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ASSESSING THE PERFORMANCE OF THE NEURAL NETWORK-BASED CONTROL TO MANAGE BOILERS THROUGH A REDUCED-ORDER BUILDING'S MODEL

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There is a growing need to optimize the heating ventilation and air conditioning (HVAC) systems during building operations due to its high contribution to buildings' energy consumption and the willingness to meet the international energy and climate changes targets. Predictive and adaptive controls have arisen as proper tools to reduce the HVAC's energy consumption. They can predict future scenarios and determine the optimal strategy to manage HVAC systems. In this regard, control strategies based on neural networks (NN) to manage boilers and control the temperature setbacks are attracting significant attention. This study aims to use the reduced-order building descriptions as a benchmark model for building energy simulation to demonstrate an NN-based control's effectiveness in managing boilers in buildings. Reduced-order buildings will be simulated with different meteorological locations from various climate zones to determine if the proposed control system is more efficient than a schedule-based control or if certain zones have more potential to save energy. To carry out this analysis, a set of KPIs will be used to assess the performance of the proposed control and compare the results within the different scenarios and the baseline scenario, the scheduled-based control.

Keywords: Model predictive control (MPC); Neural networks; Boiler schedule; Building simulation; Reduced-order model; Building energy consumption

Evaluación del rendimiento del control basado en redes neuronales para gestionar calderas mediante el modelo de edificio de orden reducido

Existe una necesidad creciente de optimizar los sistemas de calefacción, ventilación y aire acondicionado (HVAC) en su fase de operación debido a su alta contribución al consumo de energía y la voluntad de cumplir con los objetivos internacionales de cambio climático. Los controles predictivos y adaptativos han surgido como herramientas para reducir el consumo de energía, pudiendo predecir escenarios futuros y determinar la estrategia óptima para gestionar los sistemas HVAC. Las estrategias de control basadas en redes neuronales (NN) para la gestión de calderas y el control de retroceso de temperatura están acaparando una importante atención. El objetivo es utilizar descripciones de orden reducido de edificios como un modelo de referencia para la simulación energética de edificios y demostrar la eficacia de un control basado en NN para gestionar calderas. Se simularán edificios de orden reducido con diferentes ubicaciones meteorológicas de diferentes zonas climáticas para determinar si el sistema de control propuesto es más eficiente que un control basado en horarios o si ciertas zonas tienen más potencial para ahorrar energía. Para realizar este análisis, se utilizará un conjunto de KPI para evaluar el desempeño del control propuesto y comparar los resultados entre los diferentes escenarios y el de referencia.

Palabras clave: Modelo de control predictivo (MPC); Redes neuronales; Horario de la caldera; Simulación de edificios; Modelo de orden reducido; Consumo de energía del edificio

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1. Introduction

The buildings sector accounted for 36% of final energy use and 39% of energy and process-related carbon dioxide (CO_2) emissions (IEA, 2019). For instance, residential and commercial buildings account for approximately 40% of the total primary energy in Europe and more than one-third of the consumption energy worldwide (Homod, 2018). Most of the energy consumption in a building is consumed during its operational stage, accounting for 80-90% of its energy consumed during the whole life cycle (Asdrubali and Grazieschi, 2020).

Heating, ventilation, and air conditioning (HAVC) systems, in charge of providing thermal comfort and indoor air quality, account for almost half of the overall energy consumption in commercial buildings (Shamsi *et al.*, 2020; Yu *et al.*, 2021). Those systems are also usually energy inefficient in practice. About 15%-30% of the energy used in HVAC systems is wasted on poor design and inefficiency, such as sensor faults, device faults, performance degradation, and improper control strategies (Zhang *et al.*, 2019). Among these influential factors, the impact of control strategies on energy savings plays an important role (Sangi, Kümpel and Müller, 2019). In this term, about 40% of the energy savings of HVAC systems could be achieved by energy-efficient HVAC control systems (Bac, Alaloosi, and Turhan, 2021).

