Floor heating pre-on/off parameters based on Model Predictive Control feature extrapolation

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Abstract. Floor heating systems are typically characterized by a relatively high thermal inertia, thus they react slowly to setpoint changes. When the system turns on, an under-heating period could occur for a relative long period, vice versa when the setpoint is decreased the floor thermal inertia could lead to overheating. In residential applications, the users try to avoid these discomfort problems by using a constant setpoint, higher than the setback. In this way the average energy consumption as well as the user's bill increases. A smarter solution to mitigate this problem is to include a pre-on period parameter, so that the system will turn on a certain time before the increase in setpoint to avoid the under-heating period and a pre-off period so that it will switch off before overheating. Predictive controllers can be a solution to compensate the slow response of the radiant floor system. However, besides the need for more data, the computational power goes beyond what is available in heating systems micro controllers for residential cases. To avoid these issues, in this paper the optimal control trajectory obtained using a Model Predictive Control (MPC) approach is used to identify the pre-on and pre-off parameters to be periodically updated in the micro controller (e.g. monthly). A simulation work was carried out to compare the performance between a baseline Rule Based Controller (RBC), an improved RBC and a MPC in terms of comfort and energy use. The result is a reduction from an average of 1.1°C to 0.2°C for the worst thermal zone meaning 80% reduction of the discomfort with respect to the baseline and a slight increase of the electrical consumption of the heat pump (less than 5%).

Keywords. Radiant floor, model predictive control, feature extrapolation, pre-heating, KPI.
DOI: https://doi.org/10.34641/clima.2022.331

1. Introduction

HVAC systems account for 20% of the primary energy consumption in MEF countries [1]. Within the perspective of reducing energy consumption and fight climate changes, radiant floor heating applications are becoming more and more used [2]. An important characteristic of standard radiant floor systems is the high thermal inertia which causes a delay between the heat supply and the response in the internal air temperature. For concrete core radiant floors this has been estimated to be 1 to 3 hours [3]. This slow response can create underheating or overheating issues and consequent discomfort and/or waste of energy. In order to assess which are effectively the discomfort periods, the standard EN 12098-1:2017 [4] defines the time and temperature tolerances to guarantee the comfort levels inside the thermal zone.

A solution to compensate the slow response of the radiant floor system and reduce the consequent discomfort could be the use of advanced control strategies such as Model Predictive Control (MPC). The benefit of predictive controllers is that the heat supply can be adjusted in advance thanks to heat demand forecasts [5]. Even if it was proven that MPC can be a good solution to reduce the energy consumption of the HVAC systems, as reported in [6] most buildings today use rule-based controllers to manage the indoor conditions. This is related to the fact that there are different challenges that must be faced to implement MPC in buildings [7] and one of this is the availability of the proper hardware and software infrastructure. For example, model predictive control requires a high computational power that is not available in standard heating systems micro controllers for residential buildings. As reported in [8], MPC can be adopted for complex new commercial buildings while it may not be as solution for residential buildings because it could be too expensive.

This paper proposes a methodology to extrapolate the monthly pre-on and pre-off parameters to be implemented on a micro controller, starting from the results of an optimization problem. This methodology can be deployed as a cloud service, where the pre-on and pre-off parameters can be updated remotely on the micro controller.

This work is part of the Merezzate+ project co-founded by EIT Climate-KIC. The project focuses on sustainability issues from a social, environmental, and economic point of view, adopting measures in the sectors of energy, mobility and circular economy that are the ones with the highest impact on climate change. The project included the construction of around 800 apartments, one of them was chosen as a simulation case study for this work. It is in Milan and is characterized by two rooms and a bathroom. The detailed description is reported in Section 3.

2. Method

An optimal control problem was formulated to obtain the floor heating pre-on and pre-off parameters. In this case, the objective of the optimization problem was to find the control strategy that allows to maximize the comfort of the considered thermal zones.

Starting from the resulting optimal control trajectory, the pre-on and pre-off parameters can be estimated and included in the rule-based controller.

In order to couple the optimization problem with the detailed apartment model at the base of this study, the BOPTEST framework [9] was chosen. It allows to create an API interface between the detailed physics-based model we created using the Modelica Buildings [10] and IBPSA [11] libraries and the optimization problem implemented in a Python code using the Pyomo toolbox [12].

