ABSTRACT

Well over half of the energy consumed in the Netherlands is for the thermal demand of buildings and industries, a big chunk of which is for heating purposes of the built environment. Predominant means to achieve the same has been through natural gas boilers. Of late, renewable energy and its integration in the built environment, increasing energy efficiency of buildings are topics that are receiving much attention.

Dutch government policies are aimed at phasing out the use of natural gas for heating buildings entirely within a time period of 40 years. This will, in the years to come, lead to a larger amount of heating projects and heat pump installations using renewable sources, such as bio-based fuels, solar PV and underground thermal sources. In addition to the supply shift towards renewable energy, part of the demand is also being electrified. This means that a huge number of heat pumps are going to be installed. This also means that the need to optimize domestic energy consumption takes a whole new level of importance.

The Sustainable Roof Renovation Icoon project at HAN focuses on the development of a renovation concept that improves the building envelope and makes the installation in the home more sustainable. A new initiative, but in line with the preceding activities in this domain, the project takes the opportunity to improve the indoor environment of the dwelling through renovation of the building installations.

This work focuses on realizing a simple, reliable model to serve as a basis of advanced predictive control strategy in order to maintain the temperature within the dwelling to within required levels.

CONTENTS

– 1 –

INTRODUCTION

The National Energy Outlook puts the statistic of 2015 Dutch energy consumption from primary sources (oil, natural gas and coal) at over 2800pJ. Of the total energy consumed, built environment has the highest share of 28%, followed by the industry at 23% [1]. More than half of the energy consumed by these two sectors, is for heating purposes. The Dutch government has recognized the need for energy savings and a transition towards renewable sources. The European Union legislation makes member states committed to reach energy savings and increased renewable energy shares for 2020. Road maps are also developed towards 2050 to have a completely renewable energy system [1].

The Dutch ministry of economic affairs, responsible for energy policies, also announced a shift of paradigm: initiatives towards integration of renewable energy in the heating sector will be encouraged in order to phase-out the use of natural gas completely by 2060 [2]. Over 90% of the supply of the building related thermal demand is met by natural gas combustion in boilers [1]. In the context of transition towards renewables, this means that a lot of gas boilers will be replaced by electric-based heat pumps. In this regard, domestic heating holds considerable significance in the push towards a renewable energy system. In light of the global awareness levels, and the Paris climate agreement, the momentum towards renewables is indeed high in the Netherlands.

1.1 Icoonproject Sustainable Roof : Rationale & Background

The thermal system of a domestic dwelling is characterized by the occupants' heating demands within the dwelling structure. Also part of the system may be a local or district level thermal storage. The Sustainable Roof Renovation Icoon project at HAN proposes to tackle the heating problem within domestic housing renovation projects. The idea is to improve the energy performance of homes in the Netherlands. With a huge impact potential, this project aims to provide a financially attractive solution to preserve and renovate existing buildings.

There are two aspects to the renovation concept this project puts forth:
- a modified roof concept with attention to installation, thus optimizing the building envelope to the thermal requirements;
- a comprehensive heating system for the residents that capitalizes on the knowledge of thermal behavior of the dwelling.

This report details the work done in the latter domain.

1.2 The Domestic Heating Problem Statement

A domestic dwelling is ideally required to maintain a comfortable temperature within for the occupants. In addition to temperature control, domestic thermal demand also includes the demand for daily hot water needs of the house. Thus, there are two heat 'sinks' in the house. As for heat 'sources', electricity and solar panel power collection constitute the total thermal input to the house. While either of these sources can be used to meet the hot water requirements without additional influences, the problem of temperature control has several other influential factors.

The inside temperature T_{in} of a dwelling depends on the following. The internal dynamics and the relations of each of these to the inside temperature are part of system modeling, discussed in the next chapter.

- $P_{heating}$ [W]: Heating through heaters/heat pumps;
- $P_{windows}$ [W]: Solar Irradiation through the glass windows;
- $P_{ambient}$ [W]: Power gained/lost to the ambience which, in turn, is dependent on
  - $T_{ambient}$ [K]: the Ambient Temperature;
- P_{gen} [W]: Internal Generation (heat radiated by occupants, domestic appliances, etc).

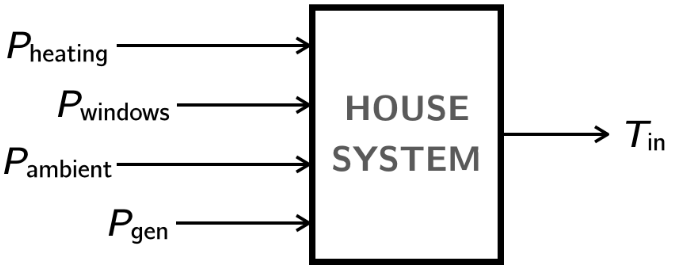


Figure 1.1 : Inputs to the house system influencing the internal temperature.

The temperature requirements over a day's 24-hour period is set keeping in mind that once the occupants are asleep, heating does not need to be maintained throughout the house. A comfortable 20ºC is expected during the remaining bulk of the day. Hence, a priori knowledge of required set points open the door to the possibility of a predictive control of room temperature. Such an advanced controller will also potentially help in optimizing the energy consumption. However, in order to build an advanced prediction based controller, the model is required to have very high accuracy.

1.3 The House

For the purposes of this project, a standard house with set specifications is put under the proverbial microscope. The house location coordinates are 52.09º N, 5.129º E. Figure 1.2 shows all the faces of the house structure, with the geographical orientation. Faces 1 and 2 constitute the roof, while 3 to 6 are the side faces.

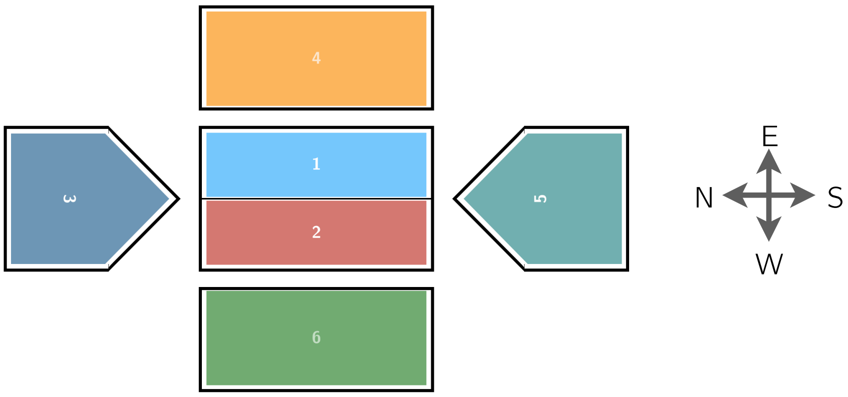


Figure 1.2 : The 6 faces and the geographical orientation of the house.

Roof surface 1 has a solar panel installed. Each of the sides have a glass window area. The two roof slopes are inclined at 40º each. Information on the glass window and the solar panel coverages is listed in table 1. Additional details of the house, structural and otherwise, are mentioned in table 2.

Surface	Glass Coverage [m^2]	ZTA Value	Solar Panel Coverage [m^2]	Efficiency (x100 %)
1	1	0.65	30	0.7
2	0	0.65	0	0.6
3	5	0.65	0	0
4	2	0.65	0	0
5	7	0.65	0	0
6	2	0.65	0	0

Table 1.1 : Coverage of Glass (window) & Solar Panel (collector) on the Structure Surfaces

Quantity	Value
Volume of concrete in the side walls	12.6 [m^3]
Volume of concrete in the floors	13.5 [m^3]
Total Concrete in the house	26.1 [m^3]
Mass of Concrete in the house	52,200 [kg]
Specific Heat of Concrete	900 [J/kgK]
Thermal Resistance (Sluggishness) of the house	23,490,000 [J/K] = 6525 [Wh/K]
Installed (Available) Power	6000 [W]

Table 1.2 : Quantitative House Details

1.4 Objective

To design an advanced model predictive controller that:

- works on an identifiable model structure, applicable on every house;
- capitalizes on the knowledge of thermal behavior of a dwelling;
- provides requisite heating through efficient energy consumption.

