Uncertainty Quantification in a Micro Mill Caster Digital Twin

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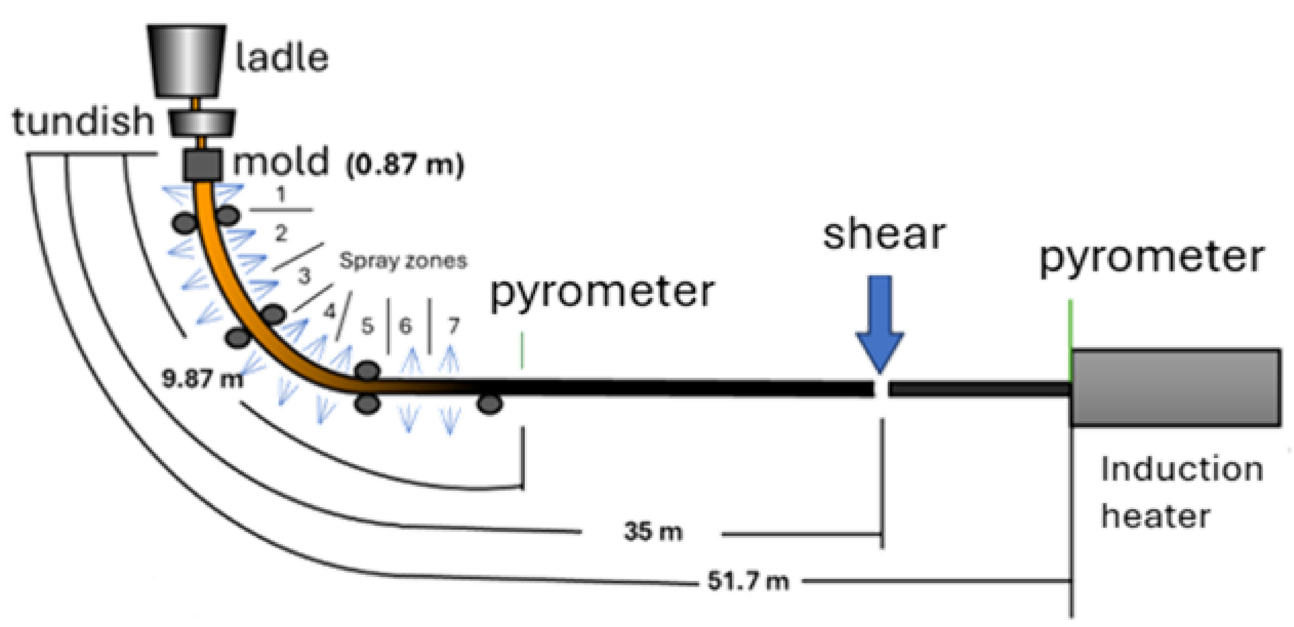
INTRODUCTION

- Micro mill caster: compact, high-speed (3-9 m/min), low-carbon
- Safe production requires real-time and accurate metallurgical length(final solidification point) prediction.
- Digital Twin enables real-time prediction & optimization
- **Critical gap: Large uncertainty in heat transfer coefficient (HTC) of the spray cooling zone & industrial sensor data limits reliability**



