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Reimagining Digital Twins: an Active-Learning Approach to Calibrating Models for Complex Systems

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IDEAS+ Integrated Data, Energy Analysis + Simulation

DIGITAL TWINS

- Computational models of the physical counterparts (such as the earth, aircrafts, buildings, and human bodies)
- Support critical decisions in reality by predicting NEW scenarios
- Simplified models and incomplete information of the physical twins
- System characteristics and boundary conditions evolve in reality
- Model construction and data assimilation are crucial in the life cycle of digital twin applications

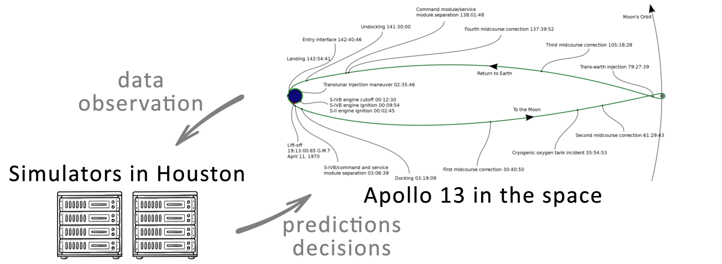


Fig. 1. The recovery of Apollo 13 was the first use of digital twins

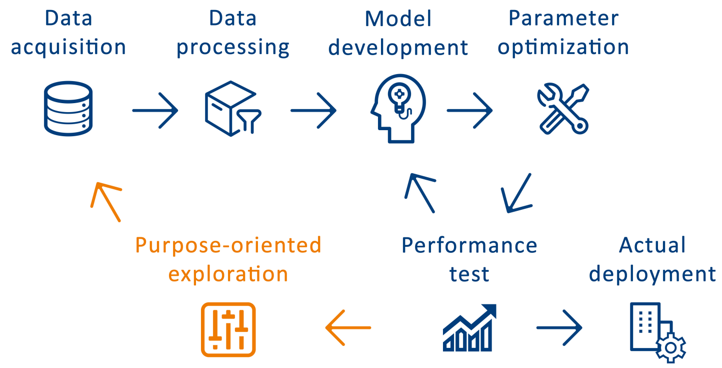


Fig. 2. Trasforming model calibration from model-centric to a data-centric paradigm

MODEL CALIBRATION

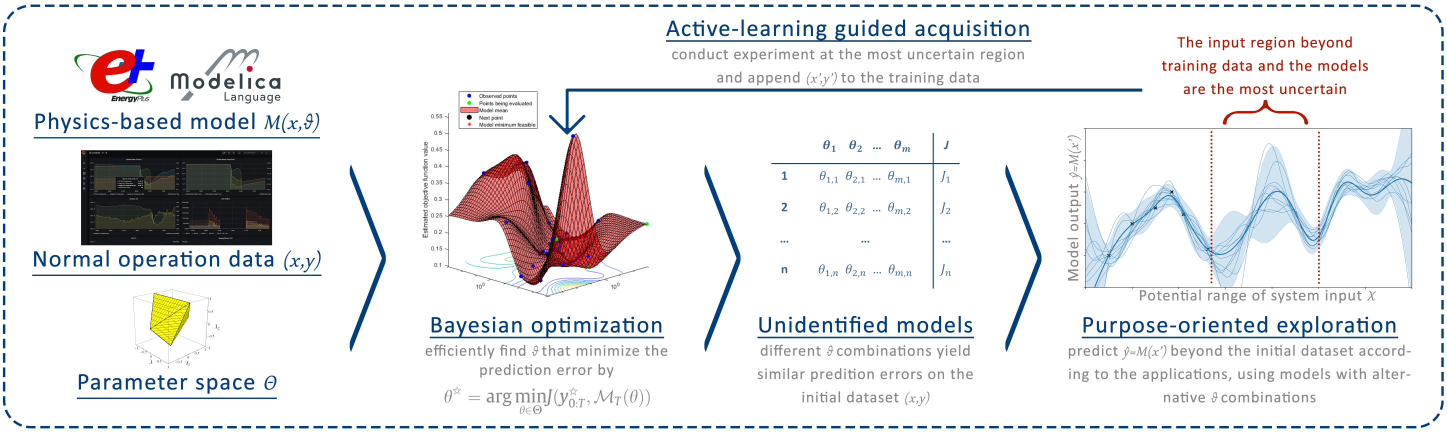
- A set of parameters to minimize the discrepancy between the model and the reality
- Identifiability issues due to the large number of parameters
- The range of decision-making requires the model to extrapolate
- Low prediction error on historical data CANNOT guarantee a representative and reliable digital twin

- Most calibration studies focus on developing advanced models or optimization algorithms
- Data availability is usually the bottleneck in practice
- Extra information to be acquired with restricted costs

Hereby, we advocate a new DATA-CENTRIC framework for model calibration, where the additional acquisition is guided by current status of digital twins.

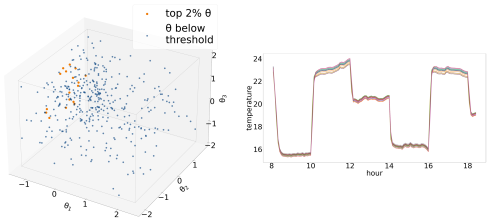
ACTIVE LEARNING FRAMEWORK

(Demonstratded for energy systems in buildings)



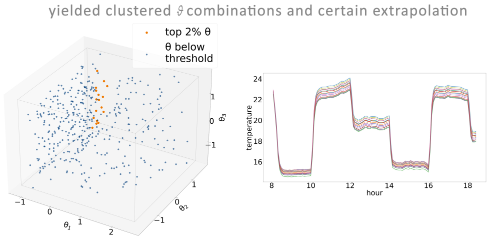
CASE I: COIL

(Simple dynamics, hard to measure)



Calibration with initial operation data

yielded clustered ϑ combinations and certain extrapolation

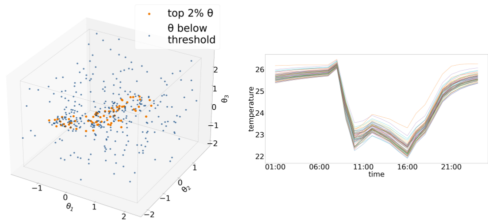


Still test with excited dataset

ϑ cluster drifted to a new region, resulting in larger uncertainty and error in extrapolation

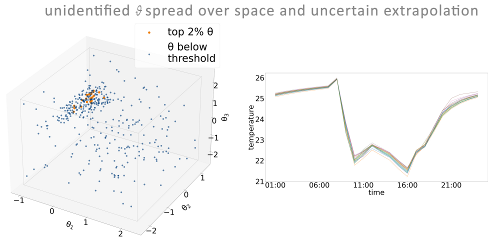
CASE II: ROOM

(Complex dynamics, easy to measure)



Calibration with initial operation data

unidentified ϑ spread over space and uncertain extrapolation



AL-acquired data appended for training

ϑ identified in a small cluster, resulting in accurate prediction with small uncertainty

KEY TAKEAWAY

- Active learning effectively improves model calibration when necessary, model evaluation is critical
- Additional data may introduce extra uncertainty, undesirable data could deteriorate the calibration
- Mismatch between data informativeness and model adequacy leads to problematic calibration

FUTURE WORK

- Other dimensions of data acquisition to be inspected: including resolution and measurements
- Generalizable quantification of dataset sufficiency for digital twins
- Epistemic uncertainty in calibrated models to be characterized into model-induced and data-caused