Model based predictive control for thermal comfort maximization in classrooms

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Resumo

Este trabalho teve como objetivo modelar o comportamento térmico de uma sala de aula. Vários sensores instalados na sala foram utilizados para obter dados relevantes. Foram também utilizados dados meteorológicos da estação presente na universidade. Estes dados foram tratados e utilizados para a criação de 2 modelos de sala de aula.

O primeiro modelo baseou-se em equações diferenciais que modelam a transferência de calor entre a sala e o ambiente envolvente. Utilizou a analogia entre componentes térmicos e elétricos para a criação das equações diferenciais.

O segundo modelo baseou-se no uso de redes neuronais. A estrutura foi testada com dados passados existentes e foi feita validação dos resultados. Foram abordadas várias particularidades do uso de redes neuronais neste contexto, bem como a influência no resultado final.

Obtiveram-se bons resultados na previsão de temperatura. O Modelo Teórico obteve um erro médio de $0.057°C$. O Modelo de Redes Neuronais obteve um erro médio de $0.049°C$. Futuros trabalhos podem utilizar este modelos como base para melhoramentos e para o controlo da temperatura da sala.

Palavras-chave: Redes Neuronais, Previsão, Temperatura, Transmissão de Calor

Abstract

The purpose of this work is to model the thermal behavior of a classroom. It will use various sensors installed in the classroom to gather relevant data. It will also use meteorological data gathered from the station that is present on the university campus. It will preprocess this data and use it to develop thermal models of the classroom.

The First type of models were based on differential equations that model heat transfer between the room and the envelope. It used the analogy between thermal and electrical components to derive the differential equations.

The Second type of models were based on Neural Networks. The structure was based on past data and validate with a different set of data. Certain particularities of the workings of neural networks are discussed and it is considered how they affect the final result.

Good results were obtained in terms of temperature forecasting. The Theoretical models obtained a Root Mean Squared Error of $0.057°C$. The Neural Network models obtained a Room Mean Squared Error of $0.049°C$. Future work can use these models as a basis for future improvement and control of the room temperature.

Keywords: Thermal Modelling, Neural Networks, Temperature Forecasting

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Glossary

ANN	Artificial Neural Network.
CFD	Computational Fluid Dynamics is a branch of fluid mechanics that uses numerical methods and algorithms to solve problems that involve fluid flows.
CTSM-R	Continuous Time Stochastic Modelling for R.
DHI	Diffuse Horizontal Irradiation.
DNI	Direct Normal Irradiation.
DTU	Danish Technical University.
GHI	Global Horizontal Irradiation.
NARX	Nonlinear Autoregressive Exogenous Neural Network.
VOCS	Volatile Organic Compounds.

Chapter 1

Introduction

1.1 Motivation

In a world where energy needs and consumption are of the utmost importance, there is a need to efficiently provide comfort with the least energy use. Reducing the use of energy has significant impact on the environment and on the living conditions of millions of people. With this in mind, the development of systems capable of automating and improving how Human society functions is in demand, with bigger and more complex environments being created every day. The first step in improving the living conditions of people is to understand the environment in which they are inserted. Knowing this, it is easier to find where improvements can be made. In the context of energy management in buildings, understanding the behaviour patterns and preferences of the occupants can lead to a more efficient climatization and higher productivity and enjoyment.

The present work is inserted in this context - trying to improve the comfort inside a classroom, where a majority of young people in the developed world stay most of their time. Their comfort can affect their performance and state of mind, sometimes being very detrimental to their health. Using systems that are easily implementable, with a small cost and capable of being generalized for different configurations of classrooms, but have a net positive impact on the occupants is a step in the right direction when trying to improve the use of energy.

1.2 Background

With the advent of the internet, more people are able to learn, easily find previous work and to publish new studies about the most varied topics. Nowadays, with the need for efficient energy use to fight climate change, more studies are being published and more examples of efficient use of energy aided by accurate prediction of indoor temperature are being presented. The efficient use of energy for climatization in buildings reduces the need for more power plants and reduces the economic cost of said climatization.

In 2013, Mateo et al. [1] explored the usage of machine learning techniques for indoor temperature prediction and compared them to classical techniques. The data was simulated from a real Building and the several different rooms were considered for analysis. It was found out that Multi Layer Perceptron with a Non Linear Autoregressive with Exogenous input (MLP-NARX) was able to performe better than a classical autoregressive model with exogenous input. (ARX) It achieved predictions errors of $0.11°C$ Mean Average Error, and was able to achieve a better performance than all the other models tested except for the month of February. It shows the power of non-linear approximators for temperature prediction - they can find relations between the data that might not be evident to the human eye and use them to perform better. Zamora-Martínez et al. [2] also explored the usage of machine learning techniques for usage in temperature forecasting, achieving a good result, although the used data was limted to 1 month.

An important contribution was made by Santos [3]. He designed the model for a 3 story building using two different techniques - Non Linear Stochastic Differential Equations, in the form of a State Space Model, and a Takagi-Sugeno Fuzzy Model - and implemented a novel technique known as Economic Model Predictive Control. After being designed, the models were proved to accurately model the behaviour of the Building and achieved a very high performance in temperature prediction and simulation. The control method implemented was able to reduce the energy consumption and the heating and cooling cost of the building, without compromising the comfort and the quality of the building environment. This dissertation will be one of the ones closely followed in the current document, as it presents the information clearly and describes in a great detail the steps taken create the models.

In order to better implement and facilitate the use of indoor temperature forecasting, Monteiro et al. [4] explored the cost of developing a model that takes information from various sensors in an Internet of Things (IoT) paradigm. It was shown that it is indeed feasible and that it can be an improvement in the general implementation of these techniques in other situations. The IoT paradigm would be used by Oom [5], Esteves [6], Lopes [7]. Oom [5] explored the design of a temperature and lighting model for a classroom. It was shown that the common assumption of a lump model for the temperature inside the classroom might hide perceptual differences. It also simulated the room for a fixed number of students and found out that the temperature easily achieves an uncomfortable level for students. Esteves [6] developed an occupation model for the same room as Oom [5], and tested a control strategy for the window blinds and the lights inside the room. It showed an improvement over the normal usage, which varies from class to class. It also took into account the outside weather to know the viability of opening the windows in different weather conditions.

The use of Artificial Neural Networks for temperature prediction and simulation were also used by Lopes [7]. He used the data from various rooms in the Civil Engineering Building of the University to develop several models, and implemented control strategies that improved the thermal comfort of the rooms. The models achieved a very good result, and the control strategy implemented showed marked improvement in the comfort of the room and the energy cost.

1.3 Objectives

This work aimed to model the heat dynamics in a classroom in order to improve the thermal comfort of the students that attend classes. It aimed to use the window blinds system already implemented in the room to regulate the temperature by automating how much heat is transferred by the sunlight. This is particularly important in the Spring and Summer, when the ambient temperature rises to an uncomfortable level, only to be worsened by the influence of sunlight. Given that these rooms don't have active ventilation by way of air conditioning, the only way to actively and remotely influence the temperature of the room is to change the position of the window blinds.

This work will use the sensors setup inside the classroom to know the real-time conditions of the room and to predict the future temperature. It will use meteorological data gathered by the university and presented on its website to know the conditions of the environment. Finally, the Wifi data gathered by the receiver present inside the room will facilitate the access to student presence data. The system will aim to use all the gathered data, transform it for use and develop a model of the classroom. It aims to use only the existing material, in order to find the viability of said systems. The work integrated real time measurement of data from the room and the environment. It also used wifi data provided by the University's systems management webite. It was done in python, an open source programming language, using already implemented toolboxes to do the calculations and validation of the results. It also used

The work will be developed with the use of an open source programming language and toolbox, so that it can be used without the need for paid license. It can also be implemented on small computers like Raspberry Pi, which can then be implemented in the modelled classroom and other rooms similar to it.

1.4 Thesis Outline

This dissertation is divided into 6 chapters: The present chapter will establish the reason for the work, as well as its importance and the work previously done in this area. It will also outline what work will be done and how it will be done. The second chapter will present the data that was gathered by the various sensors, as well as what was done in order to prepare this data for usage. It will include the description of the classroom and the environment which surrounds it. The third chapter will describe the phyical modelling technique that was used. It will explain the preliminary work needed to develop the model and the results that were obtained. The forth chapter will describe the data driven modelling technique used. It will explain how the model works conceptually and how it will work in this specific case. Finally, the fifth chapter will globally evaluate the performance of the various models and recommend future work that can be developed to improve upon this work already done.

Chapter 2

Case Study

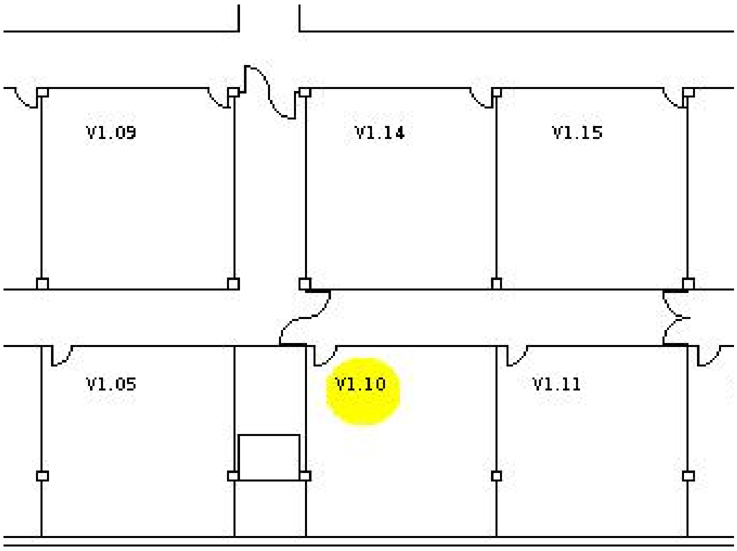
This Chapter will describe the room that is being modelled, as well as all the preprocessing that was necessary to transform the raw data collected into workable data. The room will be fully described in 2.1. The sensor data will be analysed in 2.2.1, with the meteorological data being analysed in 2.2.2.

2.1 Room Description

The classroom is located on the first floor of the Civil Engineering Building. It faces eastward with its window towards a courtyard with high trees, as well as the North Tower building to the East and the Central Building to the South-east. It has two adjacent rooms on the front and back, with a corridor opposite the window as shown in figure 2.1.

