UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ENGENHARIA
ENG. DE CONTROLE E AUTOMAÇÃO

RICARDO EHLERS BINZ - 00244015

VIRTUAL REFERENCE FEEDBACK TUNING STRATEGY FOR A UNIVERSITY BUILDING HEATING SYSTEM

Porto Alegre
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Trabalho de Conclusão de Curso (TCC-CCA) apresentado à COMGRAD-CCA da Universidade Federal do Rio Grande do Sul como parte dos requisitos para a obtenção do título de *Bacharel em Eng. de Controle e Automação* .

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Este Trabalho de Conclusão de Curso foi julgado adequado para a obtenção dos créditos da Disciplina de TCC do curso *Eng. de Controle e Automação* e aprovado em sua forma final pelo Orientador e pela Banca Examinadora.

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DEDICATÓRIA

Dedico este trabalho aos meus pais, sem eles eu não teria chegado até aqui. Obrigado por todo apoio, por acreditarem em mim, e por me incentivarem a chegar sempre mais longe.

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ABSTRACT

We consider Virtual Reference Feedback Tuning for the temperature control system of a commercial building, where the goal is to design an optimal feedback controller such that the building's temperature follows a reference. We consider the effect of external variables that can influence temperature behavior, such as weather data, human heat and thermal interactions between different parts of the building. We propose a model-free control design method based on a one-shot temperature experiment allowing to optimize human comfort and reduce energy use in comparison with standard commercial heating strategies. The main advantage of the proposed method when compared to other control strategies is that it does not require any thermal model of the building. The applicability of the proposed method is illustrated with simulations.

Keywords: Virtual reference feedback tuning, Heating system, Data-driven control, One-shot control design.

RESUMO

Considera-se o método Virtual Reference Feedback Tuning para o sistema de controle de temperatura de um edifício comercial, onde o objectivo é conceber um controlador ótimo em malha fechada, de tal forma que a temperatura do edifício siga uma referência. Considera-se o efeito de variáveis externas que podem influenciar o comportamento da temperatura, tais como dados meteorológicos, calor humano e trocas térmicas entre as diferentes partes do edifício. Propomos o design de um controlador livre de modelo baseado em um único experimento de temperatura, permitindo otimizar o conforto e reduzir a utilização de energia em comparação com as estratégias normais de aquecimento comercial. A principal vantagem do método proposto quando comparado com outras estratégias de controle é que não requer qualquer modelo térmico do edifício. A aplicabilidade do método proposto é ilustrada com simulações.

Palavras-chave: Virtual reference feedback tuning, Sistema de Aquecimento, Controle Baseado em Dados, Design de Controle One-shot.

SUMMARY

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LIST OF ABBREVIATIONS

VRFT	Virtual Reference Feedback Tuning
PI	Proportional Integral
SISO	Single Input Single Output
MIMO	Multiple Input Multiple Output
HVAC	Heating, Ventilating and Air Conditioning
PID	Proportional Integral Derivative
MPC	Model Predictive Control
MR	Model Reference
MSE	Mean Squared Error
VR	Virtual Reference

1 INTRODUCTION

As discussed in Afroz et al. (2017) and Atam e Helsen (2016), heating, ventilation and air conditioning (HVAC) systems are some of the major sources of energy consumption nowadays, representing around 20% of the total end-use energy and it is increasing 0.5 to 1% per year in developed countries. In this context, the scientific community is making great efforts to generate energy savings in this class of equipment. Specifically in the field of control science, it has been shown by Privara et al. (2010) and Ozoh et al. (2014) that predictive control methods can result in up to 40% energy savings when compared to the application of rule-based control strategies on these systems.

Multiple approaches have been developed to tackle the problem of modeling temperature behavior in buildings. Atam e Helsen (2016) and Afroz et al. (2018) present a review of state-of-the-art techniques used in the field. Although the methods may yield satisfactory results, they always present some level of uncertainty and its derivation requires a non-negligible amount of work. Moreover, building parameters can change over time due to aging of materials, changes in usage profile or even climate change, thus requiring modifications in the model.

Due to the challenges identified in modeling temperature behavior in buildings, model-free control strategies present a promising approach for the problem of controlling this process. From all the data-driven methods developed in the literature, one-shot techniques are preferred over iterative techniques for this problem: since buildings are potentially in constant use, a one-shot experiment may avoid the repetition of temperature control experiments several times, making it simpler to be implemented in real buildings with high usage.

It is worth noting that data-driven control strategies have already been applied in the context of HVAC (heating, ventilation, and air conditioning) systems in previous works. However, the majority of studies adopted model-depended strategies: Oldewurtel et al. (2012) presented an investigation on how Model Predictive Control (MPC) and weather prediction can increase energy efficiency in Integrated Room Automation while respecting occupants comfort. Kusiak, Tang e Xu (2011) derived a predictive model for an HVAC system by data-mining algorithms, then developed a multi-objective optimization model to minimize the energy while maintaining the corresponding IAQ (indoor air quality). Hu, Weir e Wu (2012) proposed that the study of a group of buildings, instead of one single building, would result in a cost effective building system which in turn will be resilient to power disruption, developing a bi-level operation decision framework that is capable of deriving the Pareto solutions for the building cluster in a decentralized manner. In contrast to those works, we propose a novel model-free control approach using the VRFT method.

Virtual Reference Feedback Tuning (VRFT), introduced in Campi, Lecchini e Savaresi (2002), is a popular data-driven control methodology for avoiding the necessity of the plant's model. When designing a closed-loop control for an industrial process, obtaining an appropriate model is usually very demanding and time consuming. If the goal is to design linearly parameterized controllers, the VRFT method proposes the tuning of the control parameters through the minimization of a cost function based on input and output data collected from the process, and the closed-loop desired behavior. With a one-shot experiment, a chosen control structure (Proportional-Integral, for example), and the performance requirements, an optimization process is used to approximate the optimal control parameters. These parameters are then applied to the control structure. Campi, Lecchini e Savaresi (2002) initially proposed the VRFT for SISO systems, and then the method has been extended to MIMO processes in Nakamoto (2004), Formentin e Savaresi (2011), Formentin, Savaresi e Re (2012), and Campestrini et al. (2016).

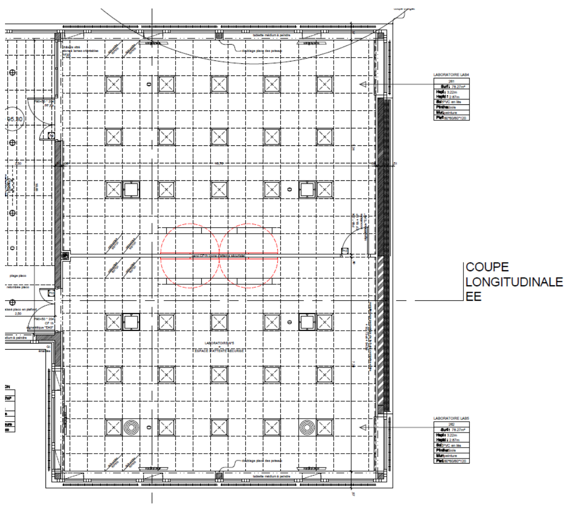
In this work, we consider the heating system of a commercial building, where the building temperature is influenced by outside weather, human heat and thermal interactions between different rooms of the building. We propose a model-free, data-driven approach for the problem of temperature regulation in buildings, considering the VRFT methodology for the control design. We consider the power applied to the heaters present in each room as the input signal, assuming that the heaters present saturation limits at zero, i.e., they cannot remove heat from the building, and upper saturation limits representing the maximum available power. To deal with the problem of power saturation, an Anti-Windup strategy has been included in the control design. Human heat, external temperature, and thermal interactions between different parts of the building are considered as environmental variables that influence the building temperature.

The rest of this work is organized as follows. The problem statement is given in Section 2. An overview of the state of the art VRFT formulation is discussed in Section 3, with the proposed VRFT strategy. The illustrative results for the considered heating system are given in Section 4. Results are discussed and summarized in Conclusion.

