Learning Complex Barn Climate and Emissions Dynamics with Simulation-Informed Machine Learning

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Introduction

- Dairy-cow barns emits greenhouse gases and pathogens, necessitating in-time monitoring. However, practical constraints limit sensor amounts, creating data gaps
- Alternatives for CFD simulation-based gap filling are needed

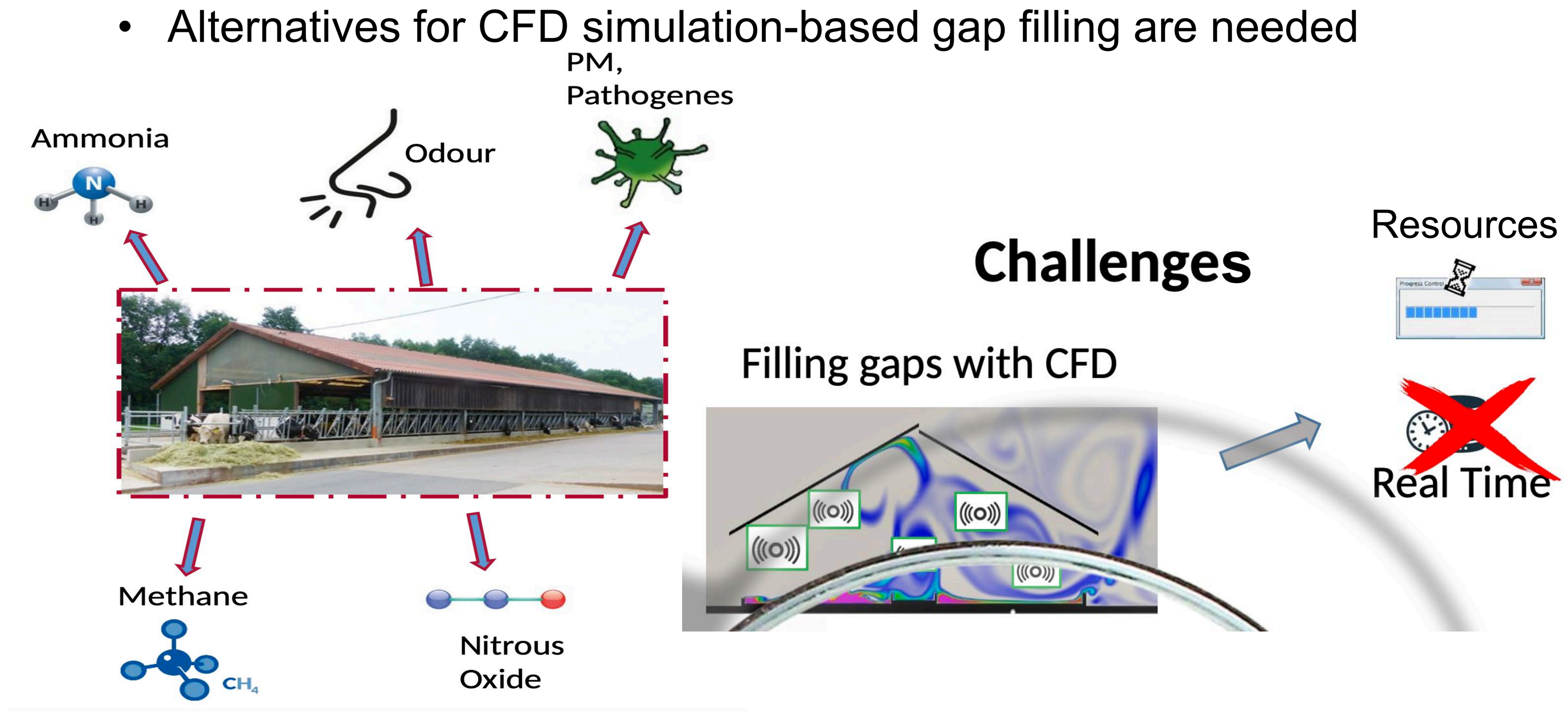


Figure 1. Motivation and Challenges of barn emissions management

Main Goals

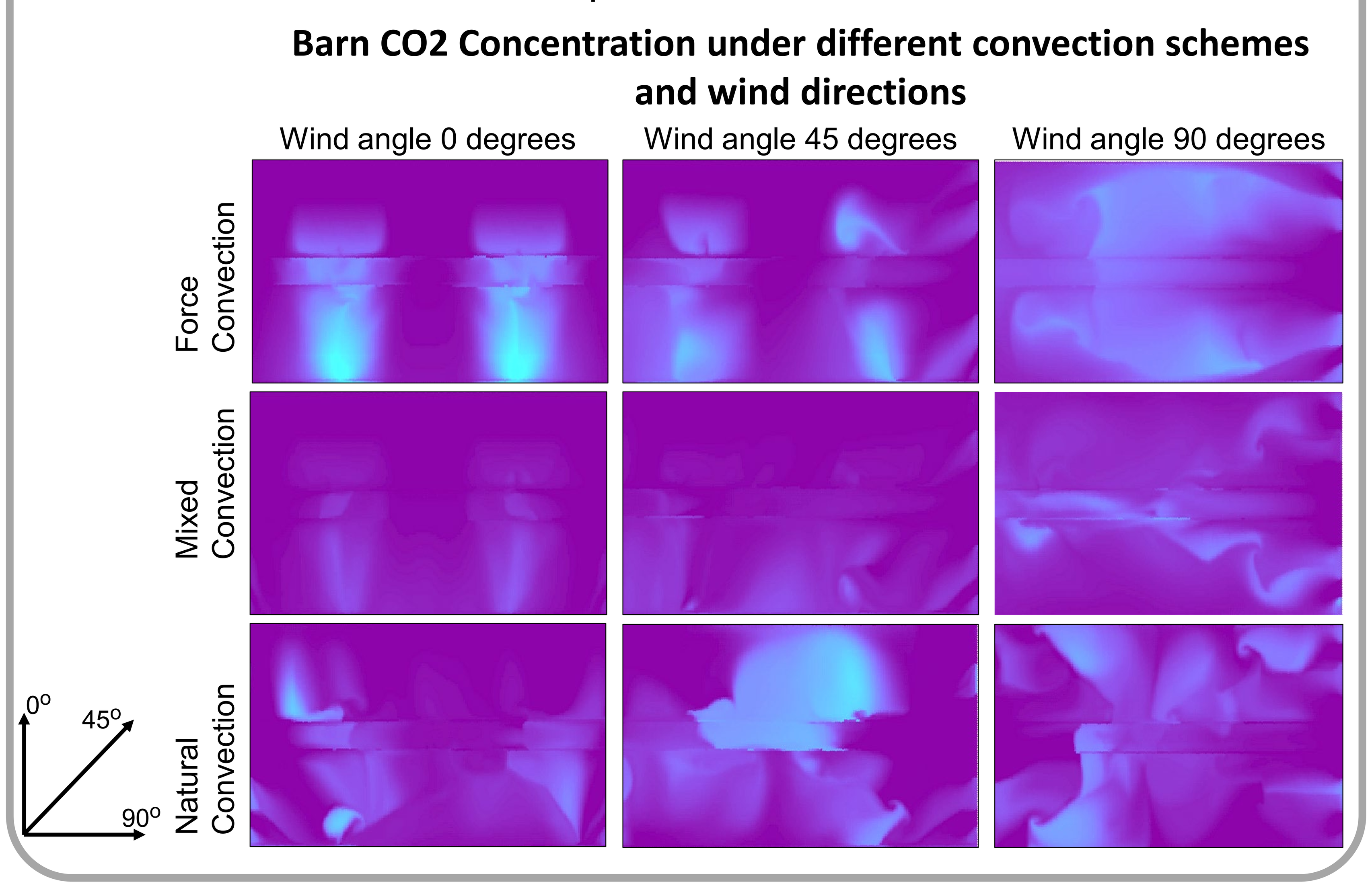
Efficiently learn comprehensive data representations with minimal sensor input by leveraging simulation-informed insights

Core Ideas

- Learn a function f: $f(\boldsymbol{x}) \rightarrow g(\boldsymbol{x})$ (Accelerate data generation)
- Then, learn a function k: $k(\boldsymbol{x}, \boldsymbol{y}) \rightarrow f(\boldsymbol{x})$ (Extrapolate sparse values)
  - $\boldsymbol{x}$: environmental factors,
  - g: CFD simulator,
  - $\boldsymbol{y}$: sensor set

Analysis

- Nodes in simulation results are grid-like distributed
- Transition between scenarios of different wind direction and convection schemes is not entirely stochastic but exhibits patterns that can be discerned and predicted



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Methods

- Convert grid-like time-independent simulations to directed graph structures that optimize homogenous behavior of neighborhoods
- Split function f to two sub-functions for better performance:
  - function f_1: dimensionality reduction using GNNs
  - function f_2: match environmental using contrastive learning
- Push the sensor data to the learned graph to get values of the remaining nodes (via function k)

