Model Based Predictive Control for Thermal Comfort Maximization in Classrooms

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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 $0.057^{o}C$. The Neural Network models obtained a Room Mean Squared Error of $0.147^{o}C$. However, neither model was able to simulate the thermal of the room independently. 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

1. Introduction

1.1. Motivation

Energy needs and consumption are of the utmost importance nowadays. There is a need to reduce the waste of energy, so that the need for energy production diminishes. One of the ways to reduce energy waste is to employ techniques that change ho energy is reduced without compromising the functions that are dependent on that same energy. One of the important uses of energy is for providing comfort in buildings, maintaining comfortable conditions for people to work. The present work will be focusing on the modelling part of the thermal comfort in a building, more specifically, a classroom. It will try to develop a model to accurately simulate the thermal behaviour of the room, serving as a basis for the development of a control system.

1.2. Background

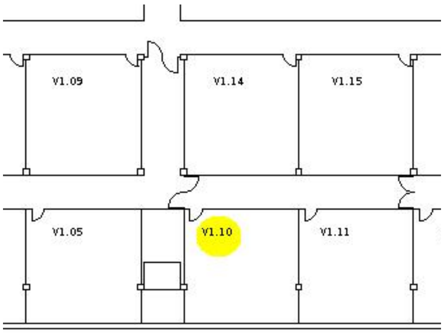
Previous work has been done on this topic, from indoor temperature forecasting [9, 15], to model development and control implementation [12, 10, 8]. Mateo et al.[9] used Multi Layer Perceptron - Non Linear Autoregressive Model with Exogenous Network (MLP-NARX) to forecast the indoor temperature with a Mean Average Error (MAE) of $0.11^{o}C$, performing better than other classical models. Zamora-Martínez et al. [15] also explored the use of machine learning techniques for usage in temperature forecasting, achieving good results despite the limited used data. Filipe [12] developed a state space model based on non linear stochastic differential equations that achieved a very good performance in forecasting indoor room temperature. A Takagi-Sugeno fuzzy model was also developed in order to represent the system in control simulations. The control technique used was very successful in maintaining the room temperature in between comfortable levels, while also reducing the use of energy in order to maintain the comfort. Oom [10] and Esteves [2] developed models to control the window blinds and the lights of a classroom. These models served as a basis for the development of the model in this work. Lopes [8] used neural networks in order to forecast and control the temperature in several classrooms, achieving a good result in terms of forecasting and in reduction of energy cost.

2. Case Study

2.1. Room Description

The classroom studied is located on Instituto Superior Técnico in Lisbon. It is located on the Civil Engineering Building and faces the north tower and a courtyard. It has two adjacent rooms on the front

(a) Outside View of the room



(b) Inside Location of the room

Figure 1: Room Location

and back, with a corridor opposite the window.

The classroom has a maximum number of 50 students. There is a projector in the front close to the window. It has two sliding windows that can only be operated by someone inside the room. The window blinds and the lights can be controlled by an automated system.

2.2. Database Description

There are various sensors inside the room that collect environmental data. It measures temperature, humidity, CO2 concentration, Lux, and concentration of unidentified particulates. The data is measured every five minutes. There is also a Wifi repeater that can provide the number of users connected to it. The measured amount can be higher than the capacity of the room, so the biggest amount that was considered was 45, because the attendance very rarely achieves the maximum. There is some error when taking this into consideration because the Wifi repeater connects to user from other rooms, but it is the only way to gather data of this kind. The attendance provided by the School System is not trustworthy because there are no checks to see if a student really attended that class. Students can frequent other classes without explicitly changing their schedules. There is a meteorological station in the University that measures the outside temperature and solar radiation. These values are also measured in five minute intervals. The radiation measured is the global horizontal radiation - it was measured against two clear-sky models [3, 5] during a cloudless day and the results align very closely, as seen in figure 2.

