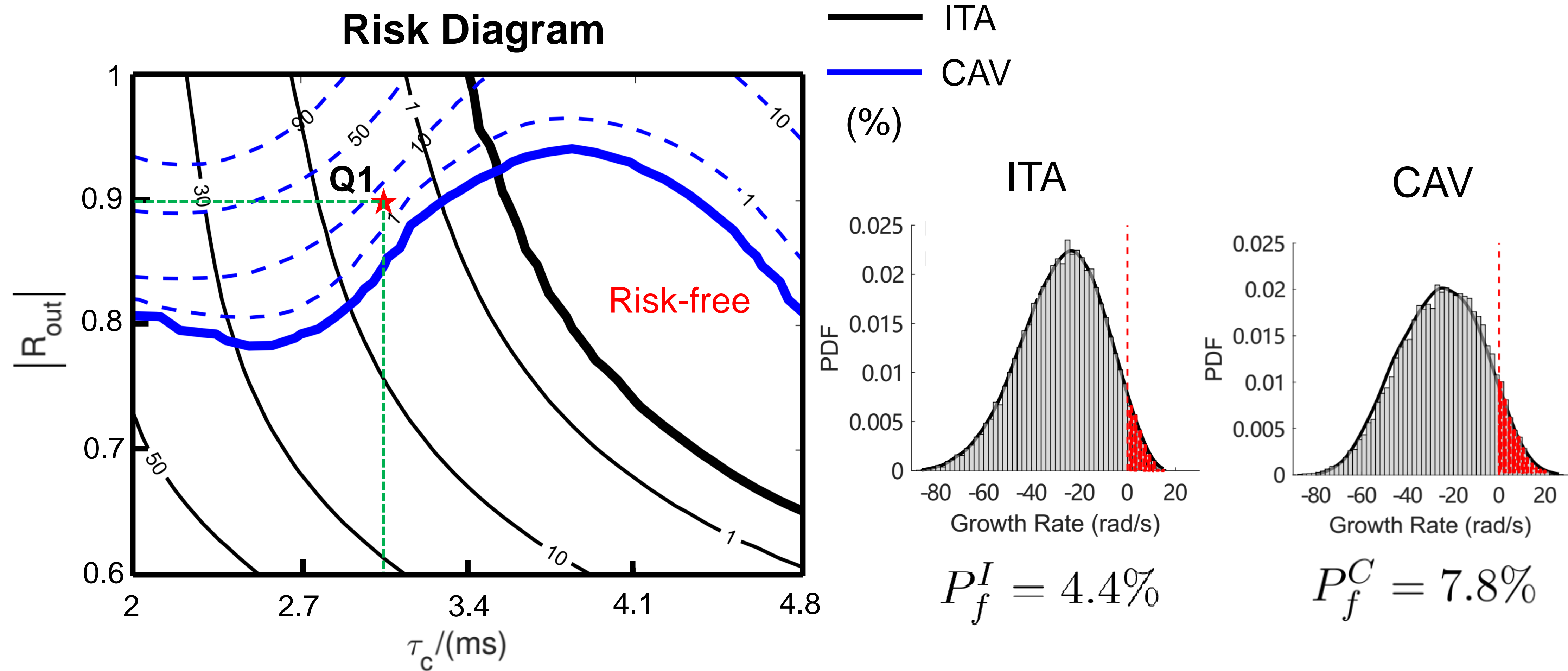
Parameters	Nominal	Range
Flame (units: ms)	τ_1	$0.9\tau_1^0 \sim 1.1\tau_1^0$
	σ_1	$0.9\sigma_1^0 \sim 1.1\sigma_1^0$
	τ_{s1}	$0.9\tau_{s1}^0 \sim 1.1\tau_{s1}^0$
	τ_{s2}	$0.9\tau_{s2}^0 \sim 1.1\tau_{s2}^0$
Acoustic BC		

$$\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$$

Risk diagram visualizes the risk pattern over the entire parameter space

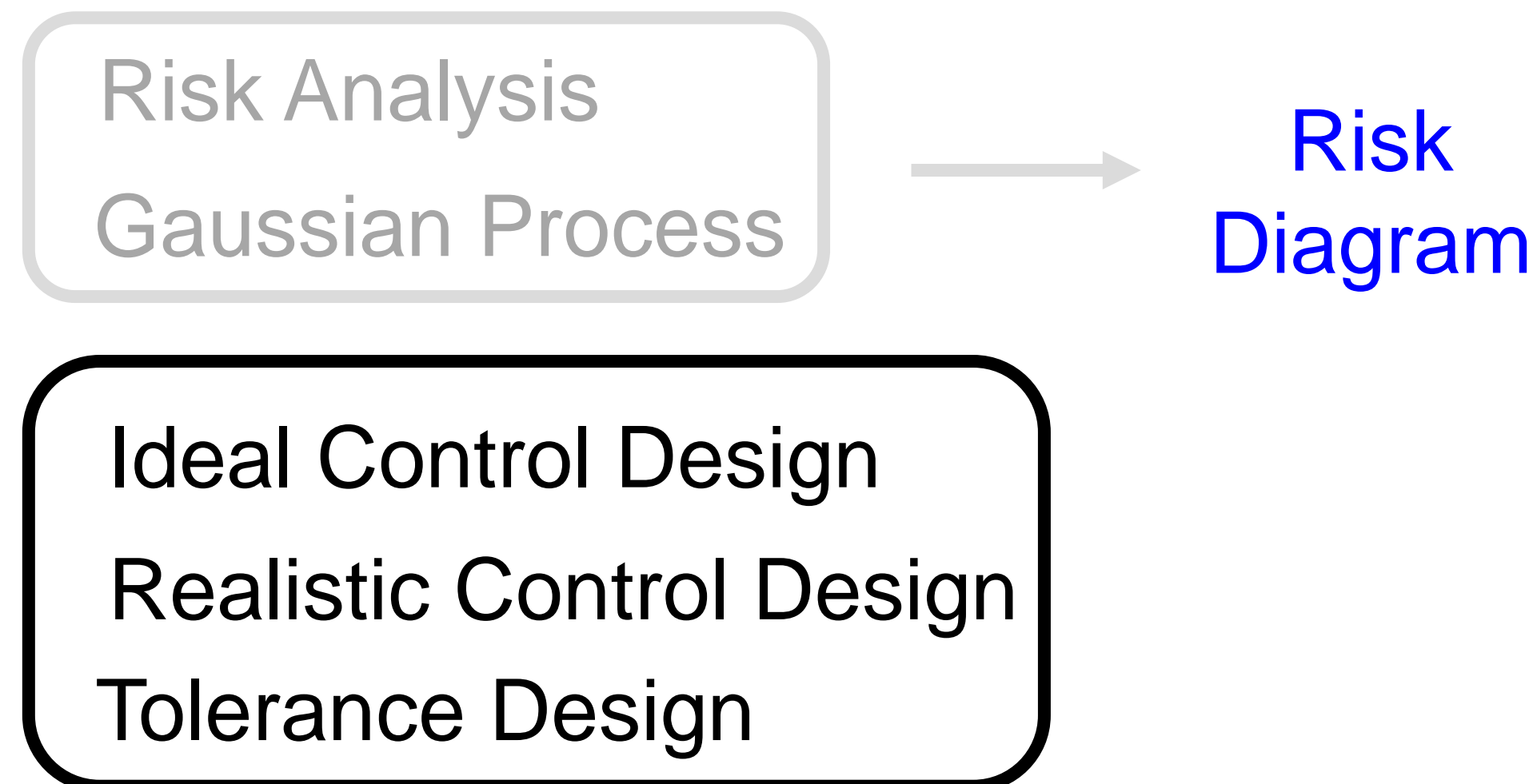


Each point in risk diagram has two associated PDFs



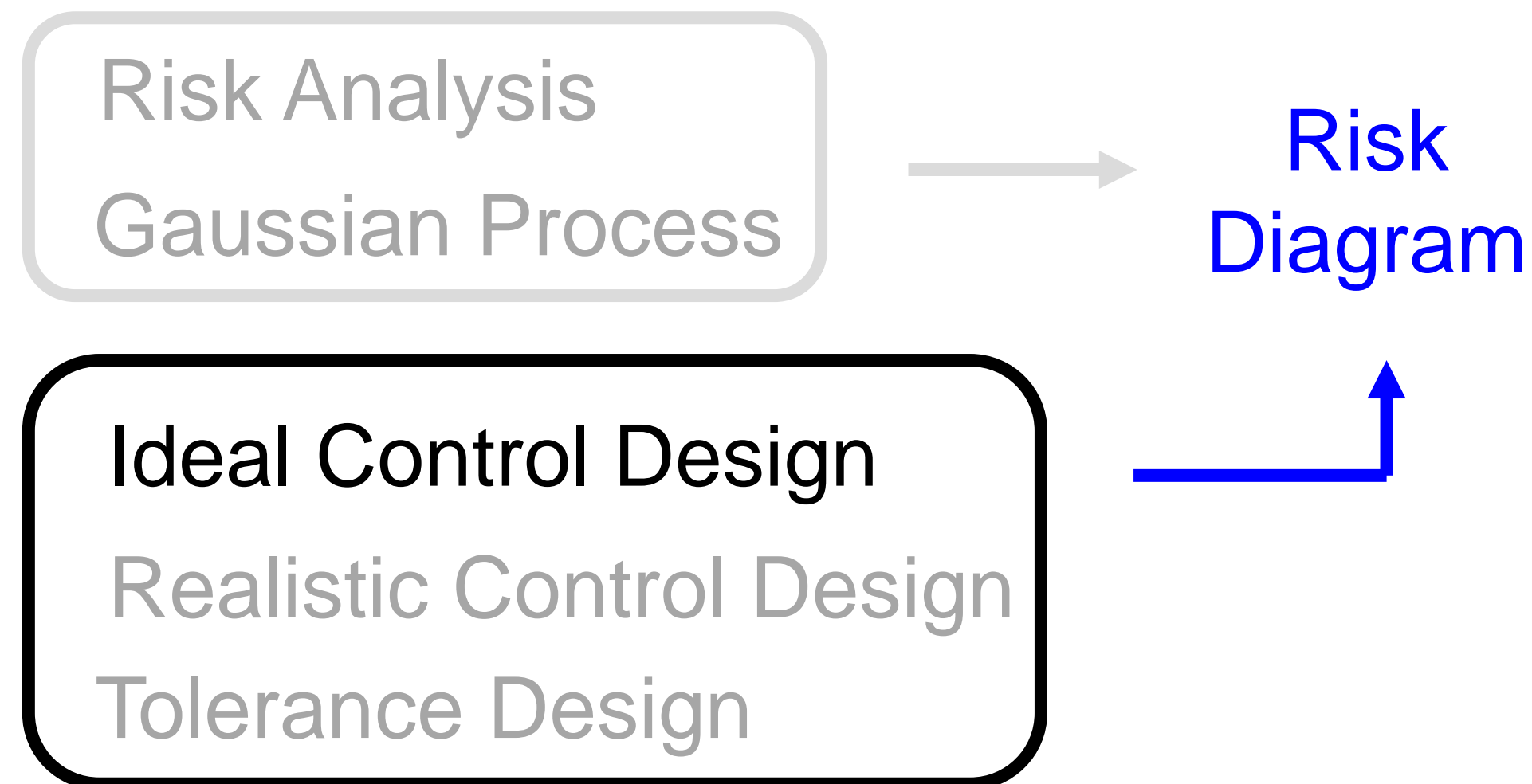
Presentation overview

- Motivation
- Thermoacoustic problem settings
- ▣ Robust design tasks



Presentation overview

- Motivation
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Both modes have certain level of risk to be unstable

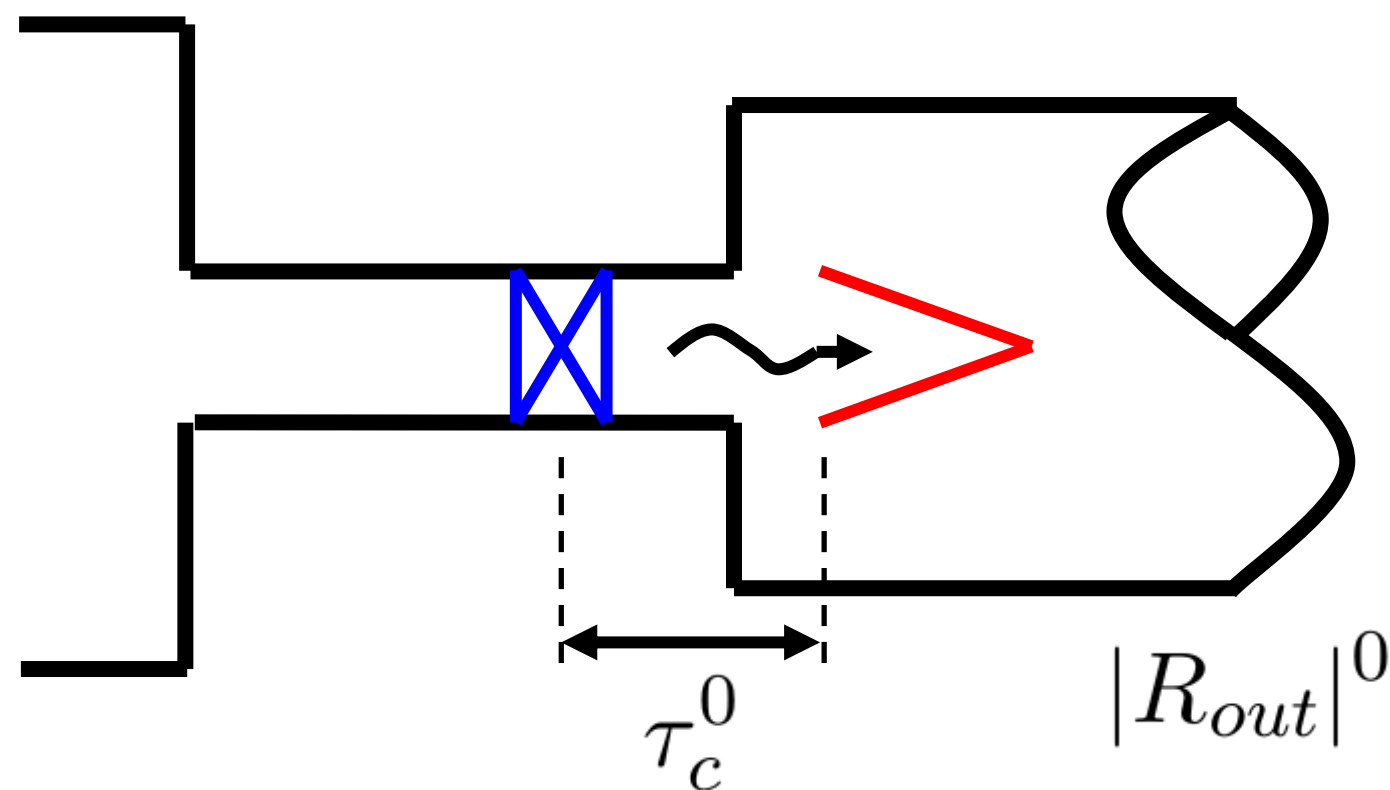
Q1: Risk Analysis

Known: $\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$

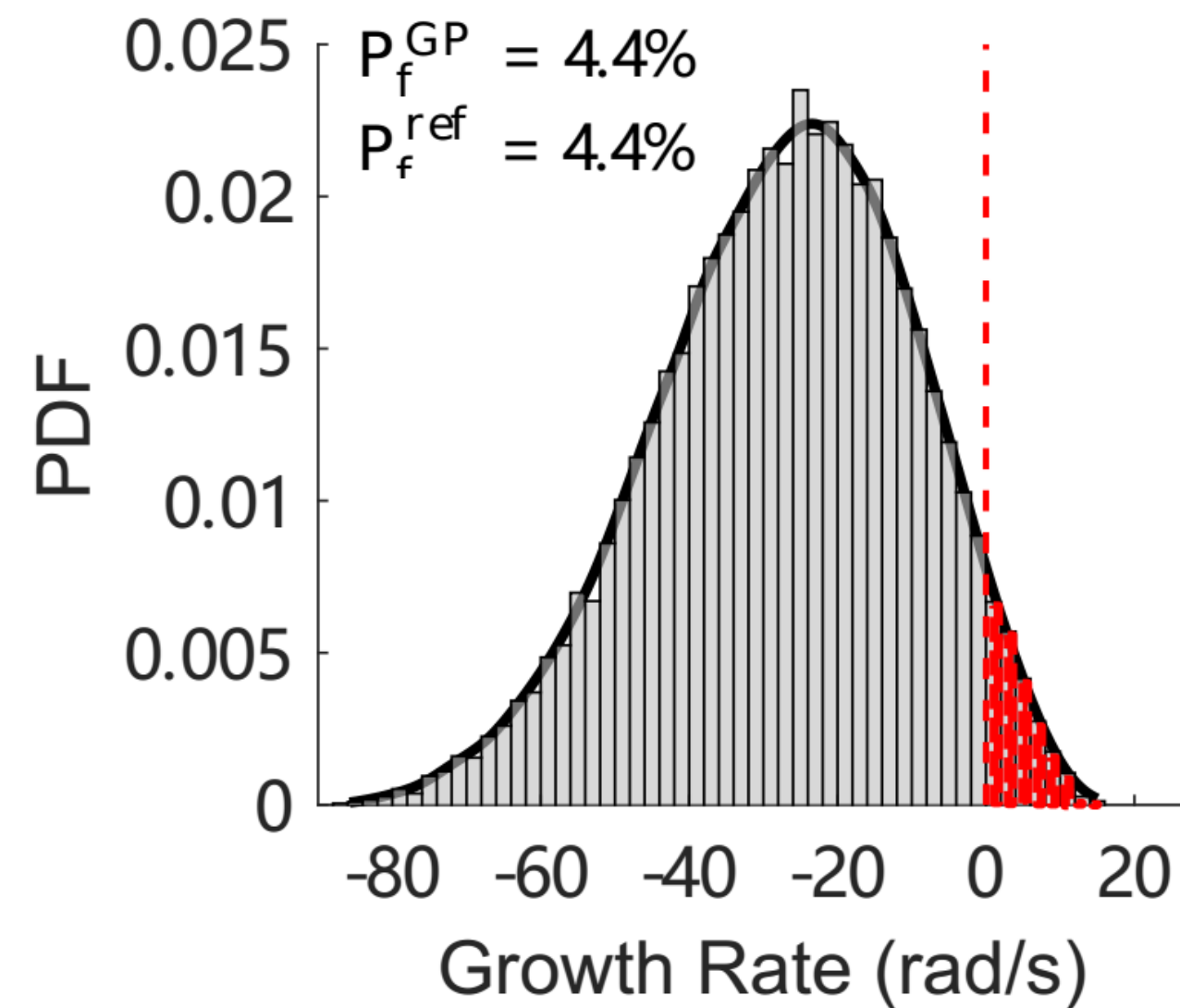
$$\tau_c = \tau_c^0, |R_{out}| = |R_{out}|^0$$