In this context, building energy management systems (BEMS) is essential in optimizing the HVAC systems and would result in considerable savings (Killian and Kozek, 2016; Li *et al.*, 2020; Yang *et al.*, 2020). However, the control strategies implemented on those systems are scheduled-based (Macarulla *et al.*, 2017). In addition, BEMS generates and stores data that is rarely utilized to get knowledge to optimize the HVAC systems' operation (Xiao and Fan, 2014). The advancement of HVAC optimization techniques as model predictive and adaptive controls has led to the development of multi-objective functions such as minimizing energy consumption and operating cost and maximizing thermal comfort (Afram and Janabi-Sharifi, 2017). In this context, the neural network (NN) based optimization approach as a predictive control transformed conventional control logic into more intelligent control to improve thermal comfort and energy efficiency (Moon and Han, 2012).

In addition, providing an accurate decision making on the energy efficiency of HVAC systems, relies on building simulation tools to assess their performance in different scenarios (Heidarinejad *et al.*, 2017). Simulation is currently used to model the energy performance of HVAC systems in buildings (Srivastava, Yang and Jain, 2019). To simulate building energy performance, applying building energy models as a benchmark is crucial to designing an NN controller (Harish and Kumar, 2016). In this frame, reduced-order models can be applied to assess the performance of the NN-based control strategy as a benchmark. Reduced-order models represent a good basis for simulating the energy behavior of buildings to accurately predict energy performance (Giretti *et al.*, 2018).

Furthermore, the importance of considering building standards such as ASHRAE is established by highlighting that they do not provide climate-sensitive guidelines for HVAC operation settings and optimization analysis (Papadopoulos *et al.*, 2019). Moreover, indoor temperature set-points are different in moderate and cold climates, indicating different settings to optimize the NN control system (Guo *et al.*, 2020). Thus, by developing a valid benchmark building model, energy savings and thermal comfort can be better compared in those climates. Then, the outcome of the building performance simulation can evaluate the energy performance of buildings over time (Attia, Shadmanfar, and Ricci, 2020).

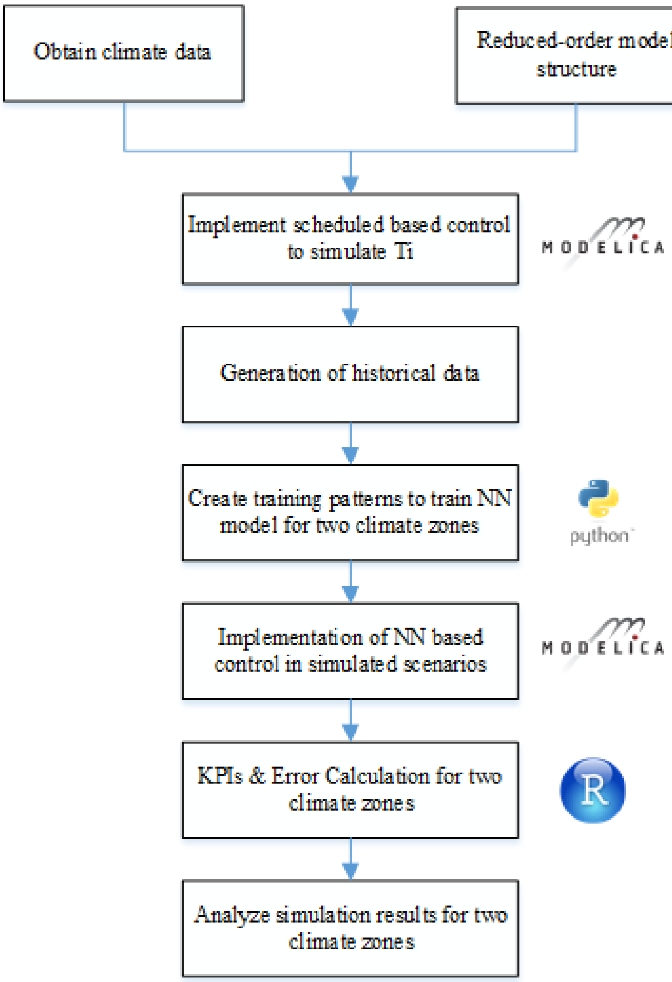
This study aims to use the reduced-order building descriptions as a benchmark model for building energy simulation to demonstrate an NN-based control's effectiveness in managing boilers in buildings. It compares the performance of an NN-based control in two different locations and climate zones. To do so, a reduced-order building model will be simulated with two meteorological locations from various climate zones to determine if the proposed control system is more efficient than a schedule-based control or if certain zones have more potential to save energy. As detailed later, a set of KPIs was used to assess the performance of the proposed control and compare the results within the different scenarios and the baseline scenario, the scheduled-based control.

