

# System-Level Analysis and Design under Uncertainty

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December 15, 2017

# Introduction

# Electronic Systems

- Omniscient
- Omnipresent

# Analysis and Design

- Challenging
- Consequential

# Uncertainty

- Lack of knowledge
- Inherent randomness



# Fabrication

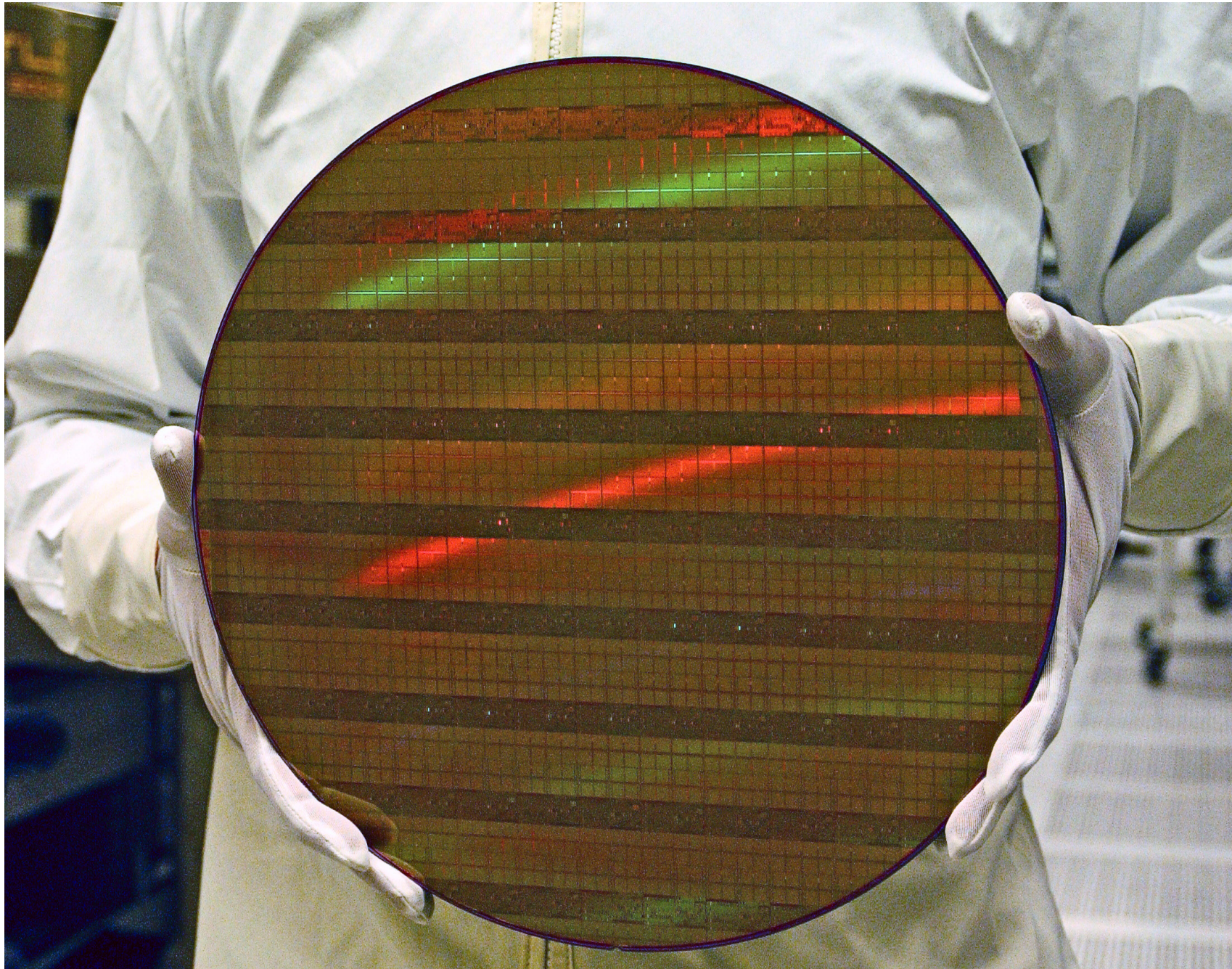
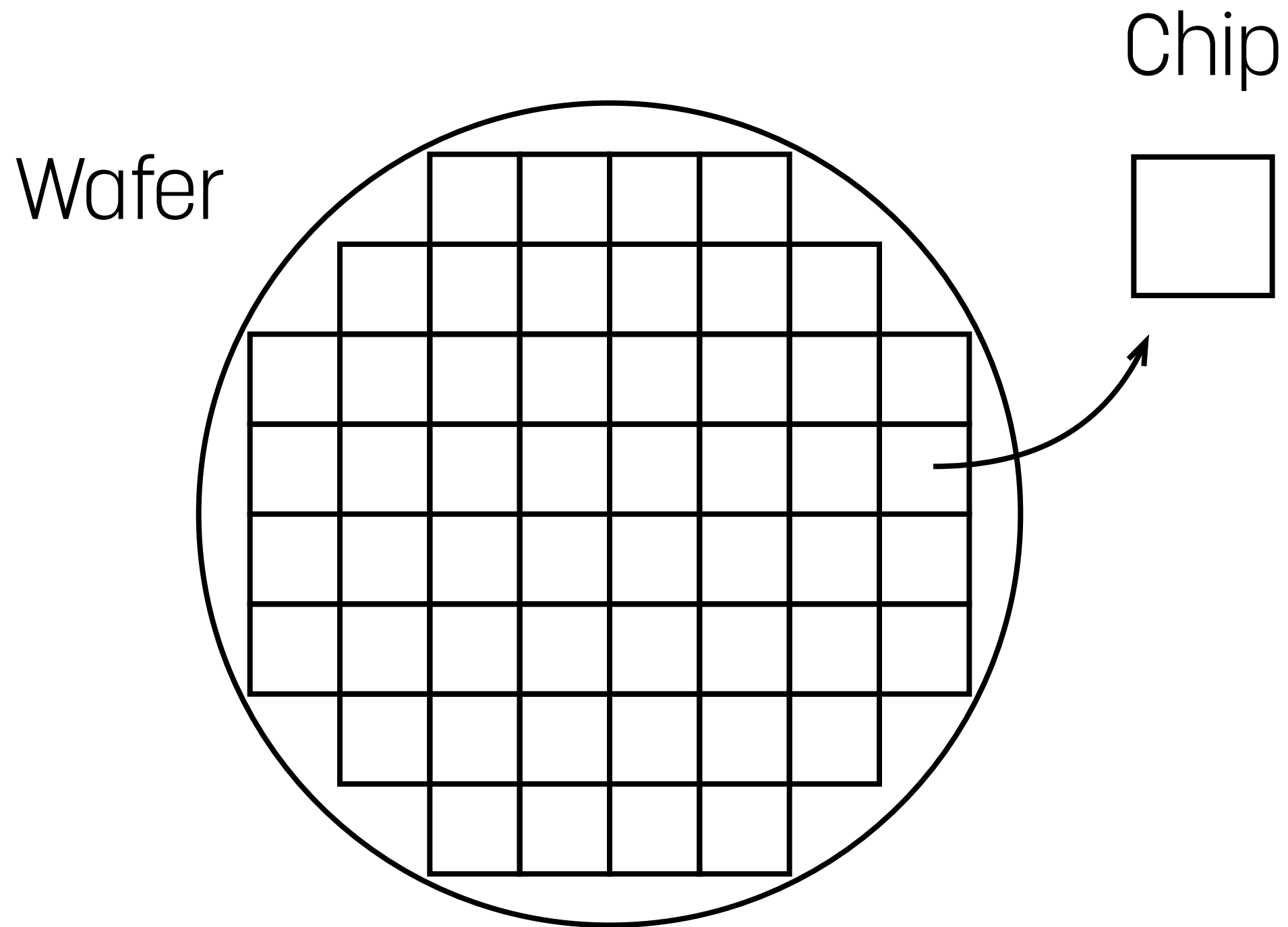


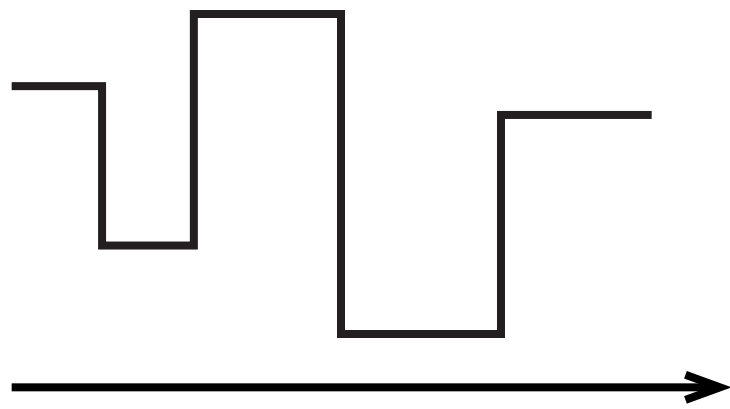
Photo: Intel, <https://goo.gl/mHMxe1>



# Fabrication

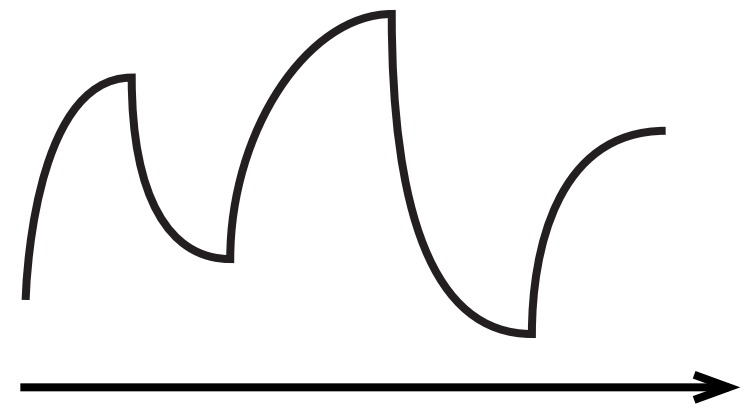
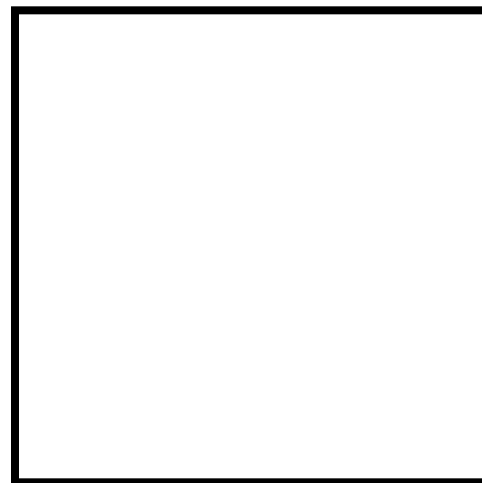


# No Variation



Certain

Certain

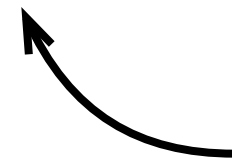
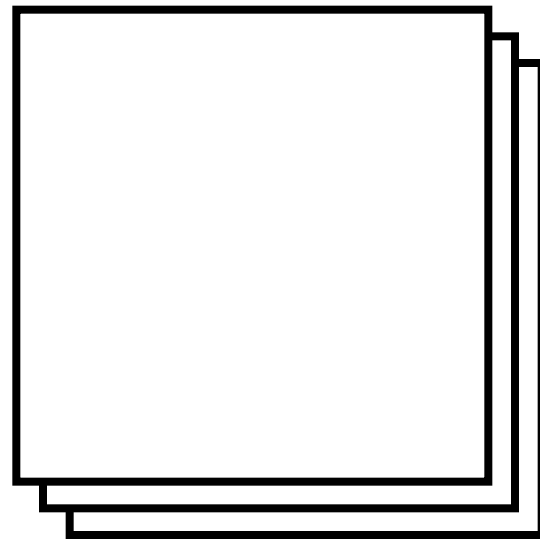


Certain



# Process Variation

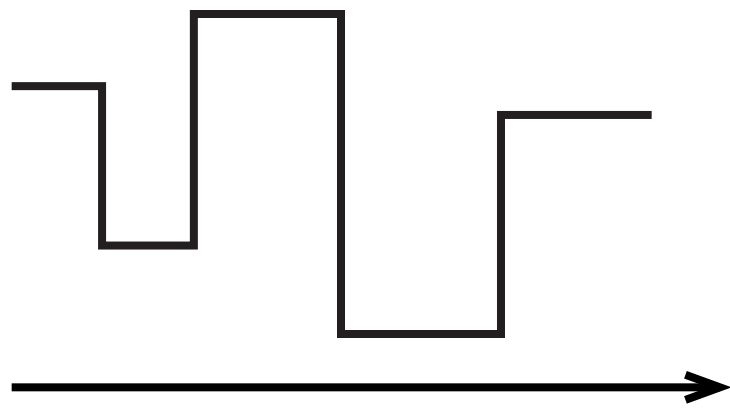
Uncertain



Which one?