Solve: $P_f^I = \int_0^\infty PDF(\alpha) d\alpha = ?$

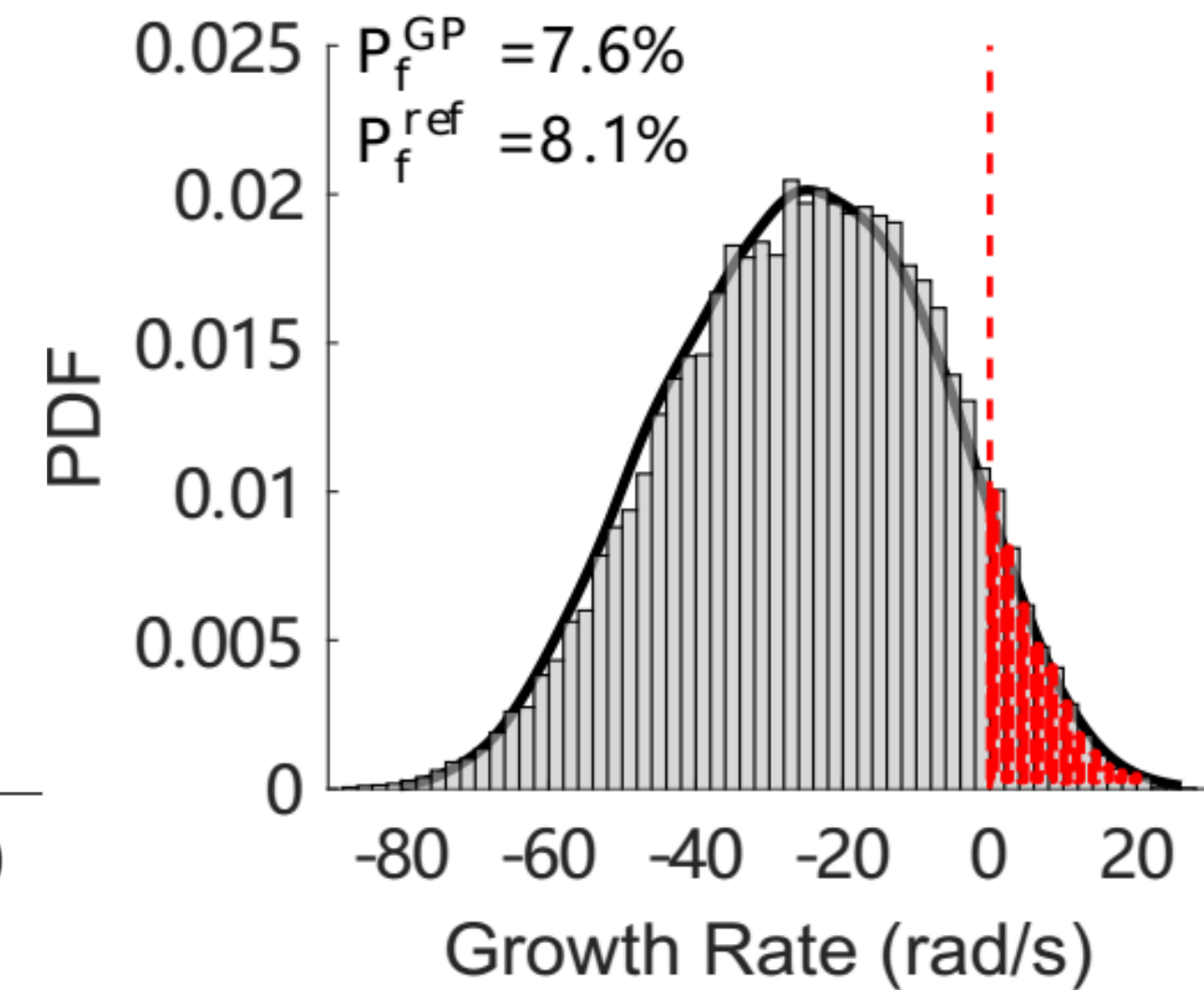
$P_f^C = \int_0^\infty PDF(\alpha) d\alpha = ?$



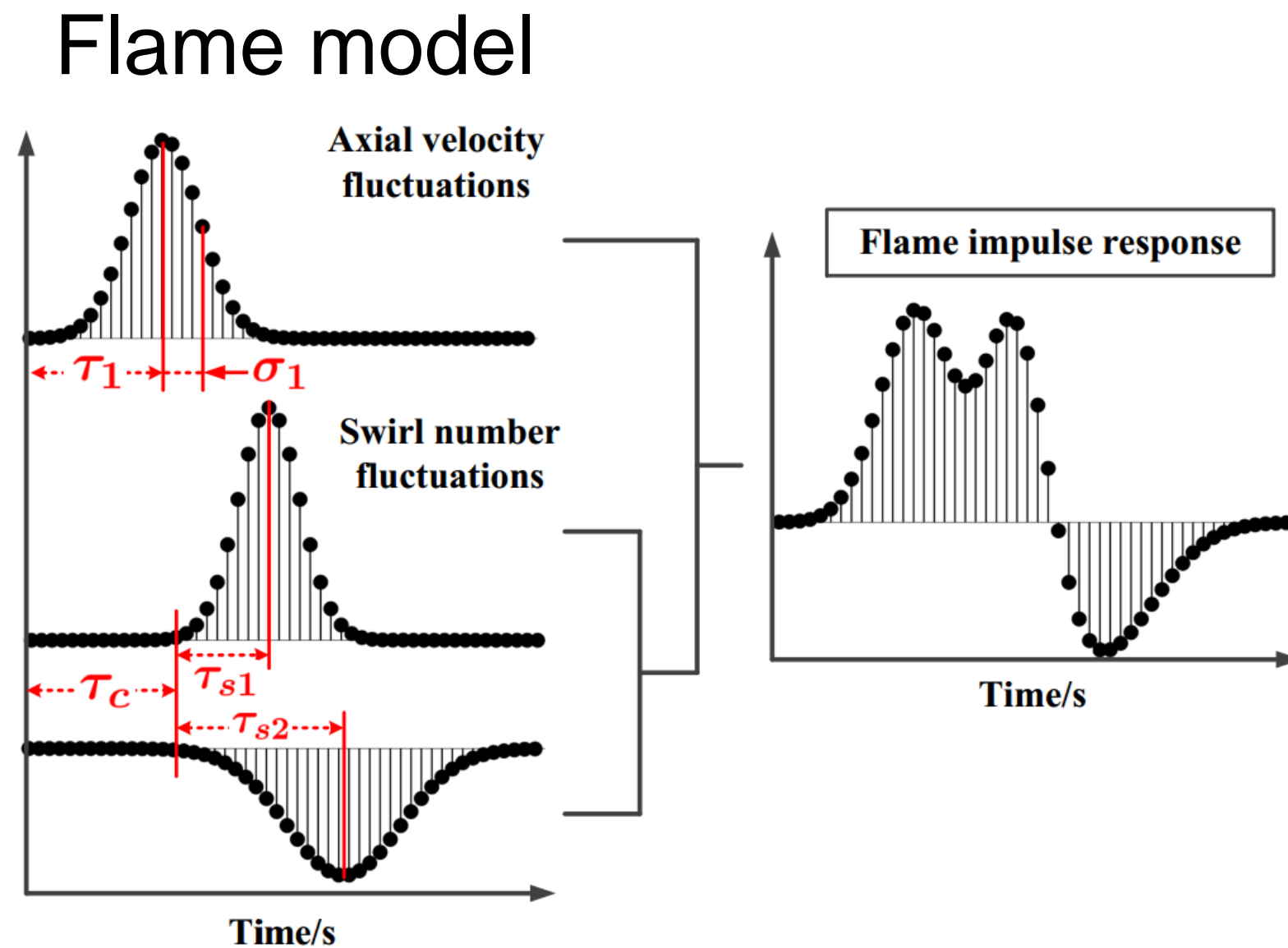
ITA Mode



Cavity Mode



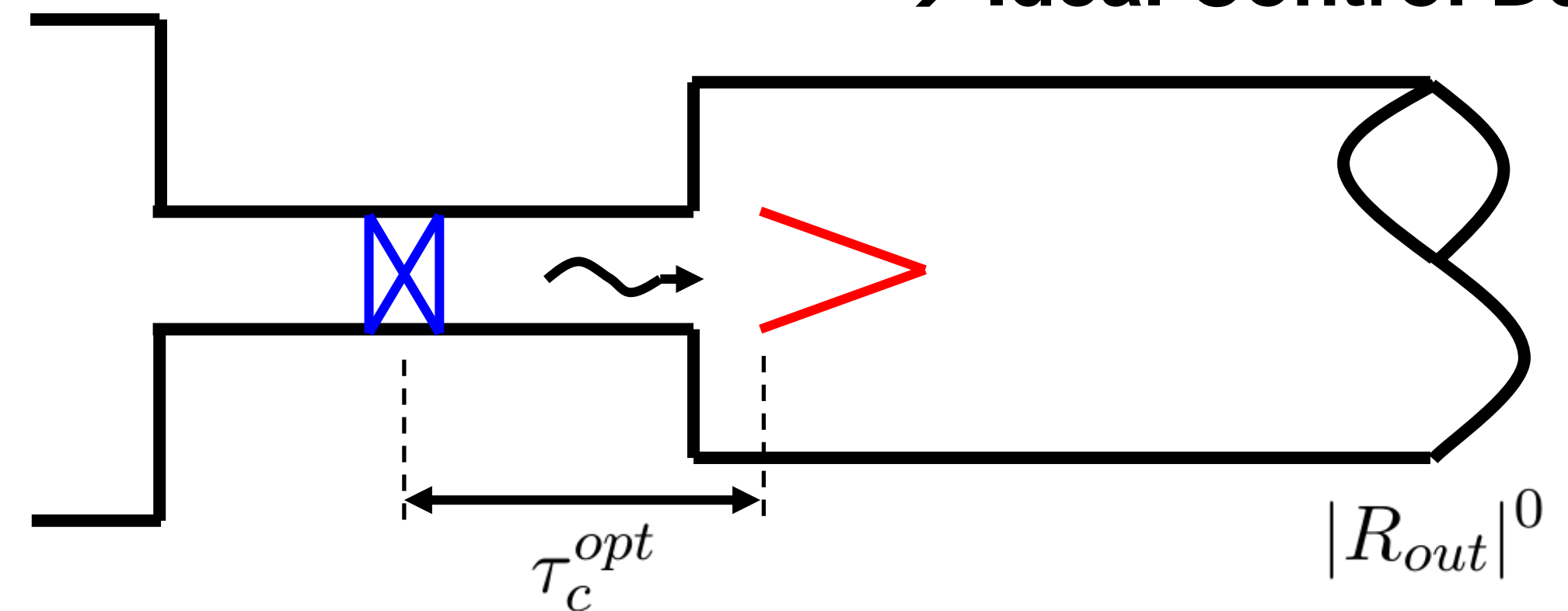
Ideal control design: A first step towards risk mitigation



Known: $\tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$
 $|R_{out}| = |R_{out}|^0$

“Q2: using τ_c as a control factor, what is the required minimum modification of τ_c to eliminate the risk of instability of both cavity and ITA mode simultaneously?”

→ **Ideal Control Design**



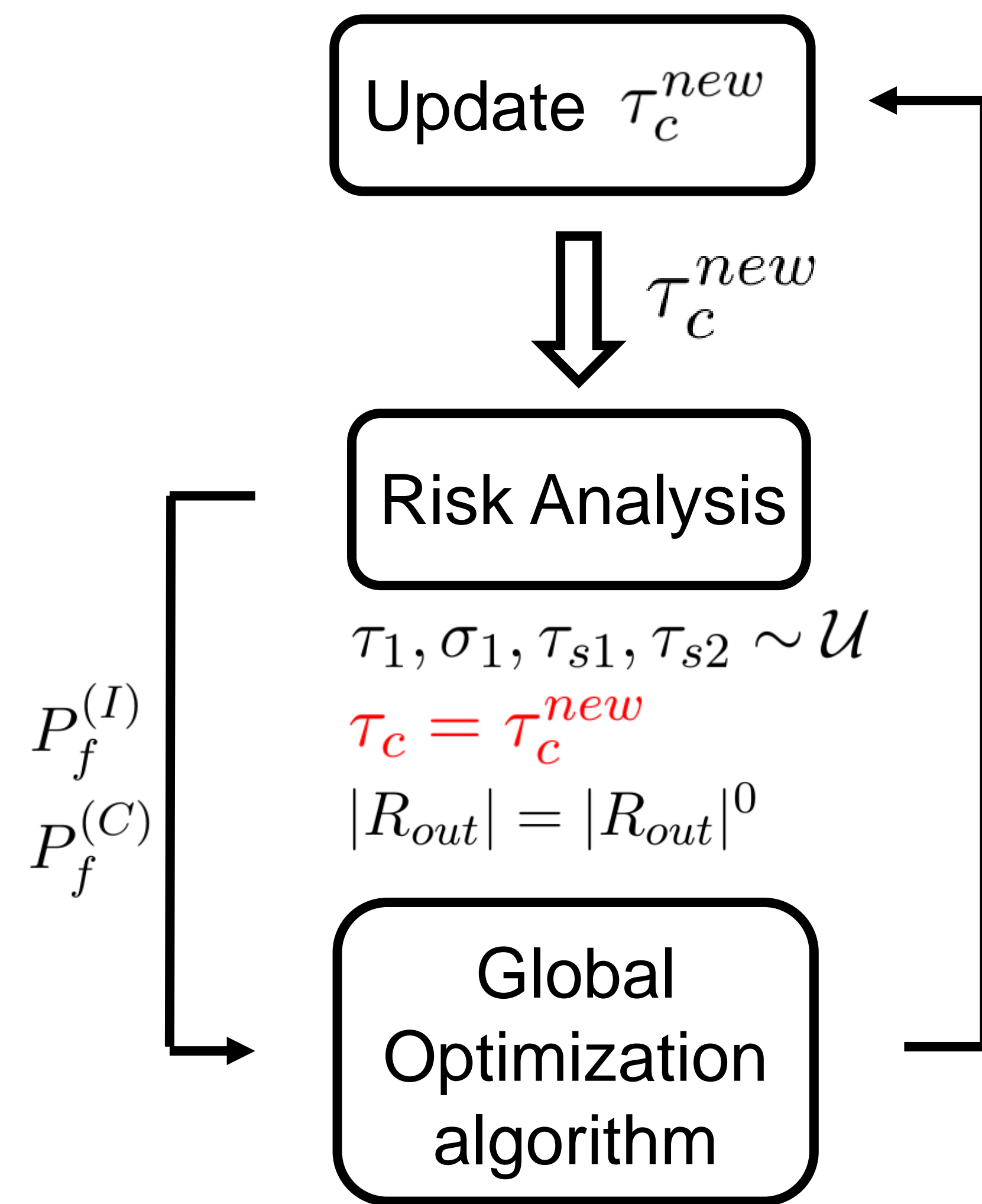
$$\min_{\tau_c} f(\tau_c) = (\tau_c - \tau_c^0)^2$$

subject to : $P_f^{(I)}(\tau_c) \leq 0.1\%$

$$P_f^{(C)}(\tau_c) \leq 0.1\%$$

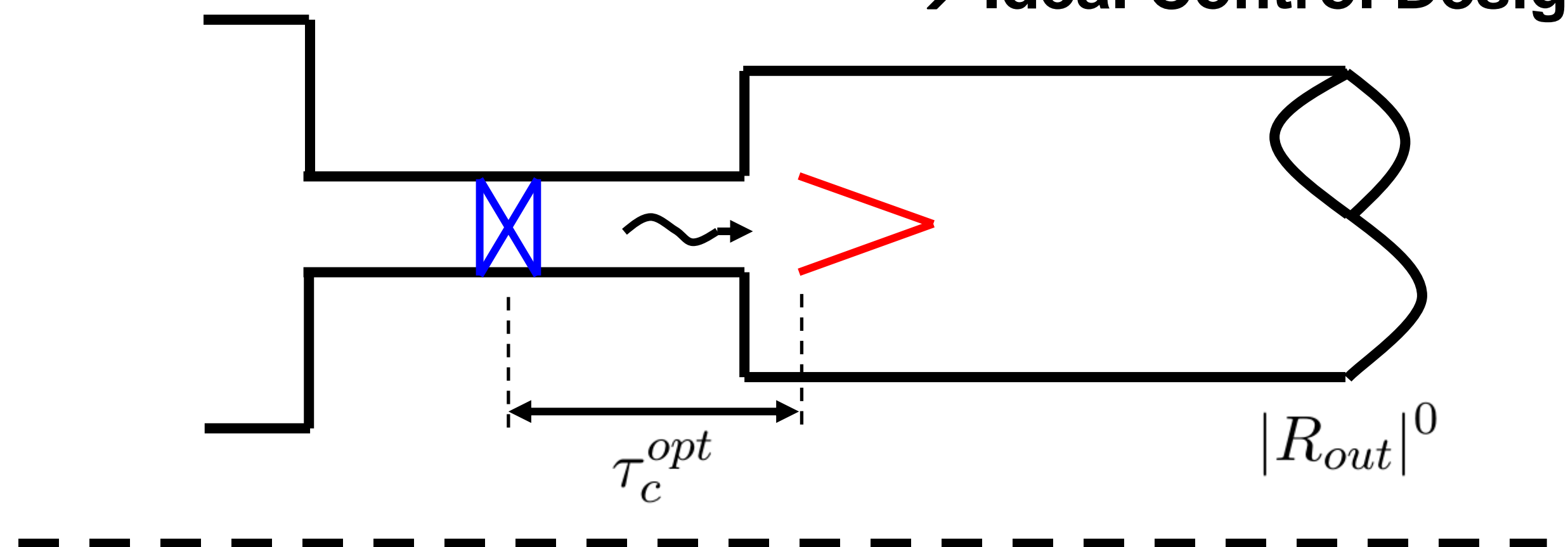
$$2\text{ms} \leq \tau_c \leq 4.8\text{ms}$$

Ideal control design: A first step towards risk mitigation



“Q2: using τ_c as a control factor, what is the required minimum modification of τ_c to eliminate the risk of instability of both cavity and ITA mode simultaneously?”