(a) Outside view of Room due North

Figure 2.1: Room Location



(b) Inside Location of Room

Figure 2.1: Room Location

The classroom has a maximum capacity of 50 students in normal classes, with 25 being the maximum when an exam is occurring. It has a projector screen in the front close to the window. It has two sliding windows that can only be operated by someone inside the room. There is an automated control system installed that is able to lower the 2 window blinds independently of each other, with an extra 2 positions for hybrid coverage of the window - more light entering from the top portion with the bottom being more opaque to light and vice-versa. The lighting system can also be controlled by the automated system, turning on the lights on the right or left side of the room independently.

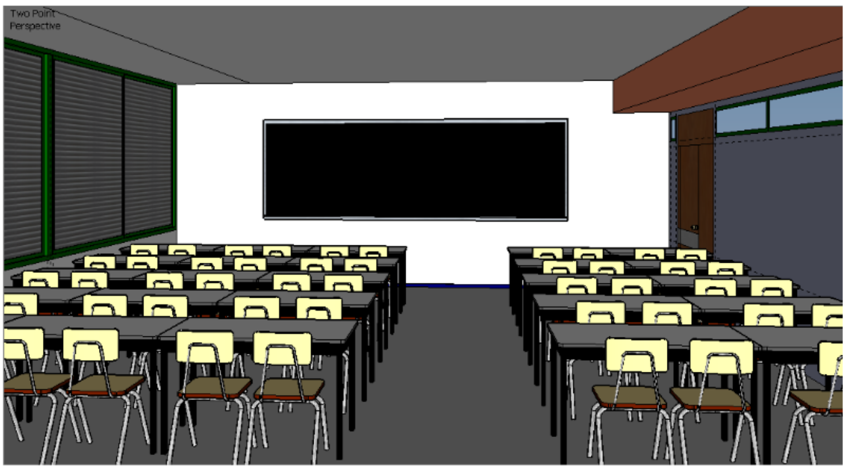


Figure 2.2: Room Configuration. Retrieved from Inês Pestana[5]

2.2 Database Description

2.2.1 Room Sensor Data

The classroom has a sensor which collects various data - temperature, humidity, carbon dioxide concentration, volatile organic compound, lux and unidentified compounds data. The sensor has a sample time of approximately 5 minutes and saves the measured data for various days. The measured data can be accessed starting from the most recent measurement and going backwards in time. Since the log is not permanent and old data will be erased, a script was written to access and save the previous days data every day. This data was aggregated and analysed afterwards.

Day	Time	Timezone	Temperature	Humidity	CO2	VOCS	Lux	PCPM10	PCPM25
15/03/2019	00:00:27	UTC	19.84	43.24	570	285	0	3	2
15/03/2019	00:05:28	UTC	19.81	43.32	577	283	59	3	2
15/03/2019	00:10:27	UTC	19.78	43.27	557	284	55	3	2

Figure 2.3: Example of data collected in 15 minutes

In figure 2.3 the Temperature is in ^oC, the CO2, Volatile Organic Compounds (VOCS) and PCPM10 and PCPM25 (other compounds) are presented in parts per million (ppm); the humidity in $\%$; and the Lux in Lux.

Wifi Data

The room has a Wifi emitter that logs the amount of users that are connected to it. However, the students in the other rooms will also connect to it, masking the real amount of students inside the modelled room. Based on attendance patterns it was decided to hard cap the data at 45 students, 10% less than the maximum of 50 students. Lower values were taken as indicating the real amount of students inside the room. This approximation introduces some error due to students outside the room connecting to the Wifi. The other attendance data available is based on students enrolled in that specific class. This data might be used as a first estimate of attendance but knowing that there is nothing to guarantee that a specific student attends the class they enrolled in, it might have a bigger error compared to the Wifi data.

2.2.2 Meteorological Data

The University has a meteorological station installed in the South Tower Building. The measured data can be accessed with the internet in [8]. It measures ambient and sensible temperature - in ^oC, as well as solar radiation - in W/m^2, relative humidity, precipitation - in mm/hr and barometric pressure - in $mbar$, with a sampling time of approximately 5 minutes. It can measure wind direction and speed, although there is no available wind speed data, only direction.

From the data itself it is not clear which radiation component is being measured so it was tested against two clear-sky models - Haurwitz [9] and Simplified Solis [10] - to see if it was Global Horizontal

Irradiation (GHI) - measured on a horizontal sensor, Direct Normal Irradiation (DNI) - only the direct solar component of the radiation, or Diffuse Horizontal Irradiation - only the diffuse component of the radiation. Since the normal pattern of radiation is similar to a normal distribution on a cloudless day, the first day of August was chosen for the comparison, as shown in figure 2.4.

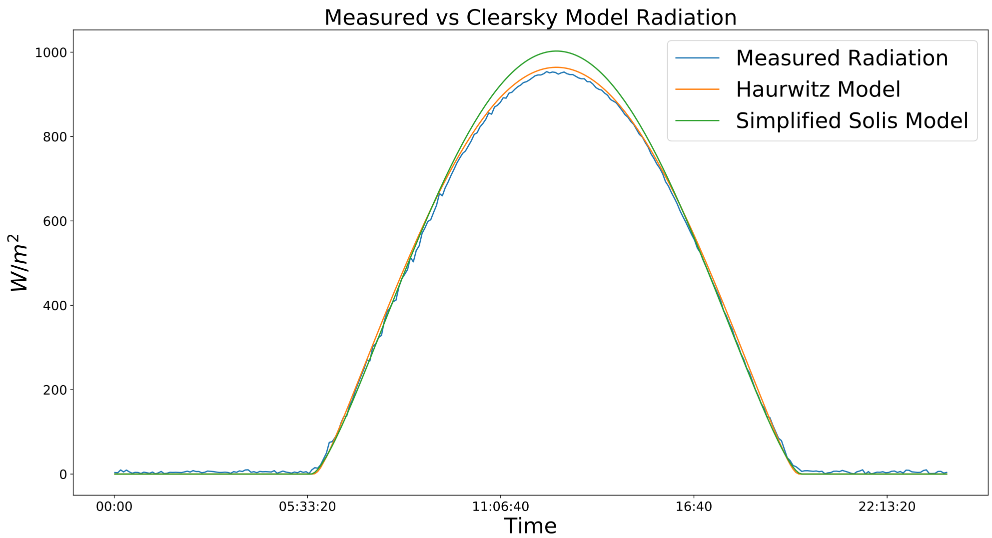


Figure 2.4: Comparison between the measured Radiation and Predicted GHI by Clear-sky models

As it can be seen on figure 2.4, the measured data closely aligns with the prediction made by the Haurwitz model [9], so it can be assumed that the radiation being measured is the GHI. In order to use this data in the models it needs to be decoupled into DHI and DNI, which affect the room differently during the day. The DNI will only affect the room during the morning until around midday due to the rooms orientation, as described in 2.1, while the DHI will affect the room during the whole day. Although the high trees and buildings on the outside will obstruct the DNI and affect the DHI, this effect is hard to quantify without a radiation sensor outside the room and will not be taken into account when developing the models in the following chapters.

In order to obtain the values of DNI and DHI, the ERBS Model [11] implemented in pvlib [12] was used. It takes into account the measured GHI and the solar zenith, as well as the date in which the measurements were made. Another model, DIRINDEX [13], was explored, but there were very high values of radiation in the first and last measurement - it only measures values when there is sunlight. The comparison is shown in figure 2.5.

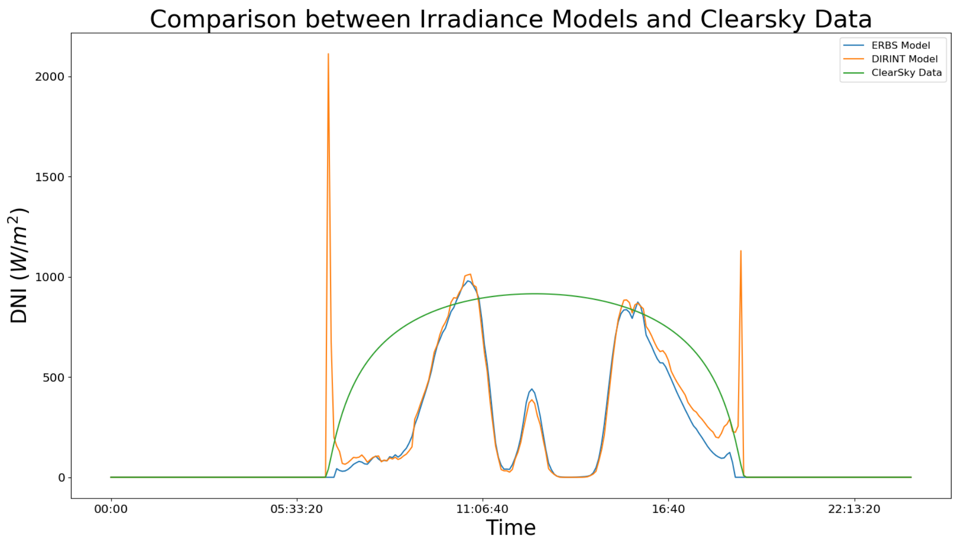


Figure 2.5: Comparison Between DIRINDEX and ERBS DNI Values

The final value of DNI is obtained after taking into account the direction that the window faces. This value was calculated using the RC Building Simulator toolbox [14], which takes into account the geographical coordinates of the room, as well as the orientation of the window.

2.2.3 Data Preprocessing

All the data that was collected contained impurities - misalignment between time series, missing data, duplicate measurements and some degree of noise. In order to fix these impurities, several techniques were used. Firstly, the duplicate measurements were removed, in order to get only 1 measurement for a specific time - all sets of data had this problem. Secondly, the missing data was imputed by way of a zero order hold. Thirdly, the data was passed through a Savitsky-Golay filter [15] in order to smooth the measurements. This type of filter has been widely used since its invention in signal and data analysis. Because the room temperature data had more measurements than the rest of the data for the same time span, it was put through a spline with the same polynomial degree of the Savitsky-golay filter - so that no more smoothing was done, and compressed to the desired size. The difference in length was small in the first place, occurring sporadically and only with 1 or 2 more measurements than the theoretical maximum for one day.

Chapter 3

Physical Model

This Chapter will describe the modelling process that was used to develop the grey-box model. The physical phenomenons that are important to the development of this model will be described in 3.1. The modelling process and considerations will be discussed in 3.2, with the full results of the modelling being presented in 3.3.

