Gas Turbine Uncertainty Using Bayesian Statistics

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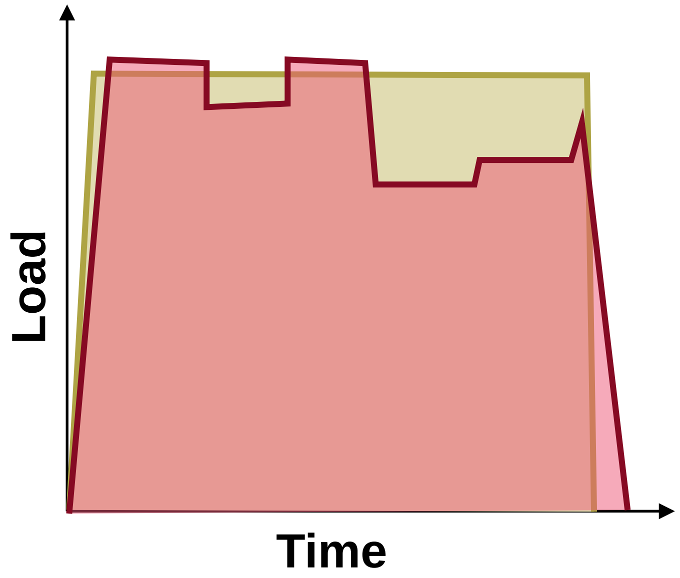
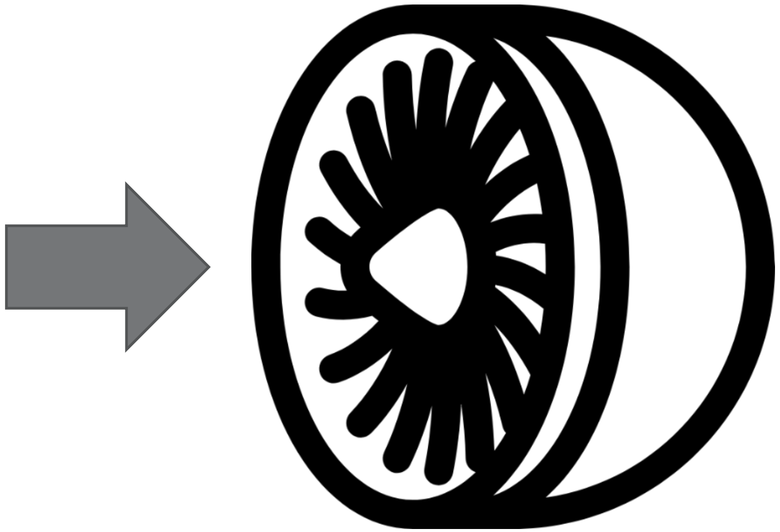
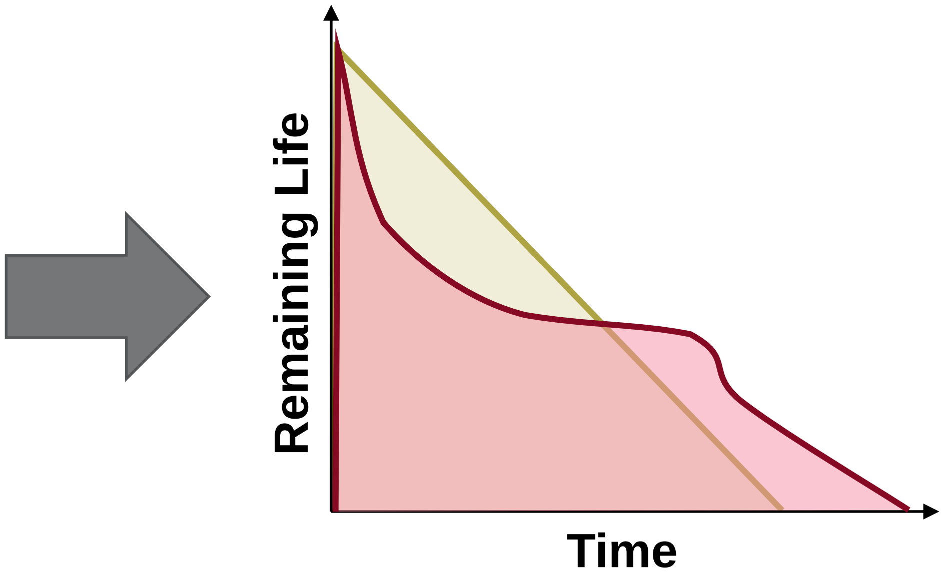
SYSTEMS AND ENGINEERING TECHNOLOGY

Context and Introduction

- Increasing tendency to use Condition Based Lifing Approaches for Gas Turbines
- These use real operational data instead of bounding operation traditionally assumed
- Open the opportunity to extend or intelligently manage the lives of components



