Student Conference Proceedings
Vol 2, No 1, 2026, Article ID 2576, 4 Pages

Student Conference Lübeck

Proceedings Article

A Gymnasium Environment for Reinforcement Learning-Based Temperature Control in Naturally Ventilated Calf Barns

Muhammad Haris Ibrahim[a,*] · Malin Böttcher[b] · Mohamed Hail[b,*]

[a]Study program Robotics and Autonomous Systems, Universität zu Lübeck, Lübeck, Germany
[b]Institut für Telematik, Universität zu Lübeck, Lübeck, Germany
[*]Corresponding author, email: muhammad.ibrahim@student.uni-luebeck.de; m.hail@uni-luebeck.de

Received 24 February 2026; Accepted 17 June 2026; Published online 10 July 2026

Abstract
The health and well-being of calves strongly depend on barn climate conditions. Ventilation is regulated by conventional control strategies, leading to suboptimal thermal conditions. Reinforcement learning (RL) polices promise a better solution but require realistic and computationally efficient environments. We present a fast and accurate Gymnasium environment for temperature control in calf barns. A reduced-order thermal network was coupled to an airflow network and simulated in an integrated manner using Differential Algebraic Equation solvers and packaged in the Gymnasium interface. The presented models were validated against measurements made on a case study calf barn, achieving a Root Mean Squared Error of 1.1 °C.

I. Introduction

Thermal conditions in the calf barns strongly impact the calf health, growth, and well-being. Poor barn climate, characterized by extremely high or low temperatures, can cause casualties [1]. Most of the calf barn buildings are naturally ventilated. The indoor temperature depends on a complicated interaction between outdoor weather, animal metabolism, and the building's ventilation system [1]. Ventilation is usually regulated by manually controlling the openings or by fixed-schedules and rule-based heuristics, which result in suboptimal thermal conditions under changing weather. Consequently, conventional control approaches fail to maintain optimal climate conditions in the calf barns.

Reinforcement learning (RL) provides a promising alternative by learning control policies directly through interaction with the environment, which is particularly well-suited to systems characterised by non-linear dynamics and uncertain disturbances. However, directly training and deploying RL policies in livestock buildings is impractical due to safety, animal welfare and data constraints. This necessitates the development of realistic simulation environments for training and evaluation.

Existing building simulation tools, such as EnergyPlus [2], provide detailed simulation of building physics but are not well-suited to be used as Gymnasium [3] environments. They are computationally expensive, provide limited flexibility for custom control actions and are not designed for high-frequency control interactions required by RL training methods.

To address these limitations, this work presents a fast and accurate Gymnasium environment for training and testing RL control policies for temperature control in calf barns. We model the transient temperature response of the building using a reduced-order thermal network model coupled with an airflow network, which are solved in an integrated manner and wrapped in a Gymnasium-compatible interface. Model parameters are identified using building-specific data. Lastly, the developed models are validated against measurements made on a case study calf barn.

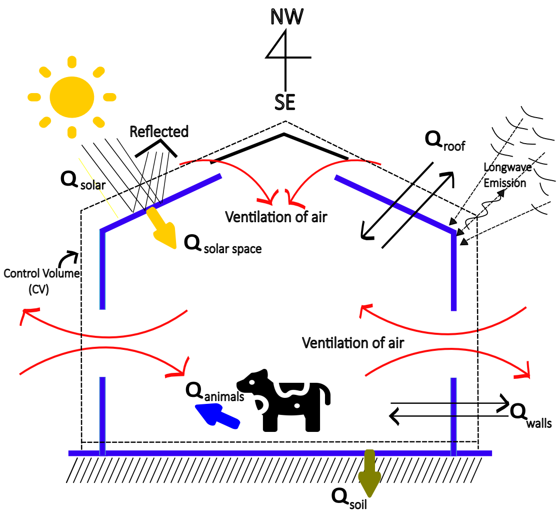

Figure 1: A schematic of the calf barn with the various modes of heat transfer with the surroundings.

II. Methods and Materials

This section describes the modelling, simulation, validation and environment design framework used to develop the Gymnasium environment.

II.I. Case Study

For a case study, we collected data from a calf barn at the facilities of the Lehr und Versuchszentrum (Teaching and Research Centre) Futterkamp, Germany. The calf barn has three gates, two curtains and a roof ridge ventilator for natural ventilation (Figure 1). It also contains a ventilation fan and a perforated tube system for mechanical ventilation. The volume of the building is around 2300 cubic meters, and the floor area is 553 square meters. It is occupied by around 40 to 50 calves of various weights and ages throughout the year. We installed temperature sensors at ten points inside the building. The ten readings are averaged to get a mean indoor temperature. Additional sensors recorded control inputs like gate status, curtain positions, and fan power at every timestep. The measurements were made from July 2025 to October 2025. A weather station mounted next to the building recorded weather conditions.