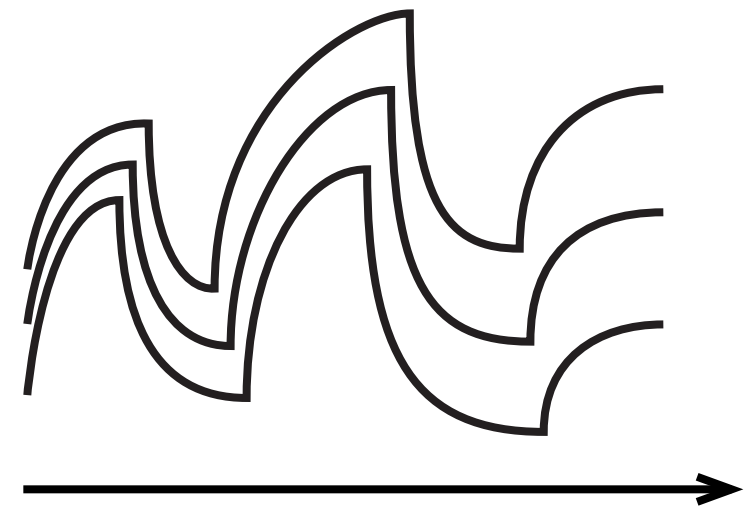
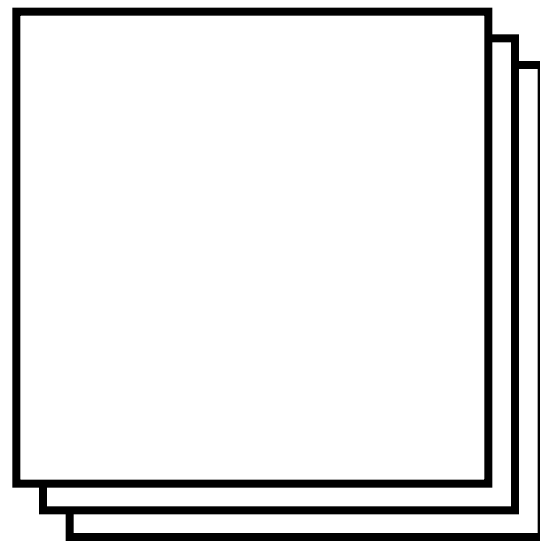
# Process Variation

Which one?



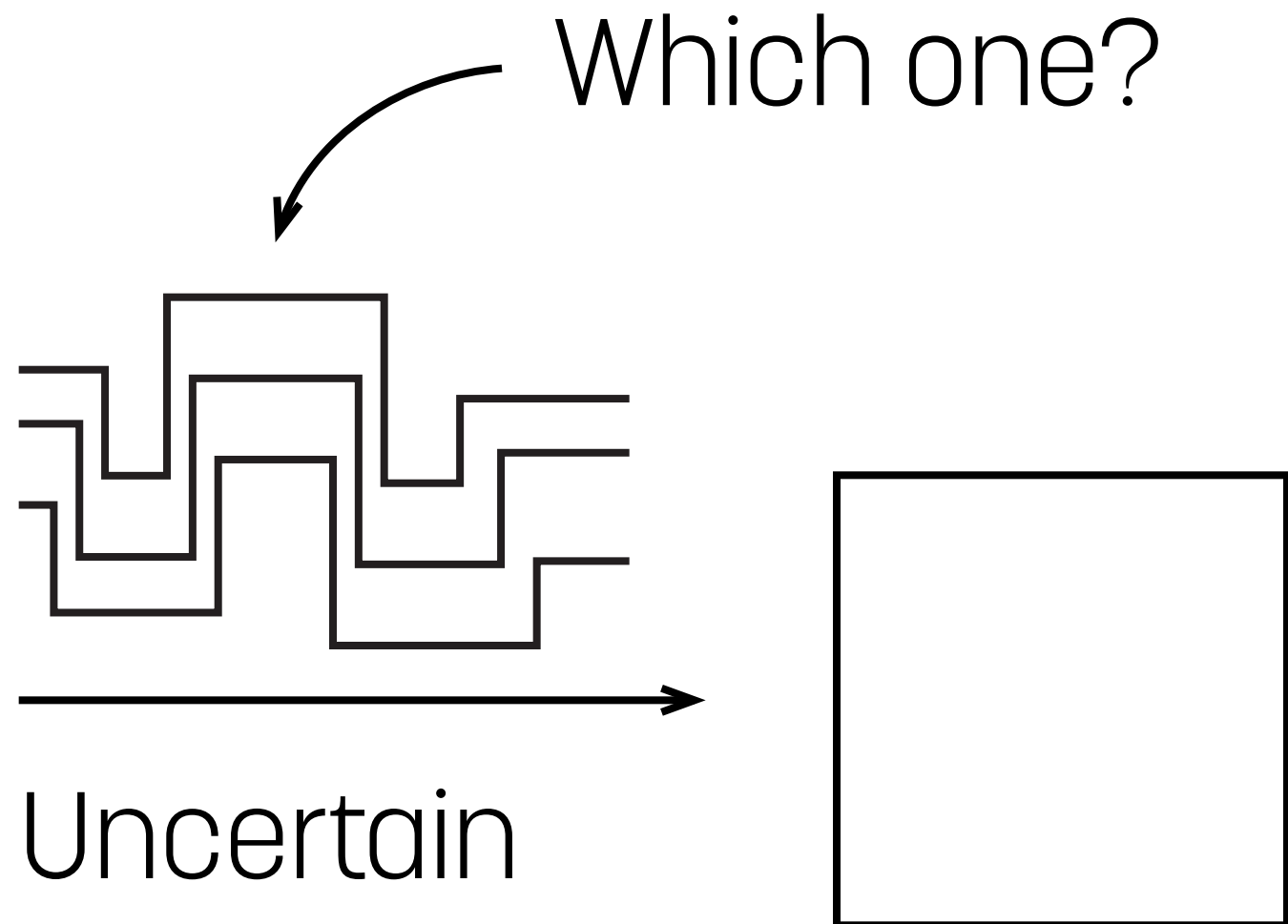
Certain

Uncertain



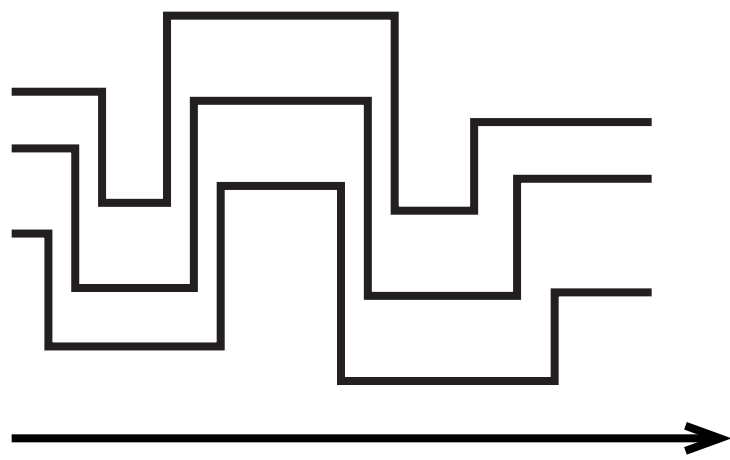
Uncertain

# Workload Variation



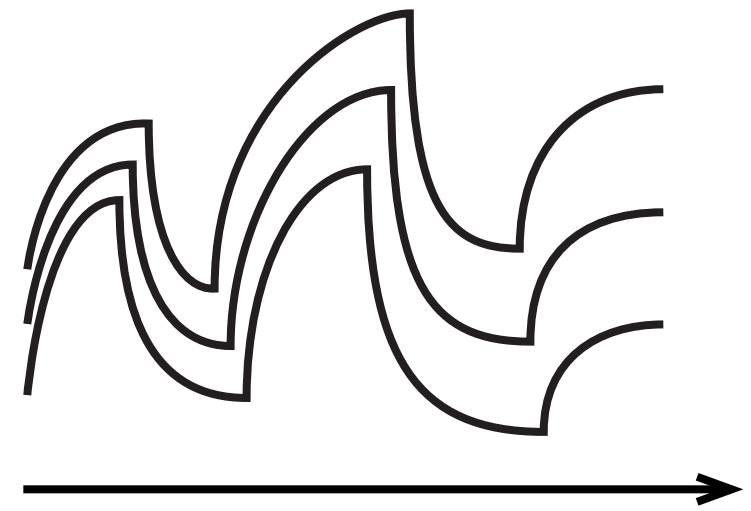
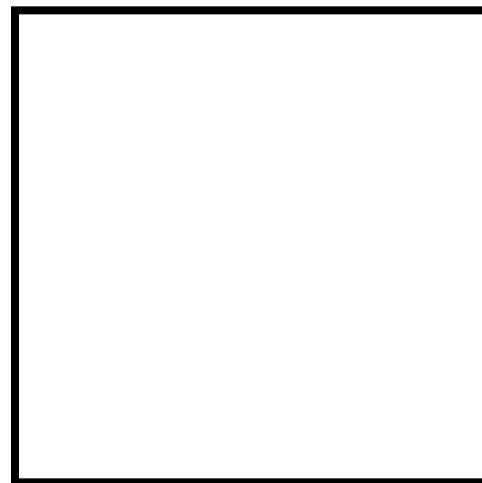
# Workload Variation

Which one?



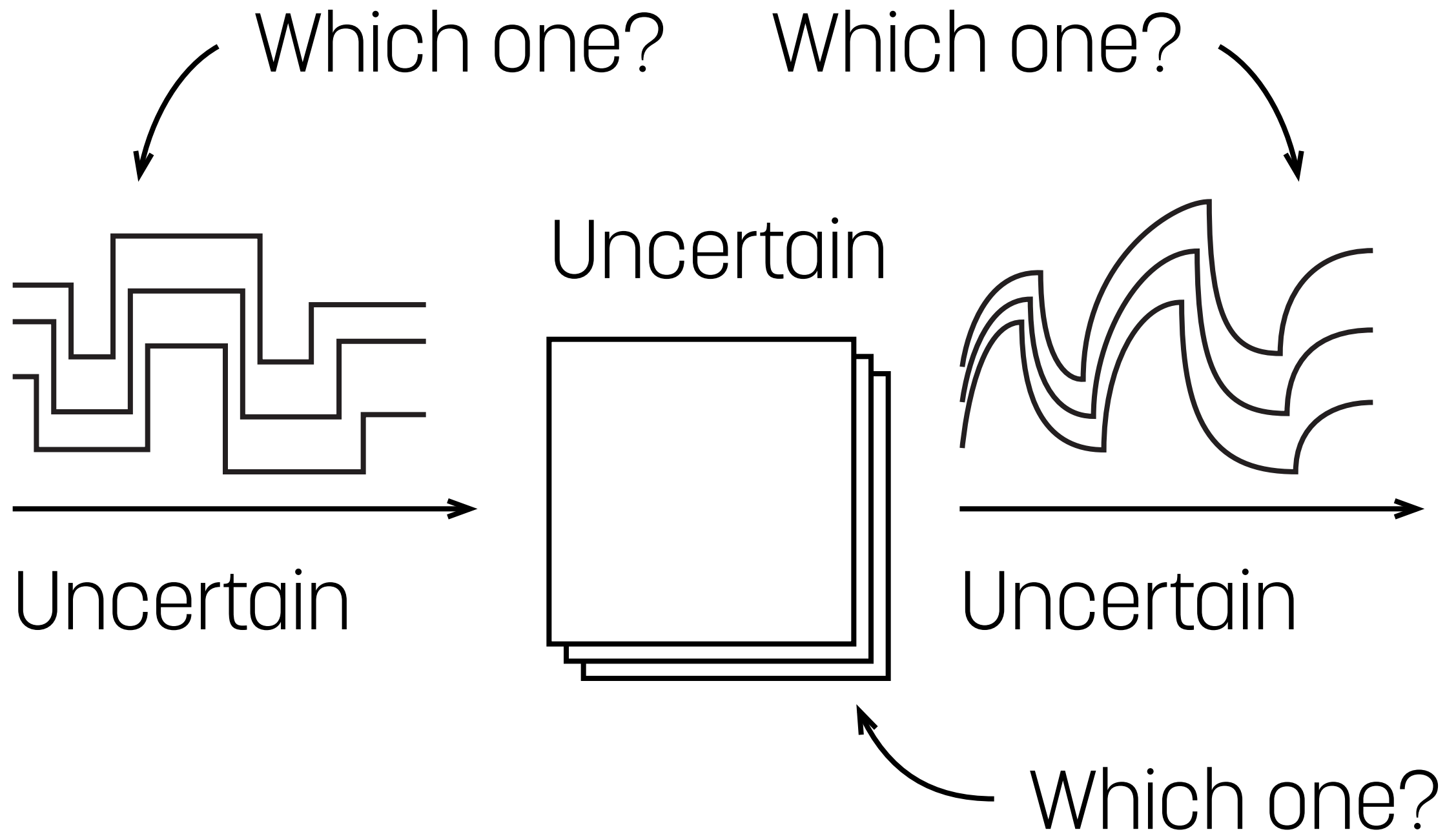
Uncertain

Certain



Uncertain

# Analysis and Design



# Motivation

- Uncertainty
  - Inevitable
  - Deleterious



# Objective

- Provide the designer with effective and efficient techniques for analysis and design under uncertainty

# Outline

1. Analysis and Design with Certainty
2. Characterization of Process Variation
3. Analysis and Design under Process Variation
4. Analysis under Workload Variation
5. Resource Management under Workload Variation

# Analysis and Design with Certainty

# Power and Temperature

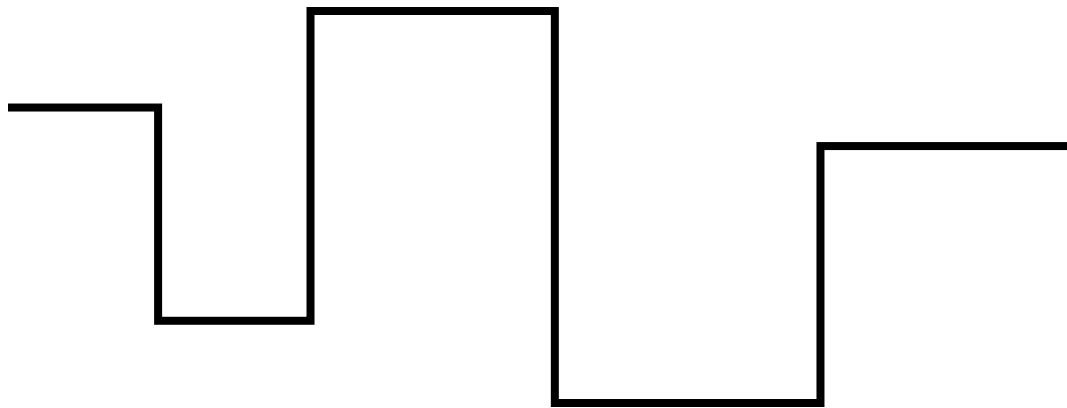
- Highly important
  - Energy efficiency
  - Reliability

