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Advanced Control Strategies for Optimal Operation of a Combined Solar and Heat Pump System

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This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

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Dedication

To

My Parents, My Siblings, My Wife and My Supervisors

Dr Mahroo Eftekhari and Dr Thomas Steffen

Abstract

The UK domestic sector accounts for more than a quarter of total energy use. This energy use can be reduced through more efficient building operations. The energy efficiency can be improved through better control of heating in houses, which account for a large portion of total energy consumption. The energy consumption can be lowered by using renewable energy systems, which will also help the UK government to meet its targets towards reduction in carbon emissions and generation of clean energy. Building control has gained considerable interest from researchers and much improved ways of control strategies for heating and hot water systems have been investigated. This intensified research is because heating systems represent a significant share of our primary energy consumption to meet thermal comfort and indoor air quality criteria. Advances in computing control and research in advanced control theory have made it possible to implement advanced controllers in building control applications.

Heating control system is a difficult problem because of the non-linearities in the system and the wide range of operating conditions under which the system must function. A model of a two zone building was developed in this research to assess the performance of different control strategies. Two conventional (On-Off and proportional integral controllers) and one advanced control strategies (model predictive controller) were applied to a solar heating system combined with a heat pump. The building was modelled by using a lumped approach and different methods were deployed to obtain a suitable model for an air source heat pump. The control objectives were to reduce electricity costs by optimizing the operation of the heat pump, integrating the available solar energy, shifting electricity consumption to the cheaper night-time tariff and providing better thermal comfort to the occupants. Different climatic conditions were simulated to test the mentioned controllers. Both on-off and PI controllers were able to maintain the tank and room temperatures to the desired set-point temperatures however they did not make use of night-time electricity.

PI controller and Model Predictive Controller (MPC) based on thermal comfort are developed in this thesis. Predicted mean vote (PMV) was used for controlling purposes and it was modelled by using room air and radiant temperatures as the

varying parameters while assuming other parameters as constants. The MPC dealt well with the disturbances and occupancy patterns. Heat energy was also stored into the fabric by using lower night-time electricity tariffs.

This research also investigated the issue of model mismatch and its effect on the prediction results of MPC. MPC performed well when there was no mismatch in the MPC model and simulation model but it struggled when there was a mismatch. A genetic algorithm (GA) known as a non-dominated sorting genetic algorithm (NSGA II) was used to solve two different objective functions, and the mixed objective from the application domain led to slightly superior results.

Overall results showed that the MPC performed best by providing better thermal comfort, consuming less electric energy and making better use of cheap night-time electricity by load shifting and storing heat energy in the heating tank. The energy cost was reduced after using the model predictive controller.

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1. **Ahmad, M. W.** Eftekhari, M. Steffen, T and Danjuma, A.M. (2013) Investigating the performance of a combined Solar System with Heat Pump for houses. Published in **Energy and Buildings**.
2. **Ahmad, M. W.** Eftekhari, M. Steffen, T and Danjuma, A.M. (2013) Control strategies for optimum operation of a solar heating system combined with a heat Pump. Submitted to **International Journal of Automation and Computing**.
3. **Ahmad, M. W.** Eftekhari. M and Deng, J. (2010) Model predictive control and Simulation of a solar water heating system with an ON/OFF controller. In Proceedings of **International Conference on Control, Automation, Robotics and Vision, Paris, France**.
4. **Ahmad, M. W.** Eftekhari. M and Deng, J. (2010) Model predictive control for Airport terminals-A review. In Proceedings of **International Conference on Control, Automation, Robotics and Vision, Paris, France.**
5. **Ahmad, M. W.** Eftekhari. M and Steffen, T. (2012) Model development of a solar system combined with heat pump. In Proceedings of the **18th International Conference on Automation & Computing, Loughborough University, Leicestershire, UK**.
6. **Ahmad, M. W.** Eftekhari. M and Steffen, T. (2012) Model development and control strategies for a soalr system combined with heat pump. In Proceddings of **45th IEP conference, Karachi, Pakistan**.

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List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial neural network
ASHRAE	American Society of Heating, Refrigeration and Air conditioning Engineers
ASHVE	American Society of Heating and Ventilating Engineers
BEMS	Building energy management system
BRE	Building Research Establishment
CET	Central England Temperature
COP	Coefficient of performance
DCLG	The Department for Communities and Local Government
DECC	Department of Energy and Climate Change
ET	Effective temperature
FLC	Fuzzy logic control
GA	Genetic algorithms
GMV	Generalized minimum variance
GPC	Generalised predictive control
HP	Heat Pump
HMI	Human Machine Interface
HVAC	Heating, ventilation and air conditioning
IEA	International Enegy Agency
IEO	Internal Energy Outlook
IES	Integrated Environmental Solutions
ISO	International Standard Organisation
LP	Linear programming
MIMO	Multiple input and multiple output
MPC	Model predictive control
NSGA-II	Non-dominating sorting genetic algorithm
OECD	Organization for Economic Cooperation and Development

PI	Proportional and integral
PID	Proportional, integral and derivative
PMV	Predicted mean vote
PPD	Percentage people dissatisfied
QP	Quadratic programming
SCRI	The Salford Centre for Research & Innovation
SISO	Single input single output
S-S	Steady-space
TRNSYS	Transient Systems Simulation Program
UKCIP	UK climate impact program
VAV	Variable-air-volume

List of Symbols

A_1	Area of the heat transfer section for conduction heat transfer (m^2)
A_2	Surface area for convection heat transfer (m^2)
A_c	Area of solar thermal collectors (m^2)
A_c and B_c	Jacobian matrices
C_1	Capacity of wall layer 1 $(J.K^{-1})$
C_e	Heat capacity of the evaporator $(J.kg^{-1}K^{-1})$
c_p	Specific heat capacity of water $(J.kg^{-1}K^{-1})$
C_r	Heat capacity of the refrigerant $(J.kg^{-1}K^{-1})$
C_{res}	Rate of convective heat loss from respiration (Wm^{-2})
C_{sk}	Rate of convective heat loss from the skin (Wm^{-2})
e_r	Error between reference and tank temperatures (K)
E_{res}	Rate of evaporative heat loss from respiration (Wm^{-2})
E_{sk}	Rate of total evaporative heat loss from the skin(Wm^{-2})
f_{cl}	Clothing area factor
F_R	The collector heat removal factor
I	Solar radiation intensity (Wm^{-2})

I_{cl}	Clothing insulation$(m^2K.W^{-1}, Clo)$
H	Metabolic heat generation (Wm^{-2})
h	Convective heat transfer coefficient $(Wm^{-2}K^{-1})$
K	Efficiency coefficient of the compressor
k	Thermal conductivity $(Wm^{-1}K^{-1})$
k_i	Integral controller gain
k_p	Proportional controller gain
$\dot{m}$	Mass flow rate of water between tanks $(kg.sec^{-1})$
$\dot{m_{c1}}$	Mass flow rate of refrigerant in the condenser $(kg.sec^{-1})$
$\dot{m_{e1}}$	Mass flow rate of refrigerant in the evaporator
M	Metabolic energy production per unit body area (Wm^{-2})
m_c	Mass of the condenser (kg)
m_e	Mass of the evaporator (kg)
N_u	Control horizon
$\dot{Q}_e$	Heat transferred into the evaporator (J)
$\dot{Q}_c$	Heat transferred out of the condenser (J)
$\dot{Q}_{in}$	Heat transferred into the heat pump cycle (J)
$\dot{Q}_{out}$	Heat transferred out of the heat pump cycle (J)
Q	Output weight
Q_r	Energy received by the solar collector (W)
Q_{res}	Total rate of heat loss through respiration (Wm^{-2})
Q_{sk}	Total rate of heat loss from the skin (Wm^{-2})
q_{cond}	One-dimensional heat conduction (W)
q_{conv}	Convection heat transfer (W)
q_{stored}	Stored heat energy inside the wall layer (W)
R	Rate of radiative heat loss from the skin (Wm^{-2})
R_i	Inner film resistance (Km^2W^{-1})
R_o	Outer film resistance (Km^2W^{-1})

R_u	Weight on Input rate
$R_{\Delta u}$	Weight on input change rate
T1	Buffer tank water temperature (℃)
T2	Hot water tank temperature (℃)
T3	Heating tank water temperature (℃)
t_a	Air temperature (℃)
$T_{air,in}$	Temperature of air coming into the evaporator (℃)
$T_{c,in}$	Temperature of the refrigerant into the condenser (℃)
$T_{c,out}$	Temperature of the refrigerant leaving the condenser (℃)
$T_{e,in}$	Temperature of the refrigerant feeding into the evaporator (℃)
$T_{e,out}$	Temperature of the refrigerant leaving the evaporator (℃)
T_r	Reference tank temperature (℃)
t_r	Mean radiant temperature (℃)
$T_{w\_tank\_in}$	Temperature of water going into the buffer tank (℃)
u	Input vector of the system
U_O	Initial input value
$u_T P$	Temperature resistance on the condenser side (℃)
$u_E P$	Temperature resistance on the evaporator side (℃)
$\bar{u}$	Nominal input value
v	Air velocity $(m.sec^{-1})$
W	Rate of mechanical work per unit area (Wm^{-2})
W_{net}	Work done to the heat pump cycle (J)
x	State vector of the system
X_O	Initial state value
y	Output vector of the system
τ	Transmission coefficient of the collector
α_1	Absorption coefficient of the collector
Φ	Relative Humidity (%)

Chapter 1 Introduction

1.1 Introduction

The rapid increase in the world's energy use is one of the main concerns of today's society. This energy use has high environmental impacts such as depletion of the ozone layer, global warming, climate change etc. Buildings account for almost 40% of the final energy use in the world. In European countries 70% of this energy goes towards comfort control in buildings- for HVAC (IEA, 2008). All the energy in wood, Oil and natural gas was originally produced through photosynthesis and complex chemical reactions. Fossil fuels are the result of chemical reactions in decaying vegetation under high temperatures and pressures over long periods of time (Kreith et al., 1978). The UK government is committed to delivering 15% of its energy demand from renewable sources by 2020. Solar energy on the other hand is clean and can be delivered without pollution.

There are different renewable energy sources, which can be used to generate energy e.g. solar energy, wind energy, tidal energy, biomass etc. Photovoltaic arrays can be used to generate electricity from solar energy and these can be connected to the main grid. Solar home systems are also available to generate electricity for homes. This system consists of PV arrays, a rechargeable battery and a charge controller. The wind's kinetic energy can be captured by using wind turbines and then this kinetic energy can be converted into mechanical energy and then into electrical energy. Solar collectors have a wide variety of applications, such as solar water heating, space heating and cooling, solar refrigeration, solar thermal power plants, solar desalination etc. In solar water heating systems the main component is the solar collector, which absorbs energy and transfers it to the working fluid. Integrated collector systems use part of the tank as a solar collector. The disadvantage of this system is the thermal losses from the tank (Kalogirou, 2004). Solar energy systems can be used for hot water generation. In this application a heat exchanger is used between the solar collector and the hot water tank, which allows the use of antifreeze solutions in the solar collector loop (Duffie et al., 1991).

A heat pump is a device that transfers heat energy from a low temperature source to a high temperature sink. The use of a heat pump for space heating and hot water generation is gaining popularity day by day because of its low energy consumption compared to other equipment (Agrawal et al., 2007). The heat pump operates best at low temperature differences, when the coefficient of performance (COP) is higher and the required energy is low (Zogg et al., 2001).

Solar radiation is not available during night-time. Therefore, solar collectors can be combined with a heat pump in such a way that in times of low solar radiation the heat pump is used instead. The heat pump can also benefit from lower night-time electricity tariffs when combined with a thermal storage. The main idea behind developing an optimal control strategy in this work is that the control strategy can predict outside weather conditions and occupancy patterns in the building. The strategy will also predict any future hot sunny day and can then use maximum free energy during the day i.e. solar energy and can also predict the electricity prices and use electricity during the night.

1.2 Control System

The control system is one of the key components of any HVAC system, and it is critical for good energy performance of a building. It is also acknowledged that the heating systems are challenging to control because of swings in day-to-day and season-to-season energy and thermal comfort demands (El-Deen, 2002). The heating system of a building is always about a compromise between thermal comfort of the occupants and energy consumption. If a high level of thermal comfort is maintained at all times then energy cost will be high; and if energy consumption is minimized then thermal comfort has to be sacrificed. A smart system can try to save energy in periods of low occupancy, which significantly reduces any negative impact on thermal comfort.

There are different control strategies that are used for renewable energy systems. Classical control methods use single input single output (SISO) feedback without requiring a model of the system e.g. thermostat controlling room temperature. Such a control method is easy to implement and can be useful for a wide range of renewable systems. However, these control methods are limited and they are difficult to extend to multivariable systems without significant experience.

Further controllers have been developed in recent years which try to increase the effectiveness with complex and non-linear systems and to make them more accessible for non-control engineers. Model predictive and fuzzy logic control techniques are among these control methods. The fuzzy logic control is based on three main parts; fuzzifier, rules and defuzzifier. The drawback of this controller is that few guidelines are available on how to set rules of the fuzzification values (Marjanovic et al., 2004).

The model predictive controller (MPC) uses a model of the system to predict the future dynamics of the system. This information is then used by the controller to find the best control move. The controller uses information about past inputs and outputs along with the estimation of the current and future disturbances (Camacho et al., 2004). During the development phase of renewable energy, a system model is typically created to assess the potential performance of the system. This model can then be used by the model predictive controller, which gives a strong reason to apply the MPC. The other reason is that the MPC can be implemented and tuned without advanced knowledge of control engineering theory. This type of controller deals well with external disturbances and can handle system constraints. However, these advantages need to be investigated in detail to make sure that this controller is feasible and gives cost effective control for renewable energy systems.

1.3 Research aim and objectives

The aim of the research is to develop an optimal control strategy for a solar heating system combined with a heat pump. According to Tordorov, 2006, an optimal control strategy is a model based method which decides the control signal that will make process to satisfy physical constraints and at the same time minimizing/maximizing certain performance criteria.

This leads to the following objectives;

- A simulation model of the system, building and control will be developed as a test bed for analysing different control strategies.
- Design of a multi-input multi-output model predictive controller.
- Benchmarking a model predictive controller with on-off and PI controllers.
- Design of a thermal comfort based model predictive controller to provide better thermal comfort to the occupants as the refinement of the above.

- Use of a genetic algorithm to explore the compromise between thermal comfort and energy consumption.
- A comparison between different control methods in terms of load shifting, energy cost, thermal comfort and response to environmental changes.

1.4 Thesis organisation

A brief description of the thesis organization is given below.

Chapter 2: Literature Review

This chapter critically reviews the previous research on model predictive control applied to buildings, heating systems and thermal comfort based control. Energy trends, UK and world legislation for climate change and different incentives offered by the UK government are discussed. Thermal comfort based control research is explained. To conclude the review, a number of issues deserving further study are also indentified.

Chapter 3: Setup and modelling of the solar system assisted by a heat pump

This chapter presents the experimental setup and deduces the dynamic model of the solar heating system combined with a heat pump and also of a building. The model is developed to assess the performance of different control strategies. A lumped parameter method is used to model the building realistically with a reasonably simple model. A resistance-capacitance model is constructed for the building. Different methods to develop a realistic model of the heat pump are presented in this chapter and the solar collector and tank model are explained. Model verification is done in this chapter. A linear model and state space representation are also discussed at the end.

Chapter 4: Control Strategies

In this chapter, two conventional control strategies are applied to the solar heating system combined with a heat pump. For comparison, a basic linear model predictive control algorithm is applied to the system. Initially, all three control strategies are applied to a simple plant consisting of solar collectors and heat pump which are connected to a single tank. These control strategies are also applied to the main system. Four different climatic conditions are simulated to find out how these controllers behave in different weather conditions. The performance of all three control strategies is evaluated on the basis on two objectives: using night-time cheaper electricity tariffs (low energy cost) and storing energy during the off-peak period (load shifting). The simulation results obtained from all three controllers are also presented and discussed.

Chapter 5: Thermal comfort based control

In this chapter proportional-integral and model predictive controllers are applied to control the thermal comfort perception of the occupants. Two case are simulated, one is based on the room air temperature and the second one is on the predicted mean vote (PMV). PMV is modelled by considering only room air and radiation temperatures as the changing parameters, whereas the other four parameters are kept constant.

Chapter 6: Investigation of model and objective mismatch

In chapters 4 and 5, the linear MPC is applied to a non-linear simulation model and this model mismatch is found to cause a number of issues. These are investigated by using a linear MPC to control a linear simulation model of the system. A genetic algorithm (GA) known as a non-dominating sorting genetic algorithm (NSGA-II) is then applied to the system in this chapter, finding how linear cost and squared cost can affect energy consumption and temperature deviation from its set point.

Chapter 7: Conclusions and recommendations for future work

The final chapter considers the findings of the research and presents the main conclusions. Future recommendations are also made with regard to the areas that are worthy for further investigation.

Chapter 2 Literature Review

2.1 World and UK energy consumption

The rapid increase in world energy use is one of the main concerns of today's world. This energy use has high environmental impacts such as depletion of the ozone layer, global warming, climate change etc. According to the IEA (International Energy Agency) primary energy has grown by 49% in the last two decades (1984-2004) and the CO_2 emissions have increased by 43% (InternationalEnergyAgency, 2006). It was also shown by the IEA that there is an average annual increase of 2% in energy and 1.8% in the CO_2 emissions. These values are shown in Figure 2-1.

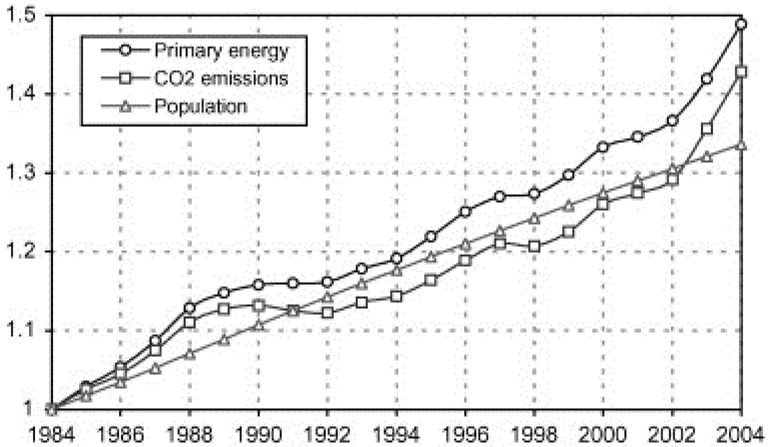


Figure 2-1: Primary Energy Consumption and CO_2 emissions. Source IEA, 2006

According to International Energy Outlook 2011 by EIA, there is a growth of 53% in the marketed word energy consumption from 2008 to 2035. In this reference case, IEO2011 also pointed out that much of the growth is in the countries outside the Organization for Economic Cooperation and Development (non-OECD) (U.S.EnergyInformationAdministration, 2011).

The energy sector can be divided into three main categories; buildings, industrial and transportation. The building category can be divided into two sub categories; residential and commercial. Residential energy use increases by 1.1% per year according to the IEO2011 reference case. The rise in residential energy consumption in the non-OECD countries is 1.9% per year whereas in OECD nations it is 0.3% per year. Commercial energy use has an average growth of 1.5% per year up to 2035 and the large share is again from Non-OECD nations.

There is also a change in the type of fuel that has been used for domestic consumption since 1970. In 1970, for the UK 39% of consumption was coal, 24% natural gas and 18% was electricity; in 1990 this changed to 8% coal, 63% natural gas and 20% electricity; and in 2011 to 1% coal, 65% natural gas and 25% electricity. This change can be seen in detail in Figure 2-2 shown below.

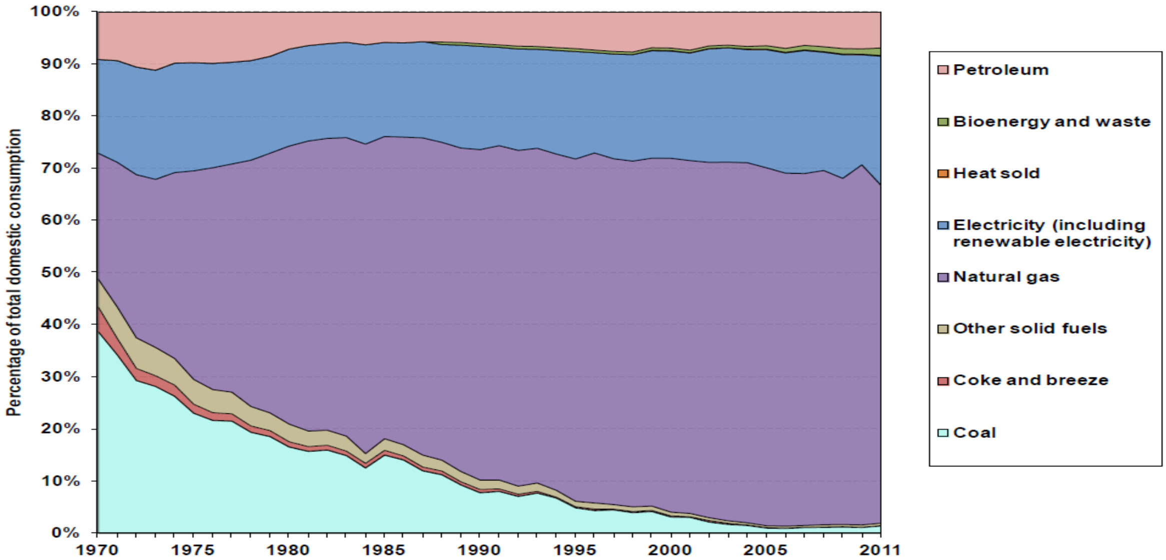


Figure 2-2: UK domestic consumption by fuel from 1970 to 2011 Source: DECC 2011

The main source of energy consumption in the domestic energy sector is for space heating, which was 60% of the total domestic energy consumption in 2011. Water heating accounted for 18%, lighting 19 per cent and cooking 3%. Figure 2-3 indicates that there has clearly been an increase in the amount of the energy used for domestic heating (DECC, 2011). It can also be shown that the main sources of energy consumption are space heating, hot water and lighting.

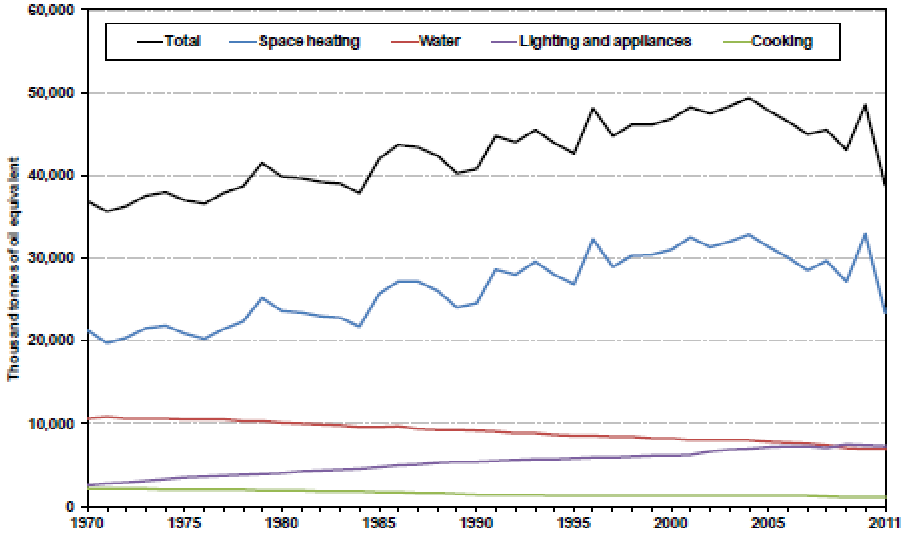


Figure 2-3: Final energy consumption of domestic sector by end use in UK Source: DECC, 2011

In Figure 2-4 projected trends in energy demand by sector are shown. It can be seen that the domestic energy demand is projected to decrease by 19% between 2007 and 2020. This decrease in projected demand is driven by energy efficiency measures and government policies on micro-generation and renewable energy (DECC, 2009a).

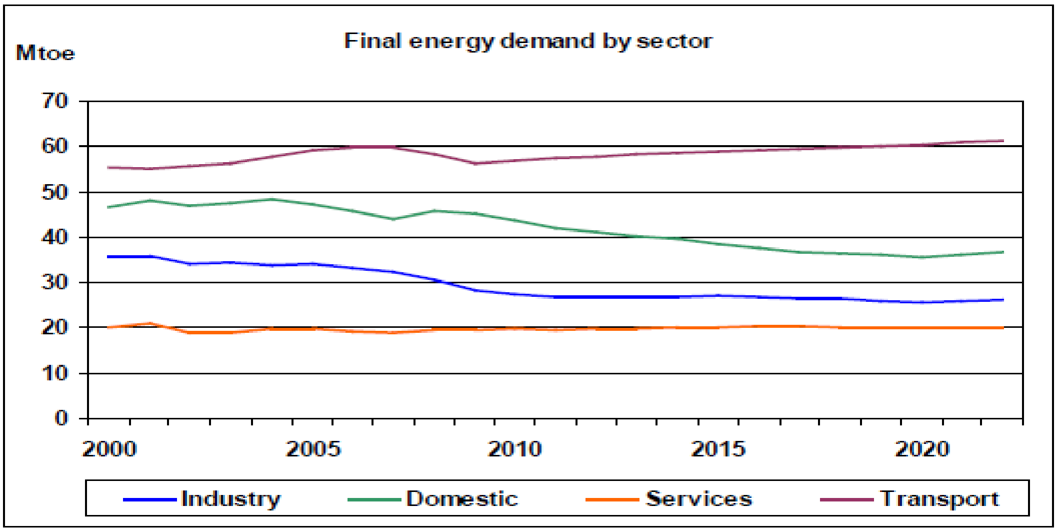


Figure 2-4: UK energy demand by sector Source: DECC, 2009a

2.2 Climate Change

Climate change is a global problem with local causes and effects, while air quality is usually a local problem. The UK government considers both to be important policy drivers. Hulme, 2002 et al., mentioned in their report on the UK Climate Impact

Program (UKCIP02) that climate is referred to as the average weather that is experienced over a long period of time, typically 30 years. In response to natural causes, the world climate has changed considerably, but recently it has also been driven by man-made influences. Human beings can affect global climate by releasing greenhouse gases –such as methane and CO_2 into the atmosphere. These gases absorb heat that is radiated from the Earth's surfaces and thus global temperature is increased by warming the atmosphere. Important natural causes include volcanic eruption,CO_2 capture in erosion, changes in the Earth's orbit and interaction between the oceans and the atmosphere.

2.2.1 Global climate Change and CO_2 emissions

The Earth's temperature is determined by a balance between energy coming to the Earth from the Sun and energy emitted by the Earth. Since the industrial revolution started, the concentration of greenhouse gases has increased, because of human activities. It is concluded by Crown (2008) that a rise in global temperature of between 1.8 to 4^{o}C is expected by the end of the 21st century. For the UK the rise in temperature is expected to be between 2 and 3.5^{o}C by the 2080s. The UK contributes about 2 per cent to global emissions of CO_2. It is estimated that this 2 per cent approximately equates to 6.2 to 6.9 billion tonnes of carbon per annum (Crown, 2008). The UK carbon dioxide emissions were 543 million tonnes in 2007 and residential emissions accounted for approximately 26% as shown in Figure 2-5 (ONS, 2009b).

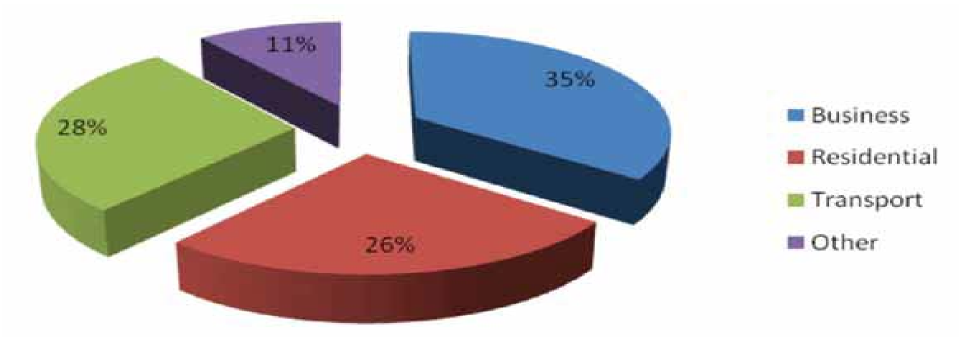


Figure 2-5: UK Carbon dioxide emissions percentage by sector wise Source: ONS, 2009b

The most useful way to describe the state of the global climate is by the average surface air temperature. The temperature has increased by (approximately) 0.74^{o}C from 1906 to 2005 (Hulme, 2002).This increase in temperature is accompanied by;

- Night-time temperatures have increased at about twice the rate of day-time temperature.
- A decrease in the amount of mountain glaciers.
- An increase in rainfall over many Northern hemisphere areas.
- A decrease in Northern hemisphere sea-ice amounts.

According to the Central England Temperature (CET) series the temperature has increased by 0.7^{o}C in the UK since 1659 and of that, a rise of around 0.5^{o}C occurred in the 20th century (UKCIP02).

2.3 Climate change policies and legislations

There are a large number of policies and legislations that have been designed to address the issue of climate change and it effect on built environment.

2.3.1 International climate change protocols

Climate change is a global issue and has to be addressed and legislated globally. The Kyoto Protocol is one of the protocols that binds countries to measure and manage their carbon emissions against set targets. This has to done by making policies including carbon capturing mechanisms, energy efficient buildings and new approaches for industry. In 2009, the Copenhagen Accord set a goal of keeping global warming under 2^{o}C through continued commitment of reducing carbon dioxide emissions. The summit also pointed out that the global warming can be kept under 2^{o}C by first identifying the imbalance between carbon emissions of developed and developing nations and then addressing them. The real issue of keeping global warming under 2^{o}C and meeting the Copenhagen Accord depends on the accuracy of the predictive model (SCRI, 2010).

The European Union has also established a number of directives to bring down the carbon emissions through the European Climate Change Programme (EU, 2006).The European Climate Change Programme started in 2000 to meet the EU's obligations set by the Kyoto protocol. The directive also came up with some issues regarding the energy performance of buildings. It addresses the following:

- A methodology for the calculation of the energy performance of buildings
- Applying energy performance standards on large buildings that have been renovated and applying minimum energy standards on all buildings

- Energy certification
- Inspection of HVAC systems, mainly boilers and ventilation equipment

2.3.2 UK Climate change legislation and policy

The UK government has published its white paper "The Energy Challenge" (DTI, 2006); issues for climate change and energy are outlined in this policy document. This policy was supported by the Climate Change and Sustainable Energy Act 2006, which binds the UK government to address fuel poverty and climate change. In a report called "Meeting the Energy Challenge" (DTI, 2007), the strategy to address some of the key issues of fuel poverty, climate change and energy security is outlined. In the Climate Change Act, 2008 targets are set to reduce CO_2 emission by 80% of the 1990 baseline set by Kyoto, by 2050. The Department of Energy and Climate Change was established in 2008, and published a strategy for low carbon transition. This strategy addresses how to avoid climate change and also points out how the UK can live with some climate change (SCRI, 2010).

2.4 Energy Sources

There are different forms of energy that are used worldwide to meet the energy requirements. These can be divided into three types i.e. fossil fuel, nuclear and renewables. The energy mode of interest here is renewable energy and is discussed below;

2.4.1 Renewable Energy

Renewable energy is a form of energy that comes from natural resources e.g. rain, wind, tides, sunlight and geothermal. It is called renewable because all these natural resources are naturally replenished. Renewable energy is not obtained by combustion of fossil fuels and therefore using renewable energy reduces greenhouse gas emissions. Most of the renewable energy sources are dependent on climatic conditions, for example solar radiations are not available during night.

According to statistics, in 2008 renewable energy supplied 19% of global energy consumption (REN21,2010). The 13% of this energy came from biomass which is primarily used for cooking and heating purposes, 3.2 % from hydropower and 2.6% from other renewable sources i.e. bio fuels, wind, solar, geothermal etc. Energy from biomass is growing slowly or declining in some regions of the world as the biomass is replaced by more efficient renewable energy forms. Hydropower is growing modestly while other renewables are growing rapidly in developed and developing countries (REN21, 2010). The renewable energy share of global final energy consumption is shown in Figure 2-6.

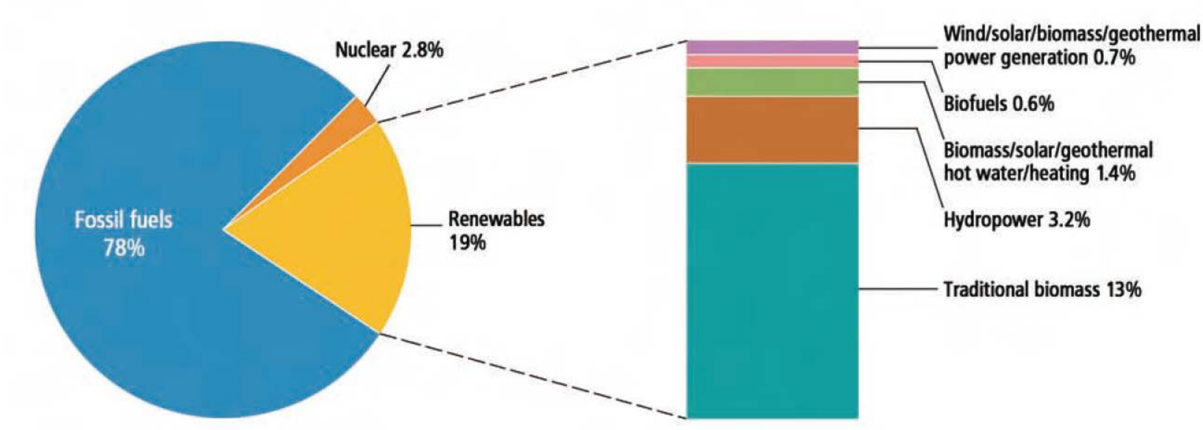


Figure 2-6: Global final energy consumption share for renewable energy Source: REN21, 2010

In 2009, the total use of renewable energy in the UK was 6.87 million tonnes of oil equivalent; of this 4.90 million tonnes was used for electricity production, 1.01 million tonnes for road transport and 0.97 million tonnes for heat generation. Renewable energy use grew by 14.6% between 2008 and 2009 and in 2010 it was more than two and half times that in 2000. Figure 2-7 shows the breakdown of that 6.87 million tonnes in terms of percentage. Biomass accounted for 80.7% of total renewable energy used, 11.6% from wind and 5.8% from hydro (DECC, 2010a).

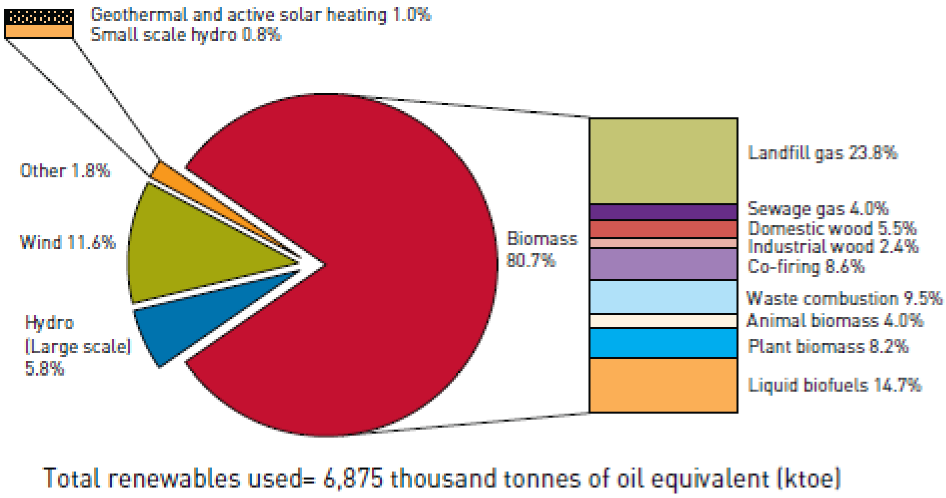


Figure 2-7:Renewable energy sources, 2009 Source: DECC, 2010a

In March 2007, the European Council agreed on a common strategy to address and tackle the issues of climate change and energy security. A target of 20% of the EU's energy to come from renewable energy sources was set by the European council. In 2008 a new renewable energy directive negotiated on this target and came up with an agreement of country "shares" of this target. By 2020 the UK has to consume 15% of its final energy consumption from renewable energy sources. This percentage is calculated on a net calorific basis and with a cap on fuel used for air transport (DECC, 2010a).

2.4.2 Renewable energy incentives and regulations

The UK government has introduced many incentives for householders in order to meet the renewable energy generation targets. One of them is the feed-in tariff but unfortunately heat pumps are not included in this scheme. Houses with heat pumps installed can gain benefit from the incentives shown below.

2.4.2.1 Renewable Heat incentive

Space heating is the main source of energy consumption in the UK and accounts for 47% of total UK energy consumption. In all non-transport sectors more than 77% of energy use is for heating. According to some data in 2011 approximately 69% of heat is produced from gas, 10% from oil, 14% from electricity and only 1.5% from renewable energy sources. To meet the target of 15% by 2020, the UK has to produce 12% of its heat needs from renewable energy. The UK government has introduced The Renewable Heat Energy Incentive (RHI) to pay to householders for the heat that is generated from renewable energy (DECC, 2011b).

The RHI is a two phased approach. In the first phase only non-domestic sectors are considered and in the second phase, the domestic sector will also be included. Currently the following renewable energy technologies are eligible under the RHI;

- Heat pumps
- Biomass boilers
- Solar thermal
- Geothermal
- Energy from Municipal solid waste
- Bio methane injection and biogas

2.4.2.2 Code for sustainable homes

Heat pumps can help users to comply with the code for sustainable homes because they produce less carbon than a conventional boiler. The code for sustainable homes has been based on the BRE EcoHomes System. The code has the following features:

- It introduces minimum standards for energy and water efficiency and therefore it requires a high level of sustainability performance.
- It uses a simple awarding system - indicated by 'stars', to rate the overall sustainability of a home. The minimum rating is one star ★ and the maximum is six stars ★★★★★★. The code considers 9 sustainability criteria and, among those criteria one is energy consumption and the resulting CO_2 emissions to the atmosphere (DCLG, 2006).