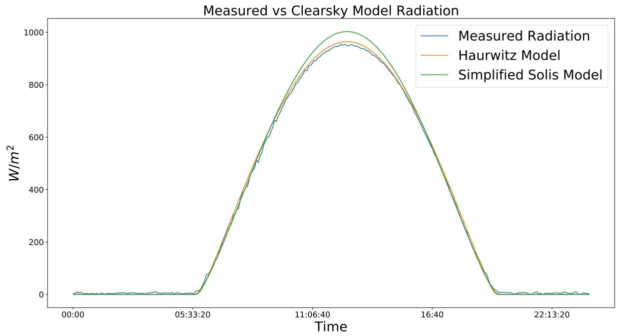


Figure 2: Comparison between the measured Radiation and Predicted GHI by Clear-sky models

In order to take into account the different components of radiation in the model - Direct Solar Irradiation and Diffuse Horizontal Irradiation - the ERBS model [1] implemented in pvlib [4] was tested. It was compared to the model DIRINDEX [11], shown in figure 3, in order to choose which model was used.

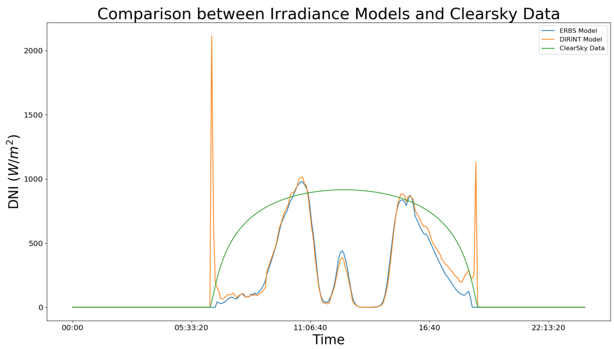


Figure 3: Comparison Between Dirindex and ERBS DNI Values

As it can be seen on figure 3, the DIRINDEX values have a very large spike in the first measurement in the morning and the last measurement in the afternoon, far exceeding the expected clearsky value. During the rest of the day it matches the ERBS model with slight differences. With this in mind, the ERBS model was chosen.

All this data needed to be preprocessed in order to be used in the development of the models. It contained missing data, duplicate measurements, misalignment between the time series and some degree of noise. In order to fix these problems, 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 [13] 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.

3. Physical Model

3.1. Model Development

The physical model developed was a grey box model - it uses heat transfer phenomenon equations in order to create the structure of the model and measured data to estimate the value of its parameters. The basis for the creation of the models were the one dimensional heat conduction shown by equation 1 and the newton's law of cooling,shown by equation 2. Dude to the low temperature value of the air, the emissive power of the room was not considered. The solar radiation considered was the one mentioned in 2.

$$\boldsymbol{q}'' = -kA\nabla T = -k\left(\frac{\partial T}{\partial x}\right) \tag{1}$$

$$q_s = hA\left(T_s - T_\infty\right) \tag{2}$$

Several Simplification were applied 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.

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

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

(5) - Convection through the windows and door 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.

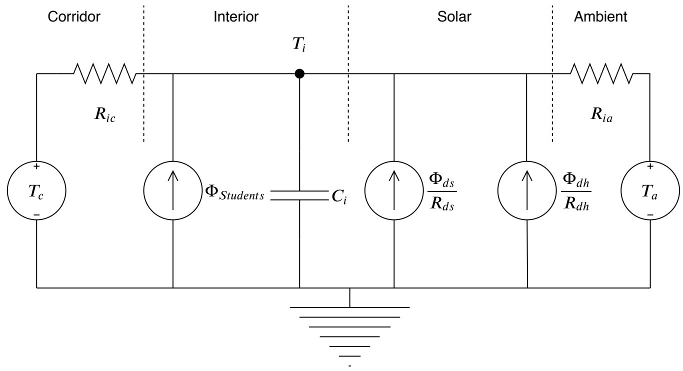


Figure 4: RC Equivalent Circuit for the 1 State model

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

Two models were obtained after applying these simplifications - a 1 State model equation 3, which considers the corridor temperature as constant, and a 2 State model equation 4 that estimates both the room and the corridor temperature. The differential equations that characterize the model were derived with the aid of the analogy that exists between eletrical and thermal systems, shown in figure 1

Table 1: Resistor-Capacitor Circuit Equivalent Components

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

$$\begin{aligned} C_i\frac{dT_i}{dt} &= \frac{1}{R_{ds}}\Phi_{ds}u_1 + \frac{1}{R_{dh}}\Phi_{dh}u_2 + \\ &\frac{1}{R_{ia}}\left(T_a - T_i\right) + \frac{1}{R_{ic}}\left(T_c - T_i\right) + \\ &\Phi_{students} + \sigma_i\frac{dw_i}{dt} \end{aligned} \tag{3}$$

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.