This Section is structured in two sub-sections. In Section 2.1 it has been described the optimization problem and the feature extrapolation. In Section 2.2 it is described the co-simulation environment

2.1 Optimization problem and feature extrapolation

The model predictive control scheme is reported in **Fig. 1**.

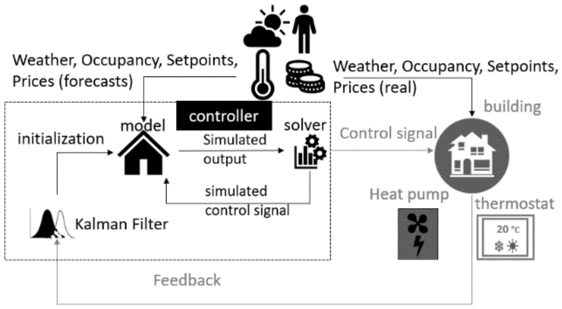

Fig. 1 – Model predictive control scheme.

In order to find the control strategy that allows to achieve the goal, it is necessary to create a simplified model that can capture the correct dynamics of the system. Then, starting from the response of this simplified model subjected to various disturbances (e.g. weather, setpoints, occupation and prices forecasts), the solver calculates the best control trajectory to achieve the "objective function", which is shown in eq. 1. In this case, the forecast is assumed to be deterministic, which means that the forecast adopted during the optimization process is identical to the input of the detailed model of the building. The optimization horizon is 24h and the control signal obtained solving the optimization problem is updated in the detailed model every 15 minutes.

The general form of the objective function can be:

$$\boldsymbol{min\, J_{tot}}\,(\boldsymbol{t}) = \int_{\boldsymbol{t}_0}^{\boldsymbol{t}_f} \sum_{i=1}^{N} k_i J_i(t)\, \boldsymbol{dt} \quad 0 \le k_i \le 1 \qquad (1)$$

Where $J_i(t)$ represents the various objectives and k_i the weighting factor associated with the i-th objective.
In this work, the following combination of objective functions has been adopted:

$$\min \int_{\boldsymbol{t}_0}^{\boldsymbol{t}_f} (k_1\, J_1(t) + k_2\, J_2(t))\, \boldsymbol{dt} \qquad (2)$$

$$J_1(t) = \left(\left[T_r(t) - \left(T_{setpoint} + \delta\right)\right]^{-}\right)^2 \qquad (3)$$

$$J_2(t) = \frac{\dot{Q}_{hp}(t)}{COP(t)} \qquad (4)$$

Where $J_1(t)$ represents the squared difference between the room air temperature and its setpoint, only in case of under heating. Furthermore, a constant offset δ is added to the setpoint to give a more robust result that will make the parameters work even in a particularly cold day. The value of δ is a tuning parameter that depends on how frequently the pre-on/off parameters will be updated. The solver will try to minimize the differences between these two temperatures to improve the thermal comfort of the users. $J_2(t)$ represents the main electric power needed by the heating system, in this case study represented by a heat pump. In order to minimize this objective, the solver will try to minimize the thermal power $\dot{Q}_{hp}(t)$ but also to maximize the heat pump Coefficient of Performance ($COP(t)$) shifting the heat demand from colder to warmer periods and working at partial load with a lower supply temperature.

The control strategy adopted in this paper tries to maximize the comfort in a specific time interval and to extrapolate some simplified rules to be applied on the energy management system installed in field. The weighting factors adopted in the objective function are $k_1 = 1$ and $k_2 = 0.05$.