The paper is structured as follows. Section 2 presents the methodology of the proposed control system. Section 3 provides the result of the simulation, followed by a discussion of the performance of the NN model for each climate zone by a set of KPIs. Finally, in section 4, the conclusions have summarized the findings, and the direction and ideas for future work are reviewed.

2. Methodology

The proposed methodology used Test Case 2 of the VDI 6007 model (Modelica Buildings Library Buildings.ThermalZones.ReducedOrder.Validation.VDI6007, 2021) to test the NN-based control system. In this section, the structure of the reduced-order model was presented. Then the implementation of NN based control system in the Modelica language was discussed. Finally, the proposed control system was applied in two climatic zones across Catalunya to examine the KPIs variation in different climatic conditions. The proposed methodology framework used in this study is shown in Fig. 1.

Figure 1: Research Methodology framework



2.1 Climate data

The first step consists of generating historical data from two different climate zones to apply the framework to simulate building energy performance using a set of KPIs. Two years of climatic data (2017-2019) were obtained from Meteocat for locations in Cataluña from warmer to colder climates. It consists of the “Malgrat de Mar automatic operational station (WT)” (https://www.meteo.cat/observacions/xema/dades?codi=WT) and the “Boí automatic station (Z2)” (https://www.meteo.cat/observacions/xema/dades?codi=Z2). Data consists of time series climate variables was recorded as follows:

- Ta: the ambient temperature (°C).
- Ps: the global solar radiation (W/m2).

2.2 Reduced-order model structure (Test Case 2 of the VDI 6007 model structure)

The Buildings library used in this study (Modelica Association Project - Libraries. Modelica.Thermal, 2021) is a free library for modeling building energy and control systems. It contains models of reduced building physics of thermal zones and accompanying models for consideration of solar radiation. In addition, it includes models for the validation of reduced-order models. The validation process is thought initially to verify the correct implementation of an analytical calculation algorithm (Modelica Association Project - Libraries. Modelica.Thermal, 2021).

Figure 2: VDI 6007 Test Case 2 model

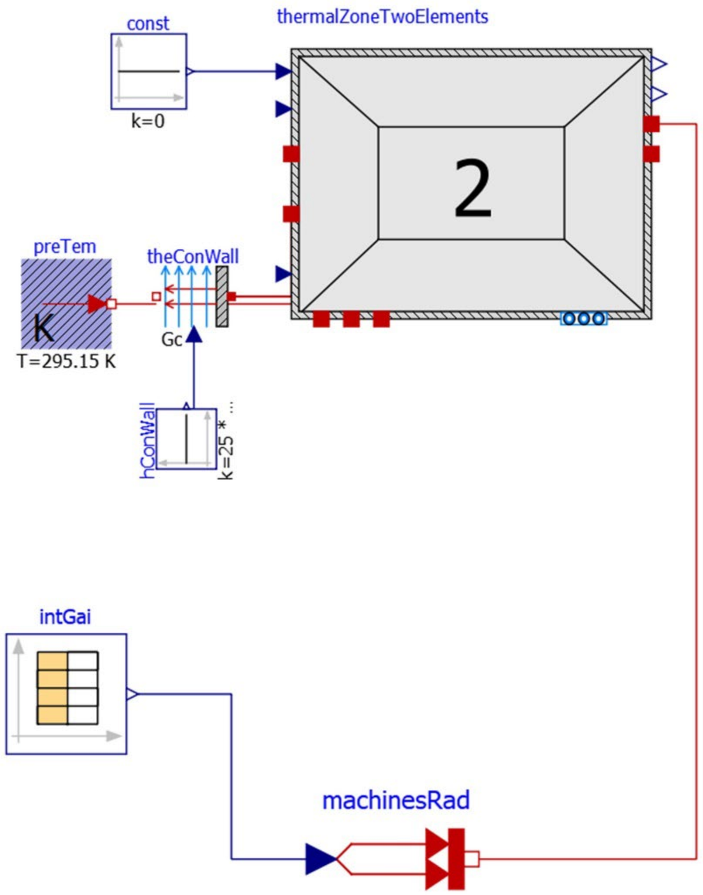


Fig. 2 shows the Test Case 2 model of the VDI 6007, which is developed in a Modelica simulation-based environment. This test case validated basic functionalities and consists of the following boundary conditions:

- Constant outdoor air temperature 22°C
- No solar or short-wave radiation on the exterior wall
- No solar or short-wave radiation through the windows
- No long-wave radiation exchange between exterior walls, windows, and ambient environment

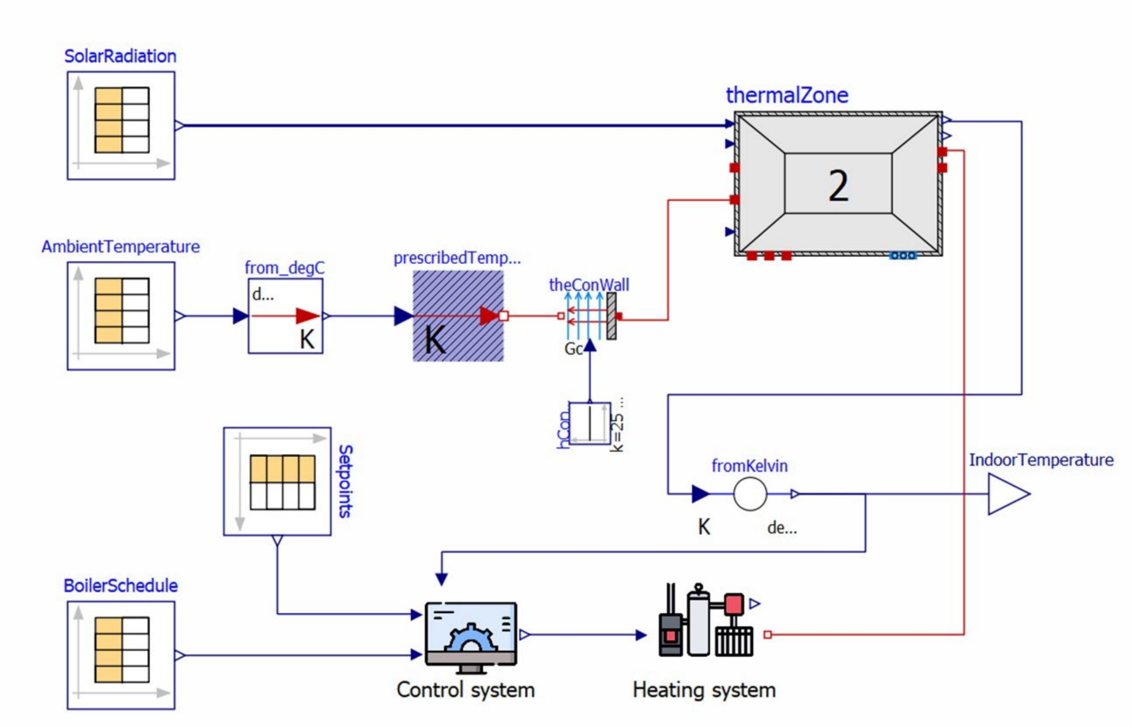
In this study, a Thermal Zone with two elements for exterior and interior walls from Test case 2 is used with the addition of a heating system and features to simulate variables to enable control of the indoor temperature, as shown in Fig. 3.

2.3 Implementation of scheduled based control to generate historical data

The structure of the reduced-order model has been implemented in a Modelica simulation-based environment. Meanwhile, the internal temperature was simulated by applying a scheduled-based control system using climate data. The boiler schedule was operated within working hours from 6:00 am to 6:00 pm via on/off conditions (Li *et al.*, 2020). The obtained output of the simulation, which is internal temperature based on calibrated reduced-order model and climate data, was used to generate a training pattern to train NN in the next phase.

Fig. 3 shows Modelica structure with scheduled-based control. The control system was regulated to achieve thermal comfort of 21 ºC bandwidth of 0.5 ºC at the start of working days at 8:00 am. The internal temperature was simulated using the calibrated model and the meteorological data. The weather component provides the solar radiation and the external temperature.