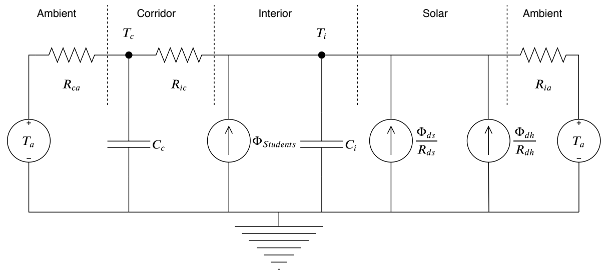


Figure 5: RC Equivalent Circuit for the 2 State model

$$C_i \frac{dT_i}{dt} = \frac{1}{R_{ds}} \Phi_{ds} u_1 + \frac{1}{R_{dh}} \Phi_{dh} u_2 + \frac{1}{R_{ia}} (T_a - T_i) + \frac{1}{R_{ic}} (T_c - T_i) + \Phi_{students} + \sigma_i \frac{dw_i}{dt} \tag{4a}$$

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

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.

The unknown parameters in the models were calculated using the Continuous Time Stochastic Modelling for R (CTSM-R) toolbox [14]. 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 [12] 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 [7] and the second the heat dynamics of the a building [6]. 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.

3.2. Results

Two different sets of data were used to estimate the parameters and validate the data. The first set of data consists of daily data from the 1st of April to the 22nd of June, while the second of data consisted of daily data from the 11th to the 31st 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.

Table 2: Estimated Parameter Values for the First Model

Parameter	Value	Unit	Description
T_c	21.8	^oC	Temperature of the Corridor
C_i	12817	$J/^oC$	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	$^oC/W$	Thermal Resistance between the Room and the Atmosphere
R_{ic}	0.001	$^oC/W$	Thermal Resistance between the Room and the Corridor

Table 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

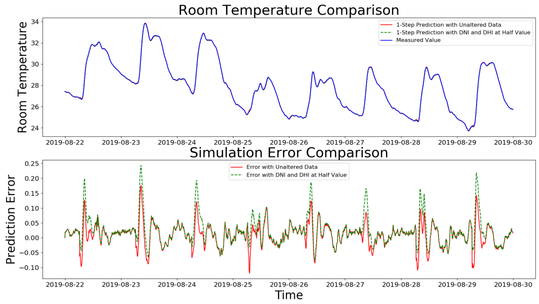
3.2.1 Results during the Holidays

As it can be seen on the figure 6 and on the Performance table 3, this model was able to accurately forecast the temperature 5 minute in advance, but started deviating with a bigger forecasting window. However, changing the values of the radiation did not measurably change the value of the predicted temperature. In the free simulation, the model reproduced the overall behaviour of the room, even if with an offset. The daytime simulation, 6c, achieved a better result than the free simulation, with a better forecasting performance - by design the model corrected during night time, since the control action would not work during nighttime.

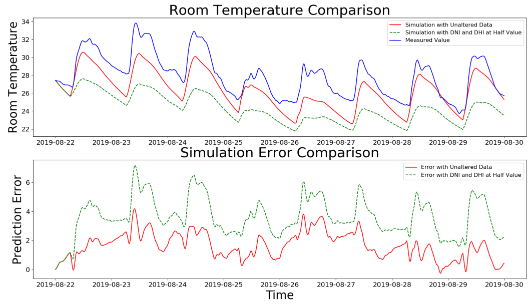
The addition of the corridor temperature improved some measures of results, but did not prove to be better overall. It has some improvements in the first days of the validation set, but towards the latter days tends to overshoot when forecasting the temperature values. This model didn't prove to be better than the 1 State model. It is important to note that the thermal capacitance of the air was estimated to be lower than the same value for the 1 State Model, which signals that the models might have focused on different aspects when estimating the parameters.