# Temperature Analysis

- Transient state
- Dynamic steady state

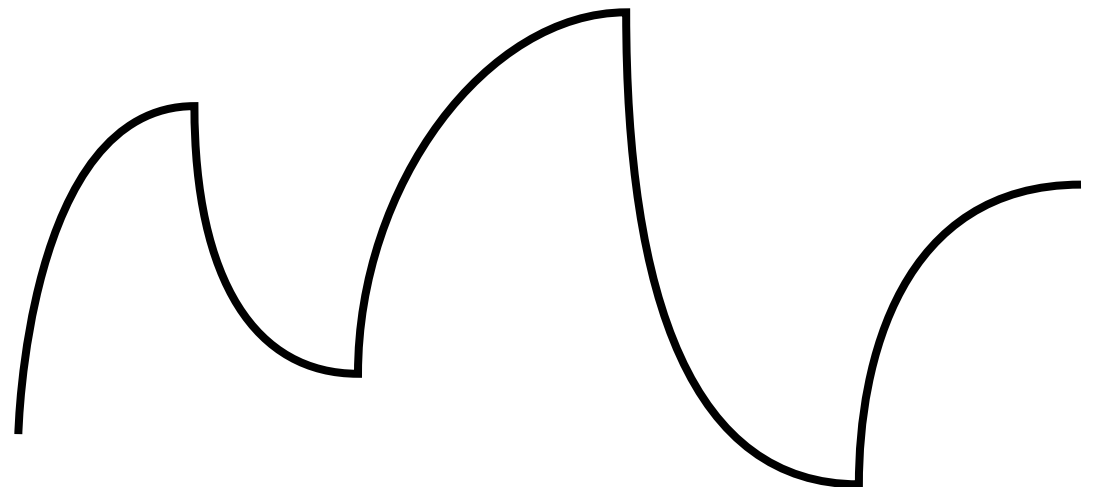
# Transient State

Power



$P$

Temperature

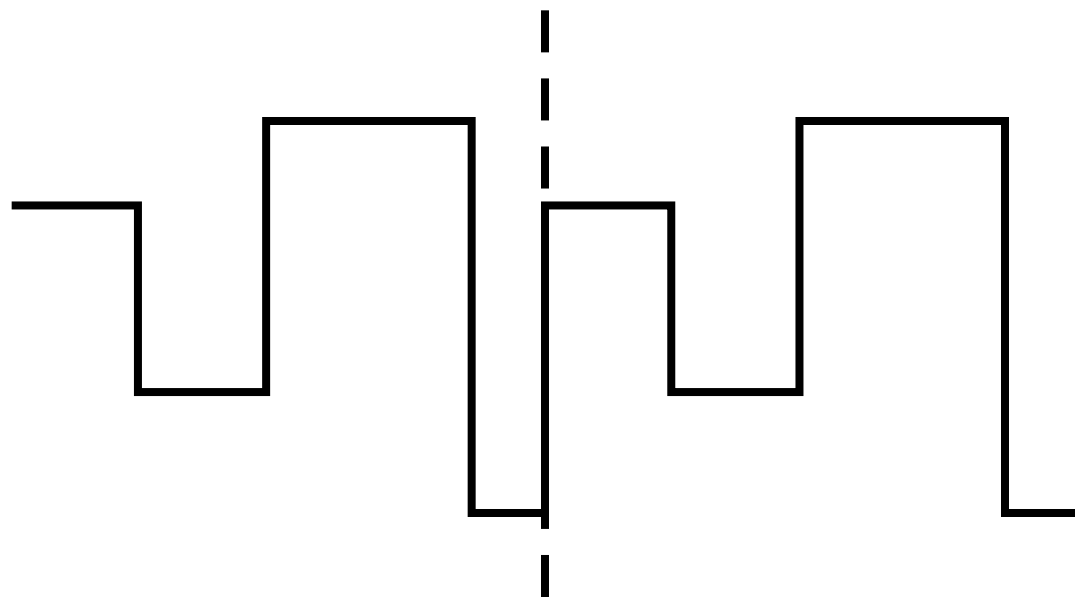


$Q$



# Dynamic Steady State

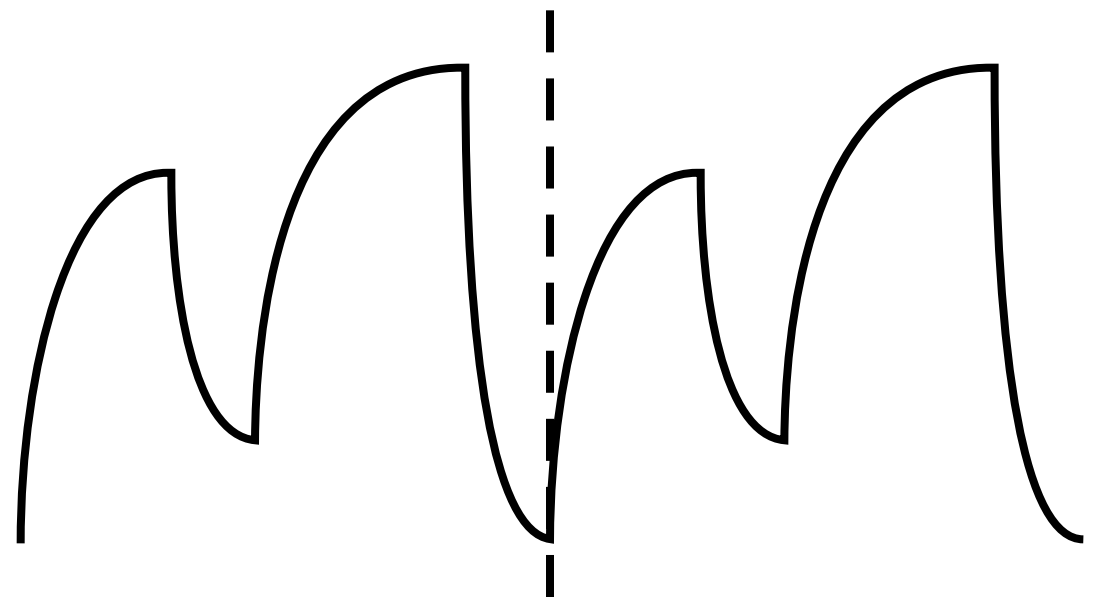
Power



P

P

Temperature



Q

Q

# Problem Formulation

- Given a periodic power profile  $P$
- Compute the corresponding dynamic steady-state temperature profile  $Q$

# Previous Work

- Slow
- Inaccurate

# Proposed Solution

- Fast
- Exact

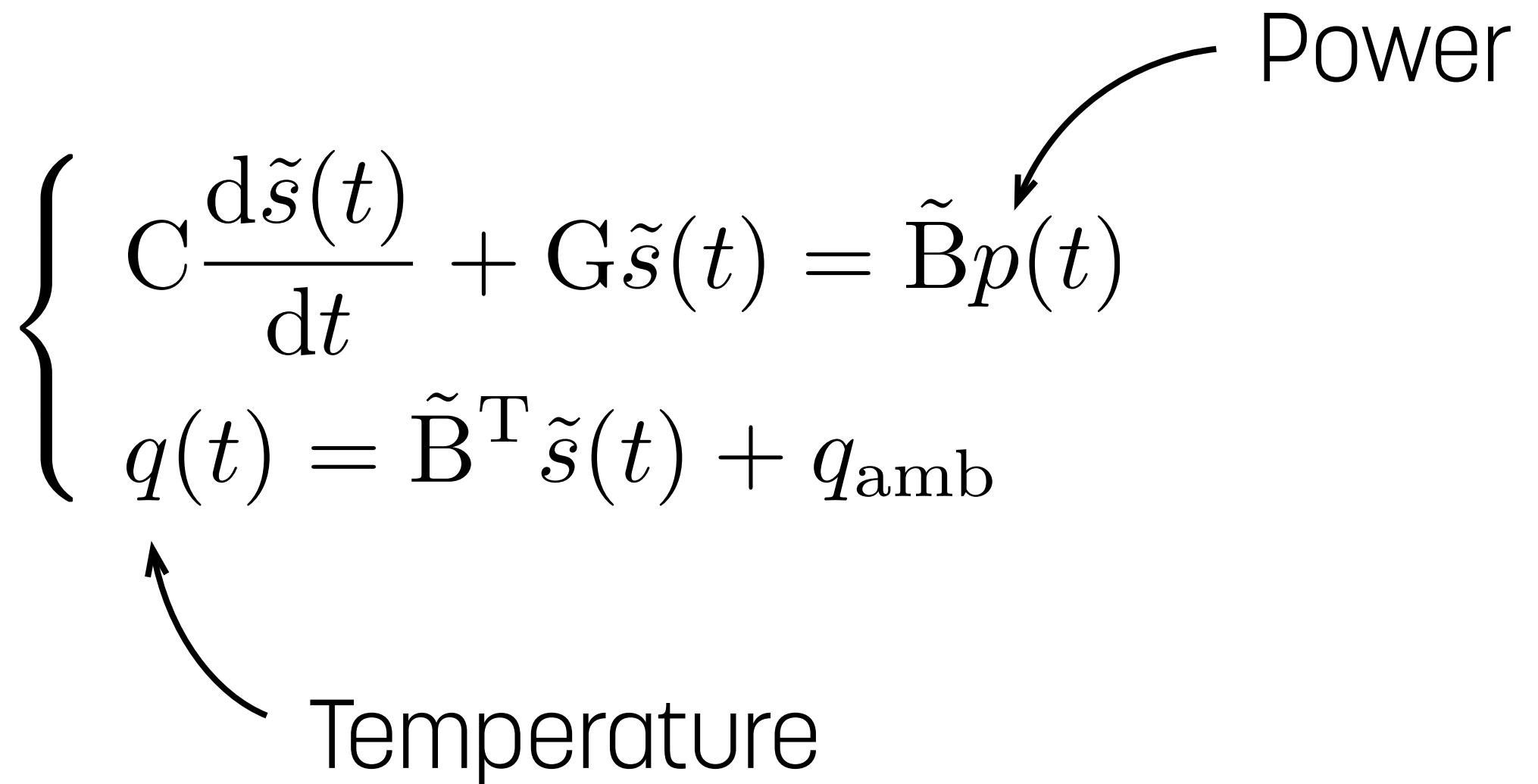
# Solution Overview

Thermal RC model

$$\begin{cases} C \frac{d\tilde{s}(t)}{dt} + G\tilde{s}(t) = \tilde{B}p(t) \\ q(t) = \tilde{B}^T \tilde{s}(t) + q_{\text{amb}} \end{cases}$$

Power

Temperature



# Solution Overview

Auxiliary transformation

$$s(t) = C^{\frac{1}{2}} \tilde{s}(t)$$

$$A = -C^{-\frac{1}{2}} G C^{-\frac{1}{2}}$$

$$B = C^{-\frac{1}{2}} \tilde{B}$$

$$\begin{cases} \frac{ds(t)}{dt} = As(t) + Bp(t) \\ q(t) = B^T s(t) + q_{\text{amb}} \end{cases}$$



# Solution Overview

Dynamic steady state

$$s_0 = s_{n_s}$$

$$w_0 = 0$$

$$w_i = Ew_{i-1} + Fp_i$$

$$s_0 = U(I - e^{\Lambda\tau})^{-1}U^T w_{n_s}$$

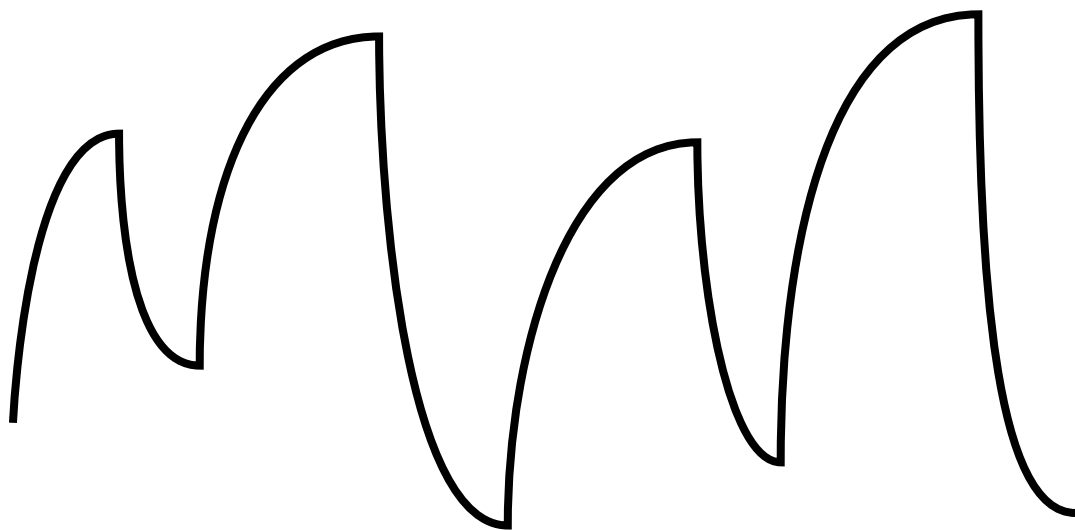
$$s_i = Es_{i-1} + Fp_i$$

# Experimental Results

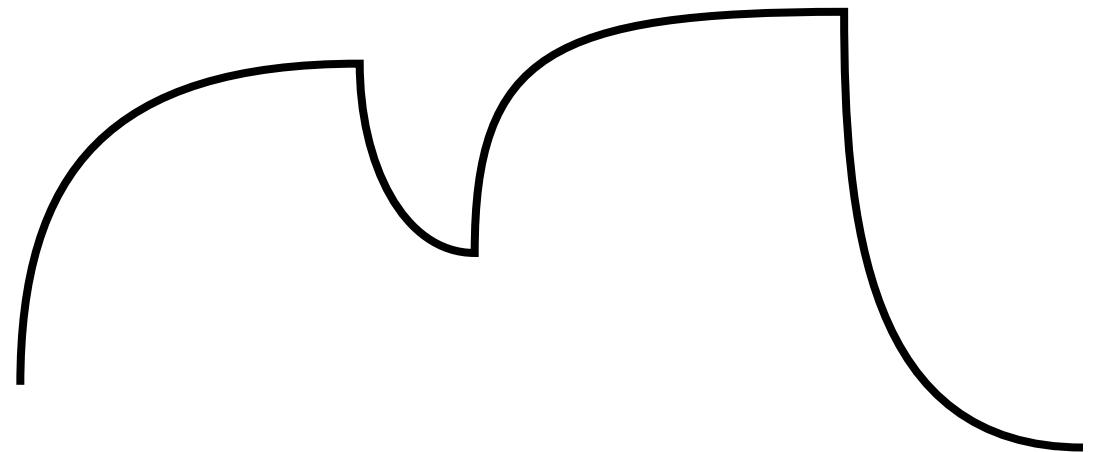
- Considered diverse scenarios
- Shown high computational speed
  - 9–170 times faster than analytical iterative transient analysis
  - 2000–5000 times faster than iterative analysis with HotSpot

