Data-Driven Co-Simulation Framework for Frost Prevention and Supply Air Boosting in MVHR Systems

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Abstract

This study presents a data-driven co-simulation framework for real-time frost prevention and supply-air boosting in mechanical ventilation with heat recovery (MVHR) systems operating in cold climates. MVHR systems play a key role in reducing ventilation heat losses in airtight buildings; however, when exposed to cold outdoor air, frost formation on heat exchangers leads to increased energy use and reduced efficiency. In Stockholm, the defrosting load alone reaches approximately 162 MW, i.e., around 4% of the district-heating network's peak capacity illustrating the importance of effective frost management strategies. The proposed framework integrates a frost-detection algorithm with a data-driven model predictive controller coupled to a neural state-space model of a full-scale MVHR unit at the KTH Live-In Lab. Implemented through a co-simulation framework, the controller dynamically adjusts fan speeds and heating-coil operation to maintain supply-air temperature while preventing frost accumulation. Simulation results confirm that the co-simulation framework eliminates frosting events, maintains stable operation, and improves energy efficiency without additional heating demand. The findings demonstrate the potential of data-driven co-simulation to enhance the resilience and performance of MVHR systems in cold-climate applications.

Keywords: Mechanical ventilation with heat recovery, co-simulation, model predictive control, frost prevention, data-driven modelling, energy efficiency.

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1. Introduction

Mechanical ventilation with heat recovery (MVHR) systems are essential components of energy-efficient buildings, particularly in cold-climate regions. They significantly reduce heat losses by recovering thermal energy from exhaust air through rotary or plate heat exchangers. However, when outdoor air temperatures drop during winter, the heat-exchanger surface can reach subzero conditions, leading to frost formation. This process increases pressure losses, degrades heat-transfer efficiency, and can interrupt operation due to defrost cycles. The challenge of frost management remains one of the most critical limitations to achieving optimal MVHR performance in cold climates (Härer et al., 2019). Traditional frost-control strategies typically rely on preheating incoming air or intermittent bypassing of the heat exchanger. While effective at preventing frost, these approaches increase energy consumption and reduce the overall seasonal efficiency (Härer et al., 2019) . Advanced model-based control solutions offer an opportunity to maintain thermal comfort while minimizing energy penalties. Model Predictive Control (MPC) has shown strong potential in coordinating multiple actuators within HVAC systems to optimize operation under variable boundary conditions (Asvadi-Kermani et al., 2022).

In Sweden and other cold-climate countries, the impact of frost-related ventilation losses is far from negligible. In Stockholm, the total defrosting load during extreme winter conditions can reach approximately 162 MW, representing about 4 % of the district-heating network's peak capacity (Nourozi et al., 2019). This highlights the need for advanced control strategies that prevent frost while minimizing energy demand.

Recent research has increasingly focused on data-driven approaches to enhance control accuracy without requiring high-fidelity physical models. Methods such as Sparse Identification of Nonlinear Dynamics (SINDy) (Asvadi-Kermani et al., 2022; Elomari et al., 2025) and Neural State-Space (NSS) modeling enable the identification of nonlinear system behavior directly from operational data, allowing control strategies to adapt to changing system conditions (Yazdani et al., 2025) . These techniques have been successfully applied to air-handling units (AHUs) and heat-recovery systems, demonstrating improved prediction accuracy and control stability under dynamic conditions (Asvadi-Kermani et al., 2022). While data-driven methods enhance model accuracy and adaptability, their effectiveness must be validated under realistic dynamic conditions. Co-simulation enables this by integrating high-fidelity physical models, advanced control algorithms, and real-time interactions between the digital control layer and the physical MVHR system.

Building on this recent progress, this paper develops a data-driven co-simulation framework for real-time frost prevention and supply-air boosting in a full-scale MVHR unit installed at the KTH Live-In Lab. The framework integrates a frost-detection module and an MPC strategy coupled with a data-driven model identified from operational data. The co-simulation environment allows direct interaction between the controller and the physical MVHR model, enabling dynamic adaptation to frost-risk conditions. The proposed approach aims to maintain heat-exchanger stability, minimize defrosting energy, and ensure supply-air comfort throughout winter operation.

2. Methodology

This section describes the development of the proposed hierarchical co-simulation framework for real-time optimal control. The studied system is a full-scale MVHR ventilation unit (also known as an air-handling unit, AHU, or FTX system) installed at the KTH Live-In Lab.