1.5 Literature Review

Prior work in the area of implementing predictive control in a domestic heating situation not only serves as a flag to pursue the work, but provides a guide path as well. Research articles do the job of opening up the theoretical possibility. Commercial application is, as yet, a not-so-chartered territory.

The energy scenario of the Netherlands is best observed through the government's public documents such as the National Energy Outlook 2016 [1]. This document provides an overview of the energy sources and consumption patterns prevalent in the country, as well the predictions for the years to come. The PhD thesis of van Leeuwen at the University of Twente [2] presents a comprehensive study into the transition towards renewables for urban areas. van Leeuwen's modeling based work focuses on several aspects, such as the modeling the house, energy storage facilities, etc., with an eye on smart control in the urban environment. The primary take-away from this document is the modeling approach focused for an advanced control.

Afram and Sharifi in [3] conduct a decent overview of the different modeling methods of HVAC systems. There are data-driven models, there are physics based models, and there are grey-box models. While physics-based 'white box' models are helpful in understanding the dynamics of the system in detail, they are almost certainly rather unhelpful when it comes to building a controller. Pure data-driven 'black-box' models are good at accuracy, but are extremely cynical in giving any information about what's happening in the process. Grey-box models are an intermediate stage that exploits physical knowledge as well as an inverse-modeling step using measurements to estimate model parameters. Harb, Boyanov, Hernandez, Streblow and Müller concur with this idea, and present grey-box model development and validation in [4].

Bacher and Madsen in [5] present several models for the heat dynamics of a building, starting from the most basic, and moving upwards in complexity. Models presented are state-space in nature, and are in electrical analogy. The strategy to use electrical circuit analogy for a house model is quite common, and is used in [2] as well. Of the several models put forth in [5], residuals are used as a tool to identify and select the most appropriate model.

Concerning control in HVAC systems, Afram and Sharifi present a literature review of control methods in [6], with emphasis on the model predictive control (MPC). Several control methods are identified and a brief survey of each method is presented, and the performance of MPC is compared with that of other control approaches. Factors affecting MPC performance are elaborated using examples. Gaps in MPC research are also identified in their article.

An experimental approach to MPC is documented by Rogers, Foster and Bingham in [7]. The authors document their findings upon subjecting a test house environment to an MPC control. The modeling approach used in their experiment is of a recursive nature, wherein the parameters are estimated on a daily basis. The model structure also does not explicitly include the effect of ambient temperature on the inside temperature of the house. Nevertheless, it clears up the viability of MPC being usable on domestic houses.

To bring in the cost factor as a measure to minimize energy consumption, Khanmirza, Esmaeilzadeh and Markazi present, in [8], the design and experimental evaluation of MPC with energy costs included in the terms within the model. Two sources of energy, electricity and gas, are considered in their work, and the cost of each is included in the state space approach of a model that is based on thermodynamics, rather than electrical analogy. Irrespective of the approach difference, their work does emphasize the idea of energy cost minimization.

In this work, MATLAB makes up the software working environment. Typical functions are used model tuning and validation, backgrounds of which are available in MATLAB documentation, and are not listed in the references.

1.6 Outline of Report

This report is built up as follows: Chapter 1 introduces the energy scenario in the Netherlands, and the official policy in the shift towards renewables. HAN's Icoon project, and its idea of tackling the domestic heating problem is also stated in chapter 1. An overview of the work done in this domain is also provided.

Chapter 2 details the modeling, as well as the results of tuning and validation. Also included is information on the data availability. Dutch housing standards, as well as NEN data feed in to build a house data for a period of one year. This data helps tune and validate the model.

Chapter 3 documents the controller design and tuning steps, as well as simulation plots under different test scenarios. The controller is then simulated with real data over a prolonged period, and resulting plots are also included in chapter 3.

Chapter 4 provides a comparative overview of this control approach, as well as a review of the MPC design tool in Matlab. Also included in chapter 4 are reviews and recommendations to build upon the results and take the work forward.

– 2 –

SYSTEM MODELING

As noted in [3], generally there are three types of modeling approaches for HVAC systems: data-driven, physics-based, and grey-box.

In data-driven, or black-box approach, system performance data is collected under normal use, or under a specific test, and a relationship is found between the input(s) and output(s) using mathematical techniques like statistical regression, etc. In physics-based, or white-box approach, system models are derived using governing physics laws and detailed knowledge of the process. In grey-box approach, basic structure of the model is formed by using physics, and model parameters are determined using algorithms on measured data of the system and its processes.

The choice of modeling approach really falls down to the requirements within the context of the overall project. The grey box modeling approach benefits from the qualities of both the other two approaches, providing goof generalization capabilities, as well as good accuracy. In the context of this work, deep knowledge of the process is not of prime importance. Also, absolute no knowledge of the process is also not preferred. There should be some physical knowledge, but only enough to work on and eventually build a working controller. Grey box modeling fits the bill.

2.1 The Model

There are a total of 4 inputs and 1 output (figure 1.1). Of the inputs, P_{heating} is the manipulated variable (MV). P_{ambient} is a quantity entirely a function of ambient temperature T_{ambient}. Thus, T_{ambient}, along with P_{windows} are measured disturbances (MD). The fourth input, P_{gen}, is an unmeasured disturbance. In the model, only the MV and MD's are considered. The model considered here builds an electrical analogy to the house system. With a linear state-space physical part, the dynamics of the states are written as:

$$d\mathbf{T} = \mathbf{AT}dt + \mathbf{BU}dt \tag{2.1}$$

Here **T** is the state vector and **U** is the input vector. None of state or input variables constitutes either **A** or **B**, and they consist only of parameters.

$$\mathbf{U} = [\ P_{heating}\ ,\ P_{windows}\ ,\ T_{ambient}\ ]^T \tag{2.2}$$

Illustrated by the RC-network in figure 2.1, the selected model has one state variable T_{i}, and the following parameters: R_{ia} and C_{i}. The values of these are dependent on the structure of the house. The resistance term, R_{ia}, can be viewed as the thermal resistance of the walls and the 'box' of the house. The capacitance term, C_{i}, can be viewed as the heat retention capacity of the internal house environment. Thus:
R_{ia} : thermal resistance from the interior to the ambient; C_{i} : heat capacity of the entire building.

The describing differential equation is:

$$\frac{dT_{in}}{dt} = \frac{1}{R_{ia}C_i}\left(T_{ambient} - T_{in}\right) + \frac{1}{C_i}P_{heating} + \frac{1}{C_i}P_{windows} \tag{2.3}$$

Simplifying the notations in equation (2.3),

$$\frac{dT_i}{dt} = \frac{1}{R_{ia}C_i}\left(T_a - T_i\right) + \frac{1}{C_i}P_h + \frac{1}{C_i}P_w \tag{2.4}$$

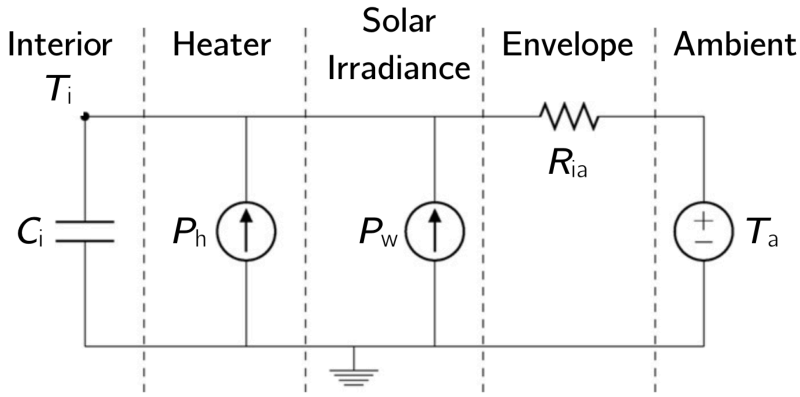


Figure 2.1 : RC Circuit of the model

Upon discretization and expansion of the equation, the resultant discrete polynomial model equation is as follows:

$$T_i[n+1] = T_i[n] + \frac{1}{R_{ia}C_i}\left(T_a[n] - T_i[n]\right) + \frac{1}{C_i}\left(P_h[n] + P_w[n]\right) \tag{2.5}$$

The measurement equation, with measurement error '*e*' is:

$$Y[n] = T_i[n] + e[n] \tag{2.6}$$

In the words of the authors in [5], this is the 'simplest' model. They go on to extend the model, dividing the house into zones, including states such as temperatures of the sensor, the building envelope, the heaters, etc. While extending the models in this manner does help them in reducing the residual errors to a great extent, the problem is the unwanted complication. As states are added, so is the need to acquire data for each of the added state and quantity. In the house setup in this work, data for the additional states is not available. Hence, so long as this model gives satisfactory performance, complications are unnecessary.