→ Ideal Control Design



$$\min_{\tau_c} f(\tau_c) = (\tau_c - \tau_c^0)^2$$

subject to : $P_f^{(I)}(\tau_c) \leq 0.1\%$

$P_f^{(C)}(\tau_c) \leq 0.1\%$

$$2\text{ms} \leq \tau_c \leq 4.8\text{ms}$$

Gaussian Process models have delivered highly accurate design

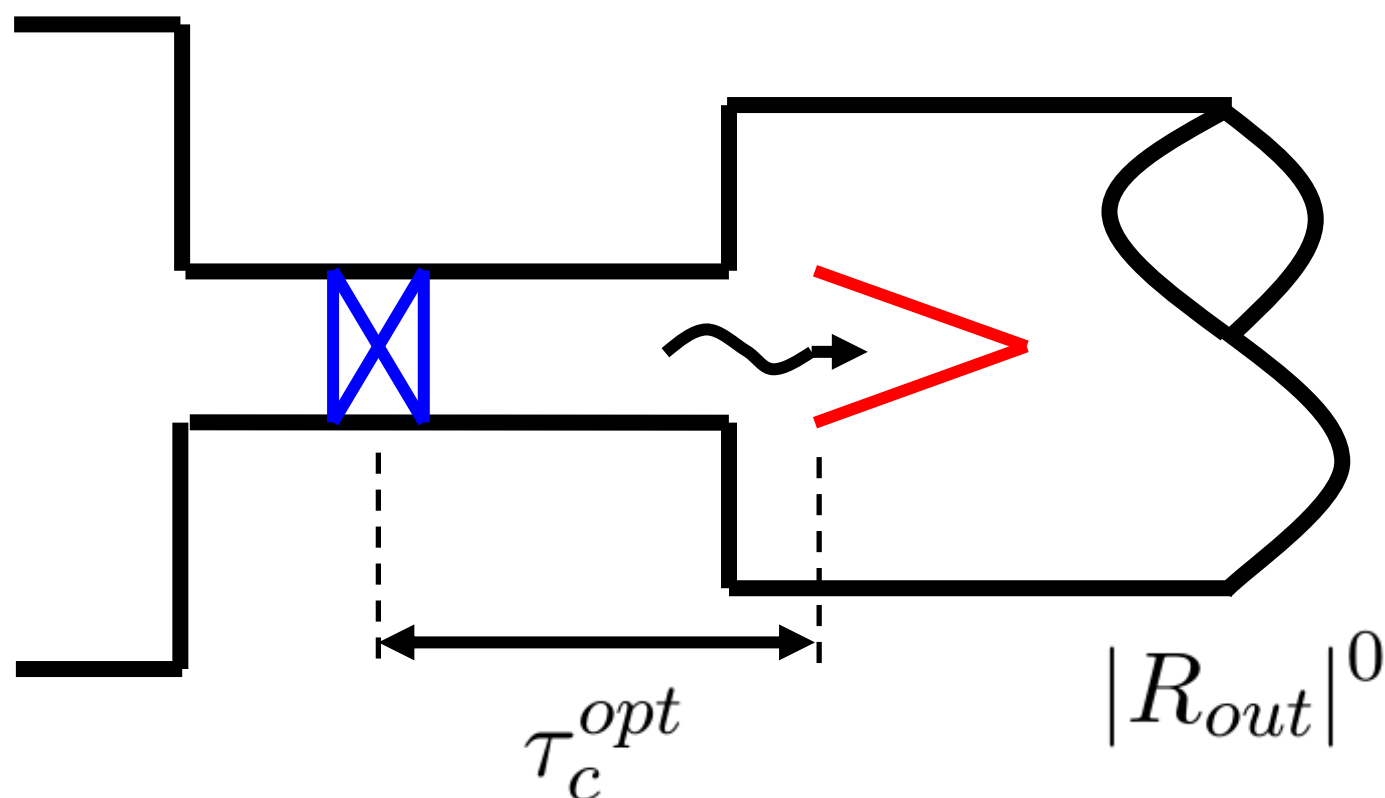
Q2: Ideal control design

$$\min_{\tau_c} f(\tau_c) = (\tau_c - \tau_c^0)^2$$

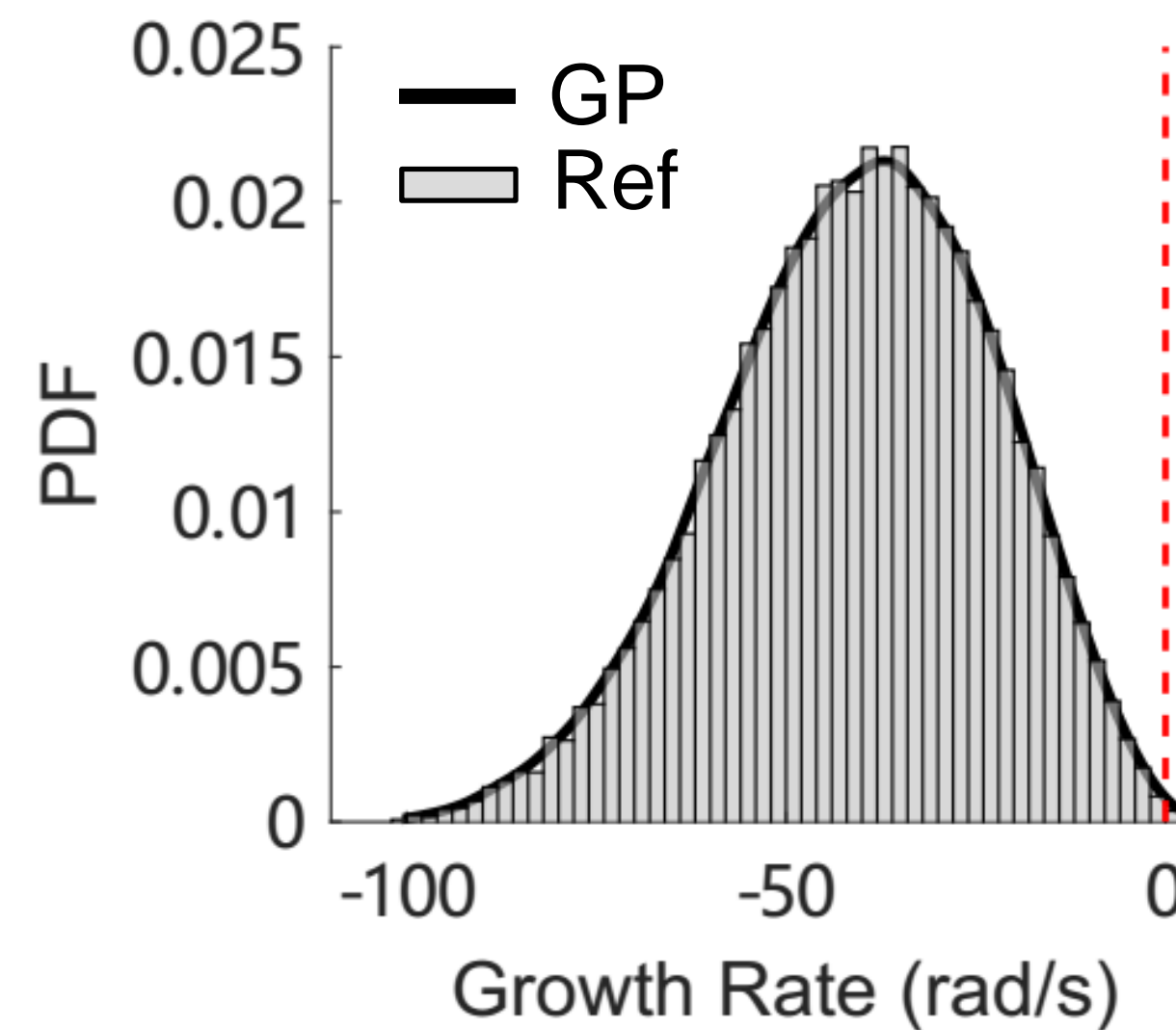
$$\text{subject to: } P_f^{(I)}(\tau_c) \leq 0.1\%$$

$$P_f^{(C)}(\tau_c) \leq 0.1\%$$

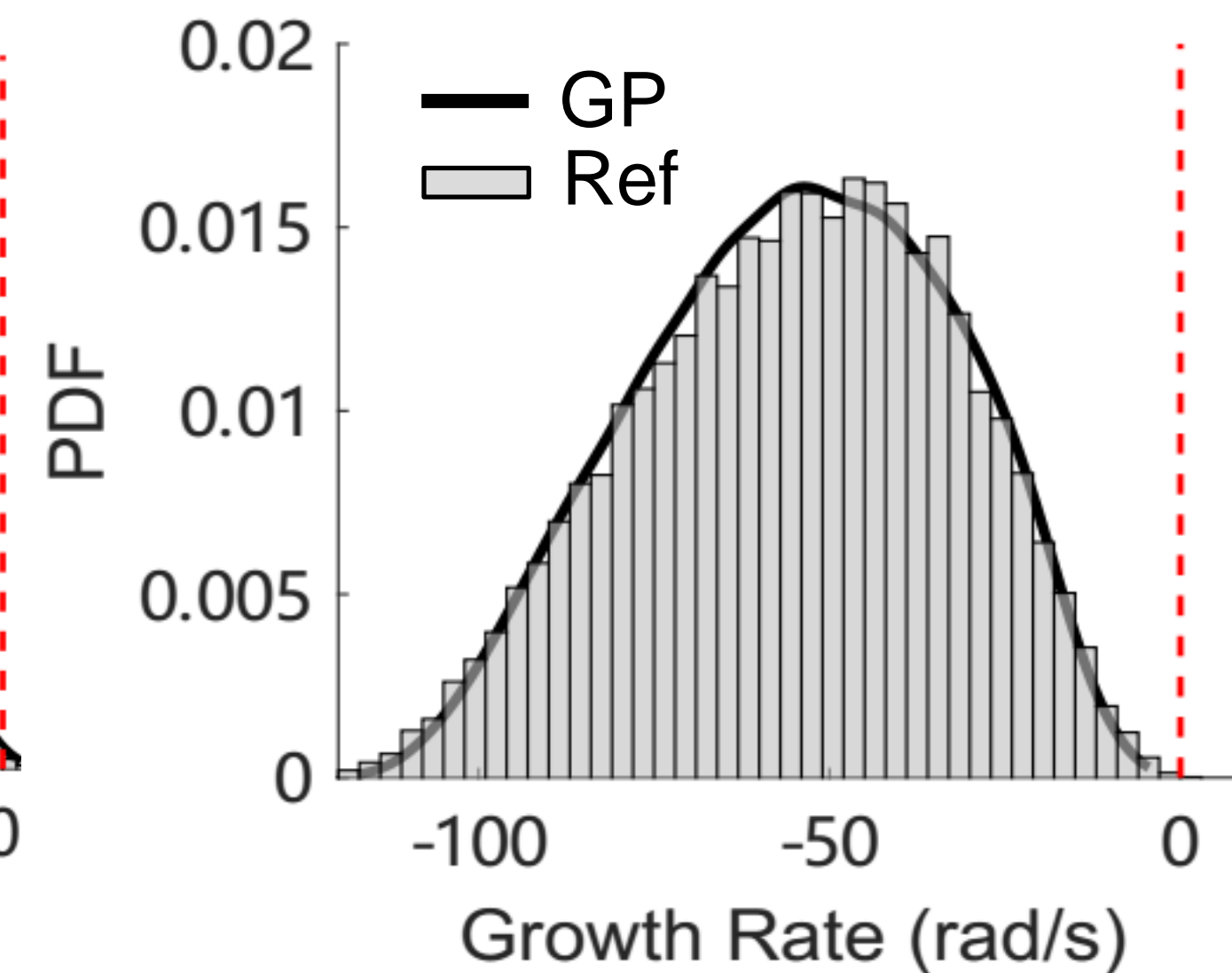
$$2\text{ms} \leq \tau_c \leq 4.8\text{ms}$$