2.5 Solar thermal collectors and heat pumps

A solar thermal collector converts solar energy to the thermal energy of the working fluid in the collector. The solar energy is absorbed by a solar collector and this heat is transferred to its working fluid. The heat energy then can be used for either heating or hot water purposes or to heat up the storage tank. Ayompe et al., 2013 analysed the thermal performance of a solar water heating system with a $4m^2$ flat plate collector in Dublin, Ireland. The experimental system consisted of a domestic scale system and it was tested for a year. The maximum recorded temperature at collector outlet was 70.4^{o}C. It was found that the average daily energy collected was 19.6MJ/d and the energy delivered by the solar coil was 16.2MJ/d. The results showed that 12,446.5MJ of auxiliary energy was supplied to meet the total hot water demand of 18,359.5MJ. Performance of an solar heating system in Cambridgeshire, UK was evaluated by the BRE, 2009. The experimental rig consisted of an automated system that incorporated the effects of the auxiliary heating system. The report showed that a household would achieve a 57% of hot water energy from the solar system. Different other research studies have been done which show the cost benefit of using the solar thermal collector but additional energy is required to meet the energy demand. By using solar thermal energy alone it has been shown in the literature that the water temperature is normally low or it takes a long time to generate the hot water. This results in a low performance of the solar thermal collector.

Crawford et al., 2004 analysed the net energy requirement of solar and conventional hot water systems including their embodied energy. The solar system provided net energy savings compared to the conventional system after 0.5 years for electric-boosted and 2 years for gas-boosted systems. The investigation of small solar domestic hot water systems based on smart tanks was presented by Furbo et al., 2005. The authors recommended the development of smart solar tanks combined with other auxiliary energy systems. From above review it can concluded that solar thermal collectors alone are not sufficient for energy requirements and some form of auxiliary energy source is required. To overcome this problem, a heat pump can be combined with solar thermal collectors for increasing the water temperature. Huang et al., 2005 studied the long-term performance of a combined solar collector and heat pump system and found that the electricity price was cheaper than the conventional gas system. The performance of a solar water heating system combined with a heat pump, using a simulation program, was also studied by Nuntaphan et al., 2009. It was shown that the payback period of system was 2.3 years. These figures show the effectiveness of such systems; however their effectiveness can be increased by using a better controller to manage the energy flow and by efficiently using solar energy.

Indoor comfort has a direct effect on occupant's productivity and is important to consider for heating control purposes. Energy saving must not put user's welfare at risk (Nicol et al., 2002), therefore below the review is done on different thermal comfort variables and indices.

2.6 Thermal comfort and its variables

According to ISO7730, 1994, Thermal comfort can be defined as: "that state of mind which expresses satisfaction with the thermal environment". This definition is also in accordance with the ASHRAE55, 1992 international standard. The above mentioned definition of thermal comfort can be considered as ambiguous, as the condition of mind and human satisfaction remains open. However this definition stresses that it is an emotional process that is influenced by different types of processes i.e. physical, physiological or even psychological (ASHRAE, 2005).

The thermal environment around a human body is generally cooler than people's skin in 'ordinary' situations. A human body dissipates heat in three ways: evaporation as sweating, convection heat transfer into the air and radiation heat transfer to the other surfaces in its surroundings. Outdoor conditions are not as homogenous as indoor climatic conditions and can be very challenging to the human body. The human body is exposed to different conditions such as air speed, air temperature, radiations, humidity and radiant temperature. Thus in order to assess human thermal environment different environmental parameters, physiological and psychological responses must be considered. The physical parameters include values of air temperature, room humidity, wind speed and radiant temperature. Metabolic rate (Met) and clothing insulation (clo value) are also needed in the thermal comfort analysis as these are important factors in heat transfer between the environment and the body (Parson, 2003). All these variables are discussed in the following sections.

2.7 Environmental-dependent variables

The room air temperature, room air humidity, air speed and radiant temperature come under the category of environmental-dependent variables and are discussed below;

The indoor dry bulb temperature is the temperature of the air surrounding the body. According to Parson, 2003 it can be defined as "the temperature of the air surrounding the human body which is representative of that aspect of the surroundings which determines heat flow between the human body and the air".

"Physically, the dry bulb temperature varies with the variation of heat exchange between bodies. The air temperature at a distance from the human body will not be the representation of the one that decides the heat flow. Similarly, the temperature closer to body surface will also not be the representation of the heat flow as it will be affected by the boundary conditions" (Parson, 2003).

The Mean radiant temperature is defined as “the temperature of a uniform enclosure within which a small black sphere at the test point would have the same radiation exchange as it does with the real environment". The mean radiant temperature and radiant temperature are good methods for quantifying the human radiant environment (McIntyre, 1980). The word sphere in the definition shows that the average is considered in three dimensions. Heat is transferred between all bodies through radiation and it is not necessary to have air or any other medium for transferring heat, the heat can be transferred though a vacuum (Kerslake, 1972).

Room air humidity- If the sweat or liquid evaporates from the body then there is heat transfer from the body into the surroundings as the liquid has taken heat from the human body making it cool down. The driving force for this heat transfer is the difference in the absolute humidity at the human skin (surface) and in the environment. As for convenience, this driving force can be considered as the difference between partial vapour pressure between at the skin surface and that in the environment. The humidity can be expressed in a number of forms; however, commonly it is expressed by two terms: relative humidity and partial vapour pressure (Parson, 2003).

The relative humidity, denoted by 'Φ' is defined as the ratio between "the partial pressure of water vapours to the saturated vapour pressure at a given temperature" (Parson, 2003).

$$Relative\ humidity\ = \frac{partial\ pressure\ of\ water}{saturated\ vapour\ pressure\ of\ water} * 100\% \qquad (2.1)$$

Indoor air velocity- Air movement across the body can affect the heat transfer from and to the body and therefore the temperature. The air movement varies in time, space and direction. For convenience it is considered to be the mean velocity intensity over an exposure time over all directions. According to ISO7730, 2005, both mean air velocity and the standard deviation of air movement should be considered. The air movement will affect the rate at which the warm air or water vapours are taken away from the body and as a result will affect the human body's temperature. The mean velocity discussed above, provides an overall value for this effect on the body (Parson, 2003).

2.8 Person-dependent variables

There are two other variables which are person-dependent, as these variables change from person to person. These variables are the metabolic rate of a person and clothing insulation. These variables are discussed below;

Metabolic rate- is also known as the activity level. The estimation of the heat generation because of the metabolism is the key to the estimation of the thermal environment. The human body derives heat from food and the energy value of that food is turned over to produce heat and energy for work. The human body produces heat from food when combined with the oxygen of the cells. A human body at rest and at a temperature of 21^{o}C is considered to have minimum metabolic rate and the metabolic activity is called 'basal metabolism'. The metabolic activity has units of $W/m^2, kcal/min/kg\ or\ Met$. 1Met is 58.15 W/m^2 and is the metabolic rate of a resting sedentary person. Metabolic rate is related to people’s body surface area, sex, age, level of fitness, environmental temperature and the amount of clothing (Winslow et al., 1949).

The total energy produced is termed the metabolic rate, M, and the total work performed by the body is termed W, then the metabolic heat production is given by following equation;

$$H = M - W \tag{2.2}$$

Although the production of the energy is a very complicated process the above equation gives an idea of how to estimate the metabolic heat generation.

Clothing thermal resistance- Clothing is one of the key factors for the study of thermal comfort. Clothing acts as a thermal resistance between the thermal environment and human body. The clothing allows a human body to maintain a proper thermal state. Clothing is included in the thermal comfort measurement by considering the thermal resistance of the clothing. The clothing value is denoted by Clo values. Gagge et al., 1941 defined 1 Clo as the thermal insulation on a person who keeps a mean skin temperature of 33°C in comfort at an air temperature of 21.2°C, relative humidity of 50% and air velocity of 0.1m/s(1 clo=0.155m^{2} ^{o}C/W). The thermal behaviour of the clothing is very difficult to quantify as it depends on a number of factors. It depends on the dry thermal resistance of the clothing; moisture transfer through clothing; heat transfer through clothing by conduction, convection and radiation; air penetration through clothing; human body posture; and many more.

2.9 Thermal comfort indices

In the early twenties much of the research work was done to find out thermal comfort indices. Different studies were conducted to find out a number index which can integrate all six basic parameters to indicate thermal comfort. The following are the few well known thermal comfort indices;

2.9.1 **Effective temperature**

A series of studies conducted by Houghton et al., 1923, Houghton et al., 1924 and Yagloglou et al., 1925, on behalf of ASHVE have led to the Effective Temperature (ET) index. In this study three subjects were asked to walk between two chambers to compare different combinations of humidity and air temperature. The subjects gave immediate responses that would be largely determined by the effect of transient evaporation and absorption of moisture content from skin and clothing. This means that the study was overestimating the effect of steady-state conditions and was useful for studies of transient effects. In this study air temperature, humidity and air velocity were plotted on charts for determining the ET index. A number of methods were also proposed to correct the ET index by allowing radiation to be taken into account and the index was then known as the Corrected Effective Temperature.

2.9.2 **Resultant temperature**

Missenard, 1935 and Missenard, 1959 determined a thermal index that was called the resultant temperature by proposing a number of methods. In order to mimic the response of the human body he used dry and wet globe thermometers of appropriate size. The researchers also attempted to solve the problem of ET index by defining a steady state form and transient form of resultant temperature. CIBSE, 1986 recommended the temperature of a 100mm diameter black globe as a resultant temperature.

2.9.3 **Equivalent temperature**

To mimic the thermal behaviour of a human body, Dufton, 1929 and Dufton, 1936 developed a heated black copper cylinder. The temperature of that black copper cylinder was termed the equivalent temperature. Bedford, 1936 conducted a study on female workers of a factory and investigated the relationship between personal feelings and physical environment. By using the thermal comfort scale, the author correlated subjective judgements with a number of thermal index values.

Other different climatic chamber studies were carried out at Kansas Laboratory in the 1960s.Houghton et al., 1923 found a comfort zone and comfort line in terms of ET index by using 130 subjects under laboratory conditions. The comfort zone was defined as those ET values over which 50% of people were comfortable. On the basis of this experiment, it was found out that the comfort zone was between 16.7-

20.6^{o}C ET with a comfort line of 17.8^{o}C ET (ASHVE, 1924). Nevins et al., 1966 used 720 college aged students (360 male and 360 female) to re-evaluate the comfort conditions as affected by air temperature and relative humidity. 72 conditions were investigated involving the combination of temperature and relative humidity. Rohles et al., 1971 also conducted a similar but more extensive study that involved 800 male and 800 female students and also extended the air temperature range from 60^{o}F to 98^{o}F. It was concluded that the air temperature for these conditions rated as comfortable covered the range of 62-98^{o}F. It was also found out that female students adapted more quickly to the conditions.

2.10 Fanger's model

The method developed by Fanger, 1970 to study thermal comfort is the most significant landmark in the field of thermal comfort. Three conditions were defined for a body to be in thermal comfort:

1. the body is in heat balance;
2. sweat rate is within comfort limits
3. mean skin temperature is within comfort limits

The objective of the research was to use six basic parameters as the inputs and to produce a comfort equation; also based on the above conditions, to calculate conditions for thermal comfort. This objective was achieved by using a rational analysis of heat transfer between the environment and the clothed body and by experimental research.

2.10.1 Thermal balance equation

A human body maintains heat balance between itself and the environment while preserving an internal temperature of 37^{o}C. The body responds dynamically to maintain a constant internal body temperature in a changing environment. If the heat output from the body is greater than the input, the body temperature will decrease and vice versa. The metabolic rate of the body offers energy to enable it to do work (W) and the remainder is discharged as heat. Heat transfer from the body is achieved through four processes i.e. conduction (K), convention (C), radiation (R) and evaporation (E). The rate of heat storage is equal to the rate of heat loss and rate of heat production. If the heat storage of the body is zero then this means that the body's heat is in balance. If there is heat gain then the storage is positive and the body temperature will increase and vice versa for heat loss.

The heat balance equation can be;

$$M - W = E + R + C + K + S \qquad (2.3)$$

If there is no heat storage then the above equation becomes;

$$M - W - E - R - C - K = 0 \qquad (2.4)$$

Normally the heat transfer through conduction is very small and can be negligible. ASHRAE, 1989 gave a practical heat balance equation as;

$$\begin{aligned} M - W &= Q_{sk} + Q_{res} \qquad (2.5) \\ &= (R + C_{sk} + E_{sk}) + (C_{res} + E_{res}) \end{aligned}$$

In above equation;

$M = Rate\ of\ metabolic\ energy\ production$

$W = Rate\ of\ mechanical\ work$

$Q_{sk} = total\ rate\ of\ heat\ loss\ from\ the\ skin$

$Q_{res} = total\ rate\ of\ heat\ loss\ through\ respiration$

$C_{sk} = rate\ of\ convective\ heat\ loss\ from\ the\ skin$

$R = rate\ of\ radiative\ heat\ loss\ from\ the\ skin$

$E_{sk} = rate\ of\ total\ evaporative\ heat\ loss\ from\ the\ skin$

$C_{res} = rate\ of\ convective\ heat\ loss\ from\ respiration$

$E_{res} = rate\ of\ evaporative\ heat\ loss\ from\ respiration$

In equation 2.5, the heat production within the body is $(M - W)$, heat loss at the skin is $(R + C_{sk} + E_{sk})$ and heat loss because of respiration is $(C_{res} + E_{res})$.

The heat balance in some circumstances cannot be a sufficient condition for comfort: e.g. the body can be in heat balance but uncomfortably cold because of vasoconstriction or uncomfortably hot due to sweating. Rohles et al., 1971 provided the equations for skin temperature and sweat rates required for comfort, which depends on the activity level. The equations are given below;

$$t_{sk,req} = 35.7 - 0.0275(M - W)℃ \quad (2.6)$$

$$E_{sw,req} = 0.42(M - W - 58.15)\frac{W}{m^2} \quad (2.7)$$

By substituting $t_{sk,req}$ and $E_{sw,req}$ in the heat balance equation, the equation becomes;

$$\begin{aligned} M - W - 3.05[5.73 - 0.007(M - W) - P_a] \\ - 0.42[(M - W) - 58.15] \\ - 0.0173M(5.87 - P_a) \\ - 0.0014M(34 - t_a) \\ = 3.96 \\ * 10^{-8}f_{cl}[(t_{cl} + 273)^4 - (t_r + 273)^4] \\ + f_{cl}h_c(t_{cl} - t_a) \end{aligned} \quad (2.8)$$

In the above equation;

$$\begin{aligned} t_{cl} = 35.7 - 0.028(M - W) - I_{cl}\{3.96 * \\ * 10^{-8}f_{cl}[(t_{cl} + 273)^4 - (t_r + 273)^4] \\ + f_{cl}h_c(t_{cl} - t_a)\} \end{aligned} \quad (2.9)$$

$$h_c = \begin{cases} 2.98(t_{cl} - Y_T)^{0.25} & 12.1 * \sqrt{v_a} < A \\ 12.1 * \sqrt{v_a} & 12.1 * \sqrt{v_a} \geq A \end{cases} \quad (2.10)$$

$$A = 2.98(t_{cl} - Y_T)^{0.25}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290I_{cl} & for\ I_{cl} \leq 0.078\ m^2.\frac{K}{W} \\ 1.05 + 0.645I_{cl} & for\ I_{cl} > 0.078\ m^2.\frac{K}{W} \end{cases} \quad (2.11)$$

2.10.2 **PMV, PPD and modelling**

Fanger, 1970 proposed that the degree of discomfort will depend on the thermal load (L). This was defined as "The difference between the internal heat generation and the heat loss to the environment for a human body that is hypothetically kept at the comfort values of the sweat secretion and skin temperature at the actual activity level". According to this definition during comfort conditions the thermal load will be zero. For sedentary activity and other activities different experiments were performed to produce the data that provided an equation for predicted mean vote (PMV) of a large group of subjects. The following scale was introduced to rate the thermal performance of the subjects;

Hot	+3
Warm	+2
Slightly warm	+1
Neutral	0
Slightly cool	-1
Cool	-2
Cold	-3

The equation for PMV is;

$$PMV = [0.303.e^{-0.036M} + 0.028] * M - W - 3.05[5.73 - 0.007(M - W) - P_a] - 0.42[(M - W) - 58.15] - 0.0173M(5.87 - P_a) - 0.0014M(34 - t_a) - 3.96 * 10^{-8} f_{cl}[(t_{cl} + 273)^4 - (t_r + 273)^4] - f_{cl}h_c(t_{cl} - t_a) \quad (2.12)$$

The number of potential complainers in a thermal environment can be determined by using the predicted percentage of dissatisfied (PPD). Nevins et al., 1966, Rohles, 1970 and Fanger, 1970 developed a relationship between PPD and PMV. The relationship is given by following equation;

$$PPD = 100 - 95exp(-(0.03353PMV^4 - 0.2179PMV^2)) \quad (2.13)$$

2.11 Adaptive thermal comfort model

The PMV and PPD indices discussed above are the steady state indices and are accepted as ISO standard 7730 and ASHRAE 55. These indices view occupants as passive recipients of thermal stimuli. Researchers argued that it is not only the heat transfer that controls how occupant perceived thermal comfort but it also depends on psychology. Also, adaption to the environment can be psychological, behavioural and physiological (de Dear et al., 2001).

Behavioural adjustments incudes all modification that a person makes consciously or unconsciously to avoid thermal discomfort. These changes can include adjusting clothing, posture, eating/drinking hot/food, opening/closing windows etc. Psychological adaptation refers to an altered conception of and reaction to sensory information. Thermal perceptions are directly tempered by occupant's expectations and experiences. Physiological adjustments are the changed in the physiological responses which result from exposure to environmental factors (de Dear et al., 1998). Brager et al., 1998 suggested that more understanding of the adaptation influence on thermal comfort can lead to more responsive control algorithm.

Both Fanger and adaptive models have been used in research but in this research PMV model will be used to perceive the thermal comfort of occupants. The PMV model is a flexible model that includes all the major variables influencing thermal sensation. Whereas, the adaptive model does not include six factors which have a known impact on the human heat balance. The adaptive model is a regression model that relates the neutral indoor temperature to the monthly outdoor average temperature. The only variable is thus the outdoor average temperature, which at its highest may have an indirect impact on the heat balance equation (Ole Fanger et al., 2002).

2.12 Control systems

A study conducted by Herring et al., 1998 concluded that over two thirds of the energy used for space heating in buildings could be saved by technical improvements. According to DTI, 2001 the building regulations have been changed in the past few decades to improve the energy efficiency of new and refurbished buildings. Due to these regulations there has not been a significant energy consumption rise from space heating over the last three decades. In addition to the regulations the government has also introduced different incentive programmes to encourage energy efficiency in new and refurbished buildings e.g. EST, Action Energy (previously known as The Energy Efficiency Best Practice Programme) and the Carbon Trust.

Building energy efficiency depends on many factors e.g. the efficiency of boiler and distribution system, the building envelope and the performance of the control system. In a report by BRECSU., 1996, it was estimated that approximately 90% of the heating systems were operated inefficiently due to lack of good control and this cost an additional 500 million pounds per annum. It can be concluded that an appropriate control is required to save energy in buildings and without an appropriate control system, a huge amount of energy is wasted and can cost in excess of millions of pounds per year.

Currently three widely used control strategies are the on-off controller, weather compensator controller and Proportional–Integrate–Derivative (PID) controller. The on-off controller and PID controller are feedback controllers whereas the weather compensator controller is a feed forward mechanism. PID controllers need some information about the dynamics of the system for good performance. Each of the mentioned control strategies is easy to tune and all are well known for single input and single output systems.

The on-off control is the simplest type of control used in buildings. It is also known as bang-bang control because it is designed to switch snappishly between on and off states. Although this control is simple but overshoots in the controlled variable (temperature) were not avoidable. The common type of on-off controller used in buildings is the thermostat for temperature control (Dounis et al., 2009). In order to solve the problem of overshoot, designers have used PID controllers.

Salsbury, 2005 discussed that the biggest drawback of using PID controller is that most building systems are multivariable, non-linear and time invariant, which makes the controller's performance to become sluggish and oscillatory. Also, improper choice of the gains can lead to make the system unstable. It is labour intensive and can be costly to implemented (Bhatia, 2012). The choice of appropriate controller gains is addressed by using auto-tuning. However, auto-tuning may lead to disruption of the plant operation and it also requires experience, extensive training and additional cost (Salsbury, 2005). Designers have attempted to address these problems by providing alternative solutions e.g. neural networks, genetic algorithms, fuzzy logic control and predictive control.

Artificial intelligence (AI) techniques have also gained popularity in the field of HVAC control since the 1990s. AI includes artificial neural networks, genetic algorithm and fuzzy logic control. Dounis et al., 1992, are considered as the pioneers of application of artificial intelligence techniques for HVAC control. Dounis et al., 2009 reviewed advanced control systems for energy and comfort management in buildings. Some disadvantages of model predictive control are also mentioned: the requirement of a model, the sensitivity of the parameters to noise and non-linearities when dealing with comfort. In this review the authors seem to discourage the use of model-based control. Later in the chapter it is illustrated that model-based control is an active area in building control applications.

Though artificial intelligence techniques are independent of a model, however the need of training data, its accuracy and a training period are serious limitations (Wang et al., 2008).Coffey et al., 2010 mentioned that artificial neural networks have a lack of building physics and therefore they are not useful for diagnostic work and cannot handle changes in the system. A reinforcement learning technique has also been used by Liu et al., 2007. This method does not use a model, instead it extract information from the operation of the system with an ANN.

There are different applications where fuzzy logic control was used in buildings. Kolokotsa et al., 2001 evaluated different control strategies for preservation of thermal and visual comfort, energy consumption and air quality. Three controllers i.e. adaptive fuzzy PD, fuzzy PD and on-off were applied. This study was carried out through simulations and it was found that the adaptive fuzzy PD consumed less energy and also gave optimum responses. Bruant et al., 2001 developed a multi-objective fuzzy logic controller. The building model was developed in TRNSYS. It was compared with an on-off controller and energy consumption was reduced by over 10%.

Fuzzy logic control has been widely used in building energy systems. The problem with fuzzy logic control is that one has to embed a lot of thinking/logic in to it. It is a way of formulizing the control objectives and all possible solutions/rules must have to be considered. Eftekhari et al., 2003 concluded that the fuzzy controller with greater number of IF-THEN rules is more stable. This means that the controller will become more complex while achieving its stability.

Therefore there has to be another control strategy which has feedback, can also contain information about the system i.e. history of the system and is also suitable for multiple input and multiple output (MIMO) systems. These criteria are met by a so-called control strategy called a Model Predictive Controller (MPC). Below is the focus of the literature survey on MPC strategy.

2.12.1 **Model Predictive Control**

Model Predictive Control (MPC) originated in the late seventies and has developed very considerably. MPC is based on a class of optimization algorithms that utilize a process model to predict and optimize the future outcome/response of a plant. The control signal is obtained by minimizing an objective function (Qin et al., 2003). The main ideas behind predictive control methods are (Camacho et al., 2004);

- Explicit use of a model to predict the process output up to a future time instant (horizon).
- Obtaining control signal by minimizing an objective function.
- Using receding strategy, at each instant the horizon extends for the same period into the future.

According to Van Den Boom et al., 2010, MPC is a methodology rather than a single technique. The main difference in the various methods is the way the problem is translated into the mathematical model. MPC technology is widely used in different application areas including the chemical industry, food processing, power plants, petroleum, automotive, and aerospace.

Camacho et al., 2004, mentioned different advantages and drawbacks;

Advantages

- It is a very attractive method of control for staff with less knowledge of control.
- The tuning is relatively very easy.

- MPC can be used to control very simple as well as very complex problems. This includes systems with long delay times and unstable systems.
- The multivariable case can easily be dealt with.
- It can compensate for dead time.
- MPC introduces feed forward control to compensate for natural disturbances.
- Model predictive controller is an easy way to implement linear control law.
- This control strategy is very useful when future references are known.
- MPC is based on certain basic principles which allow for future extensions.

Drawbacks

- Applying MPC to a practical problem can be a complex challenge.
- When constraints are considered in controlling the process, the calculation of the control input becomes much more difficult.
- The biggest drawback is the necessity for an appropriate model of the process.

MPC has proved to be a very reasonable strategy for controlling industrial processes. From a theoretical perspective, it delivers very high performance, and it is only lacking in the areas of guaranteed stability and robustness to modelling error.

The history of model predictive control can be traced back to the 1970s. Richalet et al., 1978, proposed a model to control processes. They described applications of this method (Model Predictive Heuristic control). Later on this method was known as Model Algorithmic control. In 1979 two engineers Cutler et al., 1980 from Shell came up with the idea of Dynamic Matrix Control. In both of these techniques, an explicit dynamic model was used to predict effects of future outcomes on the outputs. That is why it is known as Model predictive control.

The above two researches were very closely related to minimum time optimal control and to linear programming. This relation was recognized by Zadeh et al., 1962. The core of all MPC algorithms is known as the moving horizon principle; this principle was proposed by Propoi, 1963. In 1978 and 1979, MPC became very popular in chemical process industries. Different work has been done on adaptive control ideas, in which an attempt was made to keep future values close to the reference.

Generalized Predictive Control (GPC) was developed by Clarke et al., 1987. This method uses ideas from Generalized Minimum Variance (GMV).

Morari, 1994 formulated the model predictive control in state space context. This allows the generation of more complex problems e.g. systems with non-deterministic disturbances and noise in the measured variables. Lee et al., 1994 developed a MPC technique, which was based on a step response model. In this model state estimation techniques were used. It was shown that state estimation techniques from stochastic optimal control can be used to predict without additional complications. Bitmead et al., 1990 in their book analysed inherent characteristics of many MPC algorithms. By using state-space relationships Mohtadi, 1986 proved some stability theorems. He also studied the influence of filter polynomials on robustness improvement. The lack of stability for finite horizon receding optimization was also pointed out. These drawbacks led to further research in the early nineties.

Two methods named as CRHPC by Clarke et al., 1991 and SIORHC by Mosca et al., 1990 were developed and were proved to be stable. The problem of stability of constrained receding horizon control problem was tackled by Rawlings et al., 1993, Rossiter et al., 1993 and Zheng et al., 1994. New results have been found by Campo et al., 1987 and Allwright, 1994 by using robust control approaches. MPC is still a developing technique of control, with much yet to be developed e.g. optimization of objective functions for the worst case of the uncertainties.

2.12.2 **Model predictive Control in buildings**

The use of weather prediction to control building climate has recently gained attention and has been investigated in several research works. The following is a review of the literature on using predictive control in building services engineering

Zhang et al., 2006 described a way to tackle supervisory control problems of different systems. This work was carried out on a prototype building, with a photovoltaic array, solar air and water heating, a biomass boiler and a stratified thermal storage. The control problem was for every system to decide whether to use energy directly, store it or waste it to the environment. Different models of systems were selected and implemented in Simulink. An evolutionary control algorithm was used to optimize control strategy. The results were compared for both Building Energy Management Systems (BEMS) and MPC. In winter using BEMS, the energy consumption was 24.8% more as compared to MPC, while in spring 47.8% more energy was consumed. In summer, this consumption of energy was increased. It was concluded that MPC with an evolutionary algorithm can be used for better control. It was also found that the existing BEMS was difficult to commission because of considerable number of operational states. The building energy management system is programmed according to standard practice and is not familiar with the behaviour of the system.

Núñez-Reyes et al., 2005 applied a model predictive controller to control the temperature in a solar air conditioning plant. A Smith Predictor was used in this controller and in order to reject disturbances caused by solar radiations and the auxiliary gas heater, a feed forward control action was included. Previously, a PID controller was installed to control the inlet temperature of the absorption machine. This PID controller was unable to reject the disturbance in the inlet temperature due to oscillation in the gas heater temperature. A three input and one output model was identified. The experimental results showed that the Smith Predictor is an appropriate way to increase the robustness. It also achieved a good performance in both set point tracking and rejection of disturbances. Predictive controller’s tuning was easier than the PID controller.

Farkas et al., 2005 developed a model predictive controller for solar plant operation. This plant model was based on energy balances. The developed model was the internal part of the controller. Internal model control uses the advantages of different unconstrained MPC schemes, easy online tuning and good performance. It was shown that the internal model control performed very well with short control time and no overshooting. The system was a non-linear in nature but the predictive controller performed well. A study to design a model predictive controller to smooth the output power from a wind farm was carried out by Khalid et al., 2010. They focused on optimizing the battery storage system. Model predictive control theory was applied to a combined wind power prediction system with a battery storage system. This control action consisted of two stages i.e. prediction of wind speed and direction and secondly prediction of power output. Predicted power output was obtained by converting predicted wind speed. This controller performed better under practical constraints and achieved maximum ramp rate. It was also proposed that this controller is not only suitable to wind energy but can also be applied to other intermittent energy resources.

A research of model-based optimal control of hybrid power generation was carried out by Zervas et al., 2008. This hybrid power generation system consisted of photovoltaic arrays, electrolyser, metal hydride tanks and proton exchange membrane fuel cells. Hybrid energy systems can store energy efficiently. A neural network model was used to predict the global solar irradiations and then energy produced by the solar array was estimated. Finally, MPC was used to get an optimal control strategy. The fundamental rolling horizon principle of MPC was used to develop decision strategy. The proposed model proved to be a useful tool for decision making.

A robust model predictive control strategy was developed by Huang et al., 2009. This control strategy was to improve the performance of air conditioning systems. A first order time-delay model with uncertain time delay and system gains was used to describe the air-conditioning processes. The uncertainties in time-delay and system gains were formulated by using an uncertainty prototype. A typical Variable-Air-Volume (VAV) system was used for this research. LMI (Linear Matrix Inequality) was employed to design this controller. Model predictive control strategy was tested and was then compared with the performance of the conventional strategy (PI). It was found that for MPC the outlet temperature followed the supply air temperature when there was a sudden step change. In the case of PI, it performed well but the output response was not very fast. Robust analysis was also performed and MPC strategy responded very quickly to the disturbances. The results showed that MPC had much more robustness than the conventional PI algorithm control.

Kolokotsa et al., 2009 combined a model predictive controller with a BEMS (Building Energy Management System). The main purpose of the overall system was to predict the indoor environmental conditions and to take appropriate actions, in order to satisfy indoor environmental conditions and minimize energy consumption. The variables were modelled by using a bilinear approach, which is simple and an extension of a linear modelling approach. The controller was designed to minimize the performance index $J(k)$, which aimed to keep the variables as close as possible to the set points. It was found that the system's response to the variable was very fast and stable.

Henze et al., 2005 analyzed MPC experimentally for active and passive building thermal storage inventory. Real time experimental implementations were carried out using a 24h future horizon and a 1-h controller time step. TRNSYS software was used for the building model and MATLAB for central purposes. The controller internal model was based on TRNSYS model but the controller was actually controlling real building operation. They noticed some technical problems, but overall this approach was very successful. In their other research (Henze et al., 2004), they also found out the importance of forecasting on the model predictive controller. This research work was compromised by the converging of local minima and the communication channel was interrupted because of this. Determination of the optimal start time for heating was addressed by researchers from Honeywell control systems Ltd and the University of Strathclyde (Clarke et al., 2002). There were some concerns between control system and simulation tools (ESP-r) and optimizer. Kummert et al., 2005a and Kummert et al., 2005b studied optimal control of passive solar building with night setback. They made an attempt to minimize energy consumption. A linear S-S (steady-space) representation was used and quadratic programming was done for optimization.

Grünenfelder et al., 1985 compared different predictive control strategies for a solar hot water system with non-predictive strategies. The authors took weather prediction into account. From simulation results it was shown that for a small storage tank, the predictive control saved energy cost as compared with non-predictive strategies. This is one of the first research works that were carried on predictive strategies for renewable energy systems. Ma et al., 2009 investigated implementation of a MPC for a chilled water plant. The tanks were charged by using night-time electricity. It was found that MPC saved 24.5% of cost as compared to current manual control sequence.

Cho et al., 2003 studied a MPC strategy for a intermittently heated radiant floor heating system. From experimental results it was found that model predictive control saved between 10% and 12% of primary energy during the cold months compared to the conventional control. It was concluded that the predictive control strategy was energy efficient strategy for district heating systems. Chen, 2002 described an improved algorithm for Generalised Predictive Control (GPC). The controller was applied to a floor radiant heating system in an outdoor test-room. The performances of three controllers i.e. GPC, on-off and PI were evaluated through computer simulations. The system model was identified using recursive least squares techniques. It was demonstrated that GPC was superior to the other two control strategies in every aspect. The GPC gave the fastest response to the change in set point, and the indoor temperature showed less deviation from the set point as compared to on-off and PI controllers. There was no tuning effort required for GPC, which makes predictive control strategies more attractive than PI control.

Zaiyi et al., 2010 utilized the concept of model predictive controller to optimize the use of boilers for multi-zone heating systems. The controller was using outside air temperature, solar radiation falling on the building and supplied water temperature to the boiler as inputs, and the output was the boiler signal. Two interactive and one cascaded control loops were applied. The controller was saving energy by operating the boiler at the lowest possible water temperature, minimizing the heat loss as the water temperature is maintained at the lowest possible level and also by improving the controllability of radiator valves. Simulation results showed that the overall performance of the heating system was improved through MPC and it was easy to commission as well.

Prívara et al., 2011 applied MPC to the temperature control of a real building. It was suggested that model predictive control can maintain indoor temperature at the desired level and is independent of outside weather conditions. It was also pointed out by the authors that the proper identification of the building model is crucial. The controller was tested during the heating season of 2009/2010 on a large university building and energy savings of 17% to 24% were achieved as compared to the present controller. Paris et al., 2010 tested three control schemes i.e. conventional PID, combination of PID and fuzzy logic controller (FLC) and combination of PID and MPC. There was a saving of 26.9% of fossil energy by using PID-MPC whereas a saving of 9.8% was recorded for PID-FLC. It was concluded that PID-MPC anticipated set point changes and PID-MPC gave the best results while PID-FLC proved to be a good compromise between complexity and performance. It was also mentioned that fuzzy logic is easy to develop while MPC is hard to develop.

Different researchers have used predictive control strategy to control the thermal comfort of the indoor environment. Freire et al., 2008, did a study on the predictive controllers for thermal comfort optimization and energy savings. Different strategies for the control algorithm were proposed; some were based on minimizing energy consumption and others on thermal comfort optimization. One actuator was used for cooling and/or heating the indoor environment. Predicted Mean Vote (PMV) was considered as the thermal comfort index. A single story building and weather data for Brazil were taken to perform the simulations for model based predicted control. Five control strategies were presented in this research; three were based on the psychometric chart comfort zone and two were based on the PMV index. The controller performance was also analysed by changing the metabolic rate and the clothing index of the occupants. It was shown that all control strategies provided a better thermal environment to the occupants. The control strategies based on the psychometric chart had the maximum energy consumption of 222.47kWh and the minimum energy consumption of 98.67kWh was that of the controller based on the PMV index (Freire et al., 2008).

Castilla et al., 2011 compared different predictive control strategies to obtain a high thermal comfort level by means of different cost functions. They focused on the trade-off between energy saving and thermal comfort level. In this research two predictive strategies were employed. In the first case, an upper layer of predictive control and a lower layer of PID control were developed. The upper layer was used to optimize the indoor temperature references and then the lower layer was following these references by varying the system fan-coil. In the second approach a classical predictive controller was used. Different cost functions were also evaluated for both these strategies. The control systems were tested in a solar energy research centre, the CDdI CIESOL-ARFRISOL building. The selected strategy minimized a cost function and gave the control signal directly, whereas the other strategy used a reference governor that minimized the cost function, providing an indoor temperature reference that was the set point for a PI controller. This selection was made on three selection indices: (1) mean number of changes in the actuator state per hour i.e. on/off, (2) the percentage of time the actuator was used and (3) mean energy consumption per hour.

Ferreira et al., 2012 addressed the problem of controlling an HVAC system with the purpose of achieving a thermal comfort level and saving energy. A discrete model predictive control was applied. The predictive model was implemented by radial basis function neural networks indentified by a multi-objective genetic algorithm. The authors presented experimental results within different rooms in a building of the University of Algarve. A wireless sensor network system was deployed in the building for data acquisition. Different experiments were performed during summer and winter weather and it was concluded that the energy savings from the application of the method were estimated to be greater than 50%.

It can be concluded that model predictive control for buildings is an active research area and there has been intensive research in this field. However, there are very few applications where it is used for renewable energy systems and in most of the case it is applied to multi input and single input systems. This makes the control problem relatively simple. In this research model predictive control is applied to multi input and multi output system and also considering multiple control objectives at the same time.

2.13 Optimum Control Strategies

Static optimization methods (as opposed to MPC) have long been used to improve the efficiency of building control systems. Ke et al., 1997 determined the optimal supply air temperature by investigating the interactions between the supply air temperature and the required ventilation rate using zone reheat. Englander et al., 1992 did not compromise on thermal comfort level and minimized the duct static pressure set-point. Braun et al., 1989 found the chilled water supply temperature set point of a chilled water system by optimizing the whole system.