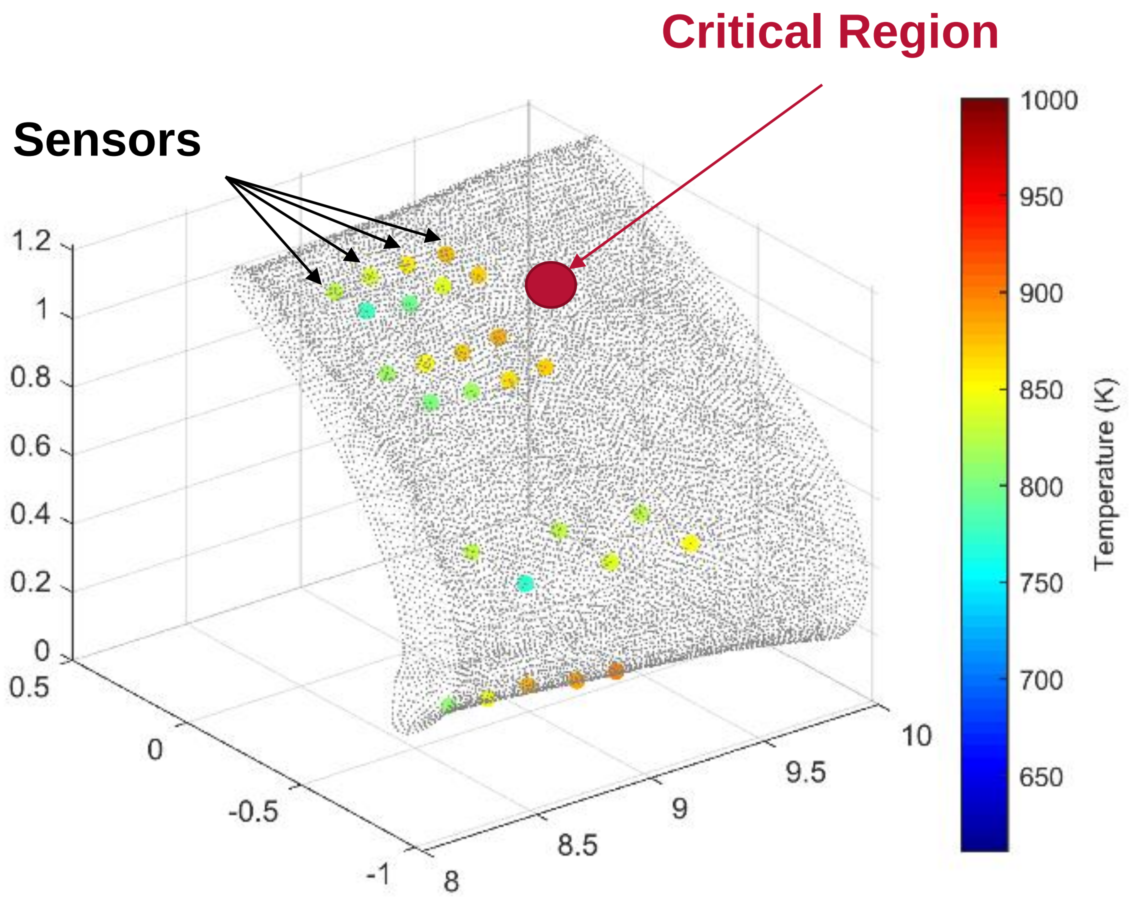




Context and Introduction

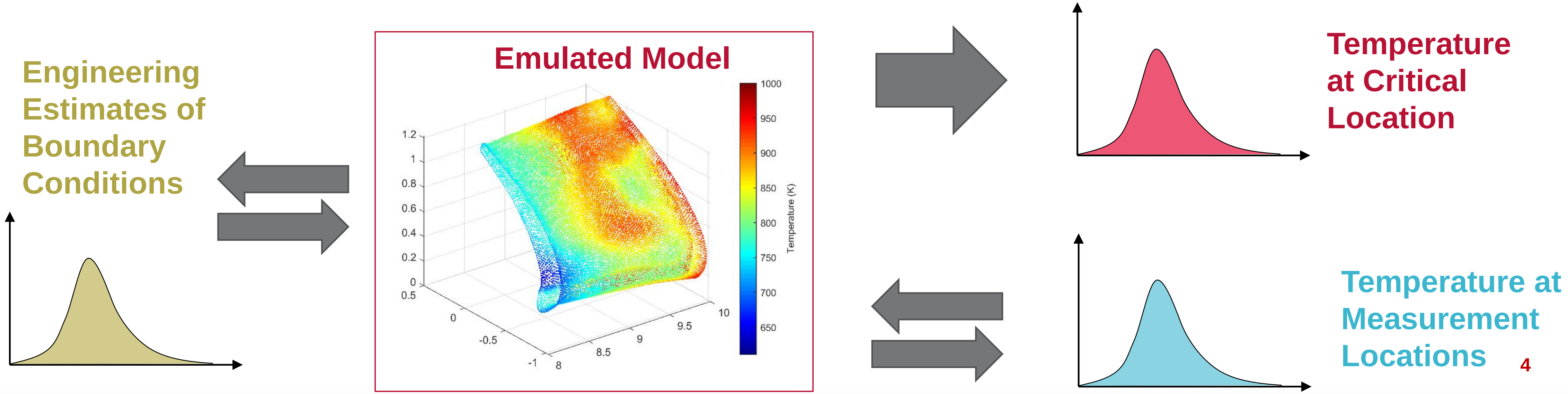
Condition based methods raise challenges for analysis:

- Focus on predicting temperature and stress of critical locations on components at all operating conditions
- Removal of operation conservatism requires assessment of prediction uncertainty
- Multiple sensors, not all co-located with critical points