2.1 Co-simulation framework

The framework integrates a high-level Energy Management System (EMS) and frost detection algorithm with a low-level model predictive controller (MPC). The co-simulation architecture (Figure 1) consists of three main layers. The high-level supervisory layer includes the EMS, which provides operational setpoints based on weather forecasts and building demand, and a frost detection module that monitors air-to-air heat exchanger conditions to trigger defrost control when necessary. The low-level control layer hosts the MPC algorithm responsible for coordinating multiple MVHR actuators to maintain the supply air temperature near its target with minimal control energy. Finally, the physical layer represents the MVHR system, including supply and exhaust fans, the rotary heat exchanger, and the heating coil, modeled in Simulink using data retrieved from the building management system (BMS).

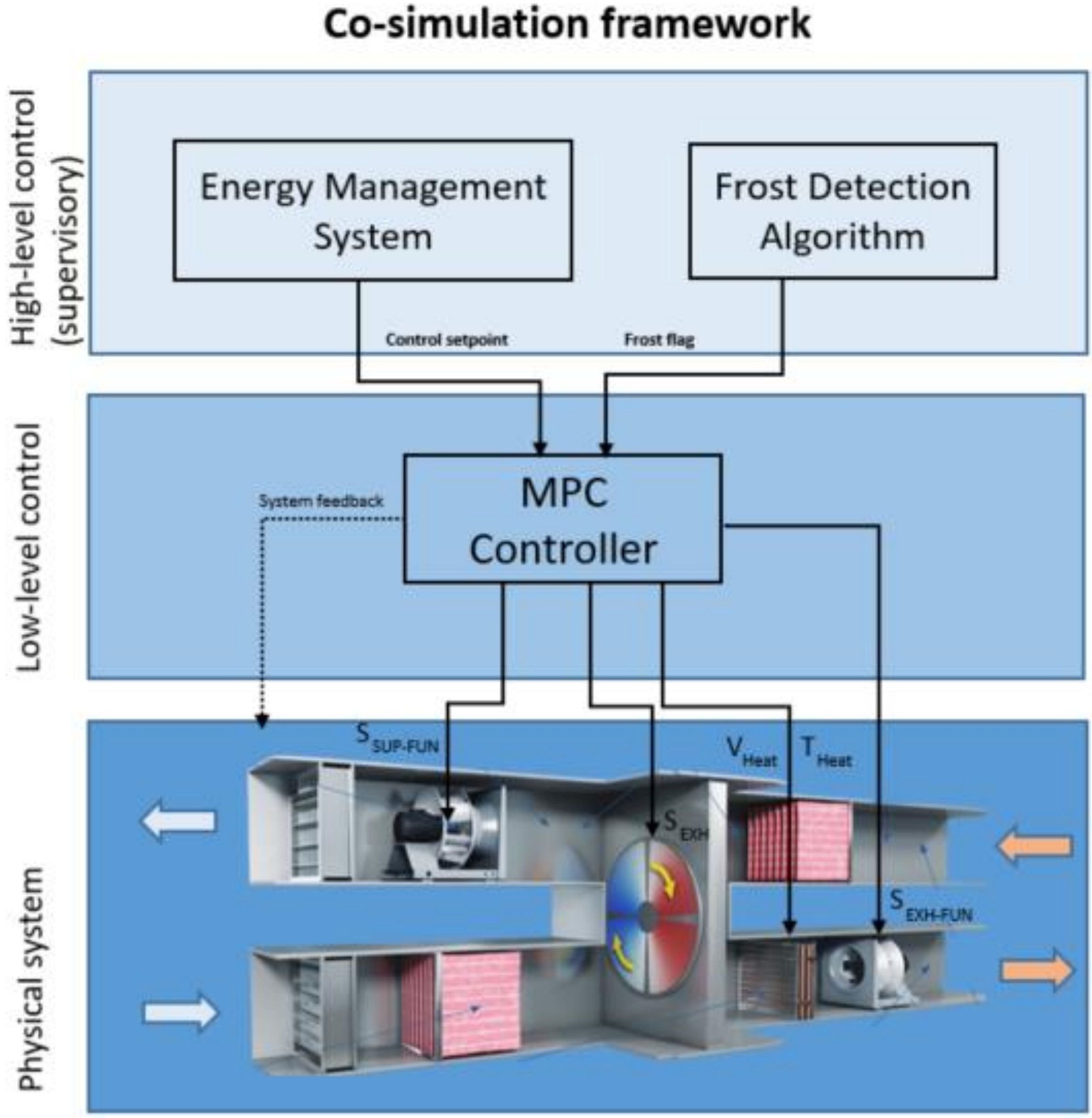

Figure 1: Co-simulation framework integrating the Energy Management System, frost-detection algorithm, and Model Predictive Controller (MPC) for MVHR operation. The MPC performs real-time optimization of the MVHR components, supply and exhaust fan speeds (S_{sup}, S_{exh}), rotary heat-exchanger speed (S_{phx}), and heating-coil parameters (V_{heat}, T_{heat}).

2.2 MVHR model development

Modeling the coupled heat and mass transfer in the MVHR unit is challenging. Nonlinear interactions between airflows, heat recovery, and coil action drive dynamics that simple linear models cannot capture reliably. We therefore adopt a data-driven neural state-space (NSS) formulation that preserves a state-space structure while using multilayer perceptrons to learn the nonlinear maps from data. The discrete-time model as:

$$x_{k+1} = f(x_k, u_k; \theta), \; y_k = h(x_k, u_k; \theta) \qquad \text{(eq. 1)}$$

Where x_k is the state vector, u_k the actuator vector, and θ the network parameters. States are chosen to represent the dominant thermo-aerodynamic behavior of the MVHR:

$$x = [T\_sup, \dot{m}\_exh] \qquad \text{(eq. 2)}$$

With T_{sup} the supply air temperature and $\dot{m}_{exh}$ the exhaust-air flow rate. And inputs drive the heat recovery and air movement:

$$u = [Q_{heat}, T_{heat}, S_{sup}, S_{wheel}, S_{exh}] \qquad \text{(eq. 3)}$$