# Thermal Cycling

More damage



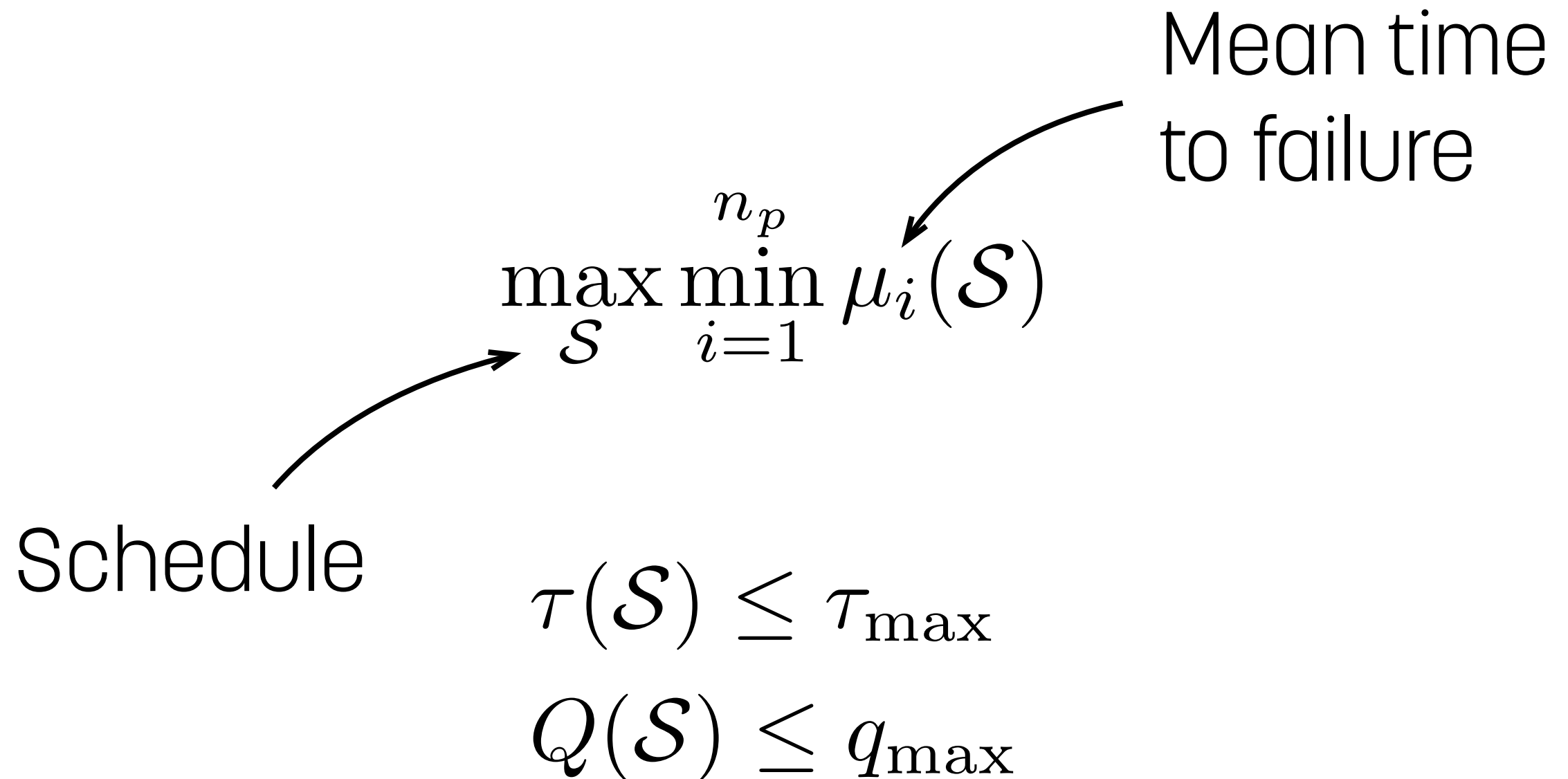
Less damage



# Reliability Optimization

- Vary the application's schedule
- Maximize the system's lifetime
- Satisfy a number of constraints

# Reliability Optimization



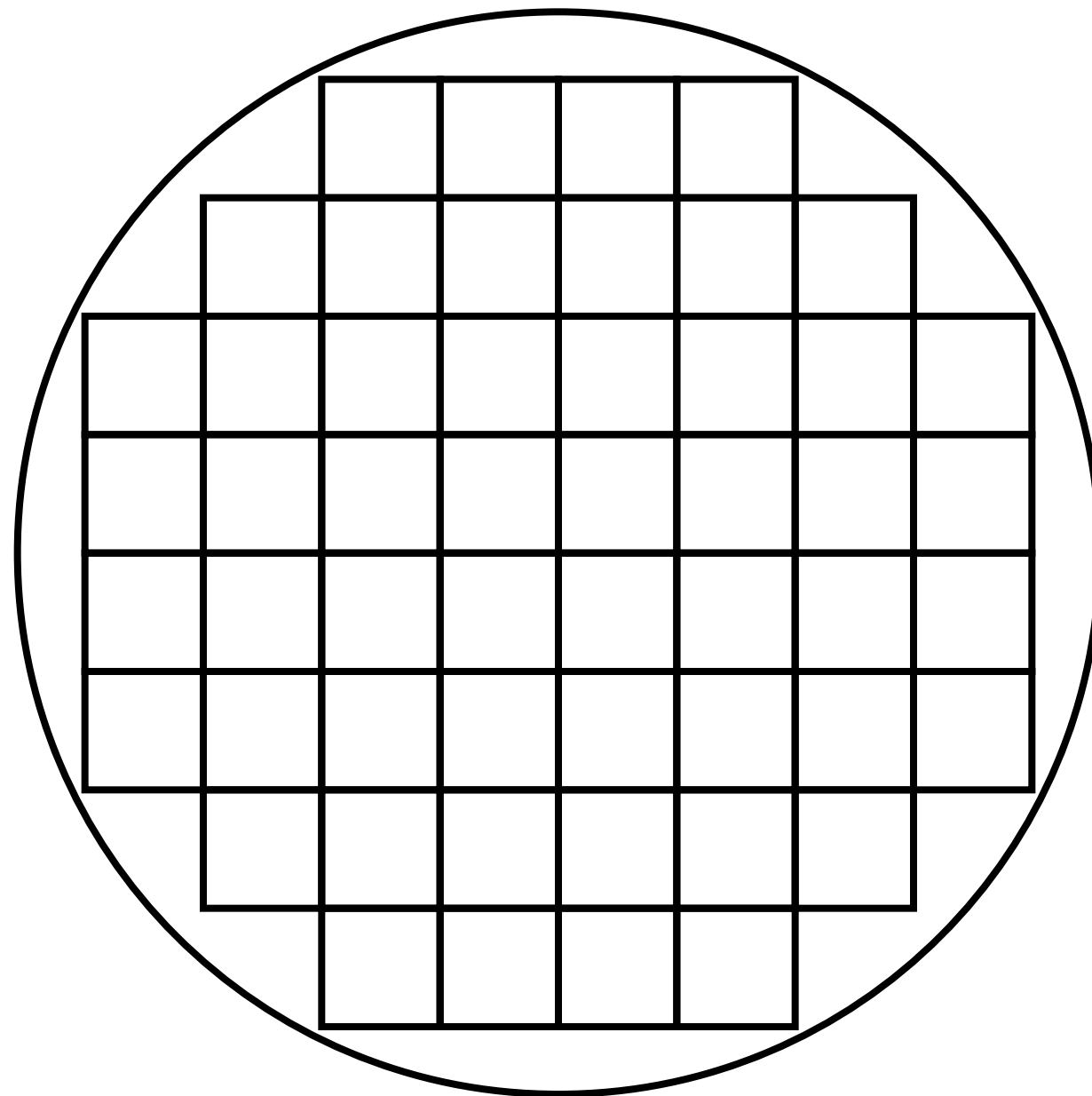
# Experimental Results

- Applied to a large set of synthetic problems and to a real-life problem
- Increased the mean time to failure by a factor of 10–70
- Maintained energy efficiency



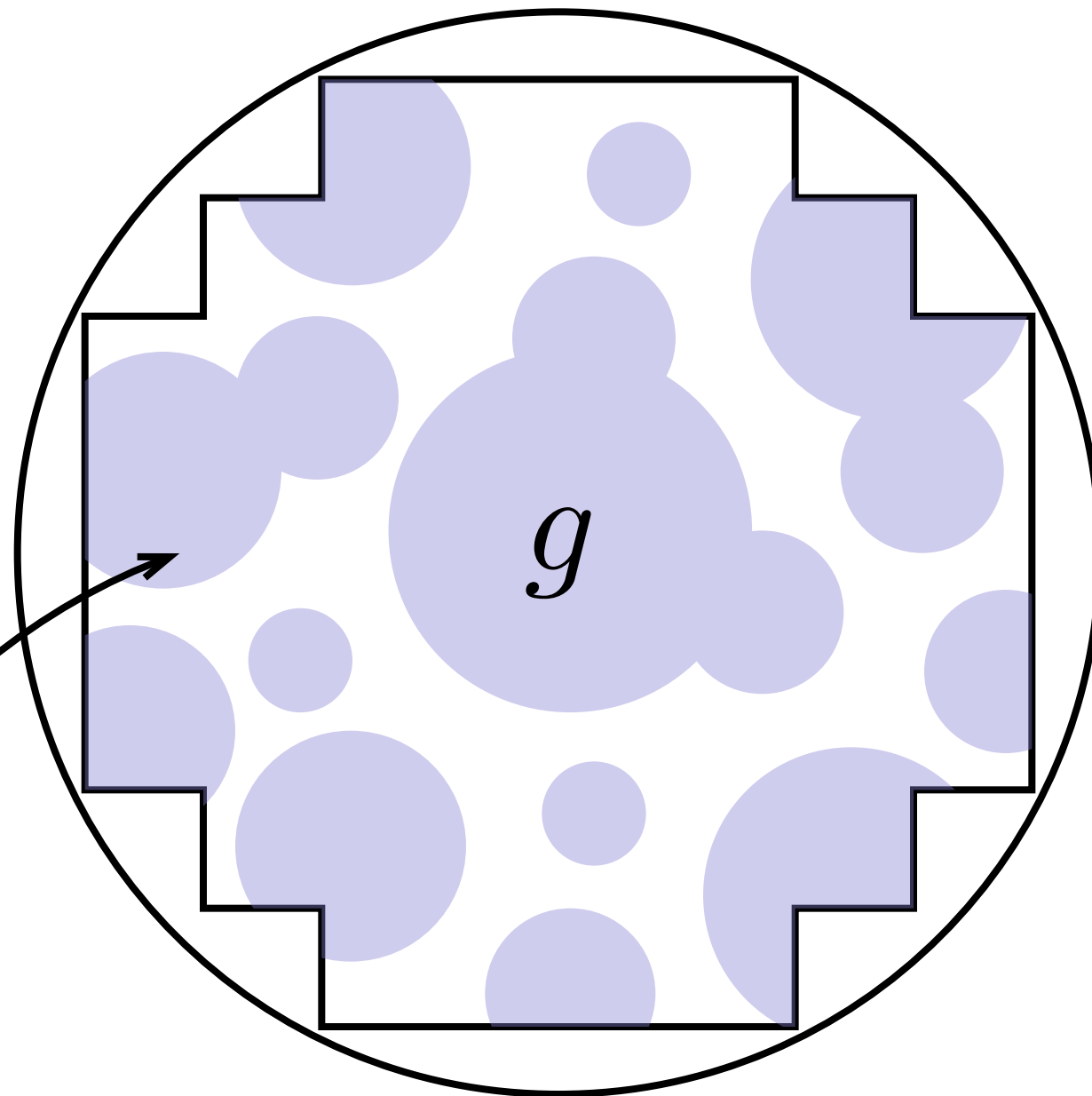
# Characterization of Process Variation

# Fabrication



# Quantity of Interest

Uncertain



Different  
everywhere

# Problem Formulation

- Given the knowledge of the technological process at hand
- Quantify the process parameter  $g$  at all locations on the wafer