2.2 House Data

The Dutch body for maintaining standards NEN, provides the year-long data on ambient temperature and solar irradiance at a geographical location within the country. Solar irradiance is of three types:

- direct,
- reflected and,
- diffused.

Each of the three is known from NEN. Since the coordinates of the house are known, irradiance data for every hour, throughout the year is available at the house location. From the knowledge of house structure, like glass coverage, the ZTA values, etc, as well as the knowledge of wind directions, the impact of the three types of solar irradiance from the six faces of the house is interpreted. This renders data of T_a and P_w available on an hourly basis for the entire year period.

Within the excel simulation environment, the house is subjected to a staircase test input of P_h for the entire year period. The response of the house constitutes the system output, T_{in}, temperature inside the house. All this data of inputs and output is transferred from excel into a MATLAB data structure file titled "HAN_HouseTest.m".

2.3 Model Tuning & Validation

As the next step in grey-box modeling, the model parameters are estimated using measured data of the system. Beyond this, the model needs to be validated as well. To this end, the year long data of the houses split into two independent sets, a 'training set' and a 'validation set'. The training set is used to estimate the coefficients in the model equation, while the validation set is where the model is ultimately put to test (table 2.1).

The model equation is repeated here to include an additional coefficient x_1, along with the parameters R_{ia} and C_i.

$$T_i[n+1] = x_1 T_i[n] + \frac{1}{R_{ia}C_i}\left(T_a[n] - T_i[n]\right) + \frac{1}{C_i}\left(P_h[n] + P_w[n]\right) \tag{3.6}$$

	Start	End	Number of Days	Number of Hours
Training Set	01/01 00:00	30/01 23:00	30	720
Validation Set	31/01 00:00	31/12 23:00	335	8040

Table 2.1 : Details of Training Set & Validation Set

Training set is chosen in January. Hence, winter data is used to tune the model. The idea behind this choice is that, heating requirements are of pivotal importance in the winter, and not as much during the summer. Getting it right for winter is, thus, far more important. With this choice, consideration of winter dynamics is elevated. Good model performance in this period is virtually guaranteed.

Linear regression is carried out on the training set to give parameter estimates. Two figures-of-merit are used to assess model performance: the coefficient of determination, R^2, and the root mean square error, *RMSE*. Over the training set, parameter estimates and model performance are tabulated below.

Parameter Estimates	x_1	1.001	[-]
	R_{ia}	0.006	[KkW^{-1}]
	C_i	6744.529	[$kWhK^{-1}$]
Model Performance	R^2	0.999	[-]
	RMSE	0.041	[K]

Table 2.2 : Parameter Estimates and Model Performance in Training Set

The values of the estimated parameters meet the expectations. The values of R_{ia} and C_i closely resemble the house settings as mentioned in chapter 2. The coefficient x_1 should have been 1, and is indeed almost 1. A visual representation of the correlation between measured and predicted values of house temperature is shown in figure 2.2. A plot of the prediction error over the training period is also shown in figure 2.3.

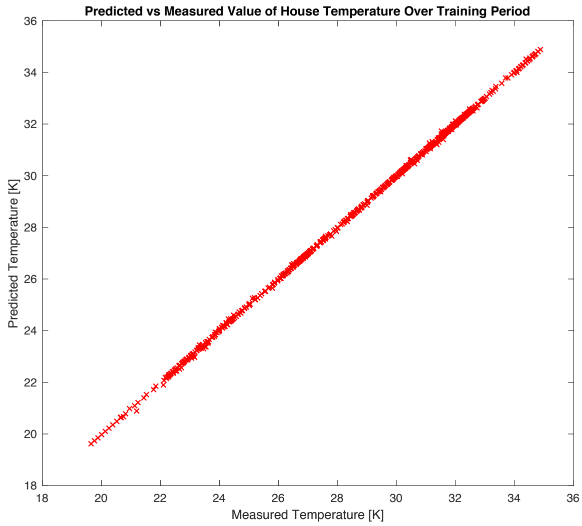


Figure 2.2 : Predicted vs Measured House Temperature over the Training Set.

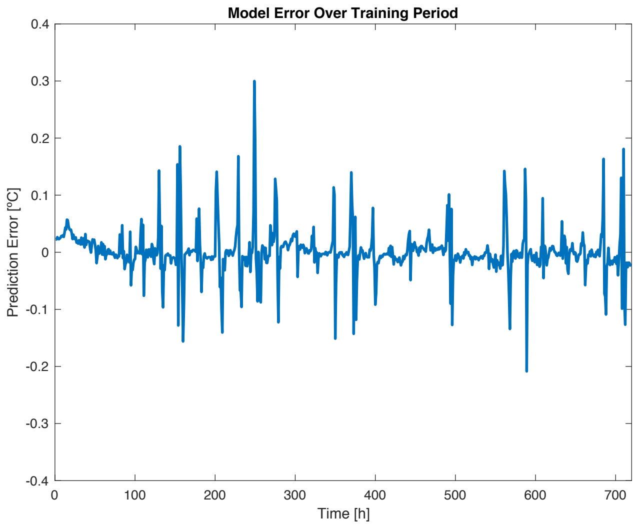


Figure 2.3 : Model Error over the Training Set.

With these favorable estimates, the performance of the model is also highly satisfactory. A coefficient of determination of 0.999 is as high as one can get. The root mean square error also stays under 1/20th of a degree Celsius/Kelvin.

The model with now-known parameters is tested on the data of validation set. Performance metrics are tabulated below, and a visual representation of the model is shown in figure 2.4. For convenience, coefficient x_1 is assumed to be 1 (instead of 1.001). The rather small change does not influence the predictions, and still keeps the model valid.

Model Performance	R^2	0.999	[-]
	RMSE	0.081	[K]

Table 2.3 : Model Performance in Validation Set

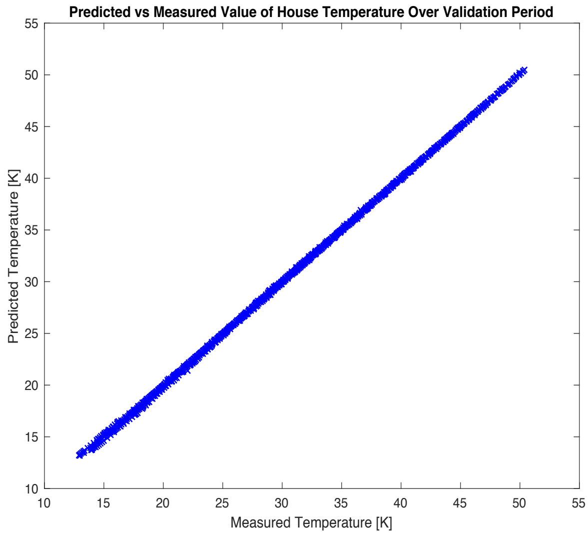


Figure 2.4 : Predicted vs Measured House Temperature over the Validation Set.

A coefficient of determination of 0.999 is strong enough an evidence to deem the model as valid. The plot of prediction error with this model is shown in figure 2.5.

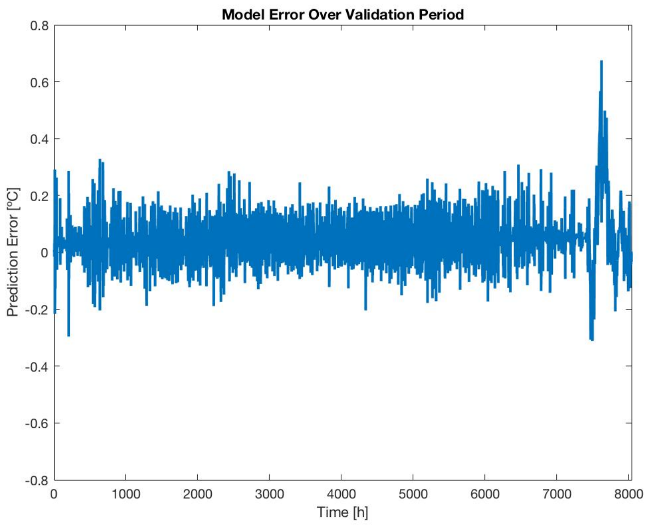


Figure 2.5 : Prediction Error over the Validation Set.