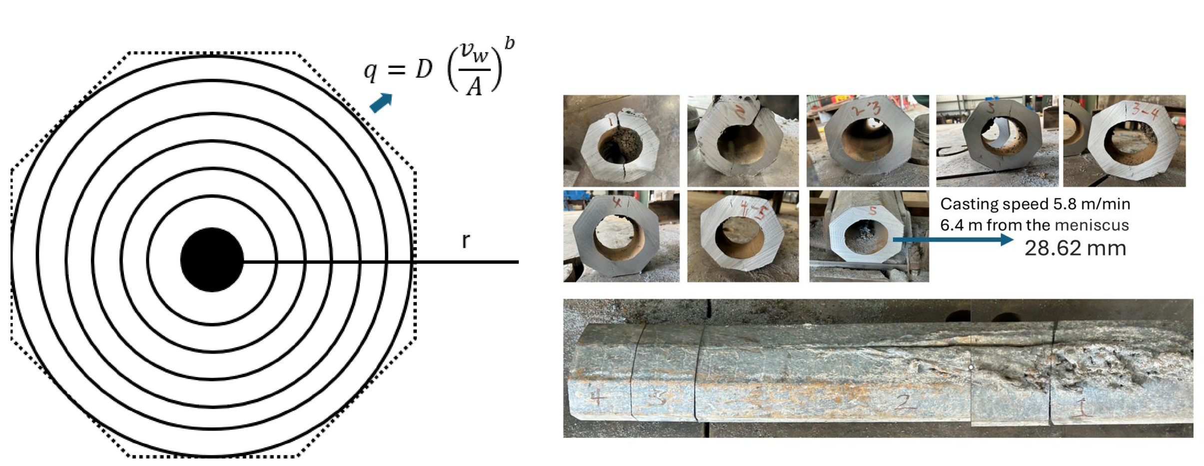
METHODOLOGY

Physics-informed digital twin

- Numerical solving governing heat transfer equation on 1D billet [1].

$$\rho_s CV\frac{\partial T}{\partial t} = \frac{1}{r}\frac{\partial 1}{\partial r}\left(kr\frac{\partial T}{\partial r}\right)$$

- Boundary condition q in the spray cooling zone depends on the pyrometer reading and the shell thickness measurement from the breakout shell

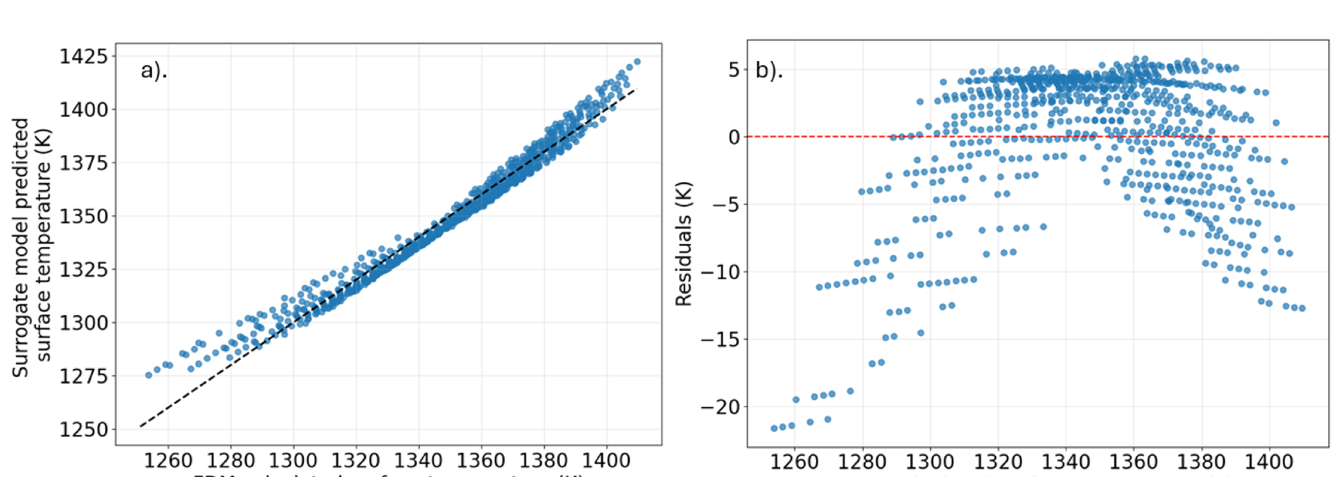


- HTC trained on two loss functions based on prediction residual errors [2].