# Previous Work

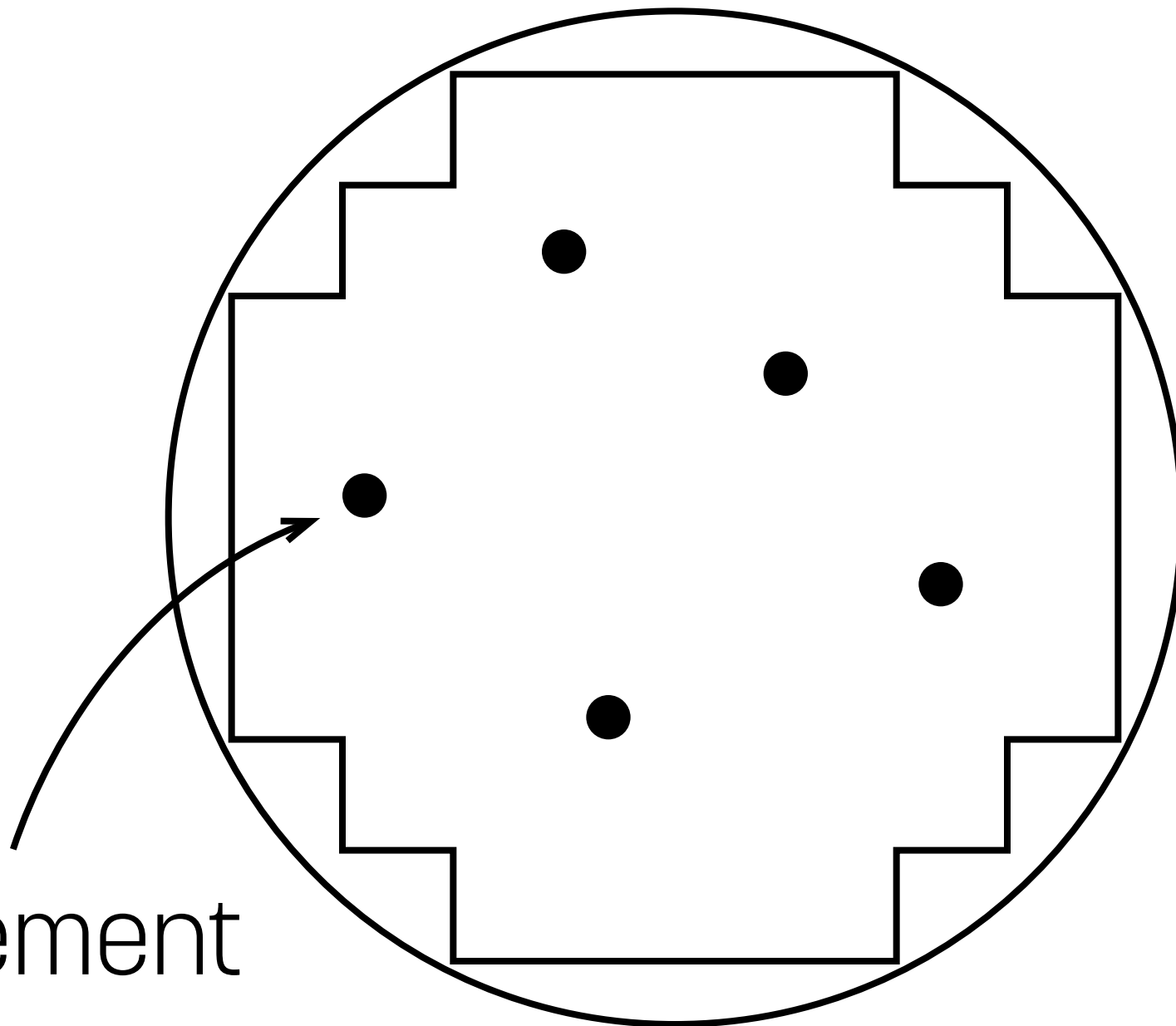
- Intrusive
- Secondary parameters

# Proposed Solution

- Non-intrusive
- Primary parameters

# Solution Overview

$$h = f(g)$$



Measurement

# Solution Overview

$$g|u \sim \text{Gaussian Process}(\mu, v)$$

$$\epsilon|u \sim \text{Gaussian}(0, \sigma_\epsilon^2)$$

Noise



Bayes' theorem

$$p(u|H) \propto p(H|u)p(u)$$



# Solution Overview

Metropolis-Hastings algorithm

$$u \sim t_{n_u} (u^*, \alpha^2 J^{-1})$$

Posterior optimization

$$u^* = \arg \max_u p(u|H)$$

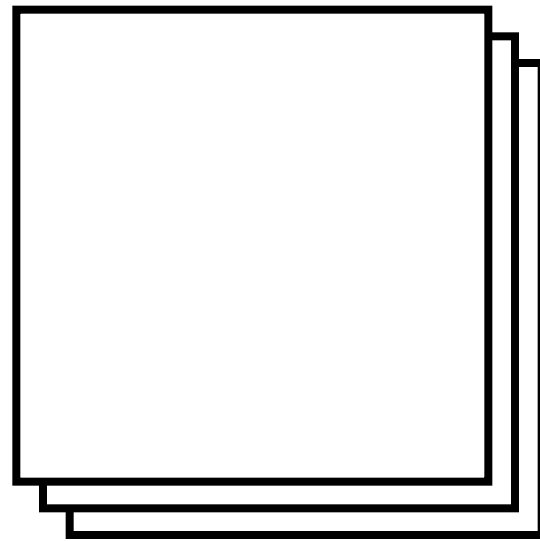
# Experimental Results

- Inferred the effective channel length from temperature measurements
- Considered diverse configurations
- Shown high accuracy and speed
  - Less than 5% of error
  - Less than 20 minutes

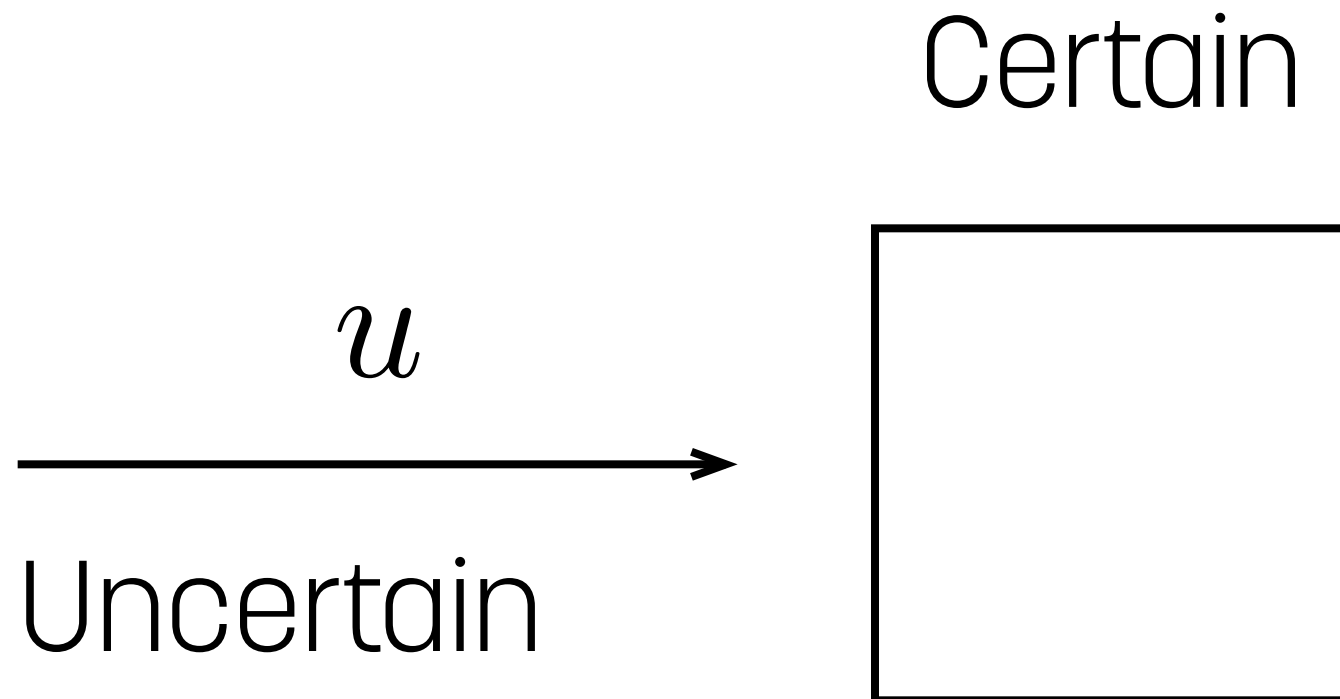
# Analysis and Design under Process Variation

# Process Variation

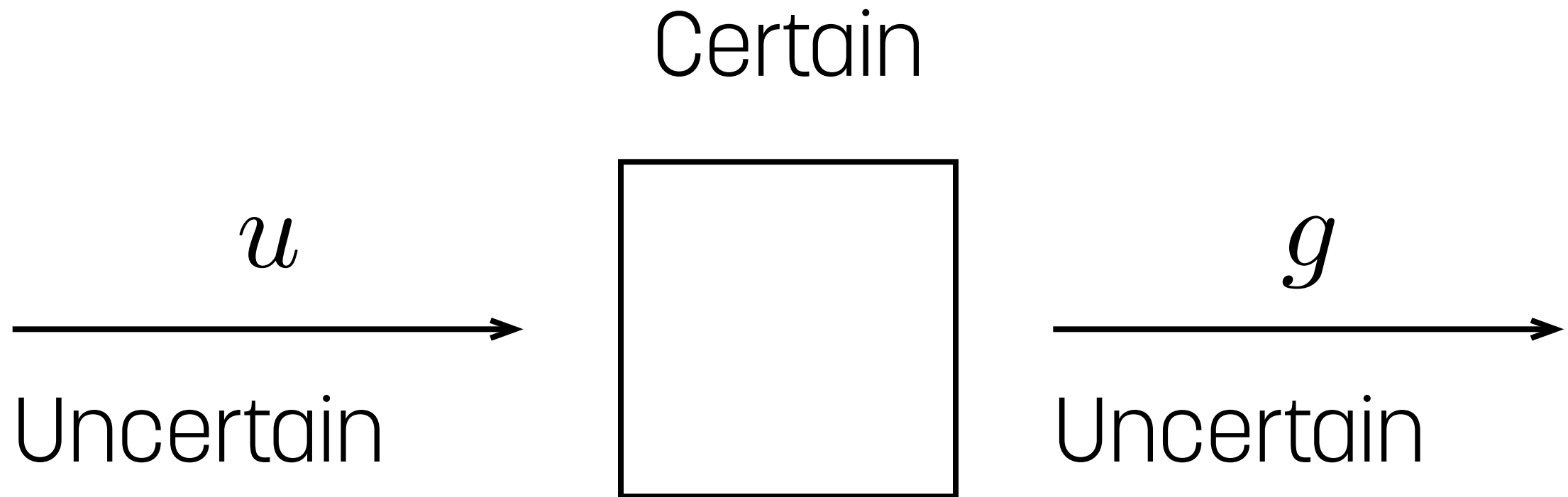
Uncertain



# Uncertain Parameters



# Quantity of Interest



# Problem Formulation

- Given the probability distribution of the uncertain parameters  $u$
- Compute the probability distribution of the quantity of interest  $g$

# Previous Work

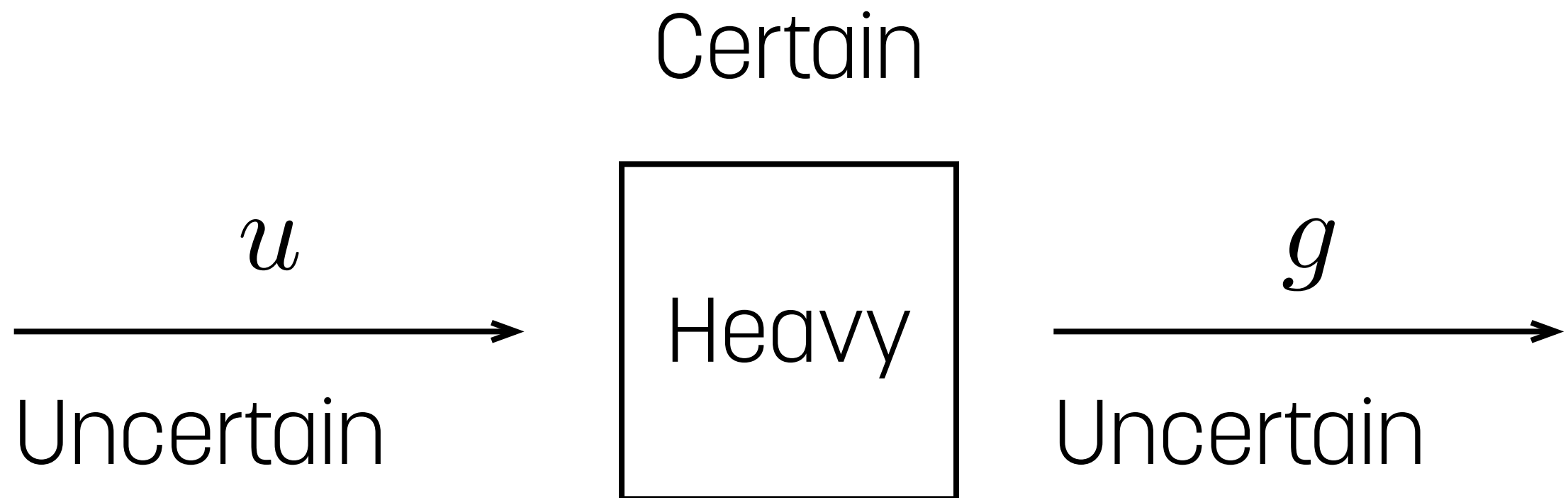
- Limited to specific quantities
- Unrealistic assumptions