ITA Mode

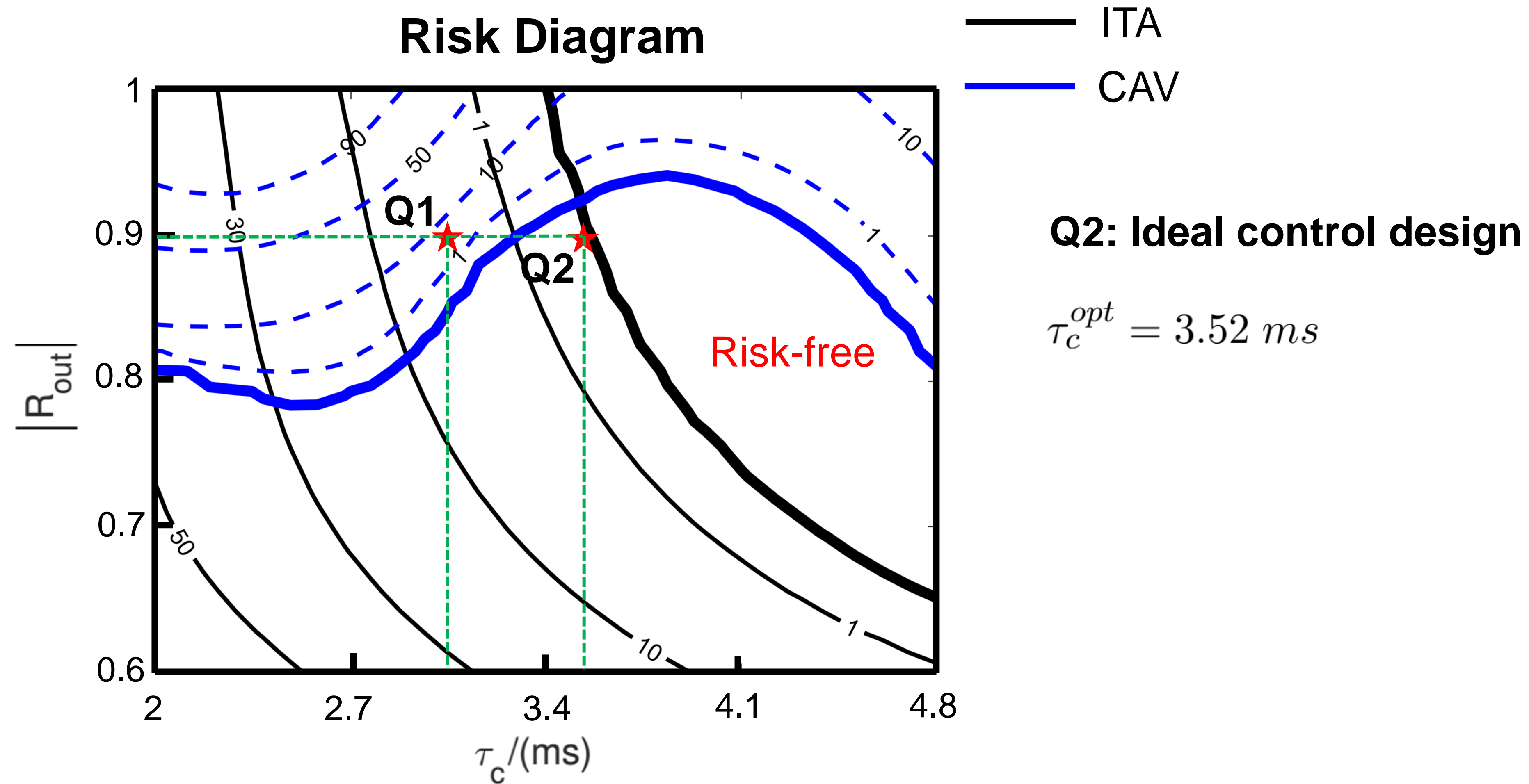


Cavity Mode



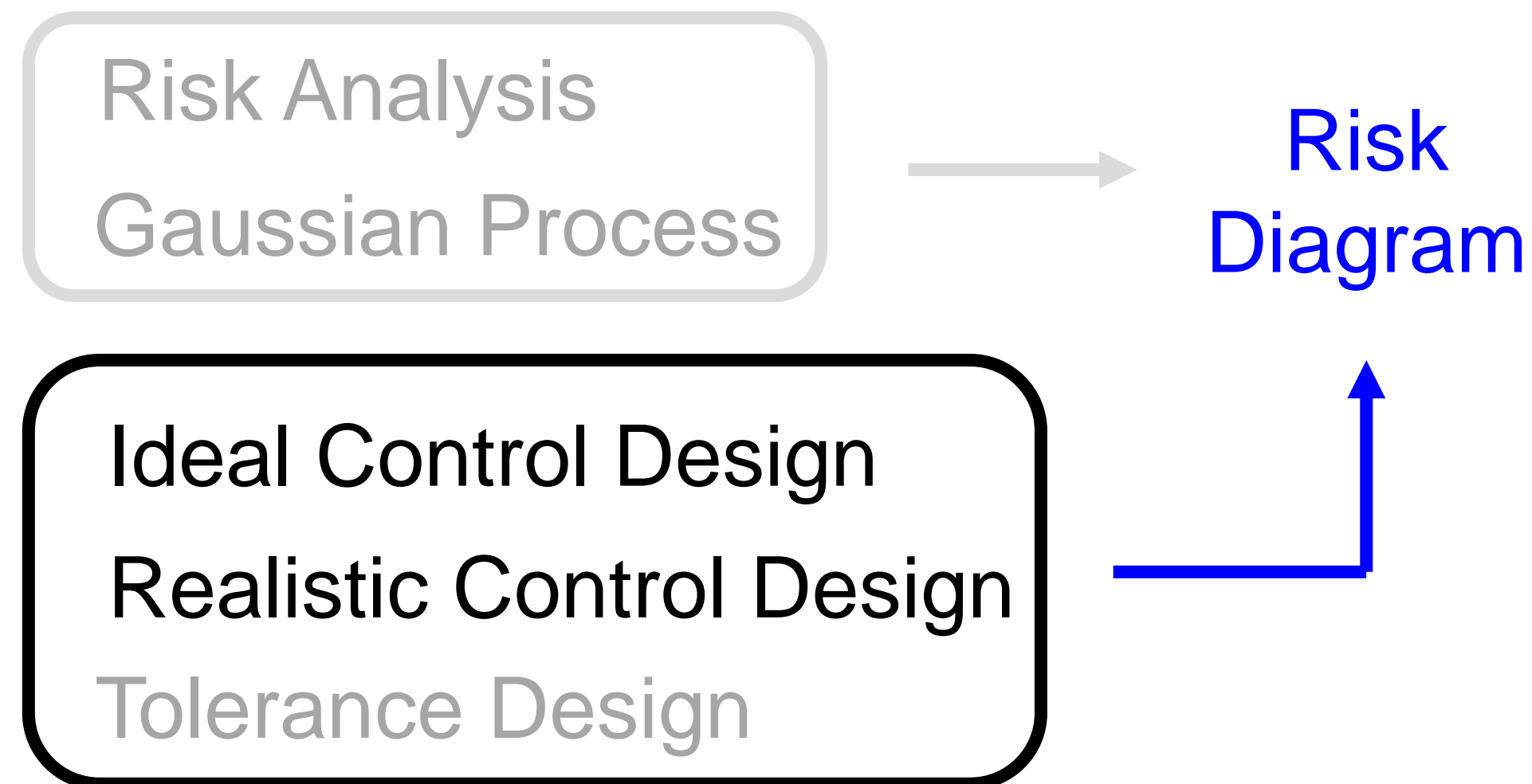
$$\tau_c^{opt} = 3.52 \text{ ms} \quad \tau_1, \sigma_1, \tau_{s1}, \tau_{s2} \sim \mathcal{U}$$
$$(\tau_c^0 = 3 \text{ ms}) \quad |R_{out}| = |R_{out}|^0$$

Risk diagram offers straightforward determination of the optimum design

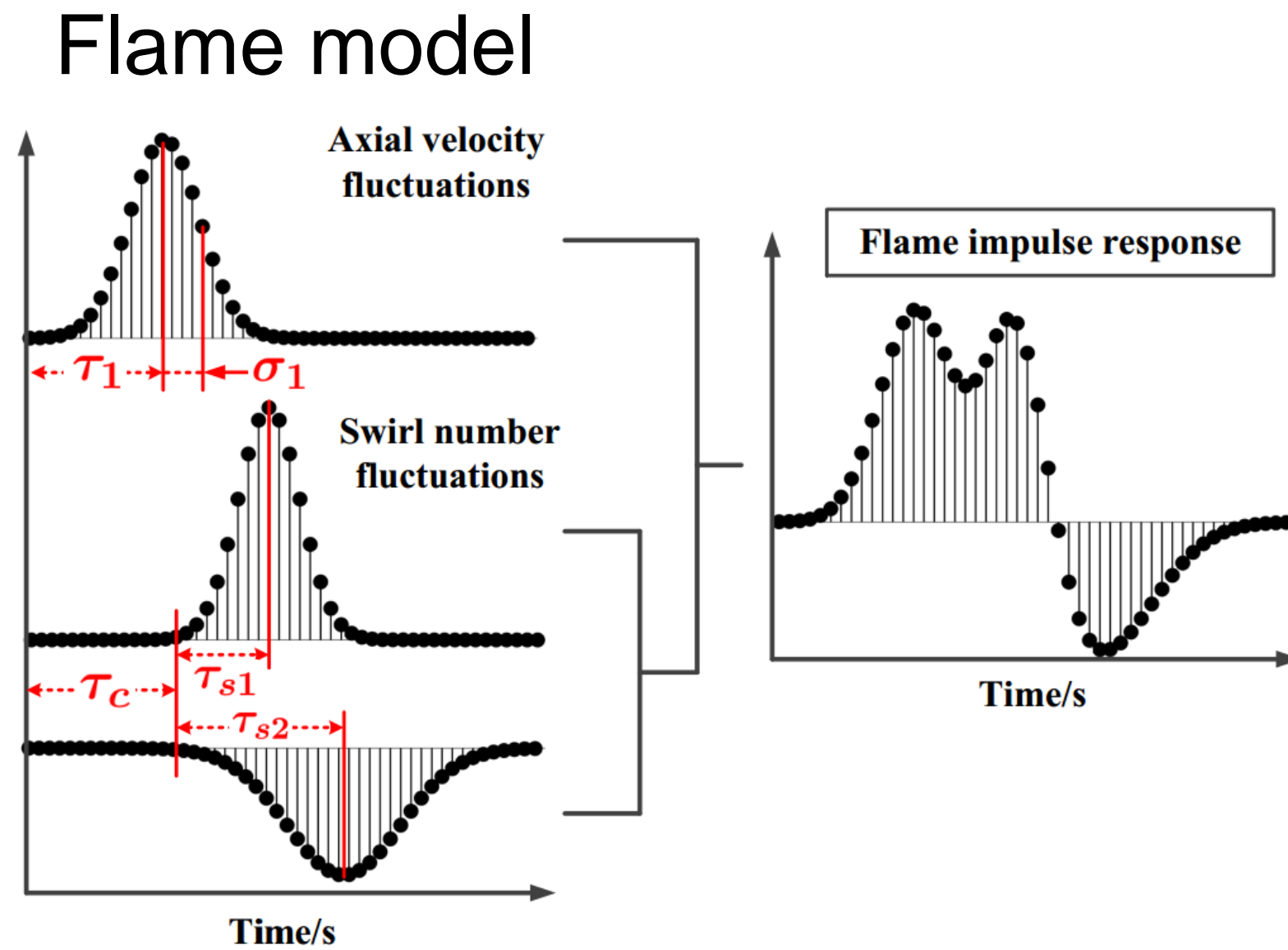


Presentation overview

- Motivation
- Thermoacoustic problem settings
- ▣ Robust design tasks

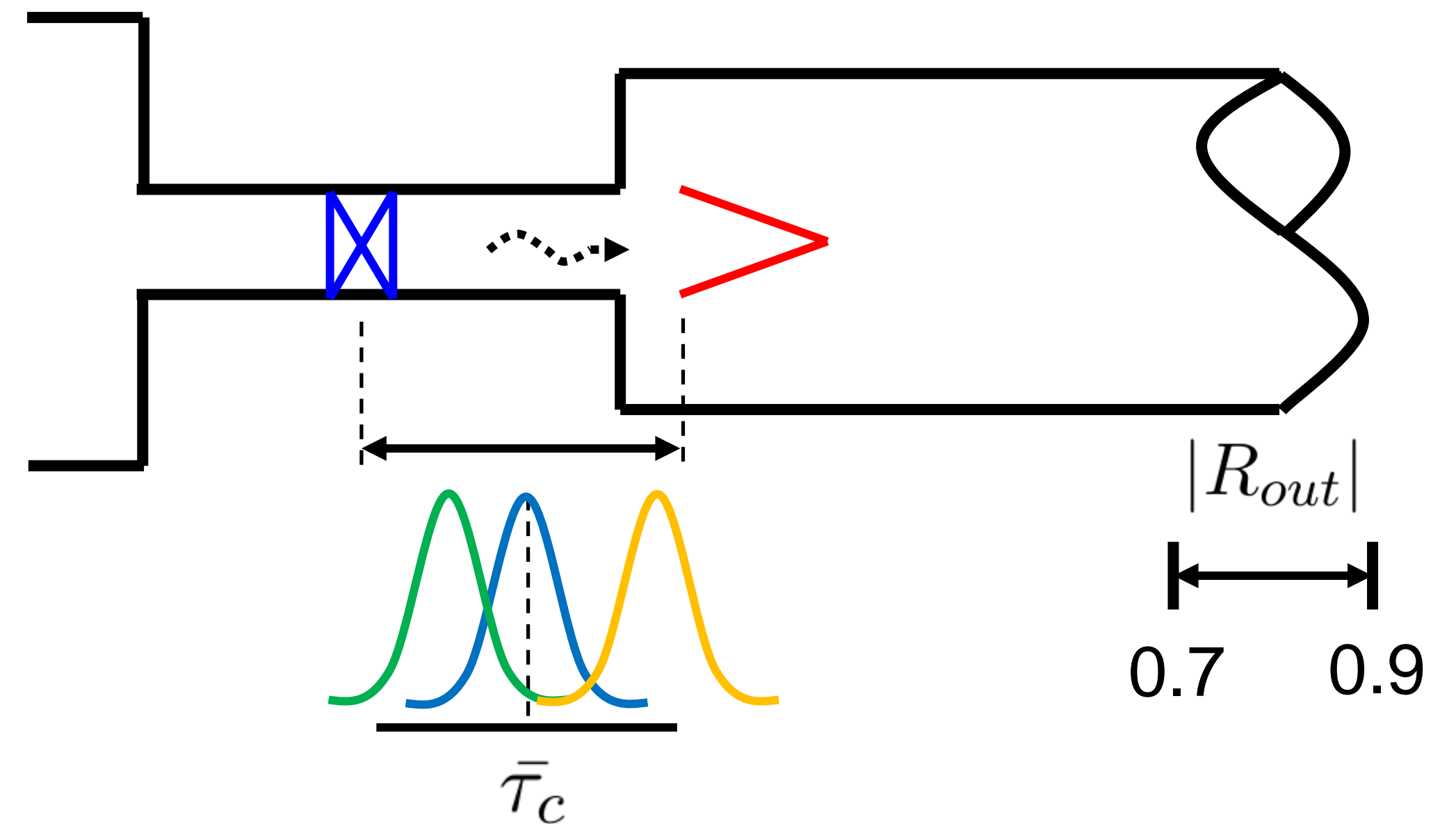


Realistic control design: further enhance the robustness of the design

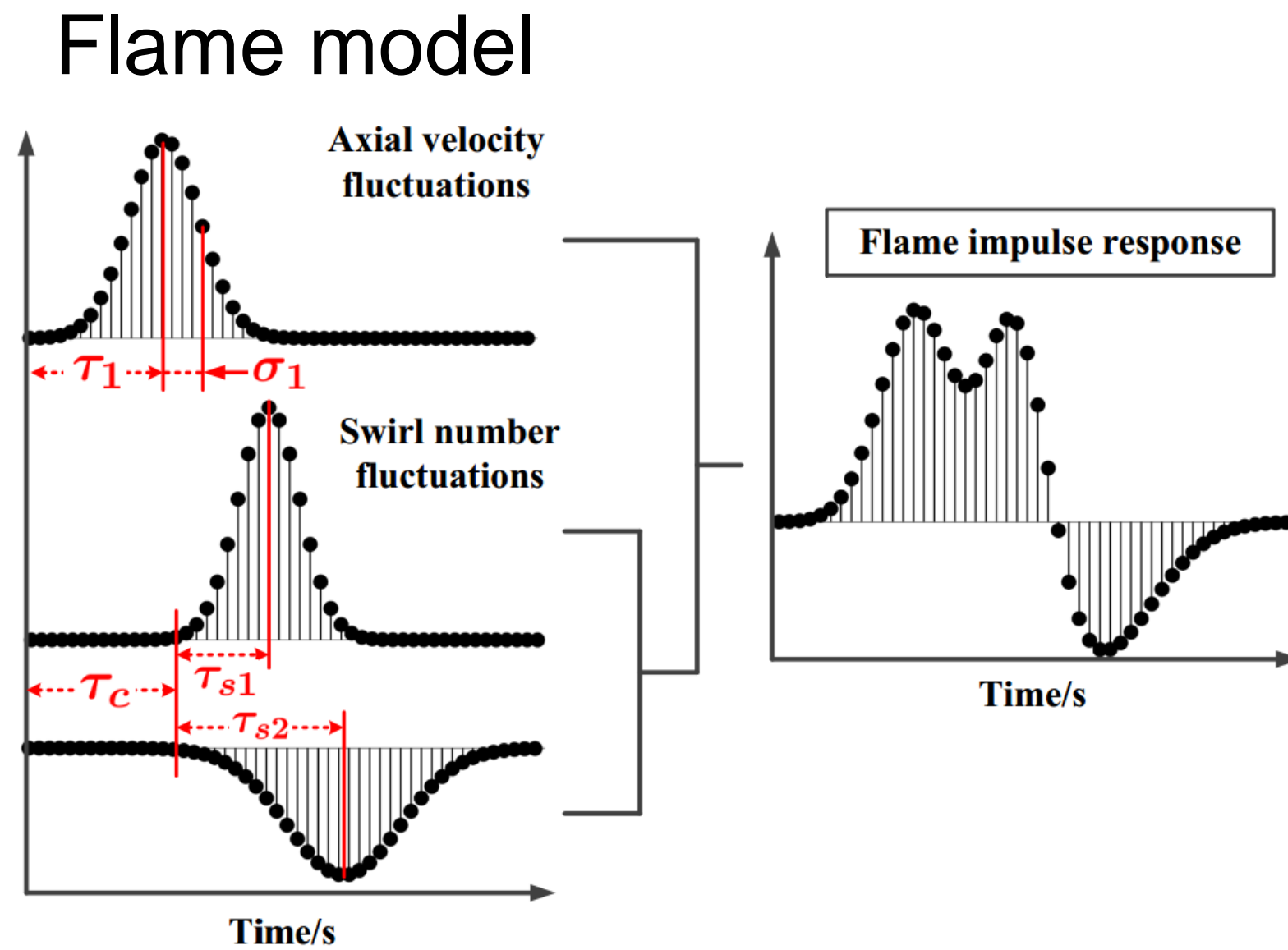


“Q3: in reality, we cannot perfectly control τ_c . Meanwhile, $|R_{out}|$ is also uncertain. Then how would these affect the decision made from Q2?”