Table 4: Estimated Parameter Values for the Second Model

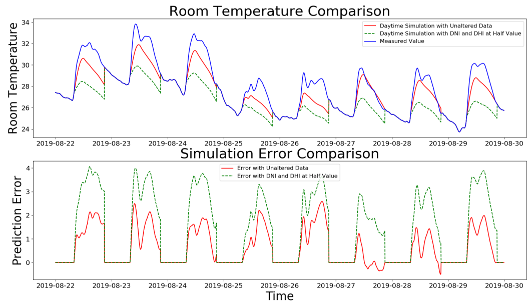
Parameter	Value	Unit	Description
C_i	8742	$J/^oC$	Thermal Capacitance of the room
C_c	245310	$J/^oC$	Thermal Capacitance of the Corridor
R_{ds}	0.044088	$1/m^2$	Window Resistance to Direct Solar Radiation
R_{dh}	0.081089	$1/m^2$	Window Resistance to Diffuse Horizontal Radiation
R_{ia}	0.0047658	$^oC/W$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



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

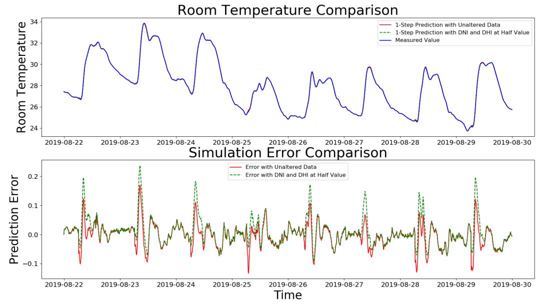
Figure 6: 1 State Model Validation

3.2.2 Results during Classes

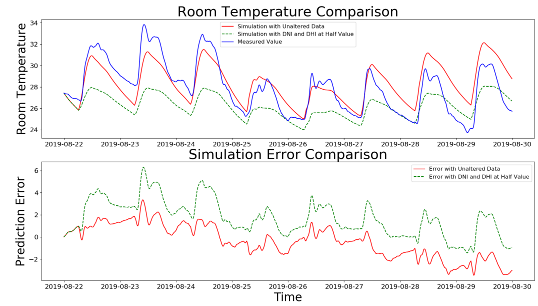
The inclusion of the students inside the room during classes worsened the results. The 1 Step Model achieved a result of 0.057^oC Room Mean Squared Error (RMSE) for the 1 Step prediction, which is a remarkable result. It proved to be better than the 2 State model, which achieved a rasult of 0.12^oC for the same task. The other results vary, with the Daytime simulation with the 1 State Model achieving a better RMSE result than the 2 State model, although where the 2 State Model predicts temperature values much lower than the ones measured, the 1 State model predicts higher temperatures than the ones measured. The Full simulation achieved mixed results, with the 1 State model overshooting with the temperature forecast with a RMSE

Table 5: Second Model Performance in Various Simulation Conditions

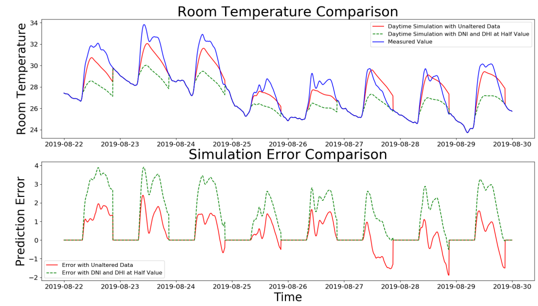
Simulation Condition	RMSE	VAF
1-Step prediction	0.04	0.99
Full Simulation	1.54	0.59
Daytime Simulation	0.78	0.9



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 7: 2 State Model Validation

of 6.54^oC, compared to the 2 State Model barely changing the forecast between 22^oC and 24^oC, with a RMSE of 2.79^oC. For implementation in a control system, the 1 State Model would be a better model to forecast the room temperature five minutes in advance.