Where $\dot{Q}_{heat}$ and T_{heat} are the heating-coil rate and water temperature, S_{sup} and S_{exh} are supply and exhaust fan speeds, and S_{wheel} is the rotary heat-exchanger speed. Measured outputs are:

$$y = [T_{sup}, \dot{m}_{exh}] \qquad \text{(eq. 4)}$$

Parameter estimation follows a one-step-ahead prediction objective:

$$min_{\theta} \sum_{1}^{N} \|y_k - \hat{y}_k(x_k, u_k;\ \theta)\|_2^2 \qquad \text{(eq. 5)}$$

Model training was performed on one year of real operational data with a 15-minute resolution. The identified NSS model accurately reproduced the MVHR's thermal and airflow behavior, providing a reliable surrogate for integration into the co-simulation framework. This model serves as a high-fidelity reference for evaluating control strategies and validating the predictive performance of the MPC.

2.3 MPC formulation

The MPC optimizes the MVHR operation to maintain the supply-air temperature close to its setpoint while minimizing control effort and preventing frost formation on the rotary heat exchanger. At each control step, the MPC solves:

$$\min \sum_{k=1}^{N_p} \left[\left(y_k - y_{sp}\right)^T Q \left(y_k - y_{sp}\right) + \left(u_k - u_{ref}\right)^T R \left(u_k - u_{ref}\right) \right] \quad \text{(eq. 6)}$$

Subject to

$$x_{k+1} = f(x_k, u_k), \qquad u_{min} \leq u_k \leq u_{max} \qquad \text{(eq. 7)}$$

Here, x_k represents the system state vector, u_k the control input vector, and y_k the predicted output (supply-air temperature). y_{sp} is the reference setpoint from the EMS, u_{ref} is the nominal operating point, and the prediction horizon is denoted by Np .

The model used inside the MPC was identified using the Sparse Identification of Nonlinear Dynamics (SINDy) method. SINDy represents the MVHR dynamics through a sparse set of nonlinear basis functions derived from measured states and inputs, providing an explicit and computationally efficient form for control. The time derivatives of the normalized state data were approximated and related to a library of candidate nonlinear terms Θ (x,u).The governing equations were identified as

$$\dot{x} = \Theta(x, y). \Xi \qquad \text{(eq. 8)}$$

Where Ξ is the sparse coefficient matrix obtained via least-squares regression with thresholding. This compact model captures the system nonlinearities of the MVHR and ensures fast computation within the optimization loop.