The result of the optimization problem described above will be a control that switches on and off the heat pump to guarantee the thermal comfort of the users. Starting from the results of the optimized simulation it is possible to extrapolate some simplified rules that allow to find the pre-on and pre-off parameters to be implemented on a rule-based controller in field. In particular, the pre-on and pre-off parameters are monthly averages. For the months of April and October they take the average only of the days that belong to the heating season, which are respectively the period from the 1st to the 15th for April and the days from the 15th to the 31st for October. They have been obtained starting from the calculation of the supplied energy to the radiant floor distinguishing between the pre-on phase and the normal operation. These two values ($Q_{preheaOPT}$ and Q_{heaOPT}) correspond to the orange and red areas in **Fig. 2**. Then the mean supply heat rate was estimated for the two phases ($\dot{Q}_{meanOn}$ and $\dot{Q}_{meanOff}$). The two areas (orange and red), underneath the thermal power curve, are respectively equal to the areas of the two rectangles, in which the two heights are $\dot{Q}_{meanOn}$ and $\dot{Q}_{meanOff}$ and the two widths are Δt_{On} and $\Delta t_{tot} - \Delta t_{Off}$. Thus, inverting the following formulas, it is possible to obtain the two parameters Δt_{On} and Δt_{Off}:

$$\dot{Q}_{meanOn} = \frac{Q_{preheaOPT}}{\Delta t_{On}} \tag{5}$$

$$\dot{Q}_{meanOff} = \frac{Q_{heaOPT}}{\Delta t_{tot} - \Delta t_{Off}} \tag{6}$$

where Δt_{tot} is the difference of time between the setpoint changes and Δt_{Off} is the time difference between the time at which the power goes below a threshold and the lower setpoint change.

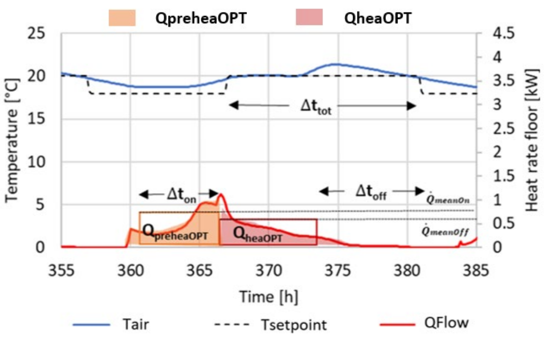

Fig. 2 – Visualization of Δt_{On} and Δt_{Off} calculation procedure.

In this way, starting from the control trajectory it is possible to obtain the two values of Δt_{On} and Δt_{Off} for each pre-on and pre-off and finally calculate the average of these values for each month.

2.2 Implementation

For this work, the Modelica "Buildings" and "IBPSA" libraries were used to develop the detailed model of a three-zone apartment with radiant floor described in Chapter 3.

In particular, for the floor heating modelling, the model called "SingleCircuitSlab" of the "Buildings" library [10] was adopted. It models the radiant slab as a thermal resistance network and uses a fictitious resistance to compute the temperature of the plane that contains the pipes. The same method is implemented in TRNSYS 17 [13]. The rule-based controller used is a tuned PI controller with 0.4 °C hysteresis on the setpoint and a tuned climatic curve on the heat pump supply temperature.
From the detailed model of the building - HVAC system a simplified model was derived through an identification process performed with the MATLAB Identification Toolbox. The simplified model is a grey box, where a thermal electrical analogy is used. This allows to identify a circuit of resistances and thermal capacities (R-C network) to represent the most significant temperatures of the building and HVAC system (**Fig. 3**), starting the identification from the data contained in the detailed model. The methodology followed for the model identification is described in [14]. In summary each thermal zone has a 7R3C circuit and they are all connected to each other.

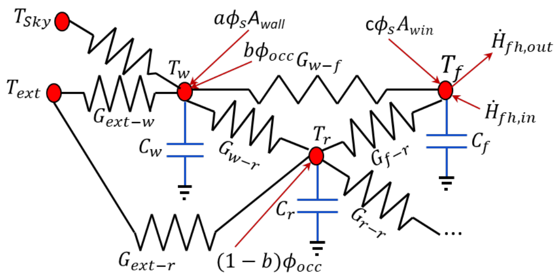

Fig. 3 – R-C network - in red are the temperature nodes T, G_i are the conductances, $\emptyset_i$ are the disturbances (solar, appliances), A_i are the wall and windows area, $\dot{H}$ are the inlet and outlet heat flow rate in the floor and *a,b,c* are the tuning constants.

After this phase, the simplified model and the optimization problem were implemented in Python using the Pyomo toolbox.