Table 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 7: First Model Performance in Various Simulation Conditions

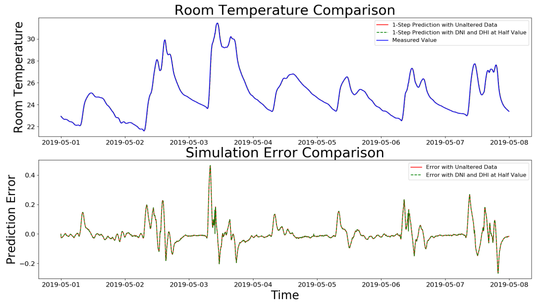
Simulation Condition	RMSE	VAF
1-Step prediction	0.057	0.99
Full Simulation	6.54	-1.54
Daytime Simulation	1.612	0.34

Table 8: Estimated Parameter Values for the Second Model

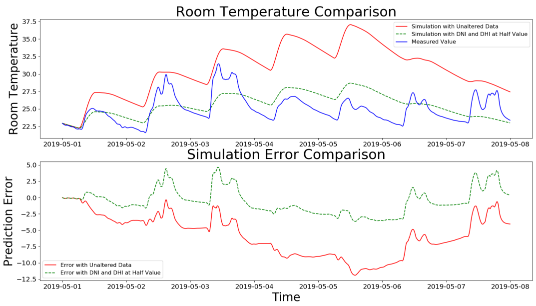
Parameter	Value	Unit	Description
C_i	233056.1	$J/^oC$	Thermal Capacitance of the room
C_c	273383536	$J/^oC$	Thermal Capacitance of the Corridor
R_{ds}	$8.758825 * 10^{-3}$	$1/m^2$	Window Resistance to Direct Solar Radiation
R_{dh}	0.02343304	$1/m^2$	Window Resistance to Diffuse Horizontal Radiation
R_{ia}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

Table 9: Second Model Performance in Various Simulation Conditions

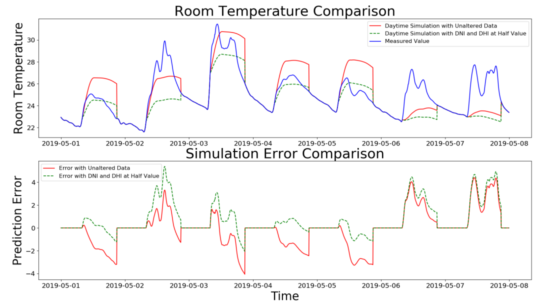
Simulation Condition	RMSE	VAF
1-Step prediction	0.12	0.99
Full Simulation	2.79	0.19
Daytime Simulation	2.54	0.07



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 8: 1 State Model Validation

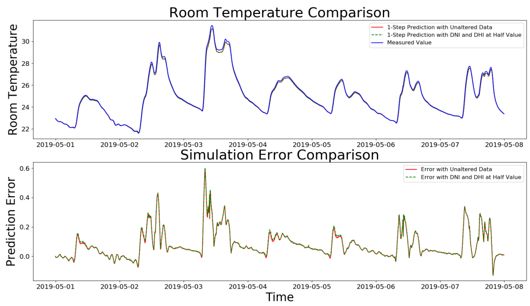
4. Data Driven Model

4.1. Model Development

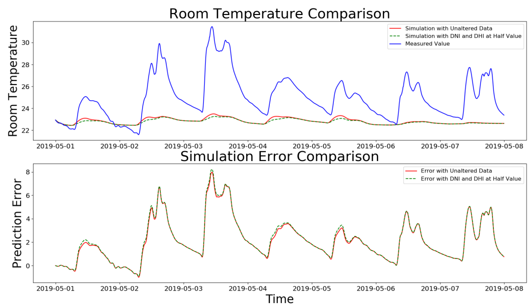
The first step in modelling a neural network is to know how the different data correlates with each other. It is also important to know how the room temperature relates with itself, because there could be a dependence on past values, which would help capture the dynamics of the system. In order to understand these relations, the autocorrelation - shows how current values of a variable relate to past ones -, partial autocorrelation - shows how current values are influenced by past values, without the values that are in between both of the analyzed values - and pearson correlation - shows linear correlation between the data.