2 PROBLEM STATEMENT

We consider the thermodynamic behavior of two classrooms located at the second floor of the Rennes campus of CentraleSupélec (Campus de Rennes, Av. de la Boulaie, 35510 Cesson-Sévigné, France). The rooms' ground plant is depicted in Figure 1. In the ground plant, windows to the outside are represented in the right; the horizontal line in the center of the image represents a wall separating the rooms; in the left side there is a wall with one door per room that separates them from the corridor (in the extreme left side of the image); the respective positions of the whiteboards are indicated by two red circles.

Figure 1: *University rooms' ground plant.*

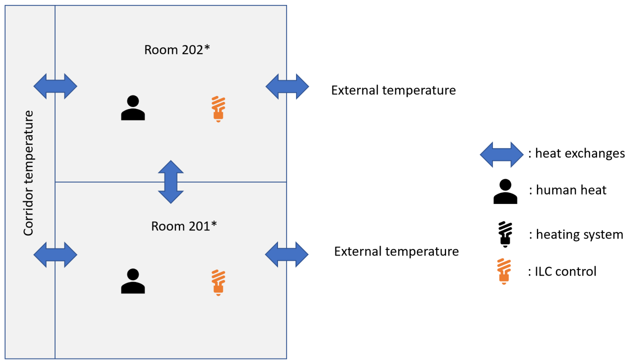


In order to simulate the actual behavior of the temperature inside the building, the model must include variables that reflect environmental influence, such as the external weather and the human heat, and variables that reflect the action of the heating system. In this work we consider the effect of the external temperature, and the human heat as the input of passive heat exchanges with the building. The heaters are considered as active heat sources, used as the control input of the system. Different parts of the building can freely interact and generate heat exchanges. Figure 2 presents a schematic of the different heat sources and heat exchanges that are considered.

2.1 White-box building model

The RC modelling considers that the behavior of temperature can be approximated to that of an electrical circuit. For that, an analogy between heat and current is proposed just as in Table 1.

Figure 2: *Heat sources and heat exchanges schematic.*



* Second floor of the CentraleSupélec building (campus of Rennes)

Source: the author

Table 1: *Analogy between thermal and electrical quantities.*

Thermal quantity	Electrical quantity
Temperature	Voltage
Heat flow	Current
Thermal conductance	Electrical conductance
Thermal resistance	Electrical resistance
Thermal capacitance	Electrical capacitance
Heat source	Current source

Source: the author.

By using an RC electrical analogy of heat conduction (white-box approach) one can approximate the temperature behavior of the rooms by a second order linear model given by

$$\begin{aligned} \dot{x} &= Ax + Bu + \mathscr{G}v \\ y &= Ix \end{aligned} \tag{1}$$

where $x = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^\top$, is the vector of the inside temperatures of the building rooms, $u = \begin{bmatrix} u_1 & u_2 \end{bmatrix}^\top$, is the vector of the power inputs of the rooms heaters, $v = \begin{bmatrix} P_{h1} & P_{h2} & T_o & T_c \end{bmatrix}^\top$, where P_{h1} is the human heat in room 1, P_{h2} is the human heat in room 2, T_o is the temperature outside the building, T_c is the temperature in the corridor, and I is the identity matrix of order 2. We assume that both room temperatures y are available, i.e., measured or estimated.

The dynamics of the building can be written in the form (1) with

$$\begin{aligned} A &= \begin{bmatrix} -\frac{1}{C_1R_{o1}} - \frac{1}{C_1R_{12}} - \frac{1}{C_1R_{c1}} & \frac{1}{C_1R_{12}} \\ \frac{1}{C_2R_{12}} & -\frac{1}{C_2R_{o2}} - \frac{1}{C_2R_{12}} - \frac{1}{C_2R_{c2}} \end{bmatrix}, \\ B &= \begin{bmatrix} \frac{1}{C_1} & 0 \\ 0 & \frac{1}{C_2} \end{bmatrix}, \\ \mathscr{G} &= \begin{bmatrix} \frac{1}{C_1} & 0 & \frac{1}{C_1R_{o1}} & \frac{1}{C_1R_{c1}} \\ 0 & \frac{1}{C_2} & \frac{1}{C_2R_{o2}} & \frac{1}{C_2R_{c2}} \end{bmatrix} \end{aligned} \tag{2}$$

Here C_1, C_2, R_{o1}, R_{o2}, R_{c1}, R_{c2} and R_{12} are physical constants that can be derived using the RC electrical analogy of heat conduction and considering the building characteristics such as materials conductivity and depth of the walls. The building model and all its parameters were developed during a university project, and all its details can be found in Azar et al. (2021). Since the building heaters are controlled by power input, we assume that the input signal $u(t)$ can be directly assigned. Thermal parameters numerical values are provided in Table 2.

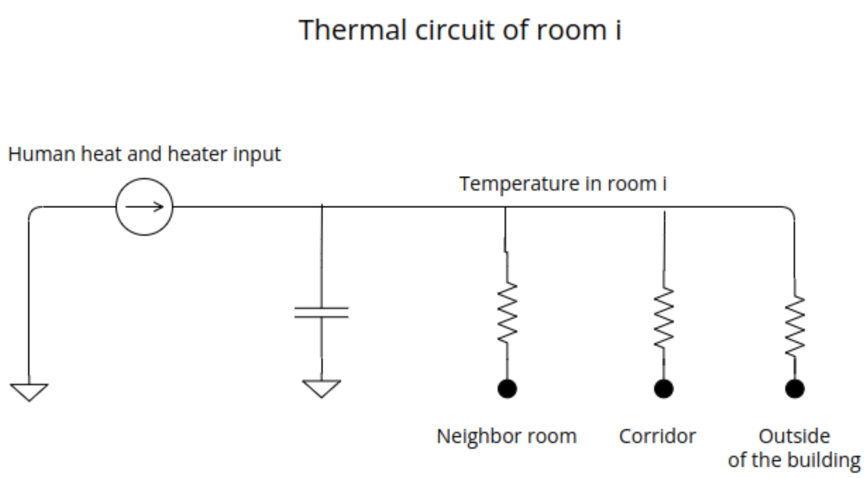
Table 2: *Thermal parameters notaion and numerical values.*

Description	Symbol	Estimated values
Thermal capacitance, $\frac{J}{K}$:		
Inside room 1	C_1	308.36×10^3
Inside room 2	C_2	308.36×10^3
Thermal Resistances, $\frac{K}{W}$:		
Between room 1 and the exterior	R_{o1}	9.370×10^{-3}
Between room 2 and the exterior	R_{o2}	7.360×10^{-3}
Between room 1 and the corridor	R_{c1}	2.068×10^{-2}
Between room 2 and the exterior	R_{c2}	7.456×10^{-2}
Between room 1 and room 2	R_{12}	9.560×10^{-3}

Source: Azar et al. (2021)

For clarity of reading, the thermal circuit proposed for the model is represented in Figure 3.

Figure 3: *Circuit proposed for modelling the university rooms.*

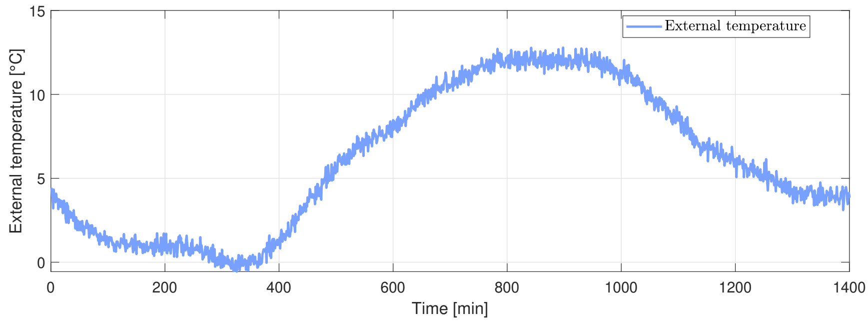


Source: the author

2.2 External weather model

The influence of the external temperature is highly dependent on the local condition under which the building is placed. For simulation purposes, the outside weather signal has been generated using the weather forecast for the city Cesson-Sévigné, France during one week of the month of February 2021. In order to have a more realistic temperature behavior, a white noise is applied to the temperature signal. Figure 4 presents the outside temperature on Monday after the noise addition.