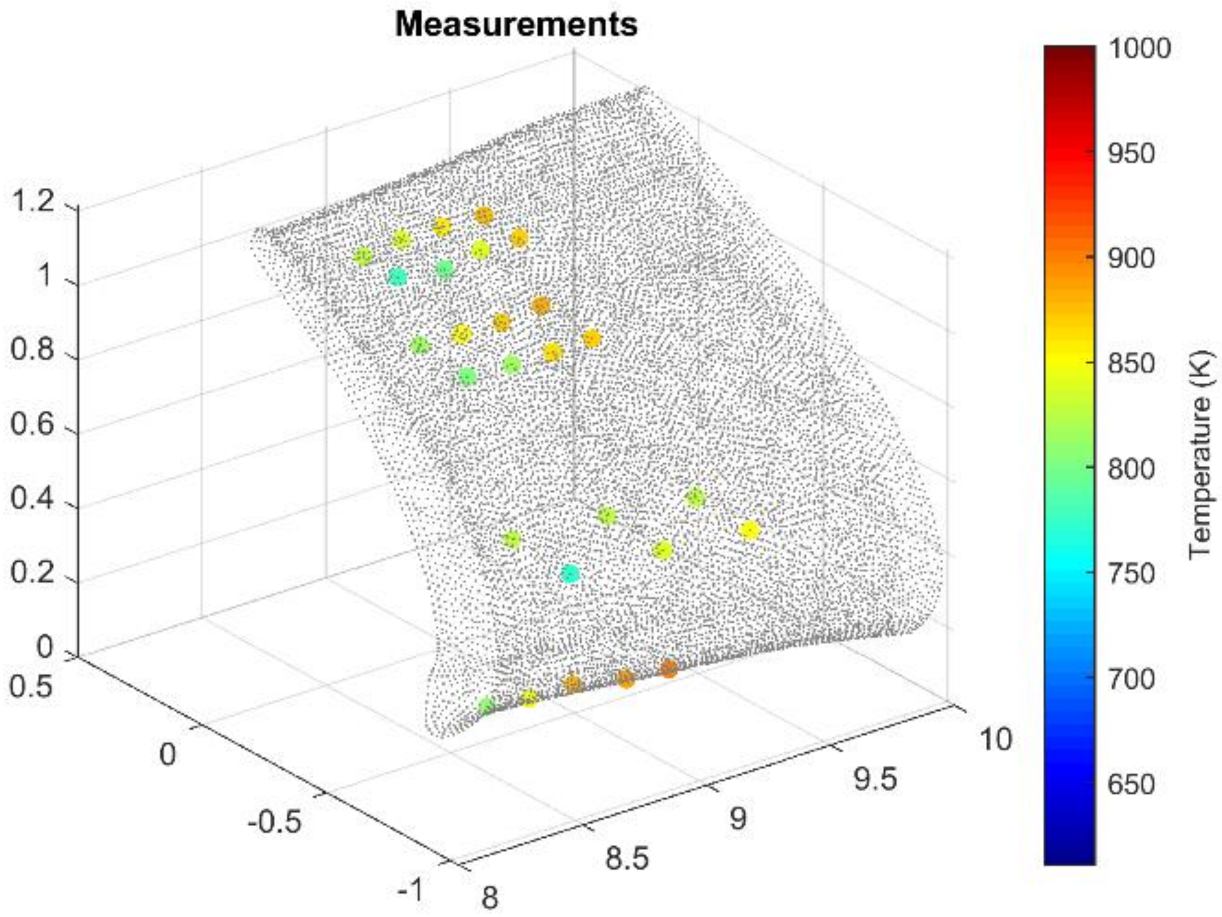
Approach

- Consider generic turbine blade
- Model boundary conditions and assumptions as uncertain parameters
- Use Bayesian inference around a physical model to combine:
  - Engineering understanding
  - Data from sensors across component
- Produce uncertain predictions of temperature in critical locations



Priors: Engineering Judgement

- Thermal models contain boundary conditions, which are informed by judgement or analysis
- Each of these is potentially uncertain
  - Boundary condition parameters can be defined as distributions – **priors**
- Samples of the **priors**, fed through the emulator, give a distribution of temperature across the blade



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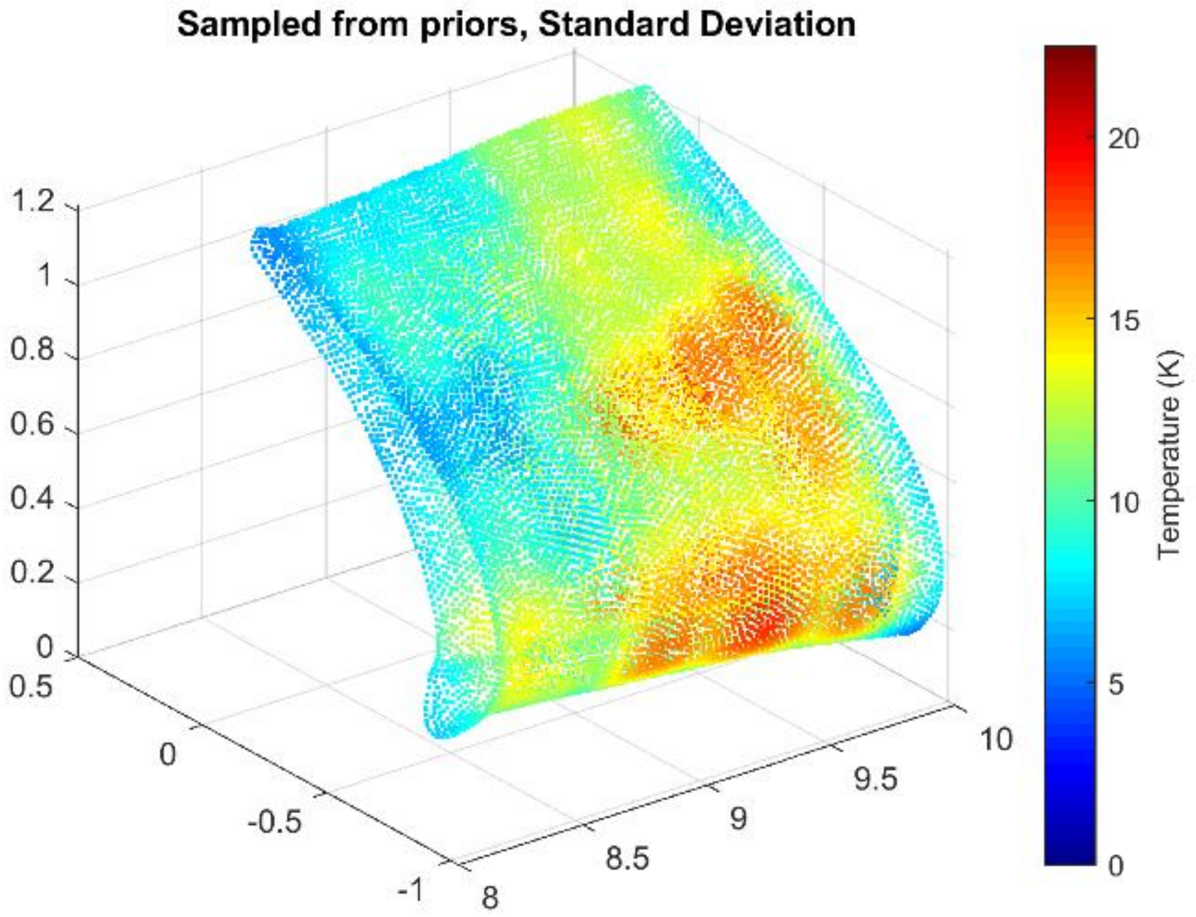