3.1 Grey Box Modelling

There are three types of models that can be developed when trying to model physical phenomenons - White Box, Grey Box and Black Box models. White Box models are characterized by being fully defined by theoretical equations and quantities, making them the easiest to explain and perhaps comprehend, although they can become very complex very easily - in this specific case there are multiple factors that can influence the thermal behaviour of the room, with Computational Fluid Dynamics (CFD) being very hard to implement and validate with the existing data. Grey box models are developed taking into account the theoretical equations that describe the dynamics of the model, with the constants that characterize de behaviour of the system being derived from real data that has been collected. This type of model is explainable and reduces the necessary complexity of the model by making simplifications to the phenomenons present, making them easier to develop and test. Finally, black box models only take into account the existing data and are very difficult to explain due to the nature of the modelling process - the relationship found between the various phenomenons is not based on any explicit physical notion. A very appropriate example of this type of model are Artificial Neural Networks, which can successfully model a process and achieve very good results, but are completely opaque when trying to understand how they work [16].

The model that is going to be developed is going to be grey-box model because the complexity of the heat dynamics is very high when considering multiple heat sources - students inside the room - inside a fluid, as well as the heat exchange between the room and the corridor or the outside environment.

The thermal behaviour of the room can be described by the three ways of heat transfer - conduction, convection and radiation. Each of these has a very important impact in the thermal behaviour of the room, and each need to be considered individually when trying to model their impact in the room.

3.1.1 Heat Conduction

The simplest way that heat can be transferred is by conduction. Given a temperature gradient in a stationary medium heat will flow from the hottest point to the coldest. It can be described by Fourier's Law which is given by equation 3.1, where $\boldsymbol{q}''$ is the heat flux, k is the thermal conductivity of the medium and $T(x, y, z)$ is the Temperature field in the medium.

$$\boldsymbol{q}'' = -k\nabla T = -k\left(\boldsymbol{i}\frac{\partial T}{\partial x} + \boldsymbol{j}\frac{\partial T}{\partial y} + \boldsymbol{k}\frac{\partial T}{\partial z}\right) \tag{3.1}$$

This equation will be applied to the various walls that are present in the room, as well as the window. Because the wall that is separating the outside environment from the room will be considered together with the window and with only the width as relevant dimension, the equation will assume a general form similar to Newton's Law of cooling given by

$$q_x \equiv UA\Delta T \tag{3.2}$$

which can be applied to any composite structure in general. This equation simplifies the model, calculating a composite heat transfer instead of 2 simple ones. The result will mathematically be the same, but the direct influence of the different members will be lost. This simplification can reduce the amount of parameters that need to be calculated.

3.1.2 Convection

While conduction is prevalent and very important when considering a stationary medium, convection becomes very important in mediums where there is mass movement with a temperature gradient. This movement can be caused by the higher or lower temperature of the fluid particles - free convection, or by an external source, with the objective of facilitating the transfer of heat from the hotter to the colder fluid - forced convection. These phenomenons can be described by the equation 3.3 with the h representing the free/forced convection coefficient

$$q_s = hA\left(T_s - T_\infty\right) \tag{3.3}$$

3.1.3 Radiation

Radiation is a very complex heat transfer phenomenon, taking into account the wave length of the radiation, the medium through which it is being transmitted, the scattering due to that medium and the physical characteristics of the objects that interact with it. The simplest way to describe this phenomenon is with the equation

$$q_{\mathrm{rad}} = \varepsilon\sigma A\left(T_s^4 - T_{\mathrm{sur}}^4\right) \tag{3.4}$$

which adapts the Steffan Boltzman law for exchange of radiation between grey bodies, ignoring all interactions between the radiation and the medium except for the temperature of the emitting surfaces. In this specific case, the radiation being considered is the solar radiation that irradiates earth during the day. This radiation can be divided into two components - direct radiation and diffuse radiation as explained in 2.2.2. Due to the low value of heat transmitted by radiation by the air in the room itself, because its temperature is very low, the only heat transfer by radiation that is going to be considered will be solar radiation.

3.2 Model Development

One of the simplest and easiest to understand techniques of modelling used when modelling thermal systems is the usage of Resistor-Capacitor equivalent circuits [17, p. 98], due to a possible analogy between electrical components and thermals components, shown in figure 3.1, when considering a one-dimensional approach to modelling. Using this technique, one is able to represent most of the heat transfer phenomenons as simple thermal balance equations such as

$$q = UA\left(T_s - T_\infty\right) \tag{3.5}$$

that can be put together in order to create a circuit that represents the thermal evolution of the elements considered. Since there is only one measure of temperature inside the room, it is necessary to consider a homogeneous medium inside the room, with its temperature rising or lowering uniformly in all directions. This simplification reduces the precision of the model because local temperature gradients are ignored. Nonetheless, without more sensors to measure the temperature gradients between various locations inside the room this is the only viable way to model the system.

The following are the simplifications and assumptions that were taken into account when modelling the system.

(1) - The room temperature was considered to be uniform in the whole room.

(2) - Only the solar radiation was considered when dealing with radiative energy transfer. The values used were the ones obtained in 2.2.

(3) - The students were considered as heat sources with constant power output.

(4) - The thermal properties were considered to be constant.

(5) - Convection was not considered due to the unavailability of data to quantify its influence on the thermal evolution of the system.

(6) - Passive Infiltration was considered initially but the estimated values were very small.

(7) - Since there is no sensor to measure the position of the window blinds they were considered to be open at all times.

Table 3.1: Resistor-Capacitor Circuit Equivalent Components

Parameter	**Eletrical**	**Thermal**
Potential	V	T
Current	I	$\dot{Q}$
Resitance	R	R_t
Capacitance	C	C_t

Taking these simplifications into account, two models were developed. The unknown parameters in the models were calculated using the Continuous Time Stochastic Modelling for R (CTSM-R) toolbox [18]. This toolbox was developed at the Danish Techinical University (DTU) to estimate parameters in continuos time stochastic state space models. It uses maximum likelihood estimator and an Extended Kalman Filter to predict one step ahead values. It has been used successfully in [3] to estimate physical parameters in similar problems. The two examples that are given by the DTU team are related to thermal modelling of buildings - the first being the heat dynamics of a wall [19] and the second the heat dynamics of the a building [20]. Although the sampling time used in the previous examples is 15 minutes, given that the available data has a smaller sample time, it was chosen to keep the sampling time at 5 minutes.

The first model only takes into account the energy balance of the room, and is described by the stochastic differential state-space model 3.6, represented schematically in figure 3.1.

$$C_i \frac{dT_i}{dt} = \frac{1}{R_{ds}} \Phi_{ds} u_1 + \frac{1}{R_{dh}} \Phi_{dh} u_2 + \frac{1}{R_{ia}} (T_a - T_i) + \frac{1}{R_{ic}} (T_c - T_i) + \Phi_{students} + \sigma_i \frac{dw_i}{dt} \tag{3.6}$$

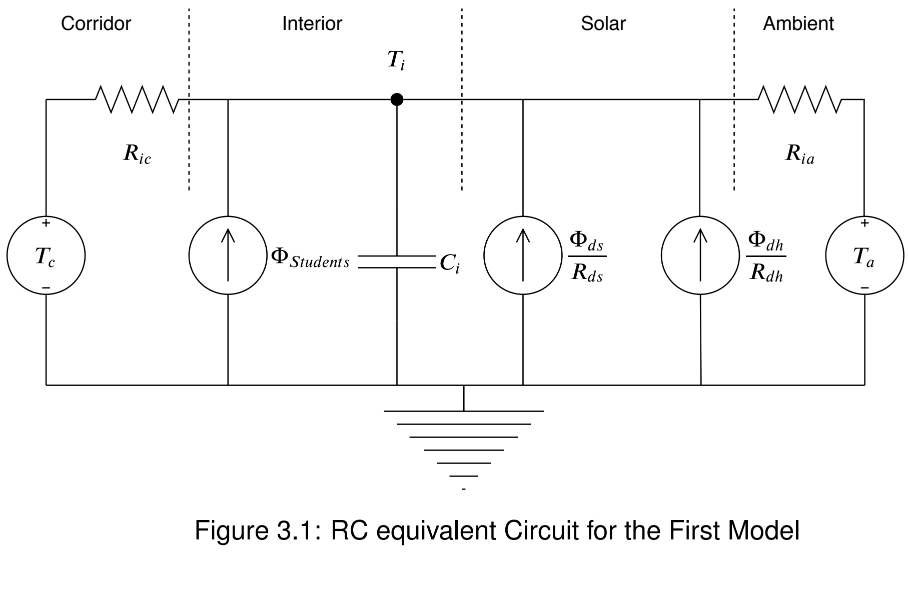


Figure 3.1: RC equivalent Circuit for the First Model

In the equation, w_i represents the standard Wiener process, with σ_i representing the diffusion term for the process state; T_i is the state variable, the one that is to be predicted and controlled; u_1 and u_2 are the control variables, which change how much the radiation heats the room; Φ_{ds} is the DNI and Φ_{dh} is the DHI. The second model takes into account both the energy balance in the room and the energy balance of the corridor. By adding another differential equation, the unknown corridor temperature is modelled instead of being a fixed value, which is not appropriate due to the change in daily temperature. The toolbox only takes into account the variable that is being measured when estimating parameters for various equations, so there is no need to add measurements of the corridor temperature. It is described by the stochastic differential state-space model 3.7, represented schematically in figure 3.2.

$$C_i \frac{dT_i}{dt} = \frac{1}{R_{ds}} \Phi_{ds} u_1 + \frac{1}{R_{dh}} \Phi_{dh} u_2 + \frac{1}{R_{ia}} (T_a - T_i) + \frac{1}{R_{ic}} (T_c - T_i) + \Phi_{students} + \sigma_i \frac{dw_i}{dt} \tag{3.7a}$$

$$C_c \frac{dT_c}{dt} = \frac{1}{R_{ic}} (T_i - T_c) + \frac{1}{R_{ca}} (T_a - T_c) + \sigma_c \frac{dw_c}{dt} \tag{3.7b}$$

Similarly to the first model, σ_i and σ_c are the diffusion terms for the process' states, with w_i and w_c representing standard Wiener processes. The states are represented by T_i and T_c, while the control variables are u_1 and u_2; Φ_{ds} is the DNI and Φ_{dh} is the DHI.

