School of Industrial and Information Engineering

Master of Science in Automation and Control Engineering

POLITECNICO
MILANO 1863

A neural network-based predictive control and data analysis of an HVAC system for an educational building

Supervisor: Prof. Luca Ferrarini

Cosupervisor: Ph.D. Soroush Rastegarpour

Master Thesis of:

Ignacio Ortega Coronado 935889

A. Y. 2020-2021

Abstract

Nowadays, the impact of the Industry 4.0 has increased during the last years and the inclusion of fields such as Artificial Intelligence and Machine Learning in new areas is taking place. To reduce the energy consumption and the ecological impact of different systems, including those devoted to the climate comfort of users in buildings, different and advanced controlled techniques appear to push forward the efficiency of such complex systems. The objective of this thesis is to examine the influence of the characteristics and the size of the dataset used for the training of the Neural Network that will be used as a prediction model inside a non-Linear Model Predictive Control (NMPC).

A short introduction analyzing the main aspects of the building and control structure of its Heat, Ventilation, and Air-Conditioning (HVAC) system is provided. Then, a reference model of the building is used to generate the data set required for training using realistic operating scenarios. Different datasets are then tested in prediction under other conditions, and in closed-loop introducing them inside the NMPC.

Some practical concerns about closed-loop bad performing prediction models as well as techniques to improve their capacity with an online approach for retraining the prediction model are introduced. Finally, this idea is extended to the case of the use of the same controller in a different building using a pre-trained model. Performance analysis of the best configuration for online retraining is then achieved.

Sommario

Al giorno d'oggi, l'impatto dell'Industria 4.0 è aumentato durante gli ultimi anni e l'inclusione di campi quali l'Intelligenza Artificiale e il Machine Learning in nuove aree si sta attuando. Per ridurre il consumo di energia e l'impatto ecologico di diversi sistemi, compresi quelli dedicati al comfort climatico degli utenti negli edifici, appaiono diverse e avanzate tecniche di controllo con lo scopo di promuovere l'efficienza di tali sistemi complessi. L'obiettivo di questa tesi è quello di esaminare l'influenza delle caratteristiche e delle dimensioni del set di dati utilizzato per il training di una Rete Neurale che verrà adoperato come modello di predizione all'interno di un Model Predictive Control non lineare (NMPC).

Viene fornita una breve introduzione che analizza gli aspetti principali dell'edificio e la struttura di controllo del suo sistema di riscaldamento, ventilazione e condizionamento dell'aria (HVAC). Poi, un modello di riferimento dell'edificio viene utilizzato per generare il set di dati necessario per il training utilizzando scenari operativi realistici. Successivamente, diversi set di dati vengono testati in predizione con altri condizioni, e in closed-loop introducendoli all'interno del NMPC.

Vengono introdotte alcune considerazioni pratiche sui modelli di predizione ad closed-loop cattive prestazioni e le tecniche per migliorare la loro capacità con un approccio online che retraina il modello di predizione. Infine, questa idea è estesa al caso in cui si utilizza lo stesso controller in un edificio diverso utilizzando un modello preaddestrato. Si ottiene quindy un'analisi delle performance sulla migliore configurazione per un retraining online.

Acknowledgement

First of all, I am grateful to Politecnico di Milano for giving me the opportunity of developing the MSc. here as a Double Degree student. All the professors have contributed in a sense to achieve this final goal of ending my studies after seven years since I started.

Particularly, I would like to thank Professor Luca Ferrarini for supporting and supervise my thesis, especially in this difficult, strange, and new period of teaching. He has had a kind of calming guide to ensure that everything was going in the right direction.

I cannot forget about my family and my friends, mainly those who have been with me in these two years living abroad, in the worst possible context, but always giving support in the most difficult moments.

Contents

List of Figures

List of Tables

1 Introduction

In this chapter, the objective of the thesis is set, and the proper structure of the document is described

Then, a brief review of the state of the art related to the scope of this thesis is presented. First, the environmental motivation and the extension of the system treated is given, followed by some review about modelling and control of building heating systems. An insight about the generation of data is provided finally.

1.1 Objective and document structure

The main objective is to continue the studies opened by Elia Manstretta in his Master Thesis [1], using NARX NN inside an NMPC. This approach aims to have a black box model-based control scheme that could be applied to different buildings. As a control structure, the cascade structure developed by F.Martinoli and G.Veronese in their Thesis Work [2]. There is one high hierarchical controller that is the one that will use the NARX NN model to control the temperature requirements for the water tank supplying hot water to the heating system of building 25 of Politecnico di Milano.

The idea of the project is to understand the set of data necessary for training the NARX NN in order to have the best closed-loop performance for the complete controller structure. The existing cascade structure is simulated under different external conditions during the heating season to obtain a set of data large enough to train the NN, evaluating then the comfort and energy performance of the NN. With that, it will be possible to understand the appropriate length of data needed and the characteristics that it should have. This knowledge can have some interesting applications regarding the possibility of using a pre-trained NN for different buildings and understand the best strategy to retrain NN not well-performing.

Chapter 2 includes a brief description of the existing building and HVAC model developed by Giuseppe Veronesi and Federico Martinoli in their Master's Thesis [2]. The controller structure is defined also here. In chapter 3 a description of the NARX NN used as a prediction model in the simulations is provided. The analysis of the data used for training and the NN performance is described in chapter 4. Chapter 5 consists of a possible application of the results obtained from data analysis, considering the retraining of bad performing models or possible applications of the NN to a building different from the original. Finally, chapter 6 summarizes the main conclusions of the thesis, giving some hints for future development.

1.2 State of the art

Nowadays, climate change and emissions of greenhouse gases, mainly CO_2, are some of the main problems that society must face. Energy efficiency is one of the main objectives of all the energy policies, trying to reduce the environmental impact. Most of the advanced countries have included policies, laws, codes, or certification schemes to improve this energy efficiency. The impact of standards, energy taxes, and government expenditures of governments in energy R&D is covered in [3].

In developed countries, the energy consumption of buildings can represent a substantial percentage of the overall energy consumption, reaching levels around 30 – 40 %. This percentage can be much higher in countries with extreme weather conditions, even higher than in other larger sectors as the industry and transport [4]. In addition, buildings are responsible for 24 % of world CO_2 emissions [3]. Furthermore, in Italy, almost 70 % of the population lives in urban areas, with an expected rise in this number in the close future [5]. This means that in the following years it will be of capital importance the reduction in the energy consumption in residential and nonresidential buildings, for both environmental and economic reasons. There is substantial bibliography analyzing the capital importance and the modelling of energy consumption. In [6], the analysis of theoretical heating models of different buildings is developed for the dominant residential edifice.

Heat, ventilation, and air conditioning (HVAC) systems play an important role in the achievement of the comfort goals for users while maintaining the CO_2 level inside the rooms. Up to now, almost 50 % of the HVAC energy demand is devoted to the comfort of the users [7]. For that, a good understanding of the functioning of these systems is a key factor when energy efficiency is pursued. In [8], a complete analysis of the energy flow in HVAC is depicted to understand where the main issues and the losses of efficiency are placed in the energy chain.

The irruption of Industry 4.0 and the Internet of Things (IoT) has also paid attention to this challenge of reducing energy consumption. The IoT consists of the core of this new set of technologies, with the inclusion of Artificial Intelligence (AI) techniques. A set of sensors is used to gather a huge amount of data that allows communication between devices and control [9]. This data can be used to monitor, learn and improve the quality and the efficiency of the processes. In smart buildings, machine learning techniques collect, treat, and manage the data. Specifically, deep learning techniques can capture the dynamics of such a complex and nonlinear system as HVAC.

Related to data acquisition, the prediction of future energy uses and building states is significant to improve energy efficiency to bring the building to the desired conditions with the maximum efficiency. The behaviour of the building is characterized and affected by many factors such as weather conditions (external temperature, humidity, solar radiation…), occupancy, or the desired temperature in the different rooms. Even more, the proper specifications of the building, consisting of the dimensions, the materials, the external surfaces have a crucial effect on the future evolution of the states [10].

To illustrate the use of artificial intelligence in building energy prediction, [11] presents the potential of artificial neural networks (ANN) in different building energy applications such as solar water heating systems, solar radiation prediction, or heating and cooling loads estimation. The main point is related to the use of NARX ANN to predict the indoor air temperature of the building or the energy consumption,

Other machine learning approaches have used Reinforcement Learning (RL) to control the HVAC. An agent is trained in different situations to take the correct action over the system, as a function of the reward obtained as a consequence of his action. In [12], a deep RL algorithm shows that the learned policy of control of the agent can achieve up to 15 % of energy savings in the building.

1.2.1 Building modelling

When modelling the building or the HVAC, different criteria can be used to classify them [13]. Attending to the nature of the equations that represent the dynamics of the building, the models can be linear or nonlinear, static or dynamic, and discrete or continuous. In this thesis, nonlinear, static, and discrete systems will be used.

The most simplified but effective modelling method is the electrical analogy, where the building is built as an electrical circuit. The complexity of the model can be tuned by adding more R and C components. The most important feature of these models is that they can be solved using electrical techniques such as the Kirchhoff law or superimposition methods. In [14], a very complex thermal model of a building is created to apply a fuzzy logic controller afterwards. The models can be further developed into nonlinear systems.

On the other hand, according to the previous knowledge of the building, the models can be classified as black-box (or data-driven), where data is collected and a mathematical relationship between inputs and outputs is found; as white-box, where the model is described following the laws and the physics that explain the detailed knowledge of the different processes; and the grey-box modelling, where the basic equations of the model are less detailed than in the white box approach, but some model parameters are unknown and may be obtained by using data collected from the system. Any of them has proper advantages and disadvantages [15].

At the same time, white box models can be subclassified into 3 more classes, depending on the level of detail. The multizone technique considers the space as a continuous and homogeneous volume, where all state variables are uniform in each point of the volume. The zonal method divides the volume into several cells and maintains the state variables in each of them. Finally, the CFD method is the most detailed one, having a huge amount of small control volumes.

Method	Building geometry and heating system	Training data	Physical interpretation
White box	Detailed description required	No training data required	Results can be physically interpreted. Easy analysis of failures.
Black box	No detailed description of the model is required	A large amount of training data required. A long period of time	Several difficulties to interpret data physically. Complex search of failure.
Grey box	Rough description of the model	Small amount of training data. Small period of time.	Results can be physically interpreted. Easy analysis of failures.

Table 1-1 Classification of models based on prior knowledge [15]

As in the previous case, there is also a subclassification of the black box methods, based on machine learning, which is mainly focused on statistical treatments of data about building energy and comfort. Some of these methods are conditional demand analysis, Artificial Neural Networks, genetic algorithms, and support vector machine (SVM).

Previous theses are very good examples of these kinds of modelling. In the Master thesis [2], a very complex and detailed model of building 25 and its HVAC system is developed for the heating season. The physical modelling of the main subunits and their thermal relations are extensively described, and different approaches to some parameter's identification. This would constitute a case of grey box modelling.

On the other side, in the Master thesis [1], the building is substituted by a NARX NN, that based on a set of data obtained with other models, trains the network to behave as close as possible to the data, and use this mathematical model to control the HVAC. In this case, a black box was the approach selected.

1.2.2 NARX Neural Network

The use of AI and machine learning is continuously under study, improving the results and performance compared to other classical approaches. Artificial Neural Networks (ANN) as a tool for modelling processes and systems outperforms standard techniques. Even more, the use of the particular structure of a Nonlinear Autoregressive with Exogenous input (NARX) NN has shown similar performance without any computational loss against conventional recurrent networks [16]. Of course, some disadvantages appear as the number of design choices increase. The selection of the number of inputs and output delays are added to the design of the structure and size of the NN, that in the case of not having prior knowledge about the system being modelled, can result in a long exhaustive search of the best structure.

NARX NN is a very useful modelling tool for making predictions about future states of the system. These predictions can be used for selecting the best action to take regarding different objectives, pursuing both comfort and energy efficiency. The use of NARX NN in building modelling is present in the bibliography. In [17], a NN is used for temperature prediction in an airport building, providing better results than the use of the classical RC linear models. This model is then used inside an MPC to achieve comfort goals while reducing energy consumption.

The choice of the inputs and outputs for the NARX NN is also an important step in the development of this kind of model. Usually, for building modelling, the inputs are external weather conditions and some other HVAC input, while the output is the proper building temperature or the wall temperature. In [18], an ANN model-based system identification for a multi-zone building is presented. Here the inputs are the external temperature and the supplied temperature by the HVAC, while the output is the temperature of each of the zones.

When making future predictions of the state of the building, it is important to consider too the possible future evolution of the external non-tunable disturbances, such as the external temperature or the occupancy, that actuates as an input for the system, or in this case for the NARX NN model. Up to now weather forecasting is advanced enough and is continuously improving for fields such as renewable energies, being particularly important in solar and wind energy. So at least in the short term in which weather temperature predictions are needed, this disturbance can be considered as known. An example of advanced forecasting is shown in [19], where a temporal convolutional network is used to provide accurate short to medium-range weather forecasts with high geographical resolution.

The importance of good weather forecasting is shown in [20], when using some advanced control techniques, the use of a poor weather forecast has reduced the controller performance.

The prediction of the occupancy of a building is a quantity more difficult and variable to estimate. In [9], a camera is used to detect the number of persons inside the building, under the assumption that by knowing the occupancy scenario that the building is facing, the most adequate energy configuration can be selected for the HVAC system. In [17], a CO2 sensor estimates the occupancy load inside the building, while to predict future occupancy the flight schedule is used.

For further details [15] has a complete review of the state of the art of building predictions and building modelling. Whereas [4] provides a complete revision of the use of ANN of residential HVAC systems, specifically inside MPC.

1.2.3 Control structure

Once that a good model for the system has been obtained, it is needed to manipulate the actuators of the model properly. For that, a good controller has to be developed. There are several control techniques to apply in this context.

The two main controllers used in buildings are on/off controller and PID control. On/off or thermostat is the most simple but effective controller possible. In fact, it is still being used in home heating and some HVAC systems. Even this simple controller can provide energy savings with respect to manual manipulation. An example of this control technique using air conditioning appears in [21]. Basically, it is a feedback controller that has two states with hysteresis to avoid chattering: one in which the heating system is activated, and one in which is deactivated based on the temperature measurement. Even when cheap and simple, it fails when trying to track a setpoint or save energy efficiently.

A PID controller is a more advanced but still simple control technique, that does not need prior knowledge of the controlled system. Given a reference and actual state, computes the error and based on this error decides the value of the control action. A PID controller is a combination of three separated control techniques: the proportional term (P) to the current error, the integral term (I) taking into account accumulation of past errors guaranteeing zero tracking error, and the derivative term (D) predicting future changes in the error computing the error rate. Depending on the system under control it can be beneficial to use only one or two of the three actions. If the dynamics of the system are slow, as is the case in heating systems, only proportional action (P), or proportional and integral (PI) can be enough for tracking a setpoint maintaining the closed-loop stability. As it is not usually a sudden change in the thermal load of the building, a derivative action can usually be omitted. The main problem of this kind of controller is that it is only considering the error for deciding the control input and it is not considering energy consumptions in its election. In [22], a two-position controller, a P controller, and a PI controller are used in a residential building heated by an HVAC. The conclusions were that the integral term is needed to eliminate the steady-state error improving thermal comfort. The P controller had a thermal comfort performance very similar to the two-position controller. In contrast, the P controller can provide a smoother response, that is less harmful to the heating system. However, none of them can provide very good energy efficiency.

The above-exposed techniques have demonstrated a strong performance in general, but for systems strongly nonlinear cannot be the best solution, needing to move to more advanced control techniques. Some of the main advanced control techniques are related to optimal control, adaptive control, and predictive control.

Optimal control techniques are model-based techniques in which the control action is derived from optimizing one specific cost function while satisfying some physical constraints. This can be very useful in the case of buildings to maximize both control objectives inside the cost function: comfort and energy consumption performance. As it is model-based, the model can be any of the models shown in the previous subsection: white, black, and grey. In [20], it is shown that using optimal controllers in an office building, the thermal comfort with respect to classical controllers is maintained while substantial energy savings are achieved. Other examples of optimal control for heating buildings are shown in [23] and [24].

The case of adaptive control consists of a nonlinear control resulting from the combination of the structure of a classical controller together with one mechanism of adaptation of the controller parameters. This adaptation mechanism is based on online performance and data obtained from the system operation. It can be useful in the case of processes with non-static dynamics or the appearance of stochastic disturbances. One example of the use of adaptive control in the heating system of a building is present in [25].

If the model developed for the building is used to make future predictions and decide the control action based on the future evolution of the system, the Model Predictive Control (MPC) is achieved. This control approach provides large energy savings, and it is more cost-effective. Also, it is more robust for future disturbances. An MPC computes the optimal sequence of inputs for the following finite time horizon and applies only the input obtained in the first instant of the sequence (receding horizon). The optimization comes from a cost function that can have several goals, being usual in the field of heating systems of buildings the comfort and energy-saving optimization. Some examples of this application together with a more detailed theoretical development can be found in [26] and [27]. In both of them, a good identification of the building model is needed in order to provide a sufficiently good prediction in the time horizon together with an accurate weather forecast. The use of an MPC in a university building brought savings of 17-24 % compared to the controller already present in the building.

This project is mainly based on the use of nonlinear MPC (NMPC) using one of the black box modelling techniques explained above: NARX NN. The NARX NN can be introduced as a model predictor inside an NMPC and select the optimal control input for the heating system in the following time horizon. The use of this machine learning model inside a predictive controller was used by Elia Manstretta in his Master Thesis [1], obtaining better results in general than the actual NMPC structure proposed by Giuseppe Veronesi and Federico Martinoli in their Master Thesis [2]. The main drawback of the use of NMPC is the computational time spent in the optimization of nonlinear processes. However, due to the slow sampling time and dynamics of the system treated, this is not a limiting feature. Other examples of the use of NARX NN together with NMPC are present in [17], [18], and [28]. In the last one, the neural network is continuously adapting to capture the time-varying dynamics of the AAC system installed in the building, constituting an example of a hybrid technique between MPC and adaptive control. This approach has outperformed other conventional controllers using non-adaptive NN or classical controllers as the PID when tracking a setpoint or disturbance rejection.

In [29], a further detailed review of building control strategies for HVAC systems, moving from classical controllers to more advanced ones.

1.2.4 Generation of data

The NARX NN model used inside the NMPC will be critical, and the data used for training it is crucial for the appropriate performance of the whole system. The data should effectively capture the building dynamics for making accurate predictions for future evolution.

Mainly there can be two approaches to follow when generating the data for training. The first one is based on measurement over a real building. The main advantage of this approach consists that the data is directly obtained from the building, making no assumptions about it. However, depending on the case, it could be that the scenarios in which the data is measured are quite limited in the case of heating of a building. If the building has a residential or educational purpose, comfort must be guaranteed even during experimentation so the desired behaviour of the heating system cannot be changed. This causes that the state and input variables that compound the data used for training have the same behaviour, only being able to capture a part of the dynamics, not resulting in a good performing model in closed-loop. In [30], the data used for training was obtained from experimentation in real stations measuring more than 500 parameters each 1 min, and only eleven of them were used for constructing the prediction model. A commercial building was experimented in [31] for collecting HVAC system data.

On the other hand, to be able to test different configurations, references, external conditions, the simulation model approach is the most used. If the model is complex and accurate enough because prior knowledge of the system is available, it is possible to obtain reliable simulations and draw robust conclusions about the results. Another advantage comes from the computational time, that it can generate thousands of data points in only seconds, not needing to wait until having enough measurements. However, if no prior knowledge about the system is present, then the results obtained in the simulations could be completely useless.

There exists several dedicated software for the creation of buildings and heating systems installed in them as EnergyPlus. Other environments as MATLAB can be used for coding the nonlinear complex dynamics of the whole system using the white-box modelling approach.

Regarding the possibilities of using different conditions of the experiment, the selection of the most exploring ones, while maintaining a reduced number of simulations is essential. The Design of Experiments (DOE) aims to create a database for training small but representative by providing a combination of cases that represents the total case space. Some of the algorithms that create this set of cases are the Latin Hypercube Sample (LHS) DOE, and the Box-Behnken DOE. These approaches generally place the set of inputs in the extremes of the input space, guaranteeing no repeatability of the data extracted [32]. A general overview of the different DOE techniques is given in [33]. The Box-Behnken DOE method was used for the controllable input variables for an HVAC, conducting in the end 28 simulations in total to generate the database. In [34], the LHS DOE method is computed in MATLAB for generating the database to train a NN representing a school building.

The simulation model can be also used to test the measurement-based approach, so it will be the environment employed to understand the differences between the type of data. Specifically, the very detailed model developed in [2] in MATLAB, will be used as if it was the real system and some realistic experiment will be carried to understand the characteristics of the real data needed to train an effective NARX NN. Also, some DOE methods will be employed to check the simulation model approach, and the capacity to adapt the NARX NN trained to buildings with different characteristics in their size and HVAC capacity.