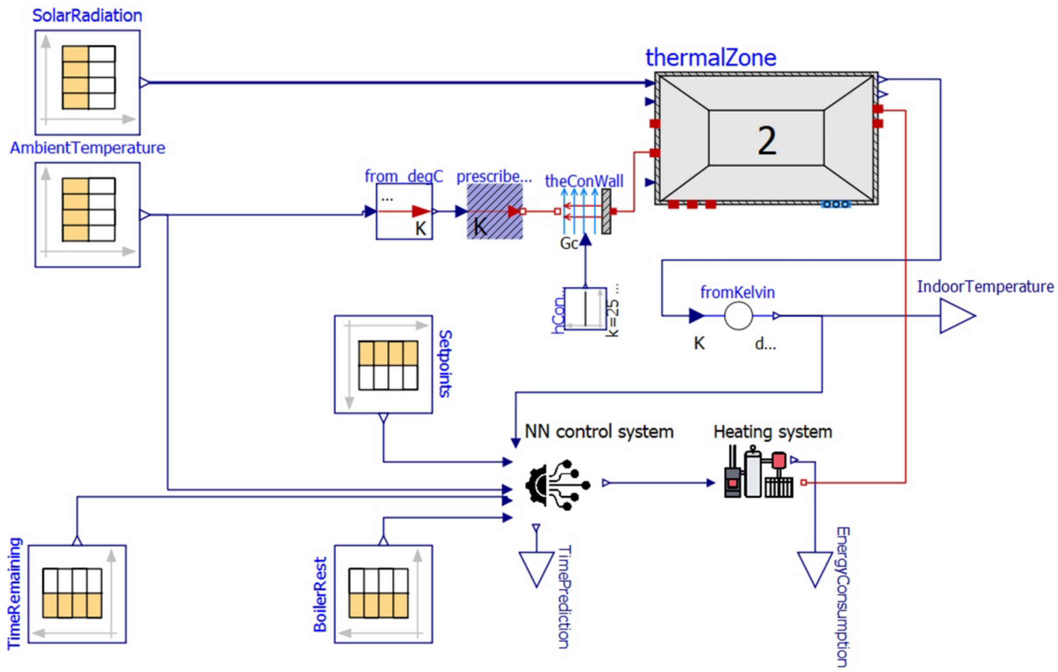
Figure 3: Modelica structure with a schedule-based control



2.4 Development of neural network control system

The scheduled-based control system was modified to an intelligent NN control (Fig. 4). The goal of NN control is to predict the operation time of the boiler based on predefined input and output variables to optimize the boiler schedule. The predictive control was implemented through input variables and the Modelica component. It includes five inputs, i.e., indoor temperature, ambient temperature, set-point, boiler rest, and time remaining. Modelica components to implement the NN control system are the thermostat and NN control. Furthermore, the NN model is installed as a tool to determine the time needed to heat the building (T_p). Finally, outputs were defined as time prediction and energy consumption.

Figure 4: Control system with the implementation of NN control



The parameters of the NN model are listed in Table. 1, which used the simple structure proposed by (Macarulla *et al.*, 2017). Also, Input variables were standardized to filter out the outliers (Zhang *et al.*, 2019).

Table 1: Parameters of the NN model

Classification	Parameter Values
Ni: The Number of Hidden Layers	1
Nh: The Number of hidden neurons	10
NTP: The number of training patterns	22
Training Algorithm	Adam Optimization Algorithm
Input Values	- Ambient Temperature (Ta) - Internal Temperature (Ti) - Increase in temperature ΔT
Output Value	- Time predicted (Tp) - Energy consumption (kWh)
Iteration	100
Activation Function	Hyperbolic Tangent Function

2.5 Key performance indicators to assess the performance of the control system

A set of KPIs was presented to assess the performance of simulations based on the NN control system. The NN model was validated using one year of data (2019-2020) of each location (see Table. 2).

- Time with comfort %: is the duration of time in terms of hours on working days (Monday to Friday from 8 am to 6 pm) when the indoor temperature is between 19.5 and 24.5 °C.

- Time with desired temperature %: is the duration of time in terms of hours on working days (Monday to Friday from 8:00 am to 6:00 pm) when the indoor temperature is in the desired temperature range (k= 21±0.5).

- Days with start comfort %: The number of working days (Monday to Friday) when we achieve comfort (T_{comf} = 19.5-24.5) at the beginning of working hour 8:00 am.

- Days start with desired temperature %: The number of working days (Monday to Friday) when the indoor temperature is in the desired temperature range (k= 21±0.5) at the beginning of working hour 8:00 am.