It can be seen on figure 10 that there is a very high correlation between the room temperature and its past values, indicating that an autoregressive model might be appropriate for use. Additionally, figure 11 show that the correlation is higher in the first two past values, decresing considerably on the third one. It can be derived from this that the past two values are more important than all other when prediction the room temperatures.

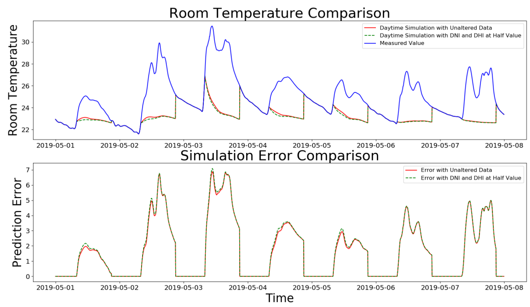
Figure 12 shows that there is a high correlation between the outside ambient temperature and the room temperature. On the other hand, the correlation between the DNI, DHI and Student attendance data is low compared to the past room temperature values. This might prove troublesome when implementing the neural network because it will assign more weight to the values that are more correlated than the ones that are less. It can devolve into a pure autoregressive model if care is not taken. As such, only the first past value will be taken into accout, because it is necessary to establish the dy-



(a) 1 Step Prediction and Error



(b) Full Simulation



(c) Daytime Simulation

Figure 9: 2 State Model Validation

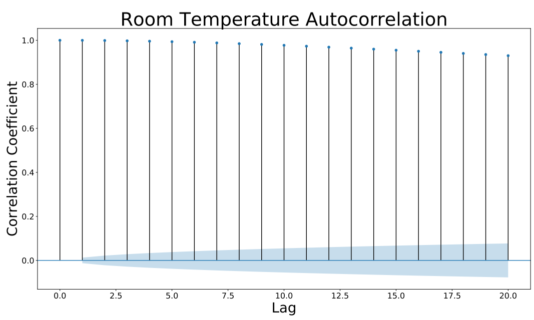


Figure 10: Room Temperature Autocorrelation

namic nature of the model. The other past values will not be taken into account in order to make the network able to be more influenced by the DNI,

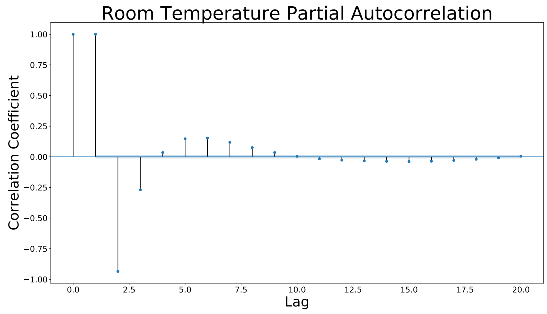


Figure 11: Room Temperature Partial Autocorrelation

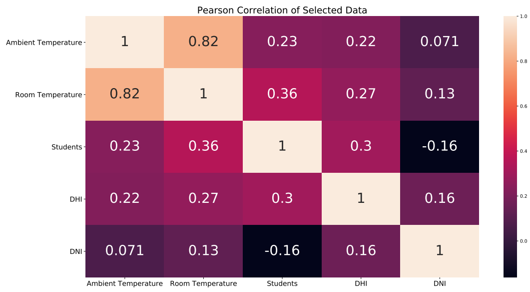


Figure 12: Pearson Correlation Coefficients of Available Data

DHI and student attendance data. After taking all of this into account, the Artificial Neural Network model chosen is a NARX network. It takes into account past values of the room temperature and the ambient temperature, DNI, DHI and the student attendance values.