2 Building model

In this chapter, the summarized description of the building model employed as the actual reference model is given based on the Federico Martinoli and Giuseppe Veronese Master Thesis [2]. This topic is also briefly described in the Elia Manstretta Master Thesis [1].

Then, the actual controller structure implemented in it is depicted there, explaining the hierarchy of it, and the main functioning of the local controllers. This structure will be used sometimes as the baseline controller when comparing performances. The parameters defined in the NMPCs and in the cost functions will be maintained during the simulations used for making comparisons in the following chapters.

2.1 Building 25

The building used for the reference model considered as the real one is based on building 25 of Politecnico di Milano, located in Lambrate. The building is divided into four floors: the basement, and 3 floors. The basement has 3 classrooms, while the first, second, and third floors have 2, 6, and 3 rooms respectively. A common area, modelled as a single room also appears on each floor.

The heating system for the building consists of an HVAC system, where the fancoils are in charge of heating the different spaces, having each room a variable number of them installed. The ventilation is carried on by 2 general Air Handling Units (AHU) that renew continuously the air while the building is occupied to maintain the CO2 level under a certain value.

2.1.1 Single room model

To model each of the rooms, and also when the model-based controller was developed, the dynamics of a single room model was followed. One main assumption considered during the modelling was that the rooms were adiabatic. This is a smooth consideration since, during the functioning of the HVAC, the temperature in the different rooms will be so similar that the heat transmission between them can be neglected. Another consideration to take is that the humidity model is not considered in this work.

On contrary, solar radiation is also not considered because the effect is more difficult to predict and more randomized. We will assume the controllers robust enough to deal with this disturbance.

Dynamic model

Each room can be modelled following the equation (2–1). The first equation describes the evolution of the air room temperature, depending on the heat introduced by the fancoils and the AHU, the heat of the people inside the building, and the temperature difference between the air in the room and the walls. The second equation is the one regarding the wall temperature dynamics, considered as uniform, depending on the proper room temperature and in the environment temperature. Finally, the third equation is considering the dynamics of the volume of CO2 in the room, which depends on the occupancy of the space and the rate of CO2 extraction of the room.

$$\begin{gathered} C_z \dot{T}_z = P_{fc} + P_{AHU} + U_{disp}(T_w - T_z) + \#_{PPL} P_{int} \\ C_w \dot{T}_w = U_{disp}(T_z - T_w) + U_{disp}(T_{env} - T_w) \\ \dot{V}_{CO2} = \#_{PPL} \frac{p_{CO2}}{V_{tot}} - \dot{v}_r \end{gathered} \tag{2–1}$$

Where:

- C_z is the thermal capacity of the room $\left[\frac{J}{K}\right]$
- T_z is the room temperature $[K]$
- P_{fc} is the heat introduced by the fancoils $[W]$
- P_{AHU} is the thermal power introduced by the AHU $[W]$
- U_{disp} is the thermal transmission coefficient $\left[\frac{W}{K}\right]$
- $\#_{PPL}$ is the number of people inside the space
- P_{int} is the thermal power produced by each person $[W]$

- C_w is the thermal capacity of the space walls $\left[\frac{J}{K}\right]$
- T_w is the space wall temperature $[K]$
- T_{env} is external temperature $[K]$
- V_{CO2} is the volume of CO2 inside the room $[ppm\%]$
- p_{CO2} is the amount of CO2 emitted by each person $\left[\frac{m^3 ppm\%}{s}\right]$
- V_{tot} is the total air volume in the space $[m^3]$
- $\dot{v}_r$ is the rate of CO2 extracted from the room $\left[\frac{ppm\%}{s}\right]$

The coefficient U_{disp} is obtained according to the dimensions and materials of the transmission surfaces. However, it has been corrected to better fit real measurements of the building.

Air Handling Unit

As it has been explained before, the air is continuously recirculated in the building with the aim to maintain low enough the level of CO2. The AHUs oversee this task, replacing the air inside the building with fresh air from outside. There are two AHUs in building 25, each of them being in charge of one of the divisions made in the building.

In order to save some energy, this entering air is preheated with the exhaust air leaving the building through a set of heat exchangers. So, these AHUs are introducing some heat in the room through P_{AHU}, as it is considered in (2–1). This heat can be computed as expressed in (2–2).

$$P_{AHU} = u_R \, nV_{tot} \, V_{tot} \rho_{air} c_{p,air} \left(T_{air,AHU} - T_z\right)$$
$$\dot{v}_R = V_{CO2} \, u_R \, nV_{tot} \qquad (2\text{–}2)$$

Where:

- u_R is the recirculation input that comes from a local controller
- nV_{tot} is the maximum number of air volumes that the AHU can extract $\left[\frac{1}{s}\right]$
- $c_{p,air}$ is the specific heat capacity of the air $\left[\frac{J}{kg\,K}\right]$
- $T_{air,AHU}$ is the temperature of the air coming from the AHU $[K]$

Fancoils

The fancoils are the main source of heating for the different rooms in the system. Each room has its proper number of fancoils, having at least one of them. The fancoil warms the air through a heat exchanger where it is circulating hot water coming from the hydraulic circuit. The value of P_{fc} can be computed as is described in (2–3).

$$P_{fc} = U_{fc}(u_{fc})\, N_{fc}(T_{feed} - T_z) \tag{2–3}$$

Where:

- U_{fc} is the thermal transmission coefficient of the fancoil, dependent on the input command u_{fc} $\left[\frac{W}{K}\right]$
- u_{fc} is the input from the fancoil controller
- N_{fc} is the number of fancoils of the considered space
- T_{feed} is the temperature of the water coming from the hot water tank $[°C]$

The thermal coefficient can be obtained from Table 2-1 according to the control input obtained from the local controllers. The output of the fancoil is subjected to hysteresis, to avoid any kind of chattering.

u_{fc}	0	1	2	3
$U_{fc}(u_{fc})\left[\frac{J}{min\ K}\right]$	0	6768	9360	11808

Table 2-1 Lookup table for the fancoils

All the previous equations constitute a nonlinear system for the single room dynamics, where the inputs are the ones of the fancoils and the AHU, the external disturbances are the number of people, the external temperature, the AHU air temperature, and the temperature of the water coming from the hydraulic circuit. Finally, the states considered here are the temperature of the space, the wall temperature, and the level of CO2 inside the space.

$$x = \begin{bmatrix} T_z \\ T_w \\ V_{CO2} \end{bmatrix}; \qquad u = \begin{bmatrix} u_{fc} \\ u_R \end{bmatrix}; \qquad d = \begin{bmatrix} \#_{PPL} \\ T_{env} \\ T_{air,AHU} \\ T_{feed} \end{bmatrix}$$

2.1.2 Hydraulic circuit

The hydraulic circuit of building 25 is formed by two heat pumps (HP), heating the water inside the water tank, which is the one that supplies hot water to the different local heating systems of the building through the low-loss header.

The water flow rate from the water tank will be constant, and the hydraulic circuit together with the water tank is considered adiabatic.

Heat Pumps

There are two different HPs providing heat to the building, one air-to-water and one water-to-water. They are the main components of introducing heat into the building, being directly connected to the water tank. The air-to-water HP uses external air as a heating source, having a variable temperature, while the water-to-water HP uses underground water, which can be considered constant, fixed at $15\ °C$.

In the case of HPs, the main parameter that can measures the energy consumption is the Coefficient of Performance (COP). This parameter is of capital importance and depends on the temperature of the involved components in the heat transfer. In these HPs, the experimental COP is shown in (2–4).

$$\begin{aligned} COP_{aw} &= \Phi_{aw} \frac{T_{tank}}{T_{tank} - T_{env}} \\ COP_{ww} &= \Phi_{ww} \frac{T_{tank}}{T_{tank} - T_{ground}} \end{aligned} \tag{2–4}$$

Where:

- COP_{aw} is the coefficient of performance of the air-to-water HP
- COP_{ww} is the coefficient of performance of the water-to-water HP
- T_{tank} is the temperature inside the water tank $[K]$
- T_{env} is the temperature of the external air $[K]$
- T_{ground} is the temperature of the ground water $[K]$
- Φ_{aw} is the scale factor of the ideal COP of Carnot for the air-to-water HP
- Φ_{ww} is the scale factor of the ideal COP of Carnot for the water-to-water HP

The final heat provided by each HP is provided given the control input of each HP and the maximum nominal heat of each of them (2–5).

$$\begin{aligned} \dot{Q}_{aw} &= COP_{aw} u_{hp,aw} \dot{L}_{max,aw} \\ \dot{Q}_{ww} &= COP_{ww} u_{hp,ww} \dot{L}_{max,ww} \end{aligned} \tag{2–5}$$

Where:

- $\dot{Q}_{aw}$ is the thermal power provided by the air-to-water HP
- $\dot{Q}_{ww}$ is the thermal power provided by the water-to-water HP
- $u_{hp,aw}$ is the control input for the air-to-water HP
- $u_{hp,ww}$ is the control input for the water-to-water HP
- $\dot{L}_{max,aw}$ is the maximum nominal thermal power for the air-to-water HP
- $\dot{L}_{max,ww}$ is the maximum nominal thermal power for the water-to-water HP

Hot water tank

This element stores energy in the form of hot water thanks to the HPs. The main advantage of having a water tank is that it allows storing the excess of energy produced, reducing losses. The estimated size of this water tank is $20\ m^3$.

To model the dynamics of the water tank, the consideration of homogeneous temperature is important. This is justified by the high flow rate entering the tank, guaranteeing a good mixing of water. The dynamics of the water tank are described in (2–6).

$$C_w \dot{T}_{tank} = \dot{m}_{water} c_{p,water} \left(T_{back,LH} - T_{tank} \right) + \dot{Q}_{aw} + \dot{Q}_{ww} \tag{2–6}$$

Where:

- C_w is the thermal capacity of the water tank $\left[\frac{W}{K}\right]$
- $\dot{m}_{water}$ is the water flow rate of the hydraulic circuit $\left[\frac{kg}{s}\right]$
- $c_{p,water}$ is the specific heat of water $\left(4186\,\frac{J}{kg\;K}\right)$
- $T_{back,LH}$ is the temperature coming back to the water tank from the low-loss header $[K]$

Low loss header

The low loss header supplies the heating subsystems with hot water from the water tank and collects cold water coming back. The temperature $T_{back,LH}$ then, should be computed as the average of the temperatures of all returning flows merging.

2.2 Controller structure

The controller for the whole building will be the cascade NMPC developed in [2] (CAS-NMPC). There are two predictive controllers of different hierarchies, each of them in charge of different dynamics.

The first NMPC (NMPC 1) observes the building dynamics and based on future predictions of the state, selects the optimal temperature for the water tank, which in the end is the main resource for heating the different rooms in the building. The second NMPC (NMPC 2) is in charge of maintaining the water tank temperature at the desired one selected by NMPC 1, manipulating the control inputs for the two HPs, minimizing their energy consumption.

Hence, the first NMPC predicts the future needs of heating in the building, and the second guarantees to have the needed temperature of water for covering those needs. Then, a set of local existing controllers uses this water to heat the rooms with simple controllers. The overall structure is depicted in Figure 2-1.

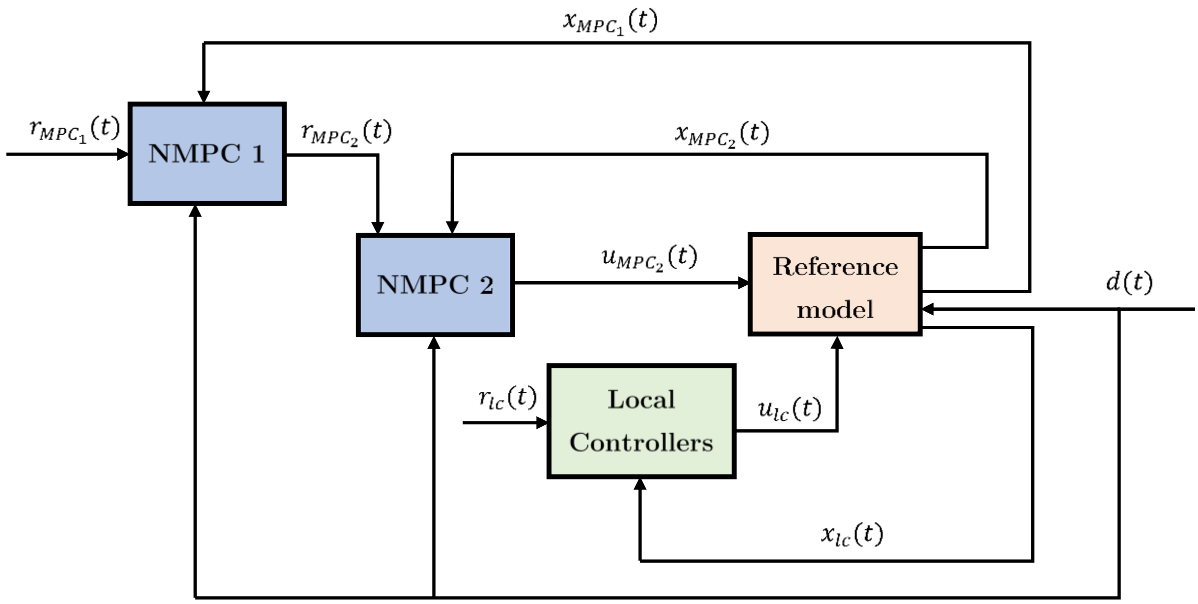

Figure 2-1 Nonlinear Model Predictive Controller (CAS-NMPC)

2.2.1 Local controllers

The local controllers are the ones existing in the building, already installed. They used the energetic resources achieved by the two higher hierarchy controllers. This thesis will consider them as untouchables and well-functioning, focusing only on the NMPC 1.

Fancoils

There are a total of 18 controllers, one for each space of the building for the control of the temperature inside it, so all the fancoils in a room are operated simultaneously with the same input command. They guarantee to maintain the temperature inside the rooms close to the reference one.

The basic structure of this controller consists of a lookup table to select the adequate power delivered by the fancoil. Comparing the reference $T_{z,ref}$ with the actual temperature of the room $T_{z,i}$, it selects u_{fc} as control action as shown in equation (2–3).

CO2 level

There is also one controller for each of the 18 rooms in building 25. The control goal is to not overcome the legal requirement of $15\, ppm\%$ in each room. Measuring V_{CO2}, a PI regulator selects u_R to provide an adequate level of recirculation. This recirculation is switched off if nobody is in the room, so the $\#_{PPL}$ should be also considered as an external disturbance. The dynamics controlled here are shown in (2–2).

Three-way valve

Finally, two controllers are placed for each of the AHUs. The goal is to control the inlet air temperature introduced in the building, by controlling the water temperature going to the heat exchangers of the AHUs.

As the dynamics inside the AHUs are fast enough, the controller considered can be an algebraic one. Each controller selects the x position of a three-way valve based on the different temperatures involved.

$$x = \frac{T_{AHU} - T_{back,AHU}}{T_{feed} - T_{back,AHU}} \tag{2–7}$$

Where:

- T_{AHU} is the temperature of the input water to the AHU $[°C]$
- T_{feed} is the temperature of the water coming from the water tank $[°C]$
- $T_{back,AHU}$ is the temperature of the water coming back from the AHU $[°C]$
- x is the valve position of the three-way valve, from 0 to 1

2.2.2 NMPC 2

As it has been explained, this Predictive Controller deals with the temperature tracking of the water tank. Given $T_{tank,ref}$, the controller operates the HPs commands most efficiently according to its cost function.

The sampling time is 4 min, while the prediction horizon includes 4 instances. This means that the NMPC 2 is making predictions 16 mins in the future about the temperature of the water tank, time higher enough than the tank dynamics.

T_{s,MPC_2}	$4\ min$
N_{p,MPC_2}	$4 \equiv 16\ min$

Table 2-2 NMPC 2 time characteristics

Structure

The model inside the NMPC is the one developed previously for the water tank. So, a nonlinear 1-state model is used.

$$C_w \dot{T}_{tank} = \dot{m}_{water} c_{p,water} \left(T_{back,LH} - T_{tank}\right) + \dot{Q}_{aw} + \dot{Q}_{ww} \tag{2–6}$$

The heat transmitted by the HPs can be computed using equations (2–4) and (2–5). The state and inputs for this controller are:

$$x_{MPC_2} = [T_{tank}]; \qquad u_{MPC_2} = \begin{bmatrix} T_{env} \\ U_{fc,tot} \\ Q_{AHU} \\ T_{z,mean} \\ T_{tank,ref} \\ \boldsymbol{u_{hp,aw}} \\ \boldsymbol{u_{hp,ww}} \end{bmatrix};$$

From these inputs the only tunable ones are $u_{hp,aw}$ and $u_{hp,ww}$. The remaining ones are measurable disturbances or local controllers output variables. It is necessary though, to constraint properly the different inputs and states along the prediction horizon (2–8). The super index defines the source from which the signal comes. The only tunable range, as said, is given to the HPs inputs.

$$
\begin{gathered}
T_{env}^{meas}(t+k) \leq T_{env}(t+k) \leq T_{env}^{meas}(t+k) \\
U_{fc,tot}^{lc}(t) \leq U_{fc,tot}(t+k) \leq U_{fc,tot}^{lc}(t) \\
Q_{AHU}^{lc}(t) \leq Q_{AHU}(t+k) \leq Q_{AHU}^{lc}(t) \\
T_{z,mean}^{meas}(t) \leq T_{z,mean}(t+k) \leq T_{z,mean}^{meas}(t) \\
T_{tank,ref}^{MPC_1}(t) \leq T_{tank,ref}(t+k) \leq T_{tank,ref}^{MPC_1}(t) \\
\mathbf{0} \leq \boldsymbol{u_{hp,aw}(t+k)} \leq \mathbf{1} \\
\mathbf{0} \leq \boldsymbol{u_{hp,ww}(t+k)} \leq \mathbf{1}
\end{gathered}
\tag{2–8}
$$

When predicting the evolution of the states during the time horizon of the NMPC, the external disturbance (the external temperature), is considered as perfectly known in advance. Another possibility would be to consider it as persistent all the time horizon but, in this thesis, a perfect prediction is considered.

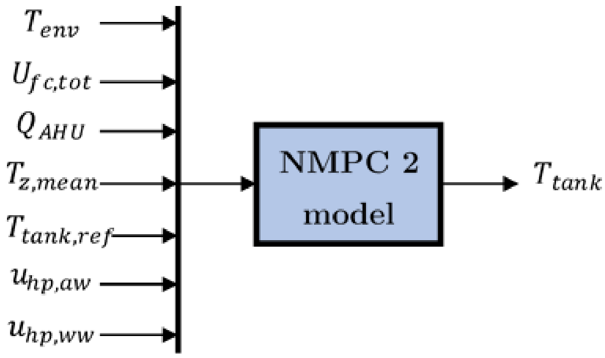

Figure 2-2 NMPC 2 model structure

Cost function

Finally, it is important to define the cost function to optimize during the prediction horizon each time step:

$$
L_{MPC_2}(t) = \sum_{k=1}^{N_{p,MPC_2}-1} \left(L_{track,MPC_2}(t+k) + L_{en,MPC_2}(t+k) \right) \tag{2–9}
$$

Where:

- $L_{track,MPC_2}(k)$ is the tracking term, ensuring that T_{tank} is close to $T_{tank,ref}$:

$$L_{track,MPC_2}(k) = w_{T_{tank}} \left(T_{tank,ref}(k) - T_{tank}(k)\right)^2 \tag{2–10}$$

Being $w_{T_{tank}}$ the weight of the tracking term.

- $L_{en,MPC_2}(k)$ is the energetic time, ensuring the saving of energy in the HPs:

$$L_{en,MPC_2}(k) = w_{HP}\left(u_{hp,aw}\dot{L}_{max,aw} + u_{hp,ww}\dot{L}_{max,ww}\right) \tag{2–11}$$

Being $w_{T_{HP}}$ the weight of the energetic term.

The election of the weights in the cost function is subjected to the mode election in the NMPC 2. There are three modes depending on the relation between the weights of the tracking and the energetic term. The ECO mode weights more the energy consumption instead of the tracking term. On the contrary, the COMFORT mode prioritizes the tracking term, focusing more on reducing the tracking error than the energetic efficiency of the HPs. There exists a third mode that is a trade-off between both called COMPROMISE.

In this thesis the mode used in the NMPC 2 is the COMFORT term, guaranteeing that the water tank temperature is always close to the desired by the NMPC 1.

2.2.3 NMPC 1

This is the higher in hierarchy controller of the CAS-NMPC structure explained before. This controller deals with the building thermal dynamics, selecting the best reference temperature for the water tank according to the future energy needs of the building.

This controller is the most important in this thesis since the NN model that is being tested is the one introduced here. The NN model used inside is better described in chapter 3. However, here it will be explained the main characteristics of the proper controller, leaving the development of the NARX NN predictive model for the next chapter.