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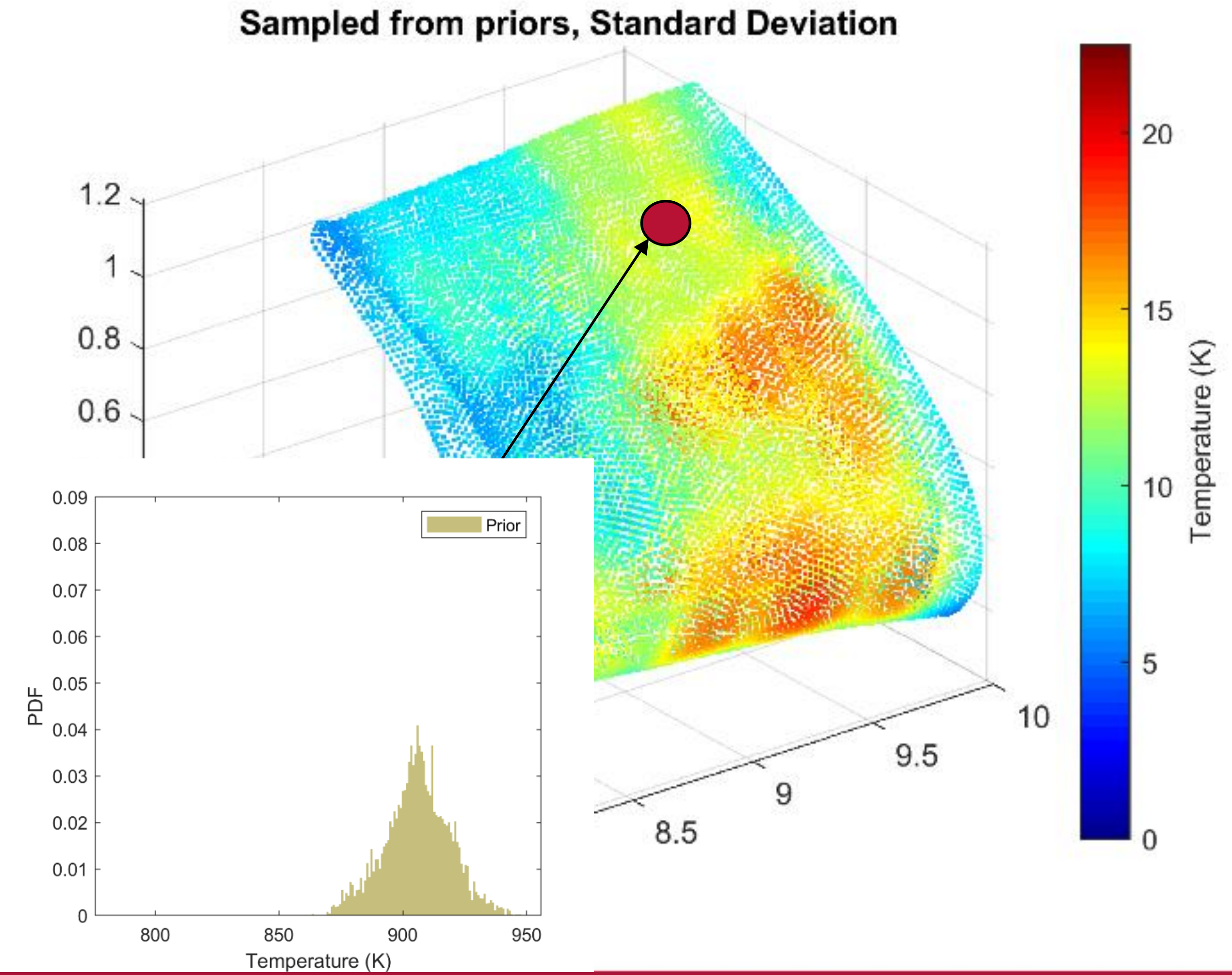
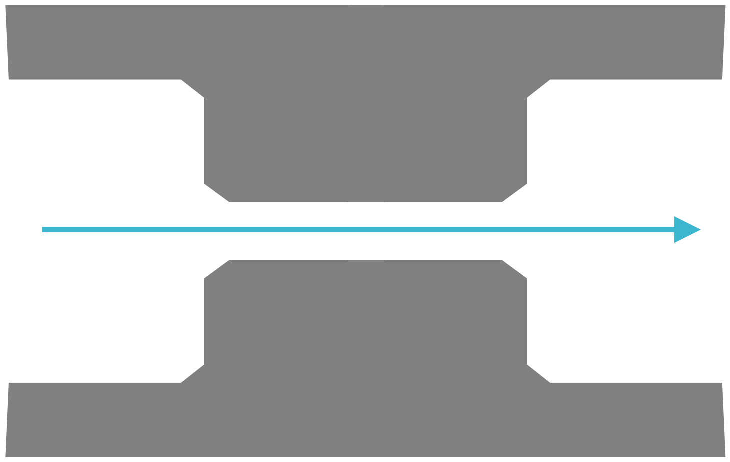