→ Realistic Control Design



Realistic control design: further enhance the robustness of the design



$$\min_{\bar{\tau}_c} f(\bar{\tau}_c) = (\bar{\tau}_c - \tau_c^0)^2$$

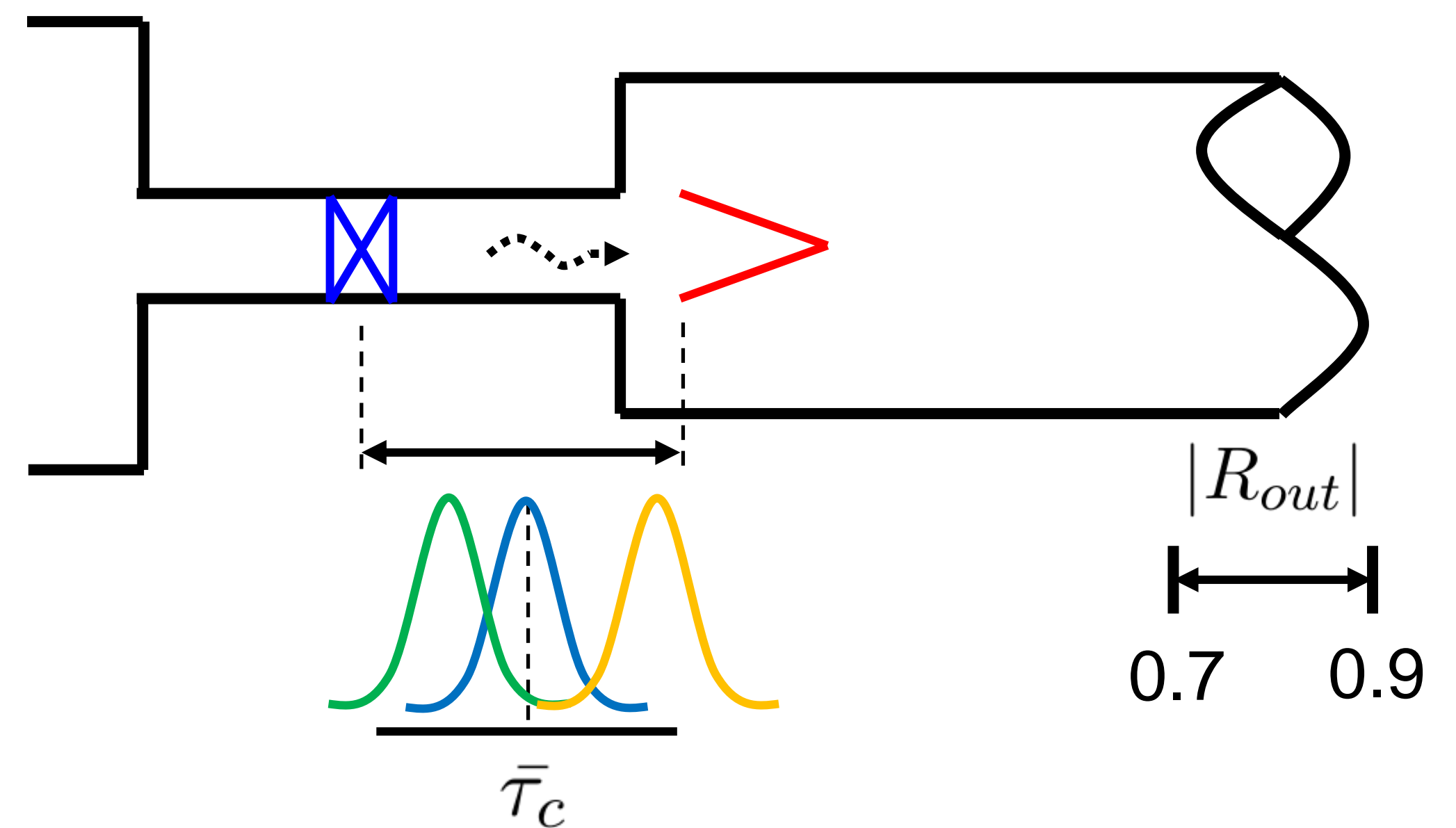
subject to : $P_f^{(I)}(\tau_c) \leq 0.1\%$

$$P_f^{(C)}(\tau_c) \leq 0.1\%$$

$$\tau_c \sim \mathcal{N}(\bar{\tau}_c, (0.05\tau_c^0)^2)$$

“Q3: in reality, we cannot perfectly control τ_c . Meanwhile, $|R_{out}|$ is also uncertain. Then how would these affect the decision made from Q2?”

→ Realistic Control Design



Gaussian Process models have delivered highly accurate design

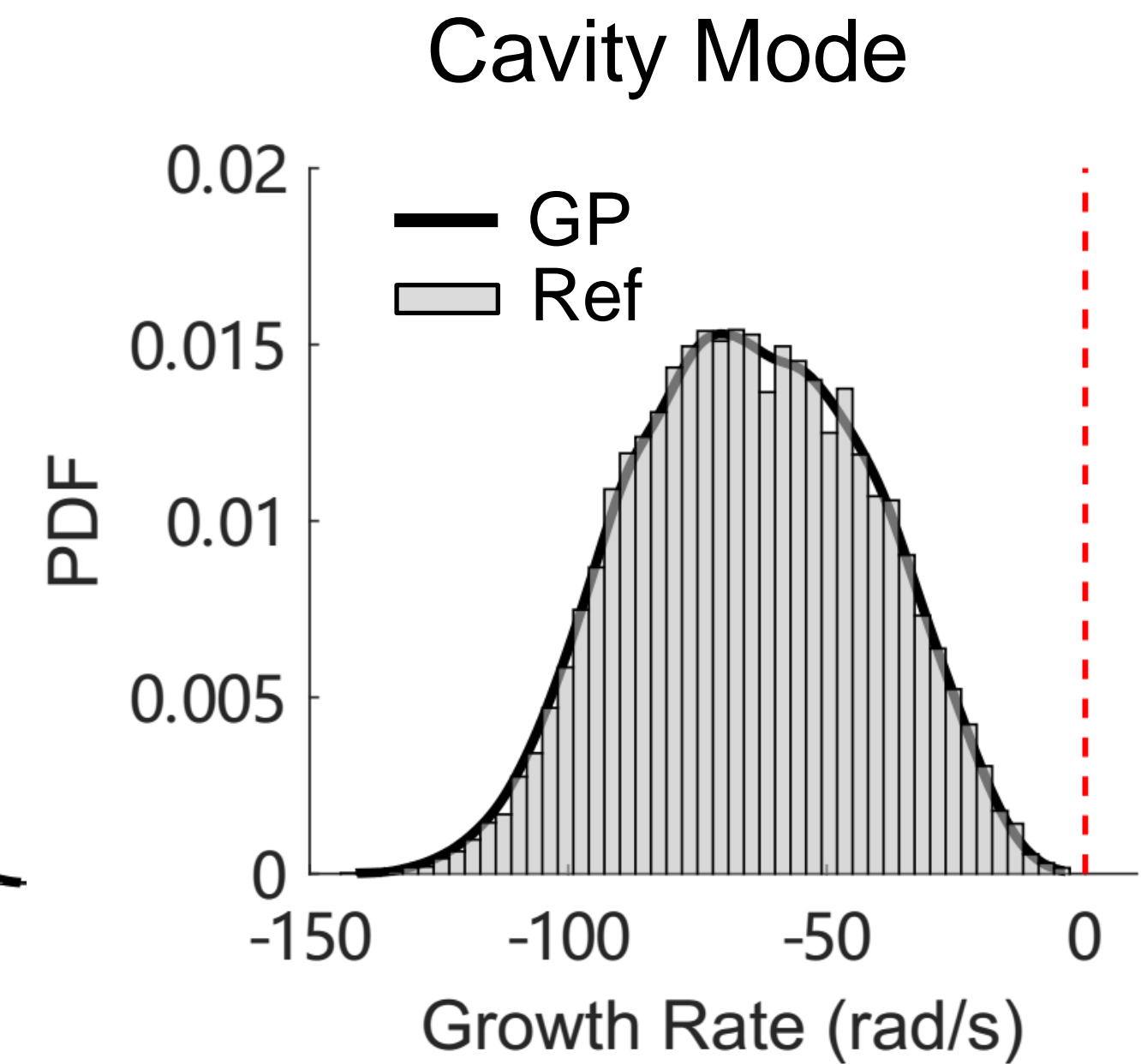
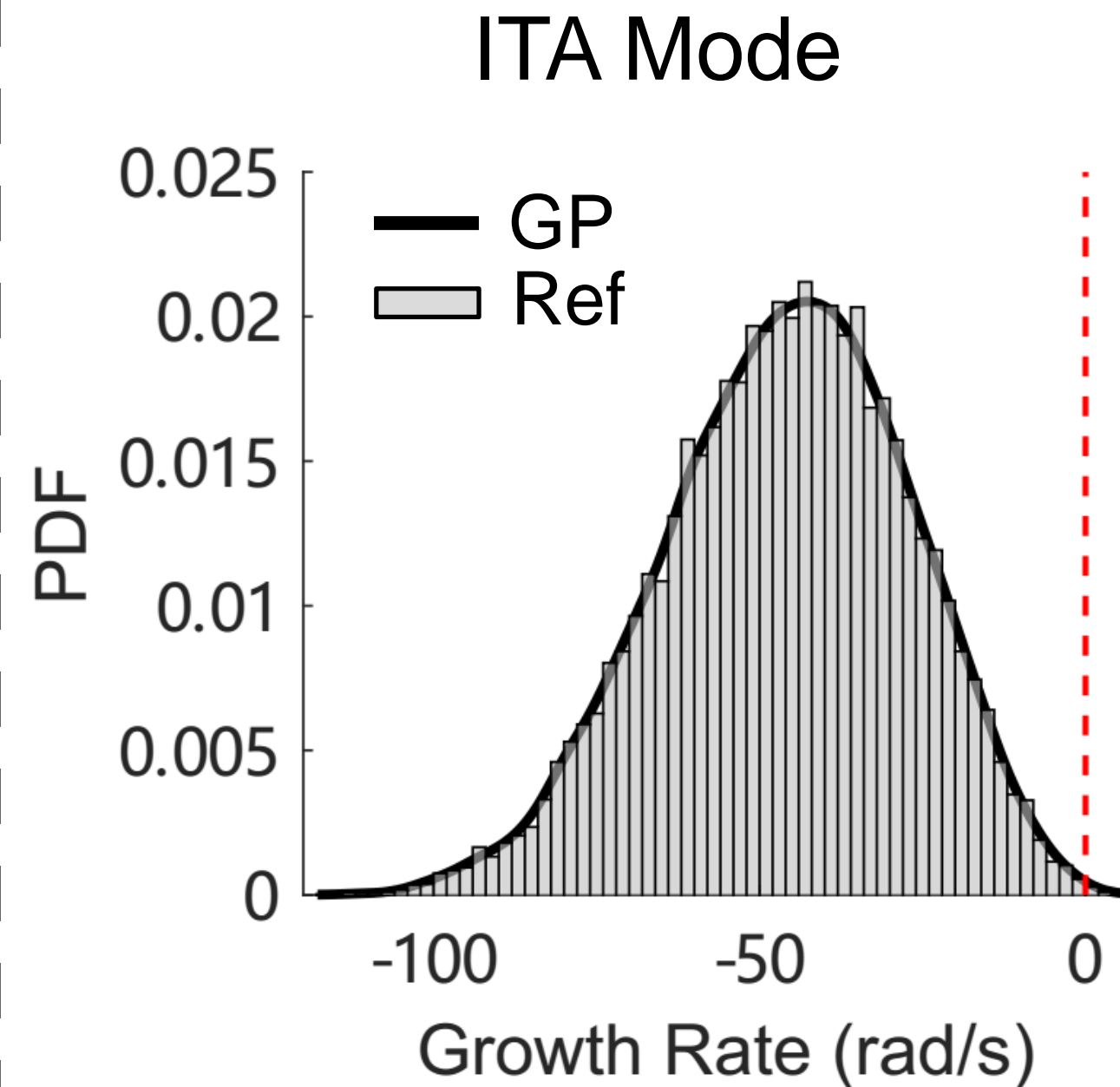
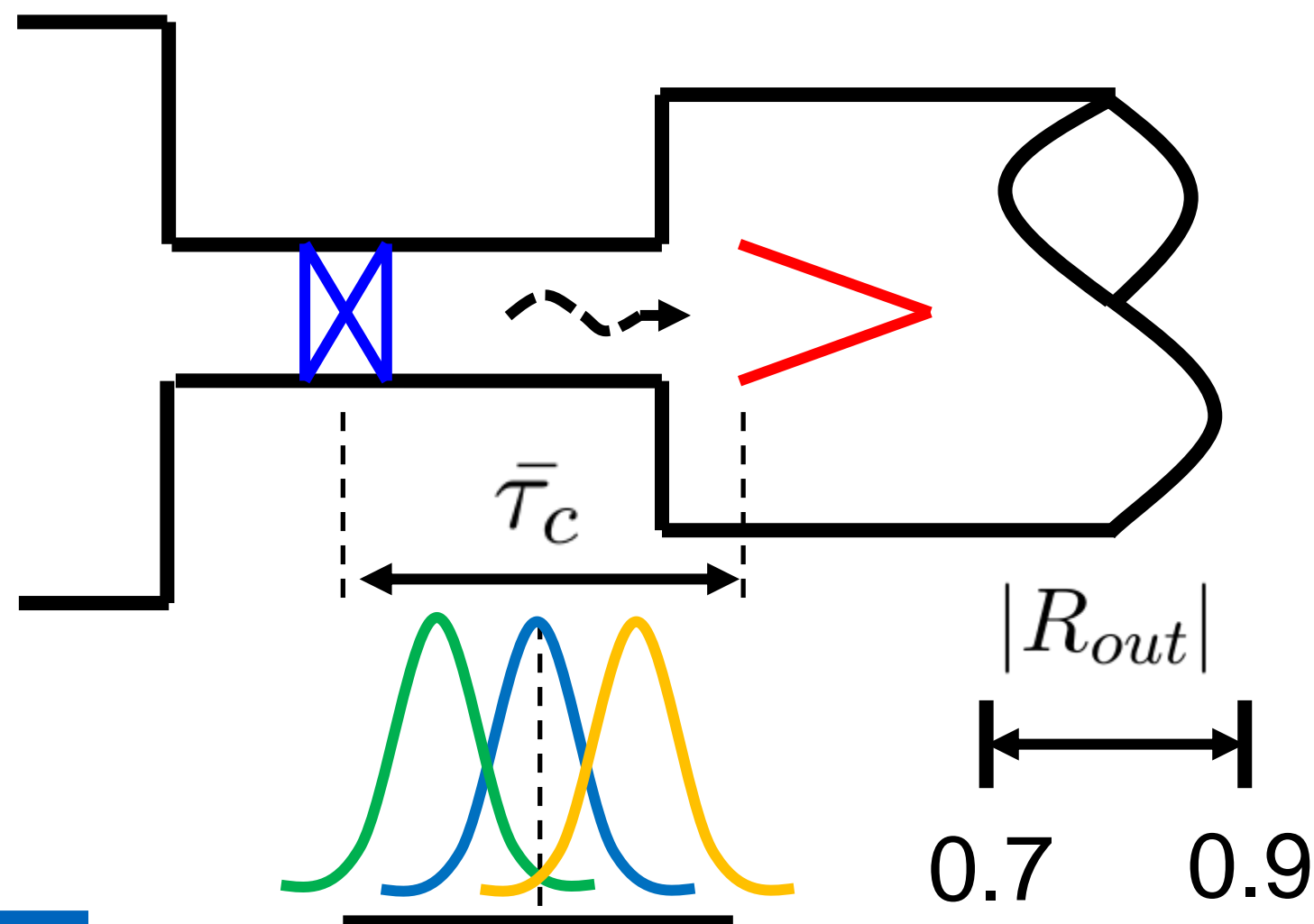
Q3: Realistic control design