II.II. Thermal Network Model

We apply the law of conservation of energy for the control volume around the building as shown in Figure 1. The one-dimensional transient heat transfer can be modelled by a 3-Resistor-2-Capacitors (3R2C) model (Figure 2(B)), which represents heat transfer and temperature as analogous to electric circuit concepts. The inside of the building is represented by a single node T_{in} with a zone capacitor. Heat flow across the combined external walls and roof is represented by a 3R2C branch for each. For simplification, we have ignored longwave radiative exchange, heat transfer through the floor, solar space heating on the inside nodes and solar gains on walls. The resulting state equations are:
$C_{w,o}\frac{dT_{w,o}}{dt} = U_{w,o}\left(T_o - T_{w,o}\right) + U_w\left(T_{w,i} - T_{w,o}\right)$
$C_{w,i}\frac{dT_{w,i}}{dt} = U_w\left(T_{w,o} - T_{w,i}\right) + U_{w,i}\left(T_{in} - T_{w,i}\right)$
$+0.66F_w\dot{Q}_{anim} + F_w(1-\zeta)\dot{Q}_{vent}$
$C_{r,o}\frac{dT_{r,o}}{dt} = U_{r,o}\left(T_o - T_{r,o}\right) + U_r\left(T_{r,i} - T_{r,o}\right) + \dot{Q}_{solar}$
$C_{r,i}\frac{dT_{r,i}}{dt} = U_r\left(T_{r,o} - T_{r,i}\right) + U_{r,i}\left(T_{in} - T_{r,i}\right)$
$+0.66F_r\dot{Q}_{anim} + F_r(1-\zeta)\dot{Q}_{vent}$
$C_{in}\frac{dT_{in}}{dt} = U_{w,i}\left(T_{w,i} - T_{in}\right) + U_{r,i}\left(T_{r,i} - T_{in}\right)$
$+0.33\dot{Q}_{anim} + \zeta\dot{Q}_{vent}$ Where T_o [K] is the outdoor air temperature. $T_{r,i}$ and $T_{r,o}$ are the inner and outer roof surface temperatures, respectively. $T_{w,i}$ and $T_{w,o}$ are the inner and outer surface temperatures of the combined walls, respectively. U_* are parameters representing the conductances [$\mathrm{W\,K^{-1}}$] of the building envelope. The $\dot{Q}_*$ are the heat gains [W].

Heat gains from the ventilation act on the zone node and the internal surfaces weighted by a parameter ζ and view factors. They are defined as: $\dot{Q}_{vent} = \rho_{in}\dot{V}_{in}c_p(T_o - T_{in})$ Where $\dot{V}_{in}$ is the incoming air flow rate [$\mathrm{m^3\,s^{-1}}$], ρ_{in} is the density of the incoming air [$\mathrm{kg\,m^{-3}}$] and c_p is the specific heat capacity of air [$\mathrm{J\,kg^{-1}\,K}$].

The solar heat gains on the roof are calculated by approximating the roof to be flat: $\dot{Q}_{solar} = \gamma I_{GHI}A_{roof}$ where γ is a parameter for the absorptivity of the roof, I_{GHI} is the global horizontal irradiance [$\mathrm{W\,m^{-2}}$] measured from a nearby weather station, and A_{roof} is the (flat) area of the roof [$\mathrm{m^2}$]

The heat produced by animals depends on the species, age, activity level and many other factors. We approximate by using a constant effective sensible heat produced by all animals. We assume that 66 per cent of this heat is convective while 33 per cent is radiative. The convective gain acts on the zone node, while the radiative gain acts on the surface nodes weighted by view factors.

II.III. Ventilation Model

Exchange of air mass across building boundaries strongly affects thermal dynamics of the building, as air flow can carry energy in and out of the system. If we apply the law of conservation of mass to the control volume, then:

$$\sum_{i=0}^{n} u_i\rho_i\dot{V}_{nat_i} + \rho_{mech}\dot{V}_{mech} + \rho_{infil}\dot{V}_{infil} = 0 \quad (1)$$

where u_i is the control input to the opening i.