2.4 Case study

The case study focuses on the MVHR installed at the KTH Live-In Lab, with a rotary heat exchanger, variable-speed supply and exhaust fans, and a heating coil , as illustrated in Figure 2. The system serves four student apartments and is equipped with a complete BMS for data acquisition and control. Historical operational data were used to train and validate both the SINDy and NSS models. The dataset includes supply and exhaust air temperatures, airflow rates, heating-coil rate and temperature, and fan and wheel speeds, recorded at a 15-minute resolution over one year. These data provided the boundary conditions and reference signals for the co-simulation environment used in the subsequent analysis.

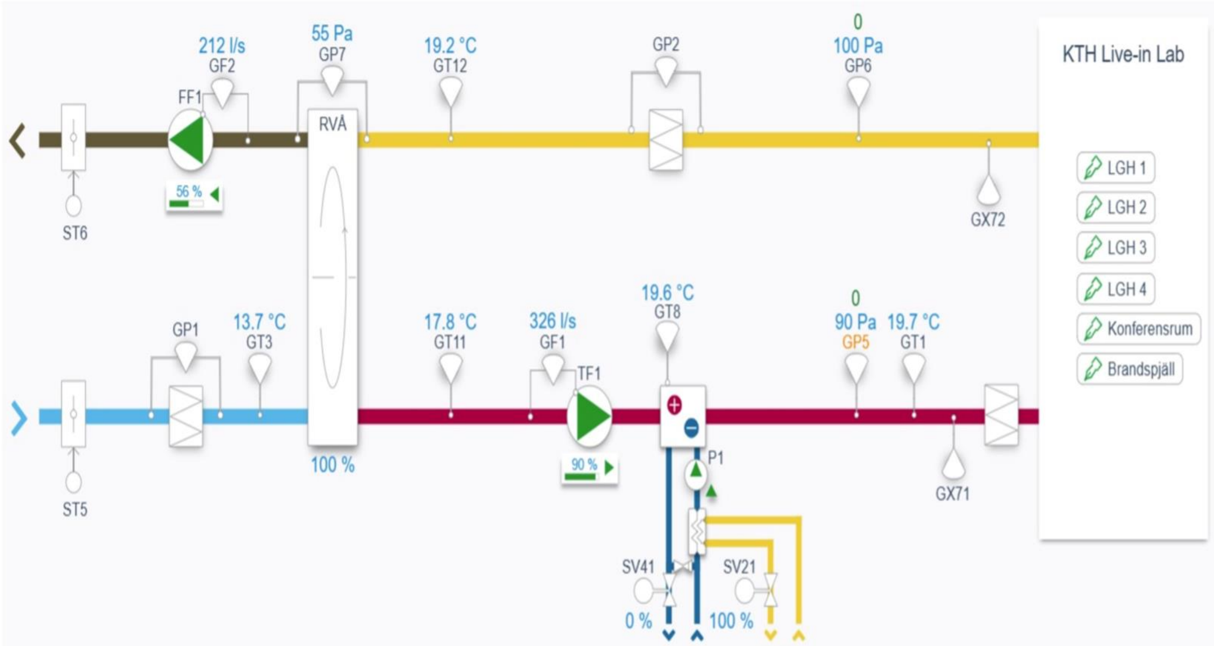

Figure 2: SCADA view of MVHR system of the KTH Live-in Lab

3. Results and discussion

This section presents the results obtained from the developed co-simulation framework integrating the data-driven model predictive controller and the frost detection algorithm. The results are organized into three parts: model validation, evaluation of the heat exchanger performance under frost-risk conditions, and assessment of the closed-loop MPC control response.

4.1 Model validation

The predictive capability of the trained NSS model was assessed against one-year operational data. Figure 3 compares the measured and simulated temperature profiles for the supply, recycled, and exhaust air streams. The model captures both steady-state behavior and transient dynamics with high consistency. Deviations between simulated and measured values occur mainly during rapid airflow fluctuations, which are influenced by sensor response and short-term turbulence effects. Overall, the NSS model demonstrates sufficient accuracy for control evaluation, with a mean absolute error below 0.5 °C for supply-air temperature and within 5 % for exhaust airflow prediction. These results confirm that the identified data-driven model reliably reproduces the thermal–airflow interactions of the full-scale MVHR unit and can serve as a robust reference for subsequent MPC validation.