$$\min_{\bar{\tau}_c} f(\bar{\tau}_c) = (\bar{\tau}_c - \tau_c^0)^2$$

$$\text{subject to : } P_f^{(I)}(\tau_c) \leq 0.1\%$$

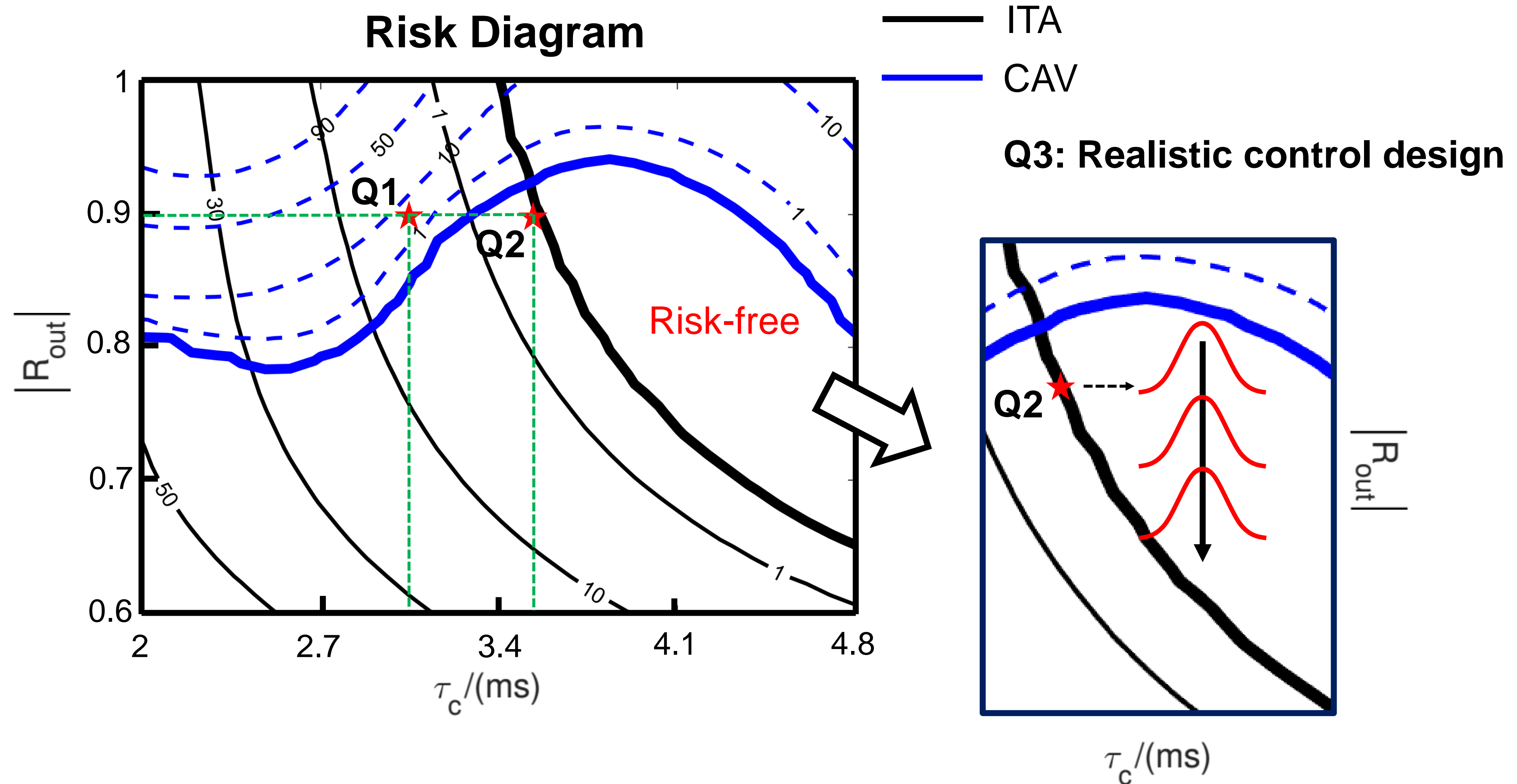
$$P_f^{(C)}(\tau_c) \leq 0.1\%$$

$$\tau_c \sim \mathcal{N}(\bar{\tau}_c, (0.05\tau_c^0)^2)$$



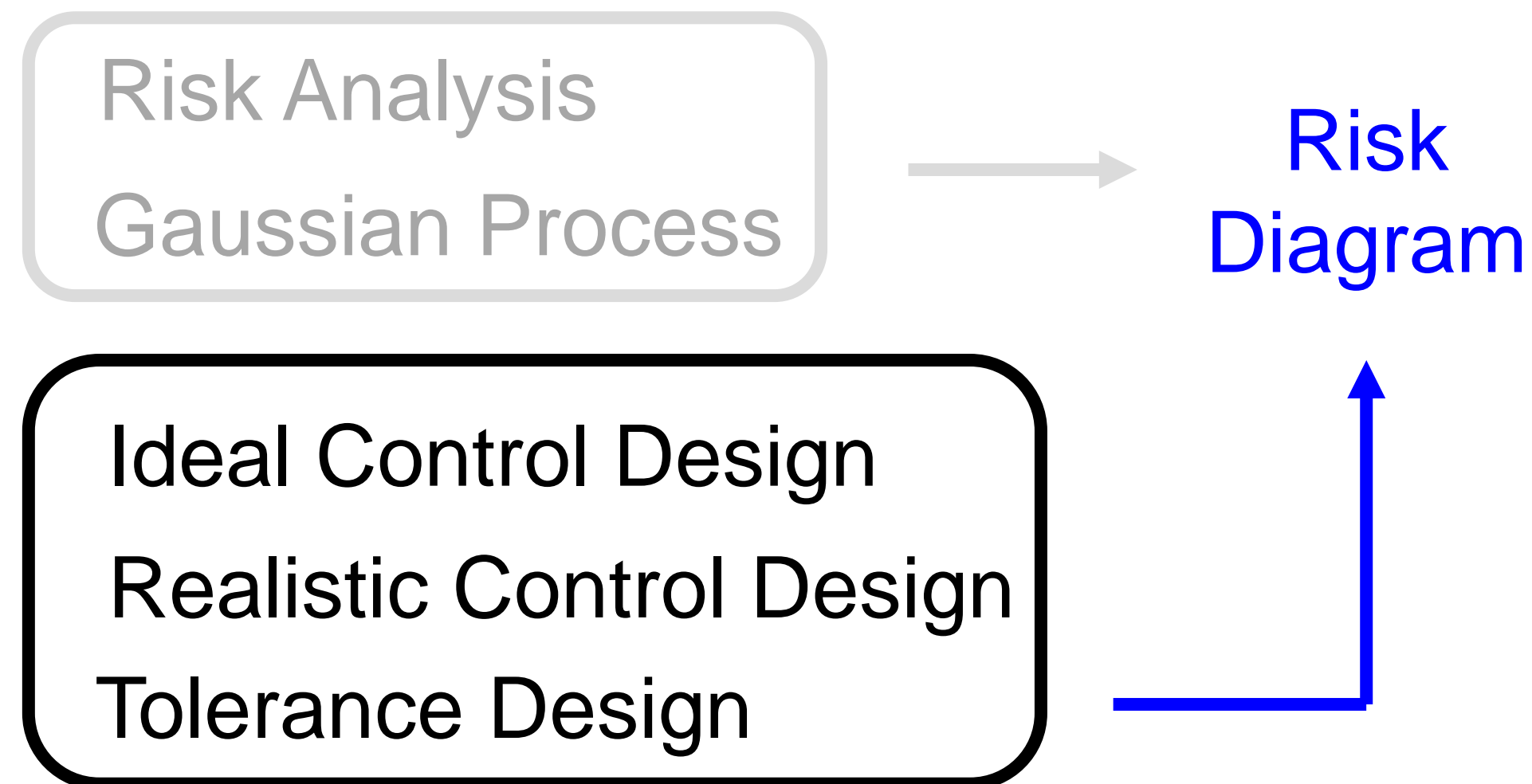
$$\begin{aligned} \bar{\tau}_c^{opt} &= 4.06 \text{ ms} & \tau_c &\sim \mathcal{N}(\bar{\tau}_c^{opt}, (0.05\tau_c^0)^2) \\ (\tau_c^{opt} &= 3.52 \text{ ms}) & |R_{out}| &\sim \mathcal{U}(0.7, 0.9) \\ & & \tau_1, \sigma_1, \tau_{s1}, \tau_{s2} &\sim \mathcal{U} \end{aligned}$$

Risk diagram indicates the direction for determining the optimum design

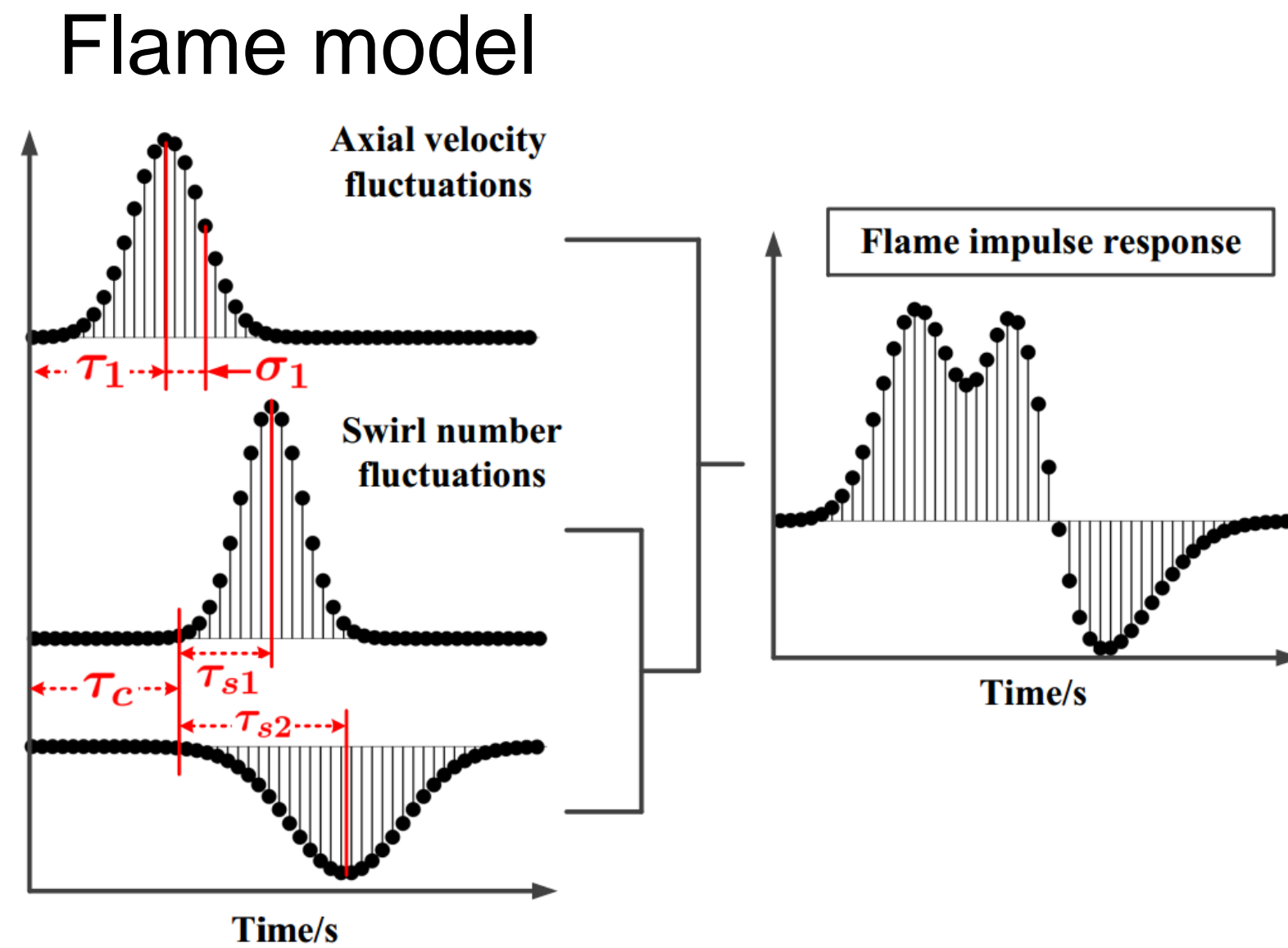


Presentation overview

- Motivation
- Thermoacoustic problem settings
- ▣ Robust design tasks

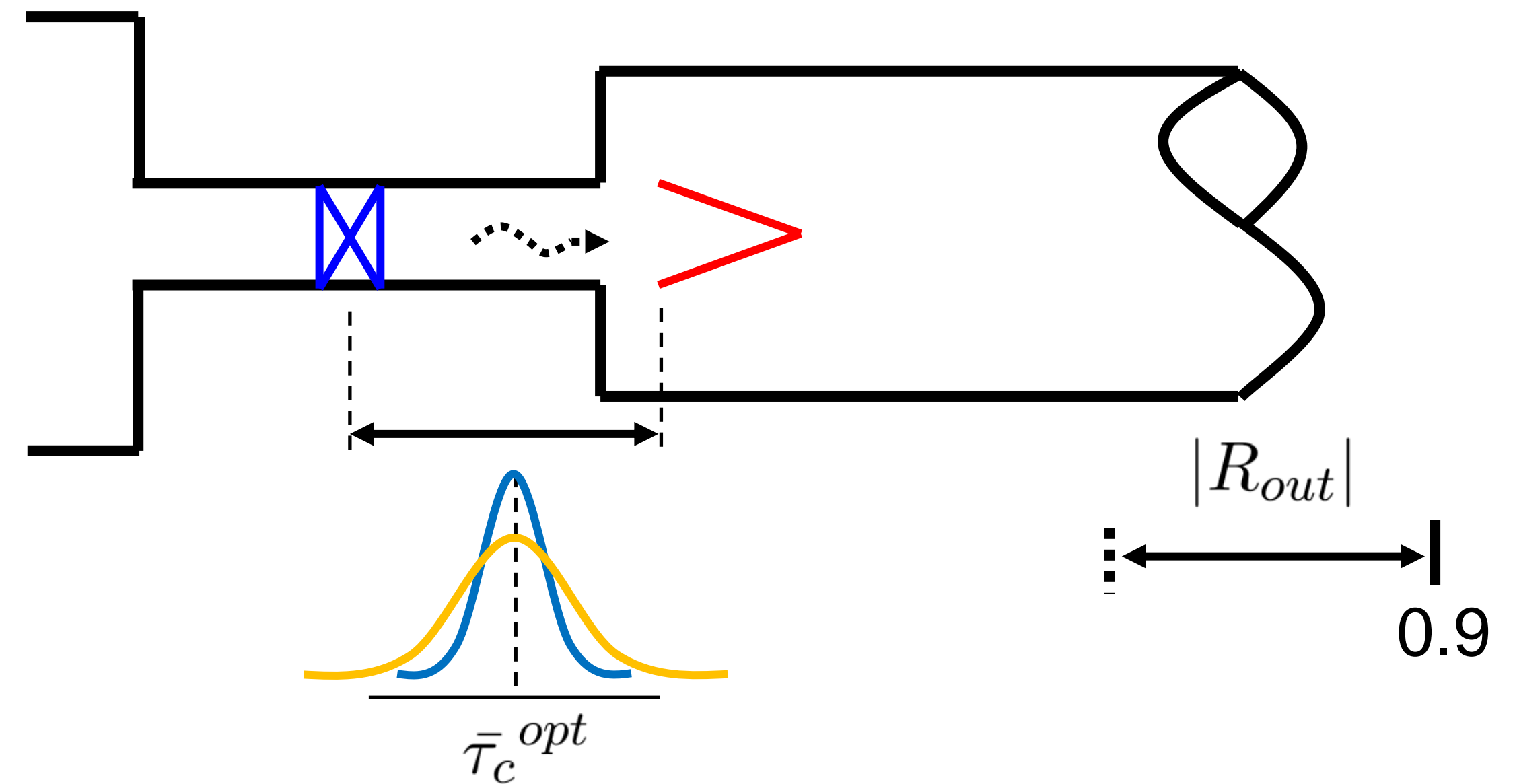


Tolerance design: A perspective of an inverse problem



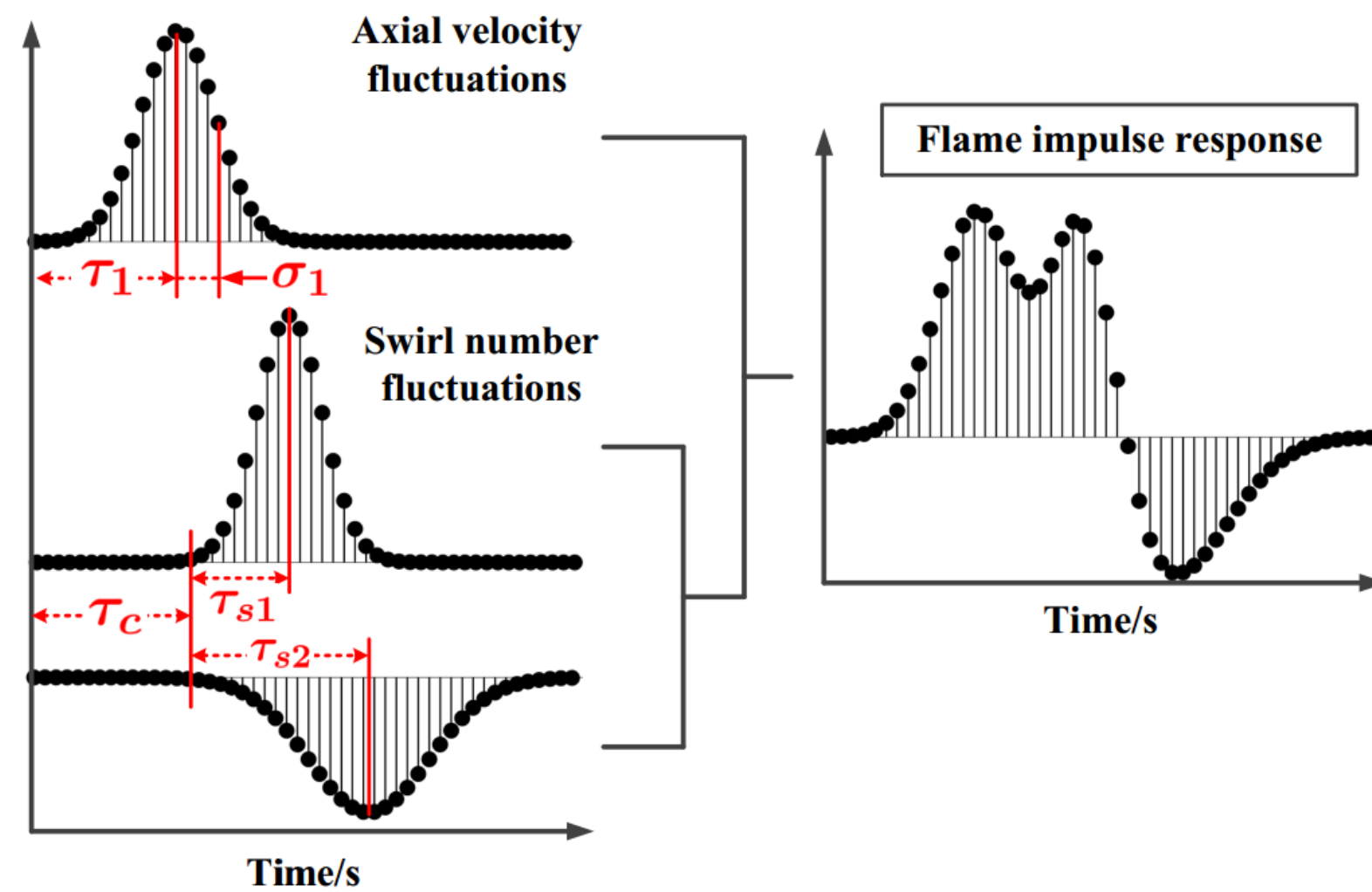
“Q4: given a certain threshold for risk factor, what are the maximum allowable variational ranges for τ_c and $|R_{out}|$?”