Figure 4: *Temperature forecasted at Cesson-Sévigné, France, February 8th 2021*

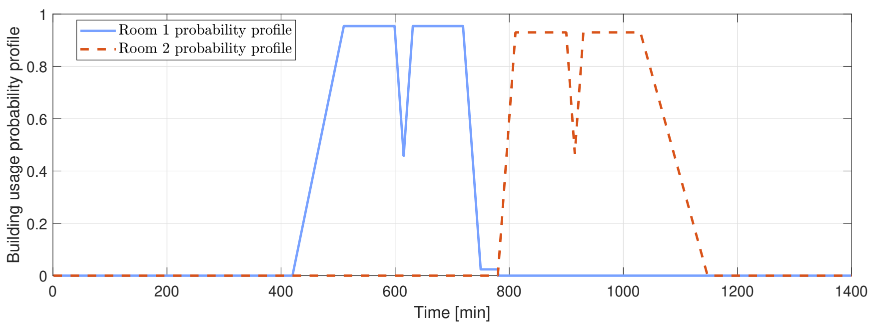


Source: the author

2.3 Human heat model

The influence of human presence in the building is highly dependent on its profile of usage. For simulation purposes, we consider that room 1 holds classes from 8h30 to 12h and that room 2 holds classes from 13h30 to 17h, each class having a duration of 1h30min and an interval of 30 minutes between classes. Classes are held from Monday to Friday and we assume that the building is empty at the weekends. Under these assumptions, one can design a probability profile for each one of the room users that describe the chances of having this user inside the room at any given time of the day. In this context, we assume that every person follows the same probability distribution of being inside the room. From Monday to Friday we design a probability distribution given by Figure 5, and in the weekend we assume that the probability of finding people inside the room is zero.

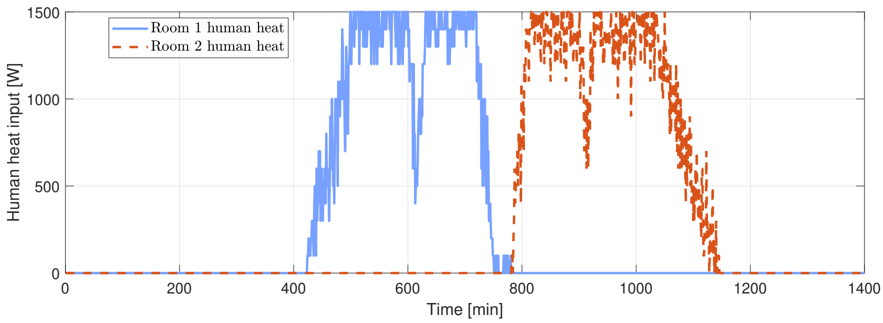
Figure 5: *Probability distribution of finding a given person inside the building from Monday to Friday.*



Source: the author

In order to simulate human heat, we check the value of the random variable representing the human presence once for every person considered in the simulation at each minute of the day. The random variable to be tested is represented by a binomial distribution, where the variable can either assume a positive value (probability of being in the room) or a negative value (probability of not being in the room). The probability to find the positive value varies according to the probability profile described above. Given the nature of the probabilistic model, the human presence of each day will differ a bit, even though it always follows the same pattern. If we consider that one person emits around 100 W of heat, we can estimate the amount of human heat inside the room. Figure 6 presents an example of possible human heat generated inside each room in a given day.

Figure 6: *Human heat generated inside the building at a random given day of the week.*



Source: the author

2.4 Control objective

In this work, we are interested in designing a closed-loop controller such that the rooms' temperatures y follow a predefined trajectory. The reference temperature trajectories $r(t) = \begin{bmatrix} r_1 & r_2 \end{bmatrix}^\top$ are defined on the finite time interval $[0,T]$ for some $T > 0$. For simulation purposes, we consider that the initial conditions of (1) match the initial conditions of the reference trajectory, i.e., $y(0) = r(0)$, avoiding unnecessary over-actuation of the controller in the first minutes of the trial.

It is worth noting that in the case of a time-invariant linear system that is not under the effect of perturbation signals the design of a PID controller usually yields satisfactory results, and the methodology is largely documented in the literature of classical control theory. In the case we are considering for this study the system is under the effect of multiple perturbation signals, such as the human heat, and the external temperature that can vary in unpredictable ways, which makes the control design more challenging. Moreover, in the design of the controller, we consider that the system model is unknown, which prevents us from applying classical control methods, and the system model is only used for simulation purposes.

3 VRFT OVERVIEW AND APPLICATION

The VRFT method is a one-shot model-free control design method. Based on input and output data collected from experiments performed on the process, the goal is to tune the parameters of a given control structure without deriving a process model.

Due to the discrete nature of data collected from physical experiments, the formulation of the VRFT method is proposed in discrete-time. For that, one must define a fixed sampling time T_s that is the time interval between two consecutive measurements of the experimental variables. The value of the variable is assumed to be constant between two consecutive measurements. Thus, one can introduce the notation $x(k)$, $\forall k \in \mathbb{N}$, where $x(k) = x(kT_s)$ for representing discrete-time quantities. To convert a given discrete-time signal to continuous time, we use a zero-order hold strategy.

The goal is to design in a one-shot experiment the linear time-invariant closed-loop controller C, which belongs to a given – user specified – class $\mathscr{C}$ of transfer function matrices, capable of generating (with a certain accuracy) the desired temperature trajectory $r(t)$, where the control signal is updated in real time.

3.1 Method formulation

As a classical formulation of the VRFT method, consider a discrete-time MIMO process with inputs and outputs represented by $u(k)$ and $y(k)$ respectively, related by a linear expression given by

$$y(k) = G(q)u(k) + v(k), \tag{3}$$

where $G(q)$ represents the unknown process model, q is the forward-shift operator, and $v(k)$ represents a perturbation signal.

The controller is parameterized by a parameter vector $P \in \mathbb{R}^p$, so that the control action $u(t)$ can be written as

$$u(k) = C(q,P)(r(k) - y(k)). \tag{4}$$

The system (1) and (4) in closed loop becomes

$$y(k,P) = T(q,P)r(k) + S(q,P)v(k) \tag{5}$$

where

$$\begin{aligned} S(q,P) &= (G(q)C(q,P) + I)^{-1}, \\ T(q,P) &= S(q,P)G(q)C(q,P) = G(q)C(q,P)S(q,P). \end{aligned} \tag{6}$$

The performance of the closed-loop system is given by a user specified transfer function T_d such that $y_d(k) = T_d(q)r(k)$, also called the *reference model*. This way, the optimization criterion can be defined as

$$J^{MR}(P) = \sum_{k=1}^{N} \|(T_d(q) - T(q,P))r(k)\|_2^2 \tag{7}$$

and the optimal parameters vector P can be tuned by solving the optimization problem $\hat{P} = \arg\min_{P} J^{MR}(P)$.

Although the problem (7) is well defined, the term $T(q,P)$ depends on the unknown process model and thus cannot be used to obtain the control parameters. Thus, a different minimization criterion, with a solution close to the one derived by (7), and based exclusively on experimental data is proposed as follows: let u_{batch} and y_{batch} be the input and output data collected on the process. With that, a virtual reference (VR) signal $\bar{r}(k)$ can be defined such that $T_d(q)\bar{r}(k) = y_{batch}$. Let us define the virtual error signal as $\bar{e}(k) = \bar{r}(k) - y_{batch}$.

The ideal controller generates u_{batch} when $\bar{e}(k)$ is given. Thus, the VRFT process can be seen as the identification of the dynamics between $\bar{e}(k)$ and $u(k)$. For the MIMO case, the VRFT cost function can be formulated as

$$\begin{aligned} J^{VR}(P) &= \sum_{k=1}^{N} \|F(q)[u(k) - C(q,P)e(k)]\|_2^2 \\ &= \sum_{k=1}^{N} \|F(q)[u(k) - C(q,P)(T_d(q)^{-1}y(k) - y(k))]\|_2^2, \end{aligned} \tag{8}$$

where N is the number of data samples and $F(q)$ is a user-defined filter. The optimal parameters can be tuned by solving the optimization problem $\hat{P} = \arg\min_{P} J^{VRF}(P)$.