Different studies have been carried out in which overall performance of the system was optimized. House et al., 1991 and House et al., 1995 proposed a system approach to optimizing multi-zone building systems without compromising thermal comfort and respecting energy use as well. Wang et al., 2000 proposed a control strategy using a system approach based on predicting the responses of the overall system environment and energy performance of VAV air-conditioning systems. It was concluded from this study that a genetic algorithm is a useful tool for finding the optimal setting to minimize the overall system cost for online control applications for air-conditioning systems. Zheng et al., 1996 addressed the problem of optimizing the thermal processes in a variable air volume system. The control strategy was based on steady-state models of the system. It was concluded from the study that optimal control can improve system responses and can also reduce energy consumption as compared to conventional control strategies. Nassif et al., 2005 developed an optimization process for a VAV system. This process used a multi-objective genetic algorithm that permitted the optimal operation of the building's mechanical system. By using this optimal control strategy, the supervisory control strategy set points i.e. supply air temperature, supply duct static pressure, reheat etc were optimized by taking energy use and thermal comfort into account. The results showed that the optimization of a supervisory control strategy could save 16% of energy for two summer months while satisfying minimum airflow rates and thermal comfort. Dovrtel et al., 2012 optimized a building cooling system by using multi-objective performance optimization. A multi-objective algorithm called NSGA-II was used to evaluate minimum fan energy use and minimal energy use for additional mechanical cooling of the building. Magnier et al., 2010 presented a study that used a simulation based Artificial Neural Networks (ANN) to describe building behaviour and then combined these ANN with a multi-objective genetic algorithm (NSGA-II) for optimization. Optimization results showed some significant reduction in energy consumption and also improved thermal comfort.

2.14 Summary

This chapter has introduced brief history of energy crises, climate change, energy security issues, international and UK government legislation on energy use in buildings. The review also showed that, to avoid energy crises, renewable energy systems have to be used to meet daily energy requirements. The UK government provides incentives to use renewable and low carbon energy systems.

The review also showed that different controllers often provide one or two key benefits e.g. good tracking, robustness, commissioning effort or self-adaptation. MPC has different applications e.g. in chemical engineering, heating, ventilation and air-conditioning systems, electrical systems and the petrochemical industry, but it is not typically used in the application of combining an air-source heat pump and a solar thermal collector. The benefit of this application is to use free solar energy when it is available and to use a heat pump when it is not. Also, the review of previous applications of model predictive control suggests that MPC is capable of providing good control when compared to conventional controllers. MPC can be used by staff with less knowledge of control. The tuning is relatively easy. The main drawbacks of MPC are that its derivation is very complex and selecting an appropriate model of the system is crucial. The literature review shows that the research on applying model predictive control to building systems has been getting more attention in recent years.

However, the reviews show that there are still few studies of:

- Development of a model for a system that consists of a solar collector and a heat pump.
- Control strategies for such a system used for domestic hot water and heating purposes.
- Development of a model predictive controller to find an optimal control solution for the system.
- Addressing the issue of compromise between thermal comfort and energy cost.
- Benefits that can be achieved by using different forms of objective functions.

The research project in this thesis aims to design and simulate a model predictive control for a solar thermal collector system combined with a heat pump. The literature review carried out on model predictive control and other control strategies suggested that a model predictive controller would be capable of dealing with such control aims, if the complexity problem can be solved.

Chapter 3 Setup and modelling of the solar system combined with a heat pump

3.1 Introduction

In this chapter a description of the plant is given with detailed methods used for modelling building dynamics, tanks and solar collector. A two-zoned building is considered and construction layers are modelled as lumps. Different methods are presented to get an appropriate model of the air source heat pump which matched with the data available from the manufacturer. The resulting model is a simple model and its coefficient of performance does match with the manufacturer's supplied data. Models of tanks and solar collector are presented in this chapter. A description of state-space and linear models used in this research are explained. The system model was verified by using different step input signals.

3.2 Experimental setup description

The solar system combined with a heat pump system is installed at the School of Civil and Building Engineering of Loughborough University as an experimental rig. It consists of a solar panel, a heat pump and accumulator tanks as presented in Figure 3-1.

Solar panels are used for heating when feasible, and the heat pump is used for heating when solar radiation is insufficient (cloudy weather, night) and for domestic hot water purposes. The heat pump has a power capacity of 6kW.

A general schematic diagram of the system is shown in Figure 3-1, where the main components of the system can be observed. The heat pump is connected to the buffer tank. The plant uses two different energy sources: the solar collector and the electric air source heat pump. Both of these can be used together or separately for heating the heating tank.

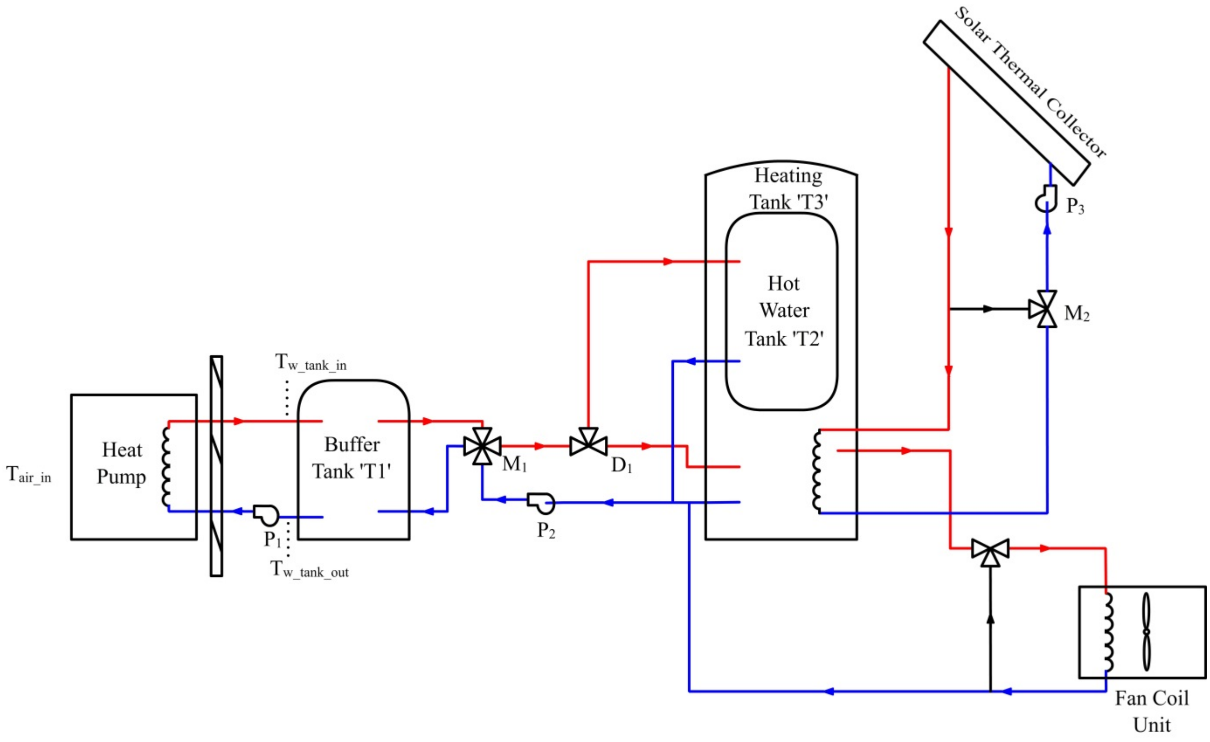


Figure 3-1: Solar system combined with a heat pump Schematic

The mixing valve M1 allows water to flow from the buffer tank (heat pump tank) into the heating tank or the hot water tank, while the diverter D1 diverts the flow to either or both of these tanks. The valve M2 allows water to bring energy into the heating tank or to take it back to the solar collectors.

The objective for the system is to supply hot water for heating and domestic hot water at the required temperatures. The control objective is to minimize the cost of electric energy for the system. If the solar radiation is low then the heat pump can be used to heat up the heating and hot water tanks. The optimum cost solution may be to operate the heat pump during the night time period when the energy tariffs are significantly lower.

The primary source of energy (solar energy) cannot be manipulated. So while it is useful, from a control perspective it is a disturbance, because changes in solar energy have to be compensated for. It is expected that solar radiation will be used when possible, and the heat pump will be used to make up for any shortfall in solar radiation.

Pictures of the main components of the system are shown in Figure 3-2:

a) The heating tank, which encapsulates the hot water tank (not visible).
b) The diverter, which diverts the flow from the buffer tank to the heating tank or the hot water tank.
c) The valve, which regulates the flow from the buffer tank to the other two tanks.
d) The current controller, which controls the heat pump, diverter and valves.
e) The buffer tank, which is connected to the heat pump.

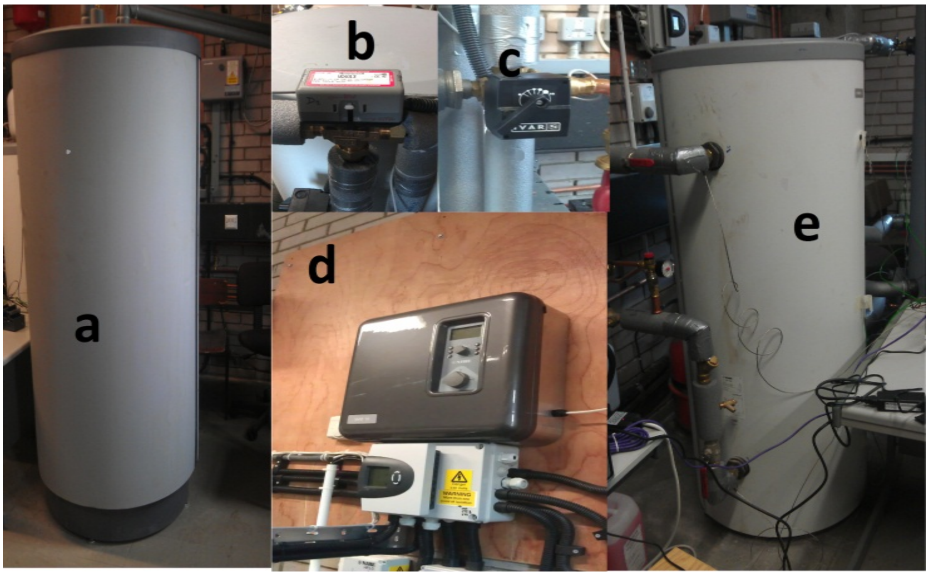


Figure 3-2: Solar system combined with a heat pump. (a) Heating tank (b) Diverter (c) Valve (d) Controller and (e) Buffer tank

3.3 System description

The main components of the solar heating system combined with a heat pump are described here.

The Accumulation system consists of three tanks. The hot water tank is inside the heating tank. The capacity of the heating tank is 450l and of the hot water tank is 300l. The third tank is the buffer tank which is 300l. It is connected to the heat pump and supplies hot water to the other two tanks when required.

Solar Collectors are used to collect solar radiation and to raise the temperature of the water of the heating tank. They use solar energy to raise the water temperature and are the primary energy source of the system. There are 2 flat plate collectors that each has a surface area of 2m^2.

Heat Pump-The installed heat pump uses air as a heat source. It is the auxiliary source of the energy for the heating tank, but it is the main (only) energy source for the hot water tank. The heat pump is directly connected to the buffer tank. The rated electric power of the heat pump is 6kW. The heat pump used is a single stage heat pump. The single heat pump is unable to modulate its power output during low load conditions, as this would cause overheating of the fluid loop. In order to solve this problem a tank is used in between the load loop and the heat pump i.e. the buffer tank. When using this setup under low load conditions, the heat pump is only run intermittently, and the load slowly draws energy from the buffer tank while the heat pump is off.

Manipulated variables

- The flow through valve M1 between the buffer tank and the other two tanks.
- The flow from valve M2 that allows the solar collector liquid to flow to the heat exchanger inside the heating tank to dissipate heat energy into the heating tank.
- The flow through D1 diverter to either the hot water tank or the heating tank.
- Heat pump On/Off switch.
- Two heater On/Off switches for fan coil units to heat the indoor environment.

Measured variables

- Water temperature in all tanks
- Solar collector output temperature or useful energy from the collector.

Objective functions

- Energy consumed by the heat pump
- Temperature deviations
- Thermal comfort

System disturbances

- Outside environmental temperature
- Solar radiation
- Domestic hot water consumption
- Occupancy

3.4 Building Model

Crabb et al., 1987 developed a simplified thermal response model of a building. In this work a single lumped construction capacitance and room air capacitance were linked together with a conduction path through a network of three resistances. The work also describes a good agreement of model internal temperature with a limited set of observed data for a school building. The impact of inputs e.g. zone heat gains on the building model was not addressed in this research. Dewson et al., 1993 found out five parameters of the Crabb et al., 1987 model by using experimental data and stated that the method can be used for online system identification.

Tindale, 1993 concluded that the second order model did not work when used for high mass construction elements i.e. materials with high thermal capacitance. A further node was added to the basic 2nd order model and convective and radiant heat transfer paths were separated. He also developed a method for the calculation of model parameters.

The model used for this research is based on the method used by Gustafsson et al., 2008 and is widely used by other researchers. Zhang et al., 2006 also used lumped approach to model the building for model predictive control. A typical construction element consists of multi-layered construction is used. Each layer of the element is defined by its thickness and material properties i.e. thermal conductivity, density and specific heat capacity. All the external walls and roof are considered to be of the same construction materials. The construction materials and properties of the external walls, roof and partition wall between hall and bedroom are summarized in Table 3-2. The building under consideration is kept intentionally simple: it consists of only two rooms; a hall and a bedroom. The hall has a south facing window and the dimensions of both the rooms are 4.27m*4.57m and 2.44m high. The total area of the south facing window in the hall is 5.83m^2. The schematic layout of the building is shown in Figure 3-3. As the normal heating load of a typical house in the UK varies between 10-12kW (approx.) and the heat pump system is of small scale therefore a simple and small building is considered. The building was simulated in specialist domain software called Integrated Environmental Solutions (IES) in order to obtain the indoor heat gains i.e. lighting, occupants and solar gains (Table 3-1). The solar gains through the window for the whole year in the bedroom and the hall are shown in Figure 3-4. As there is no window in the bedroom the solar gain in the bedroom is zero for the whole year.

Table 3-1: Internal heat gains and occupancy timings

Internal Gain Sources	Gain	Room	Occupancy Time
People	70W/person	Hall	8 hours
Lighting	8W/m^2	Bedroom	13hours
Computer	110W		

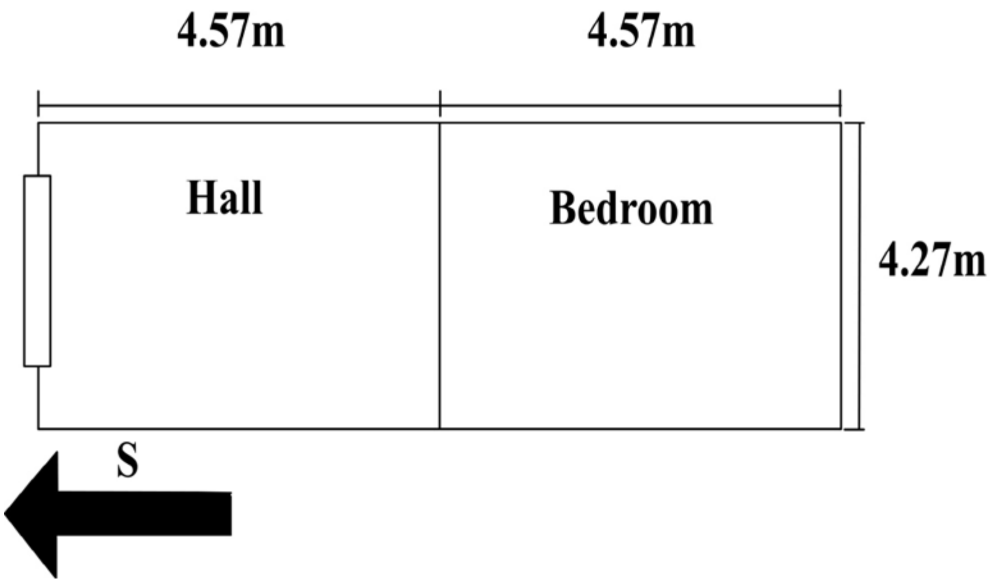


Figure 3-3: Building schematic layout

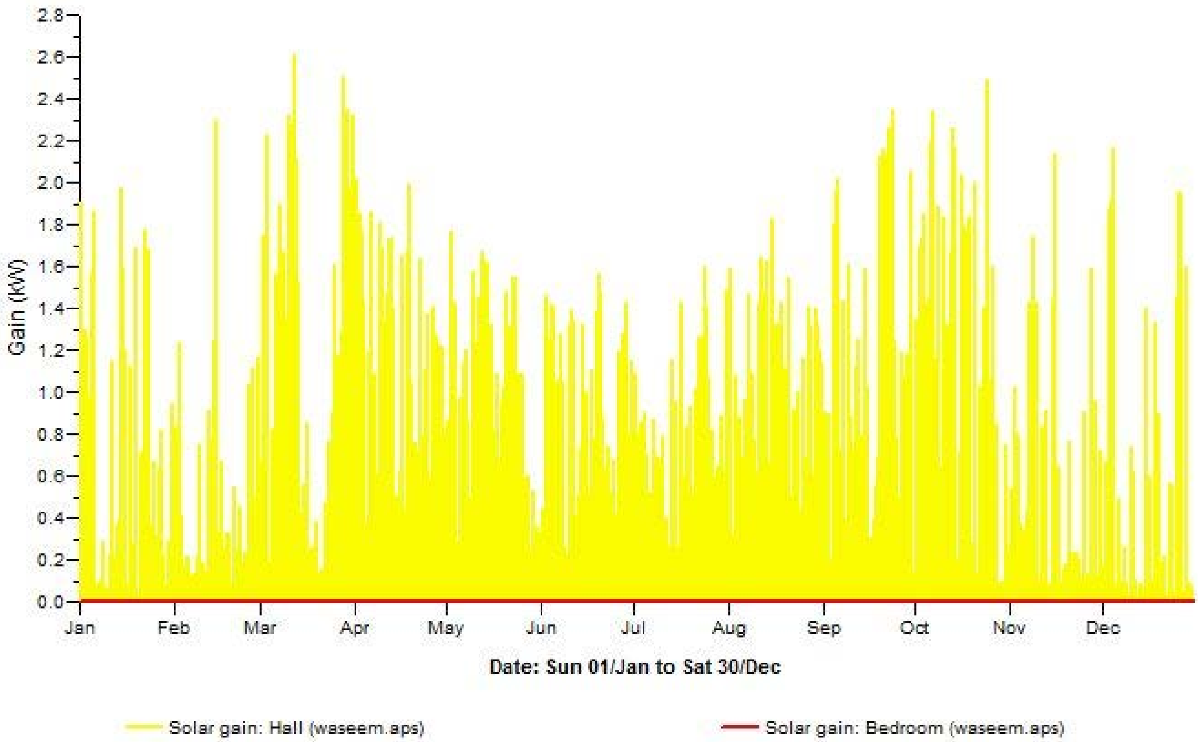


Figure 3-4: Solar gains through window

Table 3-2: House model specifications

Wall/Roof		Thickness in m	Thermal conductivity in $\frac{W}{Km}$	Density in $\frac{kg}{m^3}$
	Brick	0.1	0.84	1700
	Polystyrene	0.0795	0.034	35
	Concrete	0.1	0.51	1400
	Plaster	0.013	0.025	900
Partition Wall				
	Gypsum	0.025	0.25	900
	Air	0.1	$0.15\,\frac{K\,m^2}{W}$ (Resistance)	1.204
	Gypsum	0.025	0.25	900

A wall consists of 'N' number of layers that can be represented by ‘N’ number of thermal resistances and 'N' number of thermal capacitances. The model will also have two thermal resistances for the air contact on the inner side and outer side of the wall. A wall with 'N' number of layers can be seen in Figure 3-5. The advantage of this method when used for developing a building model by considering wall capacitance and resistance is that it takes into account the time varying effect of the building. In this case, when the outside air temperature changes it does not affect the indoor room temperature instantly and the change follows the laws of thermodynamics to transfer heat between indoors and outdoors. More importantly, effects of changes in indoor air temperature on the wall surface temperature (and therefore the radiation temperature) can be established. In the following sections a brief overview of thermodynamic laws and the equations that are used in the modelling are discussed.

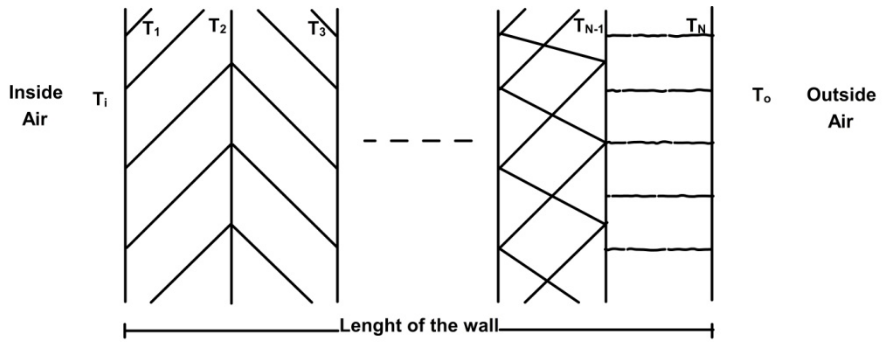


Figure 3-5: Wall divisions

The equivalent electrical diagram of a single layer wall is shown in Figure **3-6**, in which $\boldsymbol{R_i}$ is the interior film resistance, $\boldsymbol{R_o}$ is the outer film resistance, $\frac{\boldsymbol{R_1}}{\boldsymbol{2}}$ is the half resistance of the wall layer and $\boldsymbol{C_1}$ is the capacitance of the wall layer. It can be noted that for a wall of one layer there will be three resistances and one capacitance.

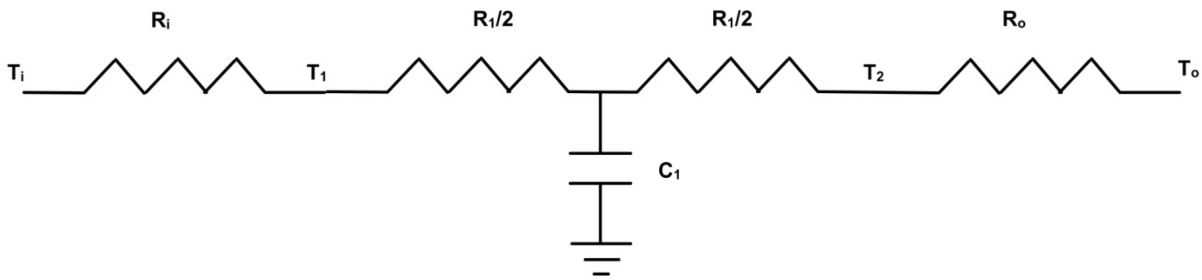


Figure 3-6: Equivalent electrical circuit diagram of a single layer wall

The resistance diagram of the hall is shown in Figure 3-7. The external wall has four layers and therefore has four resistances and four capacitances. The resistances resist the heat transfer between the layers while capacitances store heat energy. The window does not have any storage capacity and therefore represented by resistance only.

Most of the solar gain in the building is due to the solar radiation coming through the window. There is no solar gain in the bedroom air as there is no window; solar gain is only considered in the hall area. The fabric solar heat gain through walls and roof is taken as negligible because the construction considered has high thermal capacity and it tends to delay the solar gains transmissions of the heat until its direction is reversed during night time. Other heat gains are from people and other equipment i.e.

computers and lighting. There can also be partition heat gain or loss depending on the air temperature difference between the bedroom and the hall.

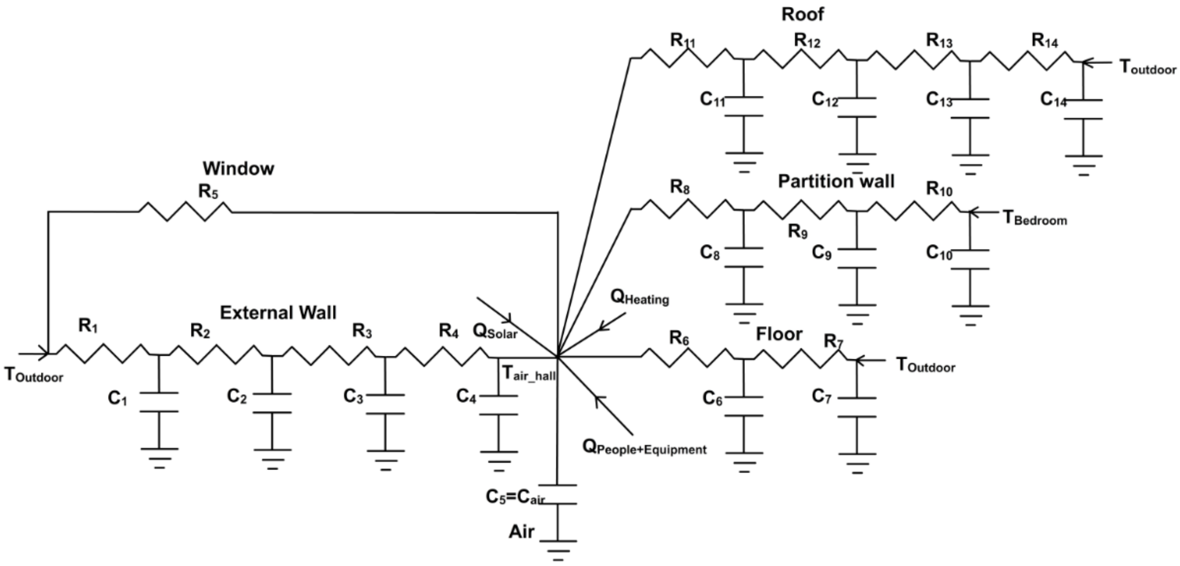


Figure 3-7: Resistance diagram of hall

3.4.1 One dimensional heat conduction

One-dimensional heat conduction can be derived from Fourier's law and is given by the following equation;

$$q_{cond} = -kA_1 \frac{dT}{dx} \tag{3.1}$$

Where $\frac{dT}{dx}$ is the temperature gradient, k is the thermal conductivity and A_1 is the area of the heat transfer section. The negative sign in the equation 3.1 indicates that the flow of heat energy is from the high temperature surface to the low temperature surface. By rearranging equation 3.1;

$$q_{cond} = -kA\frac{\Delta T}{L} = \frac{\Delta T kA}{L} \tag{3.2}$$

Equation 3.2 is the analogous to Ohm's law (V=IR). Here heat transfer (q_{cond}) is the current flow, $\frac{\mathrm{L}}{\mathrm{kA}}$ is the resistance and ΔT corresponds to the voltage difference.

3.4.2 One dimensional convection

The heat transfer between solid and gas (or liquid) is known as convection and can be described by the equation 3.3.

$$q_{conv} = hA_2(T_1 - T_2) \tag{3.3}$$

Where h is the convective heat transfer coefficient, A_2 is the surface area and $(T_1 - T_2)$ is the temperature difference between two mediums. Kirchoff's Law is used to calculate the temperature between each layer of the wall, roof and floor. In Figure 3-5 typical wall divisions are shown, where T_i is the inside temperature, T_1 is the temperature of first layer, ………,T_N is of the Nth layer and T_O is the outside temperature.

The heat transferred from indoor air to the wall can be summarized in the following equation;

$$q_{conv} = q_{cond} + q_{stored} \tag{3.4}$$

q_{stored} is the stored heat energy inside the wall layer or heat energy of lumped capacitance.

$$h_{in}(T_{in} - T_i) = \frac{k_i}{L_i}(T_i - T_{i+1}) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i\right) \tag{3.5}$$

$$\frac{dT_i}{dt} = \frac{h_i(T_{in} - T_i) - \frac{k_i}{L_i}(T_i - T_{i+1})}{c_{p,i}\rho_i L_i} \tag{3.6}$$

$$in\ above\ equation\ i = 1$$

For the middle layers the material also has capacitance and therefore heat storage capacity of the material is taken in to account. The heat balance equation will be ;

$$q_{con,1} = q_{cond,2} + q_{stored} \tag{3.7}$$

$$\frac{k_i}{L_i}(T_{i-1} - T_i) = \frac{k_{i+1}}{L_{i+1}}(T_i - T_{i+1}) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i + c_{p,i+1}\rho_{i+1}L_{i+1}\right) \tag{3.8}$$

$$where\ i = 2, 3, \ldots\ldots, (N-1)$$

For outer layer the equation for heat energy is;

$$q_{conv,N} = q_{cond,N-1} + q_{stored} \tag{3.9}$$

$$h_{out}(T_i - T_{out}) = \frac{k_i}{L_i}(T_{i-1} - T_i) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i\right) \tag{3.10}$$

Each wall layer is considered as a lumped element and modelled separately in Simulink. Each wall layer has its own capacitance to store heat energy and also has resistance to resist the heat energy flow.

Figure 3-8 shows the temperature of indoor air, outdoor air and the different layers of the wall model. The indoor air and outdoor air temperature were kept constant at 22^{o}C and 5^{o}C respectively. The initial temperature for layers was taken as 0^{o}C and the layer closer to indoor air comes very close to indoor air temperature. The plaster layer reached to the equilibrium temperature very quickly because of the low thermal conductivity while concrete has high thermal conductivity and took almost 1 day to reach to the equilibrium temperature. The last layer was of 0.1m of brick and its temperature remained closer to outside air temperature of 5^{o}C.

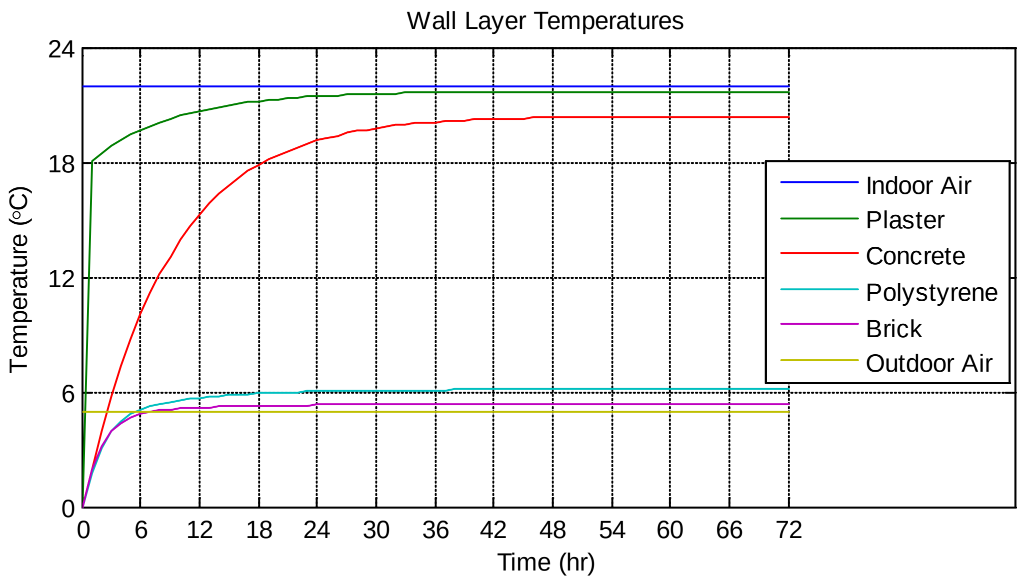


Figure 3-8: Wall layer temperatures

3.5 Heat Pump model

A heat pump is a device that transfers thermal energy from a lower temperature (Source) to a higher temperature (Sink). It reverses the natural flow of thermal energy. The operating cycle of a heat pump is shown in Figure 3-9. It consists of four components;

- a compressor,
- a condenser,
- an expansion valve, and
- an evaporator.

The condenser is used to convert the refrigerant from its gaseous state into the liquid form, while the evaporator is used to convert the refrigerant from liquid to gaseous state. The refrigerant in its gaseous state is pressurized in the compressor. It is compressed by extra mechanical work (W_{net}). This highly pressurized and high temperature fluid is then fed into a condenser where it releases its heat (Q_{out}) and changes into liquid. Then, it enters into the expansion valve and changes into a low pressure and low temperature liquid. In this state the refrigerant is fed into the evaporator, where it gains energy (Q_{in}) and changes into a gaseous state. Detailed information can be found in Moran et al., 2006.

3.5.1 **Model 1**

The efficiency of the heat pump is calculated by its coefficient of performance (COP). COP is the ratio of the heat transferred to the amount of the work done to the compressor. The COP can be approximately calculated by using the temperatures of the hot zone (water side in this case) and the cold zone (air side in this case).

$$COP = K \times \frac{T_{c,out}}{T_{c,out} - T_{e,out}} \tag{3.11}$$

Where K is the efficiency coefficient of the compressor and is assumed as 0.4 (Van Schijndel et al., 2003).

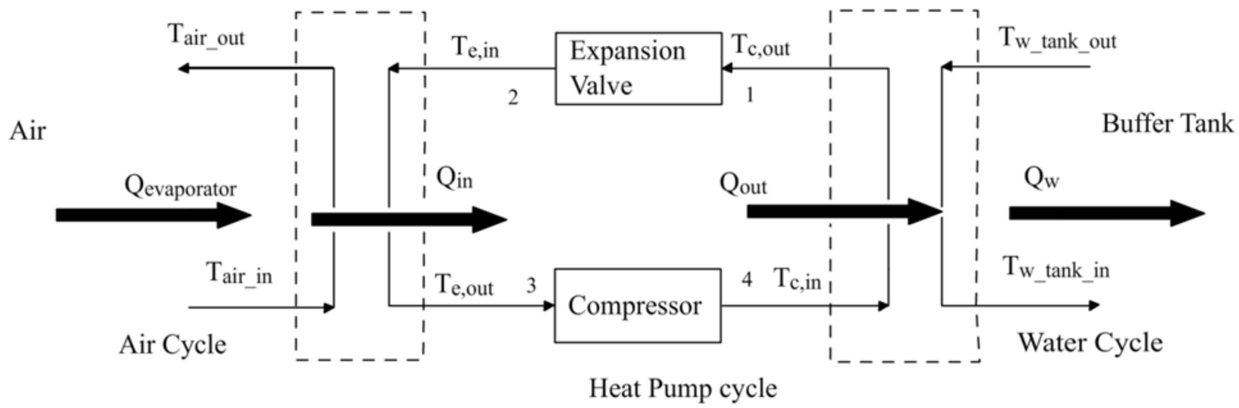


Figure 3-9: Schematic Diagram of heat Pump

Different methods are used to model an air source heat pump. Chi et al., 1982 described a heat pump transient analysis computer program. The program used first-order differential equation to describe heat and mass flow. The type of detail modelling is beyond the scope of this research. Li et al., 2010 suggested that a simple equation fit model can be used to study the performance of a solar assisted air source heat pump system. The heat pump model developed Van Schijndel et al., 2003 is used as model 1. The model has dynamic elements but the process is modelled as steady state process. The heat pump under study is an air source heat pump. Figure 3-9 shows the operating cycle and two external cycles. The air cycle is attached to the evaporator while the water cycle is attached to the condenser. It is assumed that the temperature of liquid leaving the condenser denoted as $T_{c,out}$ at point 1 is equal to the temperature of the water going into the water tank denoted as $T_{w\_tank\_in}$ (buffer tank). Similarly it is also assumed that the temperature of the refrigerant feeding into the evaporator denoted by $T_{e,in}$ at point 2 is equal to the temperature of air coming into the evaporator denoted by $T_{air,in}$.

On the basis of these assumptions;

$T_{c,out} = T_{w\_tank\_in}$ and $T_{e,in} = T_{air,in}$

Based on equation 3.11, further approximation of COP has been done by Van Schijndel et al., 2003.

$$COP = \dot{Q}_{out} / W_{net} \tag{3.12}$$

By applying heat energy gained by the evaporator, heat transferred by the condenser and dynamics of condenser and evaporator, this lead to a model given in below equations;

$$\dot{T}_{e,out=} \frac{-\dot{m}_{e1} C_r T_{e,in} + \dot{m}_{e1} C_r T_{e,out} - (COP - 1)\dot{W}}{C_e m_e} \tag{3.13}$$

$$\dot{T}_{c,out=} \frac{\dot{m}_{c1} C_r T_{c,in} - \dot{m}_{c1} C_r T_{c,out} + COP\dot{W}}{C_c m_c} \tag{3.14}$$

Equations (3.11), (3.13) and (3.14) are used as a heat pump model which is implemented in Simulink. The detail model equations are given in appendix A from equations A.1 to A.10.

From above it is concluded that the COP of the heat pump depends on the outside air temperature and the condenser outflow temperature. The heat pump operates between two different mediums (air and water), which have very different heat capacities. Air has less capacity than water, and for this reason the mass flow rate on the evaporator side is assumed to be higher than on the condenser side.

The above model did not give promising results when compared to the limited data that were available from the heat pump manufacturer (NIBE) (Figure A-1). The response of the above model was also very fast as compared to the other elements of the system e.g. building model, which means that it slows the simulation down by forcing a short time step for the global integration algorithm. The comparison is shown in Figure 3-10 below. The COP values were close at larger temperature differences but the values were very different at low temperature differences between tank and air.

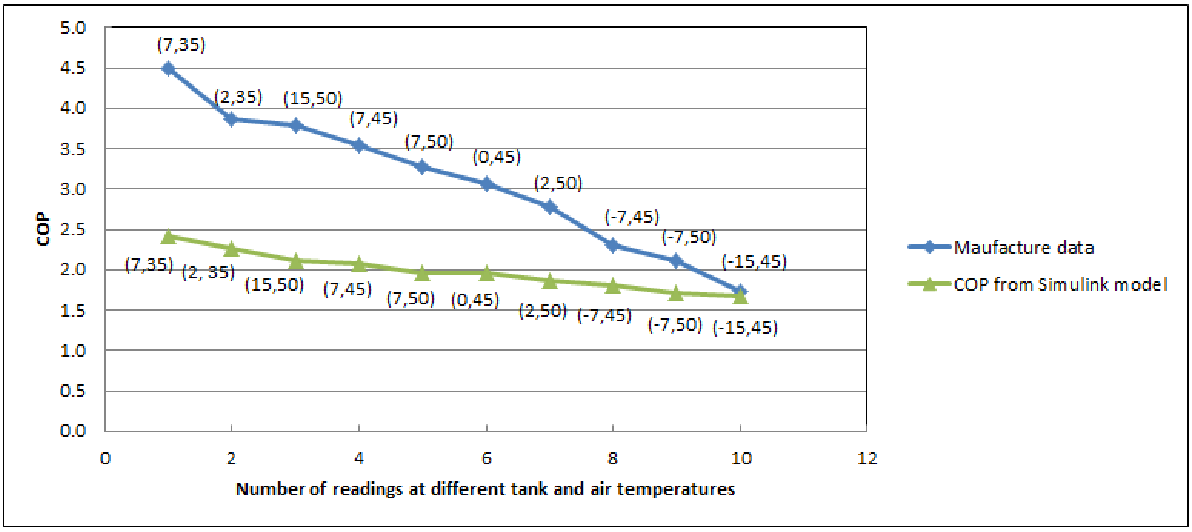


Figure 3-10: Manufacturer COP and model COP plot

From the above result it is concluded that this heat pump model (equations 3.11, 3.13 and 3.14) is not suitable for this study.