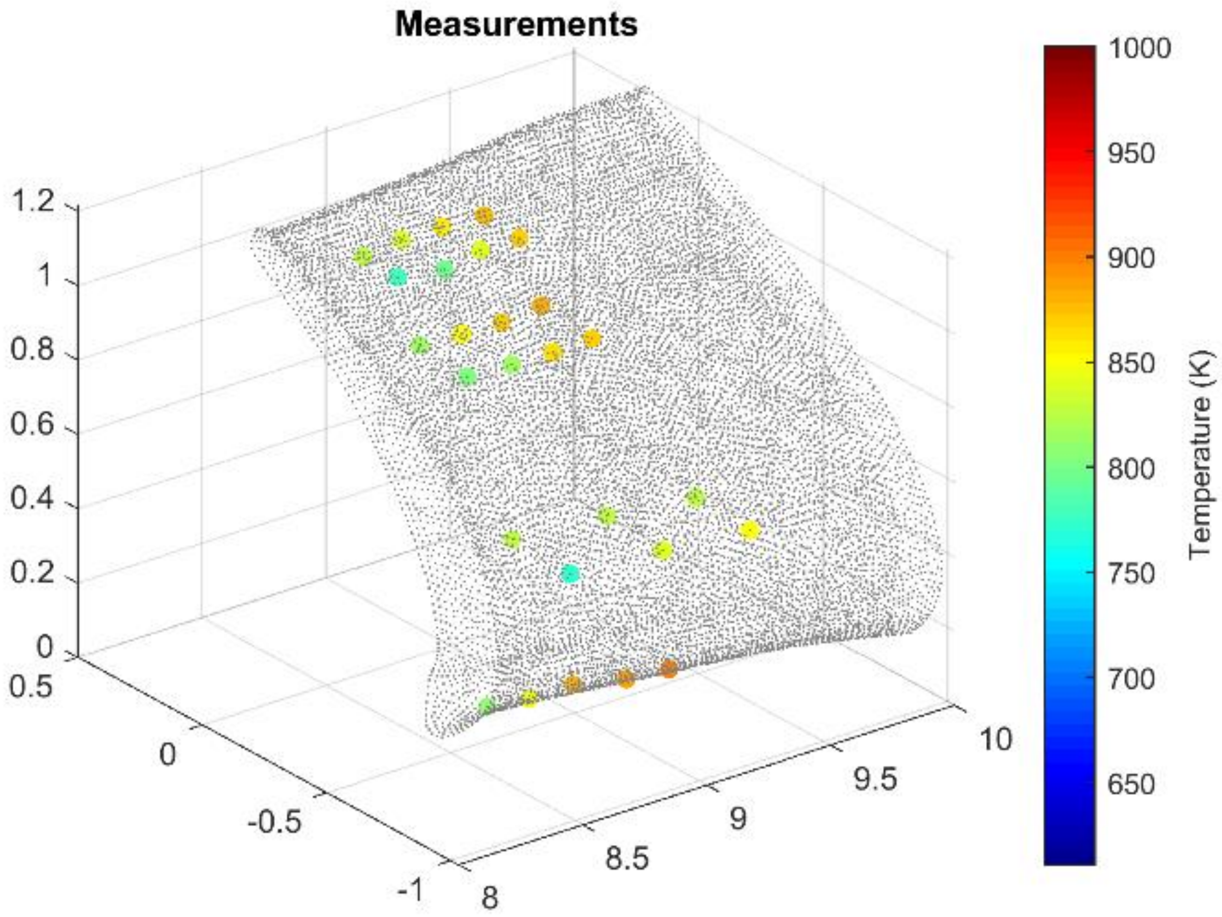
Priors: Example BC Calculation

- Example: Secondary cooling flow through an orifice / tube.
- Mass flow, pressure drop, fluid temperature, HTC calculated in 1D flow network solver.
- Uncertainty in:
  - HTC correlation, geometry, entrance effects, “known” conditions, pressure loss correlation, mass flow rate, solid wall temperature, etc.
- Can systematically derive **prior** distribution through running flow solver for varying inputs.



Likelihoods: Data

- Measurements are taken to help narrow down the uncertainty in boundary conditions
- These can inform **likelihood** distributions of the boundary conditions
  - "What boundary conditions are likely to lead to these measurement results?"