3.1.1 Filter design

As presented by Campestrini et al. (2016), there is no guarantee that $\min J^{VR} = \min J^{MR}$. In fact, the previous equality is rarely satisfied, motivating a filter choice that approximate the minima of both cost functions. Campestrini et al. (2016) shows that a good choice for $F(q)$ is

$$F(e^{j\omega}) \approx T_d(e^{j\omega})(I - T_d(e^{j\omega}))\Phi_r^{1/2}(\omega)\Phi_u^{-1/2}(\omega), \tag{9}$$

where $\Phi_r^{1/2}$ is the spectral factor of the power spectrum of $r(k)$ and $\Phi_u^{1/2}$ the spectral factor of the power spectrum of $u(k)$. Since experimental data is collected in open-loop, we can approximate $\Phi_r^{1/2} \approx \Phi_u^{1/2}$ and thus the filter is easily obtained as

$$F(q) = T_d(q)(I - T_d(q)), \tag{10}$$

3.2 Application to the temperature control problem

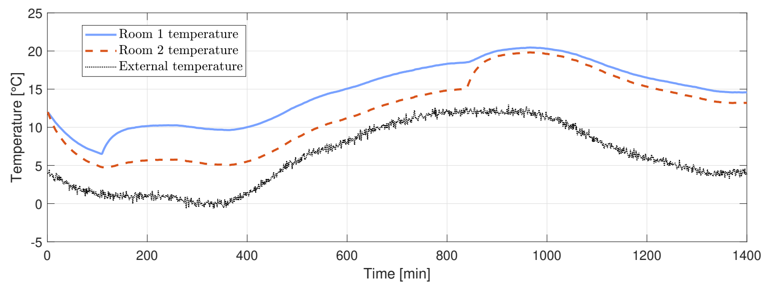
The goal of this work is to design a PID controller capable of maintaining the temperature inside the building in desirable levels, by tracking a reference signal with real-time feedback. The design of the controller is obtained by applying the VRFT method previously described with operational data collected from the room during one day of the weekend so that the users of the building are not exposed to temperature oscillations through the day that result from the open-loop experiment.

3.2.1 Experimental environment

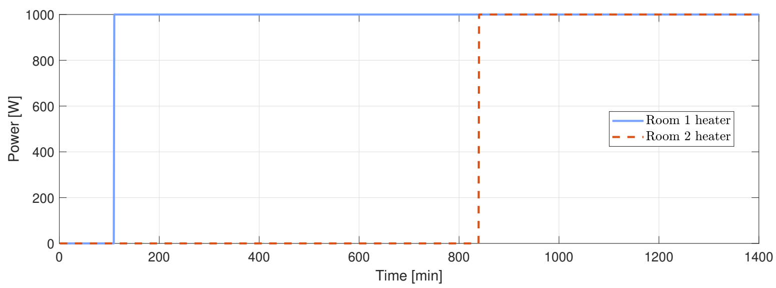
Since there is no human presence in the building during experiment phase, we have that $P_{h1}(k) = 0$ and $P_{h2}(k) = 0$, $\forall k \in \mathbb{N}$. Regarding the temperature in the corridor, we assume for simulation purposes that it stays constant at $T_c = 20°C$.

In a first moment, we design a temperature experiment in order to define an appropriate sampling time for the system. Figure 7 depicts an experiment with both rooms completely empty. Note that the temperature in the corridor is not presented, and the temperature outside the building is depicted in black. We apply one step power input in each heater, separated by an interval of 12.25 h. As it can be interpreted from the results, the system has an accommodation time of around 75 min. This indicates that a sampling time of $T_s = 60$ s could yield high enough precision to the control system. To have the input/output relation of the experiment, we register the power that is applied to the heaters and we collect temperature data from both rooms.

Figure 7: *Step power inputs are applied in the building to define an appropriate sampling time.*



(a) *Initial temperature output measured in system.*



(b) *Initial power input applied to the system.*

Source: the author

3.2.2 Desired transfer function and reference signal

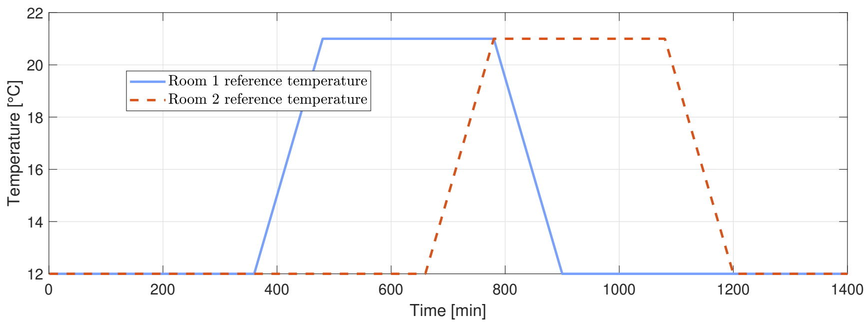
By analysing the temperature experiment depicted in Figure 7, one can conclude that the system naturally performs a first-order response to heat input. A natural choice for the desired transfer matrix is

$$T_d(q) = \begin{bmatrix} T_{d1}(q) & 0 \\ 0 & T_{d2}(q) \end{bmatrix} = \begin{bmatrix} \frac{1-a_1}{q-a_1} & 0 \\ 0 & \frac{1-a_2}{q-a_2} \end{bmatrix} \tag{11}$$

where T_d generates an output where the two room temperature are not coupled, and each one of them respond with a first-order behavior to its reference signal. For simulation purposes we consider that $a_1 = a_2 = 0.5$, which results in an approximate 2% settling time of 5.8 min, considering $T_s = 1$ min.

The desired temperature inside the building is supposed to respect two constraints. Firstly, it should prioritize human comfort when users are using a given room, maintaining temperature inside it around $21°C$. Secondly, it should prioritize energy saving when the room is empty. In order to do so, we set the temperature to $12°C$. Temperature is not allowed to decay freely so that the energy required to go back to comfortable levels is not too high. Based on the building usage profile, given by 5, we can design the reference signal as in Figure 8.

Figure 8: *Reference temperature to be tracked in the controlled rooms.*



Source: the author

3.2.3 Controller structure

The controller structure defines how many degrees of freedom the controller presents, and what variables it takes into account for generating the control signal. Two different control structures are tested for the temperature regulation problem: firstly, a full PID controller. As it will be illustrated and explained in Chapter 4, this control structure yields poor results due to the saturation of the power input. The structure of this controller is given by

$$C(q,P) = \begin{bmatrix} C_{PID}(q,\rho_{11}) & C_{PID}(q,\rho_{12}) \\ C_{PID}(q,\rho_{21}) & C_{PID}(q,\rho_{22}) \end{bmatrix} \tag{12}$$

where $\rho_{ij} = \begin{bmatrix} K_{pij} & K_{iij} & K_{dij} \end{bmatrix}^\top$ and

$$C_{PID}(q,\rho_{ij}) = \begin{bmatrix} K_{pij} & K_{iij} & K_{dij} \end{bmatrix} \begin{bmatrix} 1 \\ \frac{q}{q-1} \\ \frac{q-1}{q} \end{bmatrix} \tag{13}$$

with $i, j \in \{1,2\}^2$.