As it is the outer controller of the whole system, the sampling time is bigger. In that way the $T_{tank,ref}$ for the NMPC 2 is a stable signal, that is easy to track. For the NMPC 1, then, the change in T_{tank} is almost instantaneous in the time domain of this controller. The sampling time, in the end, is 16 min, while the time horizon is 10 time-steps (160 mins). This provides 2 hours of estimation of the future energy needs of the building.

T_{s,MPC_1}	$16\ min$
N_{p,MPC_1}	$10 \equiv 160\ min$

Table 2-3 NMPC 1 time characteristics

Structure

The model will be further developed in the next chapter, but as it has been said, it estimates future energy needs based on the setpoint and measurable external disturbances and selects the best reference temperature for the heat reservoir that is the water tank.

For making future predictions, up to know the NMPC 1 used a simple 1 room dynamic equation for estimating the room and wall mean temperature of the building $T_{z,mean}$ and $T_{w,mean}$. It is important to remark that the models considered in the NMPC 1 do not compute the temperature and the error for each room, but $T_{z,mean}$ is the average value of the different rooms in the building. The NARX NN prediction model will be discussed later. The states and inputs for this controller are:

$$x_{MPC_1} = \begin{bmatrix} T_{z,mean} \\ T_{w,mean} \end{bmatrix}; \qquad u_{MPC_1} = \begin{bmatrix} T_{env} \\ \#_{PPL} \\ T_{z,ref} \\ U_{fc,tot} \\ Q_{AHU} \\ \boldsymbol{T_{tank,ref}} \\ \dot{m}_{AHU,1} \\ T_{AHU,1} \\ \dot{m}_{AHU,2} \\ T_{AHU,2} \\ \boldsymbol{X_{use}} \\ \varepsilon_1 \\ \varepsilon_2 \end{bmatrix};$$

Where:

- $\dot{m}_{AHU,1}$ is the flow rate of the AHU 1
- $T_{AHU,1}$ is the temperature of the AHU 1
- $\dot{m}_{AHU,2}$ is the flow rate of the AHU 2
- $T_{AHU,2}$ is the temperature of the AHU 2
- X_{use} is an input variable that distributes the power required between the two HPs
- ε_1 and ε_2 are two slack variables to use in the constraints to make the problem computationally softer to solve

Not all the variables will be employed for making the prediction in the building model, but some of them are required for the computation of some quantities needed for the cost functions in NMPC 1. The tunable input that will be the final decision of the NMPC 1 is $T_{tank,ref}$, and the rest are provided by measured disturbances or other variables coming from local controllers or the NMPC 2. All of them should be adequately constrained.

In this thesis, $T_{tank,ref,min}$ is fixed at $25\ °C$, while $T_{tank,ref,max}$ is given by $45\ °C$. The external disturbances here are T_{env}, $T_{z,ref}$ and $\#_{PPL}$. As $T_{z,ref}$ is given by the user, it can be considered as perfectly known within the whole time horizon. As for the case of NMPC 2, T_{env} is going to be considered as perfectly estimated, or with an error in the prediction of the external temperature so small, that is negligible. Hence, during the whole prediction horizon, this quantity is known. Nevertheless, the estimation of the occupancy is much more difficult to predict since it is more randomized, and sensible to many factors as the date, the schedule, the global situation, or even the proper weather. For this reason, the occupancy is going to be considered persistent during the whole prediction horizon. This means that the number of people inside the building obtained when started the optimization at that time step $\boldsymbol{t}$ is going to be maintained constant during the whole prediction horizon.

$$T_{z,min} \leq T_{z,mean}(t+k) \leq T_{z,max}$$

$$T_{w,min} \leq T_{w,mean}(t+k) \leq T_{w,max}$$

$$\begin{gathered}
T_{env}^{meas}(t+k) \leq T_{env}(t+k) \leq T_{env}^{meas}(t+k) \\
\#_{PPL}^{est}(t) \leq \#_{PPL}(t+k) \leq \#_{PPL}^{est}(t) \\
T_{z,ref}^{given}(t+k) \leq T_{z,ref}(t+k) \leq T_{z,ref}^{given}(t+k) \\
U_{fc,tot}^{lc}(t) \leq U_{fc,tot}(t+k) \leq U_{fc,tot}^{lc}(t) \\
Q_{AHU}^{lc}(t) \leq Q_{AHU}(t+k) \leq Q_{AHU}^{lc}(t) \\
\boldsymbol{T_{tank,ref,min} \leq T_{tank,ref}(t+k) \leq T_{tank,ref,max}} \\
\dot{m}_{AHU,1}^{comp}(t) \leq \dot{m}_{AHU,1}(t+k) \leq \dot{m}_{AHU,1}^{comp}(t) \\
T_{AHU,1}^{comp}(t) \leq T_{AHU,1}(t+k) \leq T_{AHU,1}^{comp}(t) \\
\dot{m}_{AHU,2}^{comp}(t) \leq \dot{m}_{AHU,2}(t+k) \leq \dot{m}_{AHU,2}^{comp}(t) \\
T_{AHU,2}^{comp}(t) \leq T_{AHU,2}(t+k) \leq T_{AHU,2}^{comp}(t) \\
\boldsymbol{0 \leq X_{use}(t+k) \leq 1} \\
0 \leq \varepsilon_1(t+k) \leq 10^{10} \\
0 \leq \varepsilon_2(t+k) \leq 10^{10}
\end{gathered} \tag{2–12}$$

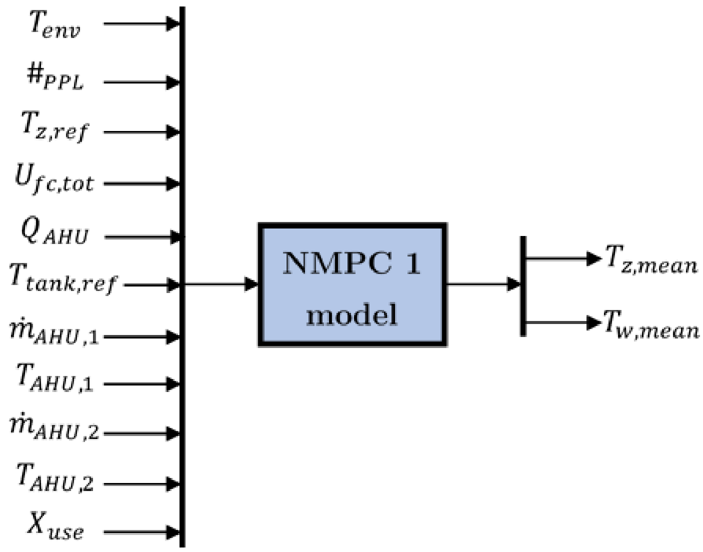

Figure 2-3 NMPC 1 model structure

Cost function

The cost function in this NMPC is also composed of two main terms:

$$L_{MPC_1}(t) = \sum_{k=1}^{N_{p,MPC_1}-1} \left(L_{comf,MPC_1}(t+k) + L_{en,MPC_1}(t+k) + \varepsilon(t+k) \right) \tag{2–13}$$

Where:

- L_{comf,MPC_1} is the comfort term, trying to make $T_{z,mean}$ as close as possible to $T_{z,ref}$:

$$L_{comf,MPC_1}(k) = w_{T_z} \left(T_{z,ref}(k) - T_{z,mean}(k) \right)^2 \tag{2–14}$$

  Being w_{T_z} the weight of the comfort term.

- L_{en,MPC_1} is the energetic term, measuring the heat consumed by two HPs at instant k:

$$L_{en,MPC_1}(k) = w_{HP_1}\left(P_{hp,aw}(k) + P_{hp,ww}(k)\right) \tag{2–15}$$

Being w_{T_z} the weight of the comfort term, and $P_{hp,aw}(k)$ and $P_{hp,ww}(k)$ are the electric power consumed by the HPs.

$$P_{hp,aw}(k) = \frac{Q_{tot}X_{use}(k)}{COP_{aw}(k)}$$
$$P_{hp,ww}(k) = \frac{Q_{tot}\left(1 - X_{use}(k)\right)}{COP_{ww}(k)} \tag{2–16}$$

The $COP(k)$ is computed according to (2–5), and Q_{tot} is the total heat required by the fancoils and AHUs, and the reason why they are needed as inputs for the NMPC 1.

- The final term is the one devoted to slacks variables, relaxing the HPs power constraints and making always feasible the optimization problem.

$$\varepsilon(k) = w_{\varepsilon}\left(\varepsilon_1(k) + \varepsilon_1(k)\right) \tag{2–17}$$

In this NMPC there are also three modes regarding the relative value of the weights of the two terms involved in the cost function. The modes are equally named than before: ECO, COMFORT, and COMPROMISE. The meaning of them is the same as the ones explained in the previous subsection.

In this thesis, the mode used for NMPC 1, as it happened before, will be the COMFORT mode, so the election of the $T_{tank,ref}$ will be made giving more importance to the tracking of the setpoint in the building rooms.

3 NARX Neural Network

In this chapter, the main aspects of NN are exposed, with its different phases in training. Then, the NARX processes are explained briefly to understand the key points about autoregressive processes. Many of these descriptions are further detailed in [35].

Finally, the combination of both in the NARX NN and its direct application to build the prediction model used in the NMPC 1 for selecting the optimal tunable input is presented.

3.1 Feedforward Neural Network (NN)

Artificial Neural Networks (ANNs) are mathematical models, that take their name from their trial of mimic human Neural Networks and their ability of learning. It is a black box model in which some inputs are taken and the output is computed, according to some parameters trained with data. In this case, the most used structure, the multi-layer perceptron (MLP), is employed. There are other typical structures as the radial basis function networks (RBFNs).

These two types are known to be universal approximators. This means that a big enough ANN could approximate any system, with the correct inputs, sizes, and outputs. Of course, it is impossible to know the correct size for a NN beforehand. It is a black box modelling technique, and it is based mainly on empirical evidence and experimental simulations. The main advantage of RBFNs is the quick training compared with MLPs. However, MLPs generally use a smaller number of neurons and parameters for complex systems with many inputs and outputs. As it is going to be the case, MLPs will be used.

Another important remark to make here is that if the output of the ANN depends not only on the current input but also on past inputs and outputs, it is called a recurrent

ANN. As the overall system will be modelled as a NARX process, we will make use of a recurrent ANN.

3.1.1 Structure

The structure of an ANN with the MLP shape includes neurons, connections, and biases. This NN shape has a finite set of layers, each of them constituted by a finite number of neurons plus one bias. Each neuron receives a certain number of inputs, sums them, and adds the bias. The result of this sum pass through an activation function, that computes the output of each neuron. In the end, the ANN can be seen as a nonlinear function:

$$\hat{\mathbf{y}} = f(\mathbf{x}, \boldsymbol{\theta}) \tag{3–1}$$

Where:

- $\mathbf{x}$ is the set of inputs
- $\hat{\mathbf{y}}$ is the set of predicted outputs
- $\boldsymbol{\theta}$ is the set of parameters, including weights and biases

The layers are classified into the input layer, hidden layer, and output layer. There is only one input layer, where the neurons receive as inputs the original inputs for the black-box model. Contrarily, there exist a finite number of hidden layers, where the values received for each neuron come from the result of the activation function of the neurons in the previous layer. Finally, there exists one output layer that takes the values of the activation function of the last hidden layer and computes the value for the output of the ANN. This last operation usually includes the operation of passing from a normalized value to the original range of the output of the NN.

The connections between neurons have different weights. The output of each neuron is multiplied by this weight, and this product constitutes the final input for the next neuron in the next layer. Then, the output of each neuron and for the output layer considering a number K of hidden layers is shown in (3–2). The shape of a possible ANN is shown in Figure 3-1. For simplicity, only some weights are depicted in the image.

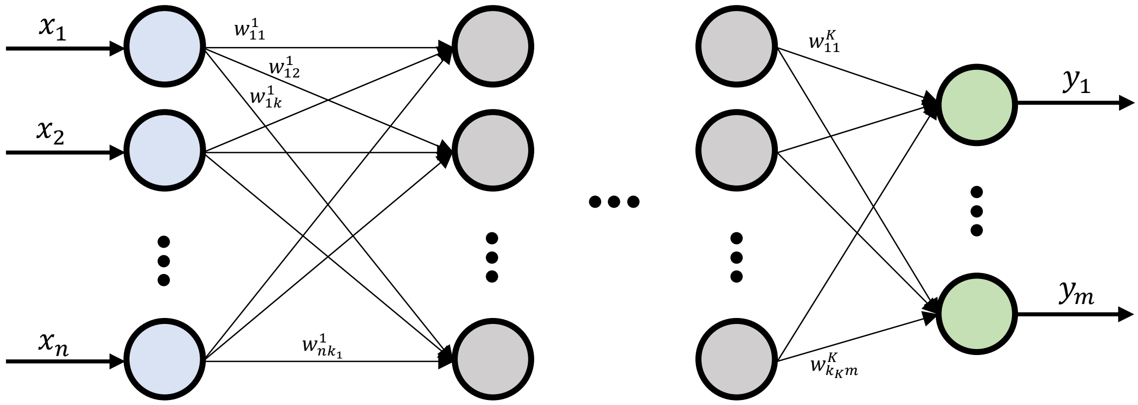

Figure 3-1 MLP NN structure

$$\mathbf{x}^k = h_{af}(\mathbf{w}^k \mathbf{x}^{k-1} + \mathbf{b}^k)$$
$$\mathbf{y} = h_{af}(\mathbf{w}^K \mathbf{x}^{K-1} + \mathbf{b}^K) \tag{3–2}$$

Where:

- $\mathbf{x}^k$ are the outputs of the neurons in layer k
- $\mathbf{w}^k$ are the weights of the connections entering layer k
- $\mathbf{b}^k$ are the biases of layer k
- $\mathbf{x}^{k-1}$ are the outputs of the neurons in layer $k-1$
- h_{af} is the activation function

It is important in the input layer to normalize all the incoming quantities. Since the type of inputs received by the NN can be of many kinds and can have a very different order of magnitude, the weights after training can be very diverse in size and complicated to train. For that, a previous normalization for guaranteeing the same order of magnitude for all inputs is required. The normalization employed by MATLAB is shown in (3–3), normalizing the input x between -1 and 1.

$$\bar{x} = \frac{2}{(x_{max} - x_{min})}(x - x_{min}) - 1 \tag{3–3}$$

Where:

- x_{max} is the maximum value appearing in the x dataset
- x_{min} is the minimum value appearing in the x dataset
- x is the input value to be normalized

In recurrent ANN, the input layer also uses as inputs past outputs or inputs. So, it uses proper values obtained in the NN by the feedback of the past outputs. x_{max} and x_{min} are automatically saved during the training procedure of the NN in MATLAB.

There are many activation functions h_{af} used traditionally in ANN with this structure. The activation functions are the ones that give the ANN the nonlinear characteristic. The most commons are the sigmoid (3–4), the hyperbolic tangent (3–5), and Rectified Linear Unit (ReLU) (3–6):

$$h_{af} = \frac{1}{1 + e^{-x}} \tag{3–4}$$

$$h_{af} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3–5}$$

$$h_{af} = \max(0, x) \tag{3–6}$$

In this thesis, is used the activation function defined by default in MATLAB for NN, that is the hyperbolic tangent.

3.1.2 Training, validation, and testing

As it has been seen, a set of weights and biases, merged in $\boldsymbol{\theta}$, together with the proper structure of the ANN are the ones that define the behaviour of the overall Network. To set the appropriate value for the parameters, training is needed. Training consists of using a dataset obtained from the real system, or in this case, from simulation over a reference model taken as the real system. This dataset should be large enough to avoid problems as overfitting, also related to the number of parameters to set. During training, the parameters are modified to make the predictions as close as possible to the real outputs given as data.

A training algorithm is needed to modify continuously the parameters of the ANN during the training. A lot of algorithms have been developed for training, mainly based on the Backpropagation procedure. By default, MATLAB uses Levenberg-Marquardt (LM) backpropagation. However, for this thesis, the Bayesian regularization backpropagation is configured [36]. Being very similar to LM, it guarantees better generalization properties, trying to avoid overfitting during training. Once finished with the training, the NN should be ready to be used, but there is still the necessity to try this NN with validation and testing procedures.

Validation is an assessment of the prediction capabilities of the NN using data not contained in the training dataset. Assessing the prediction capabilities consists of comparing the predicted outputs with the real ones of the validation dataset. For measuring the error in prediction, the Mean Square Error (MSE) is used. Validation is an essential step to check the generalization capabilities of the ANN and to understand if overfitting has appeared during training. The validation step is also useful for analyzing the best combinations of hyperparameters present in the structure, such as the number of hidden layers, neurons, or the inputs selected.

The partition between the training and the validation dataset can be randomized in the whole data set or divided into blocks. However, the correct proportion of data for training and validation must be used, since the validation performance is the one that will be used for finishing the training. The training will be performed until the validation error starts to increase again during a certain number of training instances. The validation error is a good measure of the expected generalization error of the ANN, so if at a certain instance this error starts to increase again, is a good indicator of the point at which overfitting is starting to take place. In this sense, overfitting means that the NN is trained in a way that is able to perfectly shape the training dataset, it is too particularized. In this thesis, a proportion of 75 % of data is used for training and 25 % for validation.

In the end, there exists the testing phase, in which the trained and validated NN faces a new dataset not correlated with the previous ones, with the conditions to which it will be exposed. This testing phase can appear or not, and it is recommended when the conditions in which the system is going to operate are quite different than the ones from which the training and validation dataset has been obtained.

3.2 Nonlinear autoregressive model with exogenous inputs (NARX)

In a nonlinear autoregressive model with exogenous inputs (NARX), the actual value of the output is based on the current and past inputs (exogenous), and on the past outputs (autoregressive) with a nonlinear relationship [37]. As it is typical on these prediction models, uncertainty is introduced in the form of an additive white noise (3–7).

$$\mathbf{y}(t) = f\left(\mathbf{y}(t-1), \dots, \mathbf{y}\left(t-n_y\right), \mathbf{u}(t-1), \dots, \mathbf{u}(t-n_u)\right) + \mathbf{e}(t) \tag{3–7}$$

Where:

- $y(t)$ is the output of the process at time t
- $u(t)$ is the input of the process at time t
- $n_y \geq 1$ is the number of feedback delays
- $n_u \geq$ is the number of input delays
- f is a nonlinear function
- $e(t)$ is a white noise with variance $\lambda.\ WN{\sim}(0, \lambda^2)$

In the end, it is possible to define the input vector, of dimension $n = n_y + n_u$:

$$X = \left[y(t-1) \quad \dots \quad y\left(t-n_y\right) \quad u(t-1) \quad \dots \quad u(t-n_u)\right]^T \tag{3–8}$$

3.3 NARX-NN

In this thesis, a NARX model with the shape of an MLP NN is going to be used for the prediction model inside the NMPC 1. The nonlinear function appearing in (3–7) is an MLP ANN, where the inputs are a combination of proper inputs, but adding as new inputs the input delays and the feedback delays. The prediction model function is constructed changing y for x, since the output of the NN will be a proper state of the system under control:

$$\hat{\mathbf{x}}(t) = f(\mathbf{x}(t-1), \dots, \mathbf{x}(t-n_x), \mathbf{u}(t-1), \dots, \mathbf{u}(t-n_u), \boldsymbol{\theta}) \tag{3–9}$$

Where the vector of parameters $\boldsymbol{\theta}$ of a standard NN is added. Instead of scalar values, here vectors are considered since multiple inputs and outputs are considered.

In this thesis, the structure of the NN will be the one developed by Elia Manstretta in his Master Thesis [1] because it has shown reasonably good results with a relatively simple structure. The objective of this predictor is to capture the thermal dynamics of building 25. The MLP takes only one input delay, the actual one, and three feedback delays for the state. It has one only hidden layer with three hidden neurons, as depicted in Figure 3-2. The properties of the NN used in this thesis are summarized in Table 3-1.