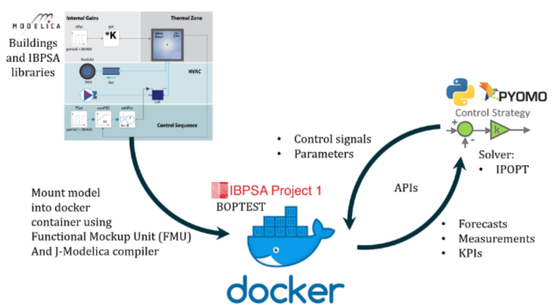

Fig. 4 – Co-simulation environment, on the left the Modelica detailed model and on the right the optimization environment in Python-Pyomo. In between the BOPTEST software is used as a wrapper for the detailed model allowing an API input/output exchange with Python

Finally, the detailed model developed in Modelica interfaces with the optimization problem through the BOPTEST framework. The BOPTEST framework allows a way to easily compile the detailed Modelica model and wrap it around a Docker container. In this way the model can freely run through an easy-to-use API interface, that can be used to obtain sensor signals from the detailed model and provide control trajectories from the optimization routine in Python through APIs.

All these steps are summarized in **Fig. 4.**

3. Case study

The case study chosen for this work is a two rooms one bathroom apartment reported in **Fig. 5**. It is in Milan (Italy) and shares two walls with two adjacent apartments (in green), a wall with the landing (in red) while the rest faces towards outside (in yellow).

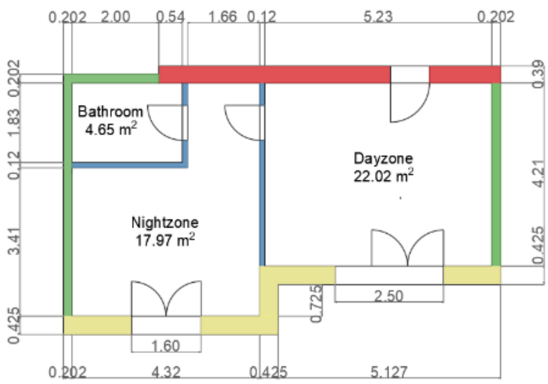

Fig. 5 – Floor Plan of apartment

It is equipped with an air source heat pump, a radiant floor, a DHW tank and PV panels installed on the roof of the building. The heat is used for both space heating and DHW production, giving priority to the latter. The most important characteristics of the above-mentioned system are reported in **Tab. 1**.

Tab. 1 – Characteristics of the system.

Parameter	Value and unit of measurement
Floor area	44.45 m²
Zones height	2.7 m
Number of occupants	1
HP nominal electrical power	1.33 kW*
HP nominal thermal power	4 kW*
PV panels area	5.5 m²
PV panels peak power	0.8 kWp

*Nominal conditions (-7°C, 35°C)

For the simulation of the considered apartment, the occupation profiles were arranged as shown in **Fig. 6** and **Fig. 7**. The first one is used for all the weekdays, while the other is used to simulate the weekends.

The other input data chosen for these simulations are function of the above-described occupation profiles. In particular, a setpoint temperature of 20°C has been chosen for occupied periods, while a setback temperature of 18°C is applied for the rest of the considered day. In the same way the shading systems of each room are fully closed when it is unoccupied while they are half opened when the considered room is occupied.