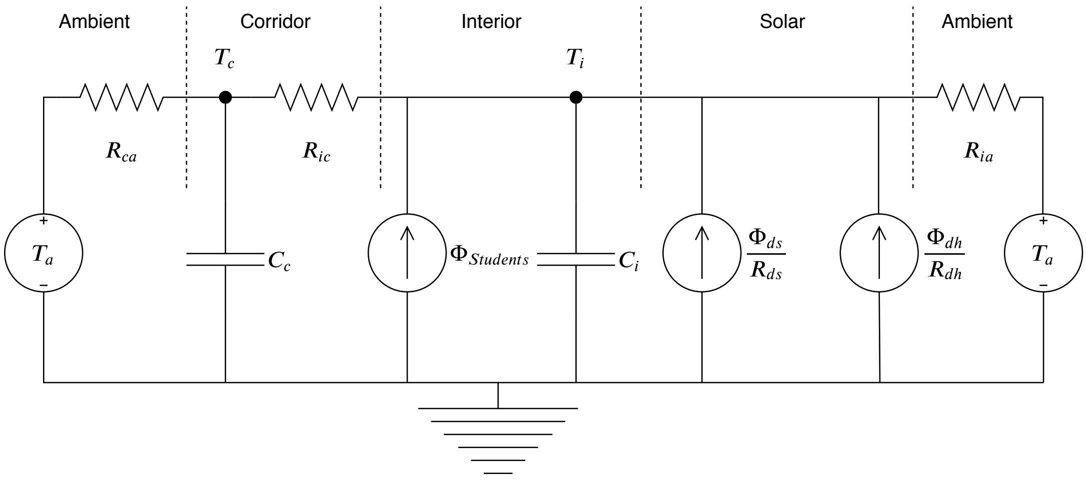


Figure 3.2: RC equivalent Circuit for the Second Model

3.3 Results

Two sets of data were available to be used. The first set was composed by daily data from the 1st of April to de 22nd of June, while the second set was comprised by data starting in the 11th until the 31st of August. The two sets are different due to the absence of students during the month of August, when the students are on holiday. For the Holidays, data from the 11th to the 21st was used to find the model parameters and data from the 22nd to the 29th was used to validate the model. For the Classes period, data from the month of April was used to find the parameters and data from the 1st to the 7th of May was used to validate the model.

3.3.1 Results during the Holidays

According to the class schedule and to the Wifi data there are no students in the room, so the models will reproduce the baseline behaviour of the heat dynamics of the room. Three working behaviours were considered in order to quantify the quality of the model that was obtained - 1-Step Prediction, where each time step the value is corrected to the measured value; Daytime Simulation, where the model will only simulate the behaviour between 8 am and 8 pm, following the measured data during the other half of the day; and Full Simulation, where the model will simulated the whole week only taking into account the initial values. The performance of the model is calculated using the Root Mean Squared Error (RMSE) and the Variance Accounted For (VAF)

1 State Model

The parameters that best represent the training data in the 1-State Model - the room temperature - are presented in table 3.2, with the associated simulations in figure 3.3. It can be seen on the figure 3.3a that the 1 step prediction doesn't deviate too much from the measured data, with the biggest error being close to $0.25°C$. It is clear that in the prediction error increases during the day, when the solar radiation first hits the room, and reduces in magnitude during the rest of the day and night. This shows that there are dynamics which affect the model that are not being modelled. Further parametrization of the model might be necessary in order to reduce the error and decouple it from the solar radiation incidence. Furthermore, changing the window blinds position in order to reduce the influence of solar radiation in the prediction results in a slightly higher error, but might not be representing the real change that would happen in the room.

Regarding the full simulation - figure 3.3b, which would be the one used to represent the room if a control scheme were to be implemented, it can be seen that the model follows the general dynamics of the room, missing some faster dynamics during the day. This might be caused by changes in the window blinds position or opening of windows, both of which affect the heat transfer to and from the room. It also shows a variable offset, higher in the first few days of the simulation and smaller in the latter ones. The highest difference in temperature is $4°C$, with the lowest being slightly above $0°C$. However, contrary to the 1-Step Prediction, changing the window blinds position affects the room temperature by reducing the temperature between $1°C$ and $2°C$ - compared to the simulation. Since this simulation is not being corrected by real values, the divergence could be caused the compounding influence of the radiation on the room temperature. After diverging in the first morning, it never recovers for the rest of the validation set.

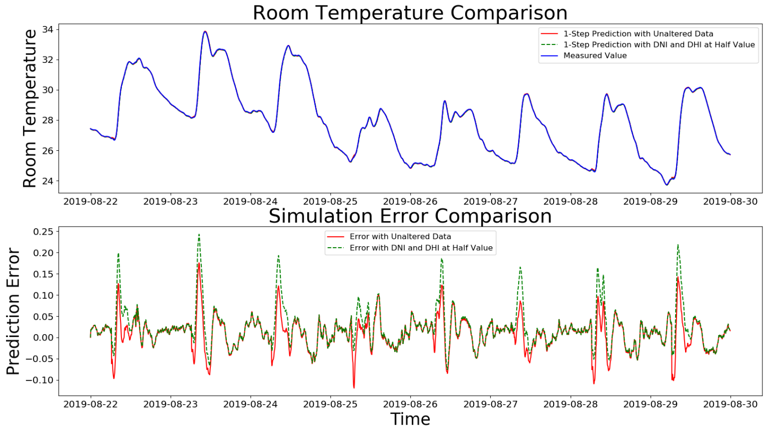
Finally, the daytime simulation - figure 3.3c, which would represent the real implementation of the system, shows values of error compared in the same period of the day compared to figure 3.3b, with the difference being the error during nightime being 0 by design. It shows an improvement of $1°C$ of error in the simulation with the full solar radiation.

Table 3.2: Estimated Parameter Values for the First Model

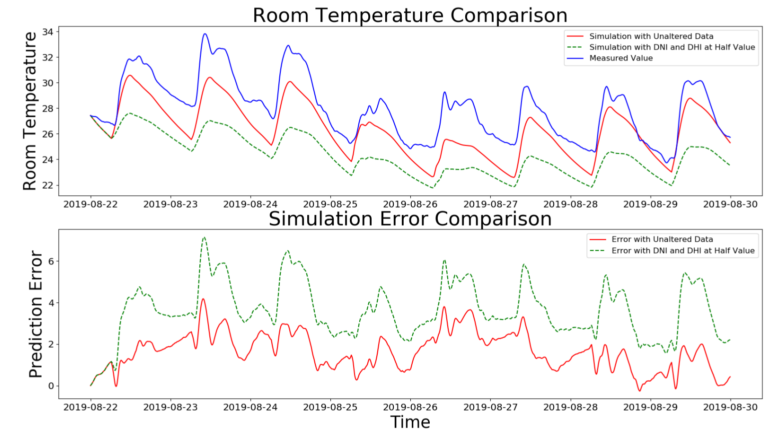
Parameter	Value	Unit	Description
T_c	21.8	$°C$	Temperature of the Corridor
C_i	12817	$J/°C$	Thermal Capacitance of the room
R_{ds}	0.03	$1/m^2$	Window Resistance to Direct Solar Radiation
R_{dh}	0.069	$1/m^2$	Window Resistance to Diffuse Horizontal Radiation
R_{ia}	0.003	$°C/W$	Thermal Resistance between the Room and the Atmosphere
R_{ic}	0.001	$°C/W$	Thermal Resistance between the Room and the Corridor

Table 3.3: First Model Performance in Various Simulation Conditions

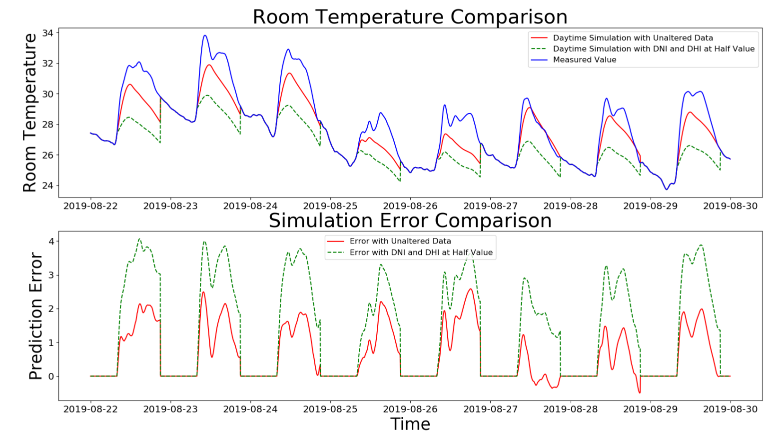
Simulation Condition	**RMSE**	**VAF**
1-Step prediction	0.03	0.99
Full Simulation	1.88	0.85
Daytime Simulation	0.99	0.88



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 3.3: 1 State Model Validation

2 State Model

One suggestion presented by the creators of the CTSM-R tool is the inclusion of another state, even if there are no measurements of the real values. As such, after consideration and testing different model configurations, it was decided that the corridor temperature could be represented by another state in order to try to improve the overall model performance.

Overall the results are very similar to the previous model, with improvements in some performance measurements but not others - tables 3.3 and 3.5. It is important to note that the thermal capacitance of the room changes drastically between the models, from 12817 to 8742, while the other common parameters have very close values. This puts into question the value obtained because such a difference should not exist if the model were being accurately estimated. Furthermore, the thermal capacitance of air is close to 12000$J/^oC$.

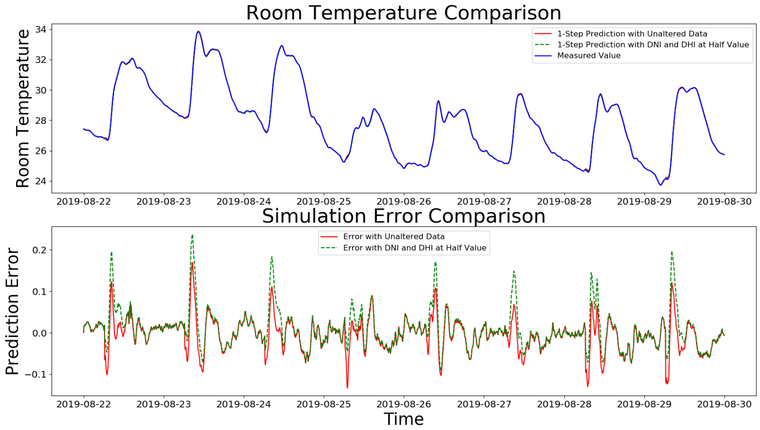
Regarding the working conditions, the 1-Step prediction shows error similar to the 1 State model, with the same overall behaviour. However, the Daytime simulation overshoots the value of the room temperature in more days and with higher error compared to the 1 State Model. The error ranges from -2^oC to 4^oC, which is not good. Finally, the free Simulation captures the overall behaviour of the room, but starts overshooting the room temperature in the last 3 days.