The second controller that is considered is a diagonal PID, not including the action relating the reference signal of room 1 with the temperature of room 2 or the reference signal of the room 2 with the temperature of room 1. Although saturation still prevents the system to perfectly track the reference signal, the results of this trial are more promising. The structure of this controller is given by

$$C(q,P) = \begin{bmatrix} C_{PID}(q,\rho_{11}) & 0 \\ 0 & C_{PID}(q,\rho_{22}) \end{bmatrix} \tag{14}$$

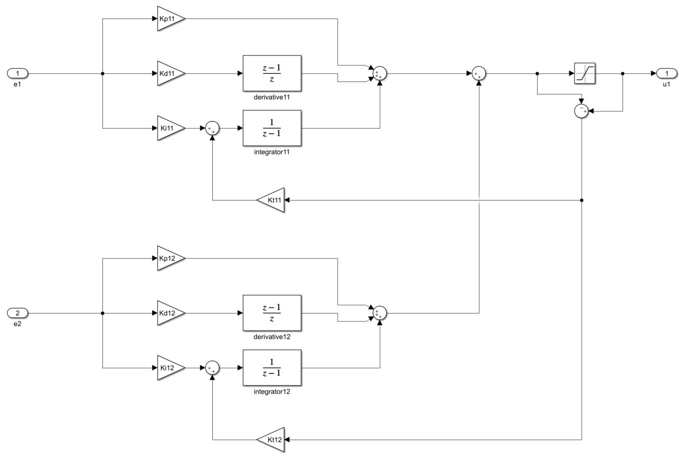
3.2.4 Filter choice

In this study we consider that the experimental data is collected in open-loop. Thus, the filter proposition given in (10) is chosen in order to approximate $\min J^{VR}$ to $\min J^{MR}$.

3.2.5 Anti-windup strategy

Due to the power input limitation of the room heaters, saturation becomes an important aspect to be evaluated. Astrom e Hagglund (2006) proposes to include an anti-windup strategy in the control structure in order to avoid windup effects in the PID's integral element. In this work we consider the multivariable extension of the anti-windup formulation, previously applied in Bordignon e Campestrini (2018) and represented in Figure 9. In addition to that, we design the back-calculation gain as $K^T = K^I/K^P$, as proposed by Bohn e Atherton (1995).

Figure 9: *Multivariable PID controller diagram with anti-windup loop.*



Source: the author

3.2.6 The algorithm

The application of the VRFT method is made in a sequence of distinctly defined step. For clarity of reading, the method's algorithm adapted to the problem of temperature regulation is detailed in Algorithm 1.

Algorithm 1: VRFT algorithm for the temperature regulation problem

```
Result: MIMO PID controller that tracks r(k) in closed-loop
Load building model for simulation as in (1)
Load human presence probability distribution as in Figure 5
Load reference temperature trajectory as in Figure 8
Set the temperature's initial state y_0
Configure the heaters for experiment mode
Run open-loop experiment and collect data
Filter experimental data
Define T_d and C structure as in (11) and (14)
Define F and in (10)
Run optimization process as in (7) and design C
while TRUE do
    if is weekday then
        Run system in closed-loop ;
    else
        Turn off heaters ;
    end
end
```

4 RESULTS

4.1 Data pre-processing

Once the experiment described in 3.2 is executed, the input and output data is collected. In order to correctly apply the VRFT method, we need to ensure that the experimental output is set to zero in the beginning of the experiment. This step is required so we can measure the difference of temperature caused by the power input in each room (even though the external temperature variation will also influence the measures, resulting in some perturbation in the controller design). In order to minimize the effect of perturbation signals in the control design, we remove from the collected signal the measurements before the application of the first power input. The processing previously described can be summarized by

$$\tilde{x}(k) = x(k+s) - x(s) \tag{15}$$

where s is the number of samples to remove. The resulting processed signals are depicted in Figure 10.

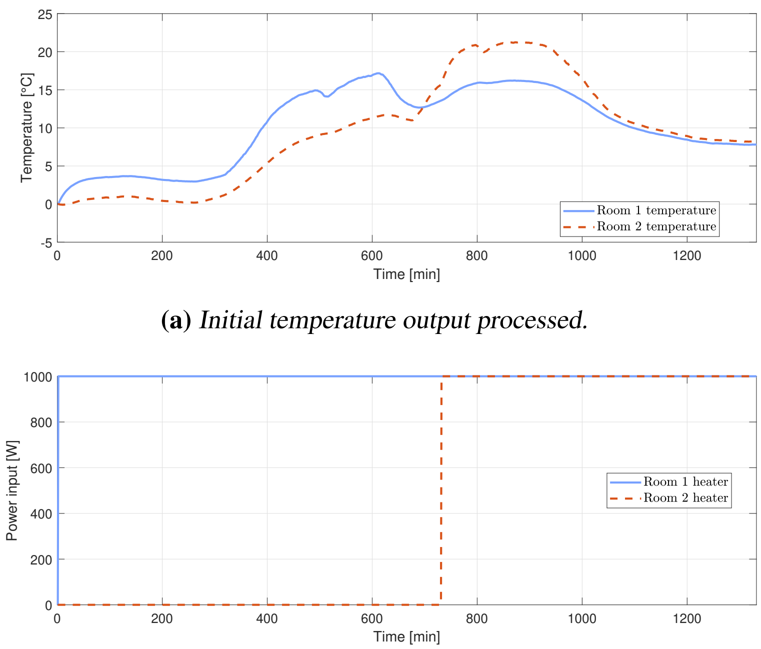
4.2 Full PID controller

When dealing with systems that accept input values in all ranges of $\mathbb{R}$, a full PID controller allows different input signals to work in synchrony to generate a desired output signal. The control elements outside the principal diagonal contribute with additional degrees of freedom, resulting in a different solution for the optimization problem (7). When running the optimization process with the structure of the controller defined by (12), the resulting controller parameters are given in Table 3. Note that the anti-windup back-calculation gains are computed as $K^T_{11} = K^I_{11}/K^P_{11}$, $K^T_{12} = K^I_{12}/K^P_{12}$, $K^T_{21} = K^I_{21}/K^P_{21}$, and $K^T_{22} = K^I_{22}/K^P_{22}$.

For illustration purposes, Figure 11 presents how the closed-loop system would behave in a normal day of building usage if it had no saturation constraints, i.e., if the room heaters could generate any level of heat (positive or negative). As the figure shows, even when the reference temperature of one room is higher than its current temperature, its heater might work with negative input to compensate high temperatures in the neighbor room.

Although the full PID controller presents satisfactory results when dealing with systems that do not present saturation in the input signals, it is not able to track the reference signal in a realistic context where heaters cannot provide negative or infinitely high heat. In order to simulate the behavior of the system under the effect of saturation, we include to the controller the Anti-Windup strategy. The resulting controller parameters are given

Figure 10: *Experimentally collected signal after initial processing.*



(a) *Initial temperature output processed.*

(b) *Initial power input processed.*

Source: the author

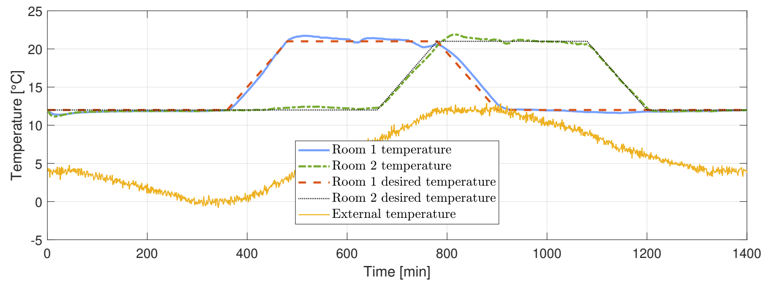
Table 3: *Thermal parameters notation and numerical values for the full PID with saturation constraints.*

Symbol	Value
K_{p11}	9.24682×10^{2}
K_{i11}	3.21699×10^{1}
K_{d11}	6.87390×10^{2}
K_{11}^{T}	3.48000×10^{-2}
K_{p12}	-1.88946×10^{2}
K_{i12}	-2.18290×10^{1}
K_{d12}	-1.37548×10^{2}
K_{12}^{T}	1.15500×10^{-1}
K_{p21}	-1.14963×10^{2}
K_{i21}	-1.78343×10^{1}
K_{d21}	-4.17702×10^{1}
K_{21}^{T}	1.55100×10^{-1}
K_{p22}	7.19280×10^{2}
K_{i22}	3.81874×10^{1}
K_{d22}	3.11384×10^{2}
K_{22}^{T}	5.31000×10^{-2}