- Energy Consumption: total energy consumption comes from heating systems (kWh) during one heating season.

Table 2: KPIs to assess model performance

KPIs	Description
1	Time with comfort %
2	Time with desired temperature %
3	Days with start comfort %
4	Days with a start desired temperature %
5	Energy Consumption (KWh)

3. Result and discussion

The NN-based control's performance was assessed by simulating a reduced-order building model in two different climate locations. The locations were selected to determine whether the proposed control system is more efficient than a schedule-based control or if certain zones have more potential to save energy. Based on KPIs analysis (Table. 3), validation results in the proposed NN control approach revealed that 100% of the time, using the NN control system in Malgrat de Mar (WT) was with comfort. The NN control system in Boí (Z2) implied a slight decrease in the time with the comfort of 99.94% and desired temperature of 99.41%. Moreover, due to less energy demand in a warm location, the monitored energy consumption for one year is lower than the cold one. Consequently, it has been proved that the boiler worked efficiently in the reporting period.

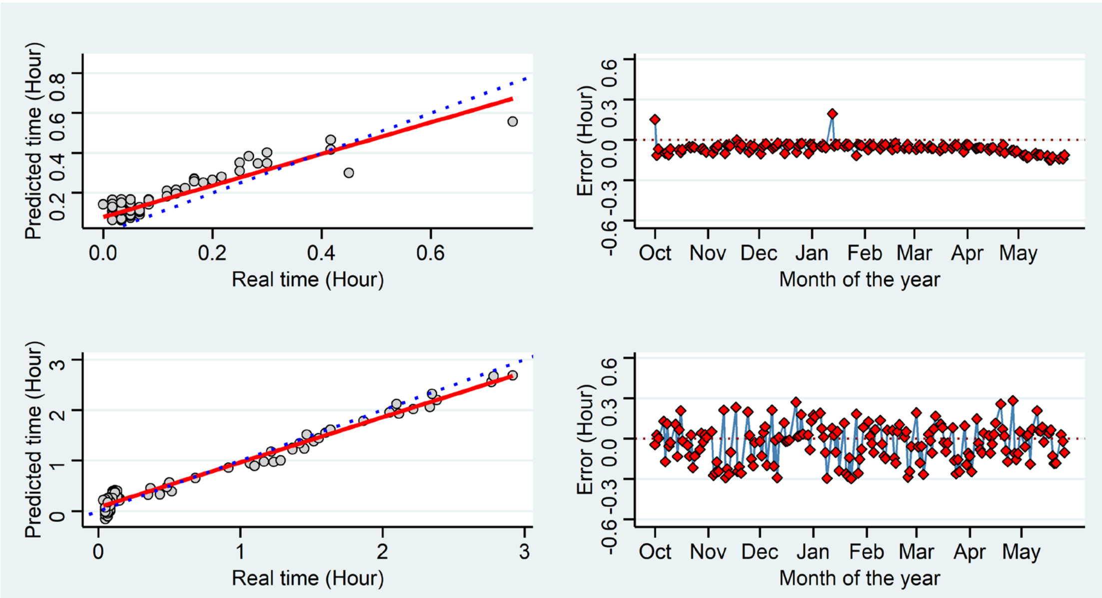
Table 3: Summary of KPIs to assess different implementations

Climate Zone	Total Energy Consumption (kWh)	%Time with comfort	%Time with the desired temperature	%Days with start comfort	%Days with a start desired temperature	Mean of internal Temperature°C
Malgrat de Mar (WT)-NN	1508280.479	100	100	100	100	20.86

Malgrat de Mar (WT)-Scheduled	1350989.113	100	100	100	100	20.84
Boí (Z2)-NN	4007019.745	99.94	99.88	99.41	99.41	20.94
Boí (Z2)-Scheduled	3814730.326	99.88	99.74	99.41	97.64	20.92

Fig. 5 shows the obtained predictive time to achieve the desired temperature at the start of the working day. The error points indicated the trend of errors in one heating season obtained from the simulation of validation data. In addition, the difference between predicted and real values was slight during one year of data. This means the prediction values were close to real values with low prediction error. It was found that short predictions always result in overestimating in a warm location and maintaining a comfort level of 100% based on KPIs. Respectively in a cold climate, larger predictions caused underestimating, and the comfort level is slightly less than 100%.