Table 3.4: Estimated Parameter Values for the Second Model

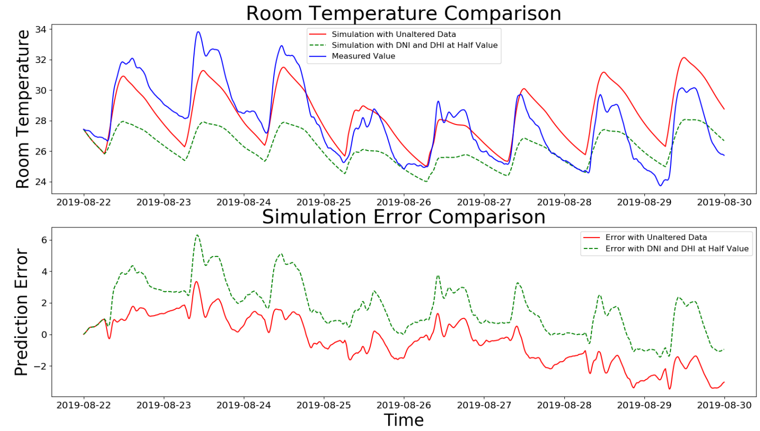
Parameter	Value	Unit	Description
C_i	8742	$J/^oC$	Thermal Capacitance of the room
C_c	245310	$J/^oC$	Thermal Capacitance of the Corridor
R_{ds}	0.044088	$1/m^2$	Window Resistance to Direct Solar Radiation
R_{dh}	0.081089	$1/m^2$	Window Resistance to Diffuse Horizontal Radiation
R_{ia}	0.0047658	$^oC/W$	Thermal Resistance between the Room and the Atmosphere
R_{ic}	0.0022	$^oC/W$	Thermal Resistance between the Room and the Corridor
R_{ca}	0.42757	$^oC/W$	Thermal Resistance between the Corridor and the Atmosphere

Table 3.5: Second Model Performance in Various Simulation Conditions

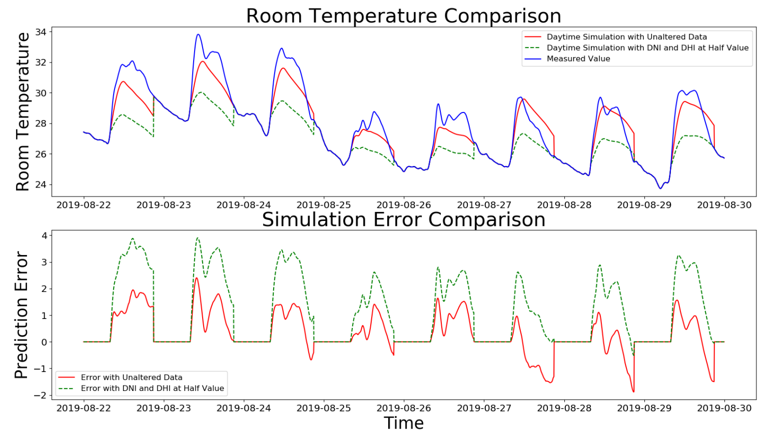
Simulation Condition	RMSE	VAF
1-Step prediction	0.04	0.99
Full Simulation	1.54	0.59
Daytime Simulation	0.78	0.9



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 3.4: 2 State Model Validation

3.3.2 Results during Classes

The critical time for usage of these models is during classes. As such, the same model structure tested above will be used to try and model the dynamics with the additional heat provided by the students. Similarly to the previous results, the models will be evaluated in the same threee working behavious - 1-Step Prediction, Daytime Simulation and Full Simulation.

1 State Model

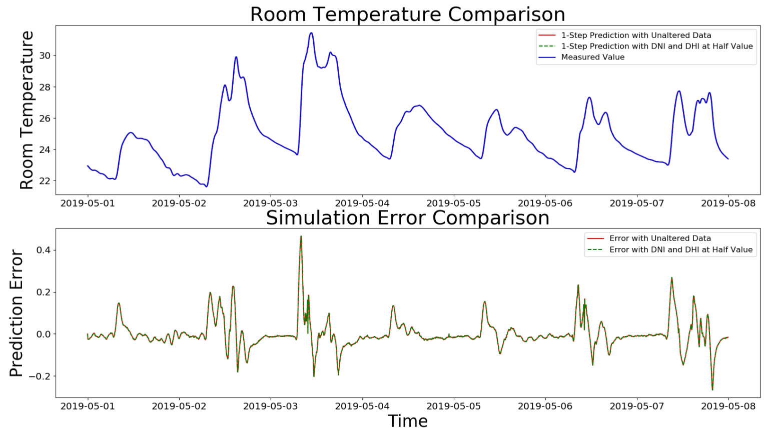
The parameters that characterize this model are presented in table 3.6, with the associated simulations in figure 3.5. Regarding the 1 Step Prediction, the model shows a variable error during the day when classes are being held in the room, while predicting the behaviour outside of these moments with low error. This is explained by the change in window blinds position, window and/or door being open, which can greatly affect the room temperature when students are present. Like the holiday model, further parametrization is needed in order to reduce the prediction error and improve the model. The full simulation behaviour is where this model fails completely, with the error in temperature being as high as 12.5^oC, which is an unacceptable value. Curiously, when changing the position of the window blinds the temperature more closely resembles the measured values, with a lower overall error, which might suggest that the window blinds were indeed not fully opened in this week, as was considered initially. The results are not improved in the Daytime Simulation, where the model manages to overshoot the room temperature during some days and undershoot in others, with the error ranging from -4^oC to 4^oC.

Table 3.6: Estimated Parameter Values for the First Model

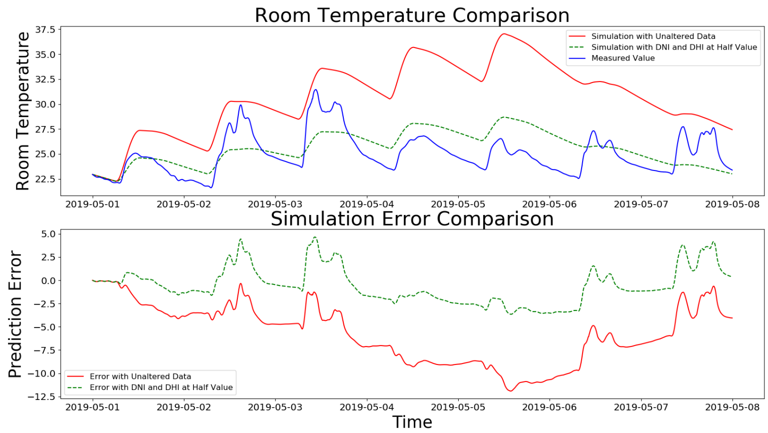
Parameter	Value	Unit	Description
T_c	21.8	^oC	Temperature of the Corridor
C_i	45369746	$J/^oC$	Thermal Capacitance of the room
R_{ds}	$1.033132 * 10^{-5}$	$1/m^2$	Window Resistance to Direct Solar Radiation
R_{dh}	$1.782774 * 10^{-5}$	$1/m^2$	Window Resistance to Diffuse Horizontal Radiation
R_{ia}	$2.04207 * 10^{-6}$	$^oC/W$	Thermal Resistance between the Room and the Atmosphere
R_{ic}	$4.134099 * 10^{-6}$	$^oC/W$	Thermal Resistance between the Room and the Corridor

Table 3.7: First Model Performance in Various Simulation Conditions

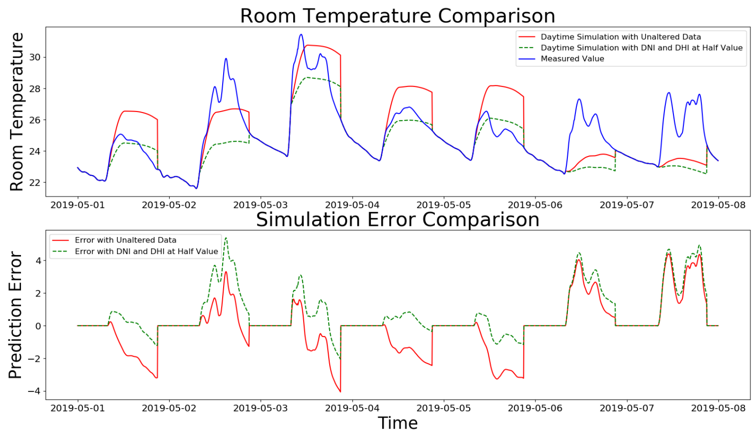
Simulation Condition	**RMSE**	**VAF**
1-Step prediction	0.057	0.99
Full Simulation	6.54	-1.54
Daytime Simulation	1.612	0.34



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 3.5: 1 State Model Validation

2 State Model

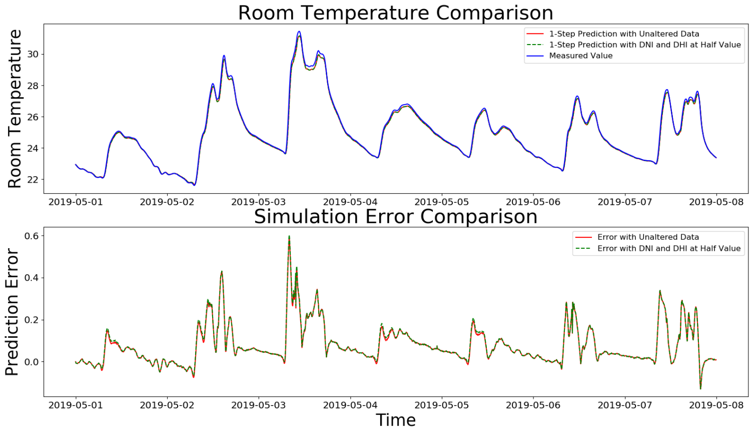
In order to improve the results of the model, the corridor temperature was added as a variable value, similarly to the model for the holidays. The parameters that were found are presented in table 3.8, with the respective simulations in figure 3.6. Considering the 1 Step Prediction, in figure 3.6a, it can be seen that the prediction error is higher during classes, and varies rapidly in these situations. The maximum error is $0.6°C$ but is not prevalent, with the error staying between $0.2°C$ and $0°C$ most of the time. Regarding the Full Simulation, the room temperature barely changes, staying between $22°C$ and $24°C$, which is a very poor result. Changing the position of the window blinds barely changes the results as well, as the parameters that affect the radiation values reduce the value of the DNI and DHI too much. It is effectively blocking most of the radiation heat that affects the room. Finally, the Daytime Simulation shows that the Room is not losing more heat to the corridor and to the outside atmosphere than gaining from radiation, with the room temperature starting to lower as soon as it starts the simulation every day.