– 3 –

CONTROL

The results of chapter 3 present a valid model upon which a controller can be designed. As mentioned in earlier chapters, the idea is to build an advanced adaptive controller. MPC is the conscripted approach. Advantages of MPC influencing the decision are:
- predictive, hence time-saving;
- ability to handle constraints;
- use of cost function to achieve multiple objective;
- integration of energy conservation strategies in controller design.

3.1 State Space Model

A favorable representation of the validated model is the state-space format. This representation works well with MPC designing in MATLAB. The discrete state-space model structure is as written below.

$$T_i(n+1) = \left[1 - \tfrac{1}{R_{ia}C_i}\right] T_i(n) + \left[\tfrac{1}{C_i} \quad \tfrac{1}{C_i} \quad \tfrac{1}{R_{ia}C_i}\right] \begin{bmatrix} P_h \\ P_w \\ T_a \end{bmatrix} \tag{3.1}$$

$$y(n) = \left[1\right] T_i(n)$$

Feed-through matrix D is 0. Values of R_{ia} and C_i have been estimated satisfactorily.
- Measured Variables (**MV**) : P_h.
- Measured Disturbances (**MD**) : P_w , T_a.
- Controlled Variable (**CV**) / Measured Output (**MO**) : T_i.

3.2 MPC Overview

MPC has become a popular methodology for enhanced HVAC control. An MPC uses the plant model to predict a set of optimal control 'moves' to minimize the error between the set point and the measured output. The first of the calculated controlled outputs is then applied to the system. At each time step, the process is repeated, thus forming the receding horizon principle. The length, or number of predicted optimal control outputs is considered as the Prediction Horizon - N_p. The length over which the predicted plant trajectory is observed in response to the predicted control is termed as Control Horizon - N_c [7].

Classically, model formulation is done in terms of incremental control moves ΔU. The cost function J is used as a metric to minimize the errors between the predicted outputs Y and defined reference set points R_s. R_b is a diagonal weighing matrix that helps in penalizing error, etc.

$$J = (R_s - Y)^T(R_s - Y) + \Delta U^T R_b \Delta U \tag{3.2}$$

The mathematics behind prediction array Y comes from Augmented Plant Model, details of which can be found in [7], among other MPC texts.

3.3 Designing

The MPC Designer application in the MATLAB environment is used. In the app window, there are three main tabs: 'MPC Designer', 'Tuning' & 'View', the names of each of which are self-explanatory. The options under the first tab are shown in figure 3.1. As expected, this forms the first steps in the controller design process.

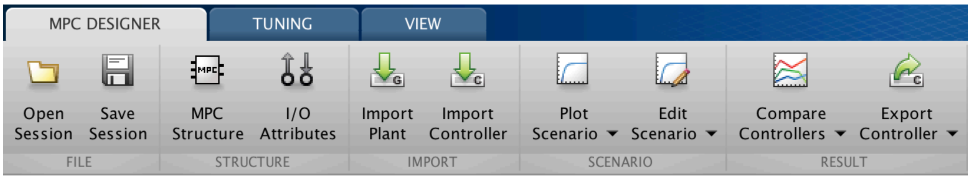
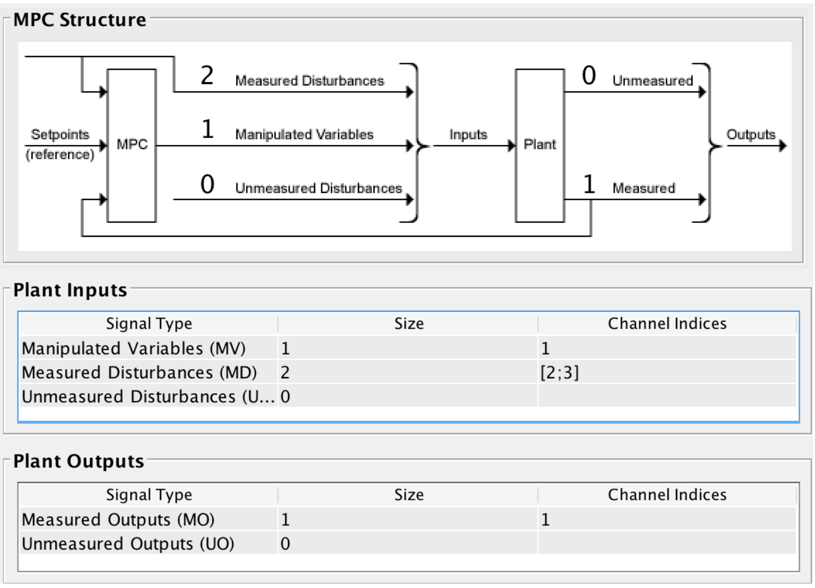


Figure 3.1 : Options under the MPC Designer Tab in the App.

3.3.1 Initial Settings – MPC Structure and Nominal Values

Specifications of inputs and output need to be specified in the MPC structure, as shown in figure 3.2. Channel indices need to be specified, as shown. The index number of each output comes from the outputs' locations in the **U** matrix of the state-space model. While in real setup, we do have unmeasured disturbance in the form of P_{gen}, it is not part of the specifications as it is not part of the model.



Signal Type	Size	Channel Indices
Manipulated Variables (MV)	1	1
Measured Disturbances (MD)	2	[2;3]
Unmeasured Disturbances (U...	0	

Signal Type	Size	Channel Indices
Measured Outputs (MO)	1	1
Unmeasured Outputs (UO)	0	

Figure 3.2 : MPC Structure Specifications.

The nominal values and other I/O attributes need to be specified in the relevant option under the same tab in the app window. For the current work, the nominal values of P_h, P_w, and T_a are set at 100 W, 500 W and 15 ºC respectively. The nominal output, i.e. the temperature inside the house T_{in}, is set at 16ºC. The different signals that are specified for each of the inputs as well as the reference set point will centre around their respective nominal value.

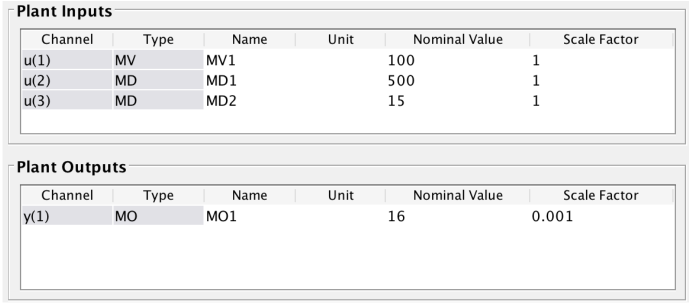


Figure 3.3 : I/O Attributes.

3.3.2 Simulation Scenarios

In MPC design, the controller is simulated in closed loop under multiple scenarios. These can be set and edited from the 'Edit Scenario' option. The editing window is shown in figure 3.3. In each scenario, different MDs, as well as the reference set point for T_{in} can be set. Simulation period is set at 24 hours (= 24x3600 = 86400 s). Reference previewing is turned on. If MD previewing is on, weather forecast will need to be used, not actual measurements. This cannot be ensured in MATLAB simulation environment, where previewing results in real data being used from the array

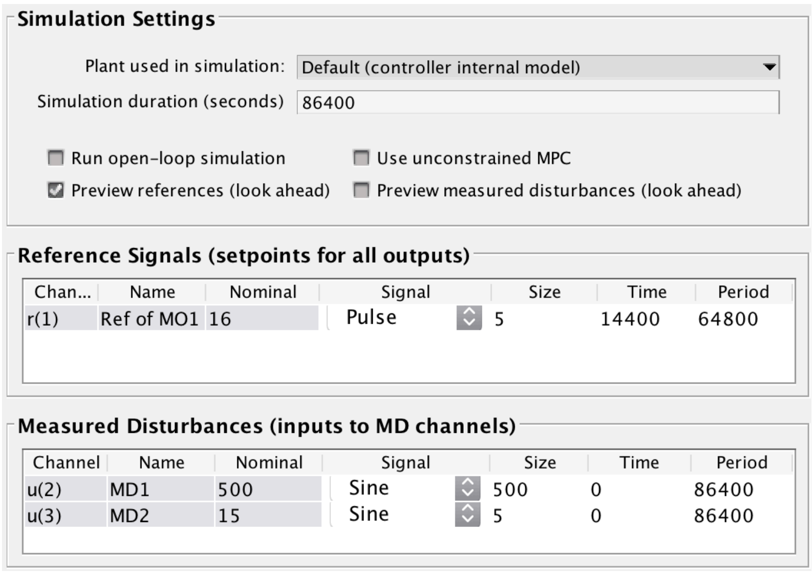


Figure 3.3 : Simulation Scenario Settings.