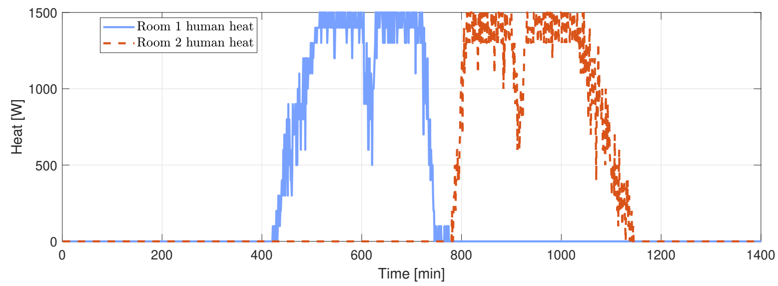
Source: the author.

in Table 3. Figure 12 illustrates how the closed-loop system would behave in a realistic environment. We consider heaters in both rooms capable of generating power output in the range $[0; 3000]$ W. Note that around 1000 min the actual temperature in both rooms are higher that the reference, and still we have the heater in room 2 delivering more than 1000

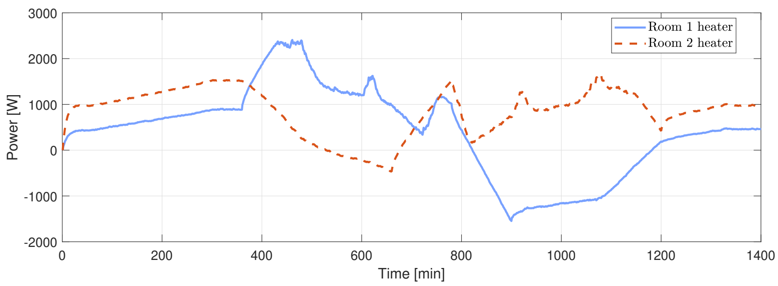
Figure 11: *Simulation of the closed-loop behavior for the full PID with no saturation in the inputs.*



(a) *Temperature output (no saturation considered in the inputs).*



(b) *Human heat.*



(c) *Power input in the heaters (no saturation).*

Source: the author.

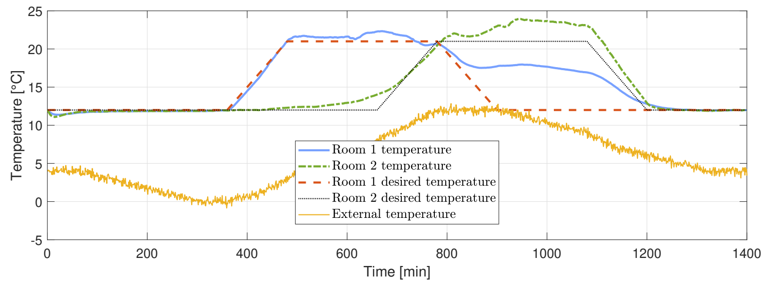
W. In this scenario we would expect both heaters to be turned off so that the temperature can naturally decrease.

4.3 Diagonal PID controller

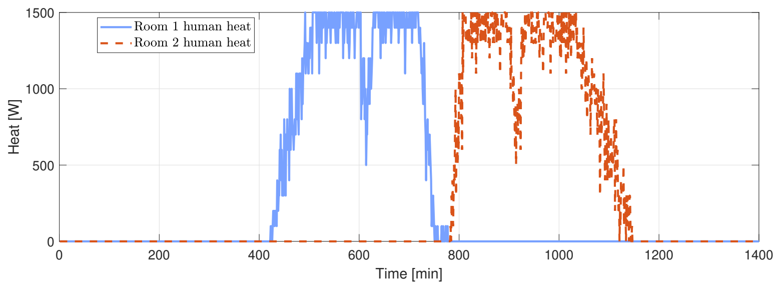
As the full PID controller is unable to precisely track the reference signal, another control structure is proposed for the problem. As it has been showed in 4.2, the full PID controller does not yield satisfactory results in a context where the input signal presents saturation limits. As an alternative to that solution, we propose the control structure described in (14). The control parameters are set at zero for the elements outside the main diagonal. All parameters are presented in Table 4. Note that the anti-windup back-calculation gains are computed as $K^T_{11} = K^I_{11}/K^P_{11}$, and $K^T_{22} = K^I_{22}/K^P_{22}$.

When working in an environment where the input signal does not present saturation limits, the controller presents a similar response to the one obtained with the full PID controller. Figure 13 illustrates how the closed-loop system would behave in a normal day of building usage if it had no saturation constraints.

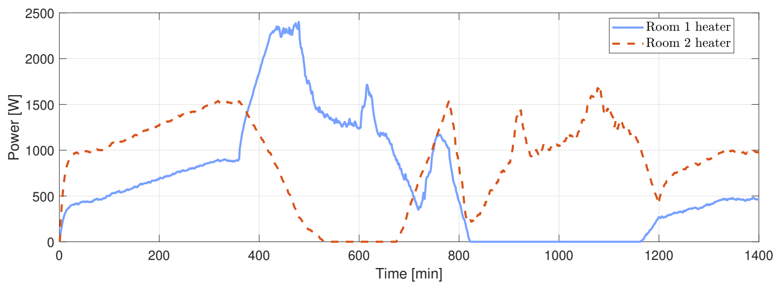
Figure 12: *Simulation of the closed-loop behavior for the full PID with saturation in the inputs.*



(a) *Temperature output (saturation considered in the inputs).*



(b) *Human heat.*



(c) *Power input in the heaters (with saturation).*

Source: the author.

The difference in performance between the two solutions become much more visible in the case where the input signal presents saturation limits. Here we consider heaters for room 1 and 2 that can provide heat input to the building in the range $[0; 3000]$ W. As it is presented in Figure 14, the output temperature signal is closer to the reference temperature when we apply a diagonal PID controller than when we apply a full PID controller. The difference between the reference temperature in room 1 and its actual temperature becomes considerably large between 800 min and 1100 min. This is due to the fact that the heater cannot provide negative power to the room, and the natural temperature decrease is not sufficiently fast in order for it to follow the reference temperature. This characteristic does not result in poor human comfort, since there are no classes in this room in the period, and no person in the room to feel the temperature difference. Moreover, the actual temperature inside the room is always higher than the reference during this period. The characteristic does not result in poor energy efficiency either, since the heater in room 1 is turned off during the entire period.

Table 4: *Thermal parameters notation and numerical values for the diagonal PID with saturation constraints.*

Symbol	Value
K_{p11}	8.400754×10^2
K_{i11}	3.08311×10^1
K_{d11}	6.410503×10^2
K_{11}^T	3.67×10^{-2}
K_{p12}	0
K_{i12}	0
K_{d12}	0
K_{12}^T	0
K_{p21}	0
K_{i21}	0
K_{d21}	0
K_{21}^T	0
K_{p22}	6.661913×10^2
K_{i22}	3.91651×10^1
K_{d22}	3.545876×10^2
K_{22}^T	5.88×10^{-2}

Source: the author.

4.4 Comparison with rule-based controllers

In this section we compare the controllers proposed in this study with commercially available rule-based controllers. The most widely spread strategy of controlling the temperature inside commercial buildings is to apply a predefined power profile to the heaters. For instance, user may decide that the best heating strategy consists in turning the heaters on with maximum power from 8h30min to 5h30min and to turn it off outside this time range. Heaters are then programmed to behave in such manner every day and no feedback control is applied. A main drawback of this control strategy is that it must be tuned by hand, requiring a user-defined input profile to be informed. For simulation purposes, we run a few experimental trials in order to find an approximate optimal solution to the problem. For the current comparison, we use the feedforward power input given by