The inputs and outputs for the predictive model have the same structure as the previous model used in the CAS-NMPC in the Master Thesis [2], using one single room space for the state variables. The set of inputs has been selected according to the variables actuating in the equation of the single room dynamics (2–1). In these equations, the heat introduced by fancoils, AHUs, and people inside the building were the main inputs, and it will have the same structure (3–10). This structure has sense from the point of view of the physics governing the dynamics. However, it will be checked in the following chapter that some of these variables have a small influence on the evolution of the state, being possible to omit them. Nevertheless, they will be maintained in the simulations because the main objective of the thesis is to analyze the effect of the size and type of dataset used for training this predictive model.

$$\begin{gathered} \mathbf{x}(\mathrm{k}) = \begin{bmatrix} T_{z,mean}(k) \\ T_{w,mean}(k) \end{bmatrix} \\ \mathbf{u}(k) = \begin{bmatrix} T_{env}(k) \\ \#_{PPL}(k) \\ U_{fc,tot}(k) \\ Q_{AHU}(k) \\ T_{tank,ref}(k) \end{bmatrix} \end{gathered} \tag{3–10}$$

Name	Symbol	Value
# of hidden layers	$\#_{hl}$	1
# of neurons	$\#_{\mathbf{neurons}}$	[3]
# input delays	n_u	1
# feedback delays	n_x	3

Table 3-1 Building 25 NARX NN structure

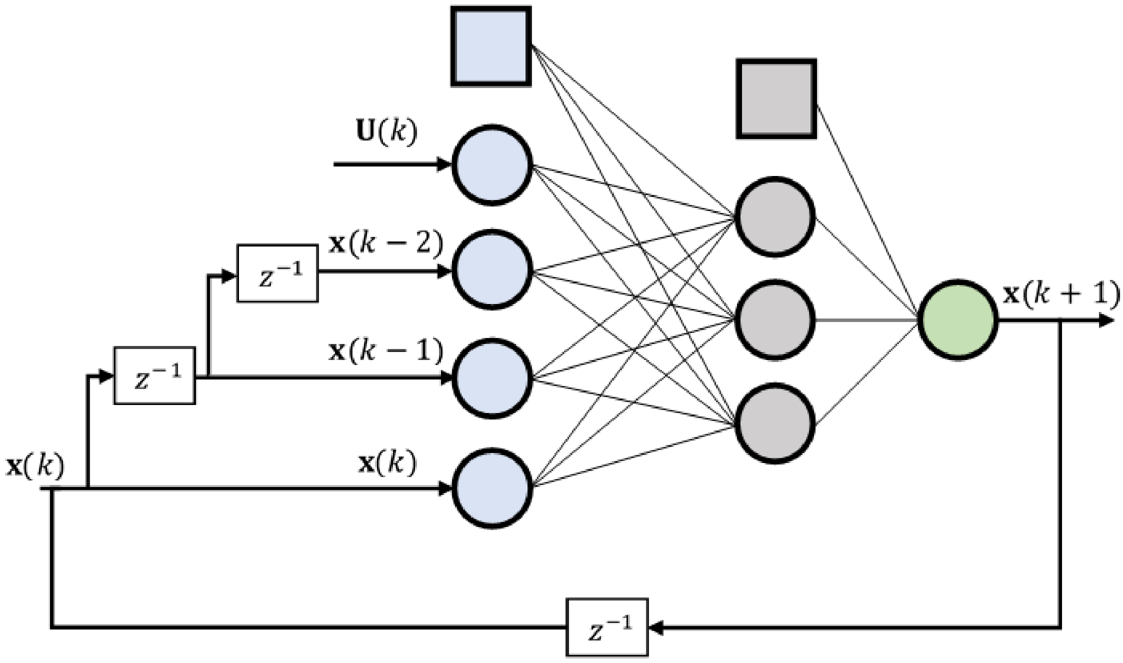

Figure 3-2 Building 25 NARX NN structure

NARX nets can be treated in two different ways: in closed-loop training or open-loop training. In the closed-loop training (also called parallel), the NN is trained by feeding the feedback delays with predicted outputs $\hat{\mathbf{x}}(k)$ for the next-step prediction. On the other side, the open-loop training (also called series-parallel), uses the actual measurement at instant t, $\mathbf{y}(t)$, for making the future prediction during training. This difference is depicted in Figure 3-3.

In this thesis, however, as future predictions will be made by the NMPC 1, the real measurements of the actual state of the building are not available in the prediction horizon. Following this reasoning, the training will be made in a closed-loop configuration. The disadvantage of this training is that it is computationally slower than the open-loop configuration. However, if the open-loop configuration was chosen, then the NN should be closed afterwards to be able to make future predictions in the absence of measurements. The problem is that the training and validation of the NN would have been done using the open-loop shape, and no real guarantees about the performance of this NN once closed are given. For that, even when slower in the training, the closed-loop configuration is chosen to have a closer to real performance NARX-NN.

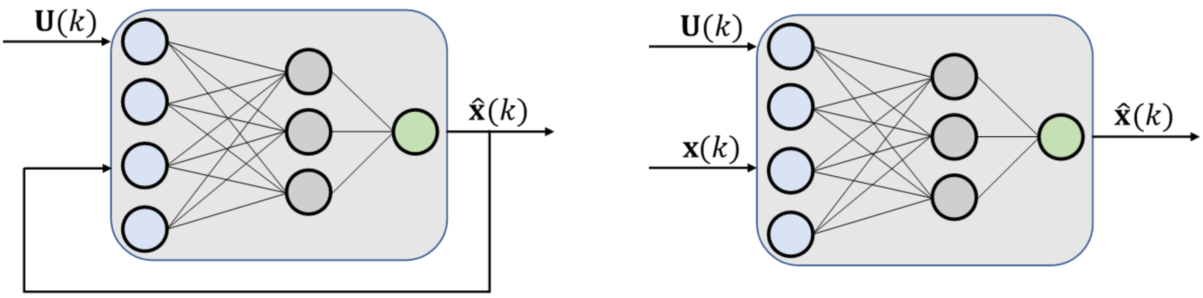

Figure 3-3 Closed and open loop NARX-NN

4 Data generation

In this chapter, several simulations are developed over the CAS-NMPC using different external data, mainly focused on the external temperature profile influence. The final NMPC 1 with the NARX NN as prediction model is shown.

A differentiation between a realistic data generation approach and one considering a simulation approach, making use of the Design of Experiments (DOE) techniques, is detailed.

Then, the prediction capabilities of the NARX NN trained using the different datasets generated are compared. Finally, their performance when using these prediction models in closed-loop inside the NMPC 1 is developed.

4.1 NARX NN NMPC1

The NARX NN prediction model developed in chapter 3, is introduced inside the NMPC 1. To maintain the same structure as the CAS-NMPC employed for generating the data, the same set of inputs is going to be introduced. As shown in (3–10), only 5 inputs of them ($T_{env}, \#_{PPL}, U_{fc,tot}, Q_{AHU}$ and $T_{tank,ref}$) are used for making the predictions. However, the remaining ones are important for computing the cost function L_{MPC_1} developed in (2–13).

4.1.1 Ad-hoc implementation

Even when the internal structure of the NARX NN is further detailed in chapter 3, for the implementation in MATLAB some manipulations are required. The NMPC program uses CasADi symbolic toolbox for introducing the nonlinear function to optimize. If the MATLAB NN toolbox is used, the resulting NN is incompatible with the CasADi NMPC already programed, and the optimization cannot be computed.

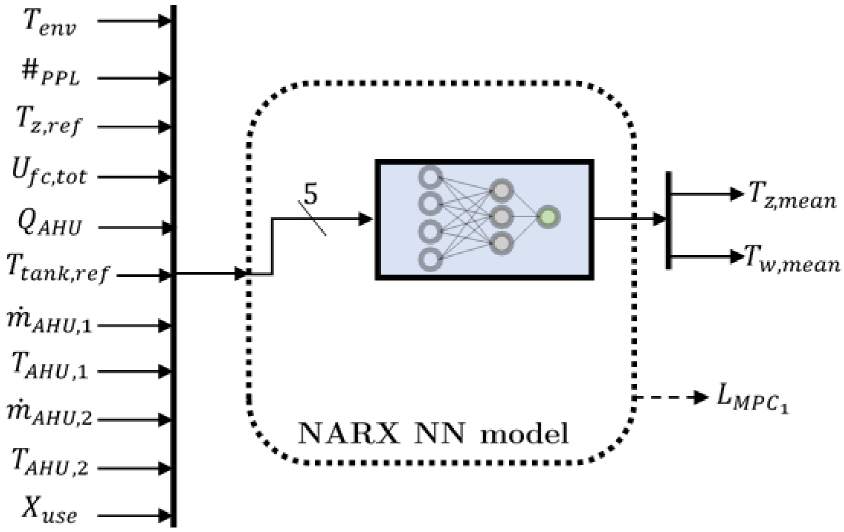

Figure 4-1 NARX NN model for NMPC 1

For that, an ad-hoc nonlinear program has been coded to construct a nonlinear function able to work inside the NMPC program. Even when it had been already developed for the given NN structure in [1], a more generalized version of this ad-hoc program has been developed. This function has the shape of (4–1).

$$\mathbf{X}(k+1) = F_{NN}(\mathbf{U}(k), \mathbf{X}(k), NN, n_x, \#_{\mathbf{neurons}}, n_u) \tag{4–1}$$

Where:

- $\mathbf{X}(k)$ is the extended state vector
- $\mathbf{U}(k)$ is the complete input vector
- NN is the network in the format trained by MATLAB
- n_x is the number of feedback delays
- $\#_{\mathbf{neurons}}$ is a vector with the number of neurons of each hidden layer
- n_u is the number of input delays

To deal with past states, an extended discrete state-space representation of the feedback outputs is provided in (4–2). An enlarged state vector including as many states as feedback delays is built. The only state that requires computation is the first one, which corresponds to the proper output of the NARX NN. The remaining states are the values taken by X_1 in previous instances up to the feedback delay, so that $X_{n_x}(k) = X_1(k - n_x)$.

$$\begin{cases} X_1(k+1) = f_{NN}\left(X_1(k), X_2(k), \dots, X_{n_x}(k), U(k)\right) \\ X_2(k+1) = X_1(k) \\ \vdots \\ X_{n_x}(k+1) = X_{n_x-1}(k) \end{cases} \tag{4–2}$$

Firstly, the program extracts the necessary inputs for the prediction from the set of all inputs introduced in the NMPC. Also, the actual state is extracted, considering as states the extended ones shown in (4–2). Then, the maximum and minimum values for the inputs and feedback states are taken from the information stored in the NN trained by MATLAB. The inputs and feedback states are normalized according to equation (3–3).

The numerical weights are extracted also as matrixes from the network trained. Taking the inputs and the feedback states as pseudo inputs, f_{NN} is implemented. Using (3–2) for each layer, and the hyperbolic tangent as the activation function for each neuron, it is possible to compute the nonlinear function providing $X_1(k)$. Finally, all the assignments for $X_2(k)$ up to $X_{n_x}(k)$ are made, and the new state vector is constructed. It is needed to normalize again but in the opposite direction given in (3–3).

$$y = \frac{y_{max} - y_{\min}}{2}(\bar{y} + 1) + y_{min} \tag{4–3}$$

Where:

- y_{max} is the maximum value appearing in the y dataset
- y_{min} is the minimum value appearing in the y dataset
- $\bar{y}$ is the normalized output value to be rescaled to its normal range

This program can deal with any number of feedback delays, hidden layers, and the number of neurons per layer automatically. However, in this thesis this function has only been simulated for the set of parameters given in Table 3-1. Once created this nonlinear steady-state representation, the NMPC can perfectly work with the extended system and make future predictions.

4.2 Data collection

For obtaining the dataset used for training, the CAS-NMPC structure developed in [2] is simulated controlling the reference model detailed in chapter 2, as if this complex nonlinear model was the real building that the NARX NN will replicate.

The reference model is going to be simulated in closed-loop, trying to replicate the real behaviour in operation. It would not be possible to excite the system in open-loop in order to avoid very uncomfortable situations for users or hazardous outputs for the whole plant.

The model inscribed in the NMPC 1 for the data collection is one simple model taking the building as a one-room space with the dynamics expressed in (2–1). Some considerations must be given for the functioning of the system.

Only the cold season is considered. This means that only the months in which the heating system is used appears. The air conditioning reference model has not been modelled beforehand, and the heating usually carries more energy consumption throughout the year. So, the summer period is excluded.

For carrying the simulations, the external disturbances and control inputs must be provided. These signals are:

- T_{env} the external temperature. The dataset of external temperature is extracted from the ARPA weather station placed in Milano Lambrate, where building 25 is located [38]. From the 2015/2016 cold period up to the 2019/2020 one, the data is downloaded. The cold period is considered the one corresponding to October to March of the following year (six months). As the weather station stores T_{env} each 10 mins, and the sampling time for simulation is 1 min, a linear interpolation is used inside to complete the external temperature profiles. This external temperature will be the main source of information to change and study in the thesis.
- $\#_{PPL}$ the occupancy profile. Although 10 weekly occupancy profiles were created attending to the lecture hours and the maximum capacity of each room (Figure 4-2 a), only one has been used, variated enough, to focus on the influence of the external temperature. It is expected that during a normal year, the occupancy

profile should be uniform along the semesters. Each occupancy profile is constituted by 18 different occupancy single profiles, one for each room.

- $T_{z,ref}$ is the setpoint for the room temperature. Initially, it has been fixed a normal regime maintaining $16\ °C$ during the night and $20\ °C$ during the working hours (Figure 4-2 b). Even when in the weekends after Saturday afternoon it is not usual to have students in the building, the setpoint has been maintained as before to see the influence of this phenomena in the training.

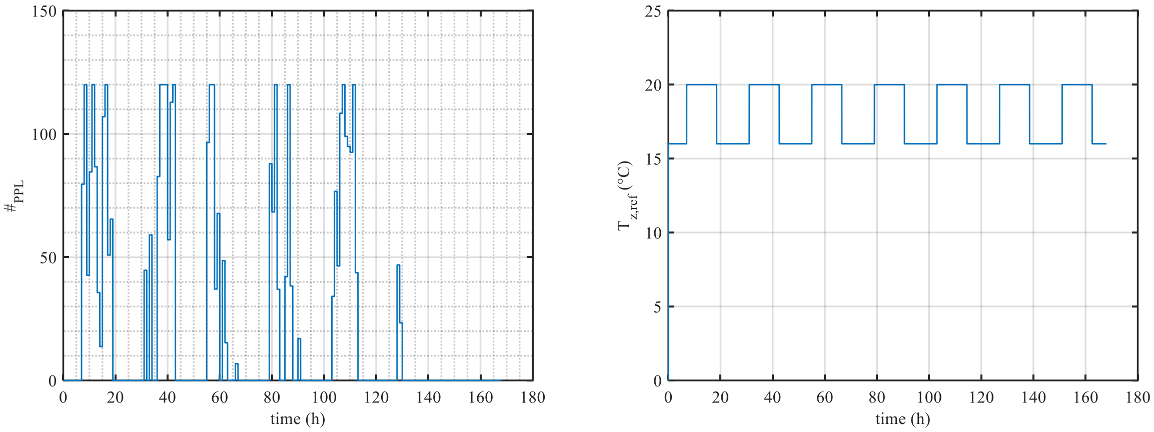

Figure 4-2 a) Occupancy profile of one room during a week b) Setpoint during a week

Once defined the input signals to introduce, the simulations can be carried out. Especial attention is given to the external temperature because is the one able to place the building in many different and environmental conditions. To do the simulations, two different approaches can be followed:

1. Firstly, the simulations can be considered as realistic. It means that the building is exposed to a real external temperature profile, with the correct occupancy and the desired setpoint. It will replicate the data collection from a real building already functioning.
2. On the contrary, it is possible to consider that we have a very good and accurate model of the building and obtain results assuming that this is a simulation environment. In this sense, we can provide different external temperatures, occupancy, and setpoint profiles to excite properly the reference model and have a richer dataset. Both approaches are further detailed, exposing their prediction and closed-loop capabilities.

4.2.1 Realistic approach

The main goal of this approach is to replicate the data collection of a real building. The people are continuously using the installations, and it could be hazardous to employ setpoints that are out of the comfort zone. It is also impossible to achieve a selected occupancy profile since it would be needed to stop or modify the main activities of the building, in this case, students receiving lessons by professors. Of course, the external temperature is also imposed, and it is not possible to modify, mix, or scale the real external conditions.

By doing simulations considering this, it is possible to obtain a realistic dataset. This set would be the one expected to have in the case of a real building, being able to understand its training capabilities. Past external temperature sequences will be given to the building in different periods and lengths, from October to March, considering the sequential characteristic required. The occupancy profile and setpoint will be the ones explained in the previous subsection. In order to take it as representative, the period 2017/2018 is selected for making the simulations.

from	**to**	**from**	**to**	**from**	**to**	**from**	**to**	**from**	**to**	**from**	**to**	**from**	**to**
Oct	Oct	Oct	Jan	Nov	Nov	Nov	Feb	Dec	Jan	Jan	Jan	Feb	Feb
Oct	Nov	Oct	Feb	Nov	Dec	Nov	Mar	Dec	Feb	Jan	Feb	Feb	Mar
Oct	Dec	Oct	Mar	Nov	Jan	Dec	Dec	Dec	Mar	Jan	Mar	Mar	Mar

Table 4-1 Training periods of 2017/2018

In Table 4-1, the different realistic simulation periods are depicted. The column “from” defines the first day of that month, while the column “to” defines the end day of that month. This defines the external temperature profile used for each data collection simulation. For simplicity, it has been considered that all months are made of four weeks. This allows the simpler subdivision of every month that will be useful for the next approach.

4.2.2 Simulation approach. Design of Experiments

In this approach, we assume that the system under simulation can be excited in the desired way to obtain any data. The setpoint can be configured at any point, having more freedom to make the system achieve different reference temperatures. On the other side, external disturbances can be imposed. As it is a simulation, warm and cold weeks can be applied as external temperature profiles. The same can be done with the occupancy profile, being possible to have different levels of occupancy each week.

Having this choice of manipulating exogenous inputs, there exists the need of having a systematic way of launching the simulations in a way that excites properly the system but maintaining a small number of simulations.

Design of experiments (DOE) is employed for this purpose. As explained in chapter 1, in [32] an overview of DOE techniques applied to computational systems is given. The main goal of these techniques is to extract as much information as possible from a limited set of simulations. The external inputs given to the simulation are placed at the extremes of the input space, avoiding the repeatability of simulations.

In this sense, Latin Hypercube Sampling (LHS) will be used. This technique takes the ranges of the external inputs for the simulations and creates a list of combinations of these inputs. The list of simulations correctly samples the input space. By using LHS, the a priori best set of combinations can be reached to excite the system in many situations. To further enter into details, [32] and [33] have more detailed information about this algorithm. In MATLAB, this function is implemented, receiving the number of simulations required. A modified version, in which the ranges of the external inputs are also provided, is employed since the original LHS program provides combinations between 0 up to 1.

The objective now is to apply a technique similar to LHS to the case of building 25, the first task to do is to correctly define the set of 3 external inputs for the simulations. Firstly, the external temperatures are going to be divided into 3 categories: cold, warm, and hot months, attending to their mean temperature as shown in Table 4-2. These categories are numbered from 1 to 3 for being computable by LHS. When constructing the input signal one of the years is selected randomly, and then one of the months of the category selected by LHS is also used at random. From that month, one of its four weeks is chosen for the final signal. The result is shown in Figure 4-3 (a).

Month	**Category**
October	Hot
November	Warm
December	Cold
January	Cold
February	Cold
March	Warm

Table 4-2 Month classification

In the case of the occupancy profile the range taken is from 0 to its maximum occupancy capacity. It selects a scale factor from 0 to 1 and applies it to the original occupancy profile.

$$\overline{\#}_{PPL}(t) = \alpha_{PPL} \#_{PPL}(t)$$
$$\alpha_{PPL} \in [0,1] \tag{4–4}$$

Finally, for the setpoint, the temperature taken is selected in 16 in the non-occupancy hours, but the upper setpoint is chosen by LHS from the range $17\,°C$ up to $22\,°C$. The final setpoint temperature is shown in Figure 4-3 (b).

$$T_{z,ref}(t) = T_{z,LHS}$$
$$T_{z,LHS} \in [17, 22]\,°C \tag{4–5}$$

In the end, even when a simulation environment is used, the reference model developed has not worked too well out of reasonable ranges of conditions. For that, a not-so-wide range of setpoints is given, and the external temperatures are not randomly created, but wisely selected, to guarantee all the possible conditions but in the working range.

To finish with the configuration of the DOE approach used here, a proper selection of the number of weeks is required. The maximum period required in the realistic approach has been from October to March, including 6 months. In this case, a period of 25 weeks is taken, following some other cases and examples from the bibliography. In [34], the LHS is used for generating the data used for training an ANN.

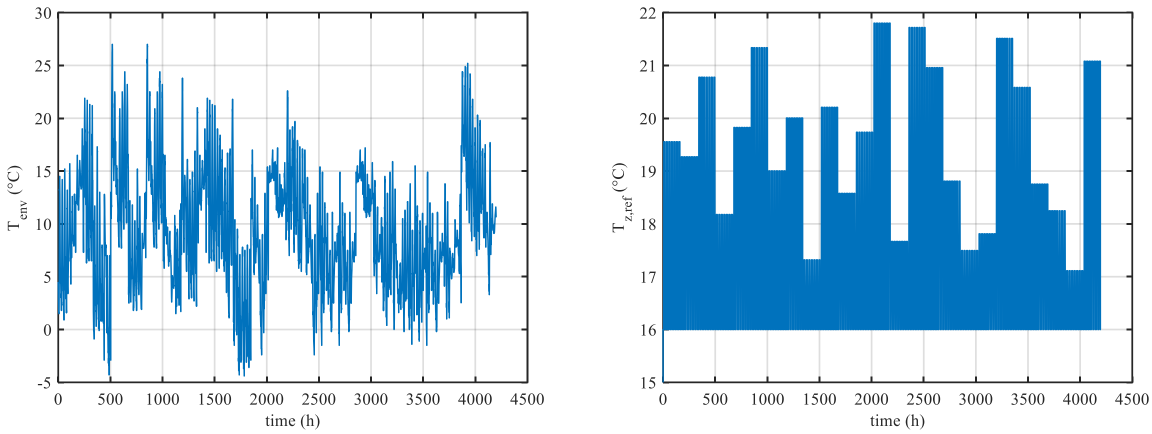

Figure 4-3 a) External temperature generated with LHS b) Setpoint temperature generated with LHS

4.3 Prediction results

In this section, the prediction capabilities of the NARX NN trained with the different datasets will be provided. The realistic approach datasets are tested as well as one example using the DOE techniques.