Figure 5: Errors of NN control prediction



As shown in Fig. 6, the prediction errors generally decreased with increasing ambient temperature. For warmer locations (WT), with an external temperature above 15 °C, errors increased to negative values, which means overestimating the time required to heat the building. However, in a cold climate (Z2), there was no significant relation between ambient temperature and prediction errors. Since external temperature does not affect predictions, this issue was addressed with different prediction horizons where occasionally overestimating and underestimating showed in results. For this reason, all KPIs were not achieved 100%.

Figure 6: Scatter plot of measured errors based on the ambient temperature of two different climate zones

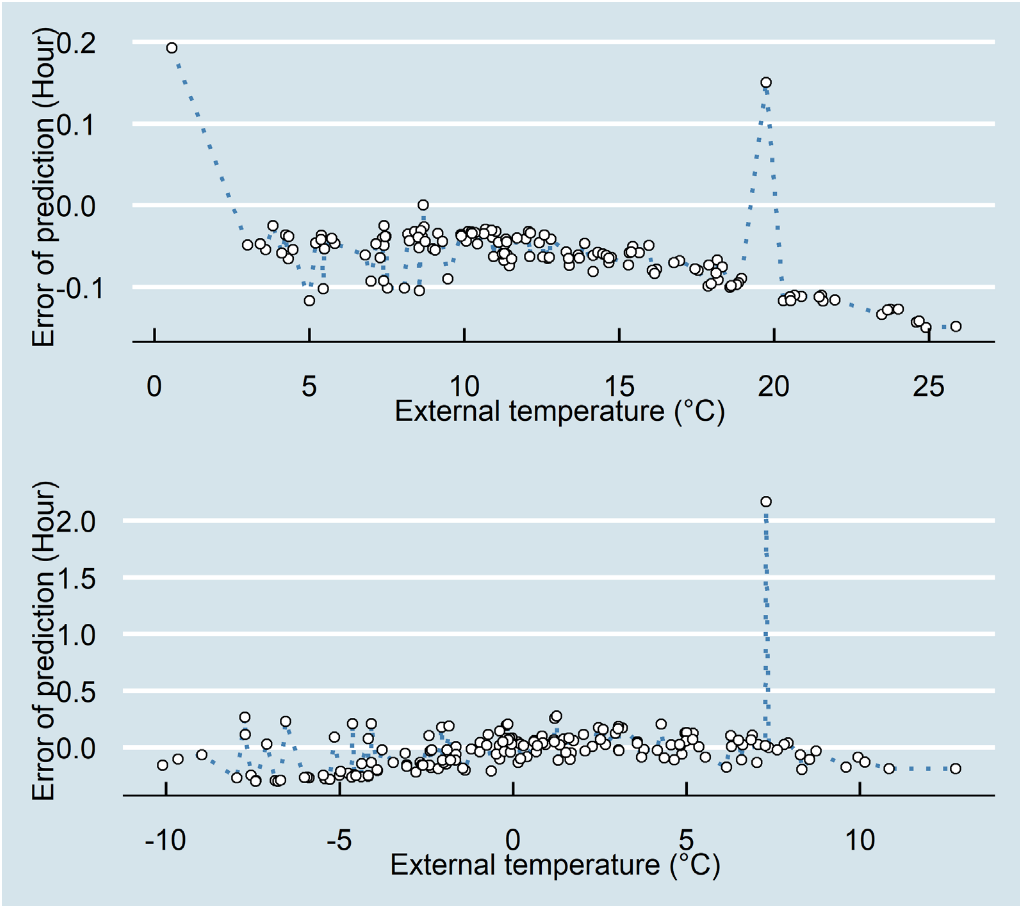
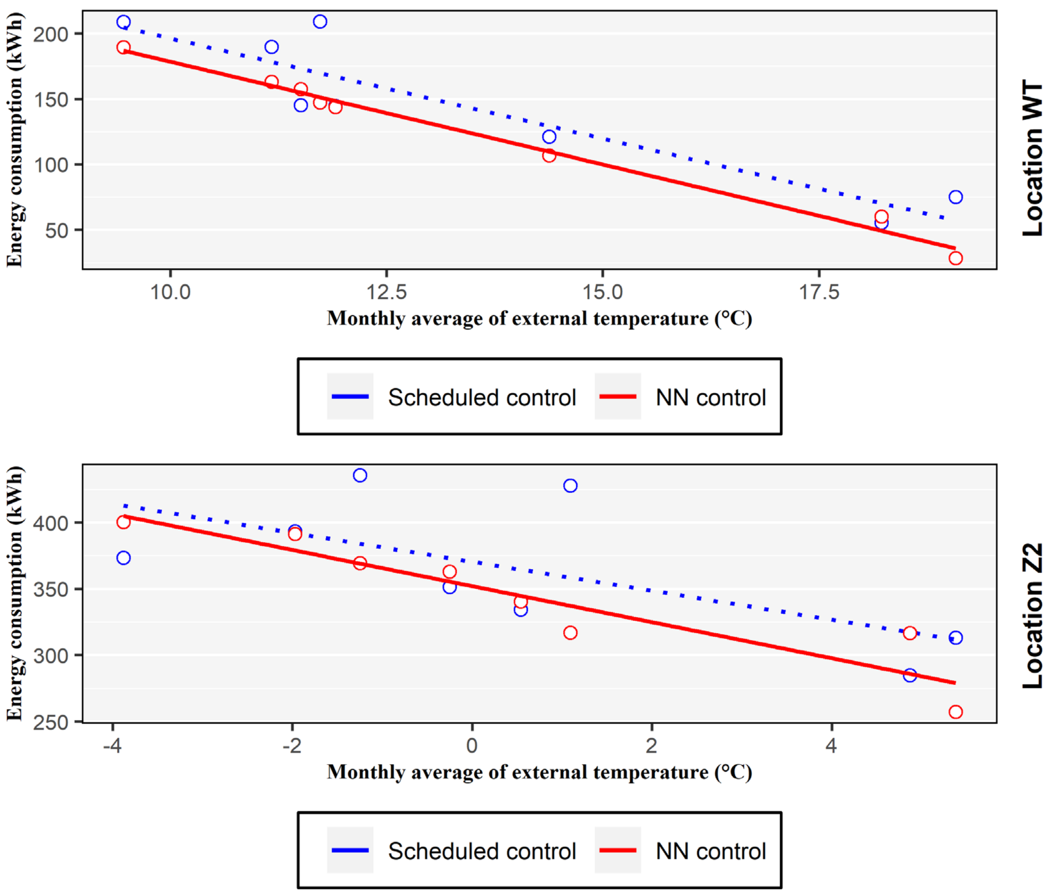