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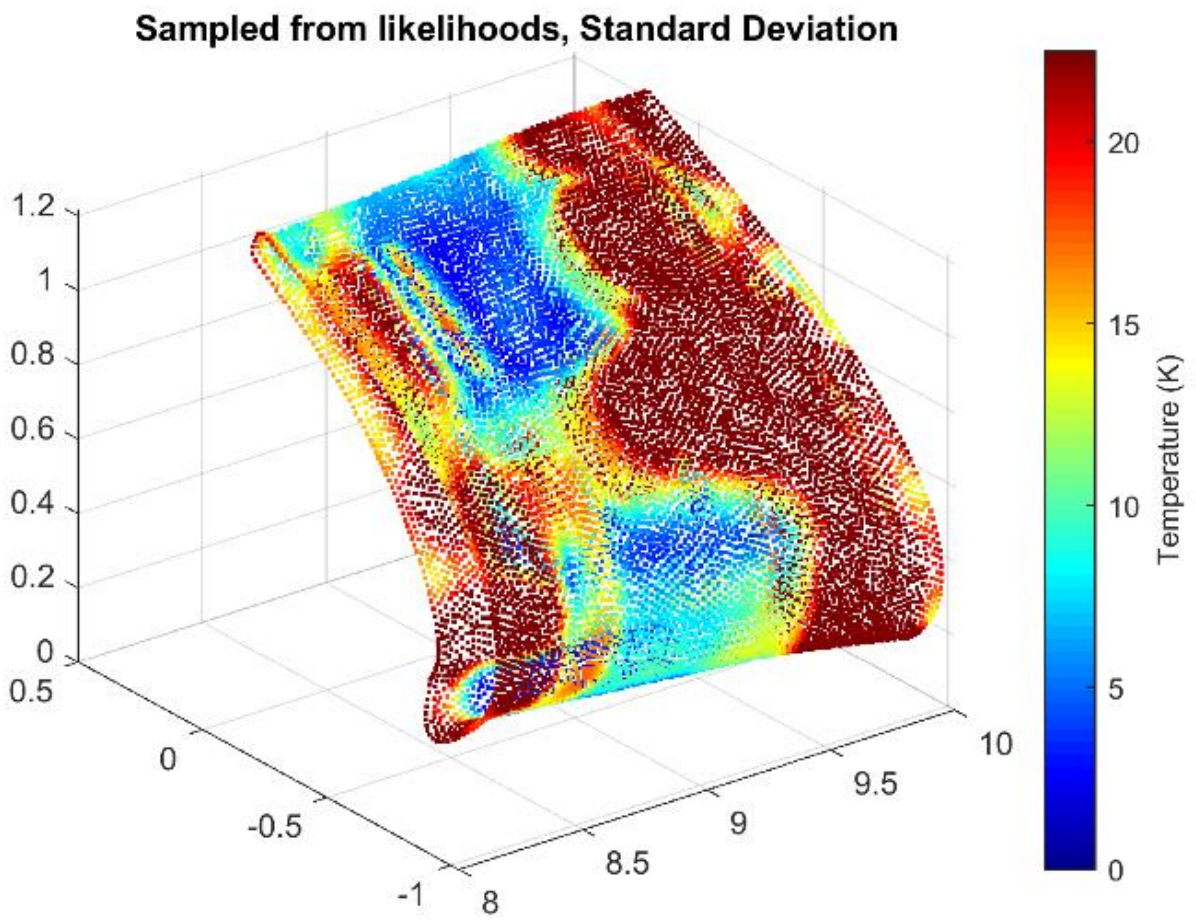

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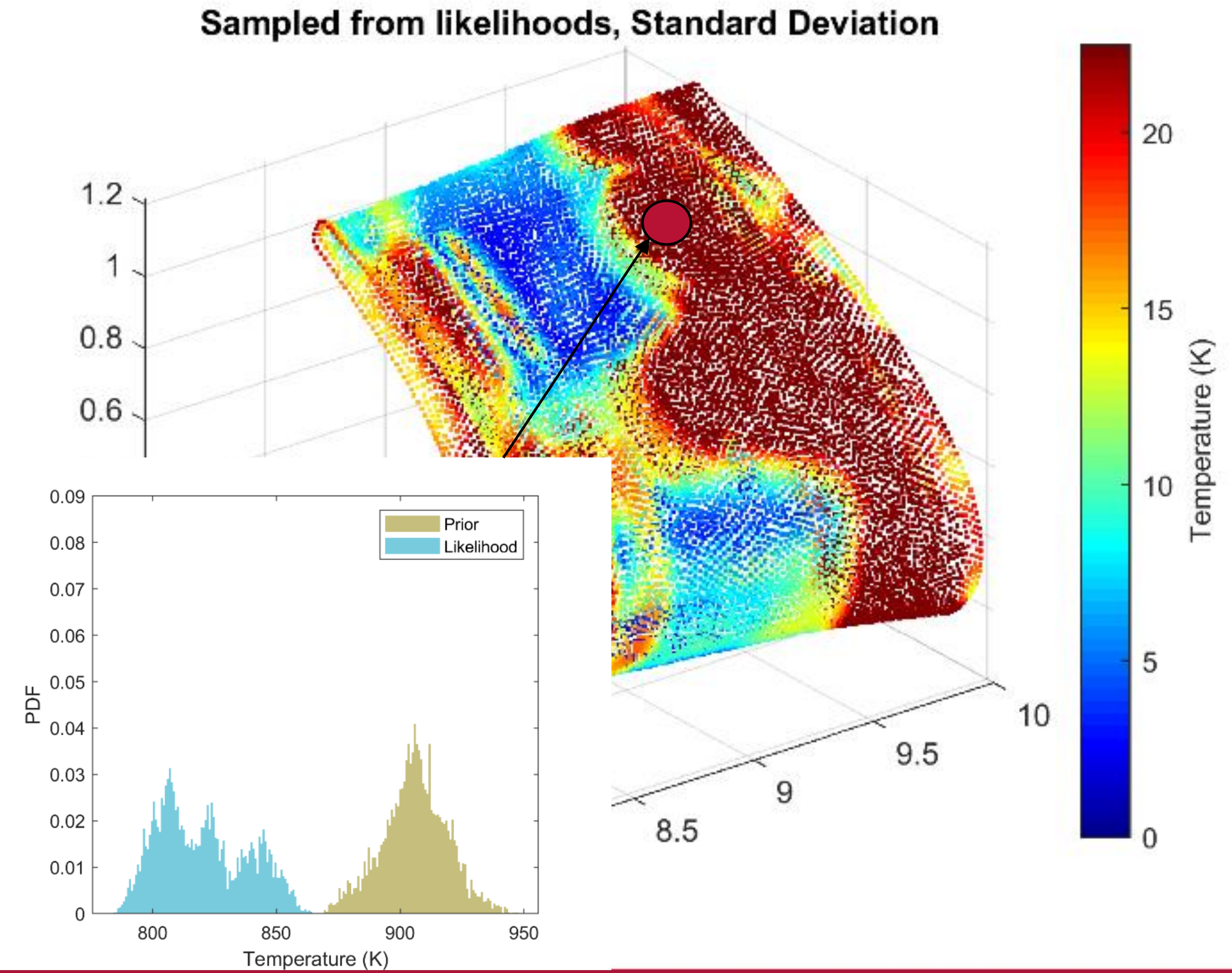
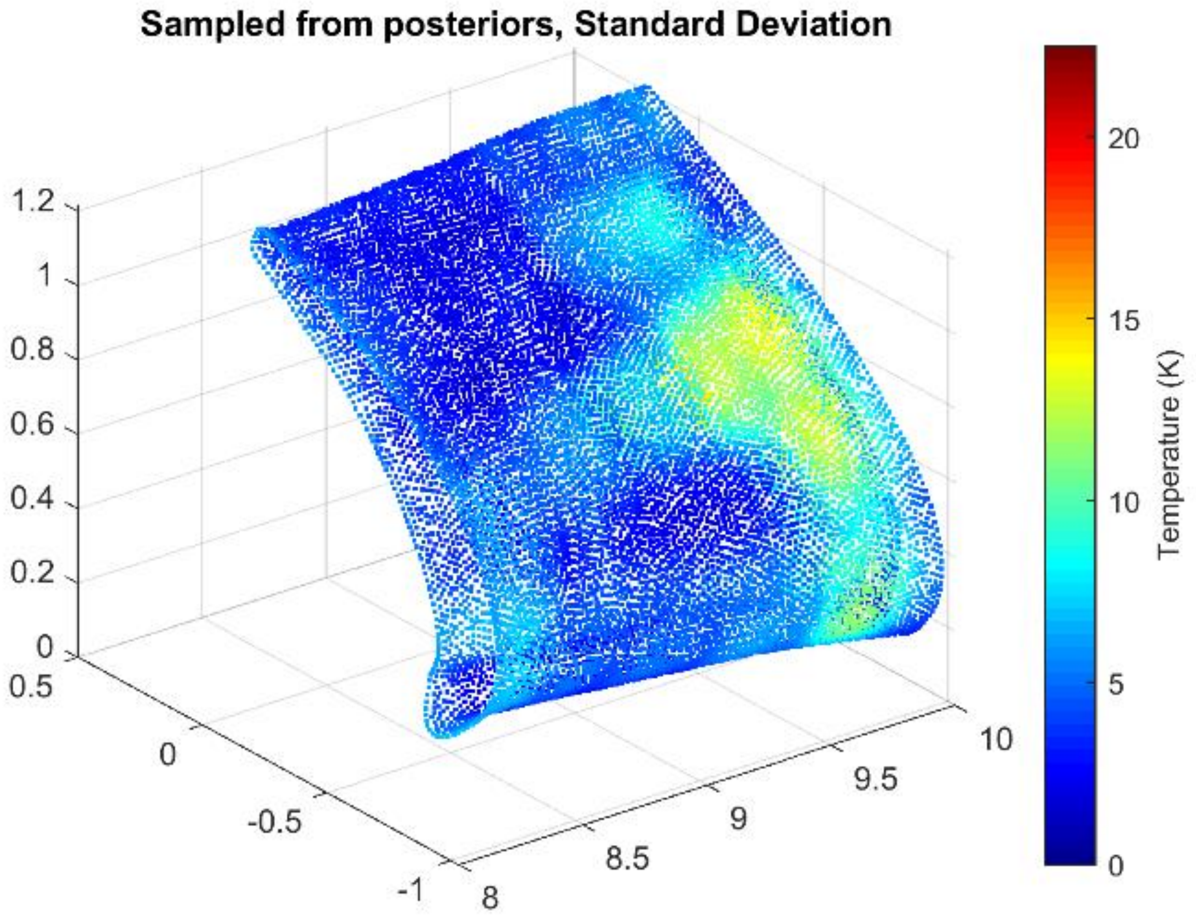