Controller behavior is observed in each scenario. Tuning is done to achieve satisfactory performance levels under plausible real scenarios. Three tested scenarios are tabulated below. Reference set points are kept identical in agreement with actual temperature requirements in the house.

	r(1) = T_{in} [ºC]	u(1) = P_h [W]	u(2) = T_a [ºC]
Scenario I	16ºC –> 20ºC –> 16ºC (6 h) (24 h)	Constant 500 W	Constant 15 ºC
Scenario II	16ºC –> 20ºC –> 16ºC (6 h) (24 h)	Sinusoid 500 ± 500 [W] (period 24 h)	Sinusoid 15 ± 5 [ºC] (period 24 h)
Scenario III	16ºC –> 20ºC –> 16ºC (6 h) (24 h)	Gaussian (size 100)	Gaussian (size 10)

Table 3.1 : MDs in Different Simulation Scenarios.

The pulse nature of reference points is, as stated earlier, in accordance to real requirements. The prime requirement is a comfortable 20ºC during majority of the day time. During the night time, when the occupants are asleep, efforts on maintaining 20ºC are not needed. This is replicated in a reduced set point of 16ºC for the first 6 hours of the day, from midnight to 6am.

3.4 MPC Tuning

To optimize the performance of the MPC with respect to performance, it needs to be tuned. The 'Tuning' tab reveals all the options available to do the same in the MATLAB app.

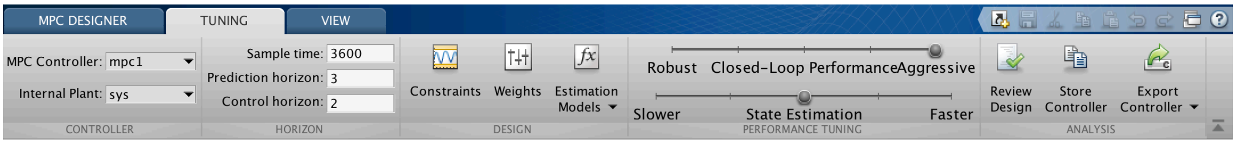


Figure 3.4 : Options Under the Tuning tab in the App

3.4.1 Constraints

There are practical limitations which are not taken into account within simulations by default. For example, in this context, the controller might signal a correction heating that is not practical realizable. The actuator, heat pump, has an operational wattage rating of 0-6000 [W]. This needs to be specified, as shown in figure 3.5.

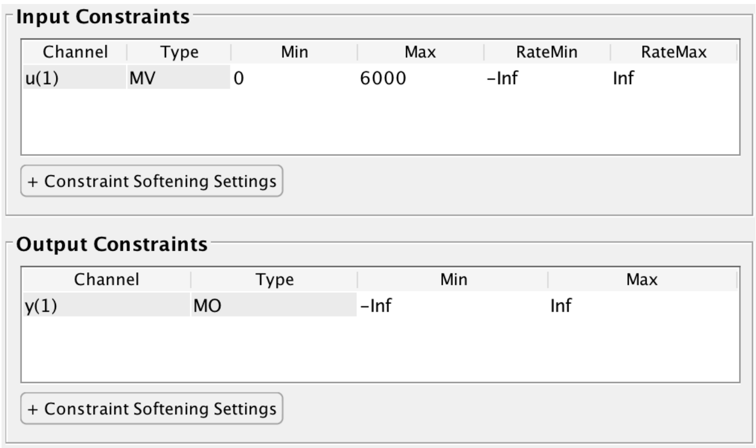


Figure 3.5 : MPC Contraints

No constraint is set on outputs as it is not a priority to limit T_{in}. The same is the case for rate of change of controller effort P_h. The most important constraint to simulate a practical scenario is the Min and Max on MV, P_h, set as shown.

3.4.2 Weights

A model predictive controller design usually requires some tuning of the cost function weights. This influences the R_b matrix in the cost function described in equation (3.2). In the app, weights can be specified to assign importance to set-point adherence, as well as punish dynamic control moves. The priority in our system is set-point adherence of the CV. Accordingly, the weight on MO (Measured Output) is set, upon tuning, to 20. Weights on MV are not changed as there is no MV target, and controller dynamics is not the worry.

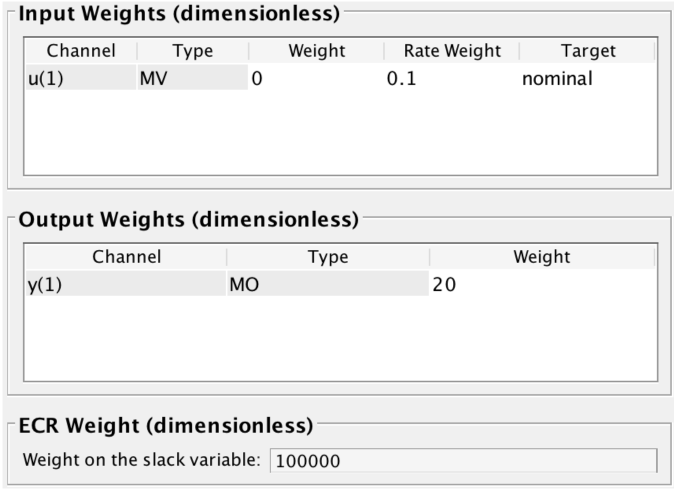


Figure 3.6 : Input & Output Weights

3.4.3 Prediction Horizon & Control Horizon

The length of prediction horizon and control horizon influences the temperature profile. This is expected, as a longer horizon length makes the MV start acting earlier in order to attain a set point. These can be manually set in the app window. Following are some nuances regarding N_p and N_c as described in MATLAB documentation.

- Recommended way is to increase N_p until further increase has minor impact on performance.
- $N_c < N_p$ is a strict condition.
- Small N_c means fewer variables to compute at each control interval, which promotes faster computations.
- If the plant includes delays, $N_c < N_p$ is essential. Otherwise, some MV moves might not affect any of the plant outputs before the end of the prediction horizon

The default value of Nc is 2. Final tuned values of N_c and N_p are described, along with other tuned parameters, with the simulation results in later sections.

3.4.4 Closed Loop Performance

The swipe tool to tune the controller performance in closed loop is set more towards aggressive, and not robustness. The intention is to get close to the set point as quickly as possible. Aggressive control moves can be tolerated. Since the state space model has one state, which is the same as the output, tuning state estimation makes no difference, and is kept the way it is by default.

3.5 Simulation Plots

The designed MPC can be reviewed for stability and other factors through the "Review Design" option. The review option also suggests what needs to be done to make the design stable, if needed.

The plots for controller performance in each of the three scenarios is shown in the figures that follow. The tuned controller is exported to Matlab script, and is then simulated for a prolonged period, with real data of P_w and T_a.