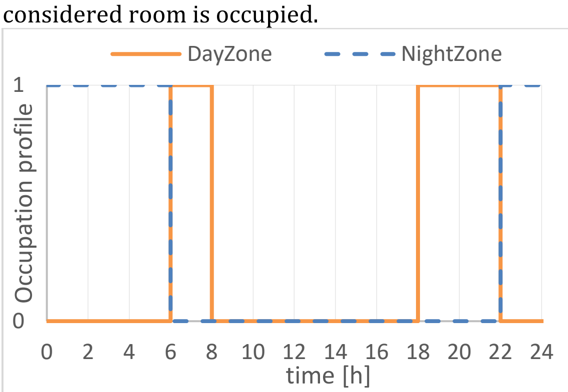

Fig. 6 – Occupation profile weekdays

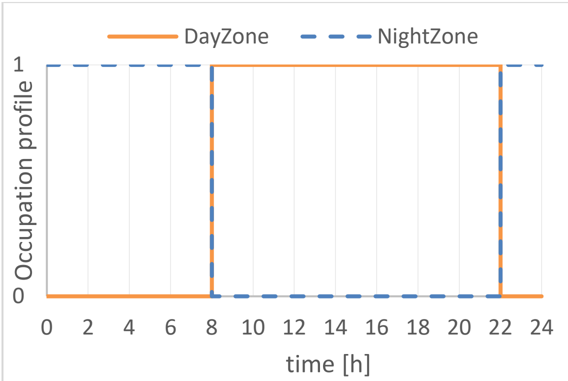

Fig. 7 – Occupation profile weekend

In addition, there are the internal gains related to the presence of people, appliances, and lighting.

Specifically, the sensible internal gain due to the presence of people is defined per person while the others are defined per unit area.

In this case study the following values have been chosen:

$$\dot{Q}_{sens} = 60\frac{W}{pers} \tag{7}$$

$$\dot{Q}_{appliances} = 2.5\frac{W}{m^2} \tag{8}$$

$$\dot{Q}_{lighting} = 4\frac{W}{m^2} \tag{9}$$

In particular, the sensible heat produced by a person respects the standard UNI EN 13779 [15] while the other two values are due to specific assumptions. In fact, since the apartment is small and new, the authors considered to have few and efficient appliances. In addition, they chose led lamps that emit a thermal power of about 80 W for each thermal zone.

In this case, only one user is present inside the apartment as reported in **Fig. 6** and **Fig. 7**.

All these contributions are different than zero only when the considered thermal zone is occupied. In addition, the lighting contribution is set to zero from 8 a.m. to 5 p.m. thanks to daylight availability.

Finally, the parameters related to the mass exchange with the external environment are summarized in **Tab. 2**. In particular, the value of the air changes related to infiltrations has been chosen considering high quality windows while the value related to mechanical ventilation takes into account the sanitary regulation of the Municipality of Milan [16] which imposes at least 20 m3/h/pers. In this case it was chosen to apply 30 m3/h/pers and 24 m3/h/pers respectively for the DayZone and the NightZone.

Tab. 2 – Infiltration and mechanical ventilation

Air changes	DayZone	NightZone
Infiltrations [1/h]	0.05	0.05
Mechanical ventilation [1/h]	0.5	0.5

4. Results

For this work, three different simulations were performed: a first simulation with a normal rule-based control (baseline), a second simulation based on model predictive control and a final simulation with a rule-based control with pre-on and pre-off parameters obtained averaging the results of the second simulation.

In Section 4.1 are reported the pre-on and pre-off parameters obtained from the calculations described in Section 2.1. In section 4.2 it is possible to observe which are the effects of the activation of the pre-on and pre-off strategies on the air temperature and the thermal power delivered by the heat pump in the three cases, while in Section 4.3 are summarized the Key Performance Indicators (KPI) of the three simulations.

4.1 Monthly pre-on and pre-off parameters

The results of the calculation reported in detail in section 2.1 are summarized in **Tab. 3** and **Tab. 4**. In particular, in the DayZone (**Tab. 3**), the pre-on is not required for the periods that go respectively from the 1st to the 15th of April and from the 15th to the 31st of October.

Tab. 3 – Average values for pre-on and pre-off parameters in the DayZone

Period	Pre-on [h]	Pre-off [h]
1st-31st Jan	1.56	0.00
1st-28th Feb	1.22	0.00
1st -31st Mar	0.20	0.20
1st-15th Apr	0.00	1.30
15th-31st Oct	0.00	0.60
1st-30th Nov	0.80	0.10
1st-31st Dec	1.40	0.10

Tab. 4 – Average values for pre-on and pre-off parameters in the NightZone

Period	Pre-on [h]	Pre-off [h]
1st-31st Jan	4.00	0.20
1st-28th Feb	3.60	0.30
1st -31st Mar	3.00	1.70
1st-15th Apr	2.20	2.20
15th-31st Oct	1.00	1.90
1st-30th Nov	2.60	0.80
1st-31st Dec	3.40	0.20

4.2 Time series analysis

To understand the benefits related to the application of the pre-on and pre-off strategies, in this section a detailed analysis of two days is shown (Friday, 19th of January and Saturday, 20th of January).