Natural ventilation is the air flow through purpose-built openings, such as the gates and curtains. The

DOI 10.18416/SCP.2026.2576

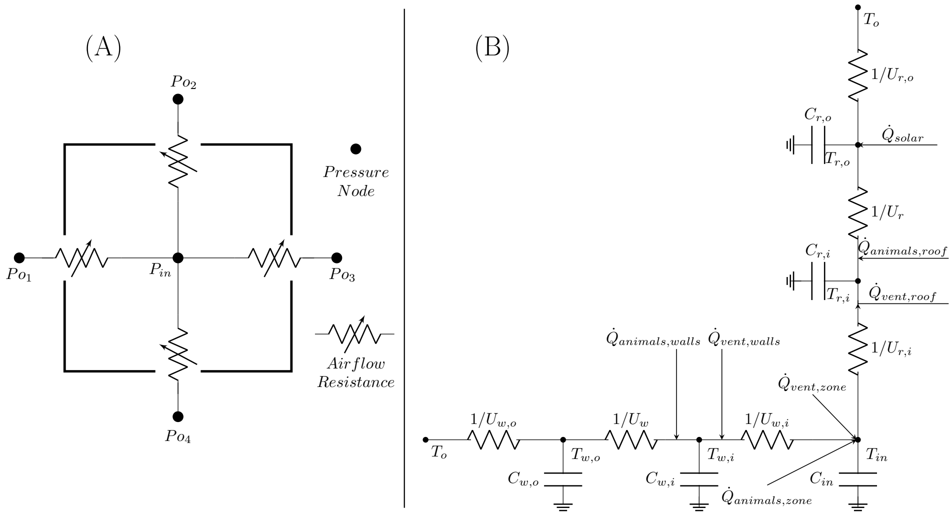

Figure 2: (A) A sample airflow network of a building. (B) The thermal network model of the building.

steady-state natural ventilation can be modelled as an airflow network, which represents the static pressure of a zone as a node and the air flow as a nonlinear resistor. The pressure developed outside of an opening due to wind and temperature difference is represented by boundary nodes. The pressure network for a sample single-zone building can be seen in Figure 2(A). We adapted the natural ventilation model from [4].

Infiltration is the air flow through unintentional openings, such as cracks. We use the empirical model of infiltration developed by [5].

Mechanical ventilation is the forced airflow from the ventilation fan and tube systems. If the air flow rate of ventilation fans and tube system at reference power $u_{fan,ref}$ is provided by the manufacturer as $\dot{V}_{fan,ref}$, we can relate this with the flow rate $\dot{V}_{fan}$ at the power u_{fan} by using fan laws: $\dot{V}_{fan} \frac{}{\dot{V}_{fan,ref} = \left(\frac{u_{fan}}{u_{fan,ref}}\right)^{\frac{1}{3}}}$

II.IV. Simulation

The zone temperature of the building depends on the ventilation heat gains, which in turn depend on the zone temperature. Specifically, the state of the building described by differential equations (II.II) - (II.II) is subject to an algebraic constraint in (1). For every evaluation of the temperature state equations, the mass balance must be satisfied. This creates difficulties in solving the combined model as it forms a system of Differential Algebraic Equations (DAE) of index 1. We implemented the model equations in CASADi [6] and used its interface to the Sundials IDAS DAE solver [7] to efficiently solve the DAE system.

II.V. Gymnasium Environment Design

The validated model is packaged in the standard Gymnasium interface. The state vector returned by the environment at every timestep consists of indoor temperature, outdoor temperature, windspeed, wind direction, global solar irradiance, and atmospheric pressure. The action space consists of fan power and open/close status of openings like gates, curtains and roof ridge ventilator. The fan power ranges from 25 per cent to 95 per cent, in discrete steps of 10 per cent. Each opening can either be fully open (1) or fully closed (0). The action space is multi-discrete. This means at each time step, a set of discrete actions must be selected—one discrete action per fan and one binary action for each opening. The reward function compares the current indoor temperature to an ideal indoor temperature selected using calf barn indoor environmental quality guidelines: $r_t = -\left(T_{in_t} - T_{ideal}\right)^2$

III. Results and Discussion

We set the parameters of the model to values appropriate to the case study building and its surroundings. We obtained three months of 24-h simulations and compared them against real measurements from the case study building. Each predicted indoor temperature at a specific time is compared to the measured value at exactly that same time to obtain absolute error metrics.