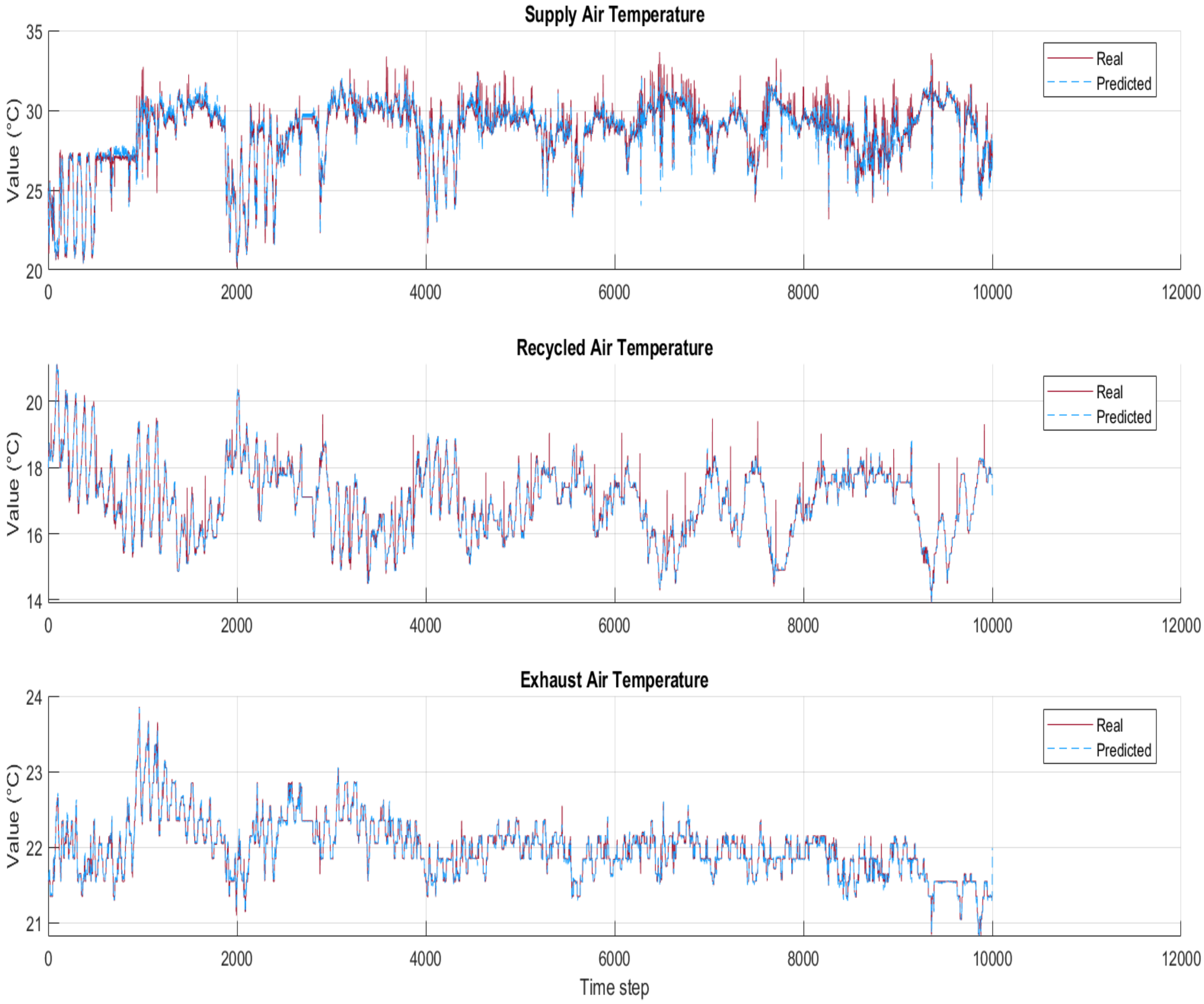

Figure 3: Comparison between measured and simulated air temperatures (supply, recycled, and exhaust) for model validation

4.2 Frost risk mitigation

The effect of regulating the exhaust-fan speed on the heat-exchanger surface temperature was analyzed to evaluate the system's resilience against frost formation. Figure 4 shows the simulated surface temperature of the rotary heat exchanger during a cold-weather period for two operating modes: a baseline case without fan regulation and the proposed frost-aware control case. In the baseline mode, the exhaust airflow remains constant, which leads to a drop in surface temperature and initiates frost accumulation, causing increased pressure loss and reduced heat-recovery efficiency. When the proposed control is activated, the MPC temporarily reduces the exhaust-fan speed during frost-risk periods, lowering the mass-flow ratio across the exchanger. This adjustment maintains the surface temperature above the critical threshold and prevents ice formation without additional heating energy. Once the risk condition ends, the controller restores the airflow to its nominal level, maintaining comfort and system efficiency. The results confirm that active exhaust-fan regulation can effectively mitigate frosting, providing a low-energy alternative to conventional preheating or periodic defrost cycles.