4.2. Results

The network was trained with ordered sets of data - 16732 training samples and 7171 testing samples. It achieved a cross validation error of 0.0068^oC, with a testing score of 0.049^oC. Looking at the results in figure 13, it can be seen that the temperature forecasting in the next 5 minutes. It didn't forecast the highest temperatures in the first 5 days, but managed to be very precise in the rest of the simulation. However, changing the values of DNI and DHI didn't significantly change the forecasting prediction. The Daytime simulation, in figure 15, shows that the network captured the overall dynamic of the system, although it tends to overshoot the prediction the bigger the forecasting window. Contrary to the 1 Step Prediction, changing the value of the DNI and DHI changed the forecasting value, predicting lower temperatures. It is worth noting that in the days in the middle of the validation set, the prediction with the lower DNI and DHI was closer to the real temperature measured, which might indicate that the window blinds might have been in a lowered position.

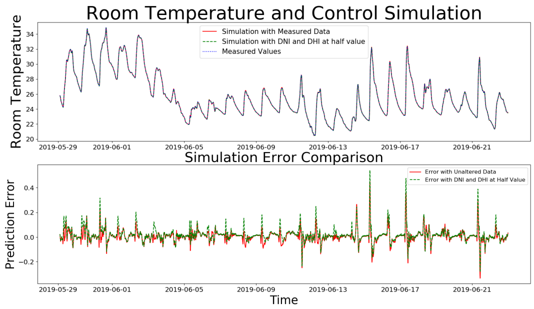


Figure 13: 1 Step Prediction and Control of Room Temperature

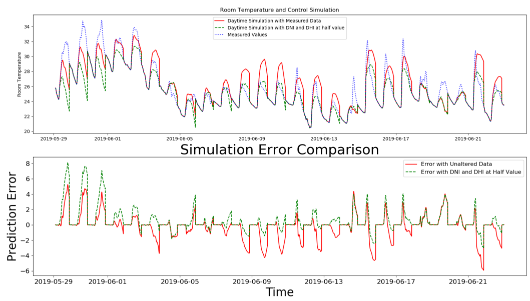


Figure 14: Daytime Simulation and Control of Room Temperature

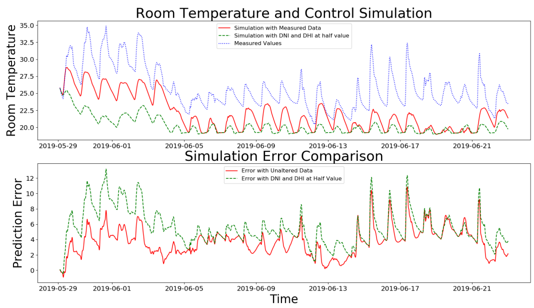


Figure 15: Free Simulation and Control of Room Temperature

5. Conclusions

In this dissertation, two modelling techniques were used to model the temperature evolution of a classroom. These techniques were different in concept, and were applied with different considerations. The Physical model used known Heat Transfer phenomenons in order to produce a model that could be interpreted and understood clearly. Its parameters were estimated to match the predicted room temperature with the measured room temperature. The Data Driven model used ANN to model the phenomenons based entirely on the available data. Its implementation was simpler in concept, with the only difficulty being the configuration of the model. The data used to derive the models was measured by sensors installed in the room and in the meteorological station present in the University. Models were used to identify some of the measured data and to obtain data that was not measured but was necessary to the development of the models. The models achieved a very good performance in the 1 Step Prediction, with the 1 State model achieving a RMSE of 0.057^oC during classes and the neural network achieving a RMSE of 0.049^oC. However, the performance was worsened when the forecasting window was increased, although the dynamic of the system was captured.

The deteriorating accuracy of the models my be caused by some of the assumptions made - 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 detrimental to the model development. While some of the models were able to reasonably predicgt the behaviousof the room, the faster dynamis 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 reproduced by the models. 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 calsses that would be attended in the room. It is suggested to do a sensibility analysis of the model parameters that were obtained for the theoretical models. These results obtained can be a stepping stone for further development and improvement of the comfort quality of the room.

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