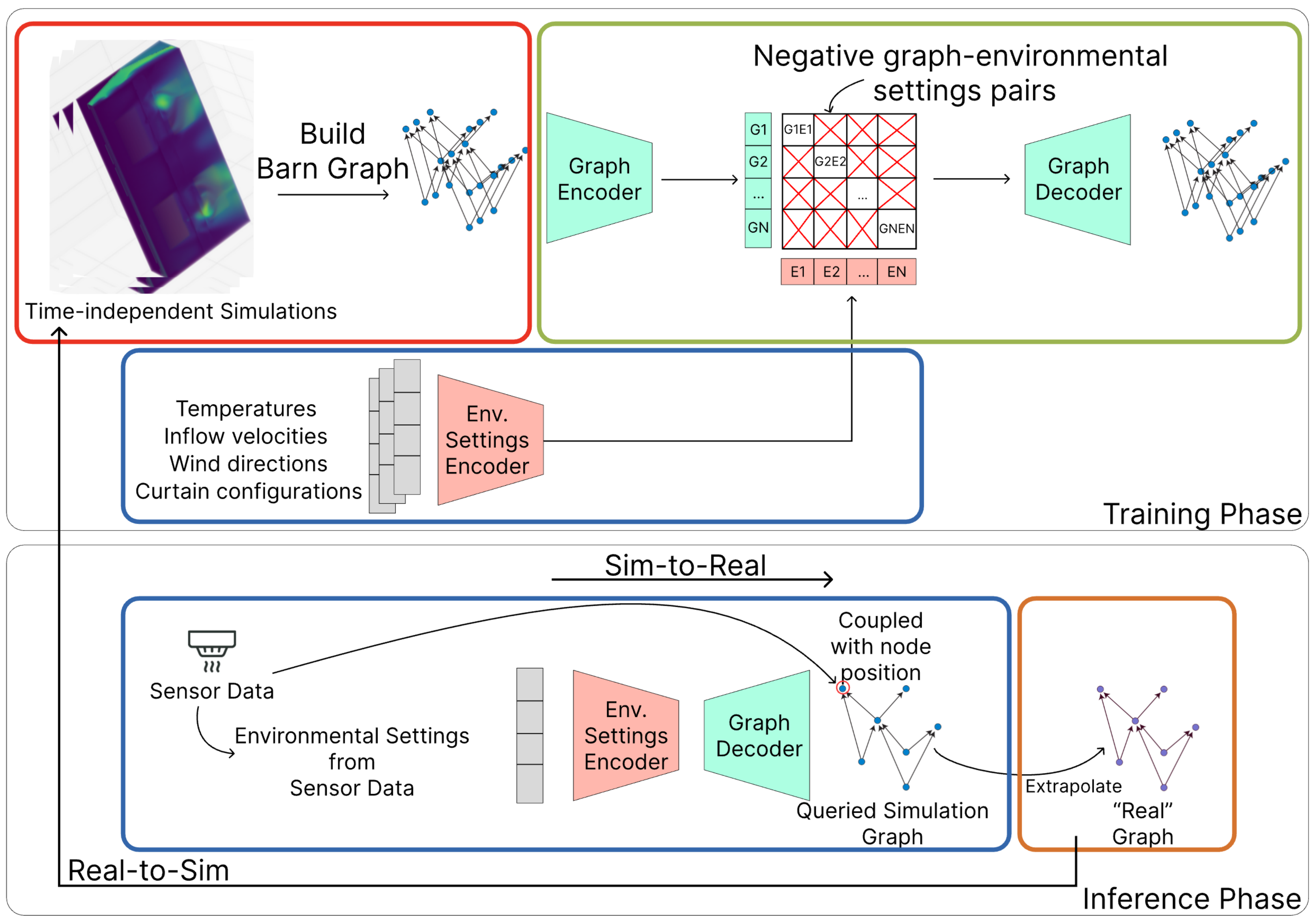

Figure 2. Sim-to-real and real-to-sim hybrid AI conceptual model

Key Takeaways

- Apply Informed Machine Learning to integrate aspects of CFD into the learning functions
- Machine Learning as the optimal approach in learning and mining complex knowledge
- Graph Neural Networks as a more potential method in learning sparse grid-like data, compared to Traditional Machine Learning
- Outlook: Generate large datasets from the feedback loop of the Hybrid AI model, then discover or explain implicit/explicit knowledge within the generated information that leads to better decision making

Please find the digital version, related work, and contact here:

References

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