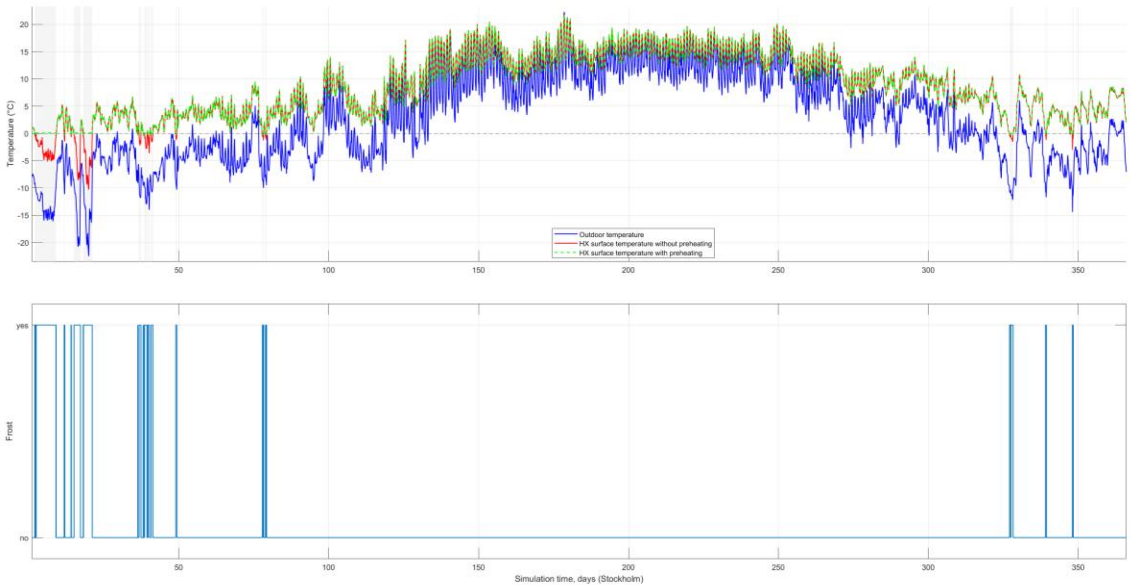

Figure 4: Heat-exchanger surface temperature with and without exhaust-fan regulation.

4.3 MPC performance under frost-risk conditions

The closed-loop performance of the proposed frost-aware SINDy-based MPC was assessed within the developed co-simulation framework. The co-simulation environment dynamically links the high-level supervisory control and frost detection modules with the detailed MVHR model. Figure 5 presents the dynamic response of the system during a winter operating sequence. The MPC maintained the supply-air temperature close to its 23 °C setpoint while coordinating the heating coil and fan speeds to ensure stable operation. When the frost detection algorithm identified a risk of ice formation on the rotary heat exchanger, the controller automatically reduced the exhaust-fan speed. This action decreased the airflow ratio across the heat exchanger, raising the surface temperature above freezing and preventing frost buildup. Unlike traditional preheating strategies, the proposed approach mitigates frosting without additional heating energy or interruptions in operation. During the defrosting phase, the co-simulation framework allowed synchronized updates between the physical model and controller, ensuring smooth transitions between operating modes. Once the frost flag cleared, the MPC gradually restored the exhaust-fan speed to its nominal range, recovering the design airflow rate while maintaining comfort. The system remained stable throughout the simulation, with all actuators operating within prescribed bounds. The supply-air temperature tracking error remained below 0.5 °C, demonstrating high prediction accuracy and control robustness.