In **Fig. 8** and **Fig. 9** are represented the trend of the air temperature with respect to the setpoint respectively in the DayZone and NightZone, while in **Fig. 10** is reported the trend of the thermal power provided by the heat pump to heat up the two thermal zones.

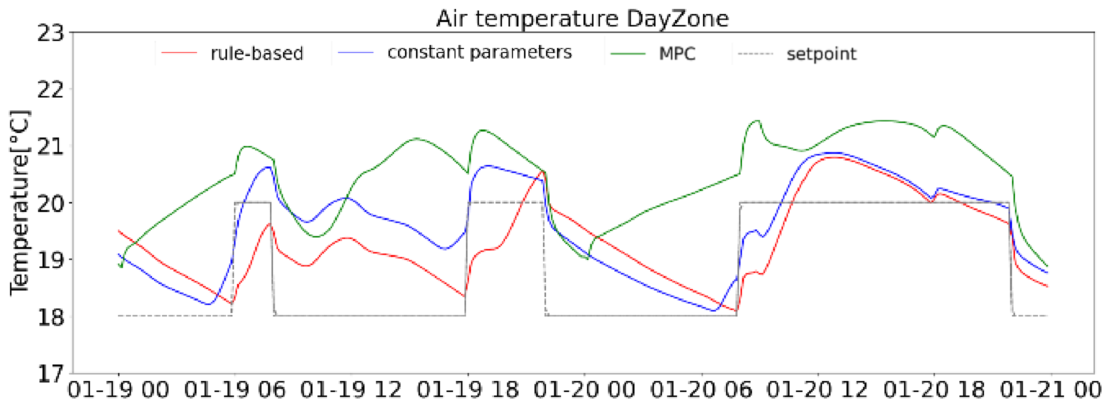

Fig. 8 – DayZone air temperature trend for sample days including weekend

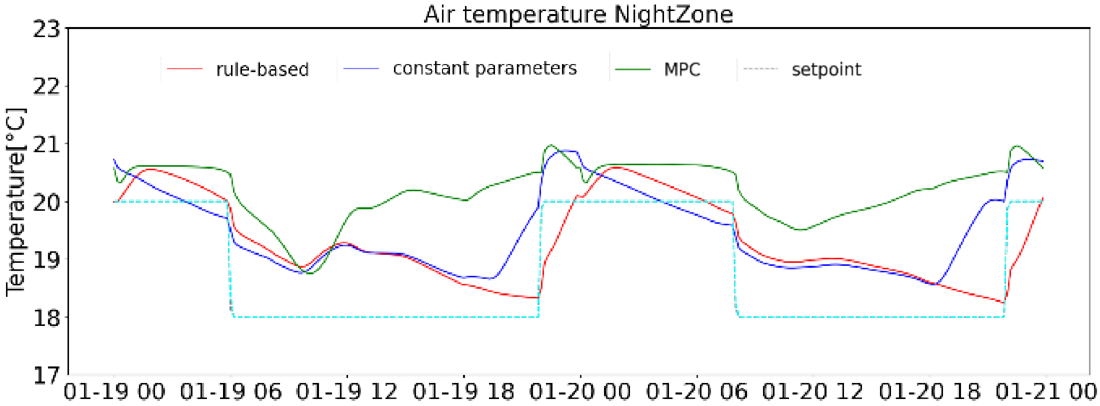

Fig. 9 – NightZone air temperature trend for sample days including weekend

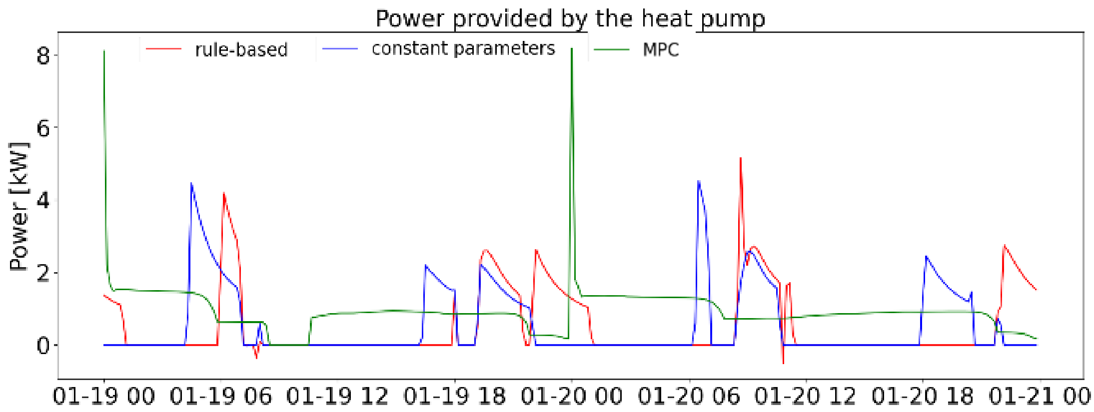

Fig. 10 – Thermal power provided by the heat pump for sample days including weekend

From the first two figures (**Fig. 8** and **Fig. 9**) it can be seen that, while with the normal rule-based control (represented by the red line) the temperature reaches the desired setpoint after about 3 hours, the rule-based control with the pre-on and pre-off parameters (blue curves) is able to follow the change of the setpoint, reducing a lot the periods of discomfort that occur in the baseline case. Finally, from the same graphs it is visible that the temperature obtained with the model predictive control strategies is consistently higher than the setpoint. This is done because the MPC is targeting the setpoint temperature plus δ °C to have a more conservative result when finding the pre-on and pre-off parameters. The big gap between the rule-based and the other controllers can be explained by the fact that in this simulation the baseline rule-based controller turns on the heat pump when the difference between the room and setpoint temperature is lower than minus the hysteresis value. This control strategy will inevitably lead to underheating. So, what expert users usually do is manually insert a pre-on / pre-off parameter based on experience. Less expert users instead will keep the systems always on, leading to a big waste of energy.