Posteriors: Data and Judgement Combined

- Use Bayes' Rule to combine **priors** and **likelihoods** into **posteriors**

- These combine data and judgement to yield lower uncertainty than either



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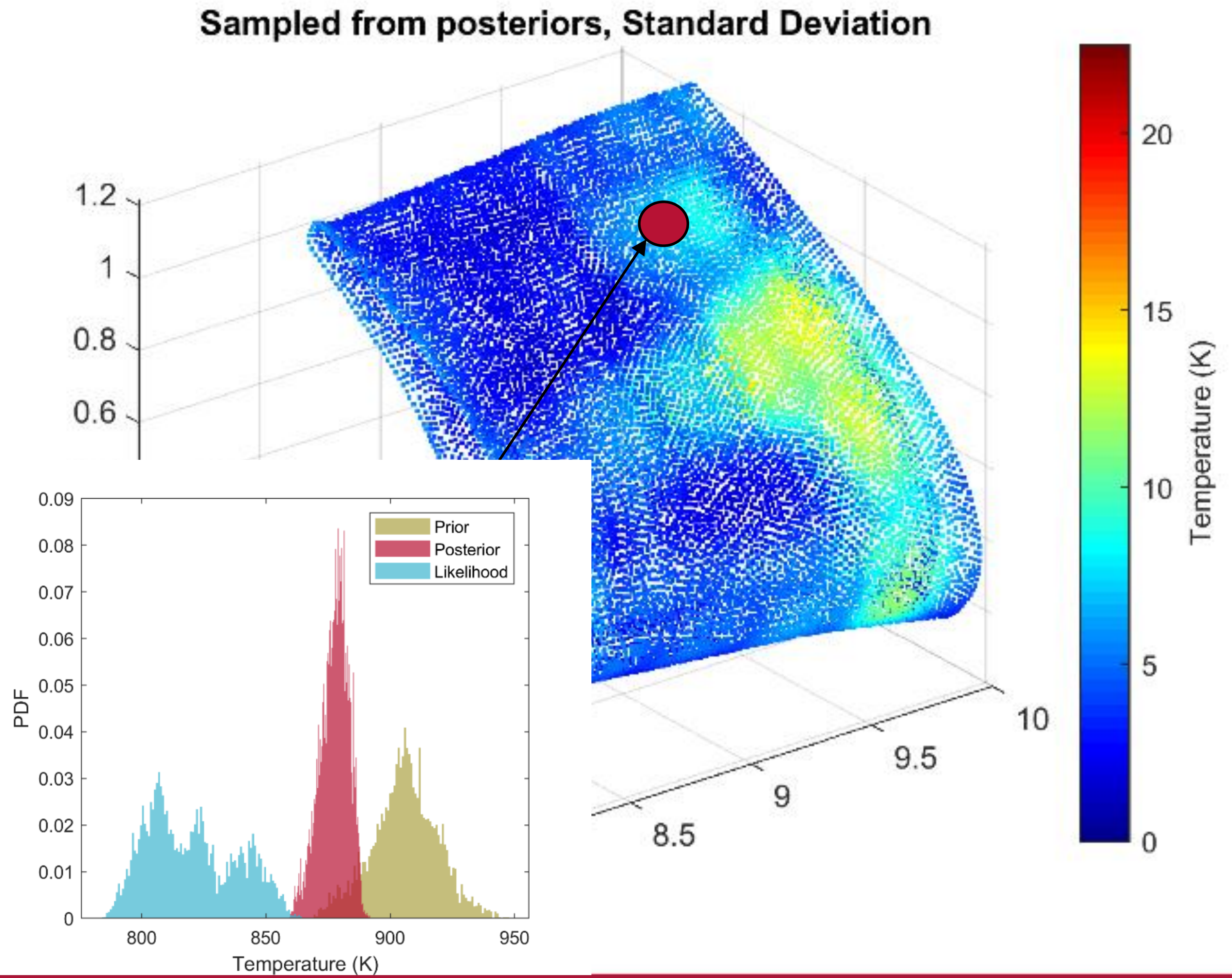