Weighted loss function

$$\frac{W}{m}\sum_{i}^{m}\left(T_{prediction} - T_{measured}\right)^2 + \frac{(1-W)}{n}\sum_{i}^{n}\left(H_{prediction} - H_{measured}\right)^2$$

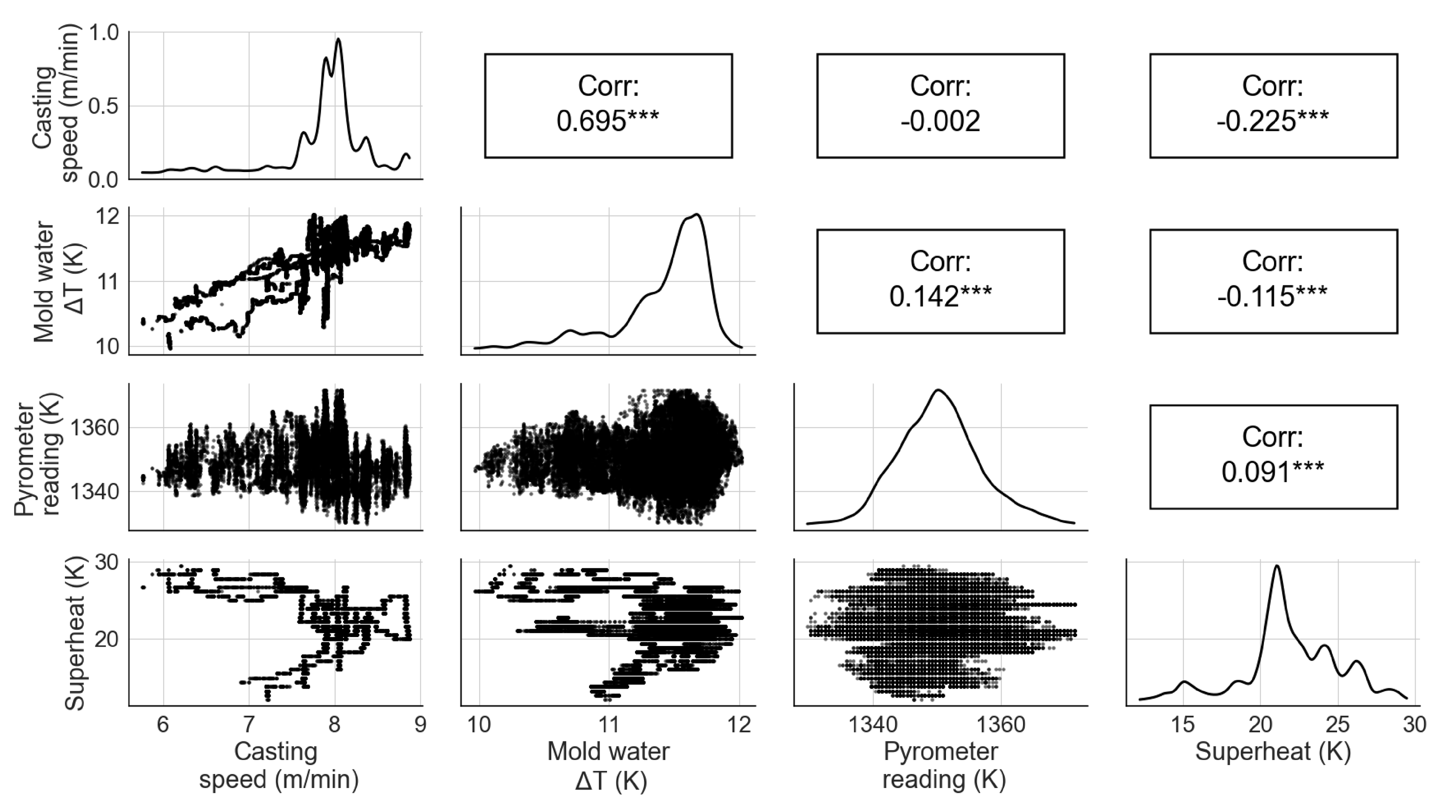
- Calibrated dataset used to train a multiple linear regression based surrogate model on surface temperature