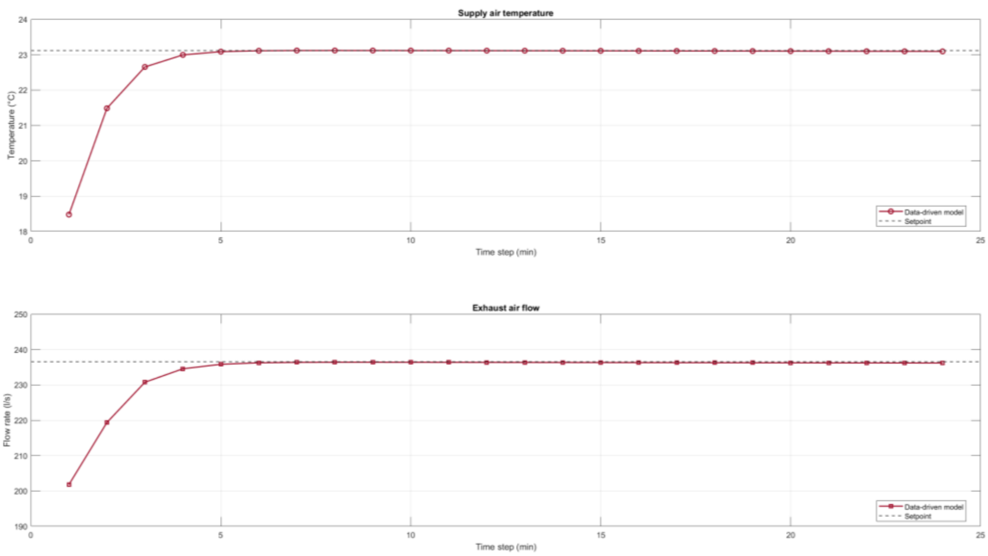

Figure 1: Closed-loop MPC response showing supply-air temperature and exhaust-airflow tracking during frost-risk conditions.

Overall, the co-simulation results confirm that the integrated frost-aware MPC improves both energy efficiency and operational resilience. By leveraging real-time coordination between the control and physical models, the framework effectively balances thermal comfort, energy use, and frost prevention. This approach provides a practical pathway for advanced supervisory control of ventilation systems operating under cold climate conditions.

4. Limitation and Future work

A significant limitation of the proposed method lies in its scalability across multiple sites and systems. The current approach requires site-specific configuration and manual integration of data from different sources, making deployment to new buildings labor-intensive and time-consuming. Each implementation necessitates substantial engineering effort to find and map data points, configure system parameters, and adapt the method to local conditions and equipment configurations.

This lack of interoperability means that while the method demonstrates promising results in controlled case studies, scaling it to building portfolios would face considerable practical barriers. The heterogeneity of data formats, inconsistent naming conventions across different building management systems, and vendor-specific protocols further compound these scalability challenges, making widespread adoption challenging.

To address these scalability limitations, future work should explore integration with semantic modeling technologies and ontology-based frameworks. Semantic models using ontologies provide machine-readable representations of building components, sensors, and their relationships, enabling applications to automatically discover and interpret system data without manual configuration. By representing system data and information in semantic models, it serves as an interoperability layer that allows the proposed method to be deployed across different sites with minimal site-specific engineering. This integration would transform the current approach from a building-specific solution requiring extensive manual setup into a scalable.

5. Conclusion

This study developed and validated a data-driven co-simulation framework for real-time frost prevention and supply-air boosting in mechanical ventilation with heat recovery (MVHR) systems. The framework integrates a frost-detection algorithm with a SINDy-based model predictive controller (MPC) coupled to a neural state-space (NSS) model of a full-scale MVHR unit installed at the KTH Live-In Lab. The co-simulation environment successfully coordinated the physical and control layers, enabling dynamic regulation of fan speeds and heating-coil operation to maintain supply-air temperature while preventing frost formation. Simulation results demonstrated that the frost-aware MPC maintained the heat-exchanger surface temperature above freezing, eliminated frosting events, and enhanced heat-recovery efficiency without increasing heating demand. The proposed approach offers a practical and energy-efficient alternative to conventional preheating or periodic defrost cycles. Given that defrosting loads in Swedish ventilation networks can reach approximately 162 MW—around 4% of the district-heating provider's peak capacity—the demonstrated control strategy represents a significant potential for large-scale energy savings. Overall, the developed framework provides a scalable foundation for advanced supervisory control of MVHR systems, improving both operational resilience and energy performance in cold-climate applications.

6. Acknowledgments

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