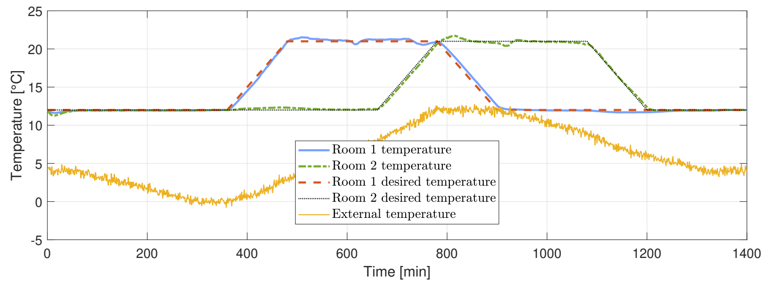
$$\begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix} = \begin{bmatrix} 750 \times \Pi(-126 + \frac{k}{250}) + 1500 \times \Pi(-576 + \frac{k}{650}) + 750 \times \Pi(-1171 + \frac{k}{540}) \\ 750 \times \Pi(-326 + \frac{k}{650}) + 1000 \times \Pi(-926 + \frac{k}{550}) + 750 \times \Pi(-1321 + \frac{k}{240}) \end{bmatrix} \tag{16}$$

where $\Pi(k)$ is the rectangular signal, defined as

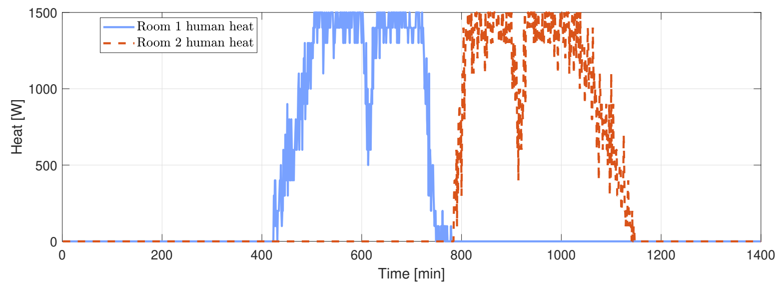
$$\Pi(k) = \begin{cases} 0 & \|k\| > \frac{1}{2} \\ 1 & \|k\| \leq \frac{1}{2} \end{cases} \tag{17}$$

Figure 15 illustrates how the system reacts to the input in a weekday of building usage, when (16) is applied. As the simulation shows, the reference temperature is tracked with much lower accuracy when compared to the diagonal PID proposed previously. Moreover, the actual temperature inside the room is regularly above the reference one, reaching around $27°C$ at 750 min. This indicates that this solution is also less energy efficient than the proposed diagonal PID.

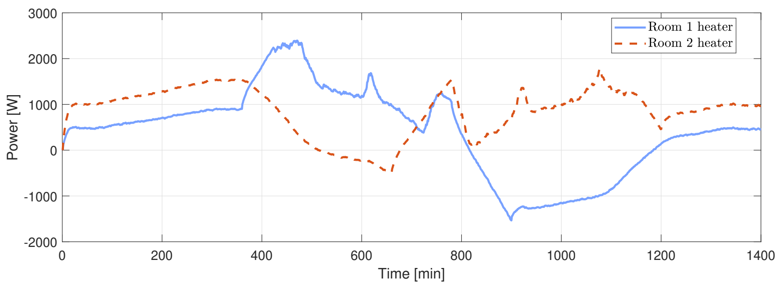
Figure 13: *Simulation of the closed-loop behavior for the diagonal PID without saturation in the inputs.*



(a) *Temperature output (no saturation considered in the inputs).*



(b) *Human heat.*



(c) *Power input in the heaters (no saturation).*

Source: the author.

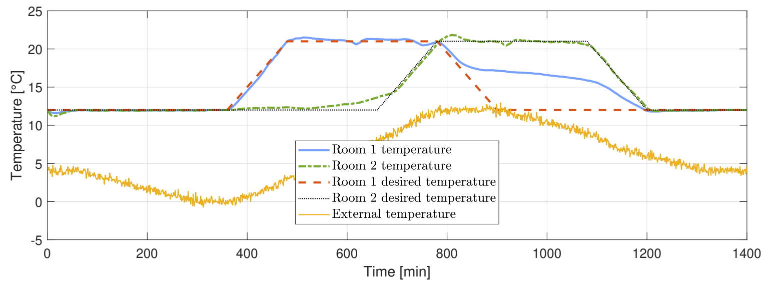
An alternative to the feedforward controller presented previously, also commercially available and detailed by Bazanella Alexandre Sanfelice; Silva Júnior (2005), is the on/off controller. This strategy consists in performing a simple feedback operation to track with a certain accuracy the proposed reference temperature. The controller's equation is given by

$$u_i(k) = \begin{cases} 0 & T_i(k) > T_{max} \\ u_{max} & T_i(k) < T_{min} \end{cases} \tag{18}$$

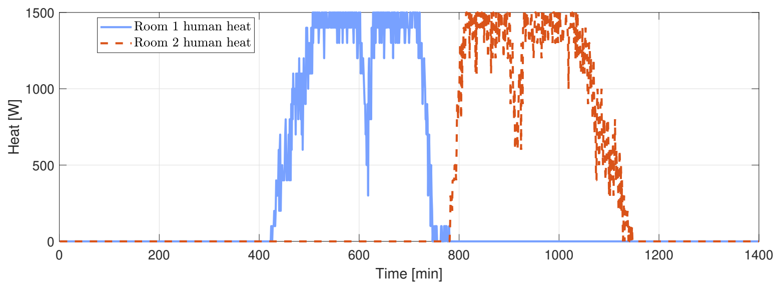
where $i \in \{1,2\}$. In the current experiment we consider $T_{max} = 22°C$, $T_{min} = 20°C$ and $u_{max} = 3000$ W, i.e., the maximum power available to the heaters. Figure 16 illustrates how the system reacts to the closed-loop control strategy in a weekday of building usage. As the simulation shows, the reference temperature is tracked with lower accuracy when compared to the diagonal PID proposed previously. Regarding the energy efficiency of the system, there is no clear conclusion of weather this solution consumes less energy than the diagonal PID one by visual analysis.

In order to accurately estimate the performance of each of the proposed solutions, we propose objective evaluation metrics. For comparing the human comfort inside the

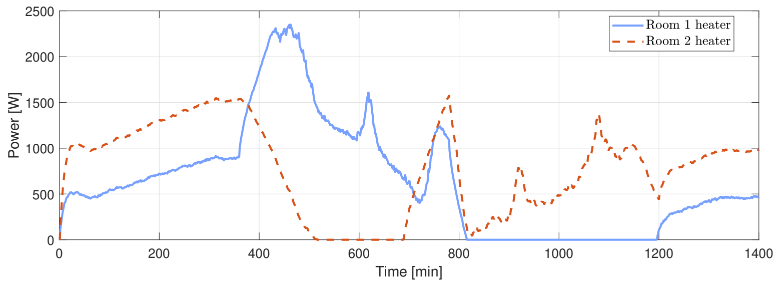
Figure 14: *Simulation of the closed-loop behavior for the diagonal PID with saturation in the inputs.*



(a) *Temperature output (saturation considered in the inputs).*



(b) *Human heat.*



(c) *Power input in the heaters (with saturation).*

Source: the author.

building, we compute the mean squared error (MSE) between the reference temperature in each room and its reference temperature during course hours. In a mathematical form, the metric is given by

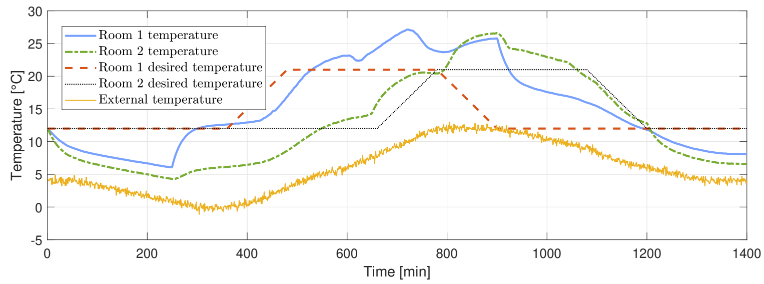
$$MSE = \frac{1}{2} \times (MSE_1 + MSE_2) \tag{19}$$

where

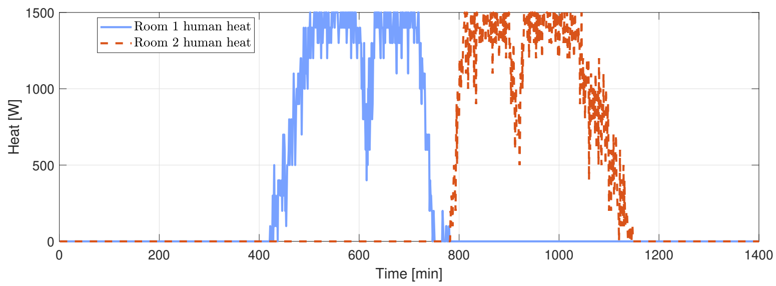
$$MSE_i = \frac{1}{D} \sum_{d=1}^{D} \sum_{k=k_{start}^i}^{k_{stop}^i} \|y_i(k) - r_i(k)\|^2 \tag{20}$$

with $i \in \{1,2\}$. D is the number of days in the workweek, k_{start}^i is the starting time of classes at room i, k_{stop}^i is the ending time of classes at room i, $y_i(k)$ is the temperature inside room i at minute k and $r_i(k)$ is the reference temperature inside room i at minute k. For an energy efficiency comparison, we compute the total energy spending in the week. In a mathematical form, the metric is given by