Then, from **Fig. 10**, it is clearly visible that the thermal power provided by the heat pump, in the case of application of the pre-on and pre-off strategy (blue line), has been anticipated (shifted towards left) with respect to the normal rule-based control (red line), while MPC keeps the system on for a longer period at a lower mean power. This is due to the fact that, as reported in eq. 1, the objective function not only promote the thermal comfort achievement but also tries to reduce the electric power consumption.

4.3 KPIs analysis

Finally, some Key Performance Indicators (KPI) were defined with the aim of evaluating the overall performance of the advanced control strategies.

In particular, the KPI related to the discomfort of the i-th thermal zone (Dis_{TZi}) is defined as the integral of the difference between the setpoint ($T_{set,i,TZi}$) and the room air temperature ($T_{air,i,TZi}$) for the heating season (from the 15th of October to the 15th of April), subdivided for the number of occupied hours ($n_{occ\ hours}$) in the same period. The integral at the numerator is calculated only in the occupied hours of each day and only when the indoor air temperature is lower than the setpoint temperature minus the hysteresis ($hys = 0.4°C$), as reported below:

$$Dis_{TZi} = \frac{\int_{t_0}^{t_f} \left| T_{set,i,TZi} - hys - T_{air,i,TZi} \right|^{+} dt}{n_{occ\ hours}} \quad (10)$$

Then it is reported the average air temperature ($T_{airAvg,TZi}$) of each thermal zone calculated considering the entire heating season and the related thermal energy need ($E_{th,SH}$) that has to be provided by the heat pump in order to maintain those conditions inside the various thermal zones. They are mathematically expressed as:

$$T_{airAvg,TZi} = \frac{\sum_{j=1}^{N} T_{air,j,TZi}}{N} \quad (11)$$

$$E_{th,SH} = \int_{t_0}^{t_f} \dot{Q}_{th,SH}(t)\, dt \quad (12)$$

Where:

- $T_{air,j,TZi}$ is the air temperature of the thermal zone TZi registered at the j-th time;
- N is the number of elements of the temperature vector during the heating season;
- $\dot{Q}_{th}$ is the thermal power provided by the heat pump for space heating at a specific time.