As explained in chapter 3, the main measurement of training performance is the Mean Square Error. For each of the training cases shown in Table 4-1, the following indexes are obtained:

- **Training error**: the MSE that the NN training algorithm is minimizing, concerning the training subset.
- **Validation error**: the MSE that the NN uses to measure its generalization capabilities, concerning the validation subset.
- **Testing error**: the MSE that the NN uses to measure the real prediction capabilities when facing completely different datasets.

4.3.1 Realistic approach

The testing error is the main tool to understand the prediction behaviour of each of the NARX NN trained. To do so, the NNs trained with the 2017/2018 dataset face each of the months of another cold period (in this case, 2018/2019 one). The testing results can be seen in Table 4-3.

From Table 4-3, some analysis can be made, especially in the zones highlighted:

- The best prediction results are those obtained when testing cold months with NN trained mainly with cold months data (red). Even more, those NN are the ones with the smallest training and validation error.
- When testing hot and warm months with these NNs, the prediction results are the worst in the table (purple).
- The NN that includes hot, warm, and cold months in the training dataset are able to obtain the best overall performance (blue), even when its performance in the cold months is worse than in the case of the NN trained with cold days.
- The best performing NN is the one using the longest dataset, including the period from October to March, which implies a good balance between hot, warm, and cold training datasets (yellow).

This set of results has been also cross-tested. A group of NNs has been trained with the cold period of 2018/2019 and tested against the months of 2017/2018, obtaining the same qualitative results as in Table 4-3 and verifying the remarks made above.

The fact that that the NN trained with cold months only behaves very well with cold months, but very bad when facing other sets of external conditions is a clear symptom of overfitting. The reason behind it is that the type of data used for testing the NN has the same characteristics as the one used for training. The data is particularized for the case in which the heating system is always active and providing a regular and periodical set of outputs for the NN.

However, when the training dataset also includes a significant set of hot and warm months, the error is more uniform across the whole testing set. This kind of months includes periods in which the heating system is active and others in which the system is switched of, allowing the NN to learn the effect of the external disturbances not influenced by the heating system.

From	To	Tr, MSE	Val, MSE	Oct	Nov	Dec	Jan	Feb	March	Mean
Oct	Oct	0,0052	0,096	0,7413	1,8254	4,0898	4,3922	3,3674	1,6707	3,0691
Oct	Nov	0,0139	0,0700	0,3395	0,2006	0,6482	0,7042	0,4276	0,2234	0,4239
Oct	Dec	0,0248	0,0613	0,2560	0,2090	0,2971	0,3088	0,2752	0,1917	0,2563
Oct	Jan	0,0135	0,0108	0,2489	0,1468	0,2896	0,3115	0,2832	0,1550	0,2392
Oct	Feb	0,0173	0,0164	0,3476	0,1720	0,3196	0,3567	0,2989	0,1631	0,2763
Oct	Mar	0,0125	0,0107	0,3838	0,1878	0,1246	0,1338	0,1304	0,1881	0,1914
Nov	Nov	0,0059	0,0100	0,9364	0,2960	0,2850	0,3520	0,2013	0,1999	0,3784
Nov	Dec	0,0077	0,0075	0,9229	0,4297	0,3542	0,3563	0,3668	0,3271	0,4595
Nov	Jan	0,009	0,007	1,0086	0,5682	0,3112	0,5193	0,3280	0,4170	0,5254
Nov	Feb	0,0051	0,0038	0,8134	0,2849	0,0904	0,0950	0,1029	0,3137	0,2834
Nov	Mar	0,0159	0,0496	1,2415	0,4596	0,1850	0,2230	0,1868	0,4308	0,4545
Dec	Dec	0,0036	0,0048	4,2294	1,4142	0,1943	0,1273	0,3258	1,1777	1,2448
Dec	Jan	0,0052	0,0055	1,0742	0,4823	0,1078	0,2550	0,1318	0,4282	0,4132
Dec	Feb	0,0046	0,0046	1,0973	0,5379	0,1037	0,2999	0,1230	0,4465	0,4347
Dec	Mar	0,005	0,0206	1,0375	0,5259	0,1079	0,1091	0,1351	0,4362	0,3920
Jan	Jan	0,006	0,0043	0,9855	0,6110	0,1303	0,1439	0,1325	0,4752	0,4131
Jan	Feb	0,0051	0,0071	1,7350	0,3836	0,1081	0,1226	0,1337	0,4627	0,4910
Jan	Mar	0,0039	0,0129	0,7817	0,3883	0,0886	0,0872	0,1293	0,3954	0,3118
Feb	Feb	0,0369	0,2547	3,9231	1,3393	0,3787	0,3669	0,4663	1,2810	1,2926
Feb	Mar	0,0065	0,0151	0,9995	0,6917	0,3491	0,3493	0,3685	0,4556	0,5356
Mar	Mar	0,0193	0,0454	1,0588	0,5229	0,2033	0,2650	0,1860	0,4611	0,4495
				1,1506	0,5561	0,4175	0,4704	0,3857	0,4905	

Table 4-3 Realistic approach prediction results (17/18 data tested with 18/19)

Because of the realistic approach, the output of the system $T_{z,mean}$ must be periodical in cold months to guarantee the comfort of the users. As the trained NN is a NARX process, if the output of the NN has periodical behaviour, in the end, the majority of the weight in the prediction is given to the past outputs, irrespective of the inputs. The set of data, even when large in the case of cold months, is not informative since it has always the same evolution.

On the contrary, the appearance of hot and warm months provides data more exciting for the whole system, which combined also with data of cold months provides a complete picture of the scenarios and dynamics that the building could face. A NN trained with this set of data is able to capture the influence of the inputs in the states, and not only the effect of past states.

This can be visualized by inspection of the weights of the NN obtained from some dataset. In this case, the NN trained with data from December to December and the one trained with data from October to March are shown in Table 4-4. As the hidden layer has only three neurons, it can be easily extracted the weights from the different inputs and feedback delays neurons to each of the three neurons in the hidden layer (Figure 4-4). Hence, it is possible to understand if some of these variables have no significant effect on the prediction of future states.

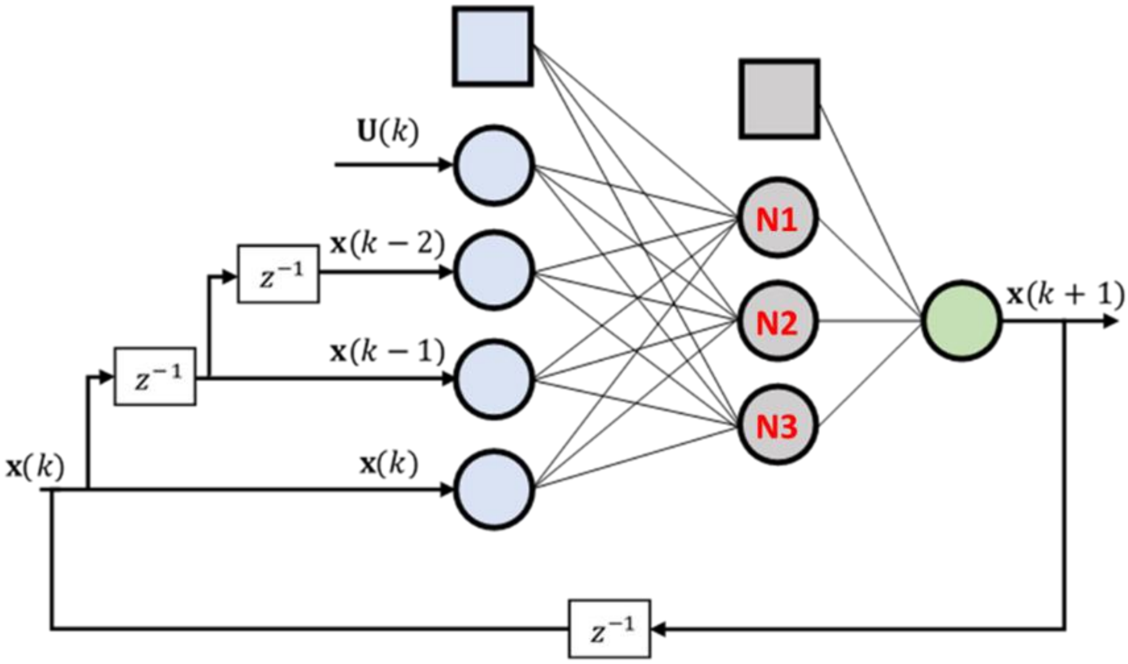

Figure 4-4 NARX NN with numbered neurons

Input	$NN_{Dec\ to\ Dec}$			$NN_{Oct\ to\ Mar}$		
	N1	N2	N3	N1	N2	N3
$T_{ext}(k)$	1,00	1,00	1,00	1,00	1,00	1,00
$\#_{PPL}(k)$	−0,06	−0,31	−1,37	−1,31 e13	−1,88	318,42
$U_{fc,tot}(k)$	−0,03	−0,01	−11,48	−0,30	−4,11	−807,83
$Q_{AHU}(k)$	−0,70	−1,58	0,41	−0,54	−2,02	−1383,48
$\boldsymbol{T_{tank,ref}(k)}$	−0,10	−0,07	−0,96	−9,03 e12	−1,73	−447,99
$T_z(k)$	−4,89	−5,77	−1,49	−3,55	−25,80	−7050,32
$T_w(k)$	48,96	−20,68	−6,11	21,65	51,72	−2547,77
$T_z(k-1)$	−1,78	−0,32	−0,13	0,43	11,13	3442,43
$T_w(k-1)$	4,60	−22,74	−0,81	27,58	−233,39	−719,91
$T_z(k-2)$	2,10	−2,36	−10,98	0,02	−11,47	3429,43
$T_w(k-2)$	0,89	42,74	6,56	12,46	182,19	3779,08

Table 4-4 Realistic approach NN weights

The above reasoning can be seen in Table 4-4. The bad performing NN trained with data from December to December is placing the majority of the weights only on the past states and the exogenous inputs have a negligible influence. For this reason, the NARX process is learned by the NN as a nonlinear autoregressive (NAR) process. This will be a problem when using this NN in closed-loop since the NMPC 1 will try to find the optimal input, but not understanding the effect of the input that is trying to optimize, $T_{tank,ref}$.

However, the NN trained with data from October to March is placing the greatest weight on the exogenous input (at least in one of the three neurons) and the effect is not negligible in one of the others. Hence, the NN understands the influence of the exogenous input and it will be possible to find a reasonable optimal for the tunable input.

4.3.2 Simulation approach

From the previous results, the DOE external inputs designed before seem to be a very useful method for guaranteeing the absence of overfitting. The prediction results shown in Table 4-5 are obtained using the explained LHS and testing it against the same cold months as for the case of the realistic approach.

From	To	Tr, MSE	Val, MSE	Oct	Nov	Dec	Jan	Feb	March	Mean
Oct	Mar	0,0125	0,0107	0,3838	0,1878	0,1246	0,1338	0,1304	0,1881	0,1914
LHS		0,0278	0,0290	0,3707	0,1813	0,1447	0,1890	0,1880	0,1999	0,2074

Table 4-5 LHS prediction results

By using the LHS approach, the prediction performances are a bit worse than when using the best performing NN with the realistic approach. However, it has the main advantage that you are providing rich data and ensuring good prediction performance instead of depending on the available dataset in real circumstances. The prediction result of a NN trained with LHS is shown in Figure 4-5, tested against the October month of 2018.

4.4 Closed-loop results

The NNs trained previously are going to be introduced inside the NMPC 1 to understand their behaviour and how the prediction capabilities are related to the closed-loop performance.

4.4.1 Performance indexes

For defining the performance of this closed-loop simulation, some indexes are going to be defined and compared afterwards:

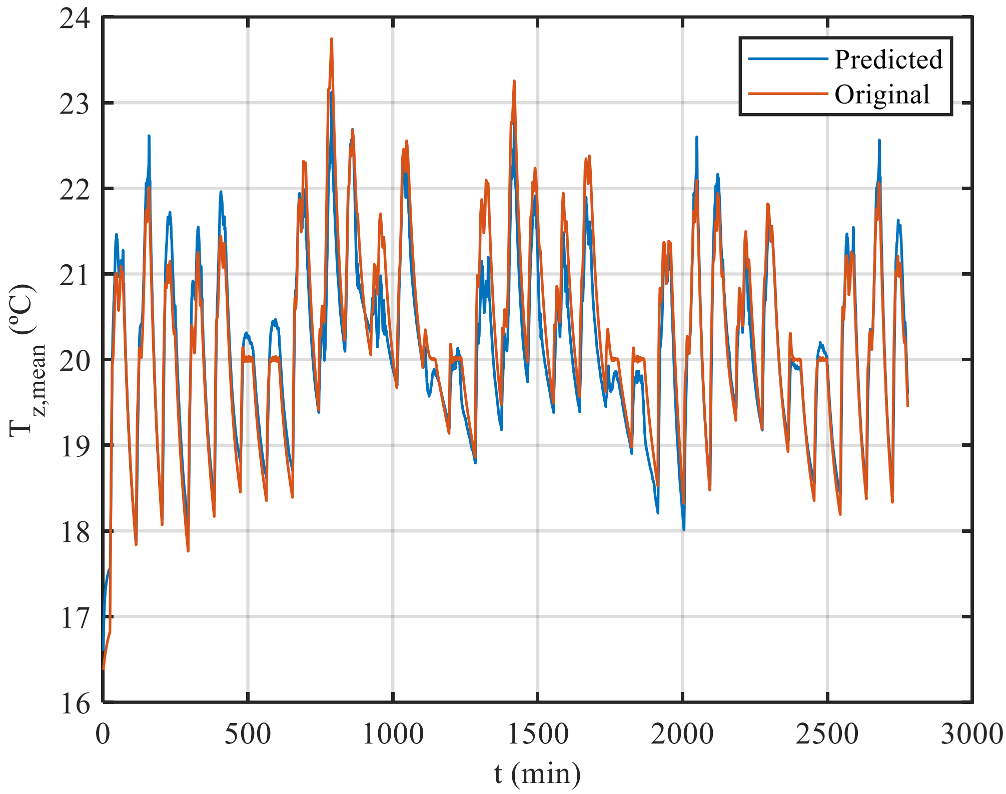

Figure 4-5 Prediction of October 2018 with NN trained with LHS

- **Mean Root Mean Square Error** ($MRMSE$): is the mean of the RMSE tracking errors in the different classrooms, omitting the common spaces of each floor:

$$MRMSE = \frac{1}{14}\sum_{i=1}^{14}\left(\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(T_{z,i}(k) - T_{z,ref}(k)\right)^2}\right) \tag{4–6}$$

Where:

- $MRMSE$ is measured in $°C$
- $T_{z,i}(k)$ is the temperature of room i at instant k $(°C)$
- n is the length of the simulation (min)

- **Mean Root Mean Square Error during occupancy hours** ($MRMSE_{occ}$): same as before but only computed for the occupancy hours, where the comfort for users is a must:

$$MRMSE_{occ} = \frac{1}{14}\sum_{i=1}^{14}\sqrt{\left(\frac{1}{|t_{occ}|}\right)\sum_{k\in t_{occ}}\left(T_{z,i}(k) - T_{z,ref}(k)\right)^2} \tag{4–7}$$

Where:

- $MRMSE_{occ}$ is measured in $°C$
- t_{occ} is the set of time instants in the occupancy hours (min)

- **Energy consumption by the HPs**: it measures the electricity used by both HPs:

$$E_{HPs} = \sum_{k=1}^{n} u_{HP,aw}(k)\,\dot{L}_{max,aw} + u_{HP,ww}(k)\,\dot{L}_{max,ww} \tag{4–8}$$

Where:

- E_{HPs} is measured in kWh

- **Cost**: the economic losses due to the energy consumption of the HPs, basically multiplying the energy consumption by an estimated price of $0.213\frac{€}{kWh}$.
- **Mean Coefficient of Performance** (MCOP): is the mean COP through the working time of the HP:

$$\begin{gathered} MCOP_{aw}(t) = \frac{1}{|t_{use,aw}|}\sum_{k\in t_{use,aw}} COP_{aw}(k) \\ MCOP_{ww}(t) = \frac{1}{|t_{use,ww}|}\sum_{k\in t_{use,ww}} COP_{ww}(k) \end{gathered} \tag{4–9}$$

Where:

- $MCOP_{aw}$ is the MCOP of the water to water HP
- $MCOP_{ww}$ is the MCOP of the air to water HP
- $t_{use,aw}$ is the number of time instants where the air to water HP is used
- $t_{use,ww}$ is the number of time instants where the water to water HP is used

- **Execution time**: a measure in seconds of the time employed to complete the simulation.

4.4.2 Realistic approach

Some closed-loop simulations in cold external conditions are done for understanding the effect of the training data set used for training the NN. Again, the best performing NN in prediction is used (the one trained with the dataset from October to March). On the other side, the NN trained with the data from December to December is also facing the same external conditions to understand the differences. These results are highlighted in Table 4-6, where a subset of the NNs trained with data of the cold period 2017/2018 is working in the external conditions of December 2018. The performance with the baseline controller structure developed by Giuseppe and Federico [2] is also obtained.

From	To	Sim Month	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	E_{HPs} (kWh)	$Cost$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{exe} (s)
CAS-NMPC		Dec	1,26	0,96	24070,59	5127,04	2,91	4,61	1115
Oct	Oct	Dec	1,37	1,25	23540,81	5014,19	2,84	4,50	935
Oct	Nov	Dec	1,26	1,03	23935,65	5098,29	2,82	4,83	1036
Oct	**Mar**	Dec	1,14	0,96	21506,67	4580,92	2,99	6,49	957
Dec	**Dec**	Dec	1,44	1,73	12914,24	2750,73	3,99	10,22	1135
Dec	Mar	Dec	1,28	0,99	21021,50	4477,58	3,31	6,20	927
Mar	Mar	Dec	1,14	1,16	15414,64	3283,32	3,55	9,80	960

Table 4-6 Closed-loop realistic approach performance (17/18 data tested with 18/19)

From Table 4-6, it is possible to compare the different closed-loop performances. In terms of tracking the reference setpoint, the NARX NN trained with data from October to March is showing better results than the baseline controller structure with the single room dynamics model inside NMPC 1 (with less energy consumption). This means that the good performing NN is providing a better estimation of future states than the single room model, being able to predict effectively future energy needs. The fact of providing better tracking performance with an HPs energy consumption reduction of 10,65 % is a key result. Also, another equilibrated dataset such as the one from December to March is providing practically the same performance in tracking, but with a cost saving of 12,67 %.

Nevertheless, the bad performing NARX NN trained with a poor dataset like the one from December to December discussed previously or the one from March to March is providing bad results, especially in the occupancy hours. In fact, the Dec to Dec NN is not able to track the reference setpoint (Figure 4-6).