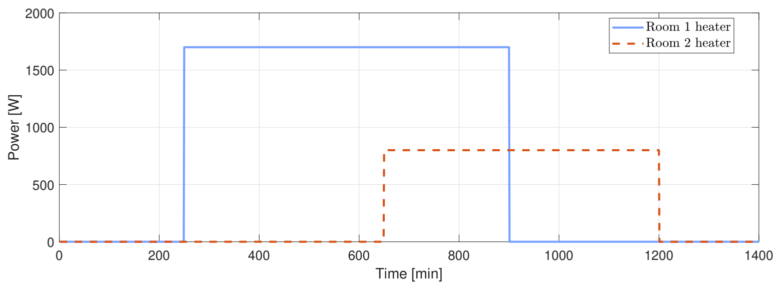
Figure 15: *Simulation of the system's behavior using a user defined rule-based controller.*



(a) *Temperature output.*



(b) *Human heat.*



(c) *Power input in the heaters.*

Source: the author.

$$Energy_{total} = \frac{1}{60 \times 1000} \sum_{k=1}^{N} \|u(k)\| \tag{21}$$

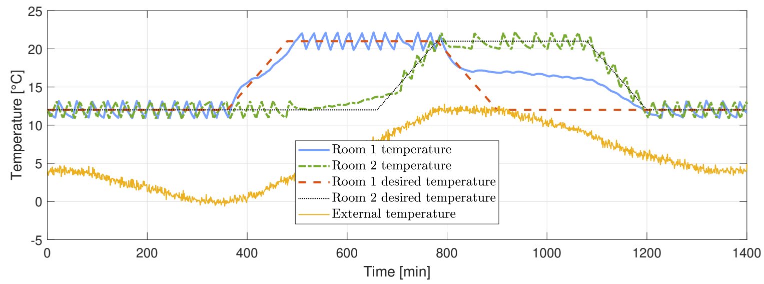
Note that we divide the sum by 60×1000 to convert W$\times$min to kWh. Table 5 presents the numerical results of the metrics for each of the proposed solutions. Note that, as predicted by visual analysis, the user defined rule-based controller presents the worst performance in all metrics. The on/off controller provides lower human comfort to the building users (and more temperature oscillations) when compared with the diagonal PID controller, while providing a similar energy efficiency.

Table 5: *Performance metrics comparison between diagonal controller and rule-based controllers.*

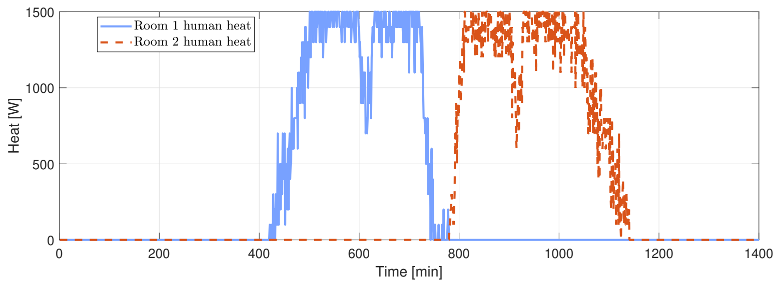
Criterion	Performance metric	Value
Human comfort (User defined)	MSE	1.096×10^{1}
Human comfort (On/off)	MSE	3.560×10^{-1}
Human comfort (Full PID controller)	MSE	6.640×10^{-1}
Human comfort (Diagonal PID controller)	MSE	1.048×10^{-1}
Energy efficiency (User defined)	$Energy_{total}$	3.250×10^{2} kWh
Energy efficiency (On/off)	$Energy_{total}$	2.143×10^{2} kWh
Energy efficiency (Full PID controller)	$Energy_{total}$	2.441×10^{2} kWh
Energy efficiency (Diagonal controller)	$Energy_{total}$	2.189×10^{2} kWh

Source: the author.

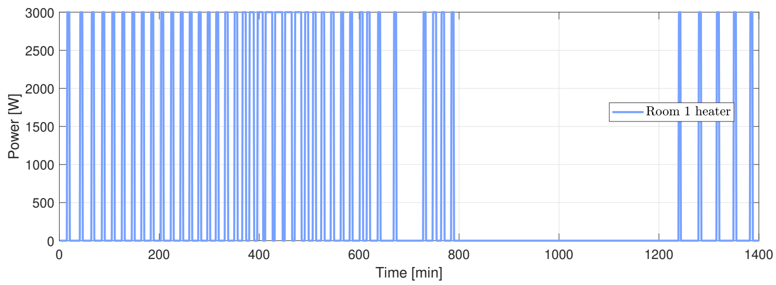
Figure 16: *Simulation of the system's behavior using an on/off controller.*



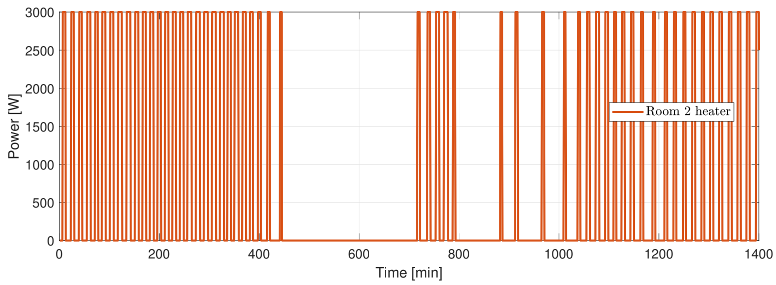
(a) *Temperature output.*



(b) *Human heat.*



(c) *Power input in the heater of room 1.*



(d) *Power input in the heater of room 2.*

Source: the author.

5 CONCLUSION

In this work we considered the problem of temperature regulation in buildings, motivated by its high representation in the total end-use energy use of around 20% and previous studies that have shown that predictive control methods can improve energy efficiency in HVAC systems up to 40%. Although modern control methods for temperature regulation is a highly discussed field in the scientific community, the majority of previous works consider model-dependent control strategies. As a novel approach, we have applied the VRFT method to tune a multivariable PID controller for regulating the temperature inside a university building, controlling two different rooms. External temperature and human heat were considered as external variables that influence the temperature behavior inside the building, and heat exchanges between different parts of the building were taken into account. As a result of the physical nature of the heaters, saturation limits were considered so that the heaters are not able to remove heat from the system and the power input limit is no exceeded. To deal with these restrictions, an Anti-Windup strategy was implemented to maintain the control signal in acceptable levels. Two different control structures where proposed for the problem: a full PID controller and a diagonal PID controller. Although the full PID controller presents acceptable precision when dealing with systems with no saturation, the saturation constraint prevents it from fully taking advantage of all its degrees of freedom, resulting in poor performance. In this context, we have showed that the diagonal PID presents higher precision and makes better use of its actuation. To evaluate system's performance with the diagonal PID controller, we propose objective evaluation metrics for human comfort and energy efficiency. We compare the performance of the proposed controller with those obtained with commercially available rule-based controllers. We show with simulation data that a simple user defined feedforward controller presents the worst performance in all proposed metrics. The on/off controller presents similar energy efficiency when compared to the proposed controller, but provides poorer human comfort, with greater temperature oscillations. Since a good PID tuning can be achieved with very little computational burden using the VRFT method, it is preferable to use this control strategy over the others used as comparison in this work. The applicability of the current results in real commercial buildings might be an interesting direction of studies for future research activities.

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