Slide 1 – Title Slide

I appreciate the kind introduction. Good afternoon, everyone. Thank you for joining this session. My name is Juwan Ha, a Ph.D. student at NC State University.

Today, I'd like to present our research work on improving energy and data efficiency in factory buildings using a Physics-Informed Neural Network-based Model Predictive Control approach, we called PINNs-based MPC.

Slide 2 – Learning Objectives

This is Learning Objectives. I will cover the two things.

First, you will understand the limitation of data-driven MPC in Factory Buildings.

Second, you will understand the concept and advantages of PINNs-based MPC Approach.

Slide 3 – Acknowledgement

Before we are diving in, I'd like to acknowledge that this research was supported by the Technology Innovation Program of Korea's Ministry of Trade, Industry and Energy.

Slide 4 – Introduction

Let's take a closer look at why improving ***HVAC systems in factory buildings*** *is so important.*

Unlike residential and commercial buildings, ***factory buildings are part of the industrial sector****, which accounts for* ***33% of total energy consumption*** *in the United States.*

Globally, manufacturers are under increasing pressure to reduce energy use and transition toward sustainability—driven by initiatives like the ***RE100 project****.*

Inside factories, ***HVAC systems alone consume 49% of non-process energy*** *and nearly* ***9% of total manufacturing energy****.*

Improving HVAC energy performance in factories is therefore not just beneficial—it's a ***critical opportunity for large-scale impact****.*

Slide 5 – Challenges in Predictive Models

Let's talk about why current predictive models aren't enough.

First, **white-box models** like EnergyPlus rely on detailed physical equations and input data. They're accurate—but often **too complex and time-consuming** to develop and deploy.

Grey-box models, such as RC models, are simpler and more efficient,
but they **oversimplify thermal dynamics** as linear systems and struggle with **nonlinear behavior**.

Black-box models, like neural networks, can capture complex nonlinear patterns.
However, they require **large, high-quality datasets** and often **lack physical consistency**.

That's why we turn to **Physics-Informed Neural Networks (PINNs)**.
PINNs combine physics-based equations with machine learning—ensuring **data efficiency**, **physical consistency**, and **robust generalization**, even with limited data.
They've been successfully applied across many engineering domains.

In our work, we apply PINNs within a **Model Predictive Control (MPC) framework**
to improve HVAC performance and optimize data utilization in factory buildings.

Slide 6 – Methodology

We followed a **four-phase workflow**.

Phase 1 – Data Generation
We built a **high-fidelity EnergyPlus model**, calibrated with field measurements, to generate detailed HVAC operating data and energy use.

Phase 2 – RC Thermal Model
Next, we created a **2R-2C network** that captures heat transfer through walls, zones, and ambient air using thermal resistances and capacitances.

Phase 3 – PINN Training
We merged a data-driven ANN with the RC model by adding the physical equations to the loss function
These physics constraints boost consistency, **accuracy, and data efficiency**.

Phase 4 – MPC Implementation & Validation
Finally, we embedded the trained PINNs model in a **Model Predictive Control** loop and compared it with a fixed-setpoint baseline, quantifying energy savings and data utilization.

Slide 7 – PINN-Based MPC

This slide shows how we implemented the **PINNs model** within a **Model Predictive Control framework**.

On the left, we define the **loss function** for the PINN. It's a weighted sum of two terms:
• Neural network loss is the standard which measure the between prediction and observed data.
• Physics equation informs loss informs prior building knowledge using 2R2C model for physics consistency.

The weighting factor lamda adjust the prior physics knowledge.

On the right side is the MPC Controller formulation.
It minimizes the gap between predicted indoor temperature and the setpoint, while also reducing RTU power use.
We apply constraints on indoor temperature limits and RTU capacity and solve it using IPOPT in CasADi.

Slide 8 – Target Building

Let me briefly introduce the target building used in this study.

This facility is a **home appliance manufacturing factory** located in **South Carolina, USA**, and falls within **ASHRAE Climate Zone 3A**.
It features **large open spaces**, typical of industrial settings, and spans approximately **348,000 square feet**

The factory operates on a **12-hour schedule**, from **3 AM to 3 PM** daily.

In terms of HVAC, the building is equipped with 13 **multiple-staging rooftop units (RTUs)**.
The **indoor setpoint temperature** is maintained at **73°F**, ensuring thermal comfort across the space.

Slide 9 – Real-World Data Challenges

In factory buildings, developing accurate data-driven models is often difficult due to missing sensors and incomplete performance data.
This leads to significant **data imbalance**, making it hard to train reliable models.

As an example, the **measured COP** of rooftop units ranged from **1.15 to 2.16**, while the **manufacturer-performance data** were significantly higher, around **3.31 to 3.64**.

One major reason for this gap is that it's extremely difficult to perform controlled experiments in real factory environments.

Factory engineers typically avoid modifying HVAC control strategies due to production risks—since any disruption can directly impact manufacturing output and profitability.

To address this challenge, we developed a calibrated EnergyPlus simulation model, using real-world data collected from the site.

Each RTU's indoor temperature and energy consumption model meets the ASHRAE Guideline 14 accuracy criteria, with CV(RMSE) values well below the 30% threshold.

This validated simulation model serves as a solid foundation for training our PINN-based controller.

Slide 10- Model evaluation

"For model training, we used three months of data for the pure data-driven ANN and only one month for the PINN. Both models were evaluated on the same one-month test set to ensure a fair comparison.

The two models share the same architecture, and their hyperparameters were tuned through trial and error. The key difference lies in the physics regularization term λ:
For the PINN, we set λ to 0.3 to incorporate physical knowledge, while for the ANN, λ was set to 0, meaning no physical knowledge was used at all."

Slide 11- Model evaluation

"Now let's look at the model prediction performance."

We compared two models: a pure data-driven ANN model, and our PINN model that incorporates prior physical knowledge.

The ANN was trained on three months of data, while the PINN was trained on just one month.

Despite using less data, the PINN significantly outperformed the ANN in both training and test periods. This clearly shows that the PINN model achieves higher prediction accuracy with less data, thanks to the integration of physics.

Slide 12- Model evaluation

Now let's look at the energy savings results.

We compared two control methods:
a baseline control with a fixed indoor temperature setpoint, and our PINN-based MPC, which optimally adjusts the setpoint every 15 minutes.

Over the one-week comparison period, the PINN-based MPC reduced cooling energy consumption by approximately 13%.
At the same time, it maintained more stable indoor temperatures, enhancing occupant comfort.

This demonstrates that PINN-MPC not only improves energy efficiency but also ensures better thermal comfort.

Slide 12- Conclusion

To summarize,
we proposed a PINNs-based MPC approach for HVAC control in factory buildings.

This method led to improved energy efficiency and better data utilization.

Key results include:

- **13% energy savings compared to baseline rule-based control,**
- **Superior prediction performance with less training data,**
- **Effective HVAC optimization in data-limited environments,**
- **And a cost-effective and scalable energy management solution.**

For future work,
For future work, we will move beyond evaluating the PINN model based on accuracy. We plan to assess its physical consistency, generalization ability, and interpretability, and explore real-world deployment of the PINN-based MPC in factory buildings.

Thank you for your attention — I'm happy to take any questions.