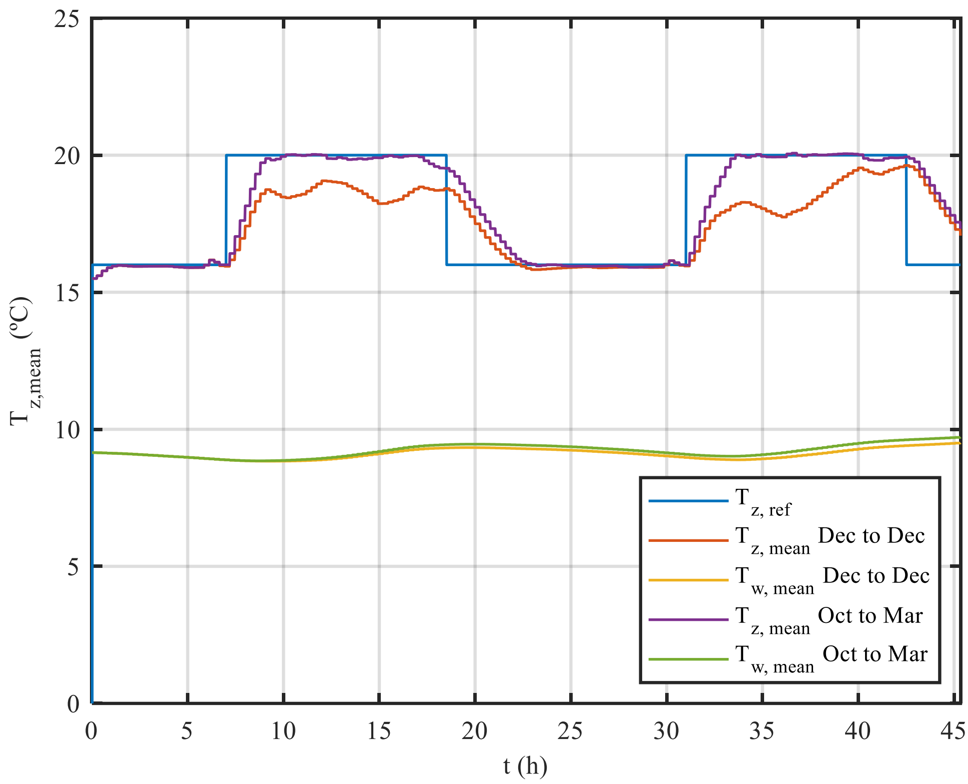

Figure 4-6 $T_{z,mean}$ obtained in closed loop by using good and bad performing NN

The main problem when facing the December to December NN consists of the bad election of the optimal tunable input $T_{tank,ref}$. As it is not going to have a predicted effect in the future states, the NMPC 1 finds the optimal $T_{tank,ref}$ in a value as low as possible. The energetic term in the cost function is acquiring importance since the value of desired water tank temperature is going to require the actuation of the HPs, but it is not affecting the future states. Because of that, the $T_{tank,ref}$ is going to be at its minimum value as described in the input constraints defined in (2–12) (this effect can be seen in Figure 4-7 b). This is the reason why the energetic consumption by HPs shown in Table 4-6 is much lower for the bad performing NN.

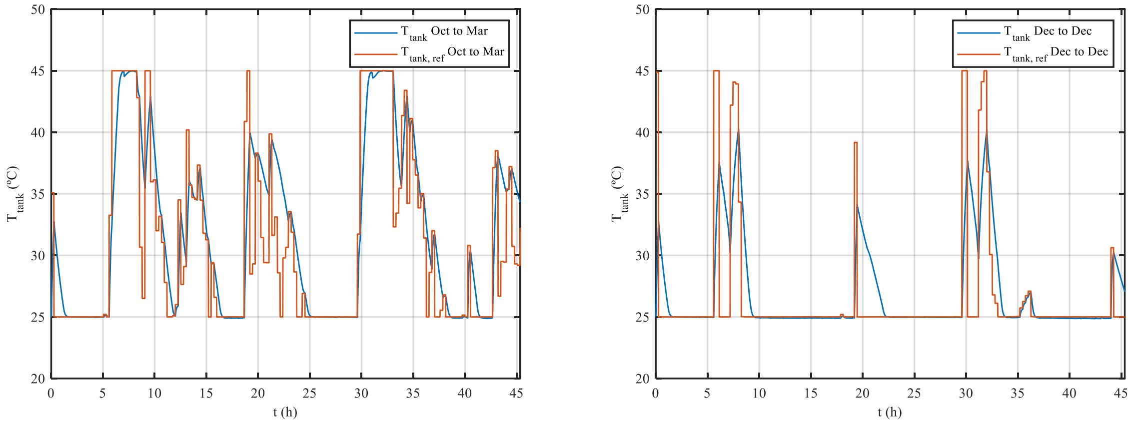

Figure 4-7 T_{tank} evolution using a) Oct to Mar NN b) Dec to Dec NN

While the Oct to Mar NN provides a mean $T_{tank,ref}$ of $32{,}8\,°C$ (which has been demonstrated to be enough for the building heating requirements) the Dec to Dec is giving $26{,}6\,°C$. In this case, even with the fancoils working at their maximum level, they do not have enough heating resources for achieving the setpoint in the rooms. The comparison between the fancoils commands in one of the rooms of building 25 is seen in Figure 4-8. As the energetic resources are very low because of bad performance, the fancoil command is almost all the time at its maximum level. With the good performing NN, it is much softer and it can work at normal levels.

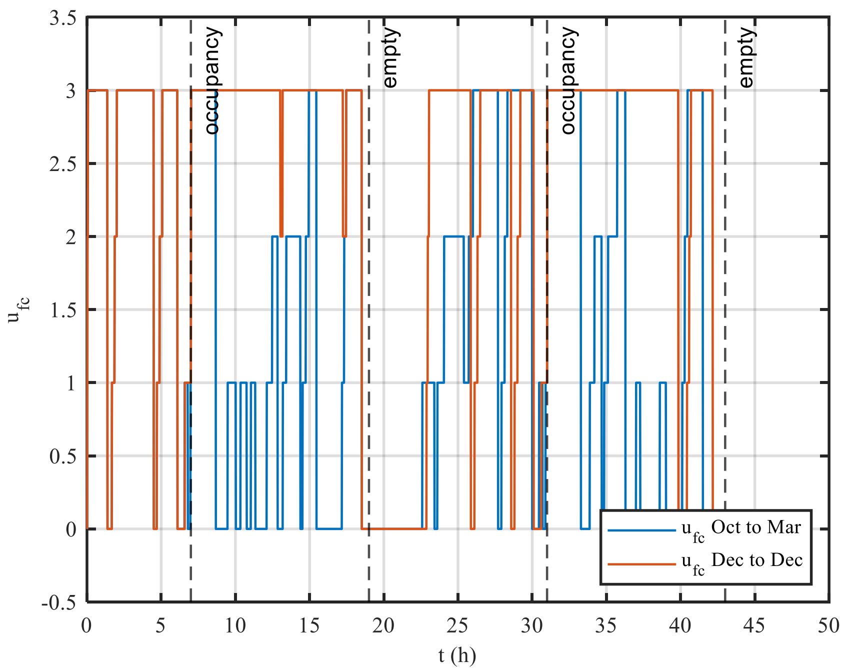

Figure 4-8 Fancoils command comparison using the realistic approach

Another problem appearing with the bad performing NN is the one related to the COP of the HPs. Even when the values obtained are substantially high in general because of the reference model given, the values greater than 9 obtained for bad performing NN are not physically feasible.

4.4.3 Simulation approach

With the NARX NN trained using the LHS technique, the results in closed-loop obtained are expected to be similar to the ones obtained for the NN trained with the dataset from October to March. The main results are shown in Table 4-7.

From	To	Sim Month	$MRMSE$ ($°C$)	$MRMSE_{occ}$ ($°C$)	E_{HPs} (kWh)	$Cost$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{exe} (s)
CAS-NMPC		Dec	1,26	0,96	24070,59	5127,04	2,91	4,61	1115
Oct	Mar	Dec	1,14	0,96	21506,67	4580,92	2,99	6,49	957
LHS		Dec	1,11	0,95	21696,05	4621,26	3,37	7,22	971

Table 4-7 Closed-loop simulation approach performance (tested with 18/19)

The tracking error is improved with the LHS technique, with a slight increase in the cost. This is caused by the more efficient use of the HPs in this case. In the prediction result analysis, the prediction error of the NN trained with LHS was worse than the one using the NN trained with the dataset from October to March. However, the NN seems to work better in closed-loop, having a better generalization capacity and a more accurate knowledge of the dynamics of the model.

4.5 Concluding remarks

The data collection employed for training the NARX NN has a key role in the real performance of the prediction model. The realistic approach has shown to have an excellent performance in prediction under some requirements. The available data for training should correspond to different kinds of months that excite the system in different ways to avoid the use of periodic and noninformative data. This is overcome in the simulation approach, where it is possible to design the set of external conditions in an effective way that guarantees the data to be rich enough for training.

Even more, the simulation approach allows the generation of a lot of data by fast simulations in different scenarios, while the data acquisition in the realistic approach is much more limited. As the building could be functioning, the external conditions cannot be imposed as variated to guarantee comfort. Even more, the speed of simulation is real-time, which takes a huge amount of time to record the needed data.

Nevertheless, the main drawback of the simulation approach is the need to rely on an accurate reference model that effectively represents the real system, trying to identify this reference model with the NARX NN. In the realistic approach, the data is obtained directly from the real building, avoiding the concern about having a realistic and accurate reference model.

The set of real data for training has shown the need of having variated external conditions, both for prediction and in closed-loop simulation. In prediction, the NN trained with hot, warm, and cold months with representative periods of each of them has shown a more generalization capability. However, the NNs trained only with cold months have a very accurate prediction in cold months but a poor generalization in other scenarios. Hence, there exist the risk of overfitting when generating the dataset in the realistic approach if the period of data used is not exciting enough.

Furthermore, the NNs obtained using a variated dataset for training have learned the effect of external inputs in the building, whereas the ones that have incurred in overfitting are practically neglecting the effect of exogenous inputs. They are taking the process as an autoregressive (NAR) process, not having practically any external effects. For that, when testing in closed-loop, the NMPC 1 is able to find an optimized value for $T_{tank,ref}$ in the case of a good training dataset but not in the case of the non-informative dataset.

Finally, the simulation approach using the LHS technique has shown a similar prediction and close-loop performance than the NN trained with a rich dataset in the realistic approach. The main advantage of this simulation technique is the guarantee that the overfitting is not going to be present in the final NARX NN, while in the case of the realistic approach it will depend on the available dataset.

5 Application

Based on the previous results, in this chapter, the possibility of using a badly trained NARX NN is explored. Firstly, online training is tried to check if it is possible to improve the closed-loop performance. Two different techniques are explored: periodic and condition-based online retraining. Differences in the performance are shown.

Then, an application for different buildings than the one used for training is also investigated with some simulations to understand some practical and commercial applications, including fault detection and mitigation.

5.1 Online training

There are two possible reasons to have a bad performing NARX NN given the dataset analysis made in chapter 4:

- Using a realistic approach with a small or non-informative dataset, typical in the case of heating systems during cold periods. This was the case of the dataset from December to December, showing the tracking performance shown in Figure 4-6.
- Using a simulation approach in which the model used as reference is substantially different from the real system under control.

In both cases, bad tracking performance is expected as the one in Figure 5-1. The main problem with the dataset is the lack of variety in it, showing a periodicity and uniformity during the days that make the data to be noninformative, not being able to capture the effect of exogenous inputs.

The main consequence of this phenomena is that the election of the control input $T_{tank,ref}$ in the high hierarchical controller NMPC 1 is not the appropriate one for temperature tracking. Then, there are not the needed energetic resources in the water tank to heat properly the building with the local controllers.

However, this bad performing $T_{z,mean}$ seems to be variated enough and has caused a behaviour in closed-loop different than when using the CAS-NMPC of Giuseppe and Federico [2] for the data collection. This new dataset has shown the required properties needed for being adequate for training the NARX NN.

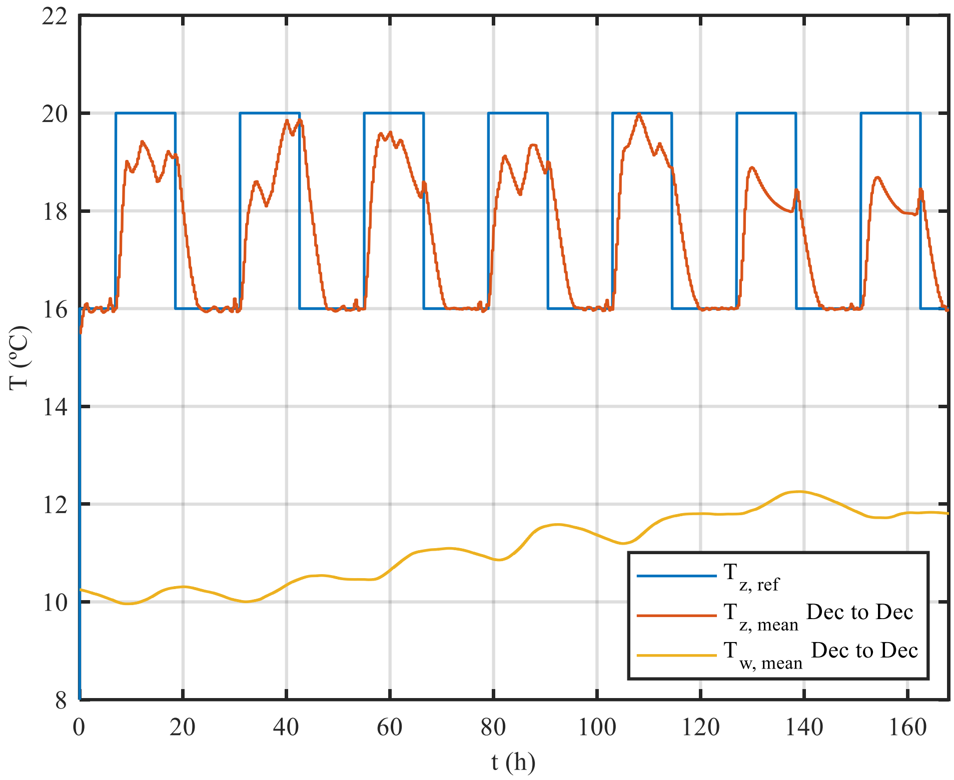

Figure 5-1 Closed-loop performance using a bad trained NN

That is the reason why the retraining appears: a bad prediction model used in closed-loop excites the system in an appropriate way for having a good dataset. So, some days of bad performance are allowed, to then use this new data generated in the real building to retrain and tune better the NARX NN. As seen in Figure 5-2, the retraining with the past data generated using a bad performing NN improves dramatically the performance in closed-loop. Two different ways are considered for retraining: periodic and condition-based online training.

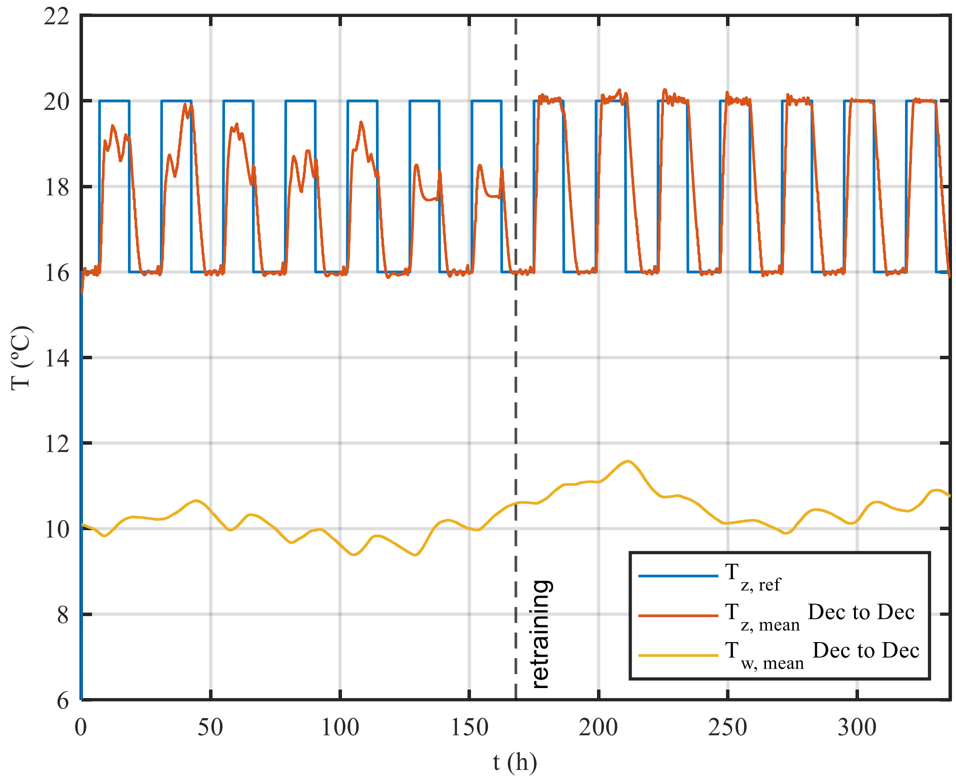

Figure 5-2 Retraining after one week of bad performance

5.1.1 Periodic online training

As the bad performing prediction model excites the model in a useful way for training, it will be tested the effect of retraining periodically. The simulations will be made with a retraining period of 7 days. The results obtained each week are shown in Table 5-1. In this simulation, the bad performing NN trained with data from December to December is used. The energy consumption is omitted since it is providing the same information as the cost. The same is done with the execution time because it maintains the same order of magnitude in each simulation (depending on the computer state) and not being repeatable.

It can be checked that the first retraining is improving dramatically the performance in tracking while decreasing the efficiency of the HPs. However, the COP of the first week is not realistic as a consequence of bad performing NN and, for that, the cost is so small since the HPs are not being required to achieve a significant $T_{tank,ref}$.

From	To	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$
Dec	Dec	1,44	1,73	88,73	4,79	10,23
Week 1		1,47	1,86	96,40	4,29	10,21
Week 2		1,34	0,95	160,19	3,38	7,68
Week 3		1,27	0,97	161,93	3,25	8,32
Week 4		1,22	0,96	142,90	3,72	8,48

Table 5-1 Periodic retraining results

The tracking performance can be also observed in Figure 5-3. The tracking error is maintained irrespective of the number of retraining but the signal behaviour is changing, being more unstable in the upper part of the square wave each time that retraining takes place.

The retraining starts to be counterproductive if the achieved performance is already acceptable. From that moment, the data used for new retraining start to be periodic and non-informative. As the weeks and retraining pass, the proportion of variated data of the first bad performing week vanishes, having only a very small quantity of informative data and falling again in overfitting. For that, it is more important to have condition-based retraining of the NN.

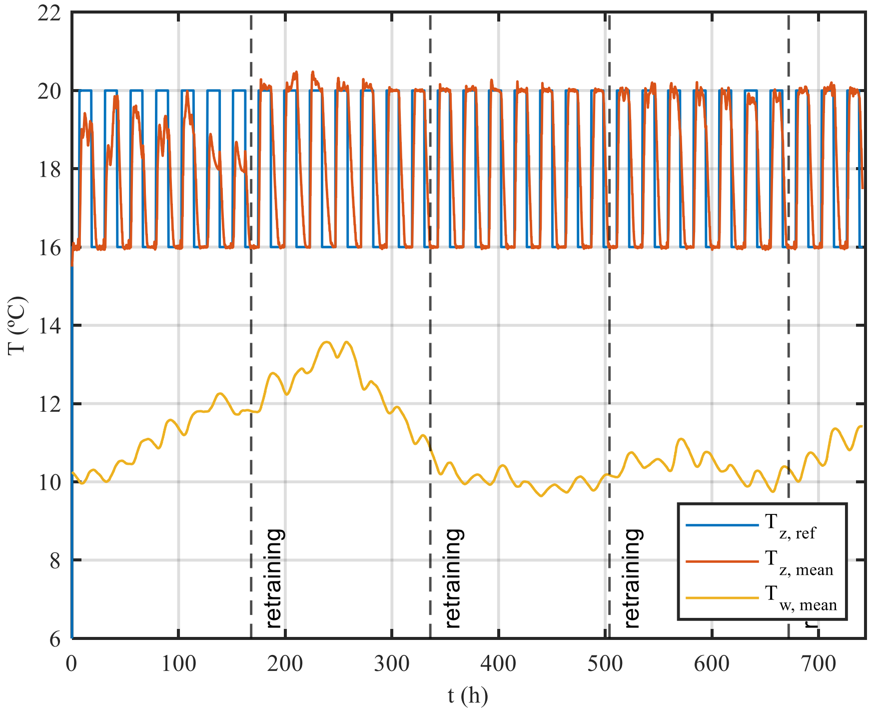

Figure 5-3 Periodic retraining evolution

5.1.2 Condition-based online training

The retraining has shown the capability to improve the quality of the NARX NN used as a prediction model for the NMPC 1. Nevertheless, if the retraining is not needed in terms of tracking, the data used for the new training is periodic and non-informative, deteriorating the initial prediction capacity of the NN. That is the reason why retraining should only be done if some condition is fulfilled.

It will remain periodical, in the sense that the condition check will be made every period of retraining. However, depending on previous performance, the retraining will take place or not. For deciding the retraining an automatic index called t_{out} will be used as a first approach. This index measures the amount of time during the occupancy hours that the temperature inside the building is outside a band of $0{,}2\ °C$ from the setpoint. By tuning properly t_{out}, it is possible to detect bad tracking, implying the need for retraining. A flowchart of this condition-based retraining appears in Figure 5-4.