UNCERTAINTY QUANTIFICATION

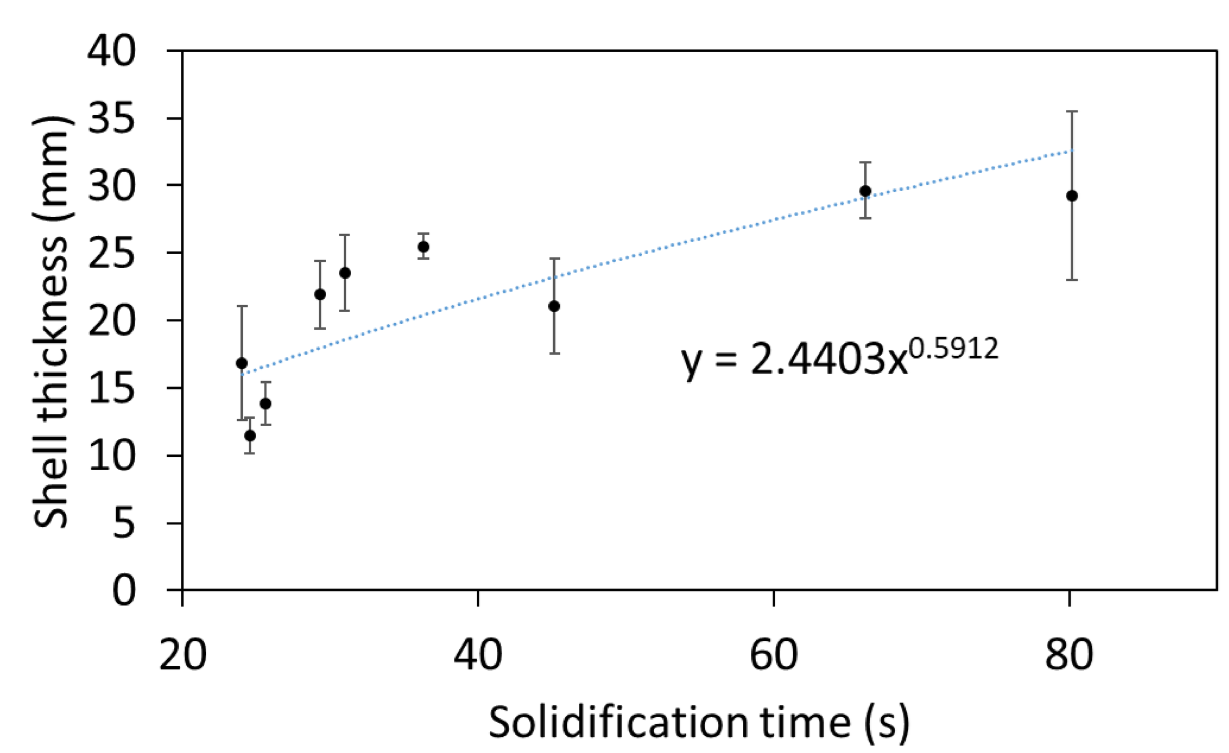
Industrial dataset

- Input parameters:
  - Casting speed (m/min), Mold water temperature (K), Superheat (K)
- Output:
  - Surface Temperature (pyrometer reading)