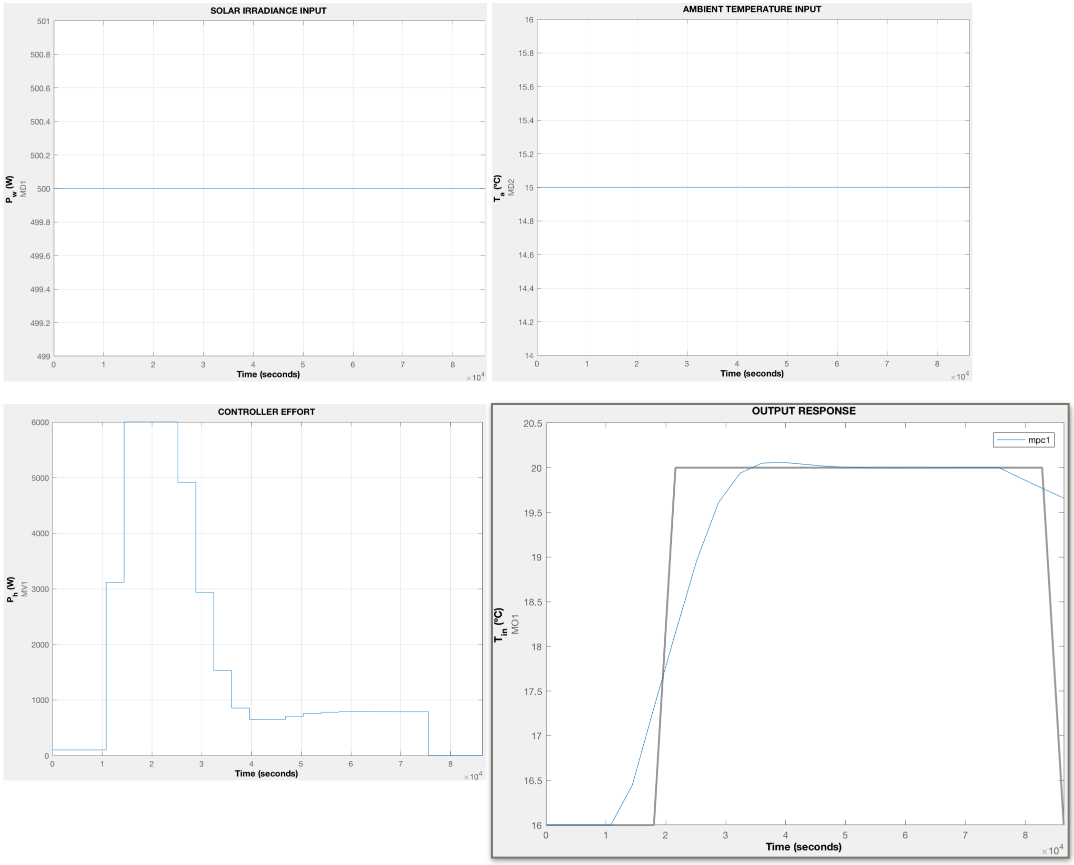


Figure 3.7 : System Inputs & Outputs in Scenario I

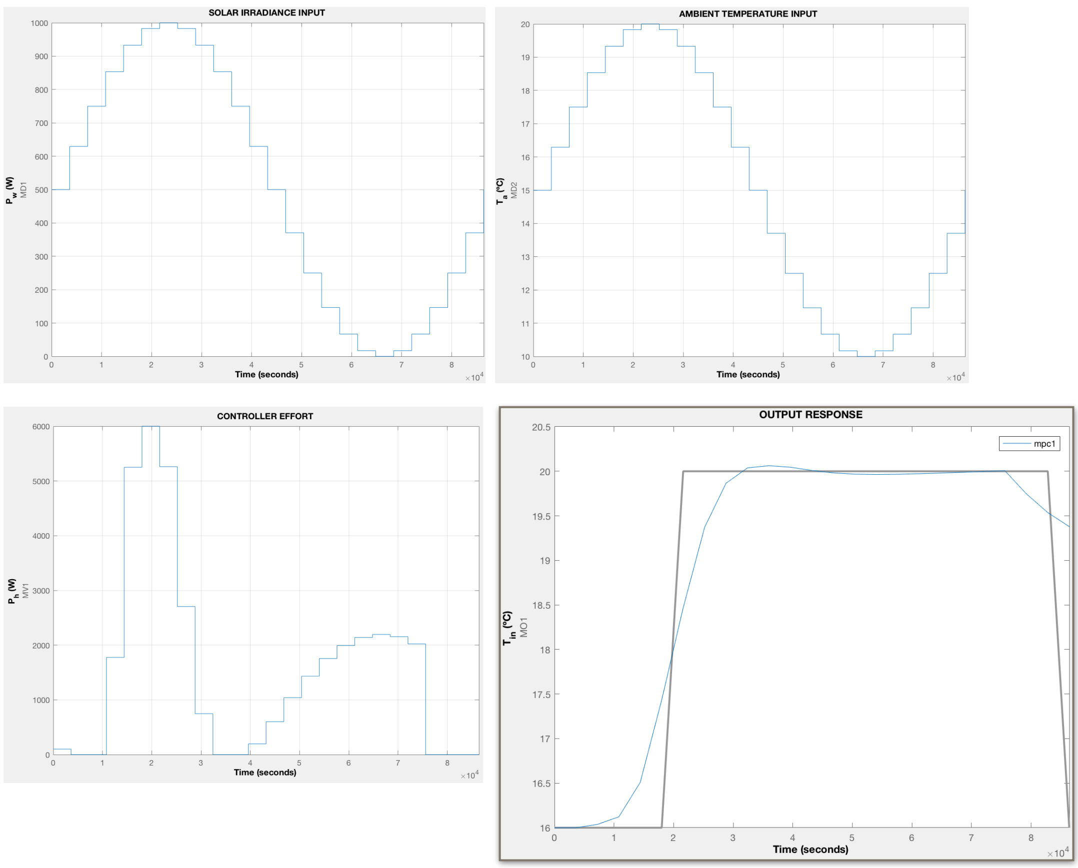


Figure 3.8 : System Inputs & Outputs in Scenario II

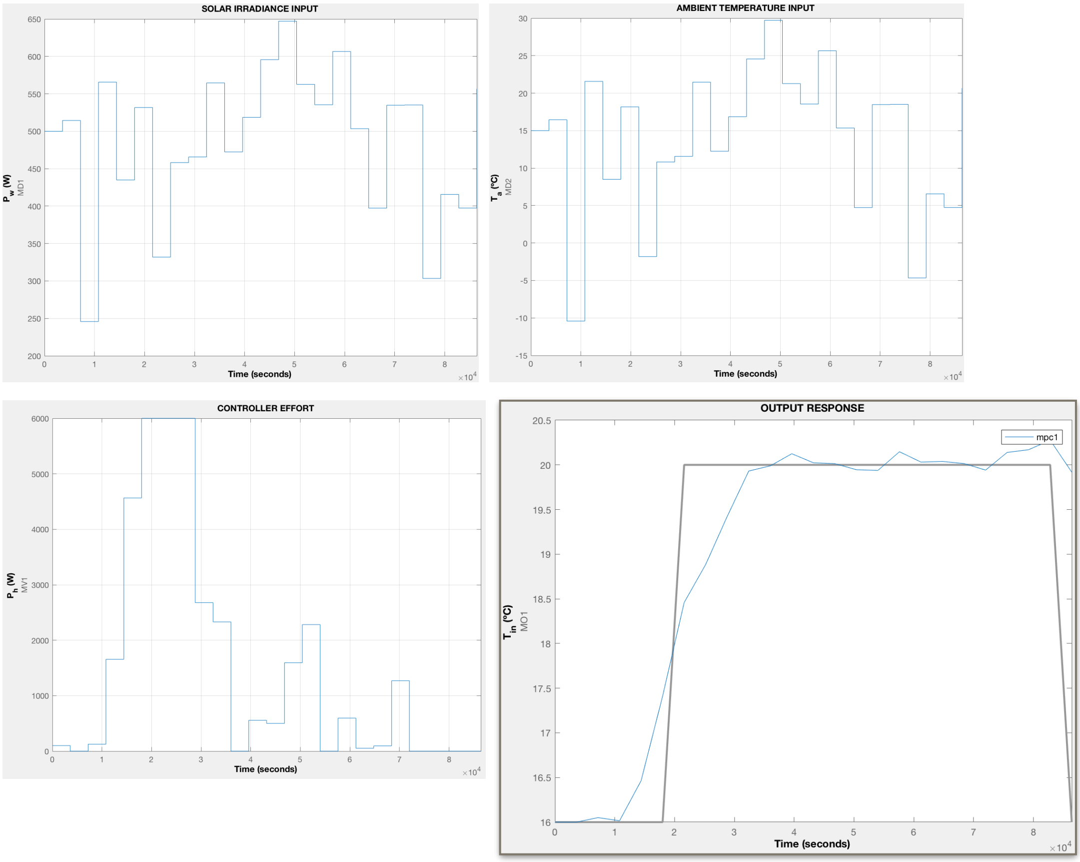


Figure 3.9 : System Inputs & Outputs in Scenario III

3.5.1 Comments on Controller Simulations

The performance of the controller appears satisfactory in all three scenarios. It must be stated here that the two set point values, 16ºC and 20ºC, are not equally important. The main purpose is to maintain comfortably warm temperature when the dwelling occupants are present. The lower set point at night is not as important, and is primarily a hint to conserve power. With these things in mind, there are a few comments worth making about the transient response behavior, prior to prolonged simulations with real disturbance data.