3.5.2 Model 2

In the second method to calculate the COP of the heat pump four other factors are considered i.e. α, β, $u_T P$ and $u_E P$. α is the thermal efficiency coefficient of the compressor, β is the recovery of losses into heat, $u_T P$ is the thermal coefficient on the condenser side and $u_E P$ is the thermal coefficient on the evaporator side. $u_T P$ and $u_E P$ incorporates the resistances of air and water on cold and hot mediums of the heat pump. The COP equation will be given by following equations;

$$COP = \alpha\left(\frac{T_H}{T_H - T_C}\right) + \beta \quad (3.15)$$

$$(T_H - T_C)COP = \alpha T_H + \beta(T_H - T_C) \quad (3.16)$$

By taking air and water resistances into account;

$$T_H = T_T + u_T P \times COP \quad (3.17)$$

$$T_c = T_E - u_e P \times (COP - 1) \quad (3.18)$$

$$T_H - T_C = T_T - T_E + (u_T + u_E)P \times COP - u_E P \quad (3.19)$$

By simplifying, this gives a quadratic equation;

$$\begin{aligned}(u_T + u_E)P \times COP^2 \\ + (T_T - T_E - u_E P - \beta(u_T + u_E)P \\ - \alpha u_T P)COP - \alpha T_T \\ - \beta(T_T - T_E - u_E P) = 0\end{aligned} \quad (3.20)$$

The above quadratic equation can be solved for COP. Different calculations are made to find the nearly fit model for the heat pump. In the Figure 3-11 different calculations are shown with different values of α, β and $u_E P$.

3.5.3 **Model 3**

The model 2 shows better results as compared to the model 1. Another method is tried below to find a much better model than the model 2. It can be seen that the curve found by the plot of inversing ideal COP and manufacturer's COP gives better results than the other COP curves. The plots of COP data from different methods are shown in Figure 3-11 and the inverse plot of both ideal COP and manufacturer's COP is shown in the Figure 3-12. The1/ideal COP values at different environmental air temperatures and tank temperature are on the x-axis and 1/Manufacturer's COP are on the y-axis. The equation used as COP calculation is also given below;

$$y = 29.278x^2 - 4.8281x + 0.4328 \quad (3.21)$$

The above equation is used as the heat pump model. The equation has an R^2 value of 0.9893, which is the coefficient of determination and is used to find out how accurate the equation will predict the future outcomes. In this case the value of R^2 is very close to 1 which means that the regression line fits the data very well. The remaining small deviations can be attributed to differences in efficiency at different temperatures.

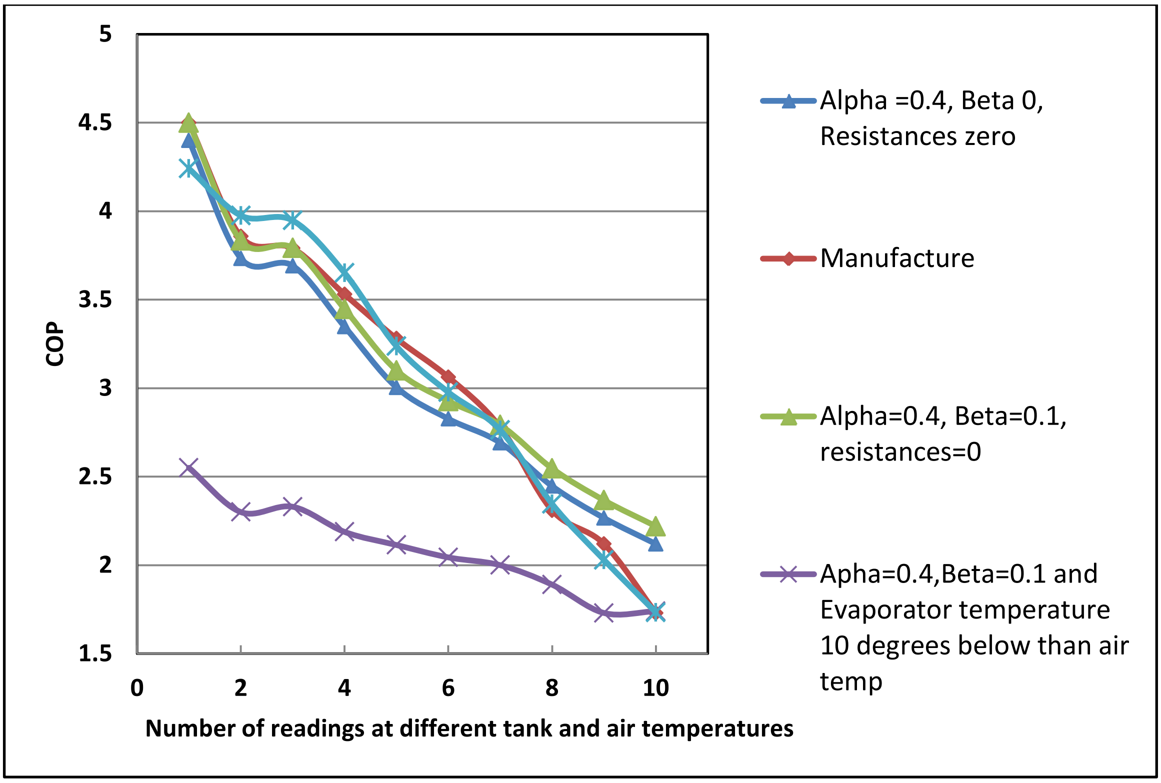


Figure 3-11: COP plots from different methods

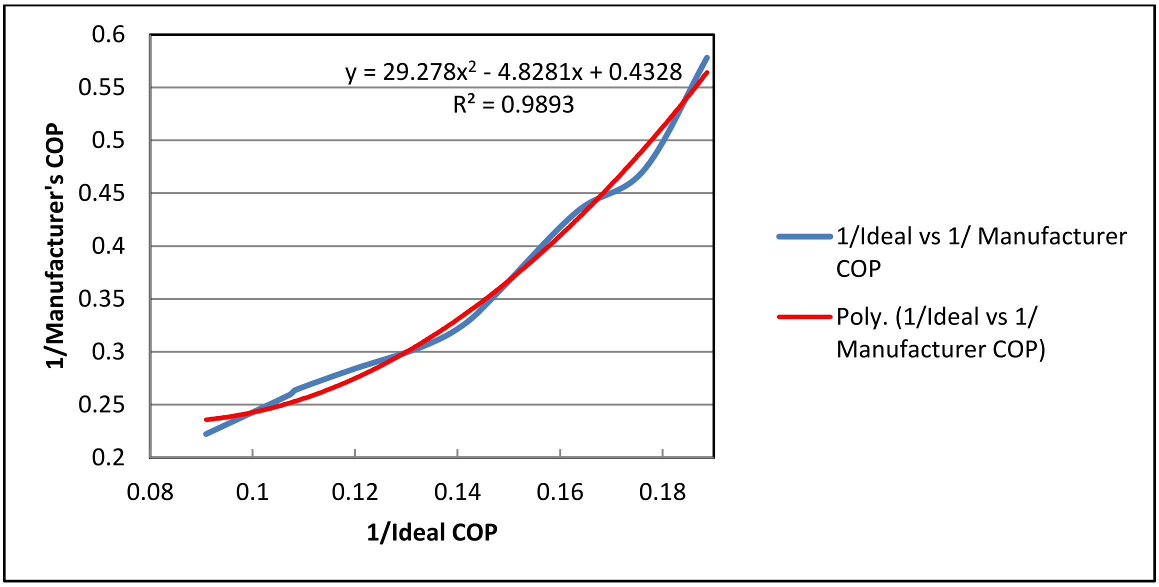


Figure 3-12: Inverse plot of Ideal COP vs Manufacturer COP

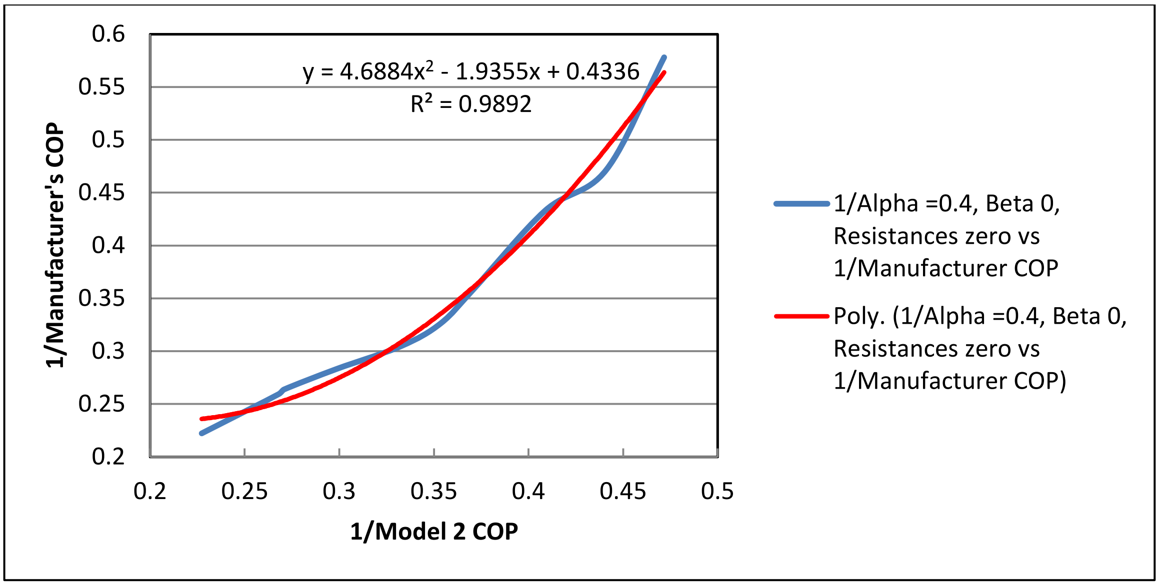


Figure 3-13: Inverse plot of Alpha =0.4, Beta 0, Resistances zero vs manufacturer COP

3.6 Solar thermal collector model

Flat plate collectors are used to heat up the water in the heating tank. The useful energy from the solar panel is calculated by using the mathematical model proposed by Duffie et al., 1991.

The solar radiation is captured by the solar panel and used to heat up water. With a solar radiation I (W/m^2) covering the solar panel of an area A_c (m^2), the energy received by the solar collector is given by;

$$Q_r = I.A_c \qquad (3.34)$$

It is known that not all of energy received by the solar collector is used to raise the temperature of water, since some of the radiation is reflected back into the sky. Only part of the radiation is absorbed by the solar plate. The conversion factor $\tau\alpha_1$ indicates the percentage of solar radiation which is absorbed by the solar collector and transmitted into the cover of panel. Therefore the energy received by the solar collectors is given by;

$$Q_r = \tau\alpha_1(I.A_c) \qquad (3.22)$$

There is also an energy loss from the solar collector surface when the temperature of the solar panel is higher than the surroundings. This loss is given by;

$$Q_l = U_L A_c\,(T_c - T_a) \qquad (3.23)$$

Therefore the rate of useful energy gained by the solar collector is given by;

$$Q_U = Q_{r-}Q_l = \tau\alpha_1(I.A_c) - U_L A_c\,(T_c - T_a) \qquad (3.24)$$

The useful energy is also measured by the amount of the energy carried by the fluid;

$$Q_U = mC_p(T_o - T_i) \qquad (3.25)$$

It is difficult to define the average collector temperature in equation (3.25), therefore a factor called "the collector heat removal factor (F_R)" is given by the following equation;

$$F_{R}= \frac{mC_p(T_o - T_i)}{A_c\,[\tau\alpha_1 I - U_L(T_c - T_a)]} \qquad (3.26)$$

The useful energy from the collector is measured by multiplying F_R with Q_U. The useful energy is;

$$Q_U = F_R A_c\,[\tau\alpha_1 I - U_L(T_c - T_a)] \qquad (3.27)$$

The equation 3.27 is called "Hottel-Whillier-Bliss equation" and is used as a collector model in Simulink. The values of $F_R\tau\alpha_1$ and $F_R U_L$ are taken as 0.68 and 4.90 (W/m^2)/^{o}C respectively. The model of the solar panel used in Simulink is shown below in Figure 3-14. The output of the model is the energy gained from solar radiation and this energy is added into the heating tank as heat input.

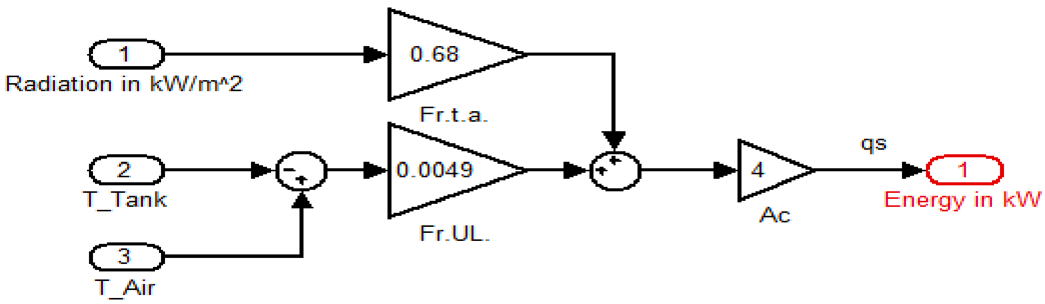


Figure 3-14: Simulink model of solar thermal collector

3.7 Energy Equations and tank model

In this section different heat transfer equations will be presented. The equations are based on energy balance and energy flow, by assuming an average temperature equal to T_b, T_h and T_H for buffer tank, heating tank and hot water tank respectively.

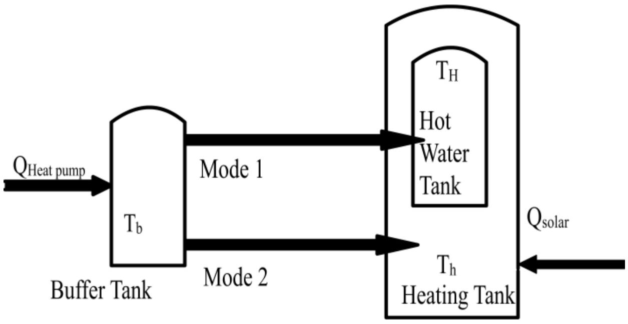


Figure 3-15: Modes of the system

The heat transferred from the heat pump into the buffer tank is;

$$\dot{Q}_{out} = \dot{W}COP \qquad (3.28)$$

Where $\dot{Q}_{out}$ is the energy output from the condenser and $\dot{W}$ is the power input. The heat transfer between the buffer tank and the hot water tank is given by;

$$\dot{Q} = \dot{m}C_p\,(T_b - T_H) \qquad (3.29)$$

There is an energy use caused by the withdrawal of hot water, as cold water is fed into the tank. It is assumed that the cold water has a constant temperature of 15^{o}C and the hot water in the hot water tank temperature is at 55^{o}C. The heat transfer between the buffer tank and the heating tank is;

$$\dot{Q} = \dot{m}C_p\,(T_b - T_h) \qquad (3.30)$$

The solar energy input in the solar tank is given in the equation 3.27. The water tanks are modelled by assuming that the water inside the tanks mixes properly and there is no temperature difference across the tank height. The second assumption is that the heat capacity of the tank is the heat capacity of the volume of the water inside the tank. The heat losses from the tanks are also considered and the losses from buffer tank and heating tank are added as the heat gain by the room air i.e. it is assumed that the tanks are placed in the bedroom. The hot water losses are added into the heat gain by the heat tank water. A Simulink diagram of the buffer tank is shown in Figure 3-16. The heat energy in kW is supplied through the heat pump and the integrator $\frac{1}{s}$ changes the tank temperature over the time. The T_Env is the bedroom air temperature.

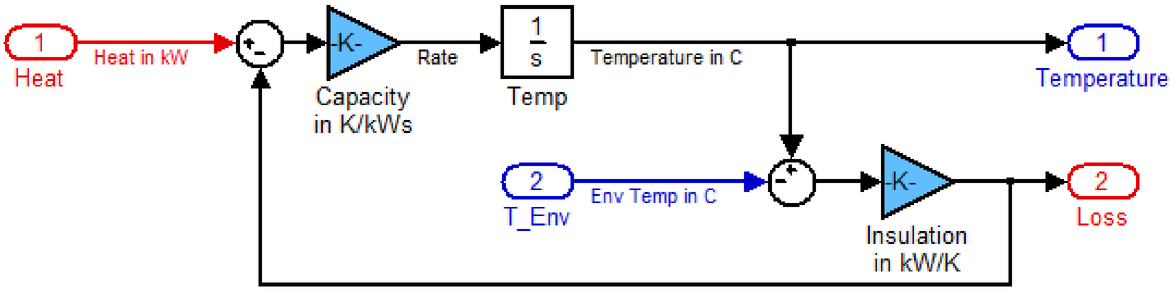


Figure 3-16: Simulink diagram of tank model

The model of the system describes the relationship between plant inputs and outputs. Below is the focus on the model of the system and its linearization. The model obtained by linearizing the plant model is a continuous-time state space model but the model predictive controller uses a discrete-time state space model therefore the details of the modelling shown below are given in discrete-time s-s form.

3.8 State - space Model of the system dynamics

In this research a linearized, state space and discrete model of the plant is considered. According to Maciejowski, 2002, the state space model of the system generally can be written in the following form;

$$x(k+1) = Ax(k) + Bu(k) \qquad (3.31)$$

$$y(k) = C_y x(k) \qquad (3.32)$$

$$z(k) = C_z x(k) \qquad (3.33)$$

In the above equations x is the state vector of the system with l-dimensions, u is an m dimensional input vector, y is a n_y-dimensional vector of measured outputs whereas z is the vector of outputs which are to be controlled (n_z dimensions). k is the time step. In this thesis it is assumed that $y = z$ and C will be used for both Cy and Cz. The model predictive control action is done at time step k by first obtaining output measurements $y(k)$ then computing the optimal plant input $u(k)$ and then applying $u(k)$ to the plant. This means there is some delay in obtaining the output measurement and then applying $u(k)$, therefore there is no direct feed-through between $u(k)$ and $y(k)$ and this can be seen in equation 3.32. In practice controlled output $z(k)$ depends on $u(k)$ and the equation 3.33 can be written as;

$$z(k) = C_z x(k) + D_z u(k) \qquad (3.34)$$

The equation 3.34 can complicate the computational process of optimal $u(k)$. This complication can be avoided by introducing another vector $\tilde{z}$ and is given by the following equation;

$$\tilde{z}(k) = z(k) - D_z u(k) \tag{3.35}$$

The above equation means that the controlled outputs depend on states only without any direct feed-through from the inputs $u(k)$.

3.9 Linear Model

In most of the control strategies a plant model is used at design and analysis stage (off-line). In model predictive control the model of the plant is directly used in the control algorithm and the resulting output signals are directly applied to the real plant. Therefore it is important to have an appropriate and good model that represents the actual plant, and to achieve a fast evaluation of the model. In reality every system has some form of nonlinearities. If a plant has a state vector X then according to nonlinear differential equation (Maciejowski, 2002);

$$\frac{dX}{dt} = f\ (X, U, t) \tag{3.36}$$

In the above equation X is the state of the plant and U denotes vector of inputs. If the plant is at some initial state of $X = X_O$ and with initial input $U = U_O$ and if there is small change in both state and input i.e. $X = X_O + x$ and $U = U_O + u$ and assuming both x and u are very small then;

$$\frac{dX}{dt} = f\ (X_O + x, U_O + u, t) \tag{3.37}$$

The above equation can be written as

$$\frac{dX}{dt} \approx f\ (X_O, U_O, t) + \frac{\partial f}{\partial X} \Big|_{(X_O,U_O,t)} x + \frac{\partial f}{\partial U} \Big|_{(X_O,U_O,t)} u \tag{3.38}$$

In the equation 3.51 higher terms of x and u are neglected. The terms $\frac{\partial f}{\partial X} \big|_{(\mathrm{X_O,U_O,t})}$ and $\frac{\partial f}{\partial U} \big|_{(\mathrm{X_O,U_O,t})}$ denote the Jacobian matrices and are matrices of partial derivatives. These Jacobian matrices can be denoted by A_c and B_c respectively. As $X = X_O + x$ and X_O is a value of X, therefore $\frac{dX}{dt} = \frac{dx}{dt}$ and the linearized model of the plant will be;

$$\frac{dx}{dt} \approx A_c x + B_c u + f\ (X_O, U_O, t) \qquad (3.39)$$

And if (X_O, U_O) is an equilibrium point then $f\ (X, U, t)$ will be zero and the linear state-space model of the system will be (Maciejowski, 2002);

$$\frac{dx}{dt} = A_c x + B_c u \qquad (3.40)$$

This is a continuous linear time invariant (LTI) state-space model. The linmod function of the MATLAB software is used to obtain a linearized model of the non-linear system. Both inputs and outputs are specified in the Simulink. To obtain the matrix A of the system model, the input is set to a specified value and the states x of the system are perturbed about the operating point. For the matrices B,C and D the states are set to the operating points and the inputs u are perturbed. The following operating points are considered to find out the linearized model of the system;

$$[u1\ \ u2\ \ u3\ \ u4\ \ u5\ \ u6] = [0.20\ \ 0.03\ \ 0.12\ \ 1\ \ 0.10\ \ 0.20]$$

$$[u7\ \ u8\ \ u9\ \ u10\ \ u11\ \ u12] = [5\ \ 2\ \ 0.1\ \ 0.1\ \ 0.1\ \ 0]$$

whereas

$u1, u2, u3, u4, u5$ and $u6$ are the electrical energy input, inner valve, diverter, solar pump input, fan coil in bedroom and fan coil unit in living room input respectively. The inputs u_7 to u_{12} denote the disturbances of the system; $u7$ is the outside environmental temperature, $u8$ is the water consumption in l/h, $u9$ is the solar radiations in kW/m^2, $u10$ is the energy gain in bedroom, the energy gain in living room is denoted by $u11$ and $u12$ is a spare disturbance for future use to reduce the time of modelling future distance if there is any. The system's linearised continuous-time state-space model is given in the Appendix B and has 22 states. The linear model was obtained by using a first principles non-linear model of the plant except for the heat pump where an appropriate model has been found that gives a good match with the manufacturer's data.

3.10 Model verification

The Simulink model is verified by initially using constant input values to find the response of the system (Figure 3-17). The system was simulated for 5 days until the outputs became stable. The system was then modelled by introducing a step input signal of the heat pump on day 9 and as expected the tank 1 (buffer tank) temperature started to increase as it is directly connected to the heat pump, and also the other tank and room air temperature started to rise (Figure 3-18). This test was applied with different settings by using some inputs to zero and changing others. The system model behaved as was expected and the energy was contained within the system.

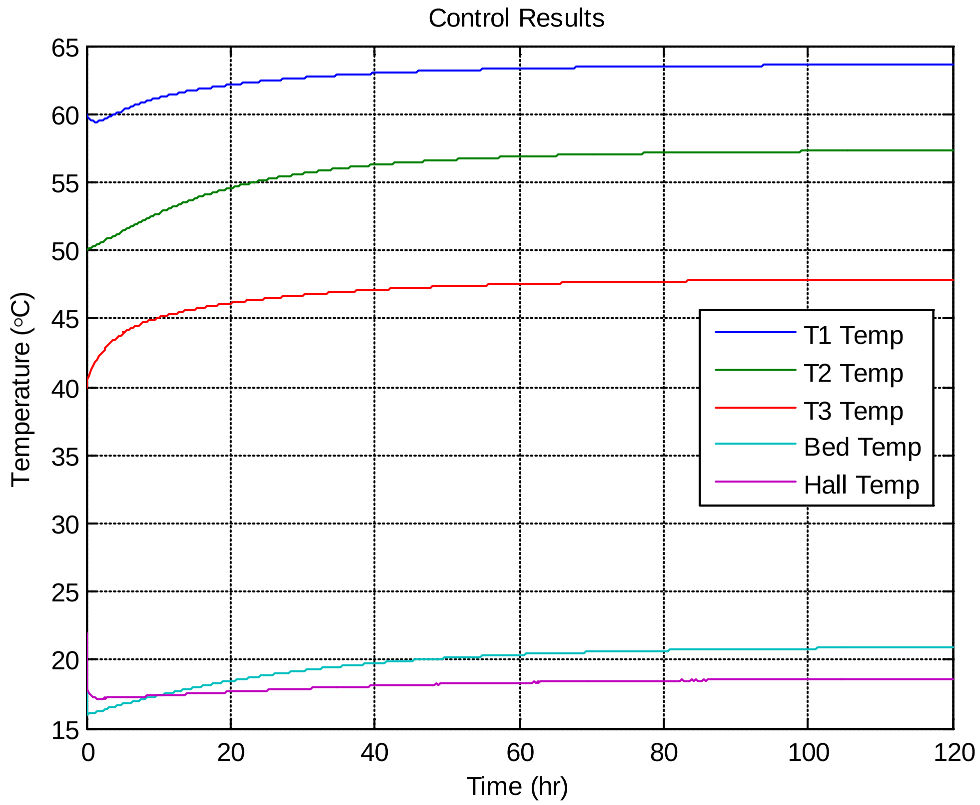


Figure 3-17: Constant inputs response of the model

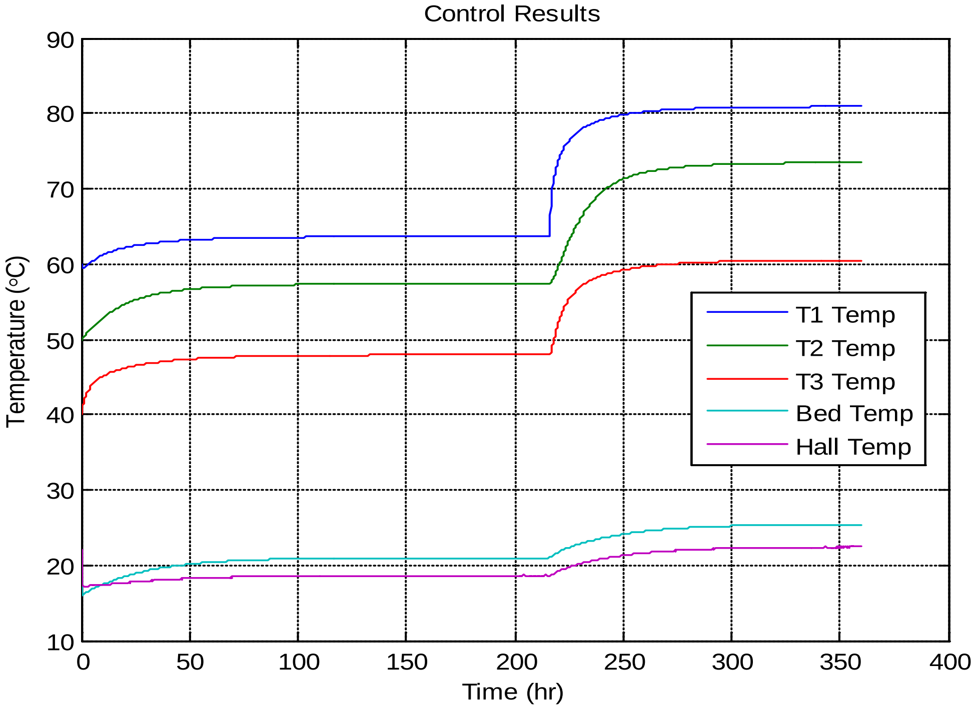


Figure 3-18: Step input response of the model

3.11 Summary

The goal of this chapter was to develop a suitable model of a solar system combined with an air source heat pump and also a model of a two-zoned building. The building model that has been developed in this chapter is a lumped model and the layers of wall, roofs etc are considered as lumps. The heat pump model also shows good agreement with the manufacturer's data available for coefficient of performance. The system model is verified by using some step inputs and it was made sure that the model behaves accordingly. The model was linearized at operating points of the system. It can be concluded that the model developed in this chapter is simple, accurate enough to be used for testing of different control strategies, and is also computationally efficient.

Chapter 4 Control Strategies

4.1 Introduction

This chapter focuses on the control strategies for a solar heating system combined with a heat pump. The aim is to test different control strategies for the indoor heating and hot water system that reduce energy consumption and make effective use of solar radiation when available. Three control strategies are investigated and applied to a solar heating and hot water system combined with an air source heat pump. Their performance is evaluated based on the results of computer simulations. Each controller is initially applied to a solar system combined with a heat pump connected to a single tank. Two basic tests are carried out for this plant i.e. with and without disturbance (solar radiation). Later on four climatic cases are simulated for the solar system combined with a heat pump. The performance of these controllers for different disturbances is investigated.

4.2 Control Objectives

There are two control objectives of the control problem. The first objective is to minimize the energy cost for heating and hot water. This can be achieved by using night-time electric tariffs which are cheaper as compared to daytime tariffs, and also by maximizing the use of available solar energy. Buildings use a considerable amount of energy and unfortunately the peak demand of building energy consumption occurs during the daytime, which makes the electricity consumption at the peak time higher than the average consumption level. This means that the power generation capacity has to be at least equal to the peak demand. The most effective way to tackle this problem is to store energy during the off-peak period and use it during the peak period which is known as load shifting. The second control objective is to provide better thermal comfort to the occupants of the building. To achieve these room air temperatures has to be maintained at a set point.

4.3 Scenarios

To compare the effectiveness of the MPC controller to alternative control schemes, several scenarios are simulated. The weather data used for the simulations is for the city of London. The normalized domestic hot water consumption data is taken from Defra, 2008, as shown in Figure 4-1. The water consumption was monitored in different houses in the UK and the values given are normalized values. The building used in this research is smaller than an average UK house but the reason of using this data is that it is used to benchmark different controllers. Lower electricity price is considered during the night time for 7 hours from midnight to 7am (the Economy 7 (E7) tariff promises 7 hours of cheap electricity, but it does not specify exactly when these are).

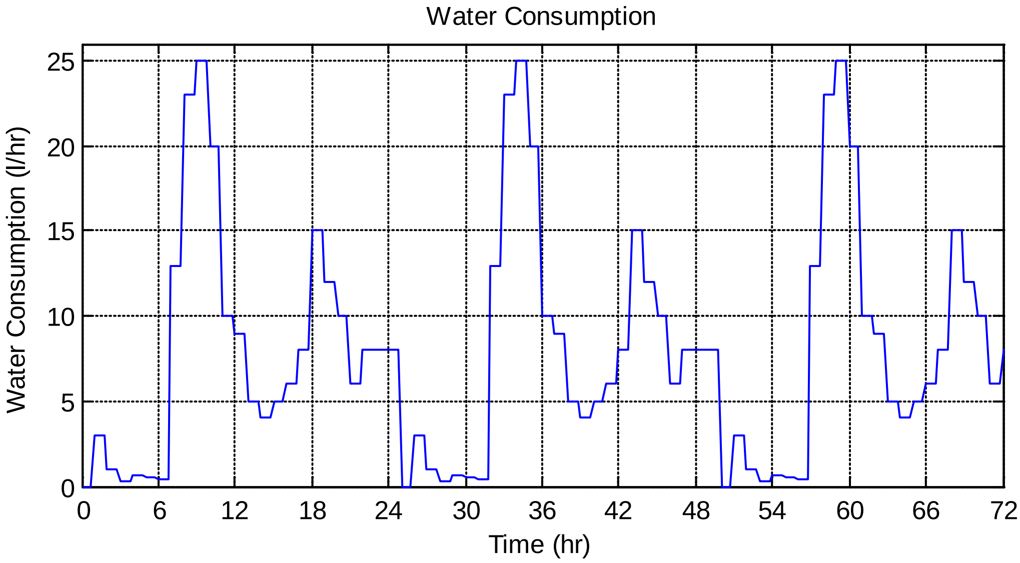


Figure 4-1: Water consumption in l/hr for 3 Days

The water consumption, solar radiations and outside environmental temperature are considered as disturbances. This means the predicted changes can be used for accurate predictions within the model predictive controller. The electricity price is considered a time-varying weight, which again is known in advance.

The simulation strategy is shown in Figure 4-2. Four different weather conditions were simulated and were combined with three control strategies: on-off, PI and MPC. In case A, the simulations were performed by considering one cold day in the middle of two medium temperature days. Case B was simulated with one sunny day in between two days having medium solar radiations. In case C the middle was taken as a hot day and for case D the middle day was a cloudy day.

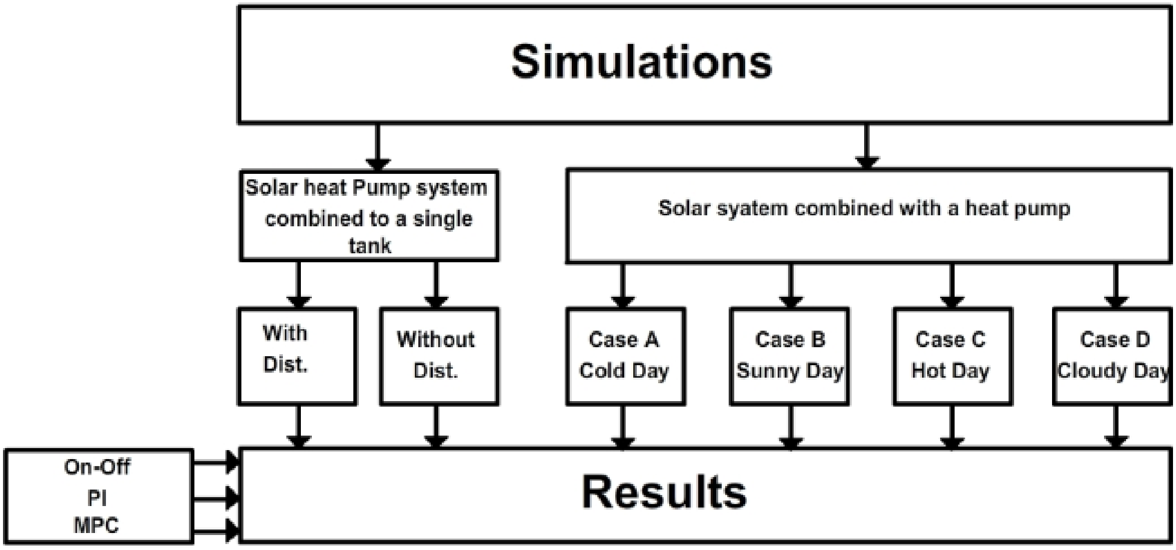


Figure 4-2: Simulation strategy

Three control strategies were evaluated i.e. on-off, PI and model predictive controllers to deal with the control objectives discussed above.

4.4 On-Off controller

The on-off controller is the simplest type of controller. The controllable device (the heat pump in this case) is turned on and off according to the sign of some tank temperature error as given by following equation;

$$e_r = T_r - T_T \tag{4.1}$$

Where, e_r is the error between reference temperature (T_r) and current tank temperature (T_T). The controller output is either on or off with no medium controller state. An element of hysteresis can be introduced to avoid rapid switching of the controller. The main advantage of the on-off controller is that it is a simple controller and easy to implement. It is a feedback controller, it is typically very robust and it does not contain any information about the plant dynamics.

4.4.1 Initial testing

Before implementing any control strategy to the system under study, a simple system is considered to understand the behaviour of the system while using different control strategies. The simple system consists of a heat pump and a tank. Solar radiations are taken as a disturbance in this system. The results obtained by controlling this simple plant with an on-off controller are shown in Figure 4-3. The controller was implemented by using a relay block in Simulink. In order to prevent frequent 'on-off' of the heat pump, a hysteresis of 2^oC was also included in the controller operation. It will allow for a certainly small error to develop before the controller switches the heat pump on or off. While this leads to an oscillation of the temperature within a band around the set point, it can significantly reduce losses and wear related to frequent switching of the heat pump.

The set point temperature of the tank was set at 55^oC but at the beginning of the simulation the tank temperature was set at 60^oC. Figure 4-3 illustrates that the controller was turning the heat pump on and off in a set pattern when there was no disturbance in the system i.e. no solar radiation input. The switch on and off points are $\pm 2^oC$ below and above the set point temperature. The controller was able to turn on the heat pump when the temperature became 53^oC and was turning it off when the temperature was 57^oC. The temperature drop was due to the heat loss from the tank to the outside environment. The energy cost with this controller to maintain the tank temperature at 55^oC was £2.206 for 3 days.

The second simulation was performed by introducing solar radiation (kW) as disturbance as shown in Figure 4-4. The heat pump was turned ON at 12:00 due to the tank temperature (output) reaching switch-on point. This also happened at around 23:00 and 29:30. The occurrence of strong solar radiation on day 2 increased the tank temperature to 72^oC. The controller did not switch ON the heat pump after 31:30 because after that time the tank temperature did not hit the switch ON point. This case resulted in a lower energy cost of £0.3775 for all 3 days due to the use of free solar energy.