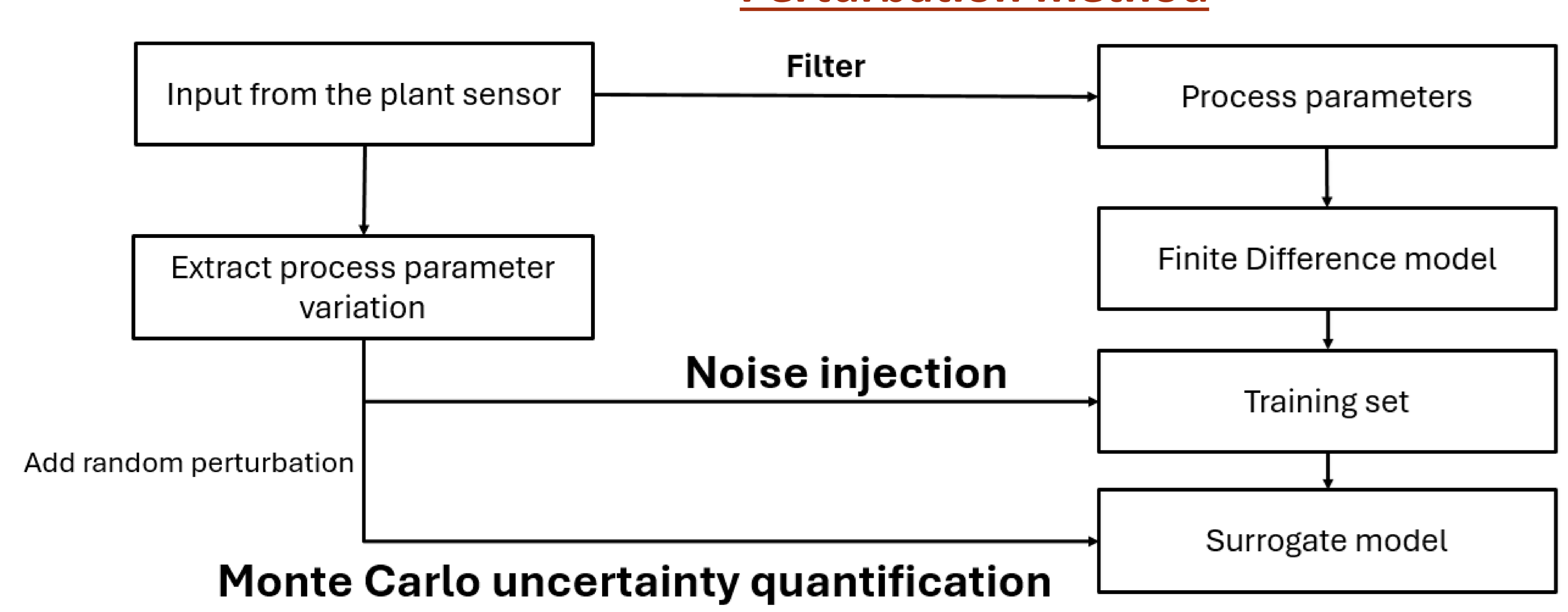


Sampling from industry sensors at a rate of 2 Hz.

Shell from the industrial breakout samples.