- In response to a set point change, the transient behavior is seen to start acting a few hours in advance. This is expected, with reference previewing, and a prediction horizon of sufficient length.
- While an advanced controller action is good when it comes to achieving the comfortable living temperature (20ºC), the same cannot be said for the other change. An early-acting control action towards the lower night-time set point (16ºC) compromises with the 20ºC requirements in its last hour or so.
- Tuning performance by changing prediction horizon lengths helped create a balance of temperature profile on either end of the set point change.

3.6 Prolonged MPC Simulations

With the MPC now tuned to attain decent performance in the three different scenarios, the controller can now be tested with real data of the measured disturbances, the solar irradiance and ambient temperature. Simulation is done over a 20 day period. Reference set points of a single day period are concatenated to form an array of set points for the 20 days. This shown in figure 3.10. For clarity of perspective, the two MDs are plotted, shown in figure 3.11. The real deal, the profile of closed loop temperature response, is shown in figure 3.12.

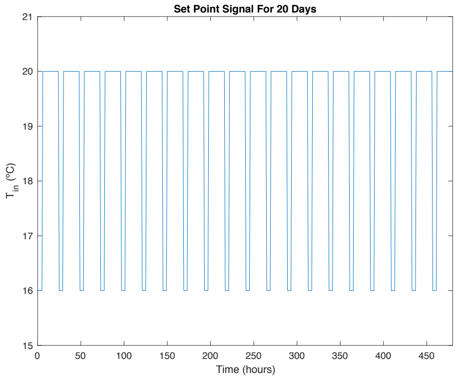


Figure 3.10 : Set Points Profile for 20 Days

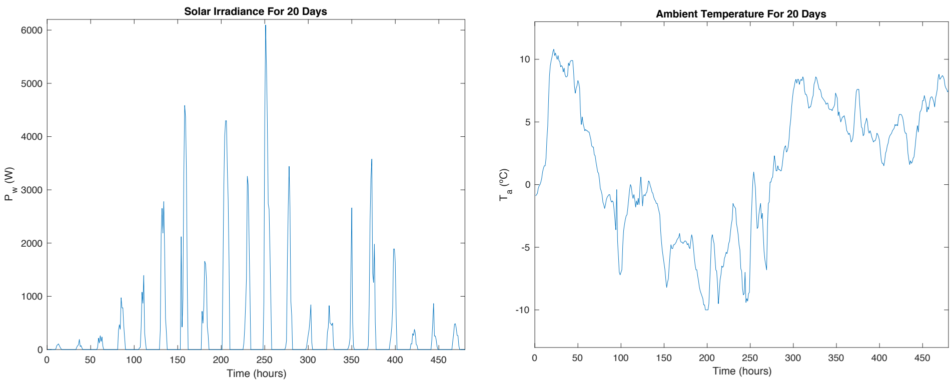


Figure 3.11 : Solar Irradiance and Ambient Temperature Profile for 20 Days.

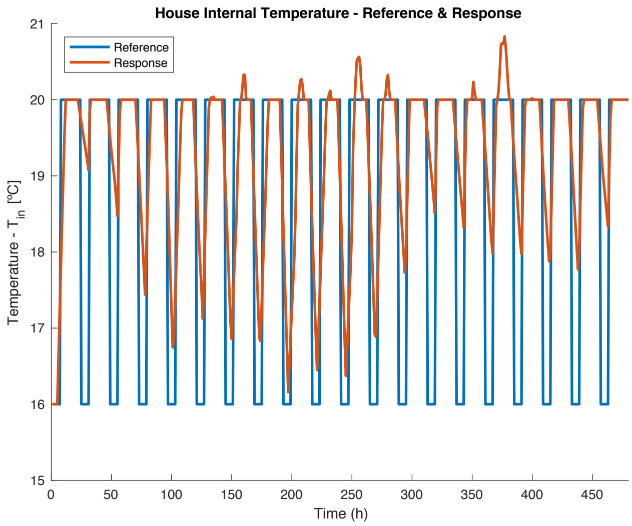


Figure 3.12 : Temperature Inside the House – References and Closed Loop Response.

The controller performance over the 20 day period looks satisfactory, except for a few instances that can be explained by the comments made in 3.4.1. With these simulation results, further analyses of controller performance and the control strategy itself can be made. Chief among the analyses is a comparison of this MPC with conventional feedback control, in terms of power consumption and consequent costs. Details on this are documented in the next chapter.

– 4 –

COMPARITIVE & CRITICAL OUTLOOK

With a decent MPC performance in simulations, there are several steps that need to be, and ones that can be taken, to further the idea of sustainable, smart domestic heating.

First, the designed MPC's performance needs to be assessed in comparison with conventional feedback control. The parameter of comparison will be power consumption. Sure the MPC has its advantages, but if it ends up in a power consumption profile that is not too much of an improvement, the scales even out.

Further, a 'user's review' of the MPC App of Matlab is also provided commenting on the freedom in the steps of MPC design and tuning, as well as the options and features in the app.

Lastly, there are always improvements possible. A section in this chapter documents the recommendations to take this work forward.

4.1 Energy Comparison

The results of MPC simulation reveal the heating requirements on the entire simulation duration. For conventional feedback control, closed loop simulations in the excel environment gives the required power consumption profile. The excel environment has a feedback control feature which was decoupled (made open-loop) for staircase tests documented in chapter 2. Hence, a comparison of the two control approaches is a good test for the MPC.

Actuator in both cases, feedback as well as MPC, is assumed to have an efficiency of 100%. This means that 100 W of energy is consumed by it to provide 100 W of heating. Figure 4.1 shows the control actions in both cases.

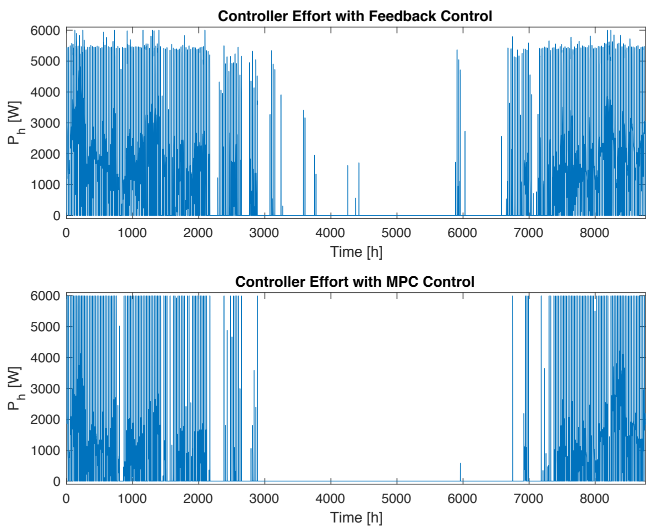


Figure 4.1 : Controller Effort with Feedback & MPC Control.

Total energy consumption is calculated by adding up all the heating requirements put forth by the controller, throughout the year. Energy costs are assumed to be €0.20/kWh. Table 4.1 lists down the calculated values in this comparison. The energy values listed in the table are only of heating requirements. Clearly, MPC brings with it a significant cut in the costs, as a consequence of a reduction in energy consumption.

Annual Energy Consumption	Feedback Control	7.2465 MWh
	MPC	4.5297 MWh
Energy Saved Annually with MPC	2.7169 MWh	
Annual Cost Saving with MPC	€543.37/-	

Table 4.1 : Feedback vs MPC – Energy Consumption & Costs

From figure 4,1 there is an evident difference in the controller behavior under both control implementations. Although the maximum amplitude of control appears to be high in MPC, the annual mean controller effort is drastically reduced from 827.23 W to 517.08 W. This is because, with its predictive nature of control, the MPC adjusts to future set points early. In addition, it also appears from figure 4.1 that the MPC is turned off for a longer duration during the off-season, as compared to the feedback control.