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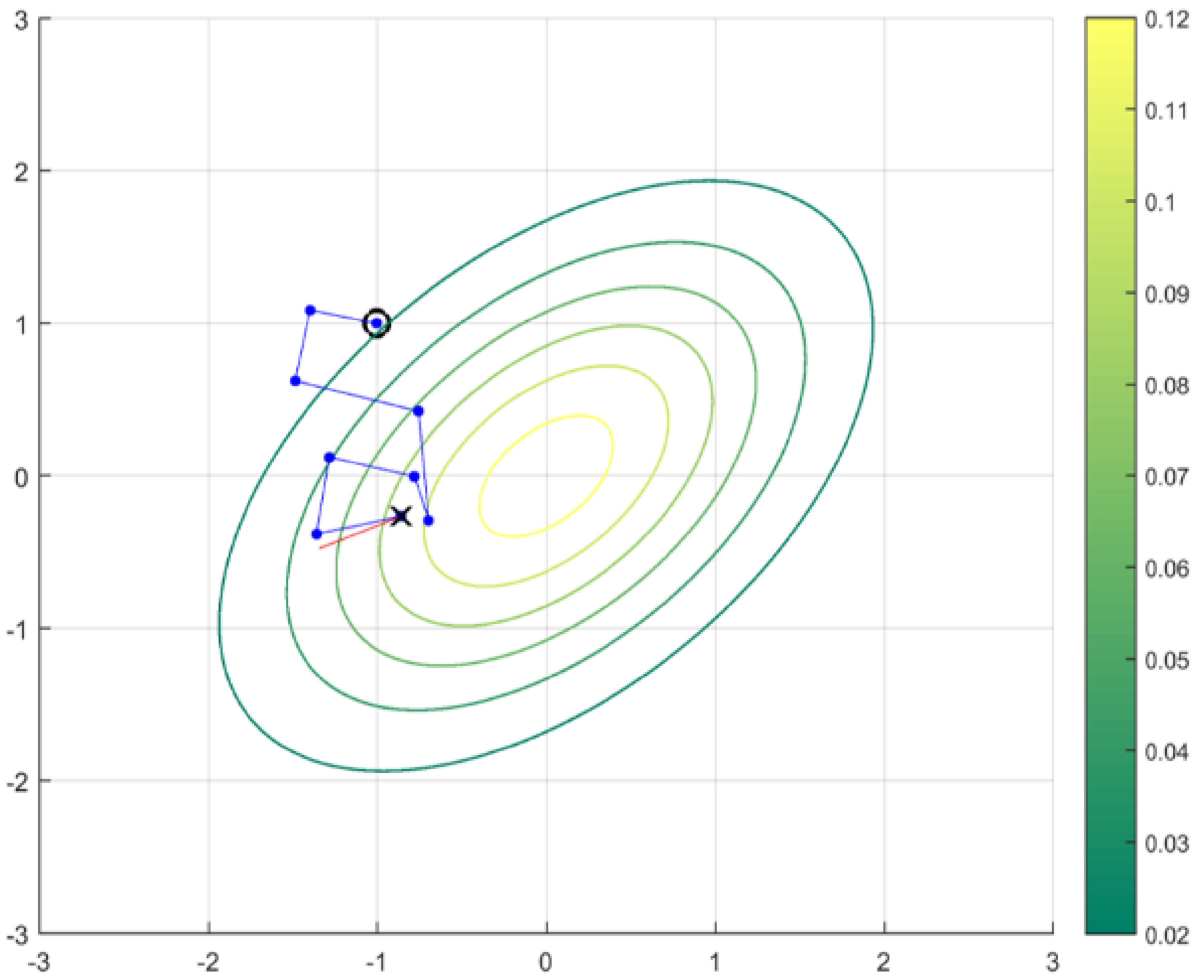
- Challenging to sample, use Markov Chain Monte Carlo



Conclusion and Applications

- Bayesian approach allows judgement and data to be combined to reduce uncertainty

- Applications:
  - Uncertainty quantification
  - Model fitting / matching
  - Digital asset diagnostics
  - Learning from field experience
  - Test and measurement specification