Perturbation method

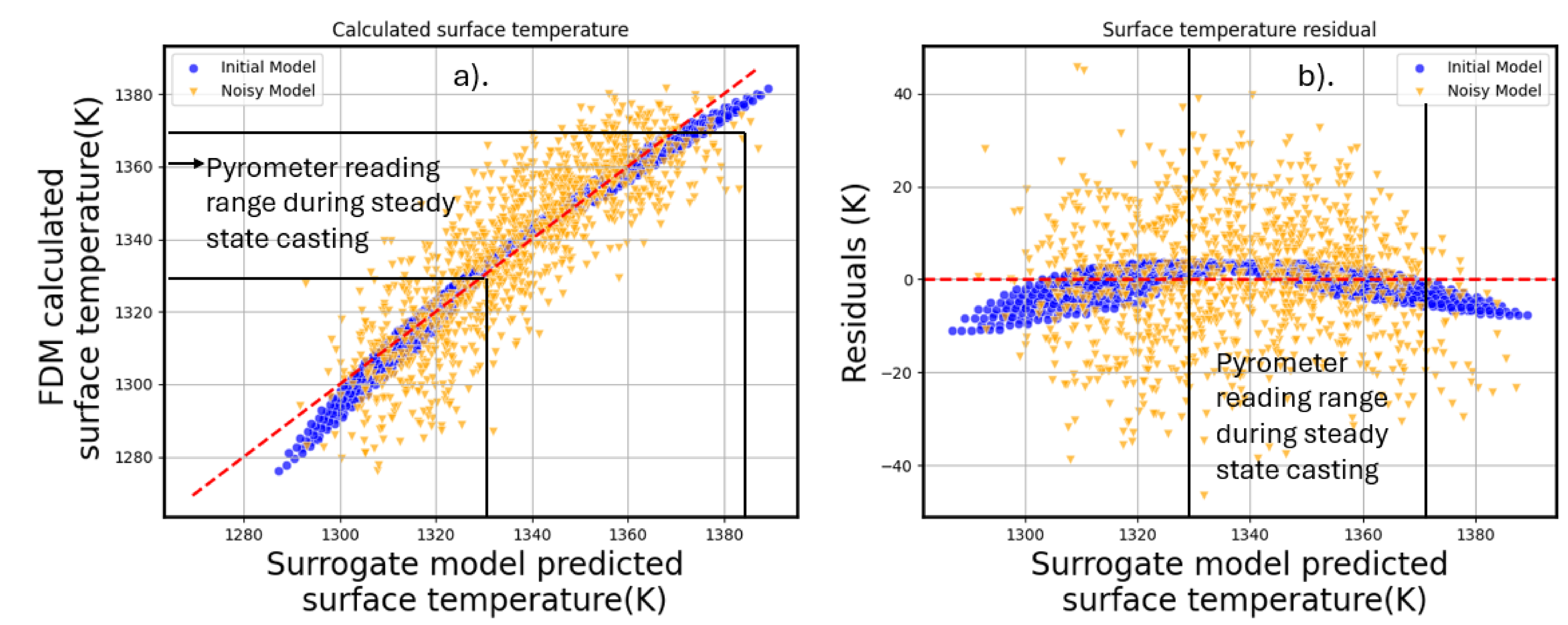


CONCLUSION

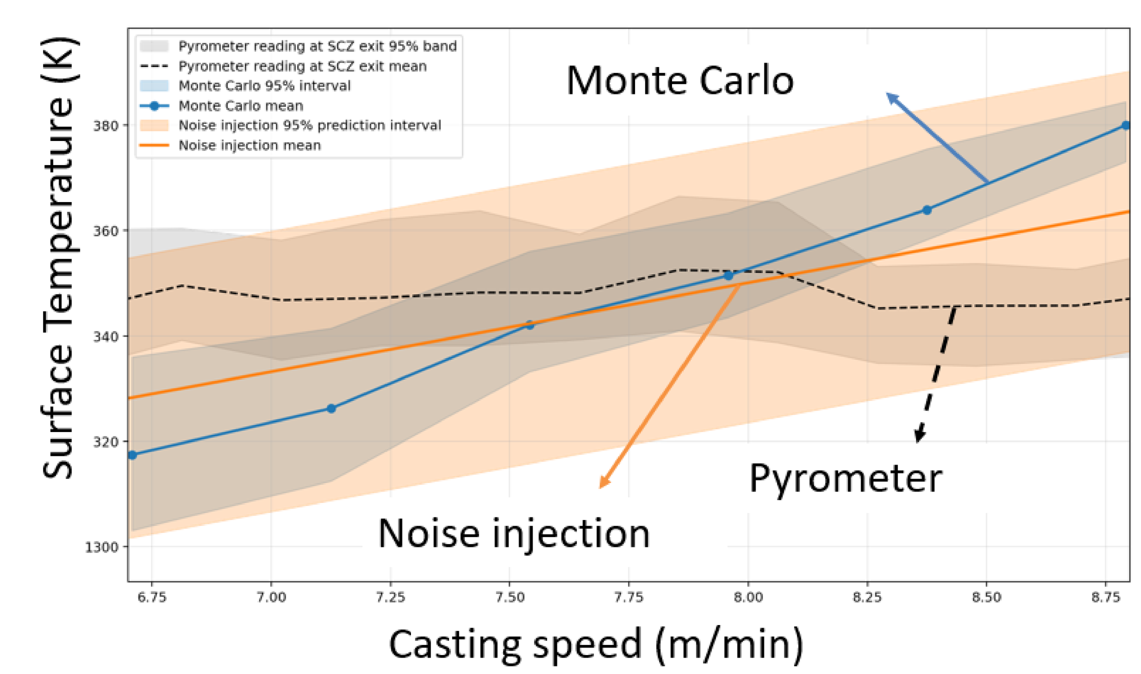
- Weighted and normalized loss functions can both fit the calibration data, but they lead to different model responses.
- Surface temperature is more sensitive to mold-water ΔT than to superheat.
- Noise injection gives a larger, more conservative uncertainty estimate than Monte Carlo input UQ.
- Below 8.33 m/min, surface-temperature variation is mainly driven by superheat and mold-water ΔT.