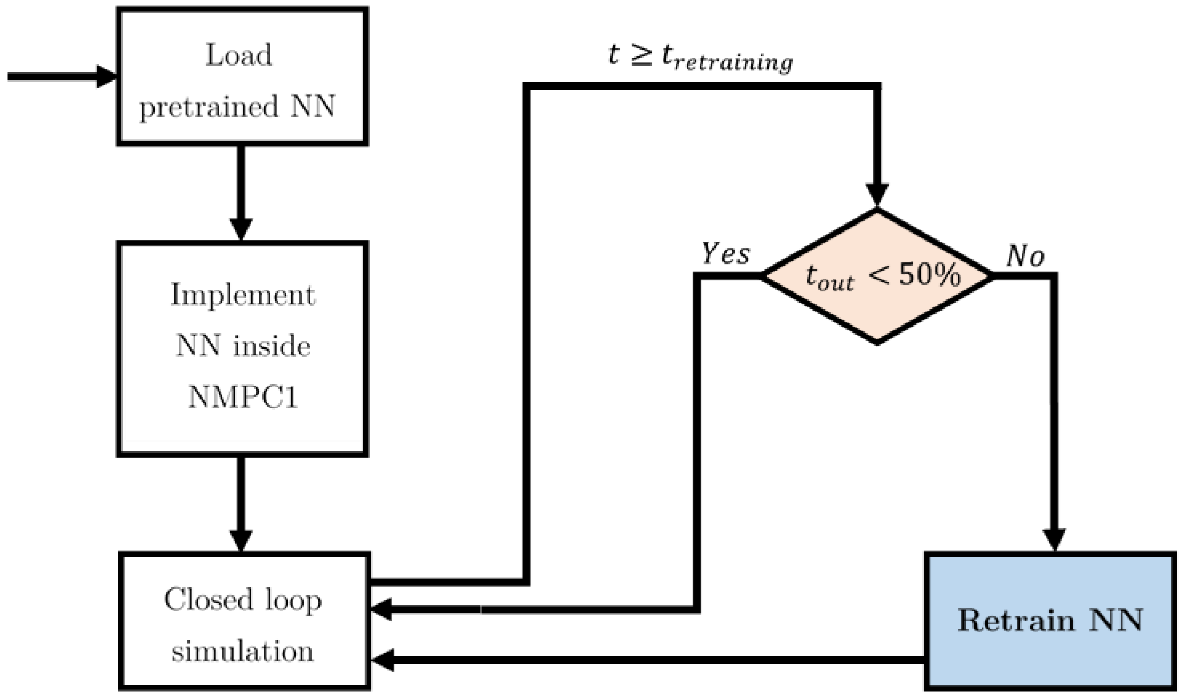

Figure 5-4 Condition-based retraining flowchart

The retraining results are shown in Table 5-2. The tracking error during occupancy hours improves the periodic retraining one. For that, the condition-based seems to be a more practical approach for the considerations made previously. Besides, the signal is more stable than in the case of periodic retraining as shown in Figure 5-5.

From	To	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$
Dec	Dec	1,44	1,73	88,73	4,79	10,23
Week 1		1,47	1,86	96,40	4,29	10,21
Week 2		1,35	0,94	1253,18	3,03	6,25
Week 3		1,29	0,96	1414,79	2,66	5,42
Week 4		1,27	0,94	1308,20	2,88	5,38

Table 5-2 Condition-based retraining results

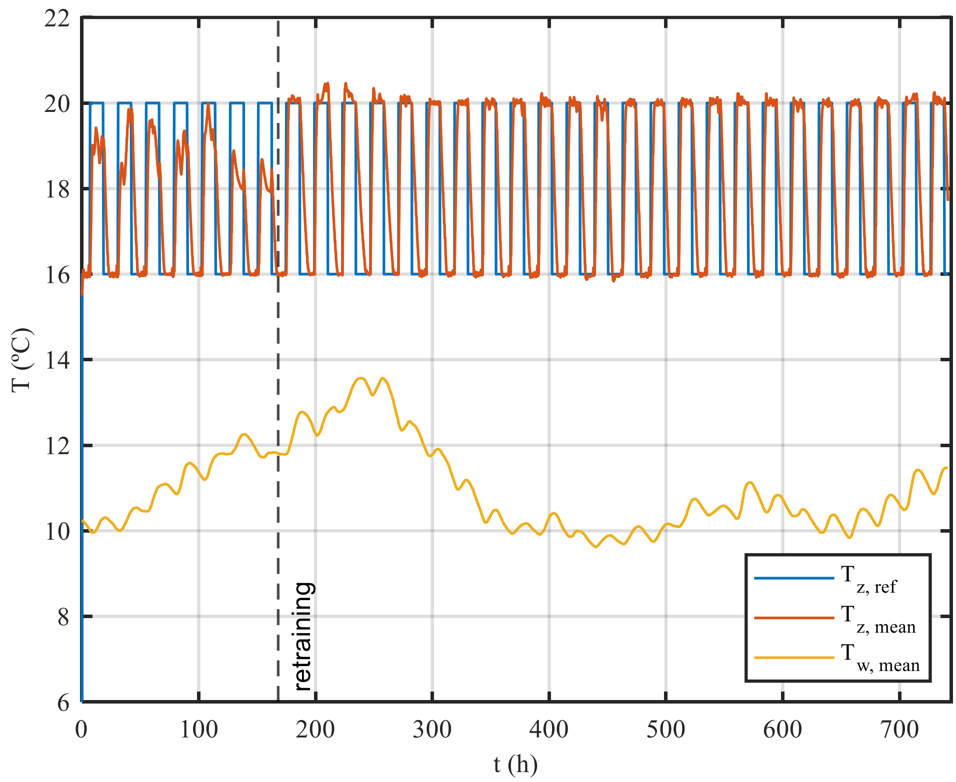

Figure 5-5 Condition-based retraining evolution

A final comparison is made in Figure 5-6, to show the effect of non-necessary retraining in the closed-loop performance, showing the best results and response in the third week if the unnecessary retraining is avoided.

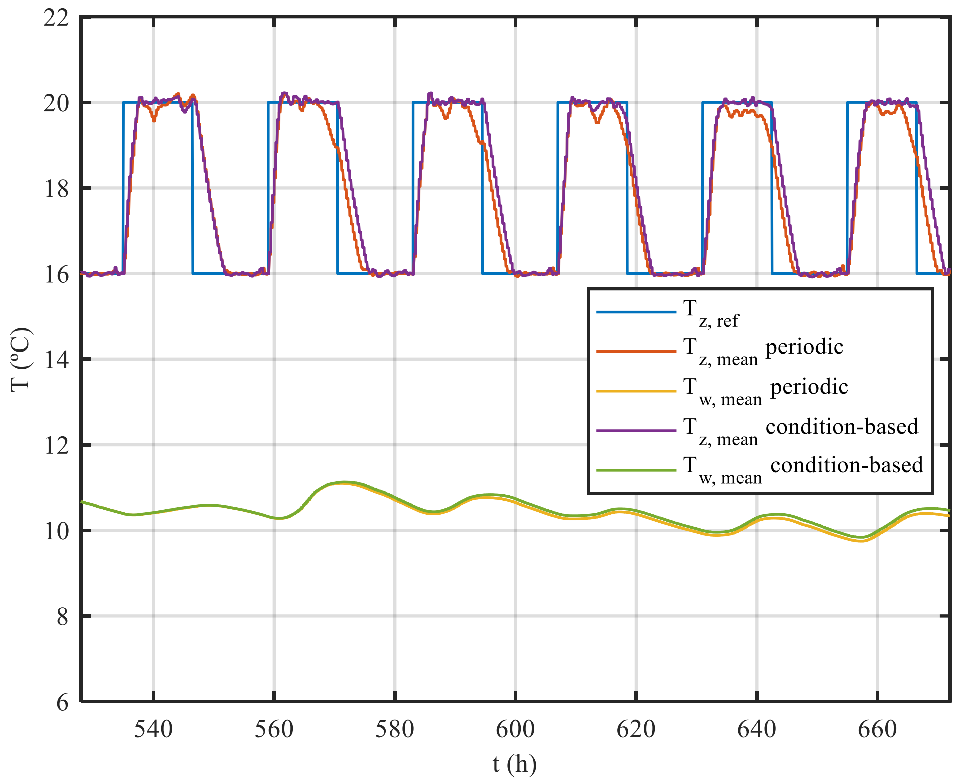

Figure 5-6 Retraining modes for the third week comparison

5.2 Extension to a change of parameters

The previous results show that adequate retraining provides the opportunity to readapt the NN to the system. Even when the NN is not good performing, it has been seen that the temperature inside the building is not going to achieve harmful or hazardous values. This can justify the use of a NN pre-trained in other buildings, or pre-trained in a simulation model that could be different from the real application building. As the response in closed-loop is not dangerous, the pre-trained NN can be used in the real building for some days and then retrained to adequate to the real characteristics of the system. For sure the building should have the same architecture in terms of controller structure and heating system. If the general structure is changed it has no sense to use this approach, since the input signal selected by NMPC 1 can be different, or the signals measured by sensors and used as exogenous inputs for the prediction model can be different.

To formalize this approach, the good performing NN trained with data from October to March has been used in the reference model but changing some characteristics. The parameters that define these changes are:

- **Scale factor**: this parameter changes the general sizes of the building directly implying the quantity of air to heat and the water tank volume.
- **Power factor**: this parameter changes the nominal power of the HPs that provide hot water to the tank.
- **Temperature factor**: this parameter scales the maximum possible temperature achieved by the water tank.
- **Flow factor**: this parameter scales the water flow inside the hydraulic system.
- **Fancoil factor**: this parameter scales the power provided by the fancoils.

If the building is scaled in size, the heating system should be scaled accordingly, to provide a new building reference model with relative realistic values. To this extension a bigger building is considered attending to the parameters shown in Table 5-3. For the retraining, the condition-based online training is used.

Scale factor	Power factor	Temperature factor	Flow factor	Fancoil factor
1,5	1,5	1	1,5	1,5

Table 5-3 Scaling factors of a bigger building

The procedure consists of using the pre-trained NN in the bigger building. After $t_{retraining}$, the index t_{out} is checked, and the retraining takes place. Once retrained, the tuned NN will face again the same set of external disturbances to see the effective difference in performance after retraining. For this purpose, the parameter $t_{retraining}$ has taken a value of 2, 4, and 7 days to understand the amount of data needed for reasonable good retraining.

The results of 2 days retraining horizon are shown both in Figure 5-7 and Table 5-4. In them it also appears a robustness simulation where the new NN faces colder and warmer external conditions. The same procedure is applied for 4 days in Figure 5-8 and Table 5-5. Finally, the simulations are done with 7 days retraining horizon, shown in Figure 5-9 and Table 5-6.

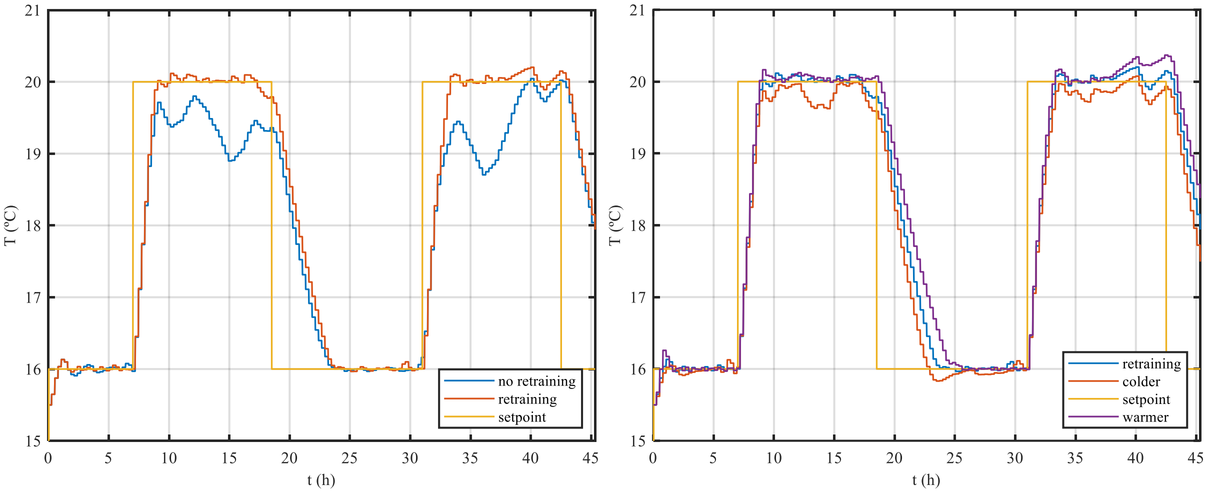

Figure 5-7 a) Retraining with 2 days b) Robustness with 2 days

Simulation	$MRMSE$ $(°C)$	$MRMSE_{occ}$ $(°C)$	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{out} (h)
Before retraining	1,35	1,18	307,73	4,75	9,95	10,11
Retrained	1,29	0,94	415,51	3,63	7,31	2,24
Warmer	1,40	0,90	458,15	2,79	4,27	3,71
Colder	1,23	0,97	380,57	4,05	9,54	5,18

Table 5-4 Retraining with 2 days results

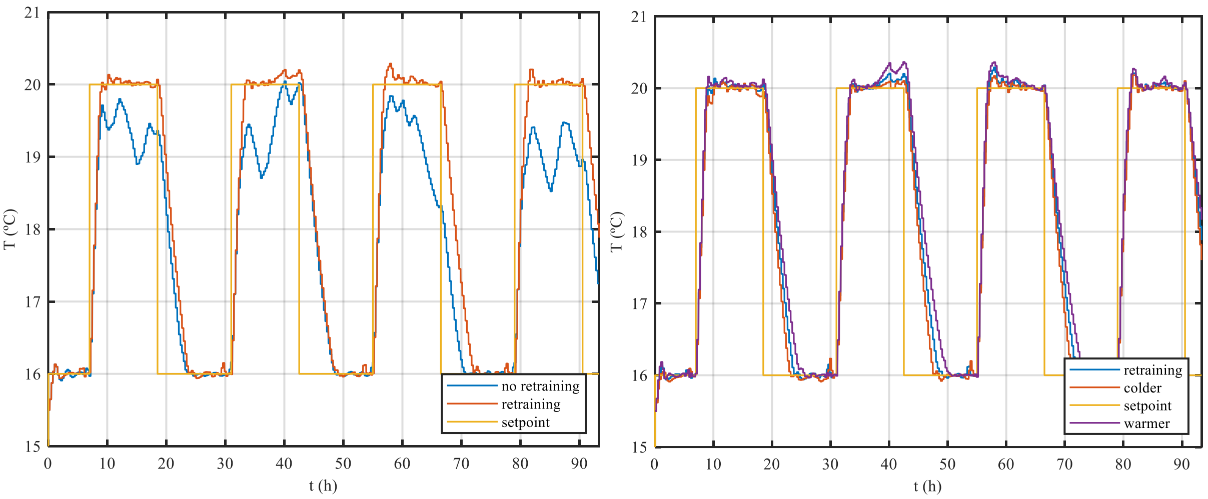

Figure 5-8 a) Retraining with 4 days b) Robustness with 4 days

Simulation	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{out} (h)
Before retraining	1,26	1,25	565,30	4,95	10,18	10,67
Retrained	1,29	0,90	968,91	3,11	5,82	2,45
Warmer	1,36	0,89	837,60	3,20	4,97	3,35
Colder	1,23	0,93	1076,67	2,97	6,47	2,31

Table 5-5 Retraining with 4 days results

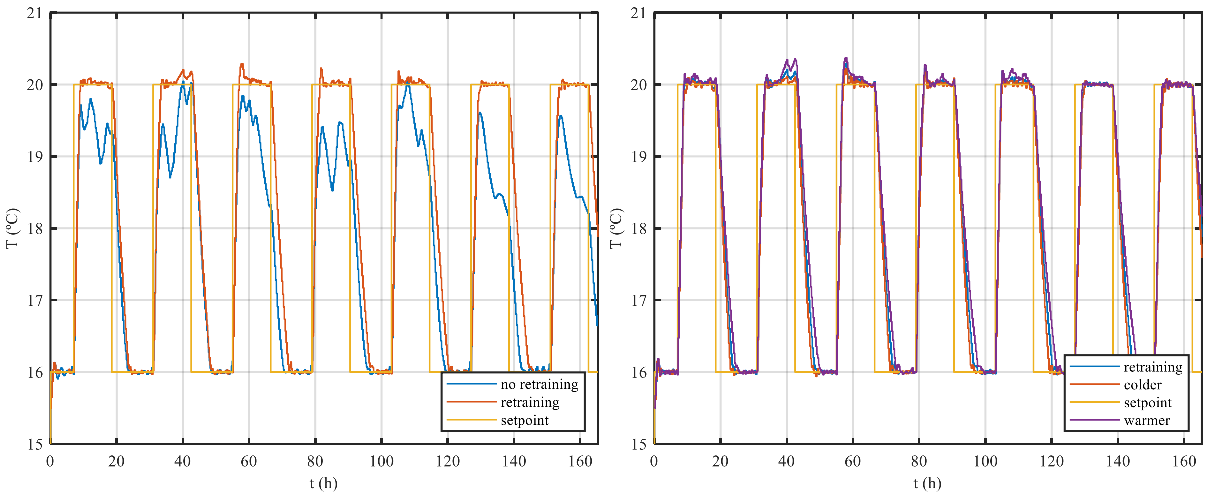

Figure 5-9 a) Retraining with 7 days b) Robustness with 7 days

Simulation	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{out} (h)
Before retraining	1,21	1,34	959,29	4,91	10,12	10,68
Retrained	1,26	0,92	1686,13	2,97	4,76	2,32
Warmer	1,34	0,91	1403,89	3,30	5,10	2,79
Colder	1,21	0,94	2026,82	2,74	4,56	2,24

Table 5-6 Retraining with 7 days results

In general, for all the set of retraining horizons, the tracking performance is dramatically improved after the retraining, and all of them has shown important robustness against a change in the environmental conditions. It can also be seen that, after retraining, the index t_{out} has not overcome the threshold of $50\ \%$ of the occupancy hours, with a value then of $6\ h$. Even when in the tables above there is no much numerical difference, it can be seen some improvement in the number of days used for the retraining. As shown in Figure 5-10, when using 4 or 7 days for retraining, the controllers can maintain high temperatures during a bigger amount of time of the occupancy hours, being more effective in terms of comfort.

Even more, attending to a rule of thumb to avoid bad training, the number of data points for validation should be at least twice the number of parameters in the NN. With the NN considered for this thesis, the number of parameters is 35 between weights and biases. Considering the sampling time of NMPC 1, the number of days for retraining should be greater than 3. That means that even when being able to obtain good results with only 2 days, to maintain the robustness and avoid overfitting it is not an adequate amount of time.

Another consideration for choosing between 4 or 7 days of retraining time is the weekly periodicity of the attendance to a university building as this is the case. If we include 7 days, we are also including weekends and the whole spectrum of the week, guaranteeing that all the scenarios that appear through a complete week are covered by the retraining.

$t_{retraining}$	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{out} (h)
Before retraining	1,35	1,18	153,87	4,75	9,95	10,11
2 days	1,29	0,94	207,75	3,63	7,31	2,24
4 days	1,29	0,90	193,78	3,11	5,82	2,45
7 days	1,26	0,92	240,88	2,97	4,76	2,32

Table 5-7 Retraining horizon results comparison

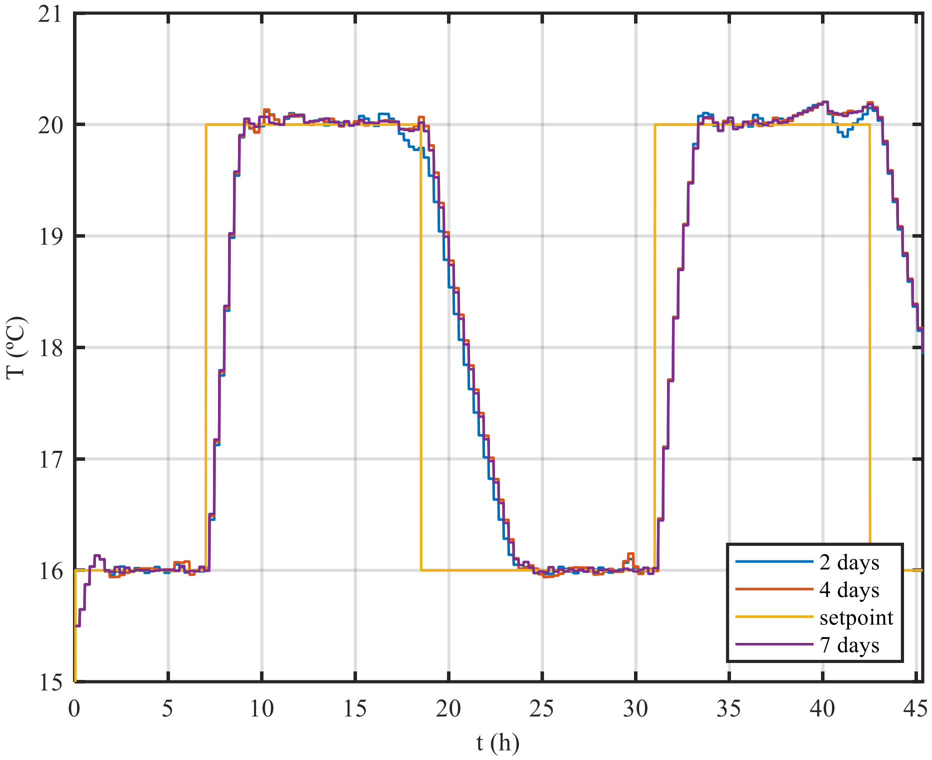

Figure 5-10 Retraining horizon performance comparison

5.3 Extension to fault detection

Another possible application of retraining is the application to fault detection. There can be some failures in the system that deteriorate the heating performance or that increase the heat loss. Even if some of the elements of the HVAC are under maintenance, the system should be able to detect these changes with its performance index and decide if retrain to readapt to the model if it was necessary because the performance is deteriorating.