4.2 Matlab MPC App - A Review

Over the last few years, MathWorks has developed apps within the Matlab environment for essential functionalities. PID Tuner was a critical addition then, and MPC Designer is a promising tool as well.

- The fundamentals of MPC designing and tuning are satisfactorily met with the app.
- The user interface is extremely convenient and intuitive.
- A final designed controller can be exported to Matlab script, or to Simulink.

But, as much as the MPC designer is helpful, it still is not an industrial MPC software. This leads to a few restrictions. An industrial MPC software has a larger set of tools to tune the controller.

- In the context of this work, the two set points, 20ºC and 16ºC are not equally important. It would, therefore, be helpful if both these set points could be ranked or weighed. Matlab does not have this feature, while industrial MPC softwares do.
- A zone around the set point value is also a helpful MPC feature absent in Matlab. The zone could be ±1ºC, around the set point of 20ºC. This would avoid unnecessary controller action for small temperature changes imperceivable to the occupants.

Some of the shortcomings can be overcome if the MPC is exported to the Simulink environment, through additional blocks. While this does the job in simulations, it does not add said features to within the MPC itself. Nevertheless, Matlab's MPC App is not intended to be an industrial MPC software. For simulation purposes, it does a great job, allowing the user to easily design an MPC, add all sorts of design features, and simulate the whole thing in Simulink, or even in script if needed.

4.3 Work Review & Recommendations

Simulations thus far show great promise in the use of MPC for domestic heating. Over the successive steps of modeling, validation, and controller design, there are improvements and considerations that, if taken into account, have the potential of improving the overall system performance.

4.3.1 Test System Recommendations

In this work, the excel simulation environment provided the virtual test-bed to test the model. The dynamics of thermal behavior of the house are taken care of, including factors such as solar irradiance which contain rather extensive computations.

Using software testing environments is popular with HVAC systems. Proven test-bed environments include accredited platforms like TRNSYS, which have been certified to be highly accurate. This puts the excel environment in a spot. One of the drawbacks in excel simulations is the absence of realistic delays. Step tests on each of the 3 inputs revealed an unconvincing transient response, with the step responses in all three cases having exactly the same time constant. This absence of delays, and same transient behaviors to each input, is probably a reason for the really high model performance.

While the ideal testing scenario will be an actual house, with known thermal properties, etc., it is indeed inconvenient to test a real house with real occupants going about their daily activities. A certified software platform like TRNSYS or its cheaper counterpart will definitely provide a better environment to replicate house behavior, and consequently assess model performances.

4.3.2 Model Recommendations

The electrical analogy model considered in this work is, as already stated, rather simple. Assumption of the house being a single zone, with a single internal temperature quantity T_{in}. This is not the case in a realistic house, which has multiple floors, furniture and of course real occupant behavior. An upgrade to the model will not include the unknown disturbance of occupant behavior, but all other measurable influences will be included. Bacher and Madsen [5] do a good job laying out multiple models, along with the performances they observed. In practice, the model will have inaccuracies, partly because of the model itself, and partly because no two houses are the same.

Further, unpredictabilities, or unknown disturbances, are deliberately separated from the grey box model in this work. These include situation around the house, as well as the occupants' behavior. Such a separation is not possible with real data. The grey box model thus has the advantage of a priori knowledge of house thermal properties, and the uncertainties can be learned with a black box model from prediction errors of the grey box model [2]. To this end, neural network model is a possible future work. The authors in [9] explore artificial neural network modeling for a house system.

4.3.3 Actuator Recommendations

The actuator forms a fundamental part of a closed loop system. It is therefore imperative to include it. Current house setups have gas boilers which will eventually be replaced. From among electric based actuators, the heat pump is a promising option. Thus, a model of the heat pump is an important next step.

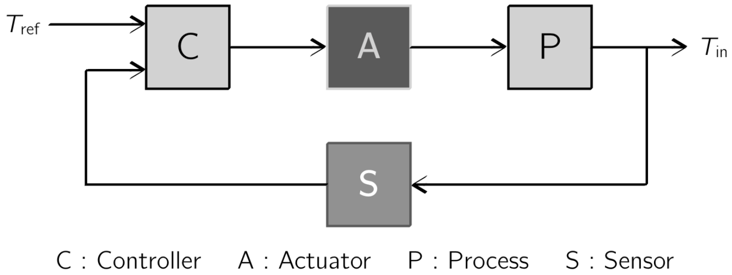


Figure 4.2 : Complete System Diagram with Actuator & Sensor.

A proper, valid heat pump model will include its own delays and dynamics. The efficiency curve of the heat will also give a clear picture of electricity demand for heating. The energy calculated thus far makes up heat energy requirements. Knowledge of heat pump will help translate that into electrical energy requirements. The sensor also forms part of the overall system, but it only needs to be considered, when things come down to implementation.

4.3.4 Comprehensive Energy Management System

The presence of solar panels on the roof of the house provides an additional input of energy to the house. The house under study has a specific coverage area of solar panels, and it is assumed that there are solar collectors that store the energy picked up by these panels. There is a more-than-decent opportunity to tap into this available energy to provide requisite heating. It should also taken into account that the energy from the solar collectors will be needed to meet the daily hot water requirements as well. Thus, the heating requirements computed by the MPC can be fed into an algorithm that decision whether said energy is provided from the solar collectors or from the grid.

4.3.5 MPC Developments

In the current simulations, being restricted to the Matlab environment, the developed MPC has its limitations as already stated in 4.2. The inclusion of a heat pump model will also raise the need to tune the controller again, as this time the dynamics of the heat pump will also play a role in closed loop behavior of the system.

In the comprehensive energy management system postulated in 4.3.4, a different MPC can be designed that operates on energy costs. Cost function, which will be minimized, will be energy costs. This needs a totally fresh model that includes energy costs, solar panels' energy collection, and solar collectors.

4.4 Conclusions

The work in this project opens the door to using MPC for domestic heating. Simulation results hold great promise, and provides a good push to take the work forward. With the recommendations stated in 4.3, there is a great potential to develop a comprehensive energy management smart and sustainable house, on the way to become a smarter, greener society.

REFERENCES

1 Netherlands. Planbureau voor de Leefomgeving, Centraal Bureau voor de Statistiek. (2016). *National Energy Outlook 2016*.

2 van Leeuwen, Richard Pieter. (2017). Towards 100% Renewable Energy Supply for Urban Areas and the Role of Smart Control. *PhD Thesis, University of Twente*.

3 Afram, A., Janabi-Sharifi, F. (2014). Review of Modeling Methods for HVAC Systems. *Applied Thermal Engineering 67*. 507-519.

4 Harb, H., Boyanov, N., Hernandez, L., Streblow, R., Müller, D. (2016). Development and Validation of Grey-Box Models for Forecasting the Thermal Response of Occupied Buildings. *Energy and Buildings 117*. 199-207.

5 Bacher, P., Madsen, H. (2010). Identifying Suitable Models for the Heat Dynamics of Buildings. *Energy and Buildings 43*. 1511-1522.

6 Afram, A., Janabi-Sharifi, F. (2013). Theory and Applications of HVAC Control Systems – A Review of Model Predictive Control (MPC). *Energy and Buildings 72*. 343-355.

7 Rogers, D., Foster, M., Bingham, C., (2013). Experimental Investigation of a Recursive Modelling MPC System for Space Heating Within an Occupied Domestic Dwelling. *Building and Environment 72*. 356-367.

8 Khanmirza, E., Esmaeilzadeh, A., Markazi, A.H.D. (2017). Design and Experimental Evaluation of Model Predictive Control vs Intelligent Methods for Domestic Heating Systems. *Energy and Buildings 150*. 52-70.

9 Magalhães, S.M.C., Leal, V.M.S., Horta, I.M. (2017). Modelling the Relationship Between Heating Energy Use and Indoor Temperature in Residential Buildings Through Artificial Neural Networks Considering Occupant Behavior. *Energy and Buildings 151*. 332-343.