Figure 7: Correlation between measured energy consumption and a monthly average of ambient temperature based on the different control system



Moreover, it can be noticed from Fig. 7 that there was a relationship between energy consumption and external temperature in both control systems. Thus, energy consumption decreased with increasing external temperature. In addition, the boiler start time was fixed in scheduled-based control, and the control system is not designed to be adapted to external conditions. In this case, scheduled control showed more fluctuation, which means lower accuracy of boiler operation. Meanwhile, the NN control system achieved the energy demand to heat the building. Where the energy consumption was less than the energy demand, the control system was not achieving comfort. As energy consumption was higher than energy demand, it caused more time with comfort than needed. In this sense, it was concluded that an efficient HVAC control system is crucial in different climate zones because some measures change heating set-points to 19-20°C and cooling set-point to 24-25°C to avoid excessive temperatures. The control approach used in this study aligned with the 40 energy efficiency milestones that aim to use 50% less energy from new building heating and cooling by 2030 and 80% less energy use by 2050 (IEA, 2021).

4. Conclusion

Optimizing HVAC systems using advanced control strategies as NN control plays an essential role in building energy management. The utilization of the NN controls system reached more energy efficiency in terms of comfort and energy consumption. The results showed that the NN control system is the optimal control, which was more efficient than a schedule-based control in two different climatic zones. The NN control system was more efficient regarding the obtained KPIs in the warm climate zone.

In this paper, we analyzed the performance of an NN-based control system in a reference building within two different climatic zones. This was an exploratory analysis, and the results showed that the proposed model performance was not affected by the location of the building. However, more experiments should be done to confirm this initial result in the future. Another relevant aspect of testing in the future is if the building characteristics or the heating system components affect the performance of the NN-based control system. This work has opportunities for future development that focuses on maximizing model performance on the task of predicting building energy consumption by considering an analysis of the potential impact of climate scenarios on energy savings.

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