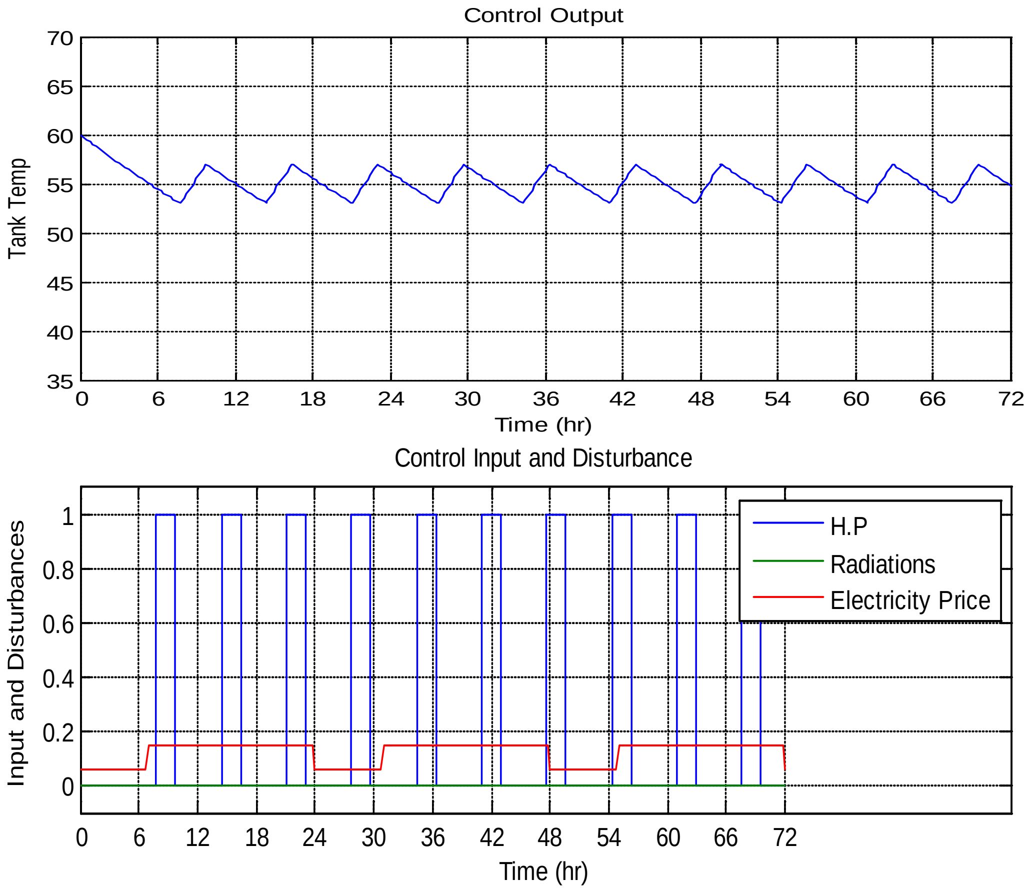


Figure 4-3: Simple plant on-off control without disturbance

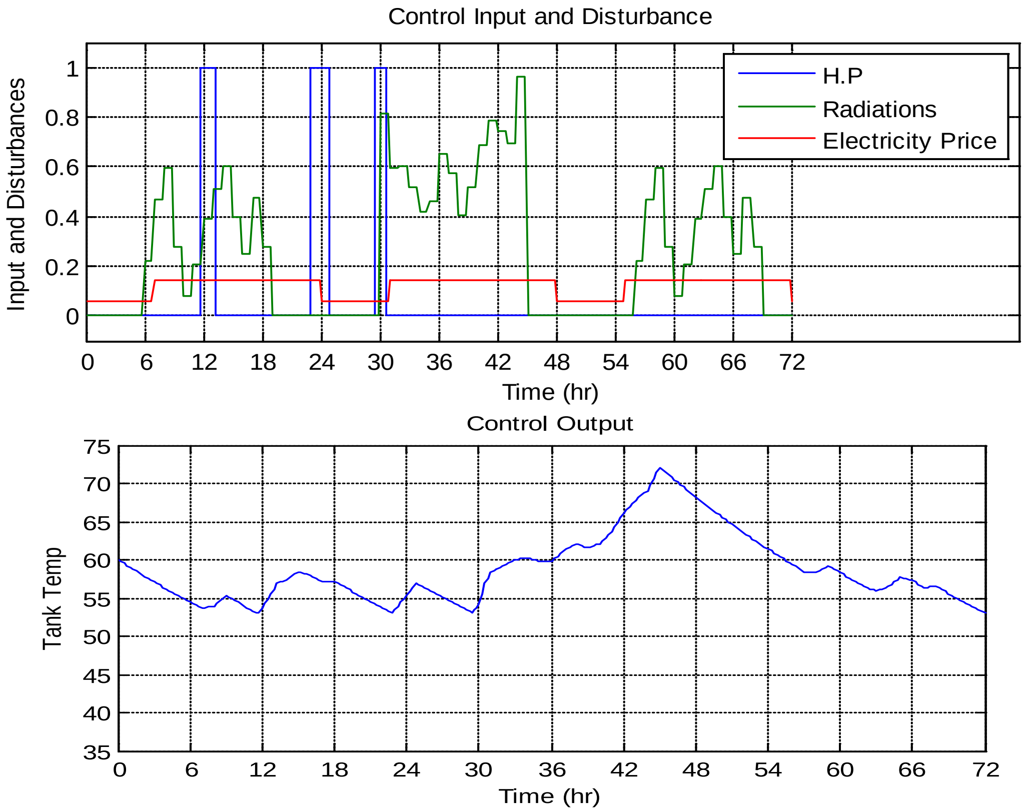


Figure 4-4: Simple plant on-off control with disturbance

Below are the results obtained for four cases by applying on-off controller to the solar heating system combined with heat pump. For all simulation cases, the solar collector pump is switched on only when the solar radiations are of 0.1kW or more.

4.4.2 **Case A**

The case A simulations for an on-off controller are presented in Figure 4-5 and Figure 4-6. From the control results plot (Figure 4-6) it is observed that the on-off controller took about 12 hours to bring the hall temperature to the set point temperature of 22^{o}C. The air temperature in the bedroom took about 3 hours to reach to the desired set point temperature (18^{o}C). The longer time taken by the hall air was caused by the higher heat loss due to the presence of a window. A higher heating tank temperature could be set to shorten the heating up period.

As discussed earlier the on-off controller operates between the switch-on and switch-off points. The switch on and off points for tank temperatures were -2^{o}C and +2^{o}C respectively to that of the set point temperature and for room air temperatures they were -1^{o}C to +1^{o}C respectively. In the figures T1, T2 and T3 represents buffer tank, hot water tank and heating tank temperatures respectively. Figure 4-6 depicts the temperatures fluctuating between the upper and lower limit of the temperature tolerance. The heat pump was used throughout the day without taking the night tariffs into account. The heat pump was switched ON whenever it was required (drop in tank temperatures) which means the controller does not forecast and only performs the control action on the current control variable values. The tank 2 temperature (T2 Temp) changed less frequently as compared to T1 and T3 temperatures because of the lower demand for hot water during specific hours. After 24 to 31 hours the T2 temperature dropped very slowly because the water consumption during these hours was small as shown in Figure 4-1, and again during the period from 36 to 40 hours etc.

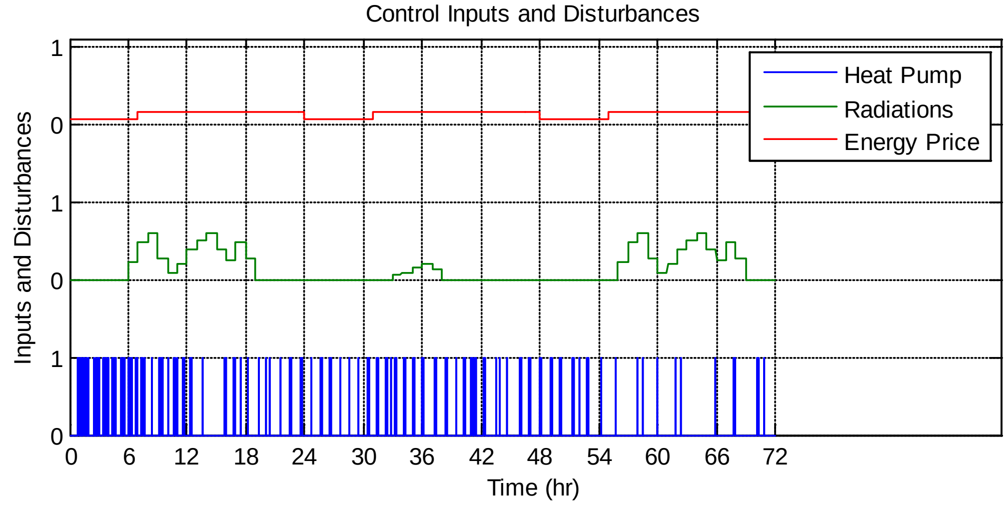


Figure 4-5: On-Off controller inputs and disturbances (Case A)

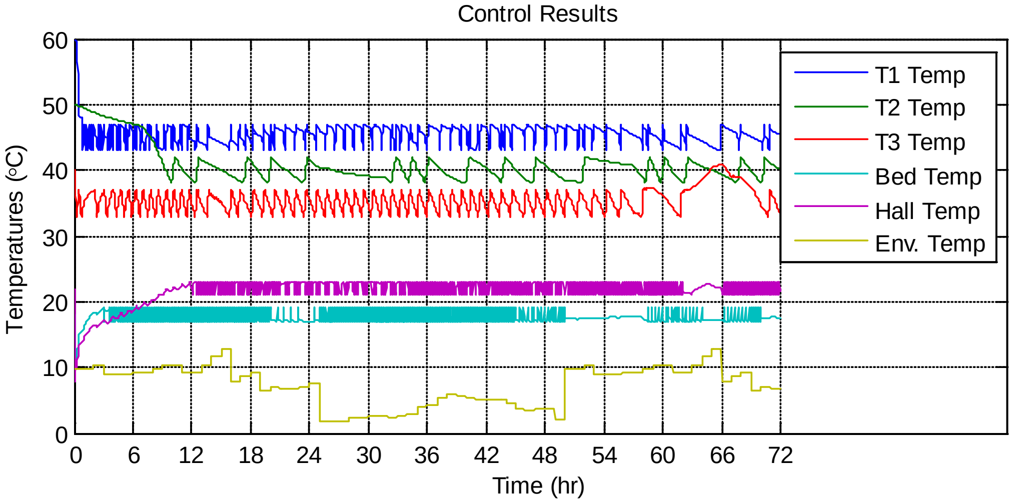


Figure 4-6: On-Off control results (Case A)

4.4.3 Case B

The simulation results with a sunny day in between 2 medium solar radiation days are shown in Figure 4-7 and Figure 4-8. The heat pump was repeatedly switched ON and OFF at the beginning of the simulation because of the drop in room air temperatures. There was an increase in the tank 2 temperature from the hour 34:00 until 44:00 because of the availability of the solar radiation. The controller did not predict any solar radiation disturbance, and so the temperature in tank 2 reached a maximum of 55^{o}C due to solar input. The solar radiation also caused an increase in bedroom and hall air temperatures. The bedroom air temperature continuously increased and remained above the upper switch ON limit because of the lower heat loss due to the absence of a window. The heat pump was switched ON less frequently during day 2 (30:00 to 44:00) because of the lesser energy demand. The only energy demand during these hours was for hot water and there was sufficient solar radiation available to cope with the heating demand of the system.

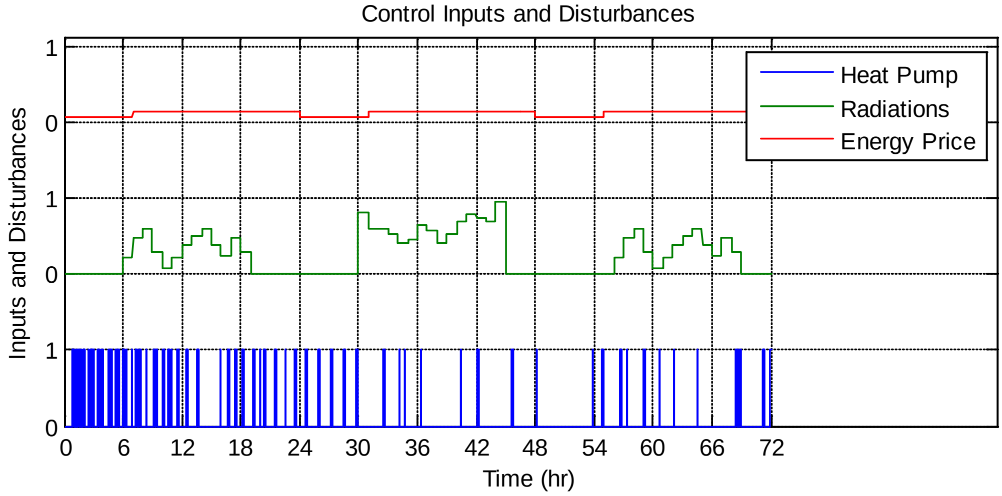


Figure 4-7: On-Off controller inputs and disturbances (Case B)

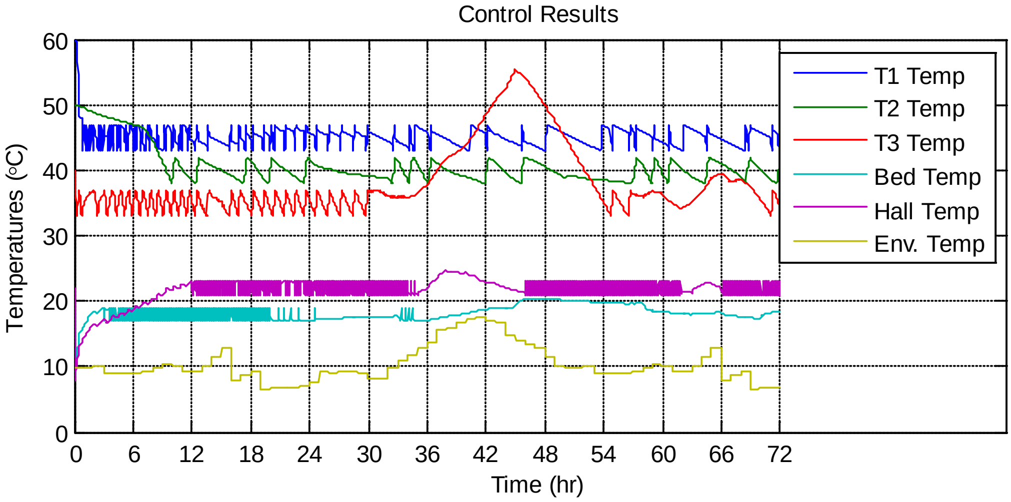


Figure 4-8: On-Off control results (Case B)

4.4.4 **Case C**

The results for case C are shown in Figure 4-9 and Figure 4-10. The heat pump was switched ON and OFF repeatedly throughout the simulation. The frequency of its turning ON decreased during days 2 and 3 because of the availability of the solar energy and hence reduced electrical energy requirement. There was an increase in tank 3 temperature (T3 Temp) from 30:00 to 44:00 due to it being a hot day. An increase in room temperatures was also noticed due to energy gain through walls, roofs, and window. From 25:00 onwards the bedroom air temperature did not come back to its set point temperature of 18^{o}C because it takes much longer to lose energy through the fabric as compared to the window (in the case of the hall).

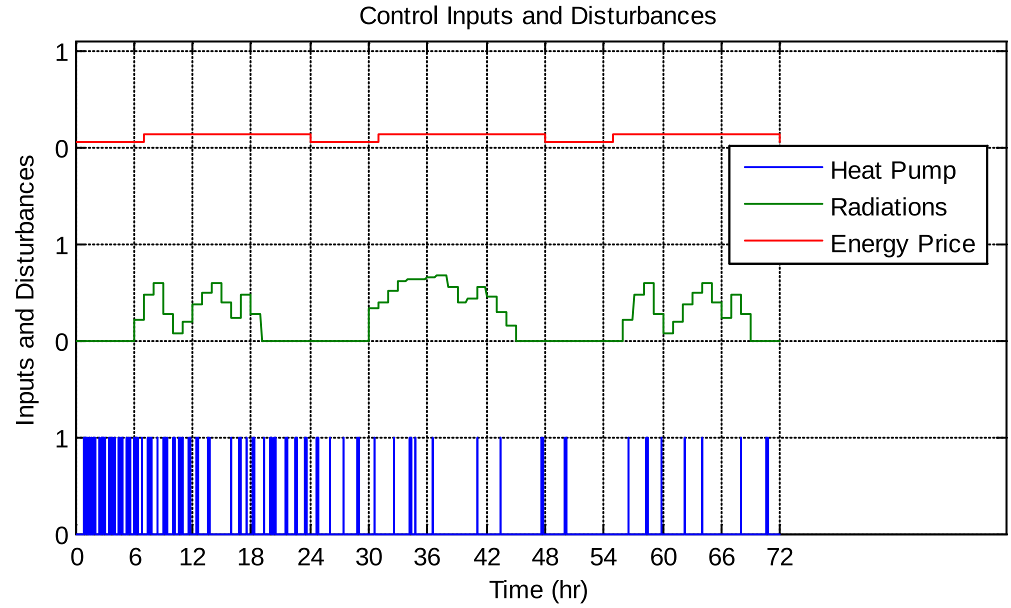


Figure 4-9: On-Off controller inputs and disturbances (Case C)

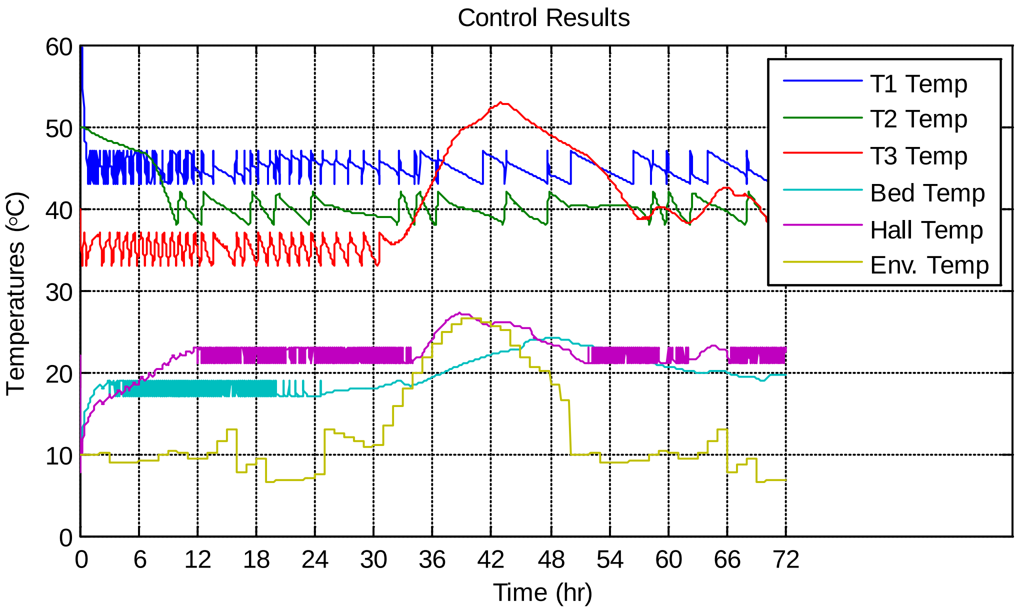


Figure 4-10:On-Off control results (Case C)

4.4.5 **Case D**

In Case D the heat pump (as in previous cases) used more energy at the beginning of the simulation to bring the room temperatures to the required set points. During the cloudy day there was not enough radiation to heat the water, however the ambient temperature was high with a maximum value of 18^{o}C at 41:00. This high temperature on day 2, resulted in an increase of the bedroom's air temperature from 25:00 hr. The time lag can also be seen in Figure 4-12: it took a long time for the bedroom air temperature to increase following a rise in the outside temperature. In contrast, the hall air temperature increased when there was an increase in solar radiation (e.g. at 38:00).

Figure 4-11:On-Off controller inputs and disturbances (Case D)

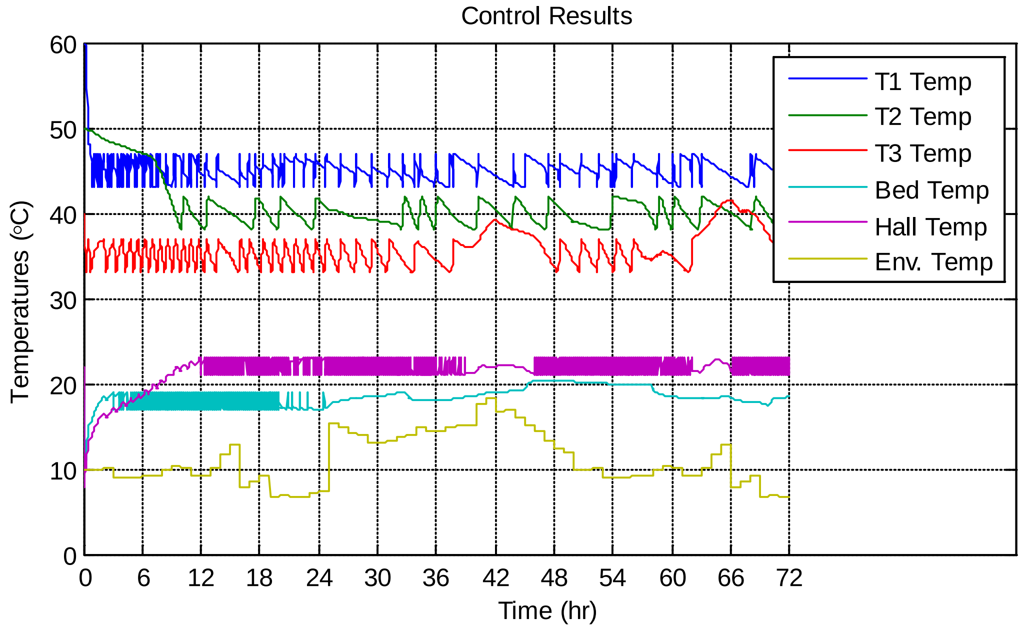


Figure 4-12: On-Off control results (Case D)

4.5 Proportional Integral controller

According to Haines, 1988, the most commonly used controller for a heating system is the proportional integral (PI) controller. A PI controller is one of the most reliable control strategies but it requires more careful parameter selection to obtain optimum performance. The choice of PI control parameters depends very much on the system dynamics. The controller used here is a discrete-time PI controller and its output is given by the following transfer function in time domain;

$$u(t) = k_p e(t) + k_i \int_0^t e(t)dt \quad (4.2)$$

In the above equation k_p and k_i are the proportional and integral gains respectively. The two gain values are the tuneable parameters and need careful adjustment for the controller to give a good performance and a stable response. The PI controller calculates an 'error' value as the difference between a measured output and a desired set point. Mathematically the error can be written as;

$$e = T_r - T_i \quad (4.3)$$

in which e is the control error, T_r is the reference temperature (the required temperature of the hot water tank) and T_i is the current temperature of the hot water tank.

In PI control, there are times when the controller experiences large control error due to the system limits, and this can cause the integral part of the controller to accumulate a very large value, causing a long settling time. This can occur for example if the water tanks are required to heat up during the night to store energy and use it during the day. This means that at the beginning of the night the control error will be large and the controller will operate at maximum power for a significant period of time to bring the error back to zero. During this period, the integral term of the controller continues to integrate and this will cause the controller to overshoot. Due to the integral term, the valve will still be fully opened even when the hot water tank temperature has reached its reference value. This changes the sign of the error, and it will eventually de-accumulate the integral term but it may take a long time to settle. This problem is known as integral windup and a number of anti-windup mechanisms are available to avoid this from happening (Hwi-Beom et al., 2012).

The anti-windup mechanism used in this work is known as the clamping method. In this method the controller stops the integrations when the sum of the control block components (in Simulink) is more than the output limits and the integrator output and controller block input have same signs. The integrator component of the PI control resumes integration when the sum of the control block components (in Simulink) is more than the output limits and the integrator output and controller block input have opposite signs. The advantage of this scheme is that it is very simple, it reliably prevents windup, and it does not impact on the nominal operation and convergence (MathWorks, 2013).

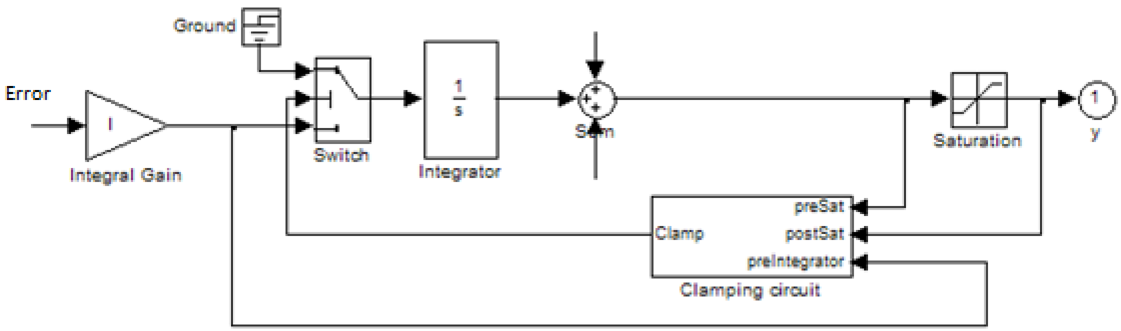


Figure 4-13: Clamping circuit (MathWorks, 2013)

The clamping circuit in the above figure determines whether to continue the integration or not. A saturation block is also included in the PI controller to control signal output values. As all inputs of the system have an operating range of 0 to 1, this is implemented by using a saturation block. The saturation block will limit any controller output to this range. It is not strictly necessary to include it in the controller, since the limit is usually applied by the plant, but it is helpful in this case to identify if the limit has been reached. This is achieved by comparing the limited with the unlimited output – any deviation is indicative of an active limit, and this is used to stop integration.

The Forward Euler method, also known as the Forward rectangular or left hand approximation is used as an integrator method to find the output of the integrator. This method is used when the sampling time is small e.g. 60 seconds. For large sampling times this method can result in an instability of the system. In Simulink a continuous time block is used and this method is one of the methods available for continuous blocks. The resulting output of the integrator block is given by the following equation using the Forward Euler method (Ascher et al., 1998);

$$y(n) = y(n-1) + K \times T \times u(n-1) \qquad (4.4)$$

Where, $y(n)$ is the output at given step n, u is the input, T is the integrator sampling time and K is the gain. A time of 60 seconds was selected as the sampling time for the PI controller. This is a very short time step compared to the dynamics of the system, which means that the integration error should be negligible.

The simple system was controlled by using a PI controller with and without disturbances. The results are shown in Figure 4-14. The PI controller without disturbance performed very well and the minimum temperature for the tank was 54.1^{o}C, which is very close to the reference temperature of 55^{o}C. The energy cost was £3.2837 for three days. In Figure 4-15 a simulation was performed by including solar radiation as disturbance and using a PI controller to control the tank temperature. The heat pump was used during the first and third days. There was no electrical energy consumed during the second day due to the availability of the solar energy. In Figure 4-15, the heat pump remained switched OFF until the tank temperature reached 53^{o}C at 57:00, after which the heat pump was switched ON by the PI controller to raise the temperature of the tank. In Figure 4-15, the tank had a maximum temperature of 69^{o}C at 45:00. The energy cost for this simulation was found to be £1.2876 for 3 days.

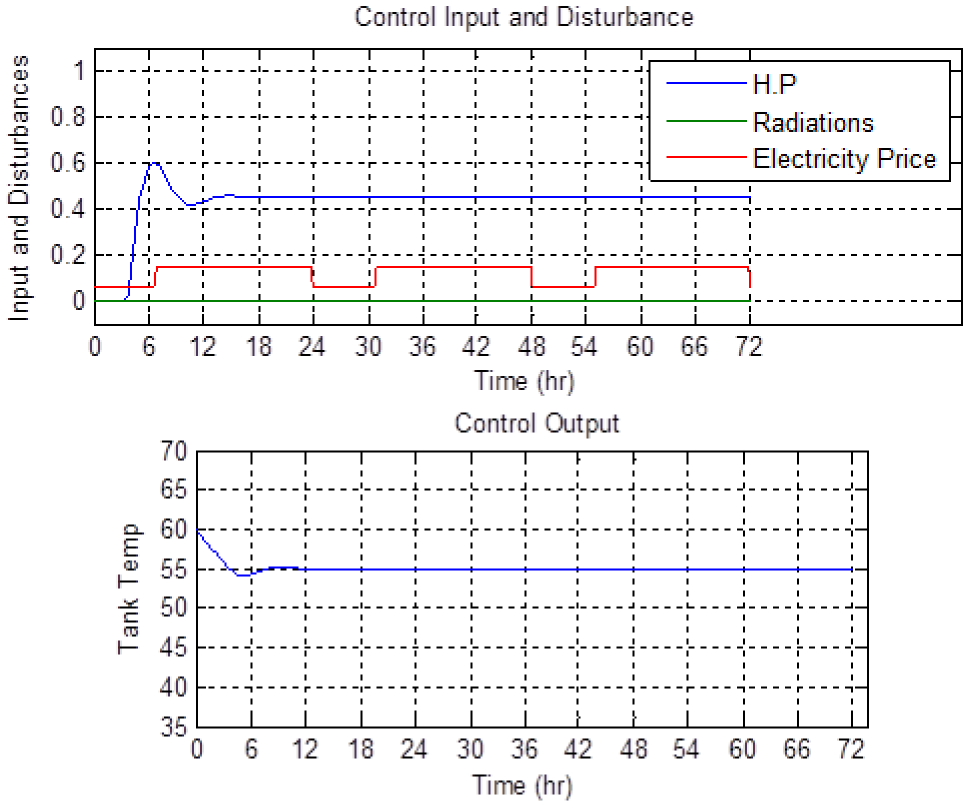


Figure 4-14: Simple plant PI control without disturbance

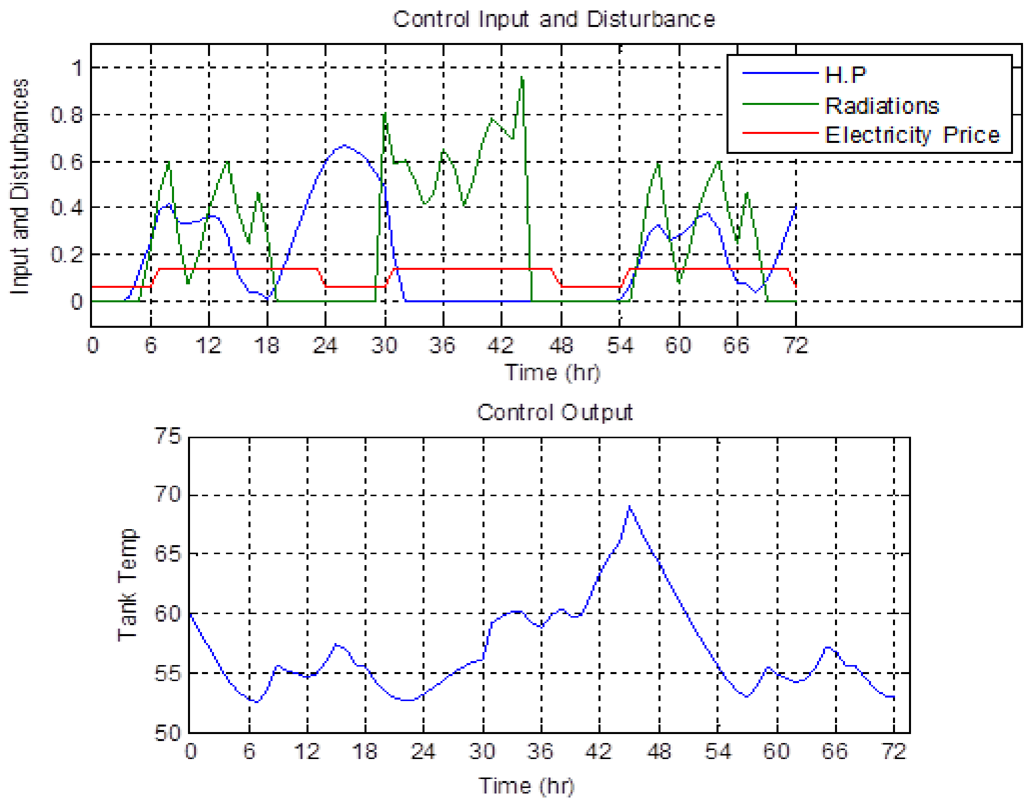


Figure 4-15: Simple plant PI control with disturbance

4.5.1 **Case A**

In simulations of case A using a PI controller, the heat pump was used continuously throughout the simulation period (Figure 4-16). From 12:00 to 18:00 and 55:00 to 68:00 it used very little electrical energy. The PI controller had not predicted any energy gain in the system because of the solar energy input. Still, because it is a feedback controller, after receiving current values of tank temperatures, it reduces the heat pump setting to the minimal amount of electrical energy required to maintain the right temperature. So the controlled variables remained nearly constant at their desired set point for most of the time. The hall air temperature took 9 hours to reach the desired set point temperatures, and the bedroom takes approximately 3 hours. There were some changes in the tank temperatures because of the high solar energy input i.e. 12:00 to 17:00 and 62:00 to 66:00.

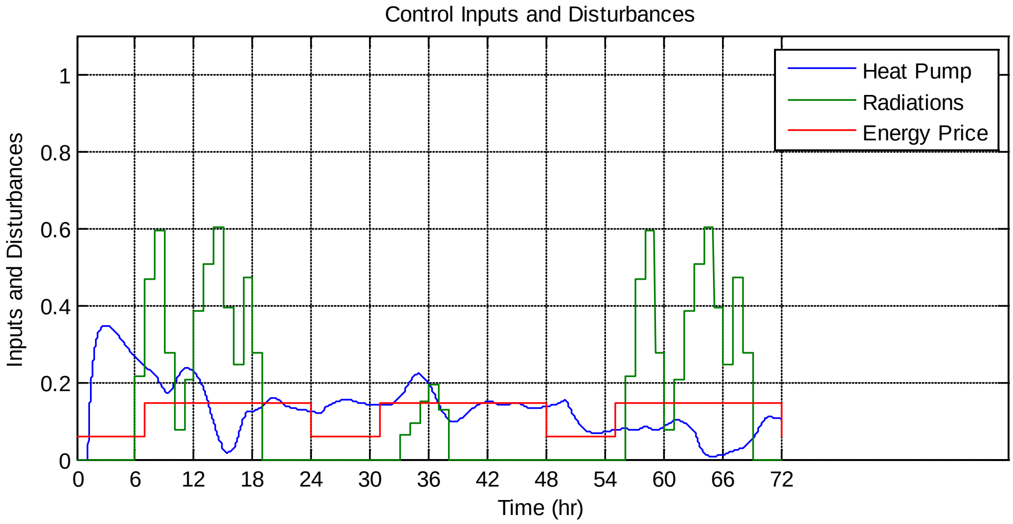


Figure 4-16: PI controller inputs and disturbances (Case A)

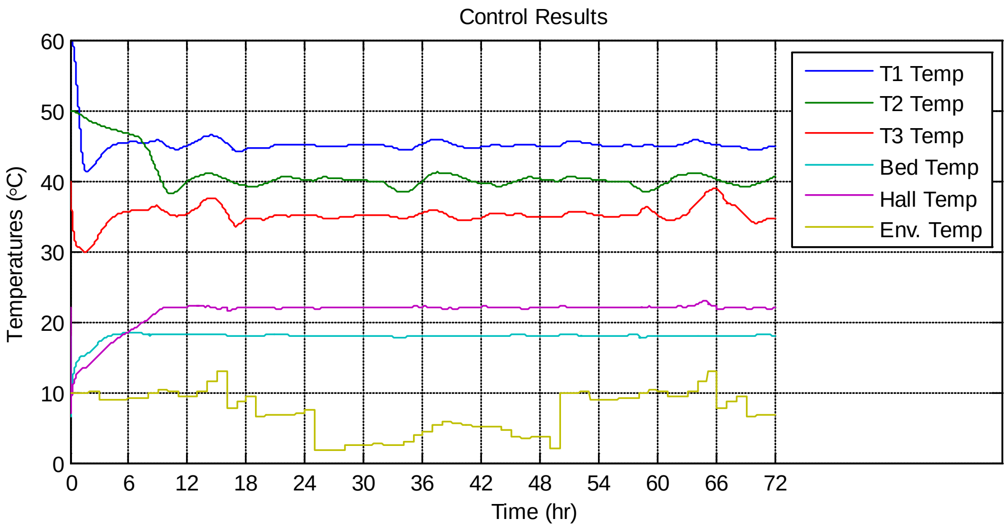


Figure 4-17: PI control results (Case A)

4.5.2 **Case B**

For the sunny day scenario (case B), the PI controller used less electrical energy during the daytime. Initially the heat pump used more energy because of the initial temperature drop of hall and bedroom air temperatures. The heat pump used less energy during the sunny day 30:00 to 44:00 not because the PI controller had predicted a sunny day, but in response to the increased tank temperatures. This trend can also be seen from 61:00 to 66:00. There was an increase in T3 temperature from 36:00 to 44:00 and 62:00 to 66:00 because of the availability of high solar energy. The air temperatures of the rooms (Figure 4-19) remained approximately constant from 09:00 (hall air temperature) and 03:00 (bedroom air temperature) until 36:00. At 36:00 there was an increase in the air temperatures because of the solar gain.