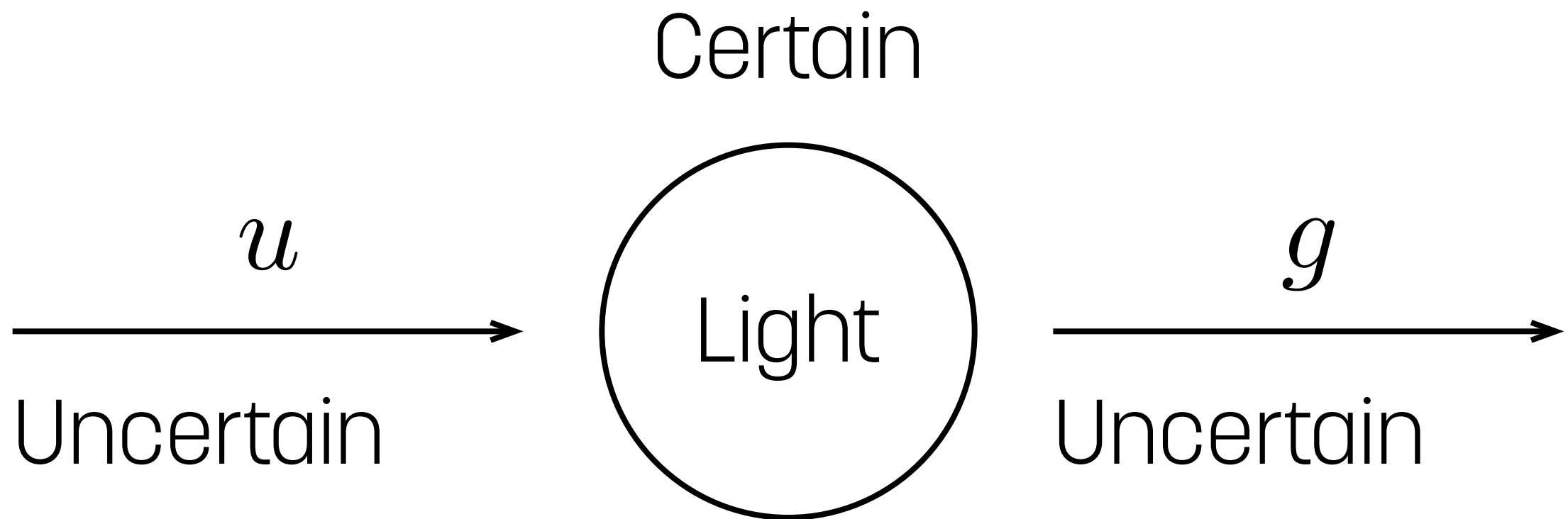
# Proposed Solution

- General
- Efficient
- Easy to apply

# Solution Overview



# Solution Overview



# Solution Overview

$$u = \mathbb{T}(z)$$

$u : \Omega \rightarrow \mathbb{R}^{n_u}$       Many dependent

$z : \Omega \rightarrow \mathbb{R}^{n_z}$       A few independent

$$g(u) = (g \circ \mathbb{T})(z) = g(\mathbb{T}(z))$$

# Solution Overview

Polynomial chaos

$$g \approx \mathcal{C}_{l_c}^{n_z}(g) = \sum_{i \in \mathcal{I}_{l_c}^{n_z}} \hat{g}_i \psi_i$$

Polynomial



Spectral projection

$$\hat{g}_i \approx \mathcal{Q}_{l_q}^{n_z}(g \psi_i) = \sum_{j \in \mathcal{J}_{l_q}^{n_z}} (g \circ \mathbb{T})(z_j) \psi_i(z_j) w_j$$

Coefficient



# Temperature Analysis

- Account for process variation
  - Transient state
  - Dynamic steady state

# Experimental Results

- Compared with extensive simulations
- Shown high accuracy and speed
  - Less than 2% of error
  - 3-5 orders of magnitude faster than direct sampling

# Reliability Analysis

- Account for process variation



# Energy Optimization

- Vary the application's schedule
- Minimize the system's energy
- Satisfy a number of constraints

# Energy Optimization

Energy

$$\min_{\mathcal{S}} \mathbb{E} (E(\mathcal{S}))$$

$$\tau(\mathcal{S}) \leq \tau_{\max}$$

$$\mathbb{P} (Q(\mathcal{S}) \geq q_{\max}) \leq \rho_{\text{burn}}$$

$$\mathbb{P} (\mathbb{E} (L(\mathcal{S})) \leq L_{\min}) \leq \rho_{\text{wear}}$$

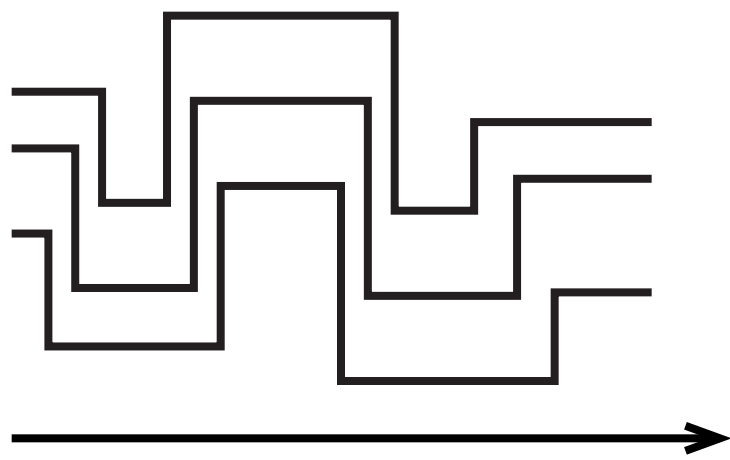
Lifetime

# Experimental Results

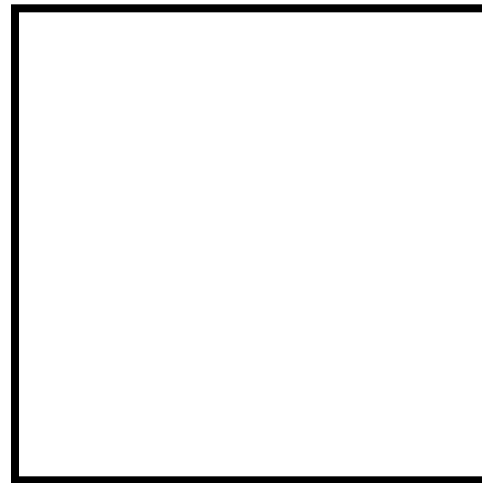
- Demonstrated the importance of accounting for process variation
- Up to 100% of solutions that ignore uncertainty might be unacceptable