Finally, it is introduced a KPI which describes the electrical energy consumption of the heat pump ($E_{el,SH}$) for providing heat to the radiant floor (space heating), that is equal to:

$$E_{El,SH} = \int_{t_0}^{t_f} \dot{P}_{el,SH}(t)\, dt \quad (13)$$

Where:

- $P_{el,SH}$ is the electrical power consumption of the heat pump for space heating at a specific time.

The summary of these KPIs is reported in **Tab. 5**.

Analysing the values reported in **Tab. 5** it appears that the value of the discomfort related to the DayZone in the Baseline case is equal to 1.104 K, which is already a low value, but it is still higher than the temperature tolerance, which is fixed to $\pm 0.5K$, as reported in the standard EN 12098-1:2017 [4]. Thus, with the use of the optimized control (PreOnOff Const and PreOnOff Var), the authors were able to respect this tolerance and to obtain a strong percentage reduction of the discomfort, higher than the 80%. For the NightZone, as it is possible to observe from **Tab. 5** the Baseline was already able to respect the above-mentioned tolerance, but the percentage reduction of the discomfort is still important.

In addition, the results in **Tab. 5** show that the optimized rule-based controller, with constant pre-on and pre-off parameters (PreOnOff Const), has comparable performance with respect to the results of the model predictive control (PreOnOff Var).

Tab. 5 – KPI comparison.

KPI	Baseline	PreOnOff Const	PreOnOff Var
$Dis_{DayZone}$ [K]	1.104	0.191 (-83%)	0.006 (-99%)
$Dis_{NigZone}$ [K]	0.155	0.006 (-96%)	0.011 (-93%)
$T_{airAvg,DayZone}$ [°C]	19.7	20.0 (+1.5%)	20.9 (+6.1%)
$T_{airAvg,NigZone}$ [°C]	19.6	19.8 (+1.0%)	20.4 (+4.1%)
$E_{th,SH}$ [kWh]	1758	1808 (+2.8%)	2874 (+63.5%)
$E_{El,SH}$ [kWh]	437	455 (+4.0%)	672 (+53.6%)

The average air temperature increases of the 1-1.5% in the case with monthly constant parameters and of the 4-6% in the case of variable parameters (MPC). The increase of temperature obviously leads to an increase of the thermal energy needs and consequently of the electrical consumptions of the heat pump.

This methodology can be deployed as a cloud service, where the pre-on and pre-off parameters can be updated remotely. In the Merezzate+ project some apartments could be used for testing the methodology. In terms of economic feasibility, it can be used for large residential complexes where the building envelope and HVAC systems can be modelled once and tweaked using data, introducing an economy of scale. For smaller residential buildings archetypes can be built and modelled, where the solution may not be optimal but still better than the baseline.

5. Conclusions

In this paper it is proposed a methodology to extract pre-on and pre-off parameters that can be implemented in micro-controllers of residential buildings. This could help managing the radiant floor heating system and solve the problems of discomfort that could be caused by its slow response.

From the control trajectory obtained solving the optimization problem, some simplified rules were extrapolated. They allow to obtain the monthly pre-on and pre-off parameters to be implemented in the energy management system installed in field thanks to a cloud service.

Then, three simulation that consider respectively a normal rule-based control, model predictive control and a rule-based control with monthly pre-on and pre-off parameters have been performed. Comparing the results of the three simulations it is possible to observe that with both the constant and variable (MPC) pre-on and pre-off parameters, the time in which the air temperature is below the setpoint is strongly reduced and this is also confirmed by the KPI of the discomfort, that undergoes a reduction higher than the 80%. For the future development of this work, the authors will consider different feature extrapolation methods. Instead of monthly, the pre-on/pre-off parameters could be updated with a different frequency. Furthermore, depending on the sensors available locally or cloud forecast different heuristic metrics will be developed.

6. Acknowledgement

The research work presented in this paper receives the support of EIT Climate-KIC through the project “Merezzate+” and REDO sgr spa.

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8. Data access statement

The datasets generated and analysed during the current study are available in the Zenodo repository, https://zenodo.org/record/6398238#.YkVWfOdByUl