The results of this study are presented in Table 1. A sample, full day of indoor temperature predictions can be seen in Figure 3. The model predictions closely match the measured data from the case study building with a Root Mean Squared Error (RMSE) of 1.1 °C. The results show that the environment is accurate for training RL control policies. Due to the lower-order nature of the model, it is also computationally less expensive and simpler than environments which use full-scale building

DOI 10.18416/SCP.2026.2576

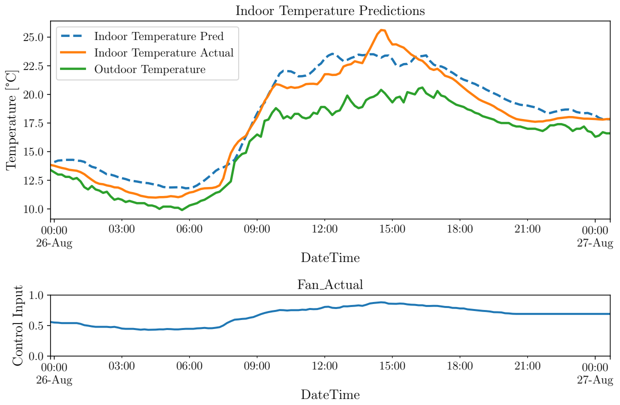

Figure 3: Indoor temperature predictions plotted against measured indoor temperature, outdoor temperature and fan control inputs

Table 1: Absolute error metrics for model predictions on the case study building

Statistic	Value [°C]
Mean Absolute Error	0.787
Standard Deviation	0.794
25th Percentile	0.241
50th Percentile	0.566
75th Percentile	1.075
Maximum Absolute Error	6.139
Root Mean Square Error (RMSE)	1.118

energy simulation programs like EnergyPlus.

However, there are some shortcomings in this environment. The validation has only been performed on 04 months of measurements, which does not cover the whole range of seasons. Longwave radiative exchange, solar space heating, and floor heat transfer have been neglected. Lastly, the environment design needs to be tested with control polices to find out better reward functions, state space and action space formulations.

IV. Conclusion

This study presented a fast, accurate and physics-based Gymnasium environment for temperature control in calf barns. A reduced-order thermal network was coupled to an airflow network and simulated in an integrated manner using DAE solvers. The models were tested against measurements made on a calf barn, achieving an RMSE of 1.1 °C. A Gymnasium compatible interface was developed to allow for training and testing RL control polices. More work is required to cover the shortcomings of the modelling approaches, validation and the environment design.

Acknowledgments

This work has been carried out at and supervised by the Institut für Telematik, Universität zu Lübeck, Lübeck, Germany.

Research funding: This study uses data collected as part of AI4CALF project which is funded by Wirtschaftsförderung und Technologietransfer Schleswig-Holstein GmbH

Author's statement

Conflict of interest: Authors state no conflict of interest.

References

[1] J. Donlon, C. McAloon, R. Hyde, S. Aly, B. Pardon, and J. Mee. A systematic review of the relationship between housing environmental factors and bovine respiratory disease in preweaned calves - part 2: Temperature, relative humidity and bedding. *The Veterinary Journal*, 300-302:106032, 2023, doi:https://doi.org/10.1016/j.tvjl.2023.106032.

[2] N. R. E. L. (NREL), Energyplus™, 2017. URL: https://www.osti.gov/biblio/1395882.

[3] M. Towers, A. Kwiatkowski, J. Terry, J. U. Balis, G. D. Cola, T. Deleu, M. Goulão, A. Kallinteris, M. Krimmel, A. KG, R. Perez-Vicente, A. Pierré, S. Schulhoff, J. J. Tai, H. Tan, and O. G. Younis, Gymnasium: A standard interface for reinforcement learning environments, 2025. arXiv: 2407.17032 [cs.LG].

[4] E. Mathews and P. Rousseau. A new integrated design tool for naturally ventilated buildings part 1: Ventilation model. *Building and Environment*, 29(4):461–471, 1994, doi:10.1016/0360-1323(94)90005-1.

[5] C. Park, D. R. Clark, and G. E. Kelly, "HVACSIM+ building systems and equipment simulation program : Building loads calculation," en, National Bureau of Standards, Gaithersburg, MD, Tech. Rep. NBS IR 86-3331, 1986, Edition: 0, NBS IR 86–3331. doi:10.6028/NBS.IR.86-3331.

[6] J. A. E. Andersson, J. Gillis, G. Horn, J. B. Rawlings, and M. Diehl. CasADi: A software framework for nonlinear optimization and optimal control. *Mathematical Programming Computation*, 11(1):1–36, 2019, doi:10.1007/s12532-018-0139-4.

[7] D. J. Gardner, D. R. Reynolds, C. S. Woodward, and C. J. Balos. Enabling new flexibility in the SUNDIALS suite of nonlinear and differential/algebraic equation solvers. *ACM Transactions on Mathematical Software (TOMS)*, 2022, doi:10.1145/3539801.