→ Tolerance Design



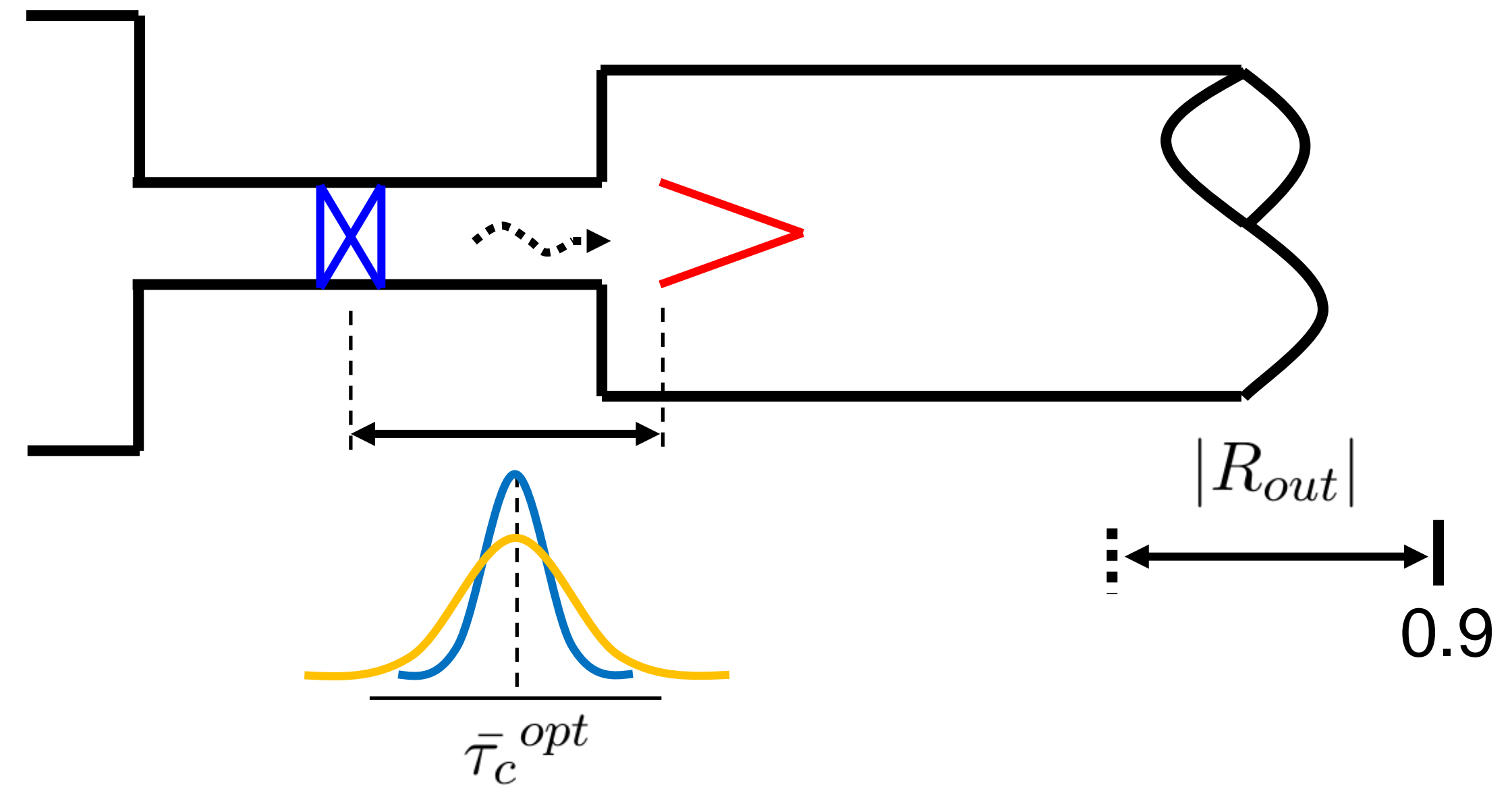
Tolerance design: A perspective of an inverse problem

Flame model



“Q4: given a certain threshold for risk factor, what are the maximum allowable variational ranges for τ_c and $|R_{out}|$?”

→ Tolerance Design



$$\max_{\sigma_{\tau_c}} f(\sigma_{\tau_c}) = \frac{\sigma_{\tau_c}}{\tau_c^0} \min_{R_L} g(R_L) = \frac{R_L}{|R_{out}|^0}$$

subject to : $P_f^{(I)}(\tau_c, |R_{out}|) \leq 0.1\%$

$$P_f^{(C)}(\tau_c, |R_{out}|) \leq 0.1\%$$

$$\tau_c \sim \mathcal{N}(\bar{\tau}_c, (\sigma_{\tau_c})^2)$$

$$|R_{out}| \sim \mathcal{U}(R_L, 0.9)$$

Pareto front visualizes the trade-off between two objectives

Q4: Tolerance design

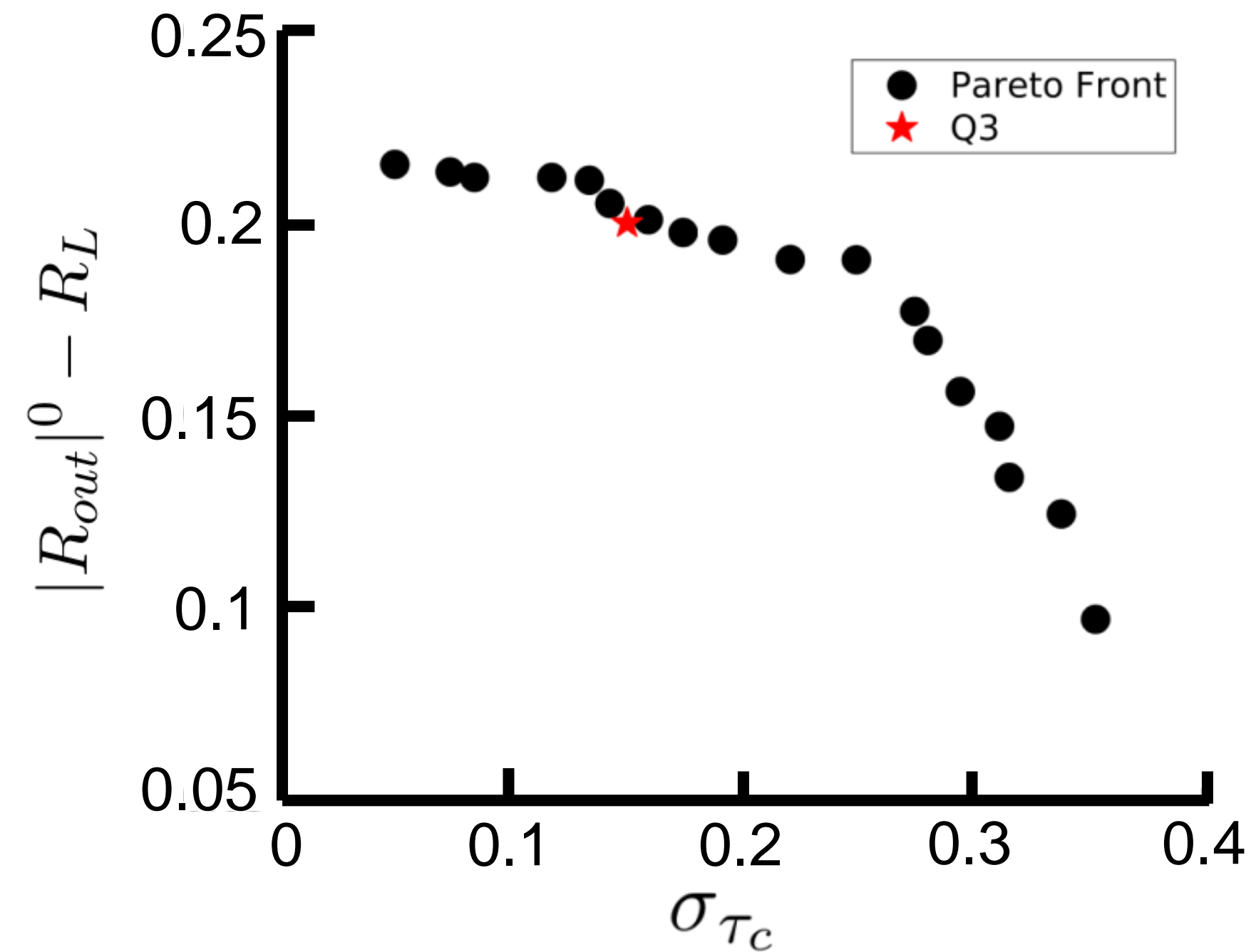
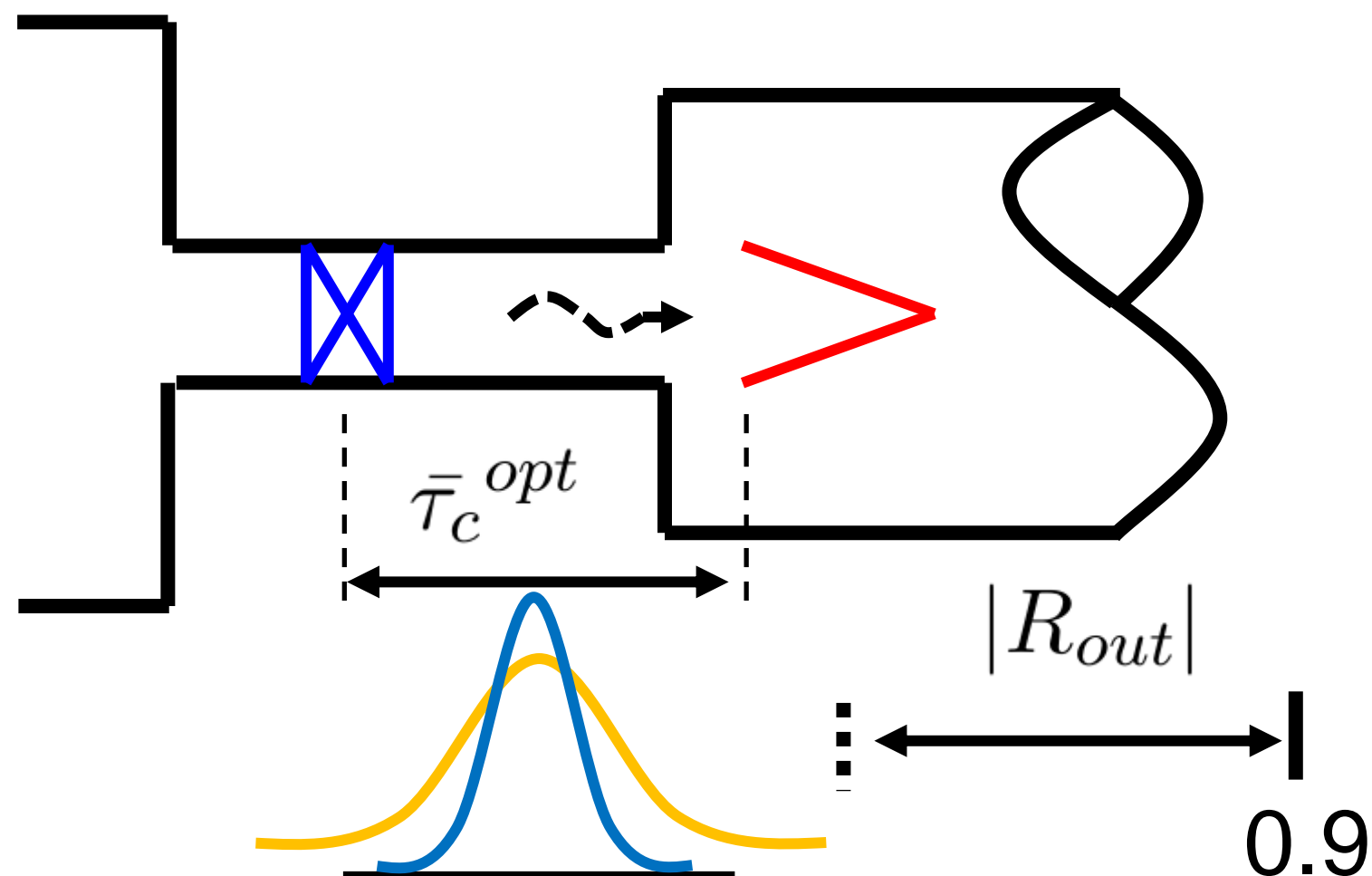
$$\max_{\sigma_{\tau_c}} f(\sigma_{\tau_c}) = \frac{\sigma_{\tau_c}}{\tau_c^0} \min_{R_L} g(R_L) = \frac{R_L}{|R_{out}|^0}$$

subject to : $P_f^{(I)}(\tau_c, |R_{out}|) \leq 0.1\%$

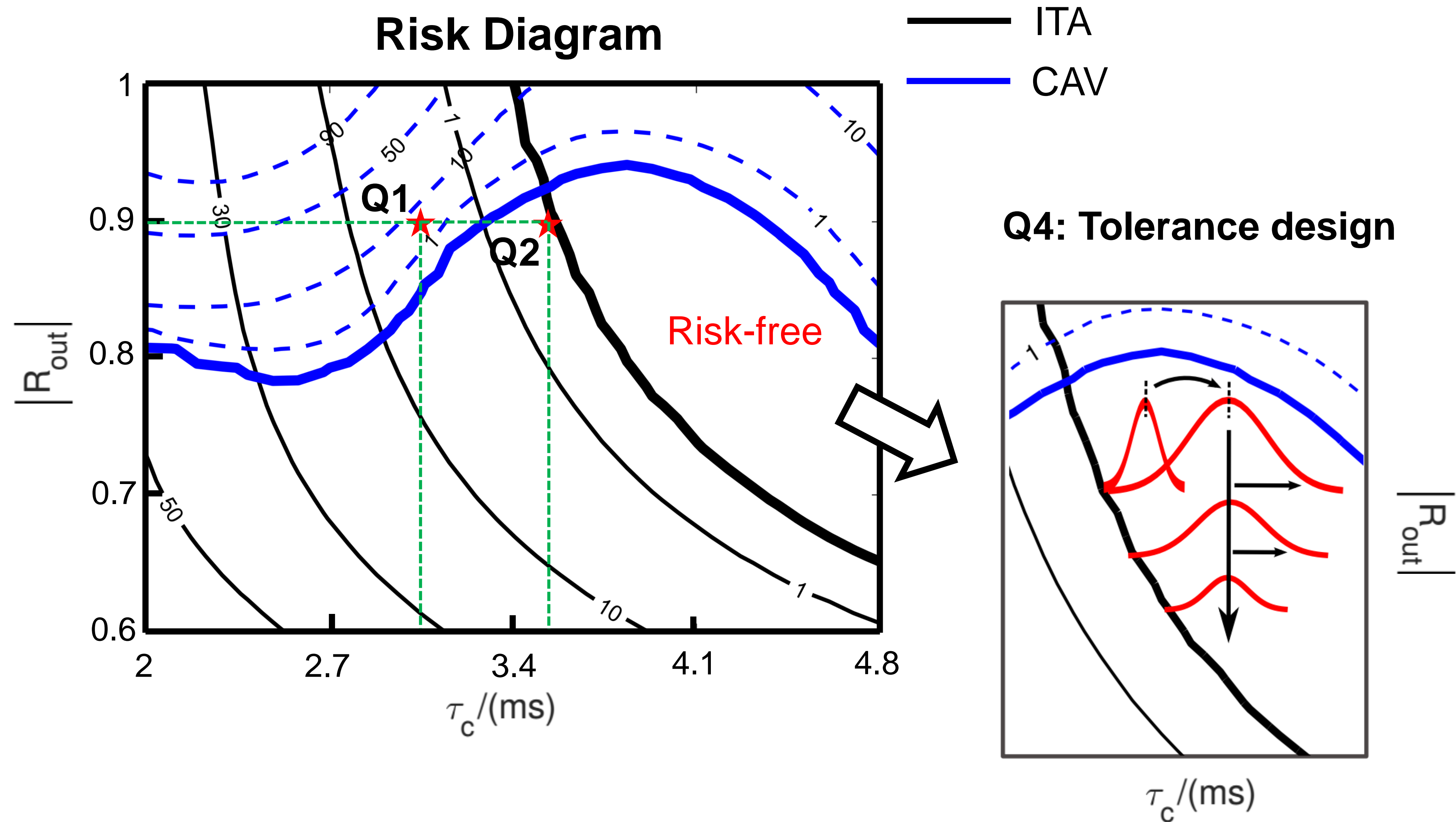
$$P_f^{(C)}(\tau_c, |R_{out}|) \leq 0.1\%$$

$$\tau_c \sim \mathcal{N}(\bar{\tau}_c, (\sigma_{\tau_c})^2)$$

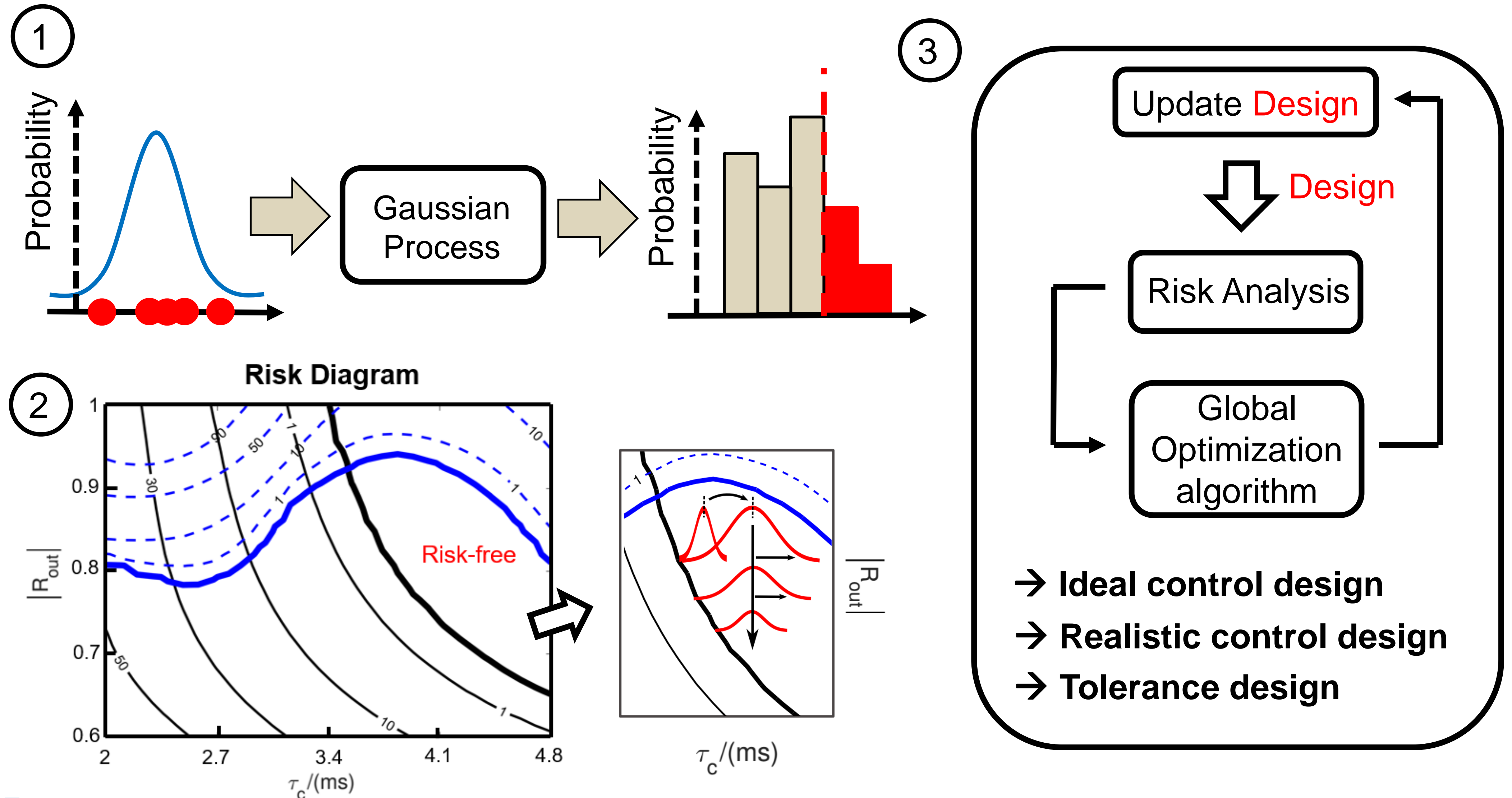
$$|R_{out}| \sim \mathcal{U}(R_L, 0.9)$$