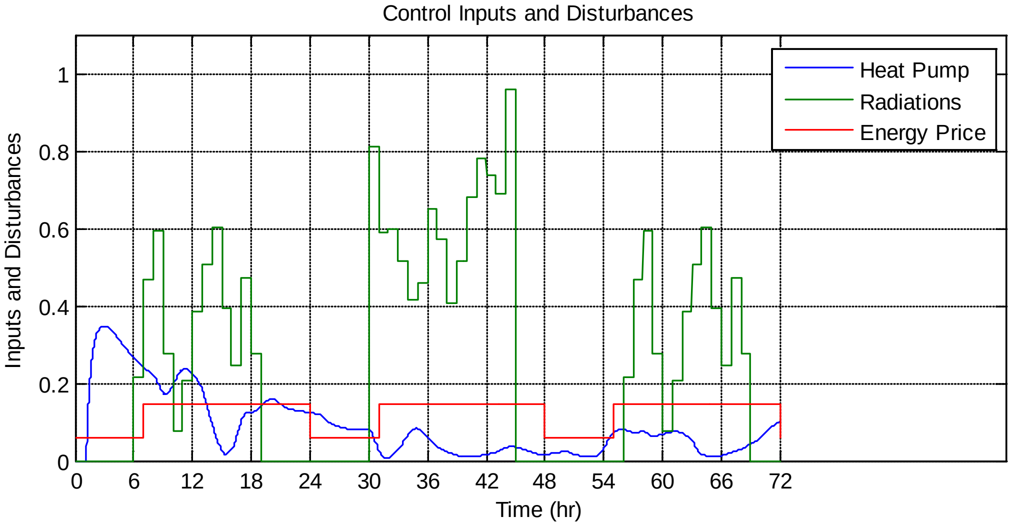


Figure 4-18: PI controller inputs and disturbances (Case B)

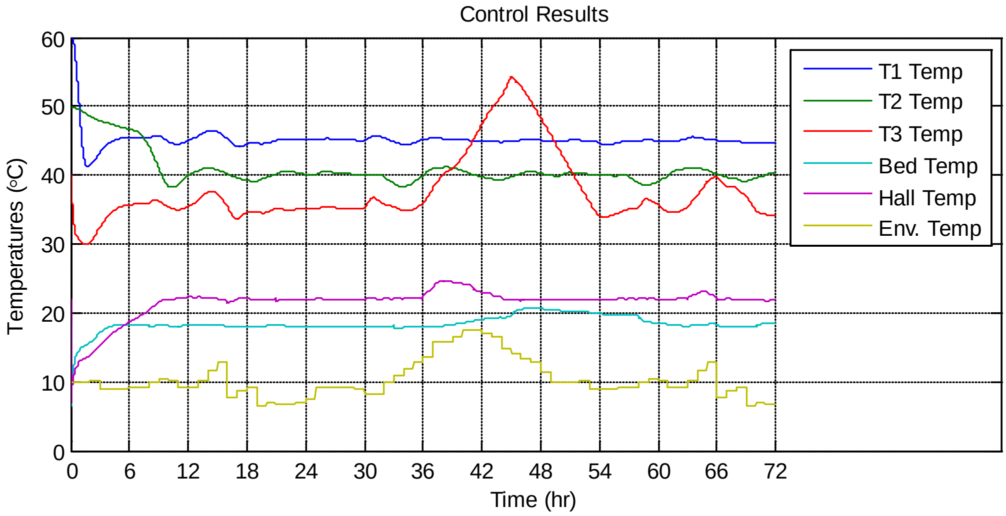


Figure 4-19: PI control results (Case B)

4.5.3 Case C

The PI controller made the heat pump use more energy at the beginning of the simulation in order to bring up the room air temperatures to their set-point temperatures. The heat pump used less energy between 12:00 to 15:00 but it started to use more energy after that due to the drop in the tank temperature until 19:00. At 32:00, the temperature of tank 3 (T3) increased because of the solar radiations and it caused the heat pump to run at lower settings. At 56:00, the drop in the temperature of tank 2 made the heat pump signal to increase. As the temperature neared the set point, the control began to increase the input signal in order to stabilize the temperature without solar energy. The bedroom and hall air took 3 and 9 hours respectively to reach the desired set point temperature and remained constant until the high solar gain pushed them above the set point. The hall air temperature became steady again at 50:00 but the bedroom temperature did not come back to the set point temperature because of the high thermal inertia (lower energy loss).

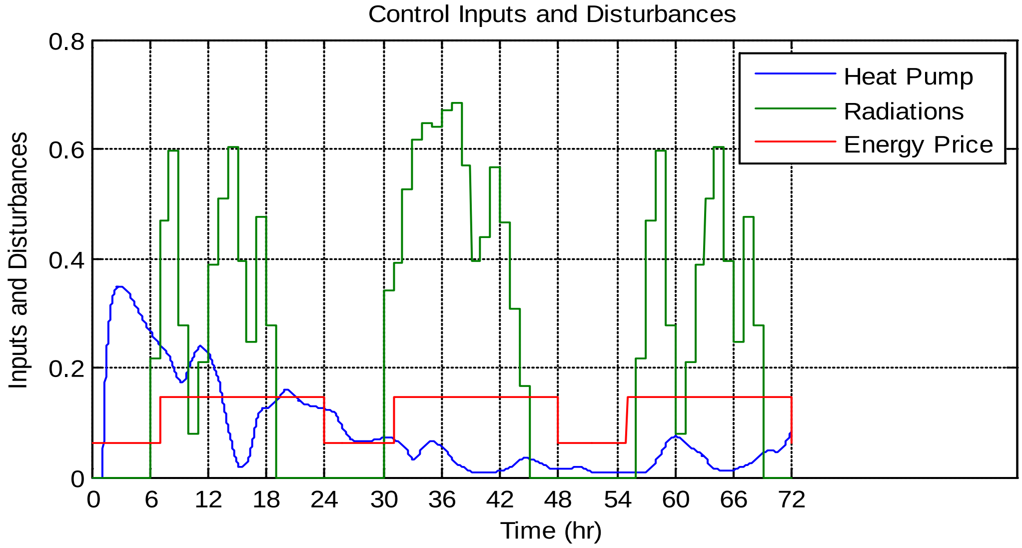


Figure 4-20: PI controller inputs and disturbances (Case C)

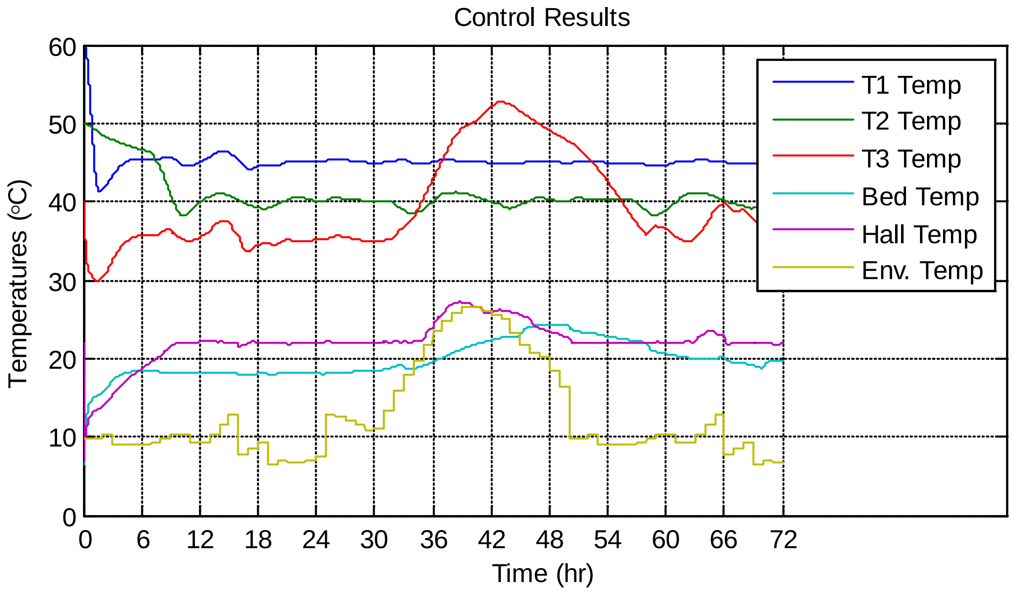


Figure 4-21: PI control results (Case C)

4.5.4 Case D

The case D results for the PI controller are shown in Figure 4-22 and Figure 4-23. The control results show that the outputs were kept by the PI controller at the required set point temperatures for most of the time. The temperature of tank 3 increased at 12:00, 38:00 and 62:00 due to increase in the solar radiation. At these hours the heat pump consumption also dropped and the heat pump was operating at lower settings. A small change in bedroom air temperature was also noticed because of the heat gain through the fabric.

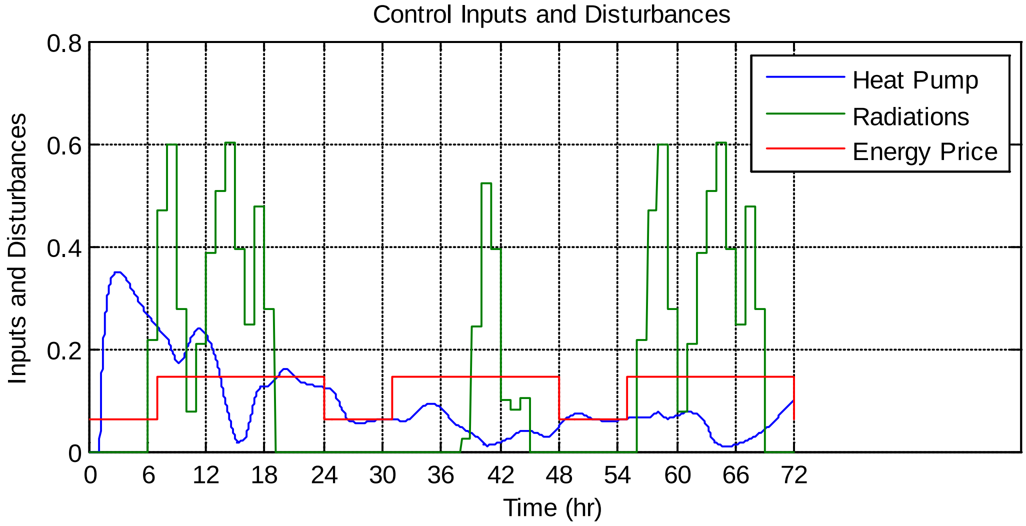


Figure 4-22: PI controller inputs and disturbances (Case D)

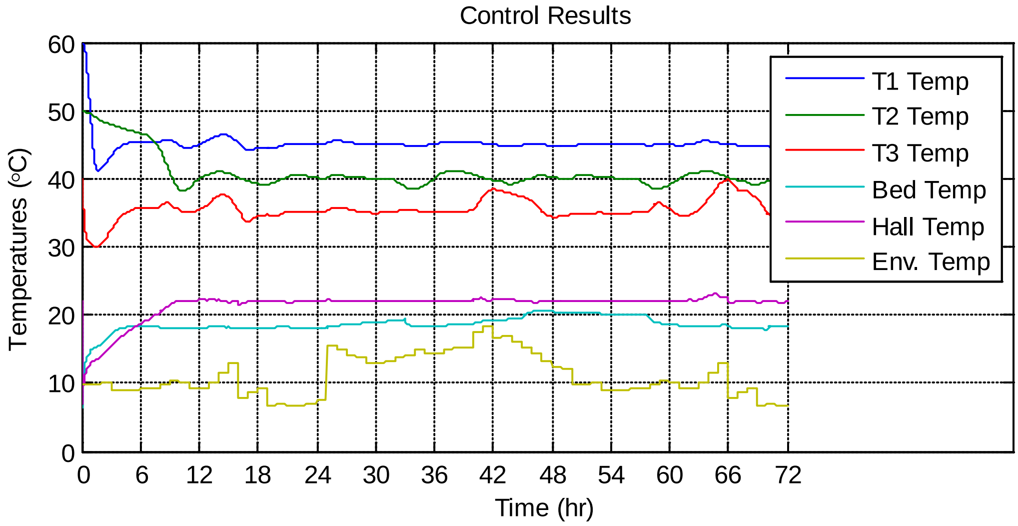


Figure 4-23: PI control results (Case D)

4.6 Comparison of On-Off and PI controllers

Both the on-off and PI controllers performed well and were able to maintain the temperatures close to their set points. The on-off controller was operating between switch ON and OFF points and this made the temperatures fluctuate between switch ON and OFF values. Throughout the scenarios, the PI controller operated the heat pump at lower settings and tried to minimize the control error. Both these controllers did not use night-time cheaper tariffs and also load shifting was not observed at night-time. The on-off controller does not need tuning and is very easy to implement. In contrast, the PI controller needs tuning of its parameters. Both controllers have a slow response time and took approximately 12 hours to bring the hall air temperature to its set point. In the coming section, to overcome the shortcomings of these two controllers, an advanced control strategy is implemented.

4.7 MPC Structure

The basic structure of the model predictive controller (MPC) is shown in Figure 4-24. The model gets data from past inputs and past outputs and combines this data with potential future inputs to simulate how the system will respond. The model then delivers predicted outputs for the future time step. This predicted output is compared with a reference trajectory to determine the deviation of the systems. These future errors are then fed into an optimizer, which tries to minimize the operating cost function. In order to satisfy constraints on outputs, inputs and states of the system, the optimizer tries different sequences of future inputs, which are fed back into the main model for evaluation.

Once the optimization has converged, and the best sequence of control inputs has been found, the first step of these is applied to the real system. At the next time step, the process is repeated using the new measurement. This leads to what is known as “receding horizon optimization”.

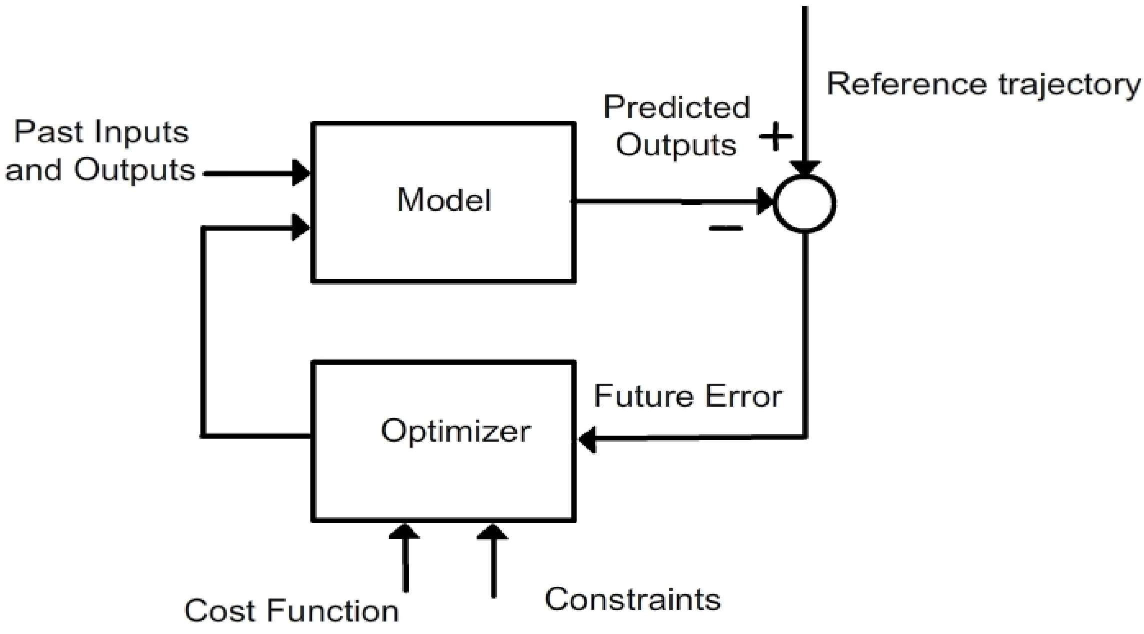


Figure 4-24: Basic structure of MPC (Source Camacho et al., 2004)

4.7.1 **MPC Strategy**

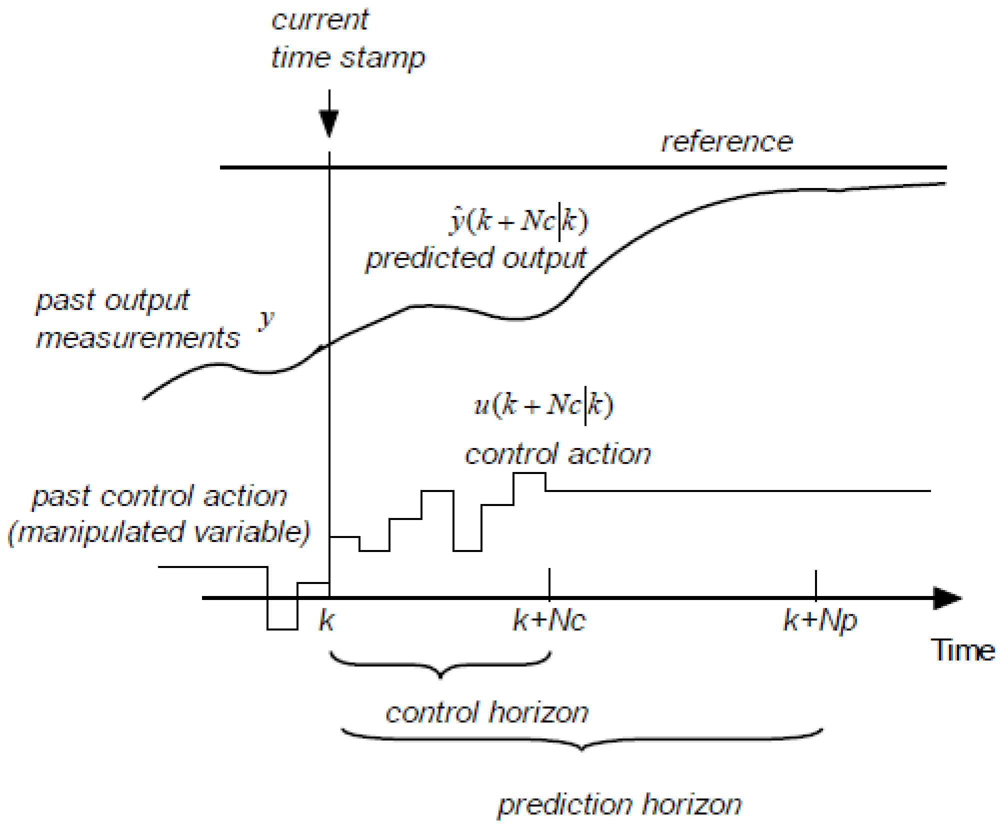


Figure 4-25: MPC strategy (Source Camacho et al., 2004)

Step 1

The future control signals are optimized to minimize an objective function. The objective function aims to keep the outputs as close as possible to the reference trajectory. This optimization is performed using backwards simulation.

Step 2

The model predicts the future outputs for a known prediction horizon N at each time step t using forward simulation. These predicted outputs depend on past inputs, system state, and (initial) future control signals and disturbances.

Step 3

The limits of the system are checked, and if they are violated, changes are applied to make sure that they are satisfied. Several different optimization strategies exist for this step, but they all require some amount of iteration between the continuous optimization of the control inputs and the discrete optimization of the limits at each time step. This step is the main reason that a long time horizon (and especially a long control horizon) can make the MPC problem very difficult to solve, because the limits have to be considered at each time step and therefore the total number of limits is much higher than first it seems.

Step 4

Once the solution is found, the first step of the control input is sent to the process. All further steps are discarded, because at the next sampling instant $y(t+1)$ is already known, the prediction horizon can be increased, and a more accurate control input can be calculated by repeating from step 1.

4.7.2 Cost function

The ability of the MPC control approach to define a detailed objective function makes this control strategy one of the most flexible advanced control strategies. The model predictive control makes use of a model of the system to obtain the control signal by minimizing this objective function. The aim of the objective function is to make sure that future output values should follow a reference signal reasonably closely, and that this is achieved with a minimal control effort. The objective function of a model predictive controller typically has the following structure;

$$\begin{aligned} J(k) = & \sum_{i=N_1}^{N_2} Q(i)\big(y(k+i|k) - y_r(k+i|k)\big)^2 \\ & + \sum_{i=1}^{N_u} R_{\Delta u}(k)\big(\Delta u(k+i|k)\big)^2 \\ & + \sum_{i=1}^{N_u} R_u(k)(u(k+i|k) - \bar{u})^2 \end{aligned} \tag{4.5}$$

In the above equation N_1 and N_2 are the minimum and maximum cost horizons and N_u is the control horizon. The coefficients Q, $R_{\Delta u}$ and R_u are the weights for output, input change rate and input respectively; these are the main tuning parameters. These parameters are adjusted to get satisfactory dynamic performance of the system. It is worth noting that Q, $R_{\Delta u}$ and R_u can change over time, and this is used to reflect the impact of changing energy prices.

The two purposes of the cost function are;

Target behaviour: The cost function can be used to specify a preference on behaviours e.g. in this case minimum energy or thermal comfort level of the occupants.

Stability: The cost function is used to stabilize the system. The quadratic structure is selected as it forms a Lyapunov function for the closed loop system and hence will tend to increase the stability of the system. However, due to the finite cost horizon, stability cannot be guaranteed under all circumstance. This is not an issue in this application, because the system is already stable.

4.7.3 Constraints

Model predictive control has the ability to include constraints in the MPC formulation. The optimization part of the MPC strategy handles these constraints directly and this is one of the key strengths of MPC. MPC constraints can be physical limitations, for instance valves cannot be operated at more than 100%, or temperature limits on the tank temperatures. The constraints can also be time varying constraints e.g. the temperature and thermal comfort level in the hall during day and night will be different. The constraints can be on the inputs, the input change rate, the outputs or states. The constraints used in this work are linear constraints and can be given by the following kind of equation;

$$u_{min,k} \leq u_k \leq u_{max,k} \tag{4.6}$$

Linear constraints are the most commonly used constraints, because they are comparatively easy to resolve. Still, introducing constraints into the MPC problem can make the optimization problem considerably more complex to solve. The system has the following constraints on tank temperature;

Table 4-1: Tank temperature limits

Output	Lower Limit	Upper Limit
Buffer tank temperature	40^oC	70^oC
Hot tank temperature	40^oC	65^oC
Heating tank temperature	30^oC	65^oC

4.7.4 System Definition

Figure 4-26 shows the basic control scheme for the current research. The energy price, occupancy prediction and weather prediction are the time varying external conditions. Together with the temperature measurements, these form the inputs to the controller. The plant model, system constraints, cost function and objective function are defined as the parts of the MPC controller. For every time step these parameters are combined and converted into an optimization problem, which then determines the output for the next time step. In the simulations the model predictive controller is using a current value as predicted value and it assumes no change in environmental conditions.

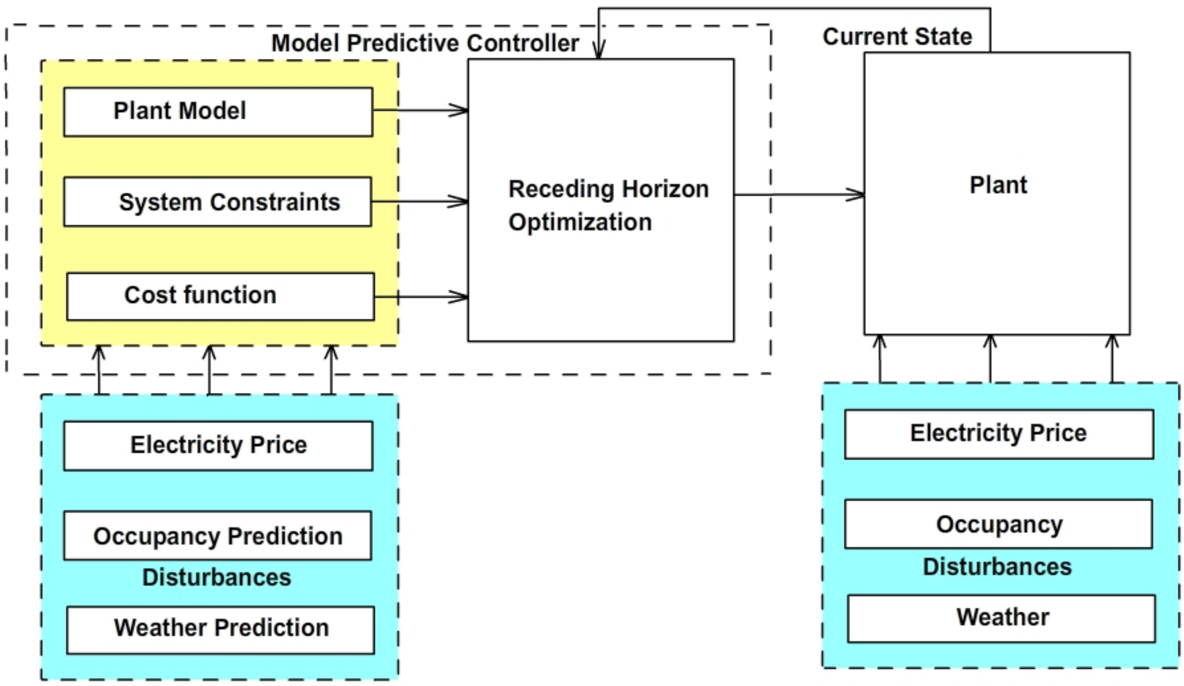


Figure 4-26: Model predictive controller scheme

Initially, the simple plant was simulated by using a sampling time of 900 seconds, control horizon of 48 steps (12hr) and a prediction horizon of 96 steps (24hr). The simulation took a significant amount of computation time despite the fact that a very simple model was used. The number of steps in the horizon was identified as the key problem. Therefore, the time step was increased to 3600sec, which leads to a prediction horizon of only 24 steps. Cigler et al., 2012 addressed the important issue of prediction horizon length. It was found that the longer prediction horizon resulted in longer computational time.

A comparison of the results in Figure 4-27 with Figure 4-30 does not show any strong differences. The energy cost of the smaller time step was £1.586 whereas for 3600sec sampling time the cost was £1.5541 for three days. There was very small difference in the evaluation of the cost function which means that the longer sampling time was adequate. It has to be mentioned that the smaller time step will respond faster to changes in the system variables, and limits will be applied to more time steps, whereas the longer time step means that limits are only enforced every hour. This can be seen in the following results: in the case of the 900sec sampling time the tank lower limit did not go below 40^{o}C whereas for the 3600sec time the tank temperature became 39^{o}C for a short period. This effect was exacerbated by modelling errors, mainly due to the linearization of the plant model because the controller does not adjust the settings until the next sampling time.

Overall, the differences between both simulation results were very small, and energy use was also nearly the same. Therefore to speed up the simulation a sampling time of 3600sec (1hr) was selected for all MPC simulations. The house and the tank system showed predominantly slow dynamics and this fact also supported the use of the larger time step.

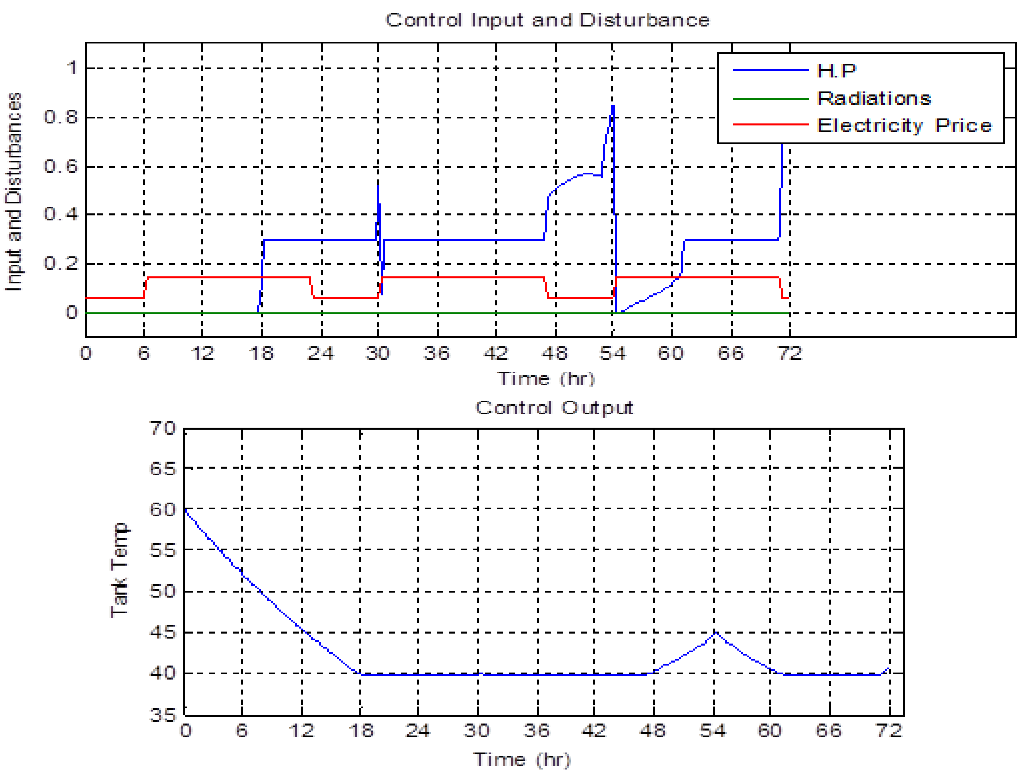


Figure 4-27: MPC without disturbance and sampling time 900, horizon 1=48, horizon 2=96

The results in Figure 4-28 show the effect of increasing the state weight. In previous simulations a weight on 1×10^{-8} was selected for the tank temperature, but in this case it was increased to 1. As can be noticed the heat pump was initially switched OFF until the temperature became 50°C, after that the heat pump was switched ON and the temperature was kept very close to the set point of 55°C. From 17:00 the heat pump remained switched ON to a setting of 0.45 in order to maintain the tank temperature.

One objective for this system was to use night-time electricity by shifting the heating load to the night period. Increasing the weight on the tank temperature prevented this effect from happening, because the necessary deviations in tank temperature would lead to a penalty that is much higher than the reduced electricity cost. Consequently, the electricity cost increased from £1.50 (in case of 1×10^{-8} weight) to £3.2765 (for weight=1). It was decided that a low weight of 1×10^{-8} was more beneficial, and this was used for all further simulations.

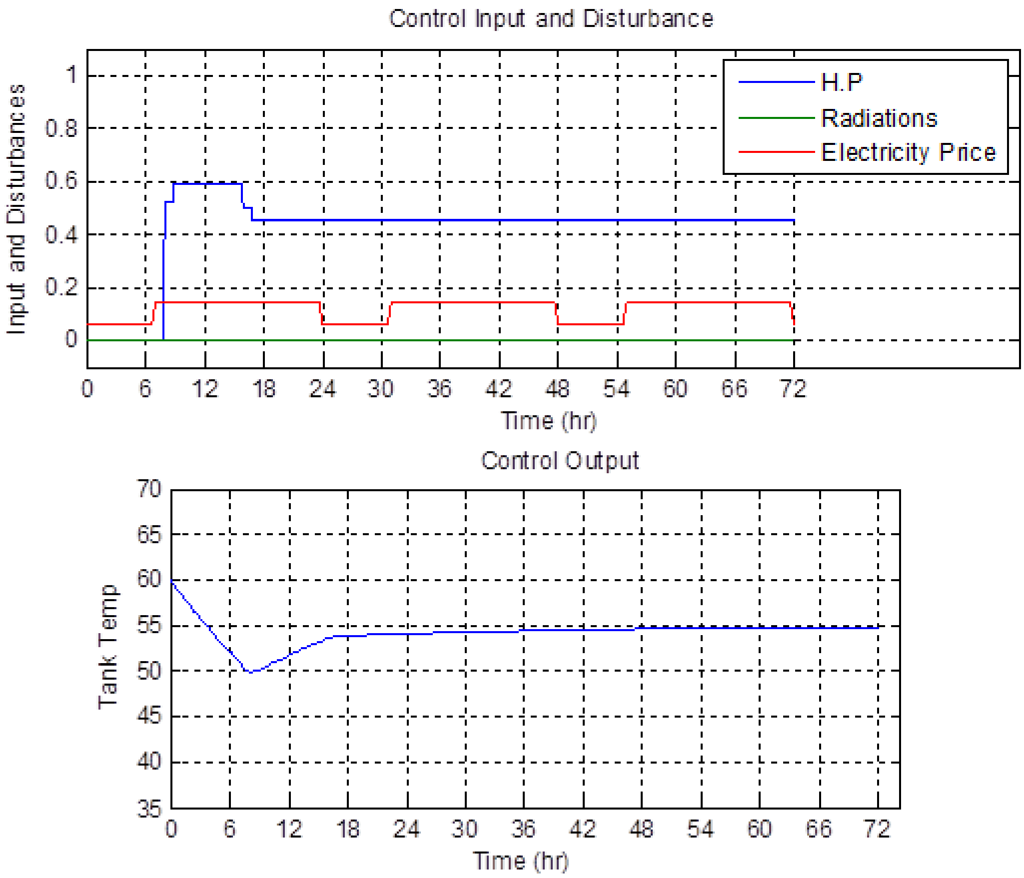


Figure 4-28: MPC without disturbance and sampling time 3600, horizon 1=24, horizon 2=24, weight on tank 1=1

4.7.5 **Plant Dynamics**

The system model is the most important part of the simulation, since the performance of the model predictive controller depends on the accuracy on the model of the plant. The modelling of the whole system was carried out in Simulink and a linearized plant model was used for the controller as previously discussed (see section 3.9).

As discussed in previous sections, the control horizon is an important optimization parameter. Figure 4-29 shows the heat pump signal for the solar heating system combined with a heat pump, for two different control horizons (12 hours and 24 hours) while keeping the prediction horizon as 24 hours. The results with a 24 hour control horizon were clearly superior, and this was for two reasons. Firstly, the longer control horizon can take into account the slower dynamics of the system (such as thermal energy stored in the walls), and it can give a better indication of future cost. Secondly, the electricity tariff changes on a daily rhythm, and only the 24 hour horizon allows the planning of the load shifting for the full day ahead. The overall energy cost reduction achieved by the longer control horizon was 0.5788% for a simulation of three days. Due to this benefit, the 24 hour control horizon was chosen for further studies.

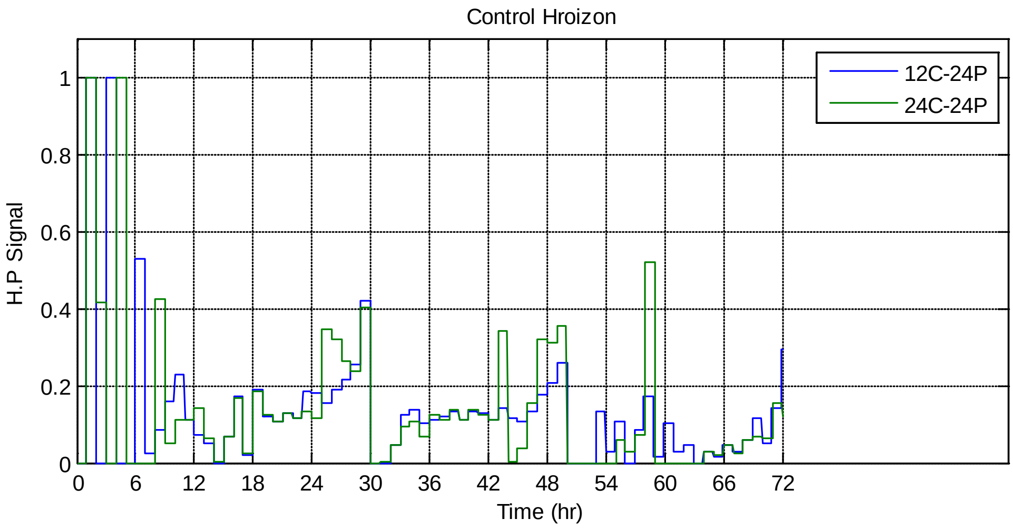


Figure 4-29: Heat pump signal at different control horizons

The MPC control simulation results for a simple plant are shown in Figure 4-30 and Figure 4-31. This case was simulated by using a sampling time of 3600 seconds, a control horizon of 24 steps and a prediction horizon of 24 steps. The result for the disturbance free case show that the heat pump did not use any electrical energy until the tank temperature dipped just below the lower limit. The tank temperature range was set at 40°C to 70°C. The weight on the tank temperature was set at 1×10^{-8}, which is very small weight, which means that the limits will dominate the behaviour. The temperature breached the lower limit by a small value (1°C), which was a consequence both of the penalization of limit violation and model inaccuracies. The tank temperature was maintained at approx. 39.5°C until the night-time tariff period came in and the controller used the maximum electrical energy to store the heat energy in the tank. The simulation results of the simple plant with disturbance show that the controller used the heat pump only when the temperature became less than the lower limit (40°C). The heat pump remained switched OFF before and after that period as the tank temperature did not fall below the lower limit. The energy cost for three days for the without disturbance case was £1.50 and for the disturbance case, as the controller used solar energy, the cost decreased to £0.0324.