Of course, this approach has sense and has application if the anomaly appearing in the system changes dramatically the performance of the overall system. If not, then the data will not be informative enough to provide good training for the new system characteristics.

In Figure 5-11, a fault is simulated, in which the HPs have lost power because of deterioration for any reason and have not the same potential of heating the water in the tank. In this case, the condition-based retraining is applied with a $t_{retraining}$ of 7 days. The fault appears at the start of the second week, so the following check will not be done until the end of that week. The retraining takes place, and the performance improves after this new retraining, as can be seen in Table 5-8. Of course, the performance will be worse than before the fault (the system is dealing with less heating capacity), but much better than before retraining.

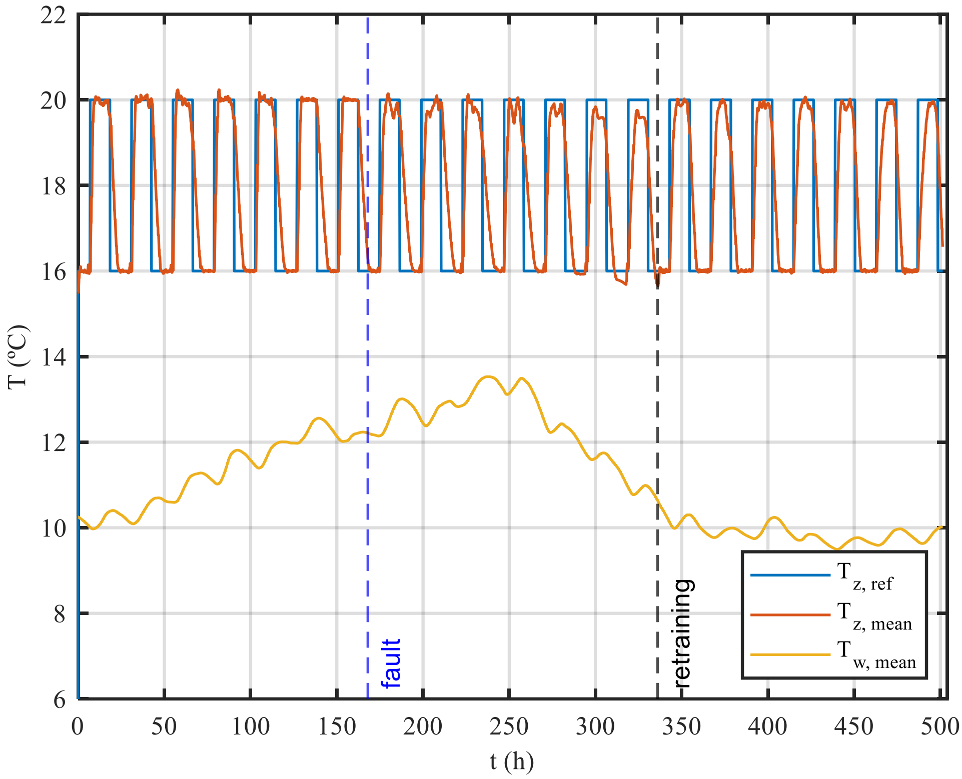

Figure 5-11 Retraining in case of a fault

From	To	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{out} (h)
Before fault		1,17	0,94	148,3	3,26	6,01	2,95
During fault		1,22	1,20	93,96	3,96	9,58	8,59
After retraining		1,14	1,13	178,11	2,87	6,25	5,2

Table 5-8 Results of retraining in case of a fault

Of course, there are faults that completely deteriorates the heating capacity. This means that there is not enough heating power to correctly track the desired temperature. So, after the retraining, the comfort performance will maintain low quality (Figure 5-12), and it will require continuously a retraining. It is always overpassing the condition of retraining. The results can be seen in Table 5-9. With these results under consideration, the need of two consecutive retrainings could be used as an alarm signal to detect the appearance of fatal errors in the heating system that compromise the heating capacity. However, only one retraining implies a deterioration in the heating system, but it is still possible to maintain a correct performance. Furthermore, if there are only small changes in the system parameters, it is still possible to fulfil the performance requirements with the actual prediction model, and a retraining is not necessary.

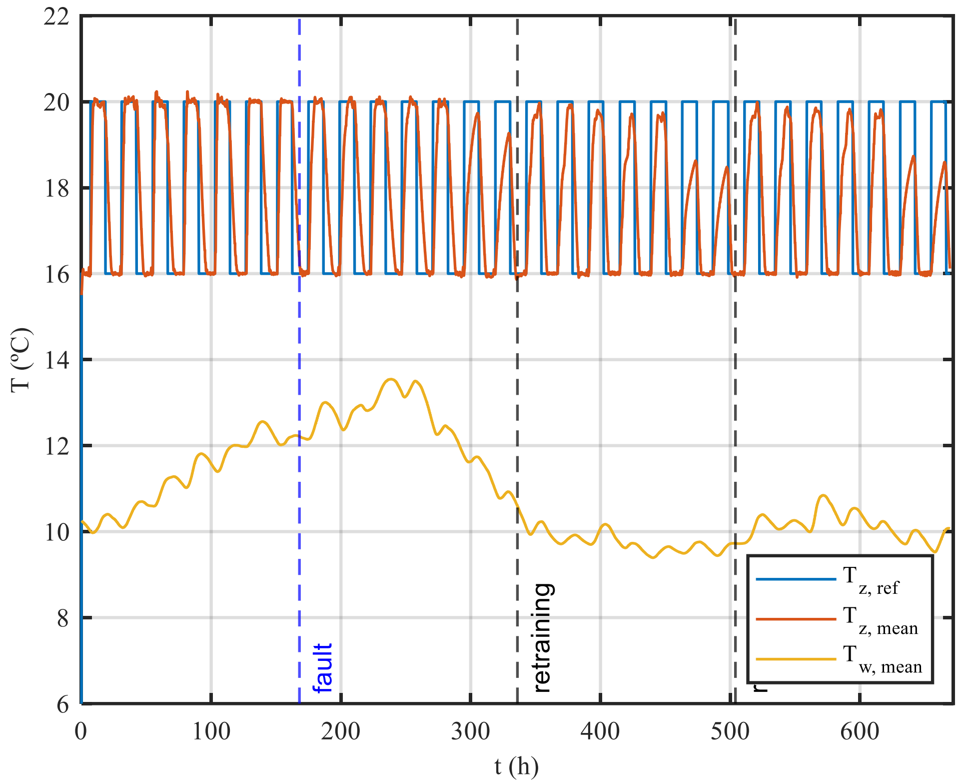

Figure 5-12 Retraining in case of a fault not compensated

From	To	$MRMSE$ (°C)	$MRMSE_{occ}$ (°C)	$Cost_{day}$ (€)	$MCOP_{aw}$	$MCOP_{ww}$	t_{out} (h)
Before fault		1,17	0,94	148,30	3,26	6,01	2,95
During fault		1,46	1,49	153,40	2,99	4,52	6,69
After 1st retraining		1,47	1,86	240,11	2,47	4,30	10,65
After 2nd retraining		1,47	1,81	229,34	2,58	4,29	10,81

Table 5-9 Results of retraining in case of a fault not compensated

6 Conclusions

In this chapter, the main conclusions about the whole set of results underlining the main contributions of this thesis are summarized. The main limitations of this analysis are detailed, concluding with the future work that can be developed from this starting point.

6.1 Summary

The thesis aimed to understand and analyze the set of data that can be used for training a prediction model of a building, to optimize the control action used in the HVAC control system. The objective of this work has been to achieve the best configuration possible for the data collection to have adequate training of the prediction model.

Firstly, the structure of the building and the heating system, together with the control architecture employed, is detailed in chapter 2. The main focus is given to the NMPC 1, and the model used to make future predictions for optimizing the control action in that controller: the reference temperature for the water tank.

The prediction model used has been a NARX NN with a particular structure that has shown good results in previous works. This structure and its implementation have been extensively defined in chapter 3.

To train the NN, two possible data collection approaches have been analyzed, both obtained in closed-loop from a complex reference model of the building and the heating system. On one hand, the realistic approach uses the reference model as a real building, using realistic sets of external disturbances. The conclusions of this analysis have shown that the periodicity observed when obtaining data during real functioning is reliant on the kind of scenario faced. If the data obtained corresponds only to a cold period, where the outputs of the NN have a periodic behaviour, the set of data is not informative, and the tuning of the NN is poorly performed.

On the other hand, if other kinds of months are employed in the training data (like warm or hot periods), the heating system is switched off or on depending on the instant, making the system face different external scenarios and obtaining much richer data for training. This phenomenon has been observed in the prediction results and closed-loop performance simulated in chapter 4.

However, if a simulation approach is considered, then the set of external disturbances can be freely selected, with the drawback that the model used for the data generation must be accurate enough. This configuration guarantees the presence of informative data.

By understanding the need for variated data, the possibility of retraining a NN when it shows a bad performance in its real application has been studied. The causes for this bad performance are variated: a bad selection of the dataset employed for training in the realistic approach; the application of the NARX NN in a real building with different characteristics than the one with which the training data set has been obtained; and the appearance of a failure in the heating system or other unexpected event that could change dramatically the overall thermal dynamics of the building. In chapter 5, the possibility of retraining the NN with a bad closed loop is analyzed. The promising results show the possibility of further development in this field of detecting changes in the configuration of systems and the possibility to readapt the prediction model to online real circumstances.

6.2 Further development

Some limitations or assumptions made during the development of the thesis have paved the way to further studies in this direction. First of all, the NN model has only been applied to the NMPC 1 to understand and capture the building thermal dynamics. However, there are other elements of the HVAC system that could be replicated with a machine learning model. It is the case of the HPs or the AHU. Mainly the HPs have their main contribution in the NMPC 2 and have caused some problems when obtaining not physically feasible COP. The models of HPs are complex and strongly nonlinear, so the possibility of substituting their simple models with machine learning ones that are more accurate could be interesting to observe. Furthermore, it would be a useful improvement to analyze the behaviour of the overall system when introducing these prediction models inside the whole controller structure of the building.

Regarding the reference model, it should be interesting to extend it also including the Air Conditioning period. The actual model is only prepared to face properly the heating season, needing further mathematical description for including the cooling season. This could open the door for combining two prediction models: one for the hot season, and the actual one for the cold season. As they are periods with different characteristics, the study of switching from one prediction model to the other could be a substantial step. It can also be interesting to understand if there can exist one general prediction model of the building including both the heating and the cooling configuration.

Continuing with the modelling considerations, it would be useful to verify the results and conclusions using a more accurate reference model by using specialized software, such as EnergyPlus. In many prior studies, the building model has been simulated considering this kind of software.

Some attempts have been made during the development of the thesis about using as a prediction model a Reinforcement Learning (RL) based one. The main limitation is the need to apply the controller firstly to a simulation environment since at the beginning it has no information of the system and must learn by trial and error. For that, the fact of using pre-trained NN with bad performance for later retraining seems to be interesting. To do so, it is needed to explore the set of experiences that the RL should face for training. Some steps have been done in this direction of using RL with NMPC in [39] and [40]. The use of RL with MPC policies for HVAC systems has also been explored in [41].

Finally, the practical application detailed in chapter 5 can be further developed. Firstly, as the condition-based approach seems to perform correctly, the automatic index chosen for the retraining should be further investigated. Up to now, the variable t_{out} is considered. The exploration of other indexes to achieve the best one that indicates the informativeness of the data is a must for the retraining applications, or even for detecting important failures in the building. Another point of further development could be the experiences with different retraining horizons, including fixed or variable retraining windows which can detect those changes faster or more effectively.

Bibliography

[1] E. Manstretta, "Model Predictive Schemes based on Neural Networks for Building Heating Control," Engineering School of Industrial and Information, Politecnico di Milano, 2020.

[2] F. Martinoli and G. Veronese, "Modeling and Control of a Building with a Complex Thermal Network through different NMPC Strategies," Engineering School of Industrial and Information, Politecnico di Milano, 2020.

[3] J. Noailly, "Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation," *Energy Economics*, vol. 34, no. 3, pp. 795-806, 2012.

[4] A. Afram, F. Janabi-Sharifi, A. S. Fung and K. Raahemifar, "Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system," *Energy and Buildings,* no. 141, p. 96–113, 2017.

[5] G. Mutani and V. Todeschi, "Space heating models at urban scale for buildings in the city of Turin (Italy)," *Energy Procedia,* vol. 122, pp. 841-846, 2017.

[6] P. Rode, C. Keim, G. Robazza, P. Viejo and J. Schofield, "Cities and energy: urban morphology and residential heat-energy demand," *Environment and Planning B: Planning and Design,* vol. 41, pp. 138-162, 2014.

[7] V. Vakiloroaya, B. Samali, A. Fakhar and K. Pishghadam, "A review of different strategies for HVAC energy saving," *Energy Conversion and Management,* vol. 77, pp. 738-754, 2014.

[8] L. Perez-Lombard, J. Ortiz and I. R. Maestre, "The map of energy flow in HVAC systems," *Applied Energy*, vol. 88, pp. 5020-5031, 2011.

[9] M. Elsisi, M.-Q. Tran, K. Mahmoud, M. Lehtonen and M. M. F. Darwish, "Deep Learning-Based Industry 4.0 and Internet of Things towards Effective Energy Management for Smart Buildings," *Sensors,* vol. 21, p. 1038, 2021.

[10] H.-x. Zhao and F. Magoulès, "A review on the prediction of building energy consumption," *Renewable and Sustainable Energy Reviews,* vol. 16, p. 3586– 3592, 2012.

[11] S. A. Kalogirou, "Artificial neural networks in energy applications in buildings," *International Journal of Low-Carbon Technologies,* vol. 1, no. 3, pp. 201-216, 2006.

[12] Z. Zhang, K. P. Lam and A. Chong, "A Deep Reinforcement Learning Approach to Using Whole Building Energy Model For HVAC Optimal Control," *Building Performance Modeling Conference,* 2018.

[13] A. Afram and F. Janabi-Sharif, "Review of modeling methods for HVAC systems," *Applied Thermal Engineering,* vol. 67, pp. 507-519, 2014.

[14] G. Fraisse, J. Virgone and J. Roux, "Thermal control of a discontinuously occupied building using a classical and a fuzzy logic approach," *Energy and Buildings,* vol. 26, no. 3, pp. 303-316, 1997.

[15] A. Foucquier, S. Robert, F. Suard, L. Stéphan and A. Jay, "State of the art in building modelling and energy performances prediction: A review," *Renewable and Sustainable Energy Reviews,* vol. 23, pp. 272-288, 2013.

[16] X. Hang, T. Hao and L. Yu-He, "Time series prediction based on NARX neural networks: An advanced approach," *International Conference on Machine Learning and Cybernetics,* pp. 1275-1279, 2009.

[17] H. Huang, L. Chen and E. Hu, "A new model predictive control scheme for energy and cost savings in commercial buildings: An airport terminal building case study," *Building and Environment*, vol. 89, pp. 203-216, 2015.

[18] H. Huang, L. Chen and E. Hu, "A neural network-based multi-zone modelling approach forpredictive control system design in commercial buildings," *Energy and Buildings,* vol. 97, pp. 86-97, 2015.

[19] P. Hewage, A. Behera, M. Trovati, E. Pereira, M. Ghahremani, F. Palmieri and Y. Liu, "Temporal convolutional neural (TCN) network for an effective weather forecasting using time-series data from the local weather station," *Soft Comput*, vol. 24, p. 16453–16482, 2020.

[20] M. Kummert, P. André and J. Nicolas, "Building and HVAC optimal control simulation. application to an office building," *3rd Symposium on Heating, Ventilation and Air Conditioning (ISHVAC 99),* 1999.

[21] G. P. Maheshwari, H. Al-Taqi, R. Al-Murad and R. K. Suri, "Programmable thermostat for energy saving," *Energy & Buildings*, vol. 33, no. 7, pp. 667-672, 2001.

[22] M. R. Kulkarni and F. Hong, "Energy optimal control of a residential space-conditioning system based on sensible heat transfer modeling," *Building and Environmen*, vol. 39, pp. 31-38, 2004.

[23] R. Yang and L. Wang, "Optimal control strategy for HVAC system in building energy management," in *Transmission and Distribution Conference and Exposition (T&D), 2012 IEEE PES*, 2012.

[24] A. Yahiaoui, . J. Hensen, L. Soethout and A. Paassen, "Model based optimal control for integrated building systems," in *6th Int. Postgraduate Research Conf. in the Built and Human Environment*, 2006.

[25] T. Leephakpreeda, "Implementation of adaptive indoor comfort temperature control via embedded system for air-conditioning unit," *Journal of Mechanical Science and Technology,* vol. 26, no. 1, pp. 259-268, 2012.

[26] S. Privara, J. Široký, L. Ferkl and J. Cigler, "Model predictive control of a building heating system: The first experience," *Energy and Buildings,* vol. 43, pp. 564-572, 2010.

[27] A. Afram and F. Janabi-Sharifi, "Theory and applications of HVAC control systems – A review of model predictive control (MPC)," *Building and Environment,* vol. 72, p. 343–355, 2014.

[28] B. Chiang Ng, I. Z. Mat Darus, H. Jamaluddin and H. Mohamed Kamar, "Application of adaptive neural predictive control for an automotive air conditioning system," *Applied Thermal Engineering,* vol. 73, no. 1, pp. 1244-1254, 2014.

[29] D. Perera, C. F. Pfeiffer and N.-O. Skeie, "Control of temperature and energy consumption in buildings - A review," *International Journal of Energy and Environment,* vol. 5, no. 4, pp. 471-484, 2014.

[30] X. Wei, A. Kusiak, M. Li, F. Tang and Y. Zeng, "Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance," *Energy,* vol. 83, pp. 294-306, 2015.

[31] X. He, Z. Zhang and A. Kusiak, "Performance optimization of HVAC systems with computational intelligence algorithms," *Energy and Buildings,* vol. 81, pp. 371-380, 2014.

[32] A. A. Giunta, S. F. Wojtkiewicz Jr. and M. S. Eldred, "Overview of modern design of experiments methods for computational simulations," in *41st Aerospace Sciences Meeting and Exhibit*, Albuquerque, 2003.

[33] J. Kleijnen, "Design of Experiments: overview," in *Proceedings of the 2008 Winter Simulation Conference,* Tilburg, The Netherlands, 2008.

[34] E. Asadi, M. Gameiro da Silva, C. Henggeler Antunes, L. Dias and L. Glicksman, "Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application," *Energy and Buildings*, vol. 81, pp. 444-456, 2014.

[35] M. Mohammadzaheri, L. Chen and S. Grainger, "A critical review of the most popular types of neuro control," *Asian Journal of Control,* vol. 14, pp. 1-11, 2012.

[36] D. Foresee and M. Hagan, "Gauss-Newton approximation to Bayesian learning," in *Proceedings of the International Joint Conference on Neural Networks*, 1997.

[37] S. A. Sata, N. Aziz, S. A. Zulkeflee and T. Zheng, "Nonlinear Autoregressive with Exogenous Inputs Based Model Predictive Control for Batch Citronellyl Laurate Esterification Reactor," in *Advanced Model Predictive Control*, Penang, InTech, 2011, pp. 267-290.

[38] ARPA Lombardia, "ARPA Lombardia," [Online]. Available: https://www.arpalombardia.it/. [Accessed 15 Diciembre 2020].

[39] S. Gros and M. Zanon, "Data-Driven Economic NMPC Using Reinforcement Learning," *IEEE TRANSACTIONS ON AUTOMATIC CONTROL,* vol. 65, no. 2, pp. 636-648, 2020.

[40] M. Zanon, S. Gros and A. Bemporad, "Practical Reinforcement Learning of Stabilizing Economic MPC," in *18th European Control Conference (ECC),* Napoli, 2019.

[41] B. Chen, Z. Cai and M. Bergés, "Gnu-RL: A Precocial Reinforcement Learning Solution for Building HVAC Control Using a Differentiable MPC Policy," *BuildSys,* vol. 19, pp. 316-325, 2019.

[42] C. Reinhart and C. Cerezo Davila, "Urban building energy modeling. A review of a nascent field," *Building and Environment,* vol. 97, pp. 196-202, 2016.