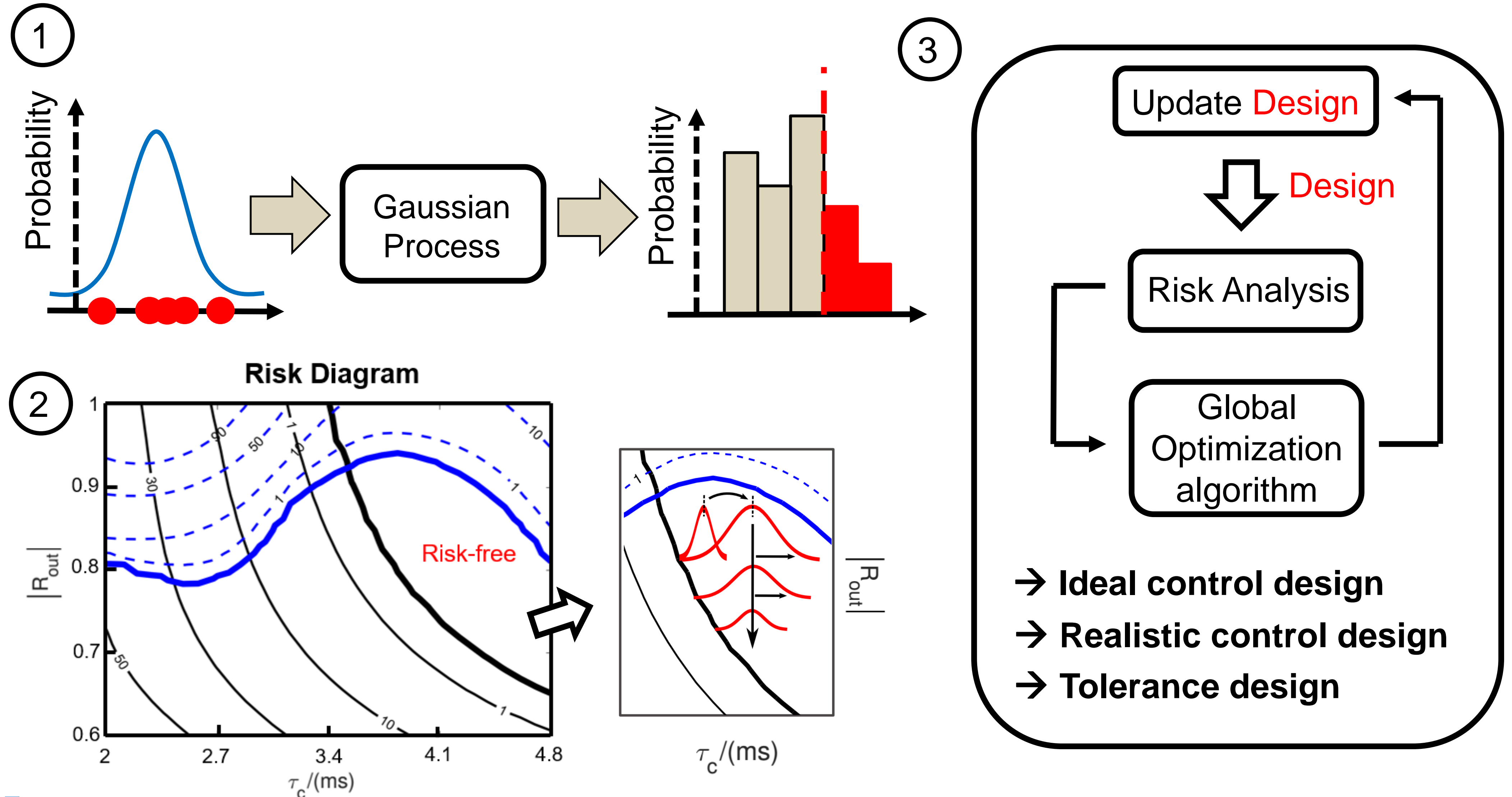


Risk diagram illustrates the trade-off between uncertainties of τ_c and R_{out}



Conclusions





Back-up: GP model training process

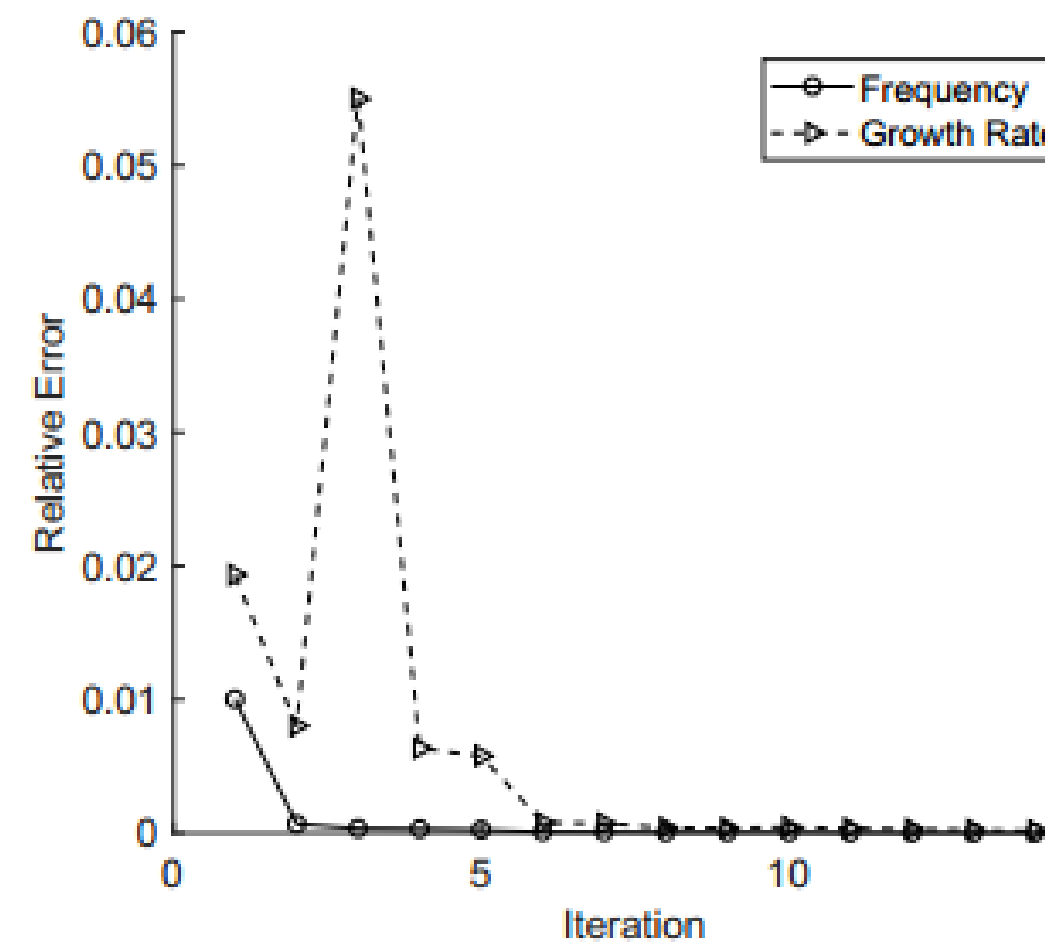
Leave-one-out cross validation

$$GE = \frac{1}{N} \sum_{i=1}^N (f_i - \hat{f}_i^{(-i)})^2$$

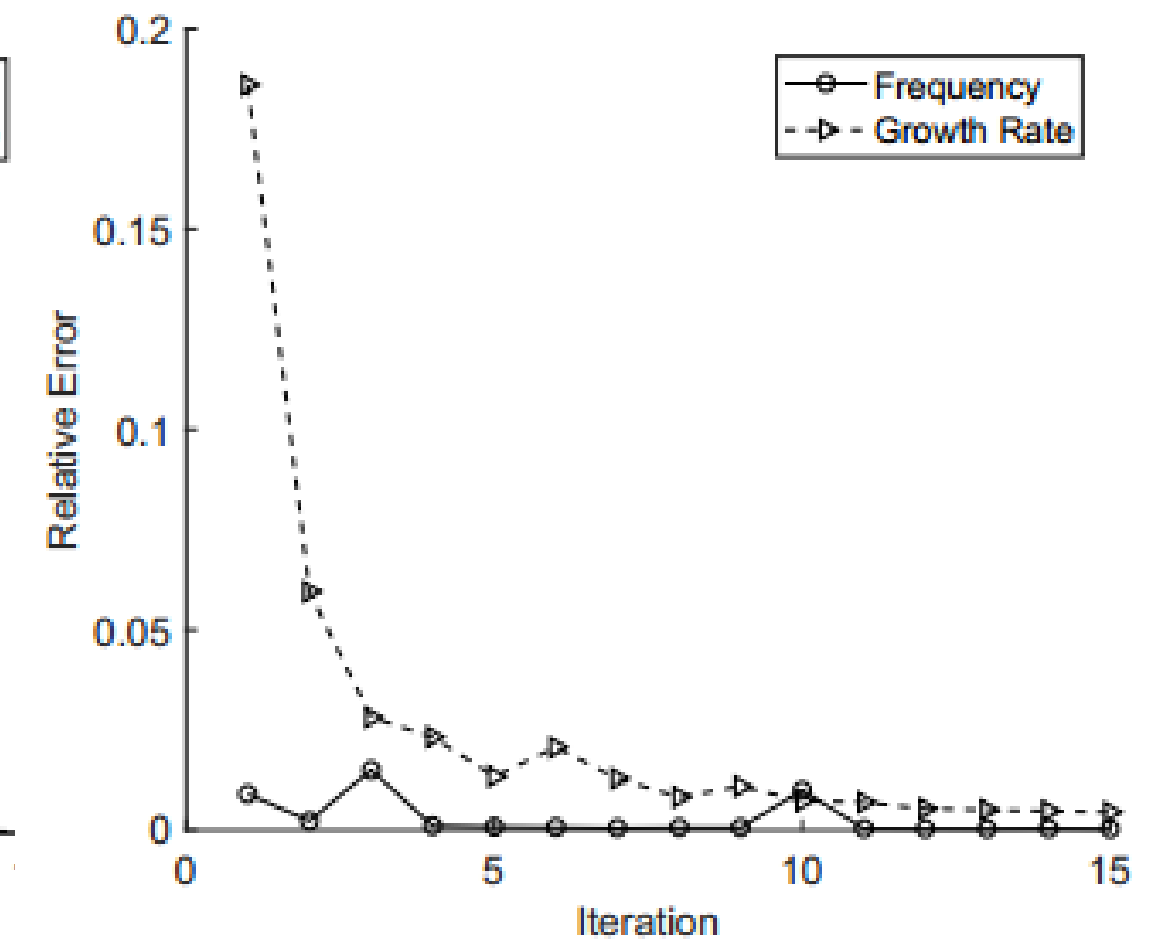
N Total number of training samples

f_i the known response of the training sample \mathbf{x}^i

$\hat{f}_i^{(-i)}$ the prediction at \mathbf{x}^i using the GP model constructed upon all training samples except (\mathbf{x}^i, f_i)



(a) ITA mode



(b) cavity mode

Back-up: time costs

Laptop PC, CPU 2.30GHz

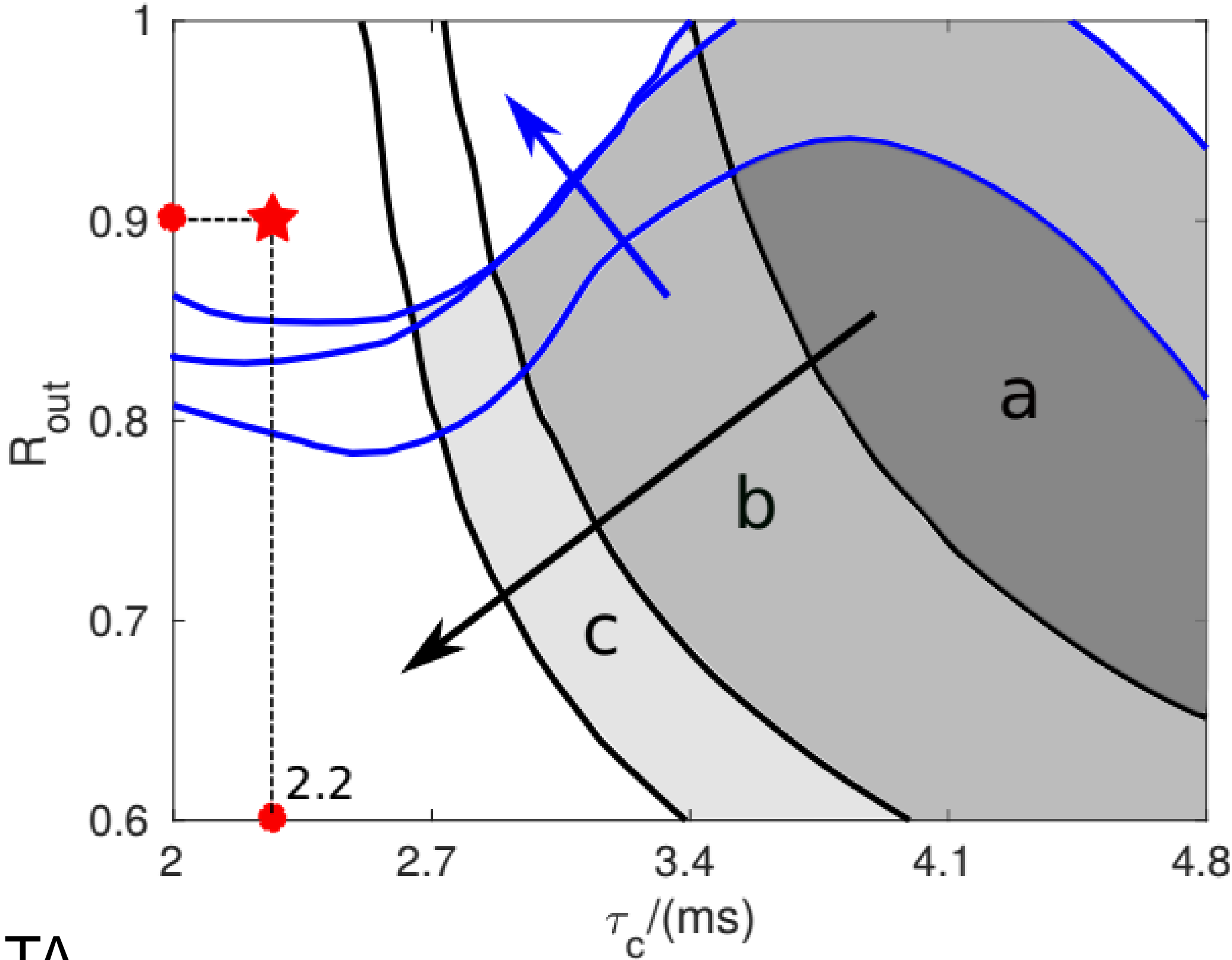
GP model training: 93s

Risk analysis (MC on acoustic solver): 271s

Risk analysis (MC on GP model): 1.3s

Back-up: Sensitivity analysis

Parameters	Case A	Case B	Case C
τ_1	$\mathcal{U}(0.9\tau_1^0, 1.1\tau_1^0)$	$\mathcal{N}(\tau_1^0, (0.03\tau_1^0)^2)$	$\mathcal{N}(\mathbf{M}, \mathbf{C})$
σ_1	$\mathcal{U}(0.9\sigma_1^0, 1.1\sigma_1^0)$	$\mathcal{N}(\sigma_1^0, (0.03\sigma_1^0)^2)$	
τ_{s1}	$\mathcal{U}(0.9\tau_{s1}^0, 1.1\tau_{s1}^0)$	$\mathcal{N}(\tau_{s1}^0, (0.03\tau_{s1}^0)^2)$	
τ_{s2}	$\mathcal{U}(0.9\tau_{s2}^0, 1.1\tau_{s2}^0)$	$\mathcal{N}(\tau_{s2}^0, (0.03\tau_{s2}^0)^2)$	



— ITA
— CAV

Back-up: take into account both parametric uncertainty and GP model uncertainty

Posterior

$$f^*(x) \sim \mathcal{GP}(m^*(x), k^*(x, x'))$$