Table 3.8: Estimated Parameter Values for the Second Model

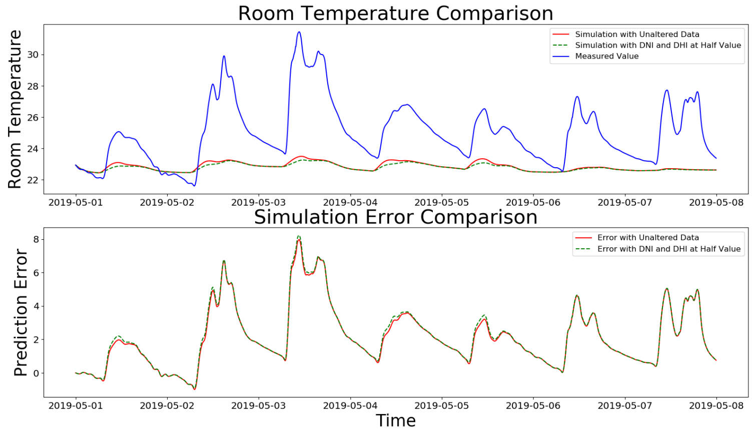
Parameter	Value	Unit	Description
C_i	233056.1	$J/°C$	Thermal Capacitance of the room
C_c	273383536	$J/°C$	Thermal Capacitance of the Corridor
R_{ds}	$8.758825 * 10^{-3}$	$1/m^2$	Window Resistance to Direct Solar Radiation
R_{dh}	0.02343304	$1/m^2$	Window Resistance to Diffuse Horizontal Radiation
R_{ia}	$1.533843 * 10^{-4}$	$°C/W$	Thermal Resistance between the Room and the Atmosphere
R_{ic}	$1.007839 * 10^{-4}$	$°C/W$	Thermal Resistance between the Room and the Corridor
R_{ca}	$3.632536 * 10^{-2}$	$°C/W$	Thermal Resistance between the Corridor and the Atmosphere

Table 3.9: Second Model Performance in Various Simulation Conditions

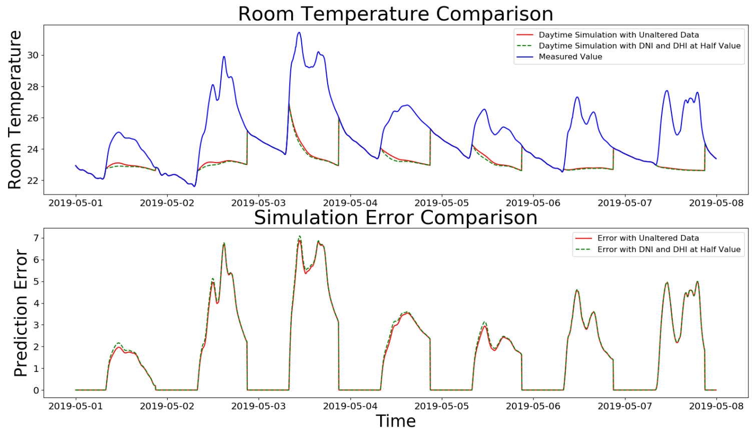
Simulation Condition	**RMSE**	**VAF**
1-Step prediction	0.12	0.99
Full Simulation	2.79	0.19
Daytime Simulation	2.54	0.07



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 3.6: 2 State Model Validation

Chapter 4

Data Driven Model

This chapter will describe the modelling process that was used to develop the black-box models. The theory behind the workings of the model will be described in 4.1. The development of the models will be described in 4.2, with the full results being presented in 4.3.

4.1 Neural Network Modelling

The chosen type of black box model was an Artificial Neural Network (ANN). This type of model is characterized by high flexibility and good usability. It takes any number of data as inputs and outputs numerical data - regression type ANN - or categorical data - classification type ANN. It uses a mathematical construct known as an artificial neuron, in figure 4.1, - a function that takes values as inputs, performs calculations with the inputs and outputs the resulting value. Neurons can be grouped in layers, which themselves can be chained together in order to improve the result, in figure 4.2. ANN models are usually trained with labelled data - either the value that is supposed to be the result of a calculation or a categorical data point associated with those inputs: Image classification and Temperature forecasting are known uses of both types of models. The training process works by updating the weights associated with each neuron with each passage of data from input to output - an optimization algorithm is used, together with backpropagation of the error, to change the weights in order to reduce the overall error - difference between the output of the network and the target value. If given enough data, time and number of neurons, ANN can approximate any continuous function, known the universal approximation theorem [21]. The complexity of the ANN is increased given that there are many types of functions that can be applied in the neurons, several different optimization algorithms and various hyperparameters that characterize the optimization and learning process.

Regression type ANN, in figure 4.3, can also be further specialized to perform autoregressive tasks. If given the its past outputs as future inputs, it can learn the time dependent pattern of the data and be used to predict several steps forward in time. It can also be given different data as extra inputs in order to improve the prediction and the robustness of the regressive mechanism.

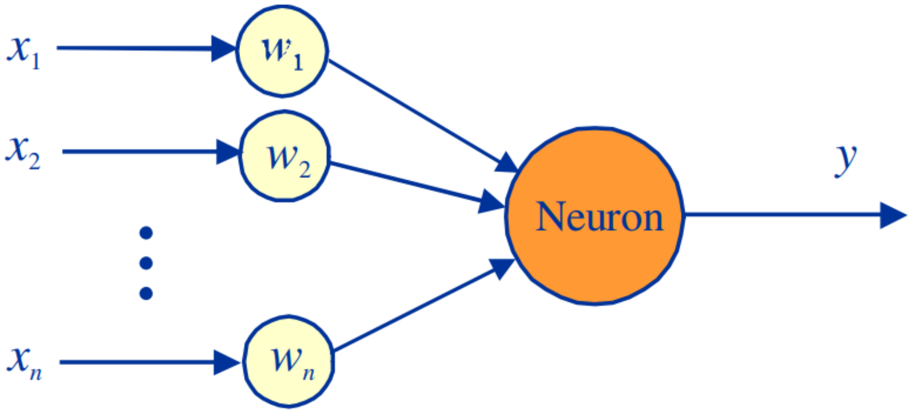


Figure 4.1: Generic Neuron, retrieved from Vieira and Sousa [22]

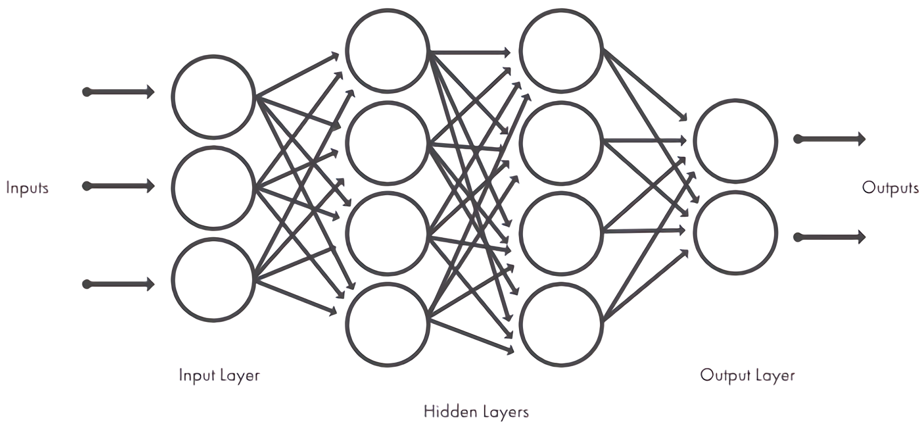


Figure 4.2: Generic ANN, retrieved from Mathworks [23]

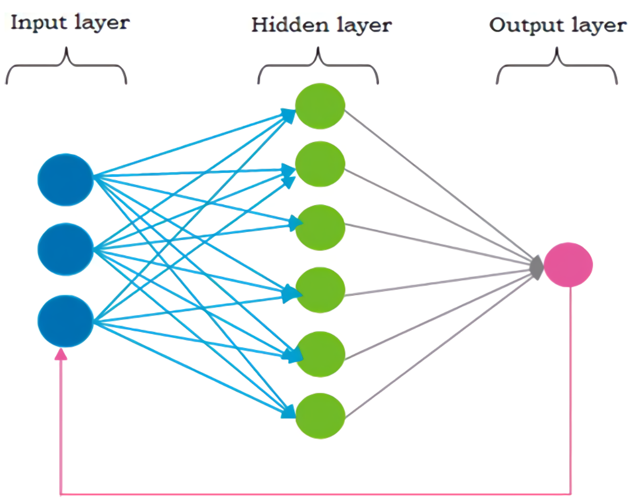


Figure 4.3: Generic NARX, retrieved from Sansa and Bellaaj [24]

4.2 Model Development

As stated in section 4.1, with enough data the ANN model can approximate any continuous function. However, not all available data is relevant to the specific task, with some data values being extremely important to the model and others having very little influence in the desired output. As such, the first step taken was to analyse the data available to understand how each variable related with itself and each other. There are several methods that can provide an insight into how the many different data variables relate with each other and with themselves, such as autocorrelation - indicates how past values of a variable influence the future ones, partial autocorrelation - which differs from autocorrelation because it analyses each past timestep ignoring the influence of the other timesteps, and Pearson correlation - indicates linear correlation between variables.

Due to the dynamic nature of a thermal system - past values affect the future values, partial and "full" autocorrelation were used to find out which past values are important.

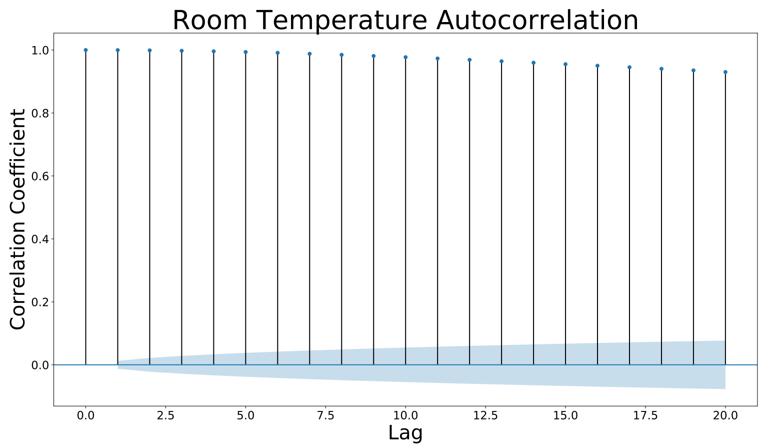


Figure 4.4: Room Temperature Autocorrelation, with lag step equal to 5 minutes

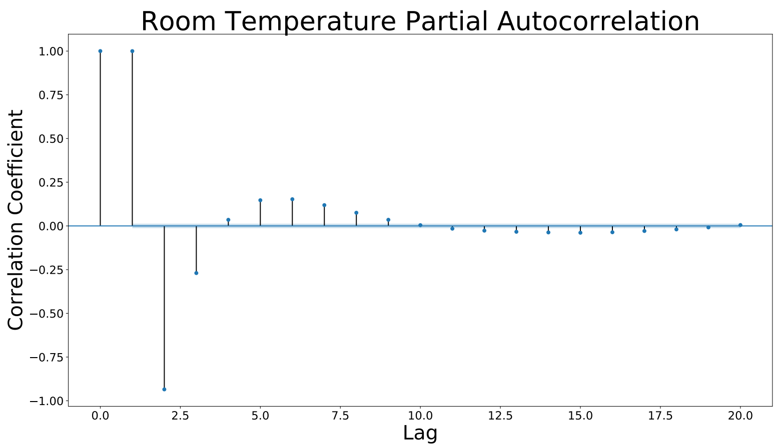


Figure 4.5: Room Temperature Partial Autocorrelation

As we can see in figure 4.4, the thermal system has very high correlation with its past values, a characteristic of autoregressive systems. It can also be seen in figure 4.5 that only the first two past values have a very strong correlation when eliminating the influence of other past values, with the third lagged value having weak correlation. While most thermal systems can be described by first order autoregressive models, this particular system can be described by a second order autoregressive model - there is a sharp drop in correlation coefficient on the third lagged value.