# Analysis under Workload Variation

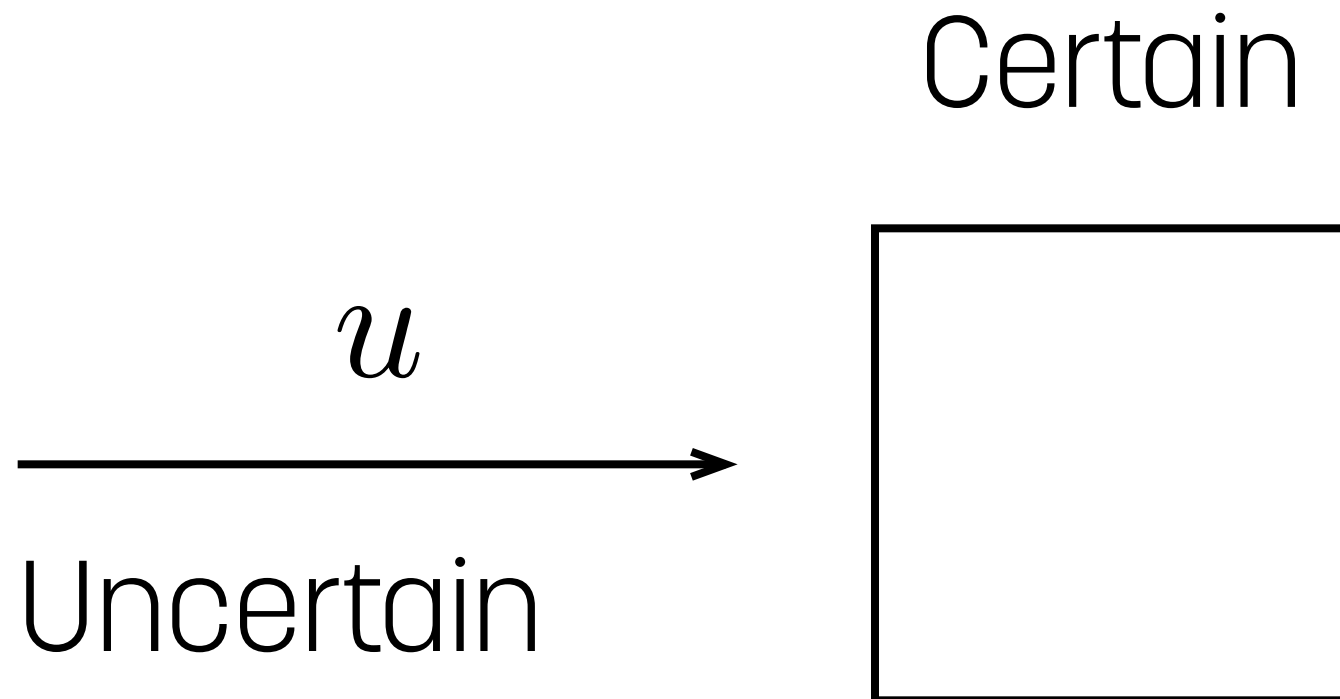
# Workload Variation



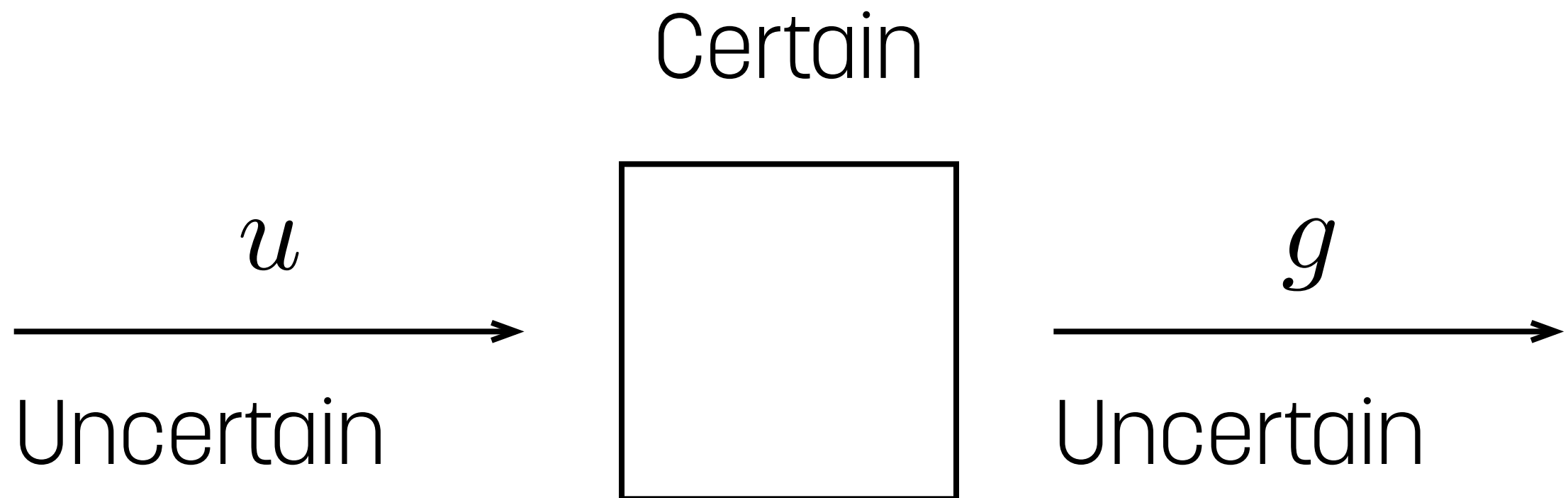
Uncertain



# Uncertain Parameters



# Quantity of Interest



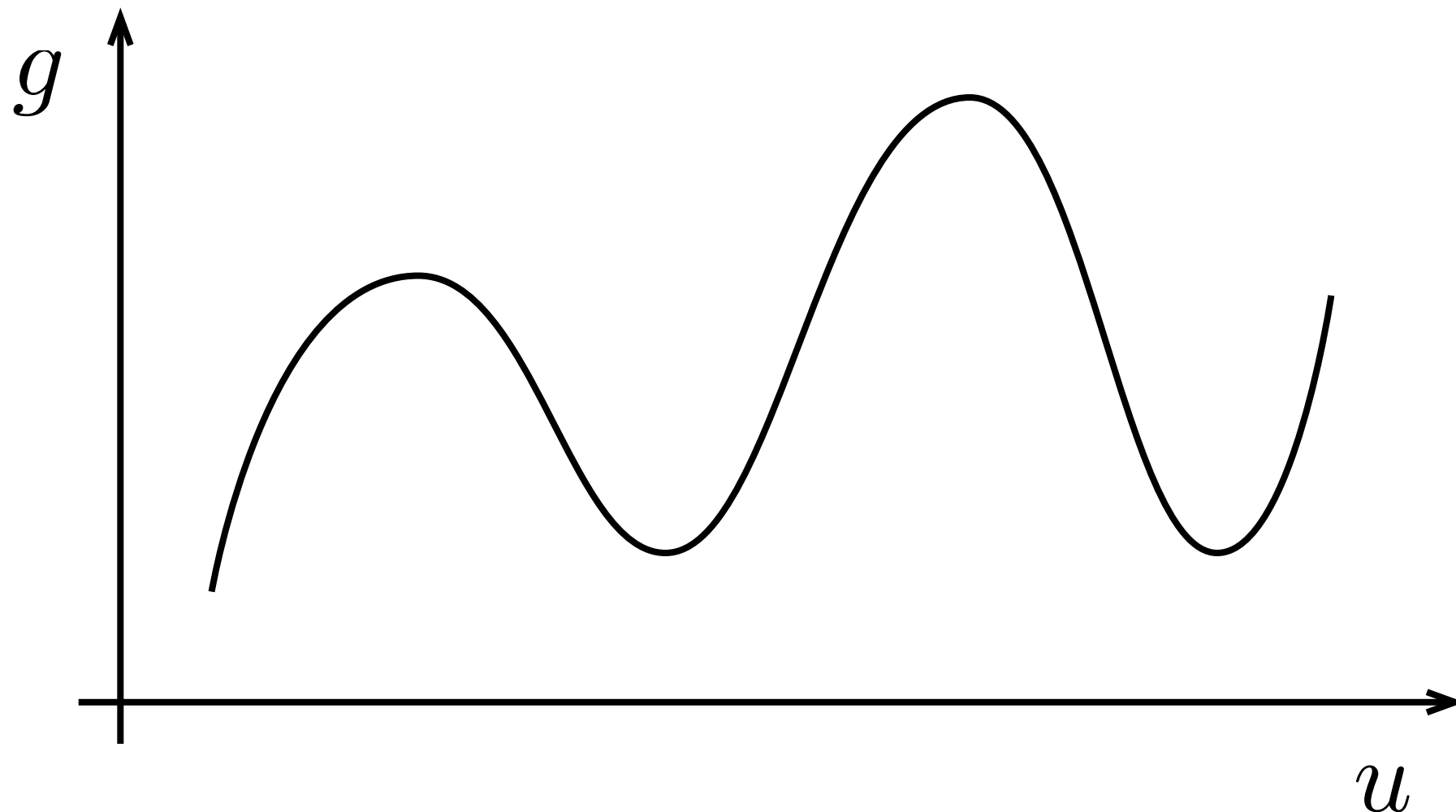
# Problem Formulation

- Given the probability distribution of the uncertain parameters  $u$
- Compute the probability distribution of the quantity of interest  $g$



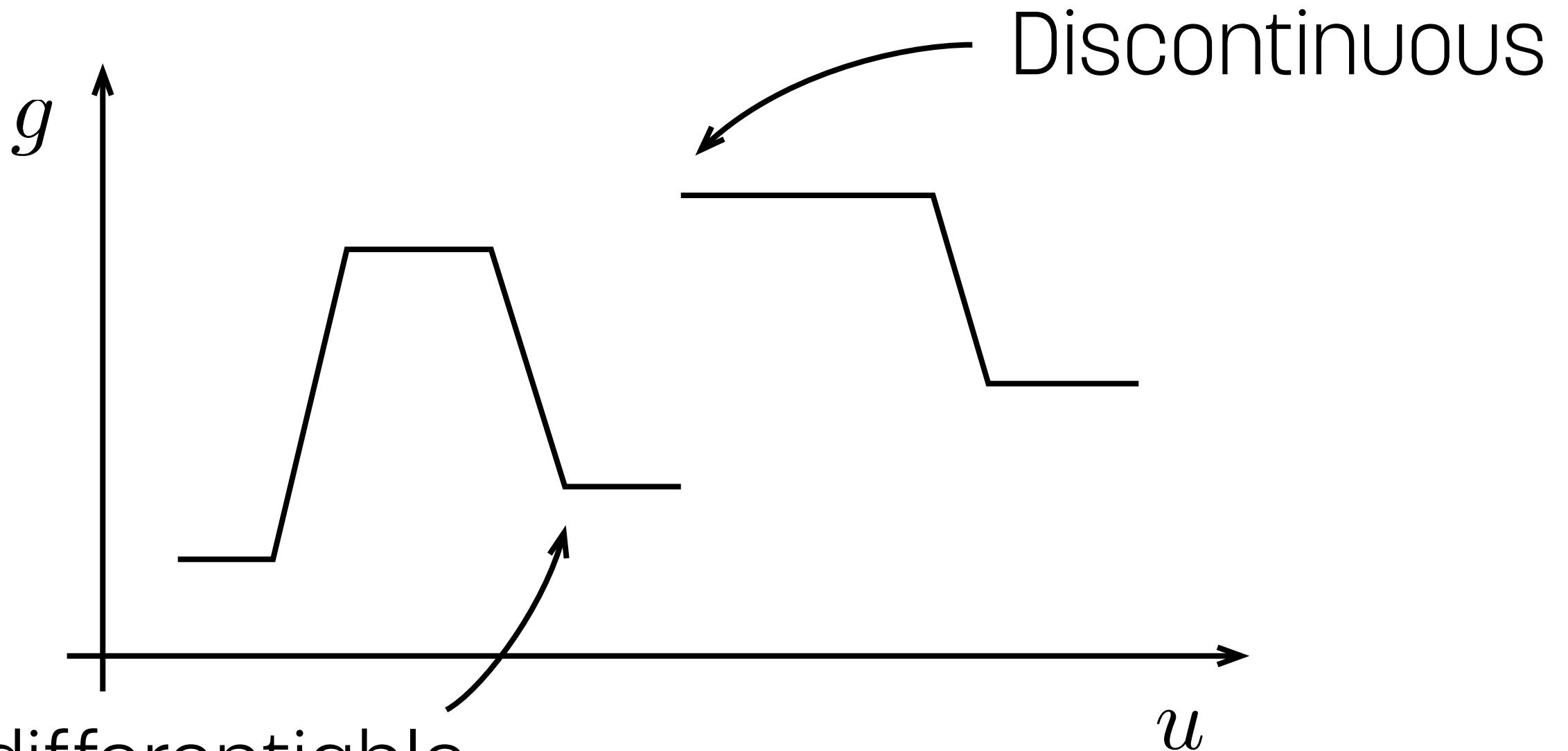
# Response Surface

$$g = f(u)$$



# Response Surface

$$g = f(u)$$



Non-differentiable

# Response Surface

- Process variation
  - Smooth, well-behaved
- Workload variation
  - Non-smooth, ill-behaved

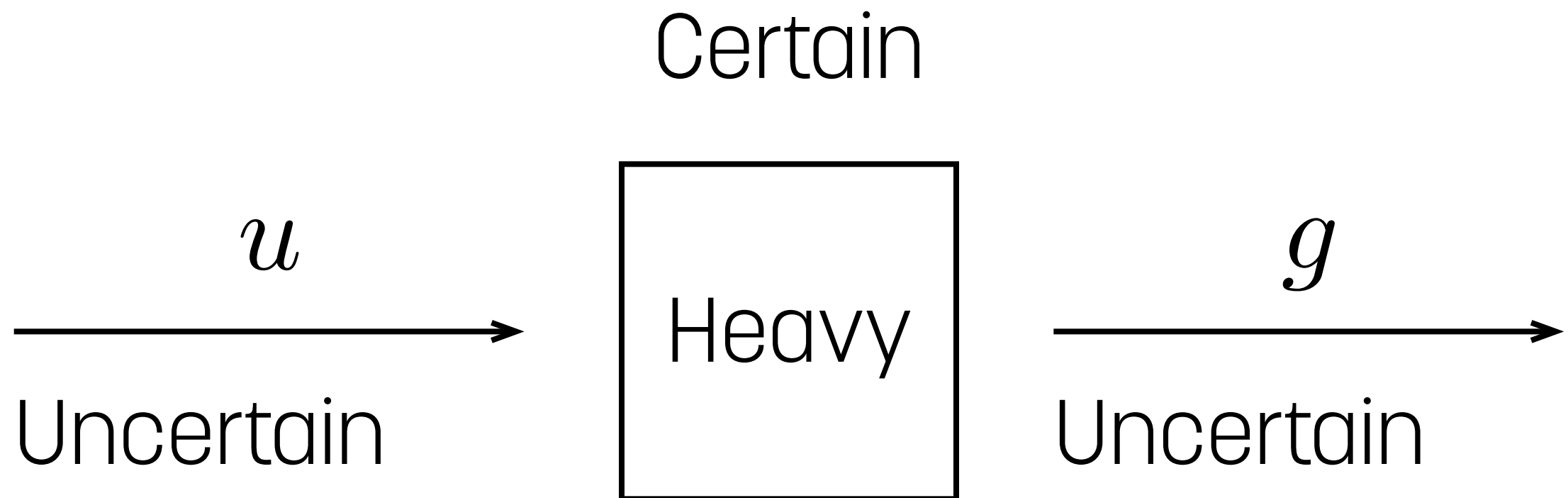
# Previous Work

- Inadequate
- Limited in use

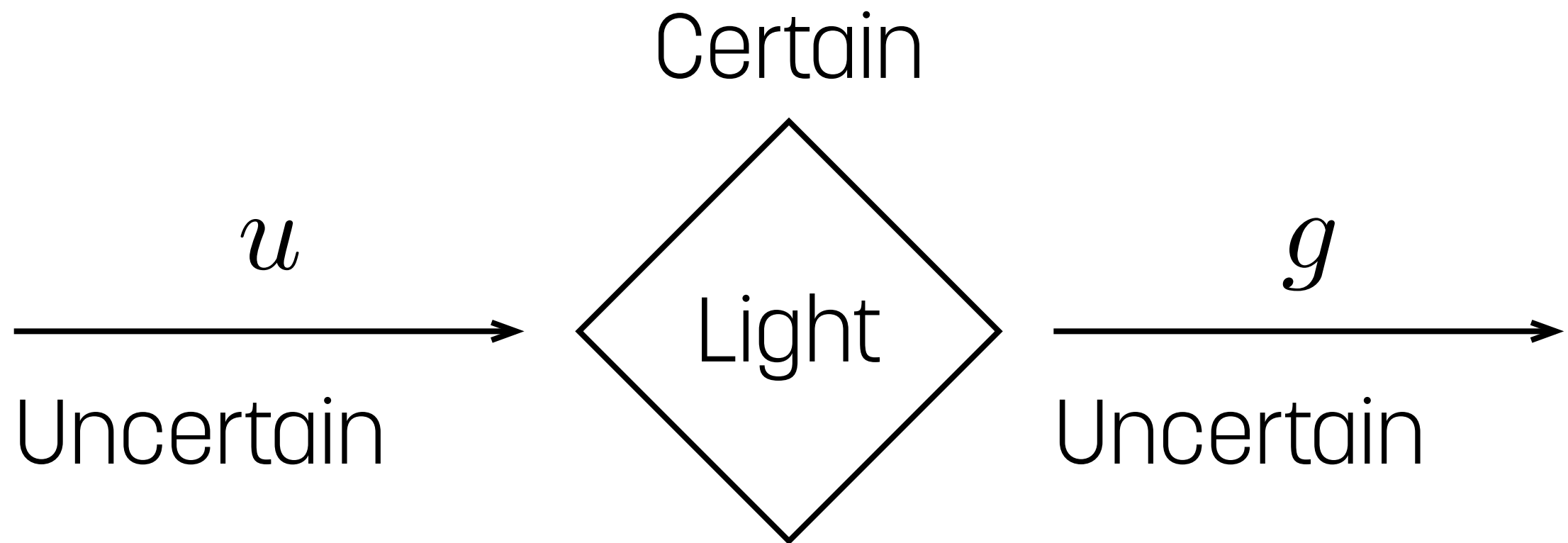
# Proposed Solution

- General
- Efficient
- Easy to apply

# Solution Overview



# Solution Overview



# Solution Overview

$$u = \mathbb{T}(z)$$

$$u : \Omega \rightarrow \mathbb{R}^{n_u}$$

$$z : \Omega \rightarrow [0, 1]^{n_z}$$

$$g(u) = (g \circ \mathbb{T})(z) = g(\mathbb{T}(z))$$



# Solution Overview

Adaptive hierarchical interpolation

$$g \approx \mathcal{A}_{l_s}^{n_z}(g) = \mathcal{A}_{l_s-1}^{n_z}(g) + \Delta \mathcal{A}_{l_s}^{n_z}(g)$$