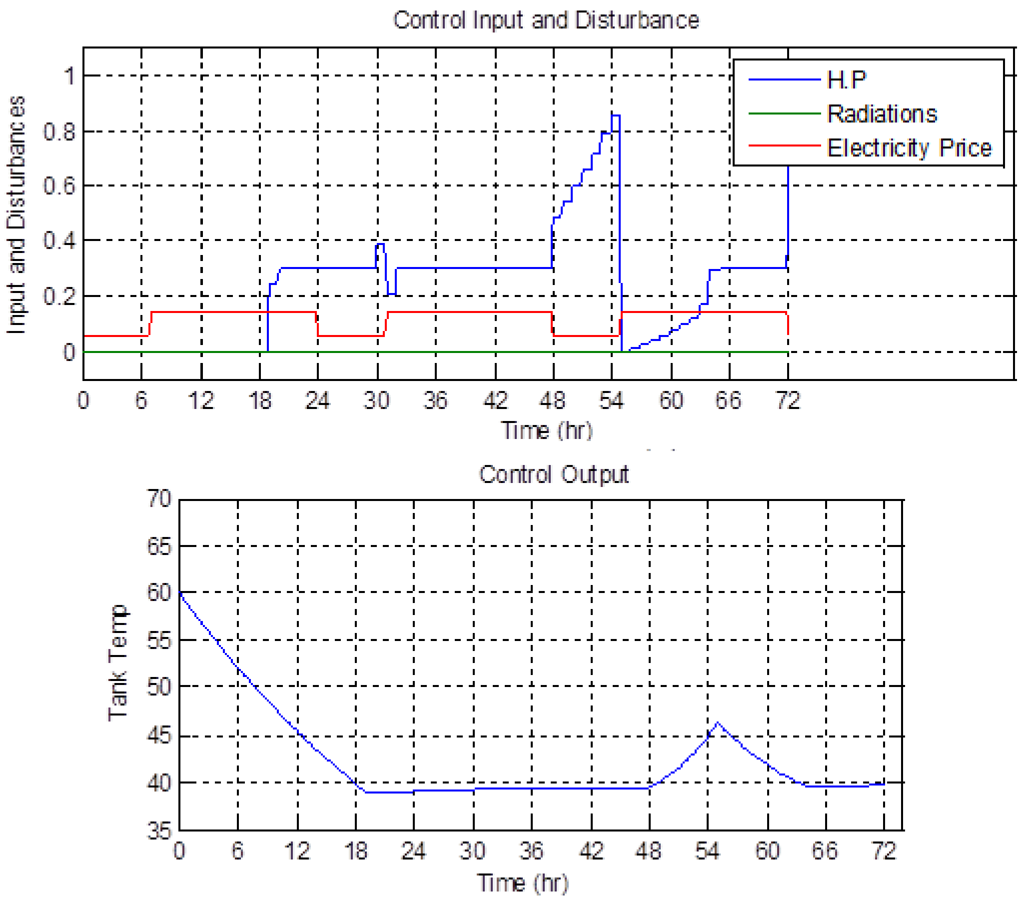


Figure 4-30: MPC simple plant results without disturbance

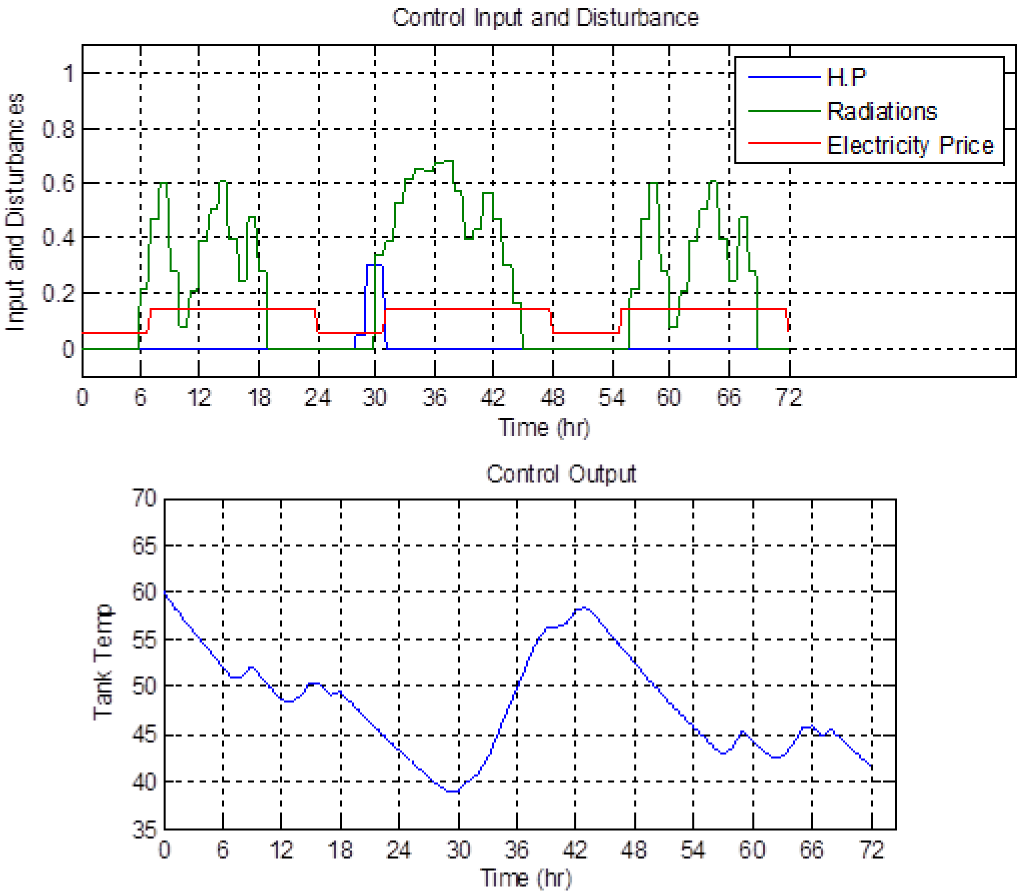


Figure 4-31: MPC simple plant results with disturbance

The simulation results obtained for different simulation scenarios by using MPC are discussed in the following sections. In all simulation cases the solar pump was turned ON when the solar radiation was more than 0.1kW, as this is the approximate threshold for a positive energy gain.

4.7.6 **Case A**

The simulation of case A was performed by considering a cold day in between two medium temperature days as shown in Figure 4-33. The medium day had maximum radiations of 0.6kW and the cold day had a maximum of 0.2kW of radiations as shown in the Figure 4-32. The initial temperatures of tank 1, tank 2, tank 3, bedroom air and hall air were set at 55°C, 50°C, 40°C, 18°C and 22°C respectively. The bedroom air and hall air temperatures dropped initially because at the beginning of the simulation the wall layer temperatures were all set to 0°C, causing the rooms to cool down initially. The model predictive controller took approximately 3 hours to bring the room air temperatures to the set point temperature of 18°C in the bedroom and 22°C in the hall as shown in Figure 4-33. The heat pump signals are shown in

Figure 4-32 and it is evident that the heat pump used more energy at the beginning of the simulation because this was necessary to heat up the walls, and to take the benefit of the night time cheap electricity. The tank temperatures started to drop after the cheap electricity hours were finished. The heat pump used very little electrical energy during the day, as it was used only at low settings. The heat pump used more cheaper electrical energy during the night time between 25:00 to 30:00 and 48:00 to 51:00. The heat pump usage during the day was limited, and it was restricted to times when it was required i.e. during the low radiation days. This can be seen during the second day and third day. The heat pump used little energy during the third day between 54:00 to 68:00, it was even switched off for few hours during that day. On the other hand during the second day the heat pump consumed more energy because of the low solar radiation. The heat pump also remained switched OFF during the night time between 50:00 to 55:00 because the tank temperature reached its maximum limits and MPC forced the heat pump to be switched OFF in order to stay within the temperature limit constraint.

One of the objectives is to reduce energy cost via load shifting by storing heat energy generated during the night time, which can then be used during the day time when electricity is more expensive. This was evident during the time 24:00 to 30:00 and from 48:00 to 52:00, during these hours the MPC stored the energy in the tanks, which was then used during the day time. The last peak in the graph of 'T1 Temp' and 'T2 Temp' was because the tank temperatures dropped below the lower limits. Therefore, MPC used maximum energy to heat up the tanks. The room air temperatures were maintained close to the required set points of 18^{o}C and 22^{o}C in the bedroom and hall respectively. Any deviations were caused by modelling inaccuracies, which cannot be completely compensated with the long time period of 3600s.

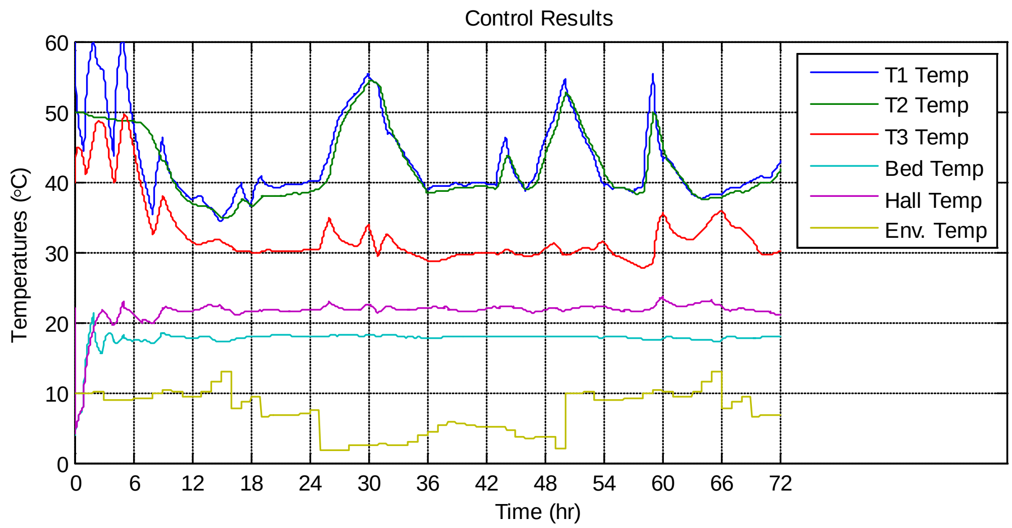


Figure 4-32: Model predictive controller inputs and disturbances (Case A)

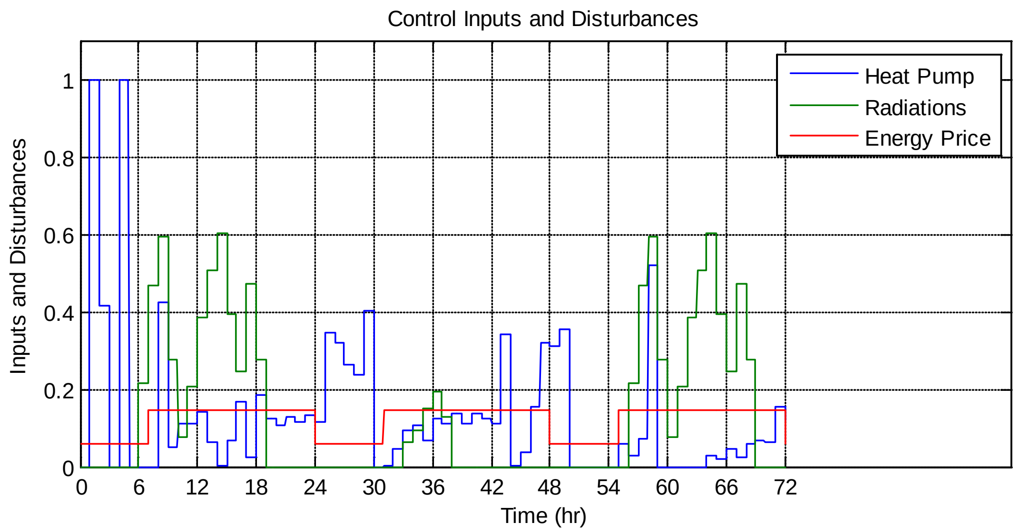


Figure 4-33: MPC control results (Case A)

4.7.7 Case B

This simulation was performed by considering a sunny day (with high radiation intensity) in between two medium radiation intensity days. The heat pump signal shown in Figure 4-34 shows that initially it used more energy to heat up the rooms (night time tariffs). During 7:00 to 24:00 it used little electrical energy. During night time between 24:00 to 31:00, although the night time tariffs were in to action, the heat pump used again little electrical energy because the model predictive controller can anticipate the effect of the strong radiation day that was coming up. There was no need to store heat energy in the tanks, and in fact it was better to keep them cool in order to create capacity for the solar energy. From 31:00 to 32:00 the heat pump was switched OFF and was used at low settings during the rest of the day. During the third night i.e. 48:00 to 55:00 the heat pump was again used at low settings because of the prediction of the future available solar energy, and it remained switched OFF from 56:00 to 59:00.

The control results are given in Figure 4-35, the figure shows that the tanks were initially charged with energy resulting in their temperature rise because of the energy demand in the rooms. The bedroom and hall air temperatures initially dropped because of the initialization of the wall layers at 0^{o}C. After 18:00 the tank temperatures become nearly constant until 36:00. At 36:00 a rise in the tank 3 temperature was noticed because of the solar energy. As the solar collectors were connected to tank 3 only, therefore a rise of temperature in that tank was noticed. The room air temperatures remained constant except during the sunny day, where there was an increase in the air temperature above set point.

There are a few interesting differences in the details. It would be expected that the MPC controller would use the prediction of the weather to proactively cool the rooms just before the high solar input, but this does not seem to be happening. Only a small difference is noticeable in the bedroom, but it is not very pronounced. Secondly, it would be physically possible to circulate the hot water from the heating tank back into the buffer tank and from there into the hot water tank. the MPC did not achieve this because the linear model did not account for the reverse heat flow. So this is an interesting opportunity to enhance the controller in order to manage further energy savings.

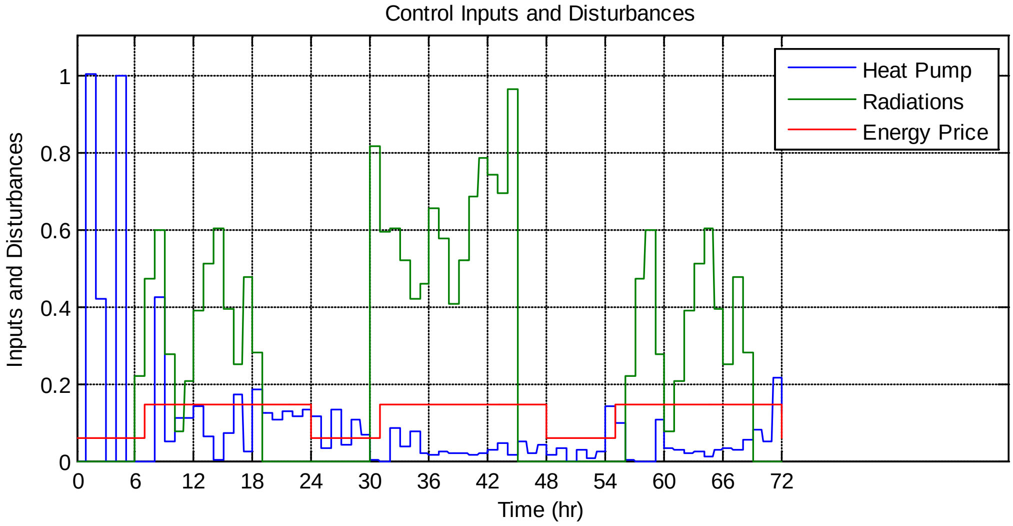


Figure 4-34: Model predictive controller inputs and disturbances (Case B)

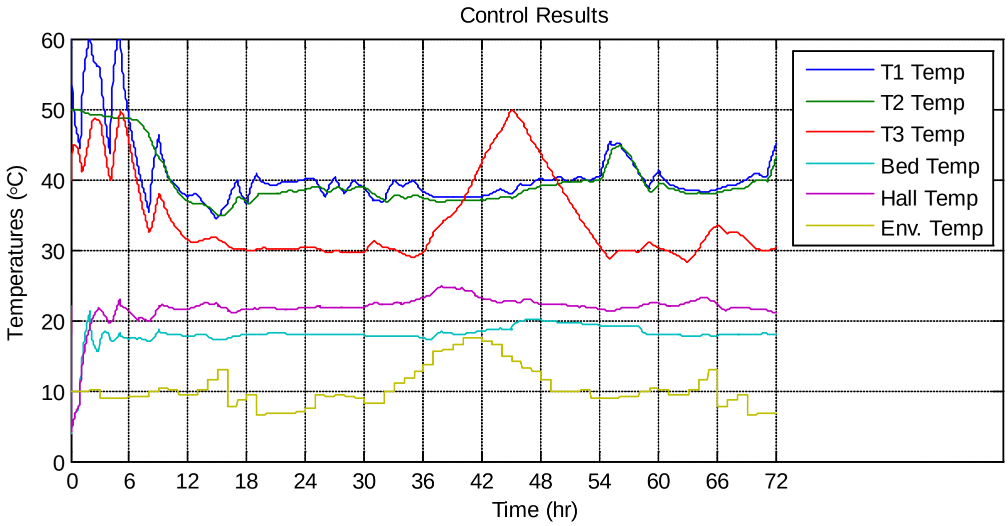


Figure 4-35: MPC control results (Case B)

4.7.8 Case C

Figure 4-36 and Figure 4-37 show the simulation results of the model predictive controller for case C. The high energy consumption of the heat pump at the beginning of the simulation was required to meet the energy demand. The time between 24:00 to 31:00 has a cheaper night tariffs, but due to the prediction of a strong radiation day the heat pump was only used at lower settings. This happened again during the night-time tariff period 48:00 to 55:00. The heat pump was only used to heat up the hot water tank, which is necessary because it is the only heat source for tank 2. The tank 3 temperature reached a maximum of 48^{o}C during the second day because of the availability of solar energy. During the second day, the rise in the hall air temperature was quicker than the bedroom air temperature because of the presence of the window. The bedroom was better shielded from the solar input, and this caused the long delay before the observed increase in air temperature there.

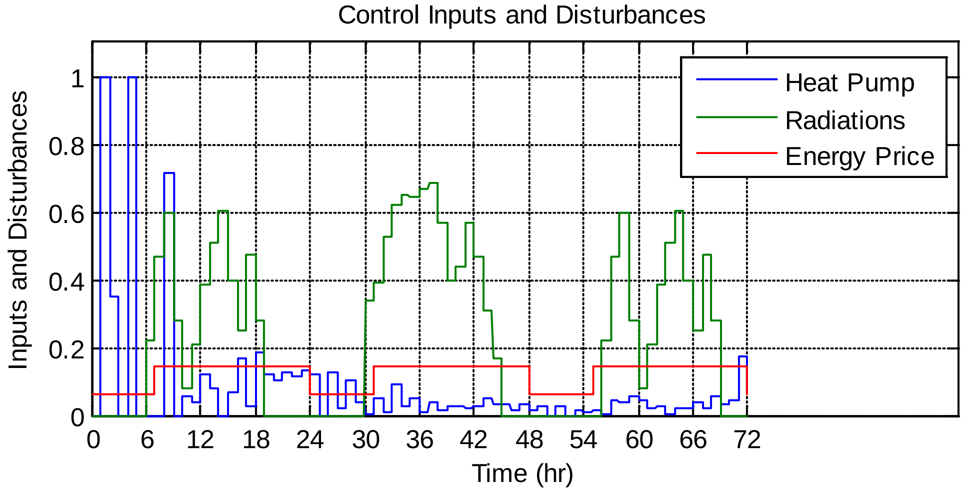


Figure 4-36: Model predictive controller inputs and disturbances (Case C)

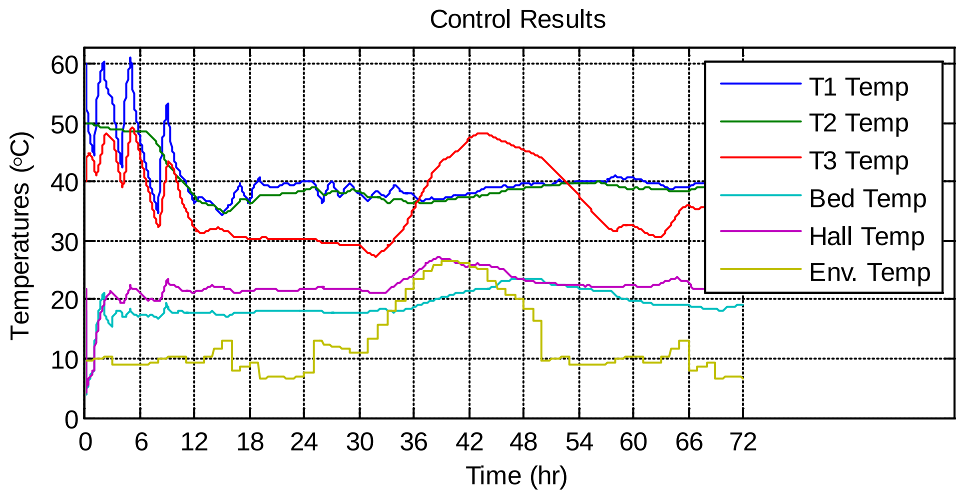


Figure 4-37: MPC control results (Case C)

4.7.9 Case D

The case D simulation results are shown in Figure 4-38 and Figure 4-39. The heat pump was again used heavily at the beginning of the simulation. From 18:00 the controller kept the tank temperatures to the lower limits. The controller did not use night time electricity to heat up the tanks as in the previous cold case. The reason is that although there was no solar radiation during the day 2, it did have a high air temperature. In the knowledge of a high temperature day, the controller predicted that the energy demand would be low and therefore the controller did not use the night-time electricity to store the heat energy. At 58:00 the controller made the heat pump run at full capacity because the tank temperatures reached their lower limit. During the next time step the tank temperatures decreased below the lower limit. At that point the controller decided to turn the heat pump ON to raise the tank temperatures again. It would have been more efficient to use night time electricity a few hours earlier.

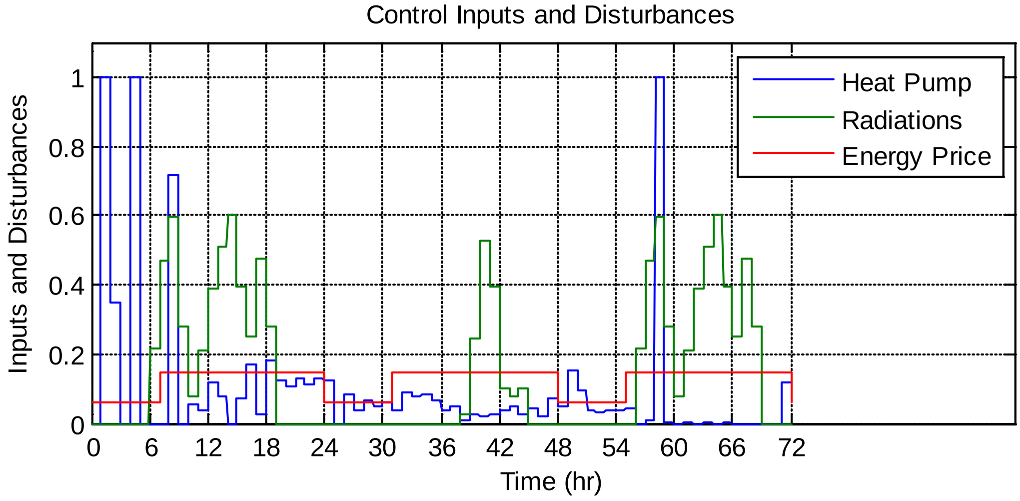


Figure 4-38: Model predictive controller inputs and disturbances (Case D)

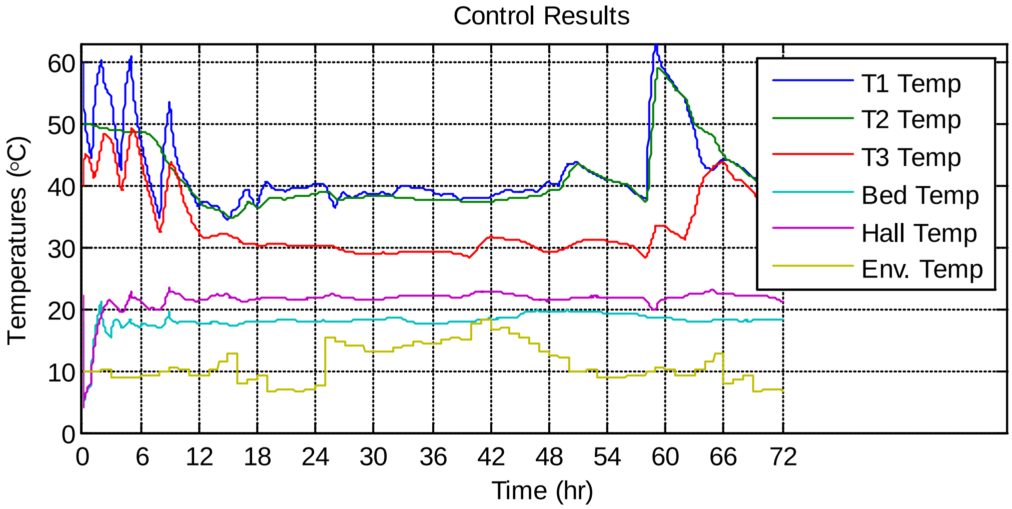


Figure 4-39: MPC control results (Case D)

4.8 Comparison of controllers

For comparing the three control strategies (discussed), case A simulations are considered. The integrated cost and integrated heat pump signal for all controllers are shown in Figure 4-40 and Figure 4-41. At the beginning of the simulation, the MPC had more energy cost as compared to the other two controllers and used more night-time electricity to bring the room air and tank temperatures to their set points. There was a further rise in MPC energy cost during the night time e.g. during 24:00 to 30:00. This means that the MPC was doing the load shifting. Whereas, for conventional control strategies the cost increased throughout the simulation time. The conventional control tried to maintain the temperatures close to set point temperatures with no effort to use night-time electricity or perform load shifting. The overall cost of the MPC for three days was lower than the other two controllers. A similar trend could be seen for the integrated heat pump signal. The model predictive controller used more heat pump signal during the night time. The MPC also used HP during the day 2 due to less availability of solar energy. The overall energy consumption of MPC was more than the other two controllers, however by using more of the heat pump for heating purposes meant that the energy had been decarbonised. The use of a heat pump is considered as one of the lowest carbon heating options available. The energy cost, heat energy and energy consumption for the three controllers (discussed) is given in Table A-1. The MPC had more energy consumption for three days of simulation than other two controllers but it had lower energy costs.

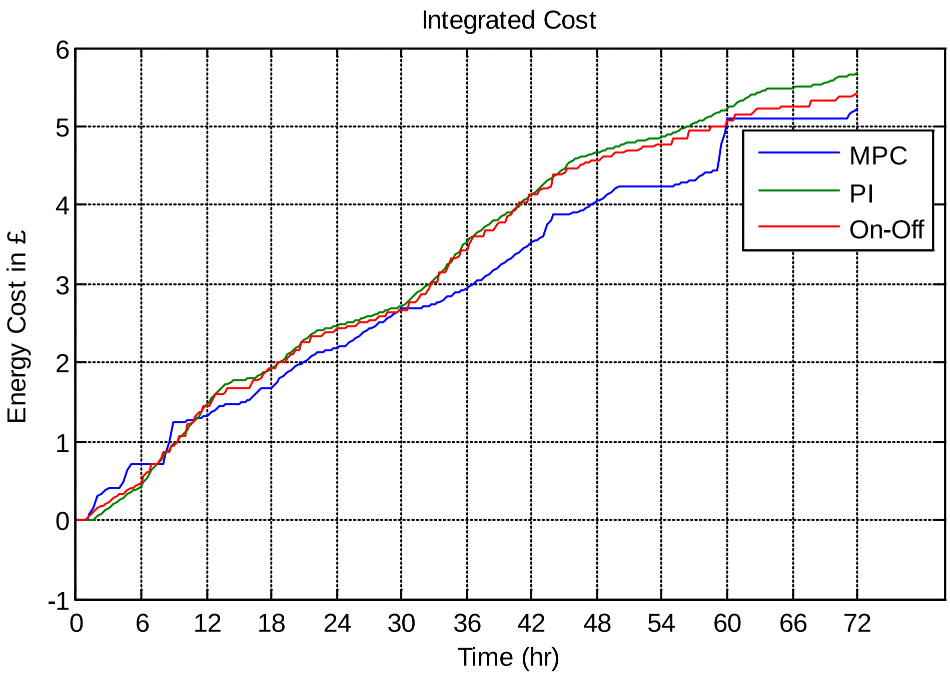


Figure 4-40: Integrated cost

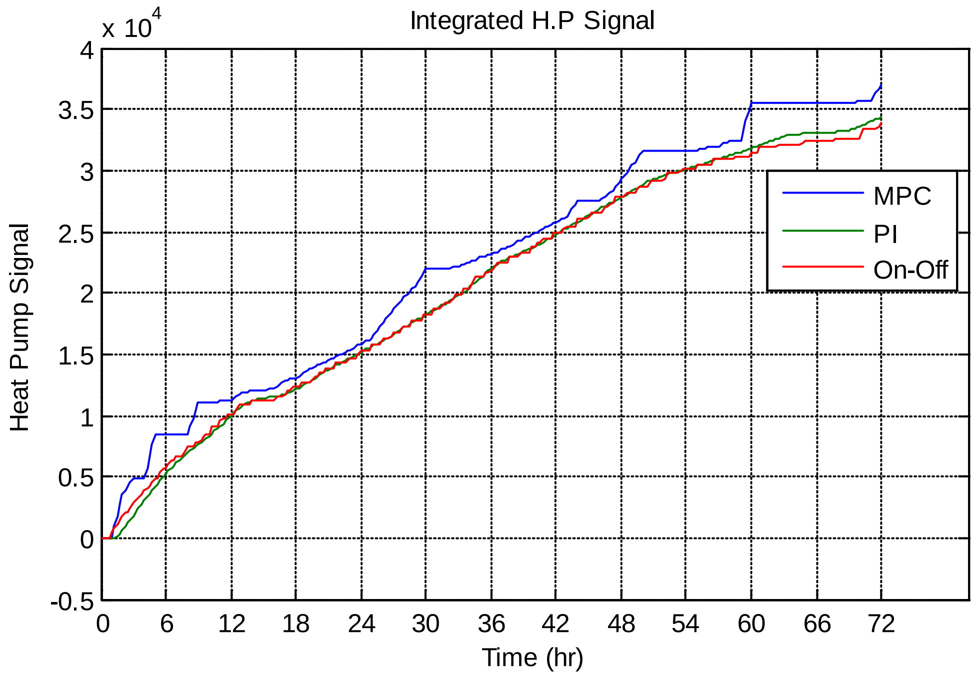


Figure 4-41: Integrated HP signal

The hall air temperature shows that MPC took less time to bring the hall air temperature close to the set point. The MPC responded quickly to the heat loss through the window, which is a large disturbance in the hall area.

Figure 4-42 shows that for case A, the MPC used more night time electricity than the PI and on-off controllers. The MPC energy cost was 12.24% less than the PI controller and 8.92% less than the on-off controller.

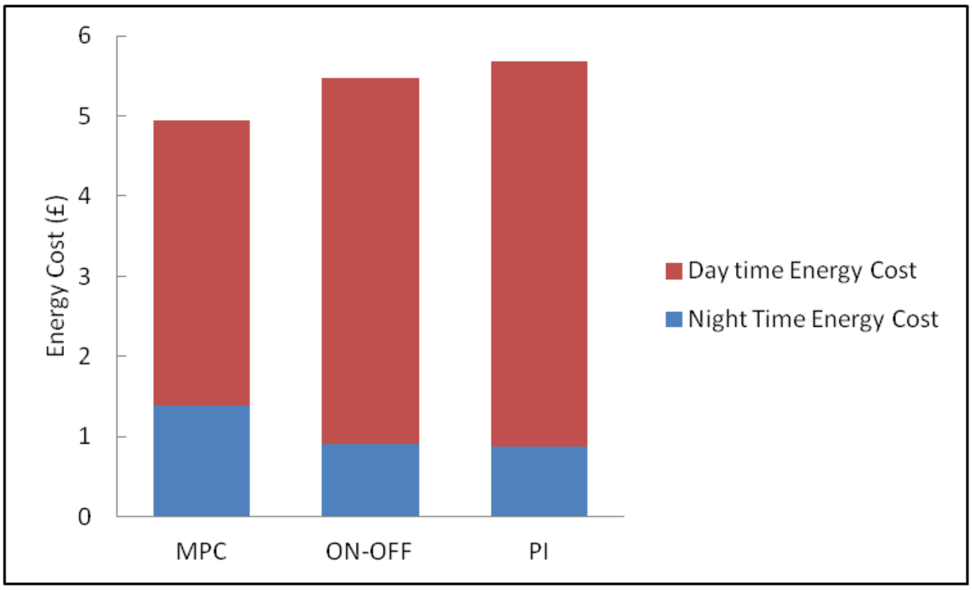


Figure 4-42: Energy price in £ for case A

4.9 Summary

In this chapter, three different control strategies (On-Off, PI and model predictive control) have been developed and implemented on a solar heating system combined with a heat pump. Both a very simple model and the full model with four weather scenarios were simulated for each controller. Simulation results for a simple plant showed that the model predictive control was able to handle the disturbance (radiations) very well and was using night time electricity in the absence of radiations.

For the solar system combined with a heat pump, 4 different environmental conditions were simulated. Irrespective of disturbances, the PI and On-Off controllers always tried to maintain the set point temperature, whereas the MPC utilized the freedom of a range of tank temperatures to reduce electricity cost by using night time electricity where appropriate. Overall, the MPC used the heat pump at lower settings during the day time, but at higher settings during the night. The load was shifted to off peak time and energy was stored in the water tanks, which was then used during the peak load time. This led to a slightly lower energy cost, but also slightly higher overall energy consumption. The model predictive controller also dealt very well in terms of integrating predictions of external variables (disturbances).

The use of a linear model led to a manageable computational time, as long as the control horizon was reasonably short. A control horizon of 10 was solved in seconds, a 24 control horizon was still feasible, but more than 40 steps were making the simulations very slow on a powerful computer (causing it to become slower than real time). The computation time also increased when system limits were relevant compared to situations where all states were clear of the limits.

Chapter 5 Thermal comfort based control

5.1 Introduction

The present chapter investigates the problem of designing and simulating a model predictive controller that is based on perceived thermal comfort. The predicted mean vote (PMV) and percentage people dissatisfied (PPD) modelling is covered in this chapter. The model predictive controller is compared with a conventional controller (PI) and it is extended to control for PMV. Two cases for each controller are simulated in which the room air temperature and predicted mean vote (PMV) are used as control variable.

Generally, thermal comfort in buildings is evaluated by using the indoor operative and mean radiant temperatures (ISO7730, 2005). In simple words the operative temperature is the average temperature of the air and the mean radiant temperature is the weighted mean temperature of the surrounding surfaces (ASHRAE, 2005). In this research only these two temperatures are considered as changing parameters and the 4 parameters (indoor air velocity, indoor air humidity, clo value and metabolic rate) are assumed as constant. Values of 0, 0.1m/sec and 1628mbar were considered for work, indoor air velocity and vapour pressure respectively. The metabolic rate and clo values for occupants in the hall and bedroom are given in Table 5-1. The occupants in the bedroom were assumed to be wearing sleepwear with a sweater and socks on and it was assumed that one occupant was sleeping while the other was seated quietly. In the hall, one occupant was considered as resting (reclining) and the other as seated quietly.

Table 5-1: Met and clo values (Sources: CIBSE guide A and ASHRAE standard 55-2004)

	Hall		Bedroom	
	Occupant 1	Occupant 2	Occupant 1	Occupant 2
Metabolic rate (Met)	0.8	1.1	0.7	1
Clo Value (Clo)	1	1	1.38	1.38

The equation for PMV was found by using the MATLAB script. The script was run and it was found out what indoor and radiation temperatures resulted in a PMV close to zero e.g. for the occupant 1 in bedroom, for both the temperatures equal to 18^{o}C, the PMV was 0.0111. This PMV was minimum that was obtained for all same combinations of temperatures. By keeping radiation temperature fixed at minimum PMV temperature the indoor air temperature was varied to find out the PMV curve for air temperature. The same procedure for repeated for PMV curve for radiation temperature. For occupant 1 in bedroom both the equations are;

For indoor air temperature;

$$y = 0.1147x - 2.0587 \qquad (5.1)$$

For radiation temperature;

$$y = 0.1067x - 1.9034 \qquad (5.2)$$

In the above two equations, y is the PMV and x is the temperature. The same method was used to evaluate PMV equations for other occupants in hall and bedroom. The plot for the hall occupant is shown in Figure 5-2 and for other occupants in the Figure A-2 and Figure A-3 in Appendix A.

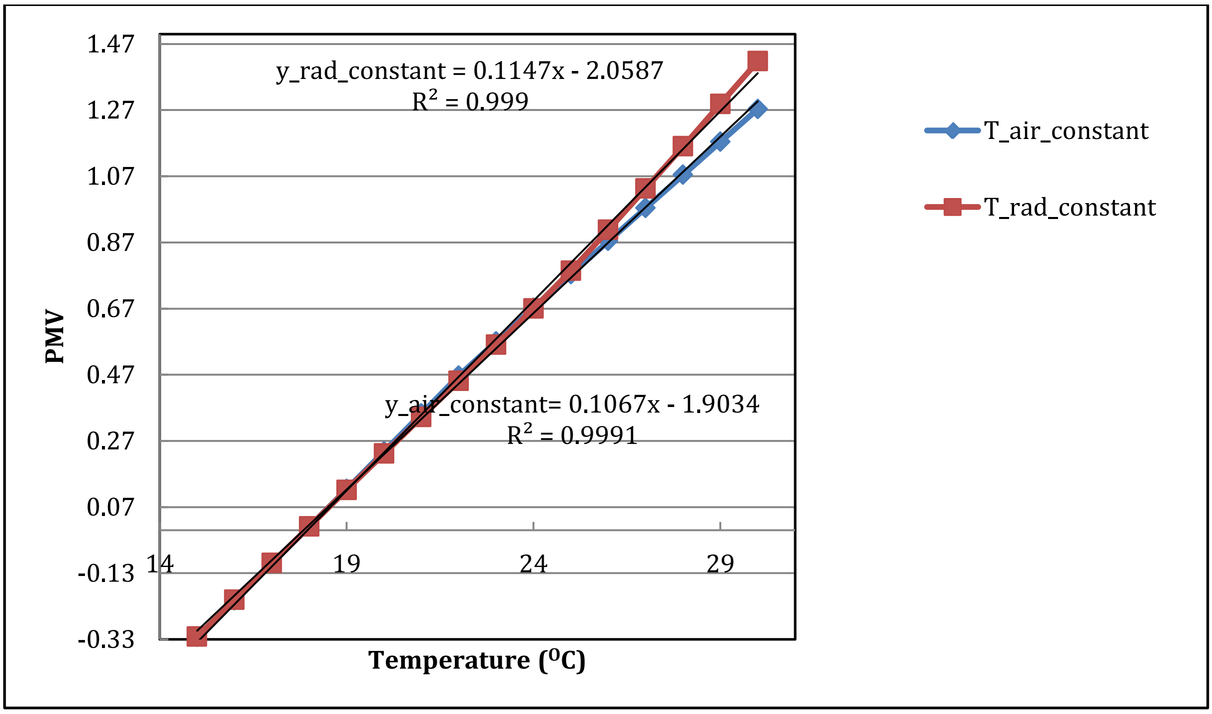


Figure 5-1: PMV plot for bedroom occupant 1

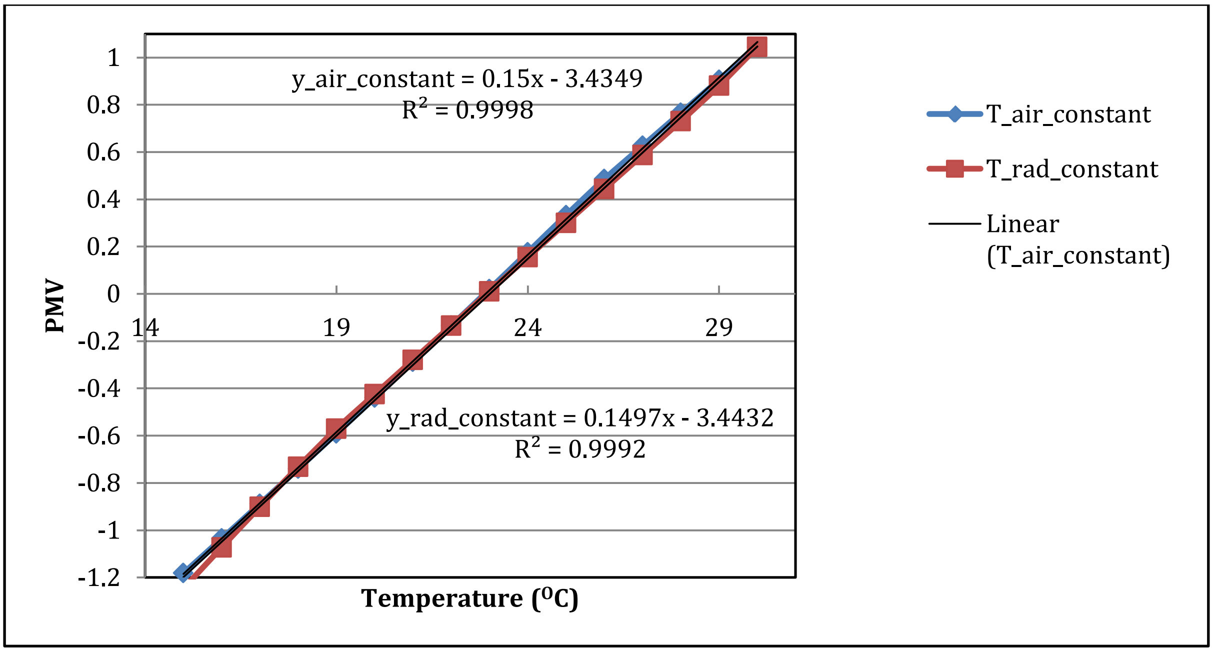


Figure 5-2: PMV plot for hall occupant 1

Fanger, 1970 also introduced another term known as predicted percentage dissatisfied (PPD) to determine the number of potential complainers in a thermal environment in which human are exposed. PPD is given by the following equation;

$$PPD = 100 - 95\exp -(0.03353.PMV^4 - 0.2179.PMV^2) \qquad (5.3)$$

This equation was plotted against PMV as shown in Figure 5-3. As it was assumed that most of the thermal parameters were in the thermal comfort range i.e. the velocity, humidity etc, it was decided to plot the PPD until 50% as there was less chance of having 100%PPD with the mentioned assumptions. The curve is asymmetric so the polynomial reduced to $y = 20.647x^2$. In this equation y is the PPD and x is the PMV. This factor of 20.647 was used as the weighting factor in the model predictive controller on heater input signals to control PMV of the rooms. The PPD is more than 0 as it is not possible to satisfy everybody at the same time.