RESULTS

Uncertainty with noise injection in training set

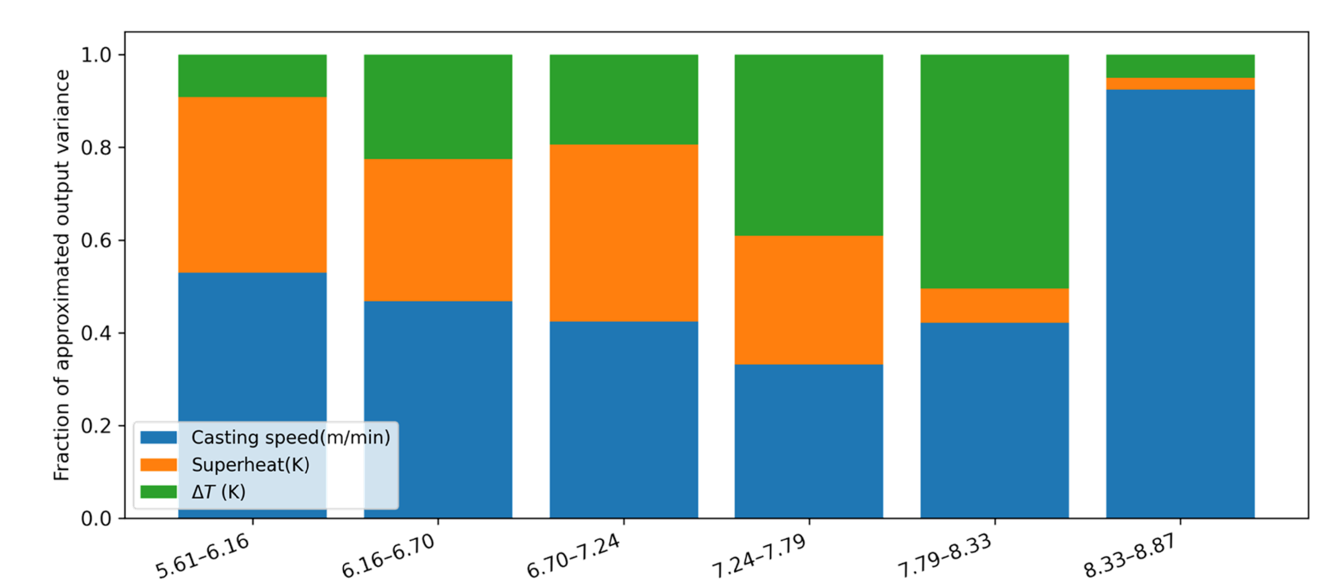


Uncertainty with Monte Carlo quantification



- Divide the industrial casting speed ensemble into 6 bins with equal numbers of datapoints
- Conduct random sampling by performing 5,000 simulations using the industrial dataset and simulating it with the surrogate model.

Input variation interpretation from the MCUQ analysis



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1. Brimacombe, J.K. Design of Continuous Casting Machines Based on a Heat-Flow Analysis: State-of-the-Art Review. Canadian Metallurgical Quarterly 1976, 15, 163–175,
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