The Pearson correlation, figure 4.6 quantifies the linear correlation between the data, and it can be seen that the correlation between the room temperature and the two components of Radiation is low - 0.27 for DHI and 0.13 for DNI. This can be counter-intuitive because solar radiation is a very important factor in modelling heat dynamics in buildings. Looking at how the data is distributed, in figure 4.7b and 4.7c, it can be seen that the very high frequency of values close to 0 - during night time and, in the case of DNI, when the solar azimuth is also less than 4.8**º South**.

The most important data that is used is the number of students inside the room. It can be seen that the correlation is 0.36, which means that having students inside the room is more correlated with a higher temperature inside the room than the radiation components. Nonetheless, the correlation is, like the DNI and DHI, influence by the high number of measurements with no students inside the room, as seen in figure 4.7d, which reduces the correlation coefficient.

Neural network weights can be hard to constraint, and using more data that can't be modified with a very high correlation with the target output can cause the network to adapt the weights to give more importance to these values instead of the ones that are going to be modified by control actions. It was decided to only use the first lagged value of room temperature. It keeps the autoregressive nature of the system, but leaves room for the neural network to assign more importance to the DNI, DHI and Student data. If more lagged values were used, given that those have higher correlation with the data than the radiation components and student occupation, as we can see by comparing the values in figure 4.6 with the values in figure 4.5, the network would very likely reduce the importance of the radiation components and student occupation and ultimately devolve into an almost pure autoregressive model.

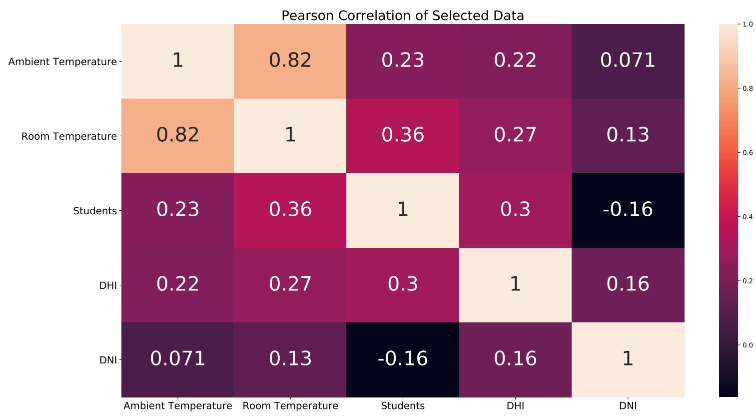
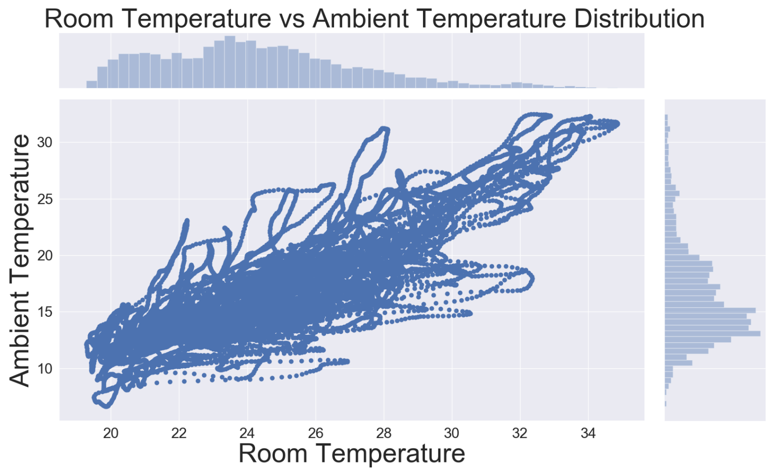


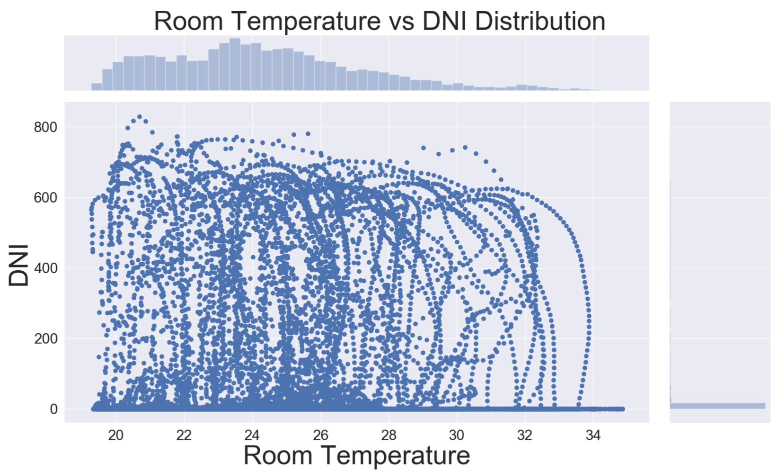
Figure 4.6: Pearson Correlation Coefficients of Available Data

Finally, neural networks can give poor results if the data is not normalized, with values with different scales being used as is. In order to improve the performance, reduce the complexity of the calculations



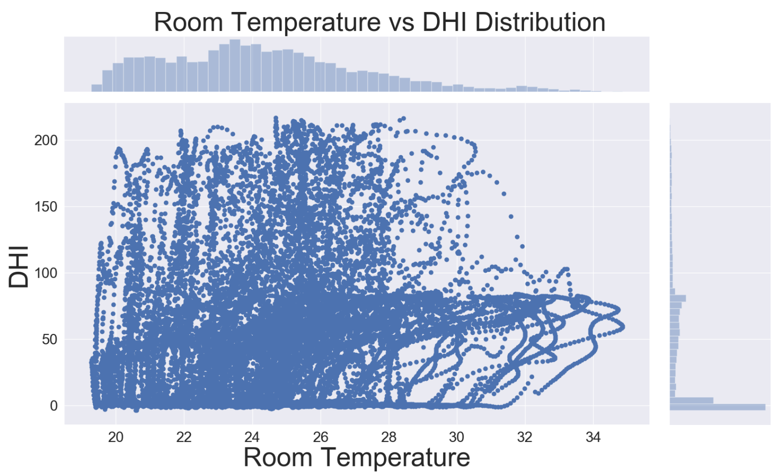
(a) Ambient Data Histogram

Figure 4.7: Data Distribution



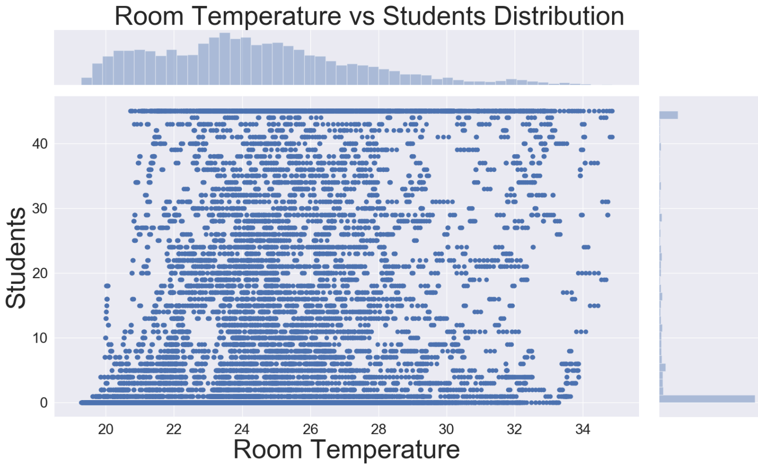
(b) DNI Data Histogram

Figure 4.7: Data Distribution



(c) DHI Data Histogram

Figure 4.7: Data Distribution



(d) Student Data Histogram

Figure 4.7: Data Distribution

and give the same numerical importance to all variables, all the values were normalized and scaled into a 0 to 1 range, independently of each other, preserving the distribution.

4.3 Results

The network architecture was chosen by cross validating with an ordered split of the available data - 16732 training samples and 7171 testing samples. The parameters that were selected are presented in the table 4.1. The solver Adam is a gradient-based optimizer created by Kingma and Ba[25] and widely used in machine learning problems. The Activation function Rectified Linear Unit (ReLU) is describe by the mathematical relation 4.1, which outputs the maximum value between 0 and the neuron output. There are other activation functions, but this one avoids the problem of vanishing gradient - gradient becomes so small that the network stops learning in the initial layers [26].

$$f(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{if } x \geq 0 \end{cases} \tag{4.1}$$

Table 4.1: Chosen Hyperparameters

Number Hidden Layers	2
Neurons/Layer	4
Activation	Relu
Solver	Adam
Initial Learning Rate	0.001
Alpha	0.001

These parameters achieved good results in 1 step prediction - with target correction at every step. The cross validation score was $0.0068^{o}C$, much lower than human perception. Looking at the results in figure 4.8, it can be seen that the prediction error is very low - root mean squared error equal to $0.049^{o}C$, which is a very good result. Nonetheless, the problem of using highly correlated data mentioned in section 4.2 can be observed - reducing the value of DNI and DHI barely changes the result of the prediction, which renders the model ineffective for use in controlling the room temperature in 1 step prediction and correction scheme. Although the real value is being used as correction in both cases, the prediction would need to be significantly different when altering the DNI and DHI values - it is close to 0.1^oC, not noticeable by humans.