Hierarchical surplus

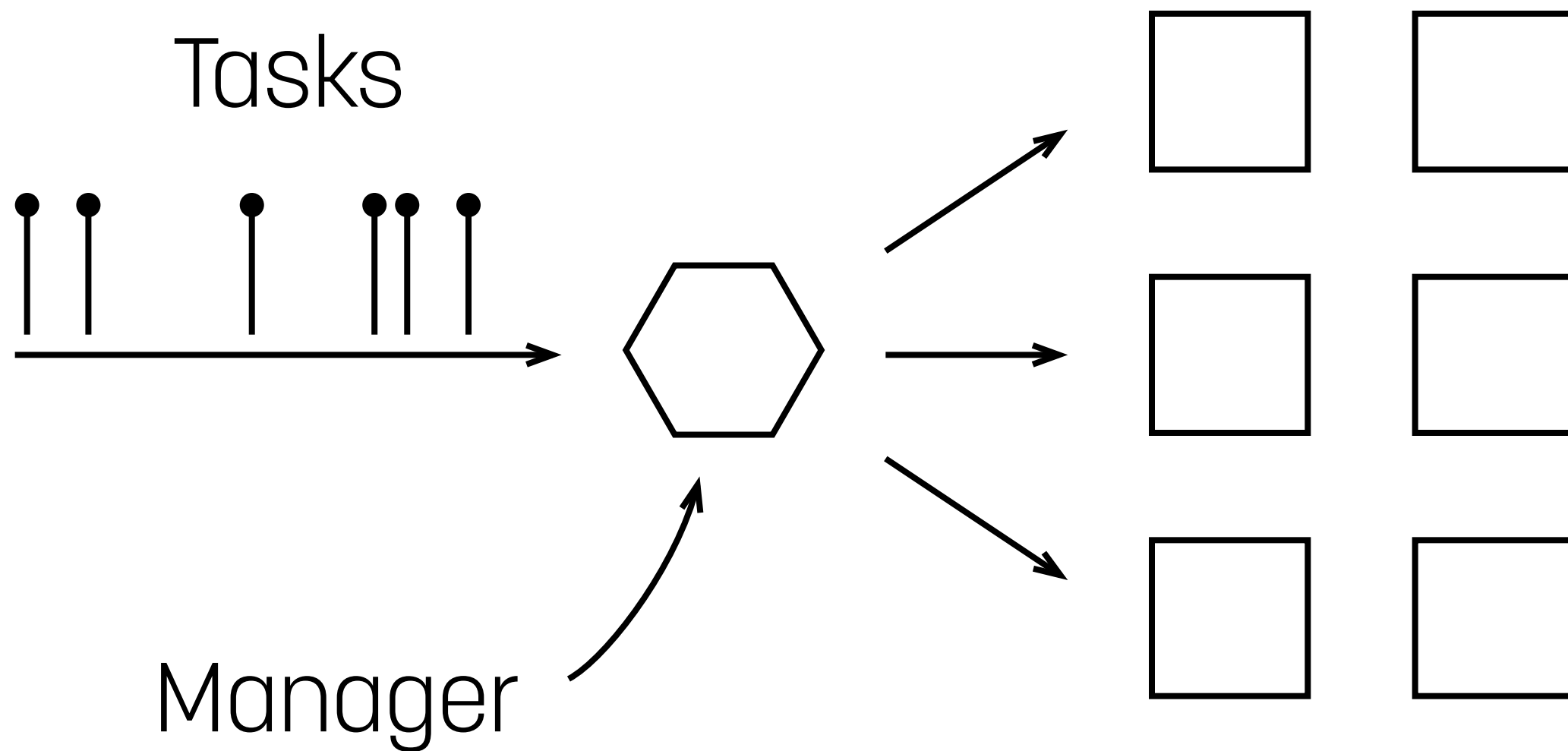
$$\Delta \mathcal{A}_{l_s}^{n_z}(g) = \sum_{i \in \Delta \mathcal{I}_{l_s}^{n_z}} \sum_{j \in \Delta \mathcal{J}_i^{n_z}} \Delta(g \circ \mathbb{T})(x_{ij}) e_{ij}$$

# Experimental Results

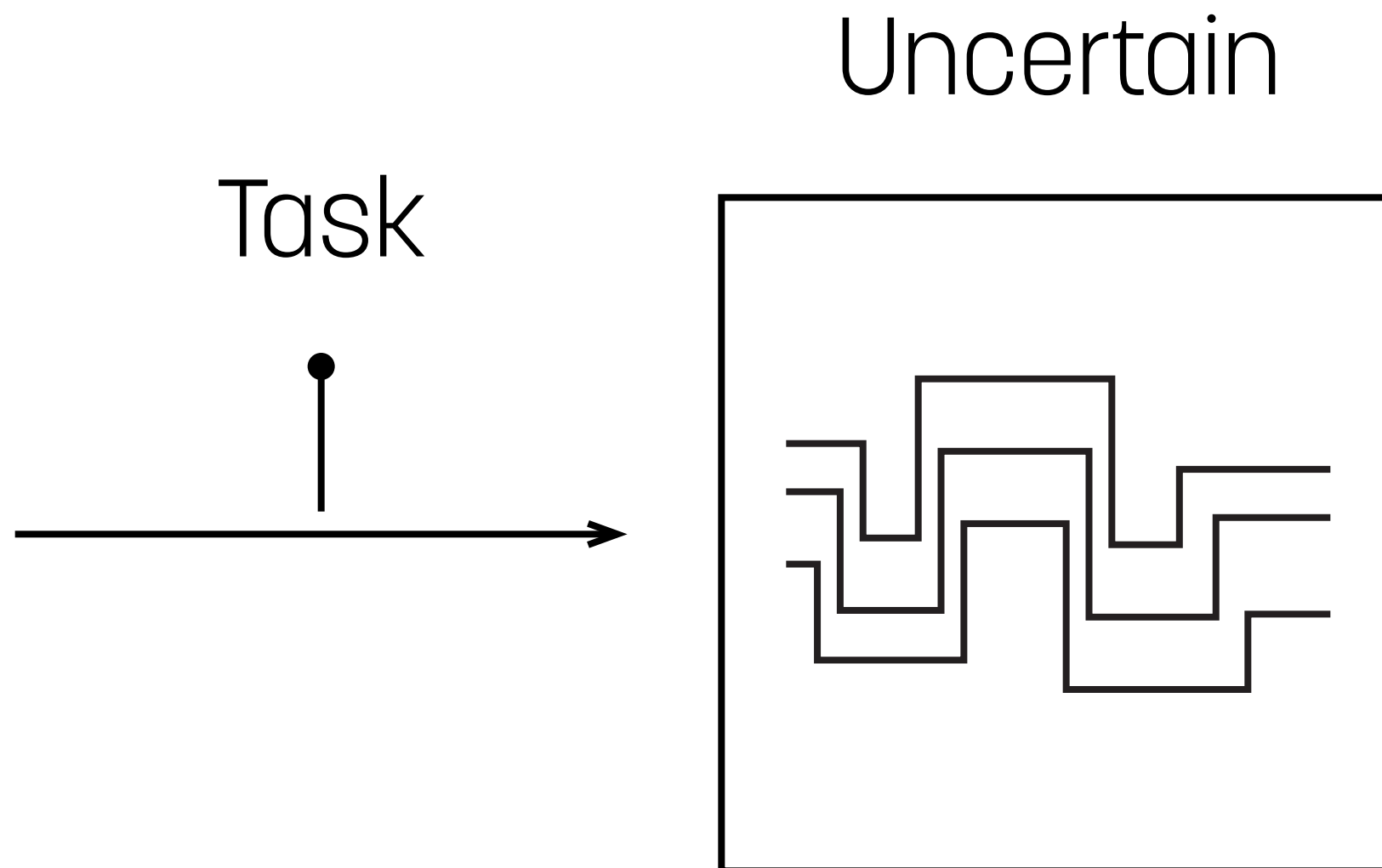
- Applied to a set of synthetic problems and to a real-life problem
- Shown computational efficiency
  - 1–2 orders of magnitude more accurate than direct sampling

# Resource Management under Workload Variation

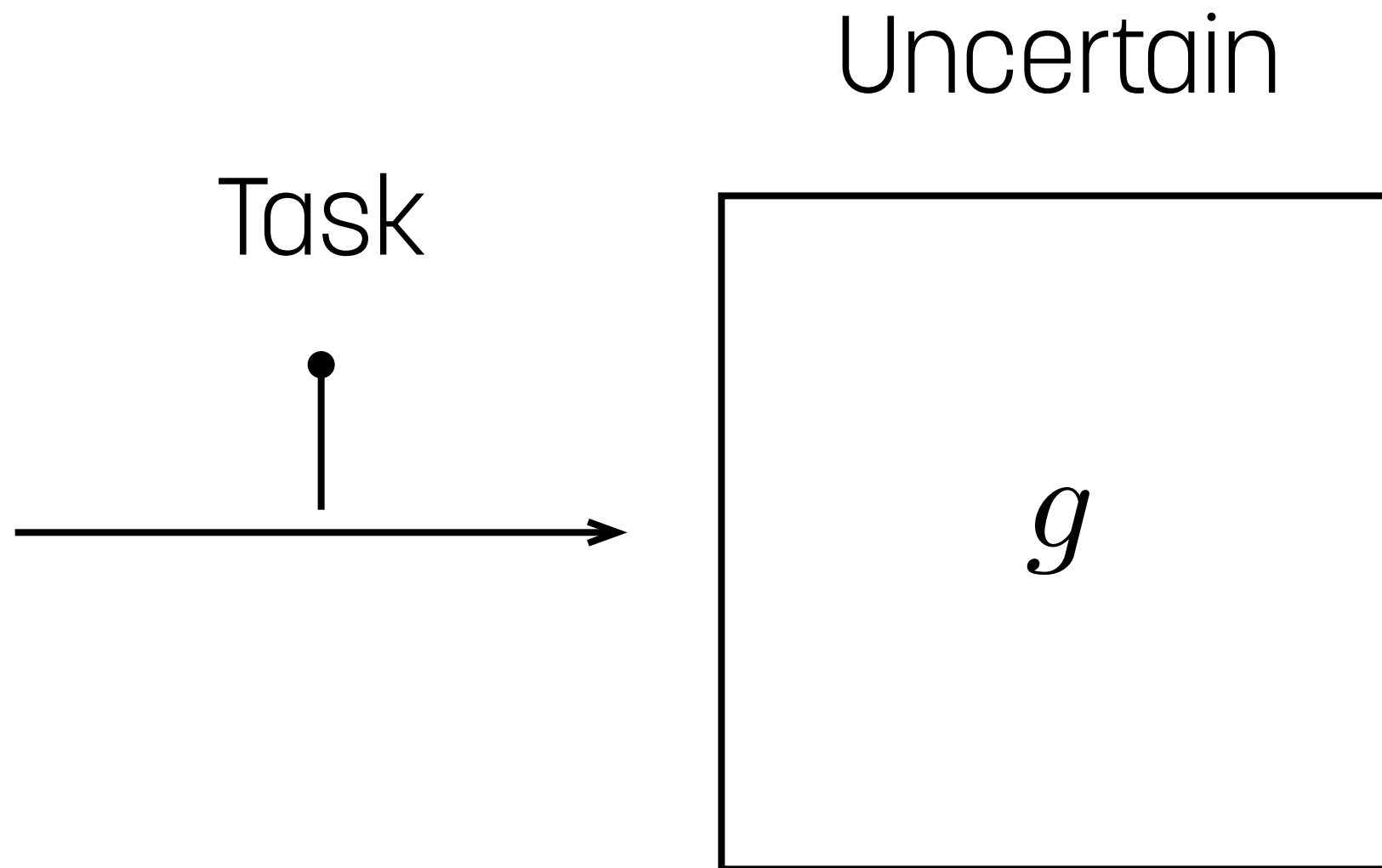
# Resource Management



# Resource Usage



# Quantity of Interest



# Problem Formulation

- Given past resource-usage traces  $G$
- Predict resource usage for individual tasks multiple steps ahead

# Previous Work

- Nonexistent
  - Only aggregate

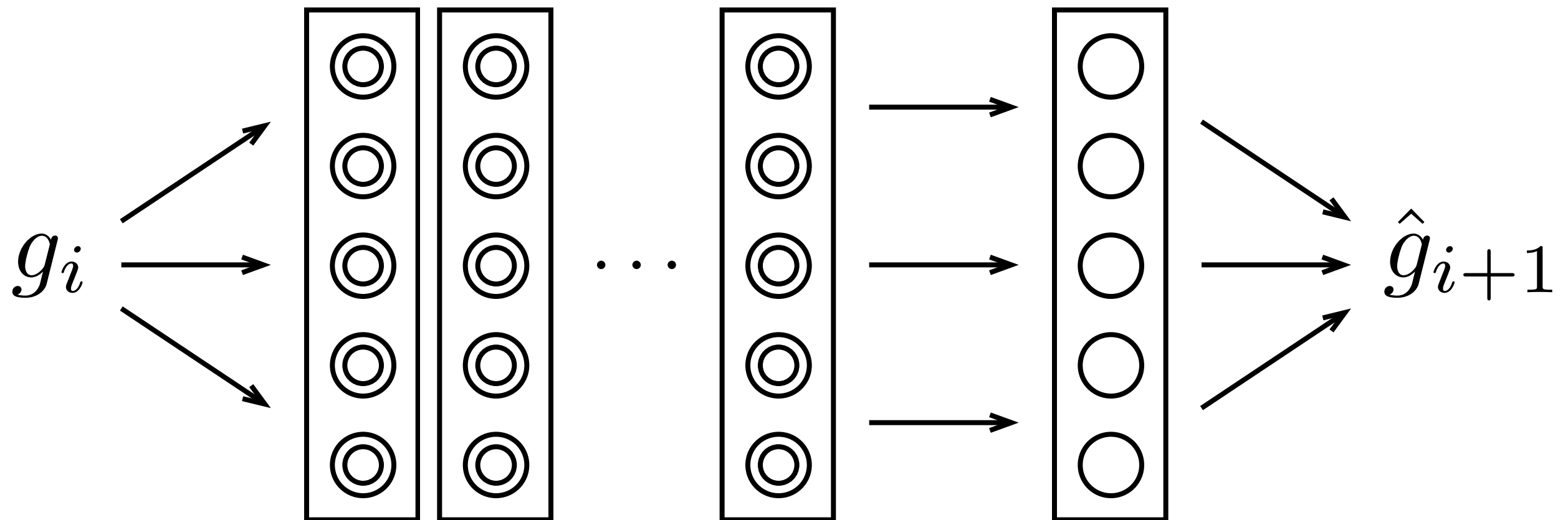


# Proposed Solution

- Fine grained
- Long range

# Solution Overview

Recurrent neural network



# Experimental Results

- Studied CPU usage in Google's computer cluster with 12500 nodes
- Shown the existence of a structure suitable for educated prediction
  - Error reduction of 47% for 4 steps ahead compared to random walk

# Conclusion

# Outline

1. Analysis and Design with Certainty
2. Characterization of Process Variation
3. Analysis and Design under Process Variation
4. Analysis under Workload Variation
5. Resource Management under Workload Variation

# Open Source

- <https://github.com/learning-on-chip>
- <https://github.com/markov-chain>
- <https://github.com/math-rocks>
- <https://github.com/ready-steady>
- <https://github.com/stainless-steel>
- <https://github.com/turing-complete>