On the other hand, figure 4.9 shows a marked difference in the predicted temperature when reducing the values of DNI and DHI during the day. This figure shows the results when the model is doing a full prediction during the day without correction between 8 am and 8 pm. During night-time the model does 1-step prediction with correction - the model will not be actively working because controlling the values of DNI and DHI, both zero, will not affect the heat dynamics of the room - considering the model used. This way, the model starts freely predicting at the correct value every morning, instead of having the prediction error propagate for the whole dataset. The root mean squared error in this case is 2^oC, higher than desired.

Taking into account the result of the 1-step prediction in 4.8, it can be interpreted that the marked difference in the predicted Room Temperature in 4.9 is due to the propagation of the prediction error. The model also overshoots in some days when using data as is, predicting a higher Room Temperature than measured. Finally, the full simulation of the room, in figure 4.10 shows that the network captured the heat dynamics of the room but the propagation of the error worsens the forecasting in a worse manner than desired.

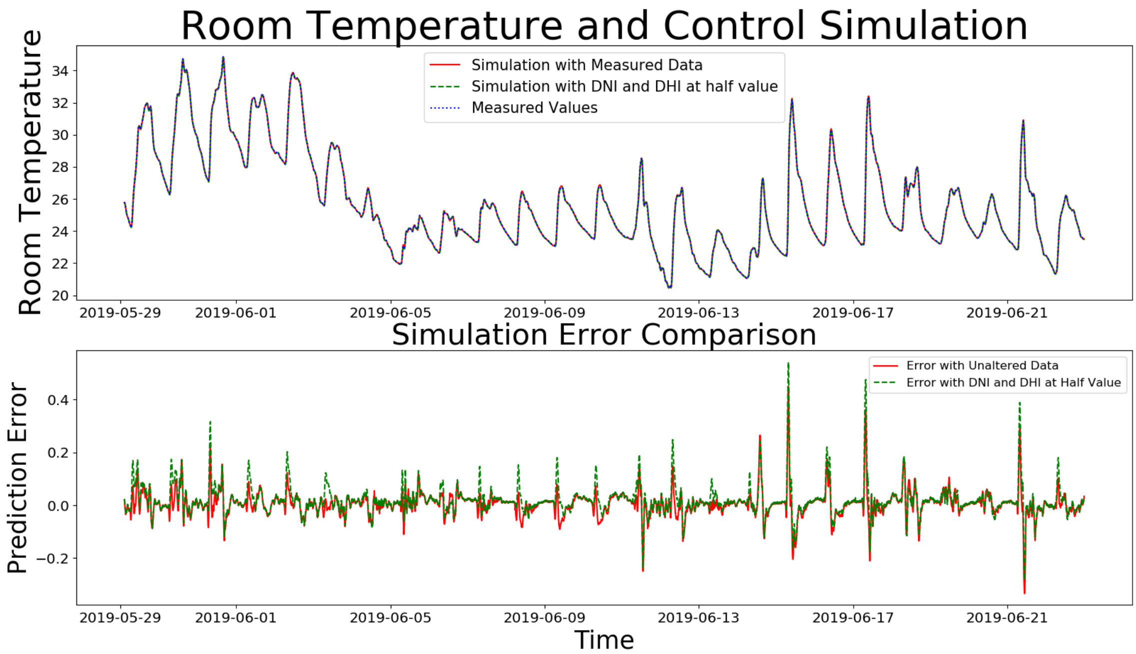


Figure 4.8: 1 Step Prediction and Control of Room Temperature

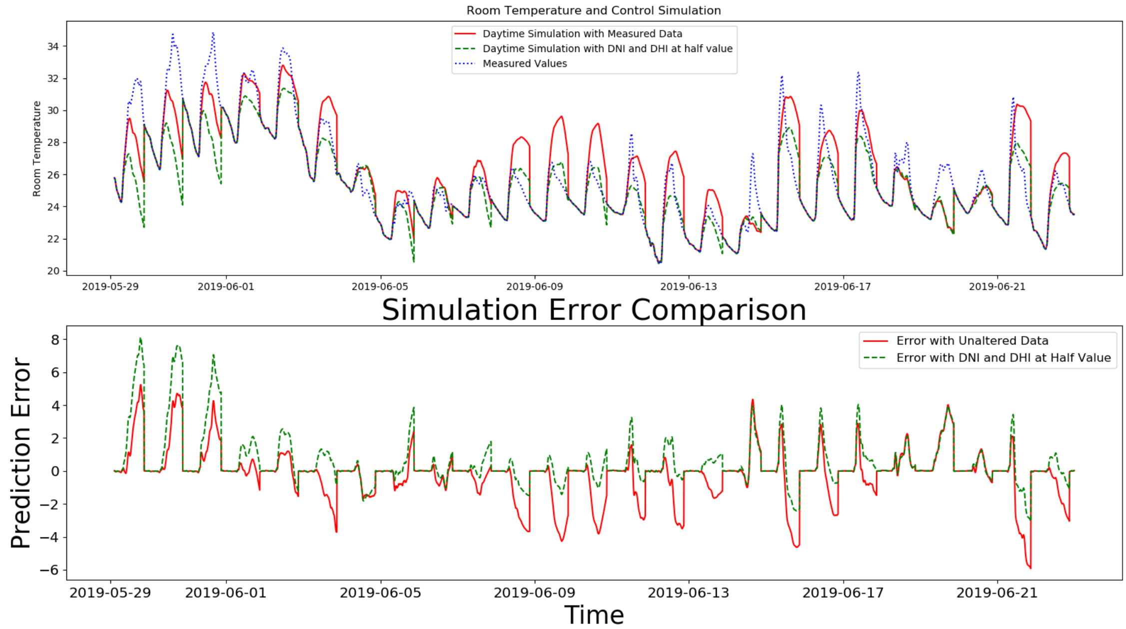


Figure 4.9: Daytime Prediction and Control of Room Temperature

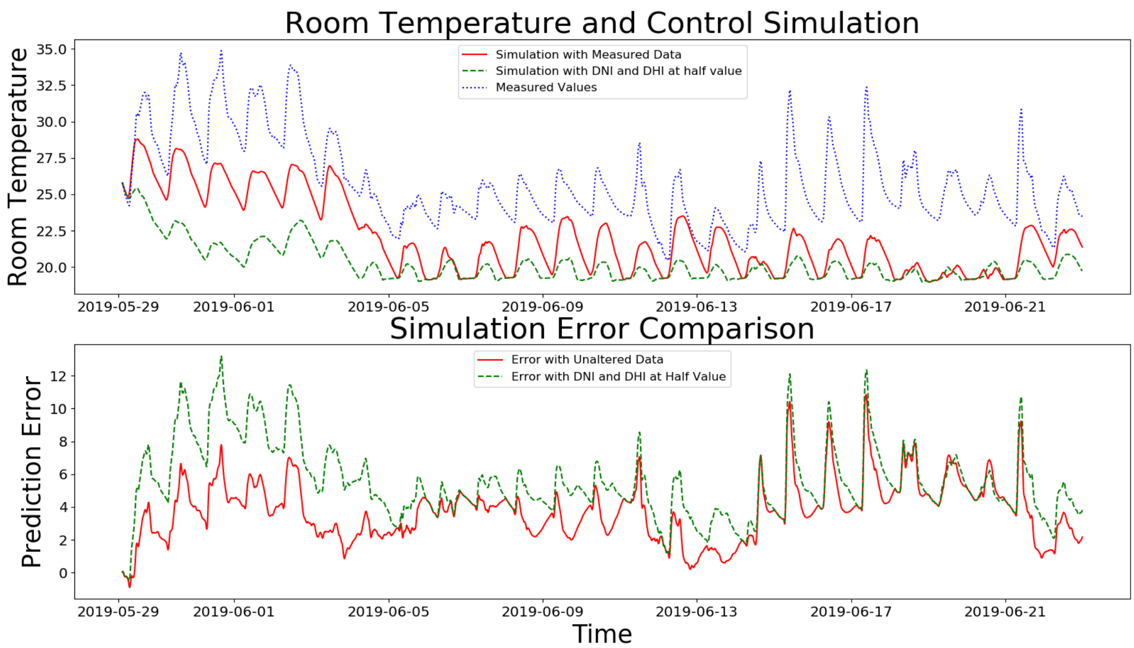


Figure 4.10: Full Simulation and Control of Room Temperature

Chapter 5

Conclusions

In this dissertation, two modelling techniques were used to model a classroom in order to serve as a basis for implementation of control strategies. These techniques were different in concept and applied with different considerations. The Physical model used known Heat Transfer phenomenons and equations in order to produce a model that could be interpreted and understood clearly. It used parameters estimated based on data, which was abundant, to try and make the model as accurate as possible. The Data Driven Model, on the other hand, used an Artificial Neural Network to model the phenomenons based entirely on the available data. Its implementation was simpler in concept, with the only difficulty being the hyperparameters and choosing the treatment appropriate for use with the available data.

In order to develop the model, a large quantity of data was captured by sensors inside the room and in the environment. This data was then preprocessed using common techniques used on similar datasets in order to facilitate its usage further on. Some data needed to be verified against model data to try to identify what was being measured, other data needed to be generated by models based on measurements and adapted to the problem at hand. After fixing all the irregularities and collecting the necessary data, the models could then be developed.

While the model was able to reproduce the heat dynamics of the room, the accuracy is not high enough. The most accurate model was the Physical model with 1 State, which achieved a Root Mean Squared Error of $0.057°C$. It achieves a poor performance when simulating the behaviour of the room taking only into account the initial values, so it was not used to simulate the result of control actions.

Similarly, the ANN model was only accurate in predicting 5 minutes in advance, achieving an accuracy of $0.049°C$ in the validation set. It closely resembled a pure autoregressive model because changing the values of the heat radiation did not noticeably change response of the system.

5.1 Future Work

Some likely causes of the worsening performance when the forecasting window is increase are the assumptions that were considered when developing the model. Having no window blinds sensor to know in which position the window blinds were during the measurements increases the difficulty because there is no reasonable justification to assume one position instead of another. Having this data would be very important in improving the parameter estimation and modelling, reducing one of the uncertainties that was very detrimental to the model development. While some of the models were able to reasonably predict the behaviour of the room, the faster dynamics associated with the presence of students - opening and closing of the door to the corridor and the opening and closing of the windows - were not hard to be reproduced by the model.

Other aspect that can be improved with further investigation and development is the implementation of a known control action for different periods of time in order to gather data containing the information that was missing in this implementation. However, this specific action would deteriorate the comfort quality of the working area, and disturb the classes that would be attended in the room.

Finally, a sensibility analysis could be performed in order to quantify the influence of the estimated parameters.

The results obtained are a stepping stone for further development and improvement of the comfort quality of the room.

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