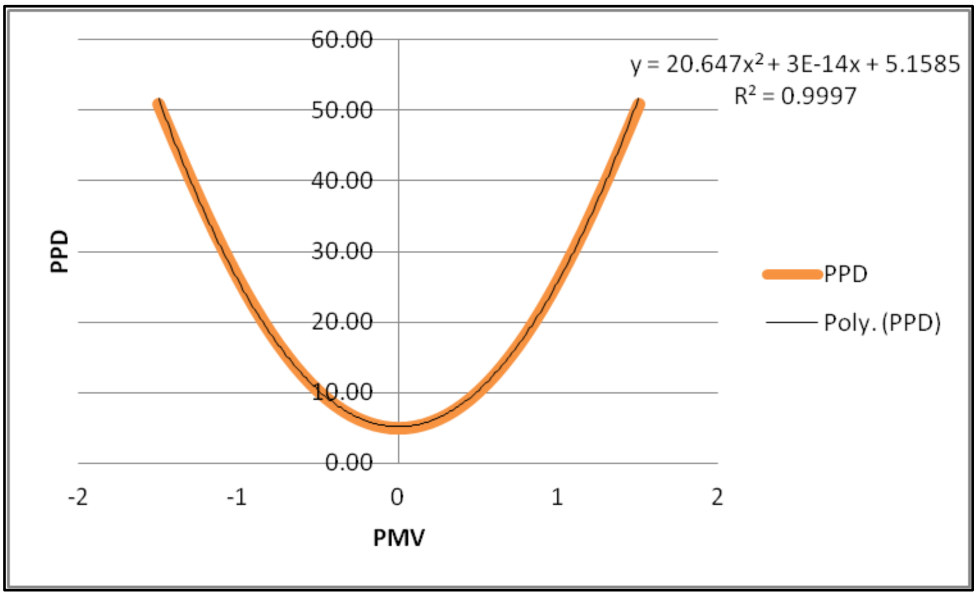


Figure 5-3: PMV vs PPD

5.2 Control Objectives

The objectives of this control problem are to use cheap night-time electricity tariffs to store heat energy in the tanks, to optimize the heat pump operation and provide better thermal comfort environment to the occupants during the occupied period. The other criterion to select better control strategy is the energy cost during the 3 days of the simulation time. In order to run the simulation an assumption of uniform air temperature in the bedroom and hall was made;

Two simulation cases were performed by using PI and model predictive controllers; the first one was based on temperature control while the second case was performed by using occupant's PMV as controlled variable. The schematic layouts of temperature and PMV based control are shown in Figure 5-4 and Figure 5-5 respectively. In temperature based control room air temperature was used for control purposes and an error was calculated by subtracting the current air temperature from the set point temperature values and this error was then fed into the controller. In PMV based controller a PMV model was used to calculate the thermal sensation of the occupants and then used for controlling the indoor thermal environment. In chapter 4, the room air temperatures were maintained to their set points throughout the simulation. In this chapter occupancy patterns were introduced in the hall and bedroom areas. The hall has occupancy between 14:00 to 21:00 while bedroom has occupancy between 22:00 to 8:00.

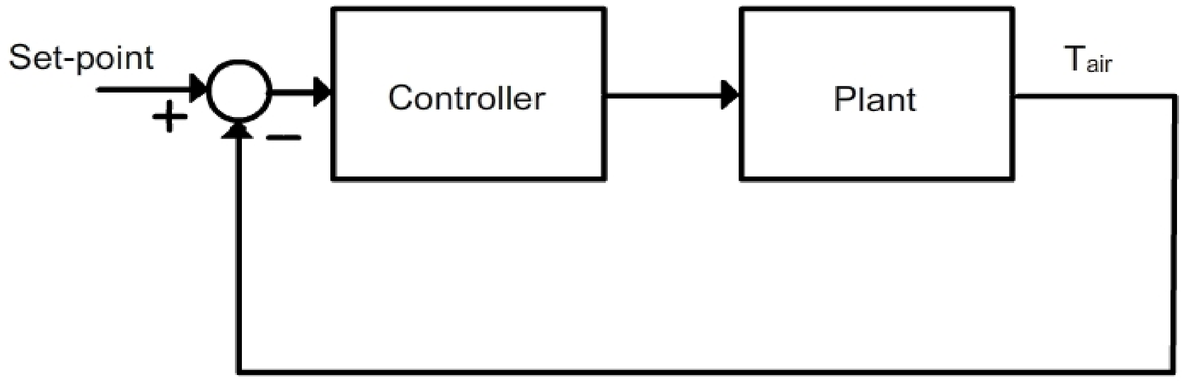


Figure 5-4: Temperature based control layout

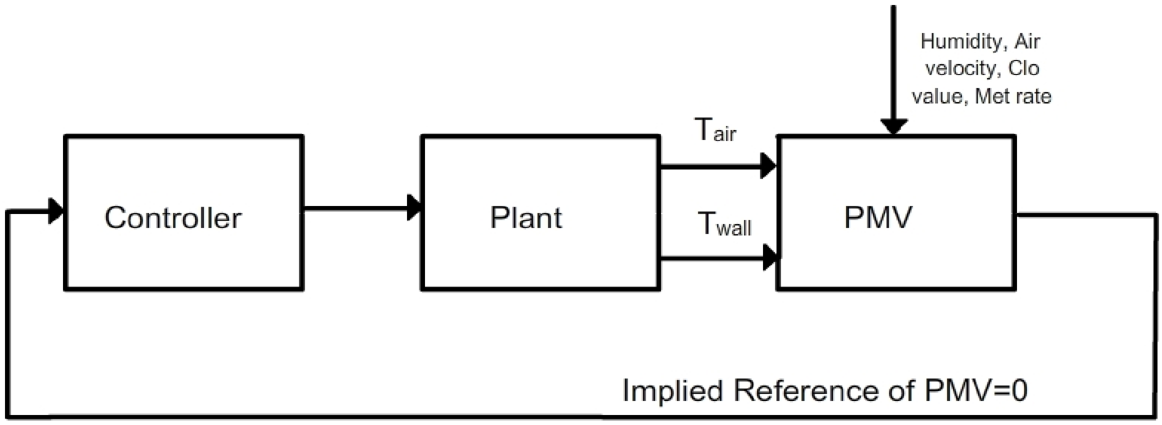


Figure 5-5:PMV based control schematic layout

5.3 Conventional comfort based control

In order to identify a reference performance for a comfort based control strategy, a conventional approach was first developed. The conventional control strategy was based on a proportional-plus-integral (PI) controller. The weather data used for the simulations was a cold day in between two partly overcast days.

5.3.1 Temperature based PI control

The first case simulation results are shown in Figure 5-6 and Figure 5-7. At the beginning of the simulation the heat pump remained switched OFF due to the higher tank temperatures. External environmental conditions (temperature and solar radiation), internal heat gains and occupancy patterns acted as disturbances. At each time step the PI controller compared current room temperature with the reference temperature and the resulting error is applied to the controller. Reference set points of 18^{o}C and 22^{o}C were used for the bedroom and hall air temperatures. During unoccupied period a temperature of 13^{o}C was used as reference temperature.

The tank temperatures in Figure 5-6 remained almost constant after 9am of day 1. Some small drops can be seen in tank temperatures and then the heat pump signal was increased by the controller to maintain it to the reference value. Figure 5-7(a) shows that the controller was able to maintain the air temperatures to their set points during the occupancy period. There was a stronger drop in the hall temperature during the unoccupied period as compared to the bedroom temperature because of the presence of the window. The heat loss was more in the hall than in the bedroom.. The hall temperature on the afternoon of day 2 took time to reach the reference temperature because of the low radiations and higher losses in the hall. The PI did not use night time electricity to get benefit of night time cheaper electric tariffs and to store energy. Overall the PI controller performed well in terms of keeping the temperatures to the desired values.

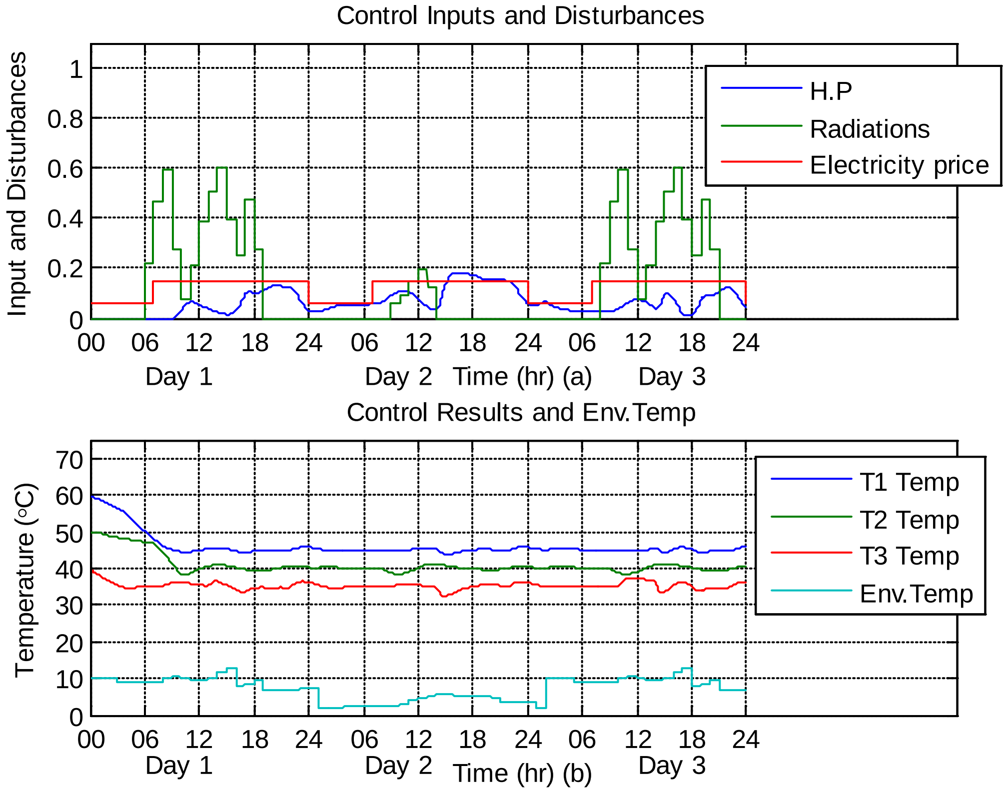


Figure 5-6: Control inputs and tank temperatures

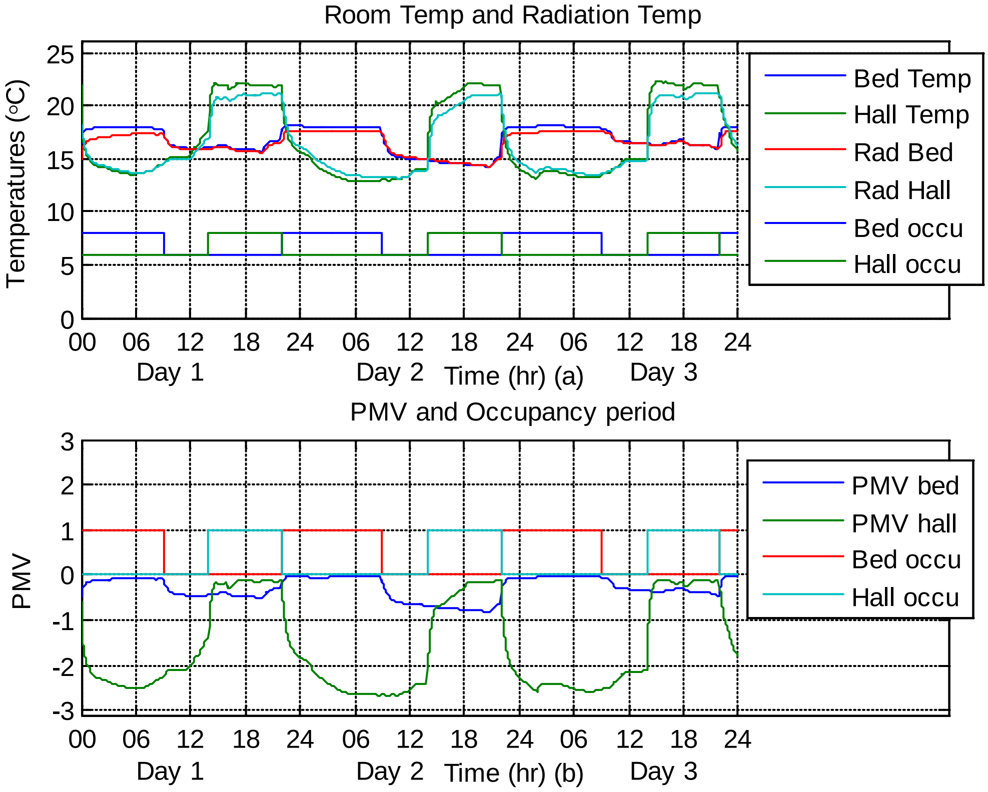


Figure 5-7: Room temperatures and PMV

5.3.2 PMV based PI control

In this simulation case the controller took current PMV value and compared it with a reference PMV value to calculate an error. A reference PMV value of 0 was used during the occupied period whereas for the unoccupied period it was taken as -3. In Figure 5-8(a) the tank temperatures for PMV based PI controller remained same as they were in the previous case. However there are some irregularities in the room temperature and PMV values. As there were losses through the window and also the system had complex dynamics, therefore it looked hard for PI controller to maintain a constant PMV value of 0. The controller after getting the error tried to bring it to zero by switching On or Off the room heater, which directly changed the temperature of the room and this resulted in change in radiation temperature. Although there were irregularities in the PMV results in Figure 5-9(b), still the PMV of the rooms were in the acceptable range of ±0.5.

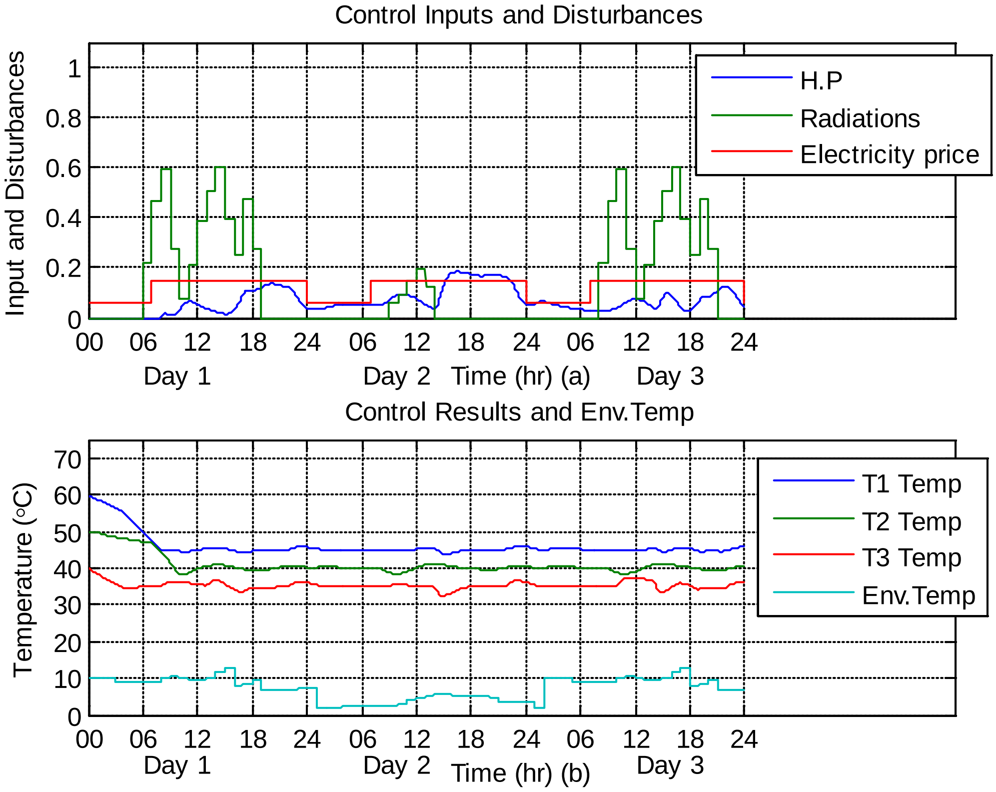


Figure 5-8: Control inputs and tank temperatures

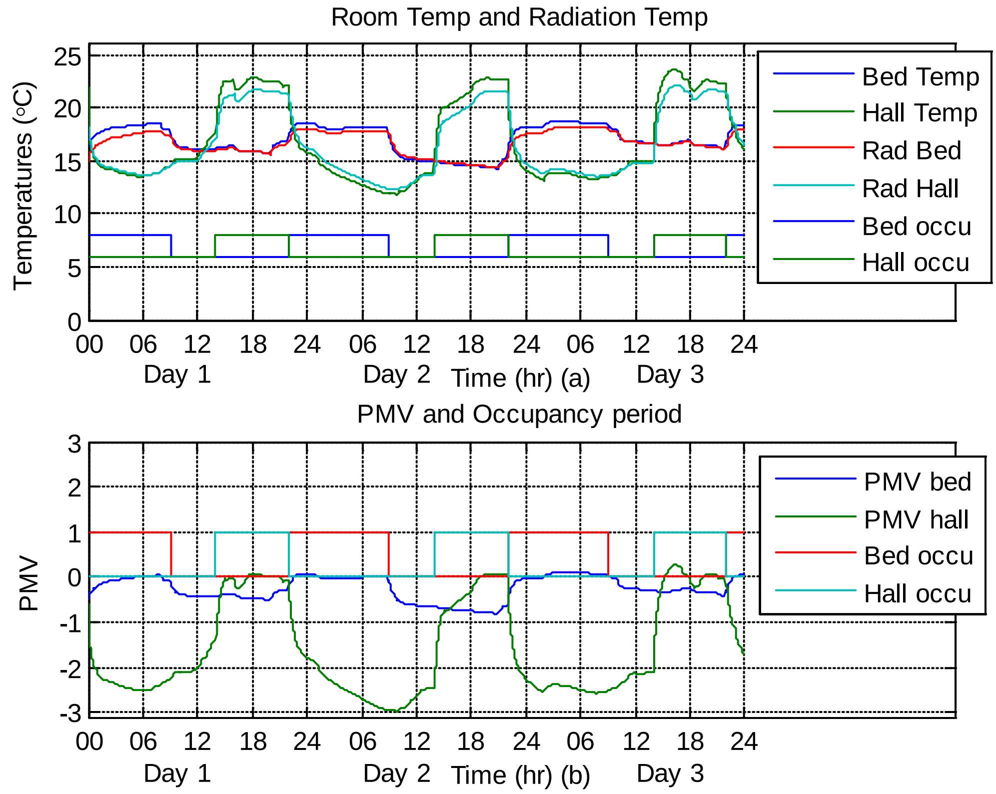


Figure 5-9: Room temperatures and PMV

5.4 Model predictive comfort based control:

A model predictive control developed for the system which was based on controlling room temperature in first case and then on a PMV basis is discussed in following sections. The architecture of a thermal comfort based MPC is shown in Figure 5-10.

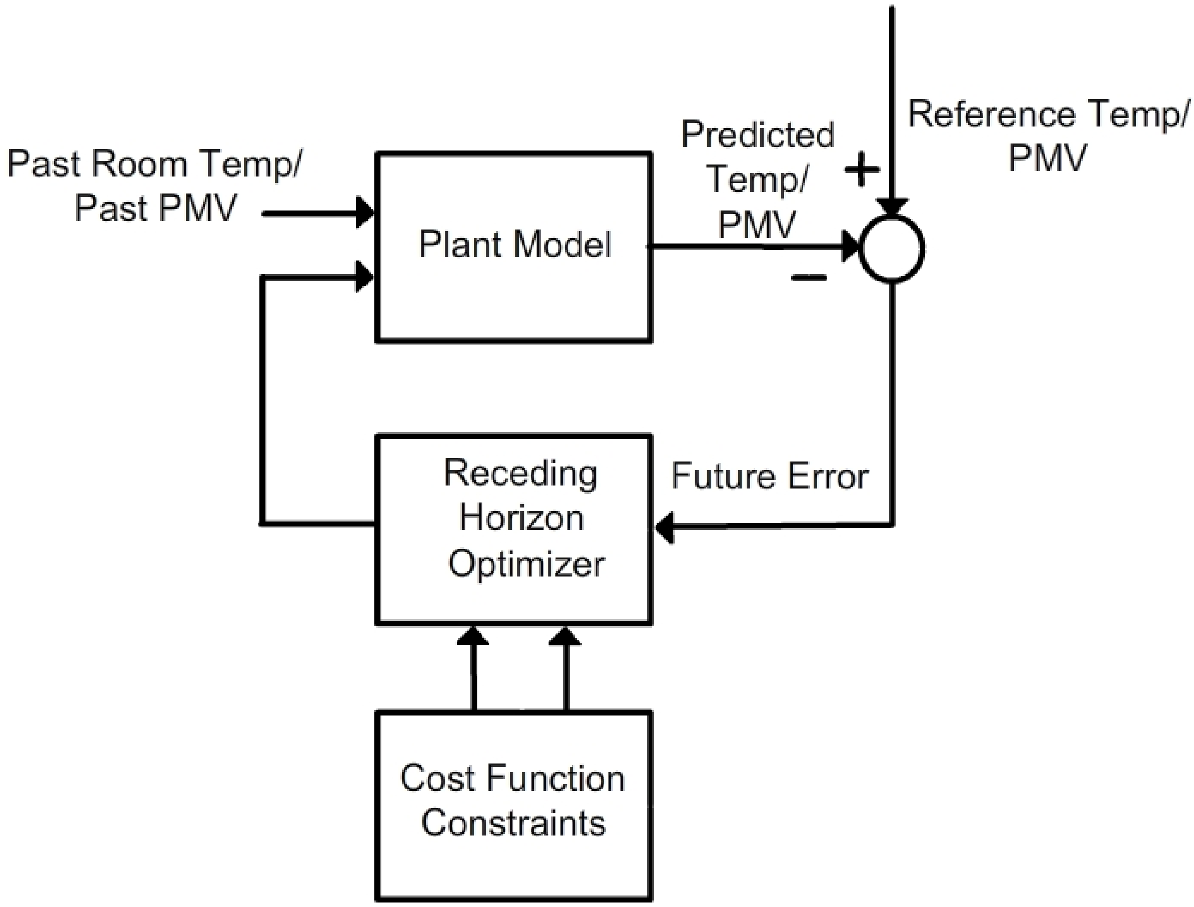


Figure 5-10: Model predictive control system architecture for thermal comfort case

The selection of MPC tuning parameters is crucial for the better operation of the controller. Below the focus is on the selection of weights on tank temperatures, weight on input change rate and control horizon.

5.4.1 Selection of tank weights and input rate weight

To obtain the objectives mentioned previously, reasonable weights have to be selected for outputs and rate of change of inputs. One part of the cost function is to minimize the weighted sum of the controller adjustments to the inputs, according to following equation;

$$S_{\Delta u}(k) = \sum_{i=1}^{N_u} R_{\Delta u}(k)\big(\varDelta u(k+i|k)\big)^2 \qquad (5.4)$$

Where N_u is the control horizon, $\varDelta u(k+i|k)$ is the predicted adjustment in the manipulated variable and $R_{\Delta u}(k)$ is the weight of that adjustment (rate of change of input) also known as the rate weight. The rate weight penalizes the incremental change rather than the collective value. Increasing the rate weight means that the controller will make more cautious and smaller adjustments or moves. Figure 5-11 shows results of hall PMV for different $\varDelta u$ weights. It can be seen that during the occupied period all three weights performed similarly but during the unoccupied period the behaviour was different. The weights on output (PMV) changed with time and were more during the occupied than the unoccupied period. A weight of 0 on $\varDelta u$ showed that the controller was not making cautious moves. This resulted in a sluggish behaviour as shown in the PMV results e.g. during 11:00 of day 1 and the early hours of day 3. A larger weight of 0.1 made the controller to be more careful and that is the reason why the PMV during the unoccupied period could only reach -2 approx. at 3am on day 2. A weight of 0.03 shows promising results, the PMV was reduced more than the other two weights during the unoccupied period. A lower value of PMV during the unoccupied periods means that the heating was switched OFF during those times and therefore saving more energy. This is also evident from the hall heater plot (Figure 5-12), the results of weight of 0.03 shows less use of energy. On the basis of these results a weight of 0.03 was selected for hall and bedroom heating inputs.

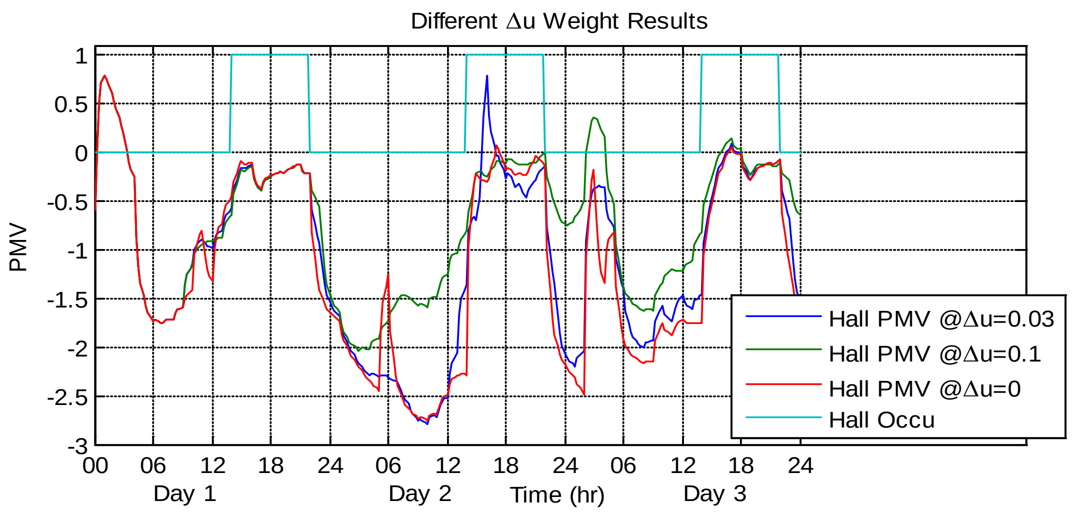


Figure 5-11: PMV results for different hall $\varDelta u$ weight simulations

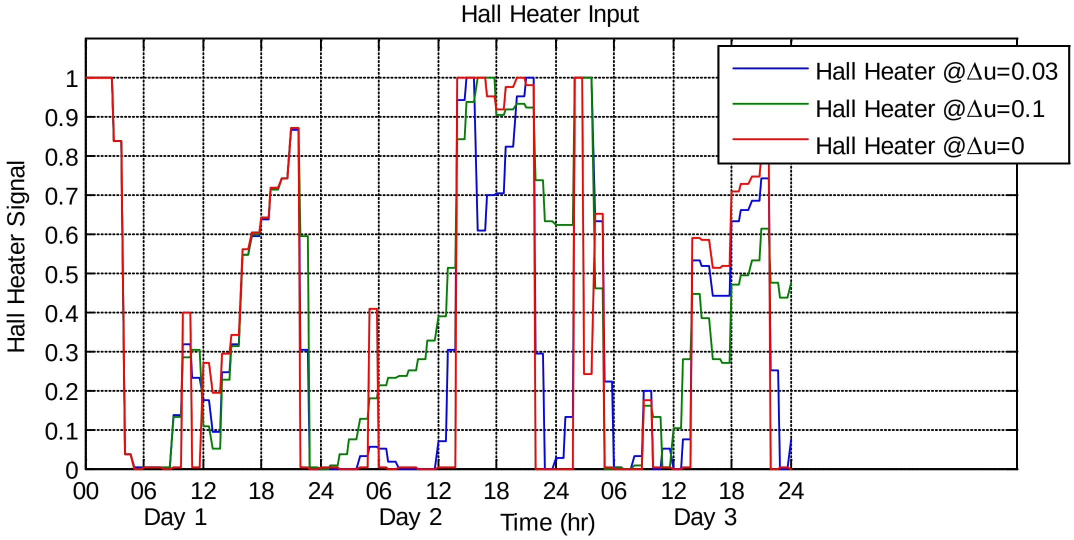


Figure 5-12: Hall heater input for different hall Δu weight simulations

The MPC also minimizes the weighted sum of manipulated variable deviation from its nominal value, according to the following equation;

$$S_u(k) = \sum_{i=1}^{N_u} R_u(k)(u(k+i|k) - \bar{u})^2 \tag{5.5}$$

In the above equation $R_u(k)$ is the input weight and $\bar{u}$ is the nominal value of the input. In all simulation cases a weight of 1 for heat pump input and a penalty of 0 was selected for other inputs. In the case when a sustained disturbance or set point change occurs, the manipulated variable must deviate for such a situation and a weight of 0 is selected. A non-zero weight forces the input back towards its nominal value. This was desirable in the case of the heat pump situation so that the heat pump performs according to the model presented in Chapter 3.

A penalty (weight) on outputs shows the accuracy with which each output must track its set point. The controller predicts the deviations of each output from its set point over the prediction horizon.

$$S_y(k) = \sum_{i=N_1}^{N_2} Q(i)\big(y(k+i|k) - y_r(k+i|k)\big)^2 \tag{5.6}$$

Where N_1 and N_2 are the minimum and maximum cost horizons, y_r is the reference for output and Q is the weight on the output. One of the objectives of the controller was to store heat energy during the night-time and to use it during the daytime. A larger weight on tank means that the controller will always keep the tank temperatures to set point temperatures and will minimize equation 5.22. This would not result in the storing of heat energy during the night and the controller will use more energy during the day as well to maintain the tank temperatures. In order to store heat during the night-time, two small weights were applied and suitable weight was selected based on the use of night-time electricity and low energy cost. The maximum use of night-time electricity will mean that the controller will store energy during the night. Figure 5-13 shows that a weight of 9×10^{-4} forced the heat pump to use more night-time electricity than 1×10^{-8} weight. The heat pump was also used more during the day time (higher electricity tariffs) with a weight of 1×10^{-8} resulting in a high energy cost. The Figure 5-14 shows the buffer tank temperature at different tank temperature weights. The buffer tank temperatures are plotted because it was directly connected to the heat pump. The controller with a weight of 9×10^{-4} increased the tank temperature during the night and on the second night the temperature reached to a value of 58^{o}C; whereas the lower weight did not store a considerable amount of energy during the night-time. The lower weight also made the controller use the heat pump during the day which was not desirable. Based on these criteria a weight of 9×10^{-4} was selected as the weight on tank temperatures.

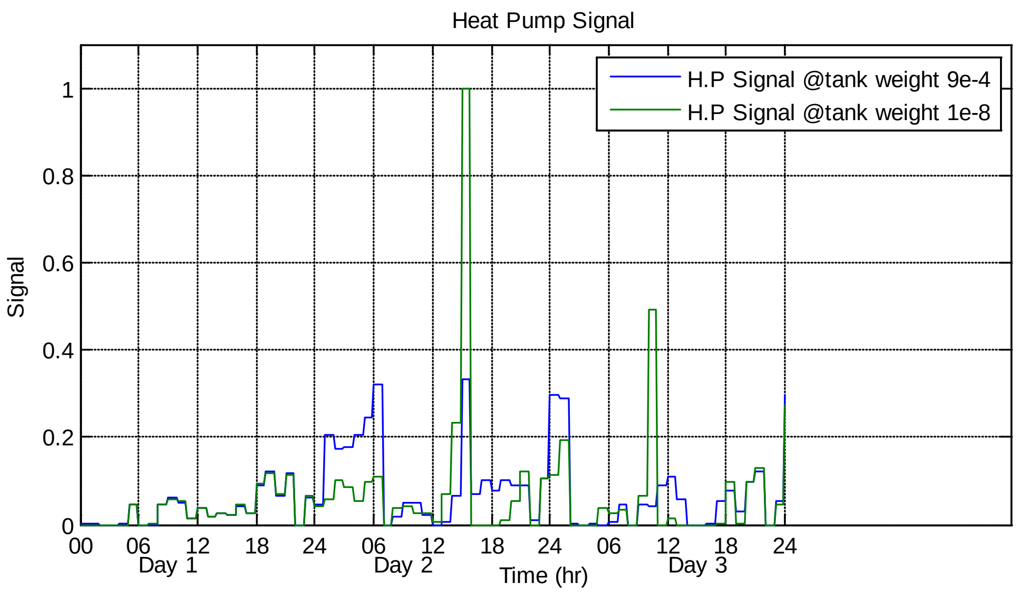


Figure 5-13: Heat pump signal for different tank temperature weights

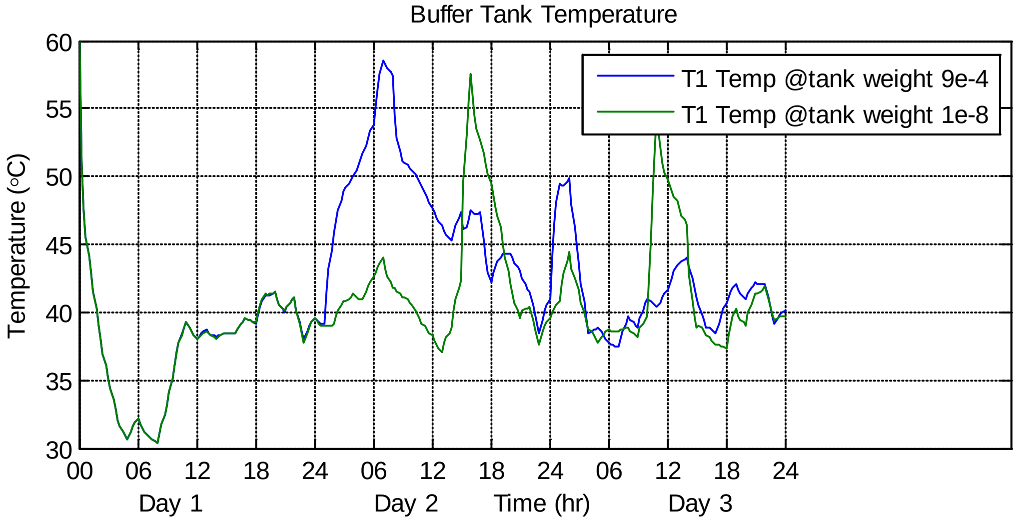


Figure 5-14: Buffer tank temperature for different tank temperature weights

5.4.2 Selection of sampling time

The selection of the control horizon is another important factor in the MPC formulation. The system was simulated with a sampling time of 900 seconds and also with a 3600 seconds sampling time. The lower sampling time took a significant amount of computational time and the whole 3 day simulation took about 24 hours. By increasing the sampling time the key problem of computational time was solved and the simulation time was reduced to approximately 15 minutes. The other reason for selecting the large sampling time was that it did take into account the slower dynamics of the system and gave a better indication of the future. The smaller time steps (900sec) mean that the variable limits will be applied to more time steps, which makes the simulation process to slow down. Figure 5-15 shows that the simulation by considering larger control steps used more heat pump during the night. Figure 5-16 shows the buffer tank temperature for two scenarios. The smaller time step simulation used more energy as compared to the larger time step simulation. The lower time steps controller stored more energy during the night-time. However, it also used more electrical energy during the daytime, as the heat pump was used more during the daytime as well because the controller was checking for limits more frequently and whenever these were violated it turned on the heat pump. The energy cost for larger control steps was £ 3.1175, whereas for the other case it was £2.922. There was a small difference in the price and the only difference was because of more energy usage during the daytime.

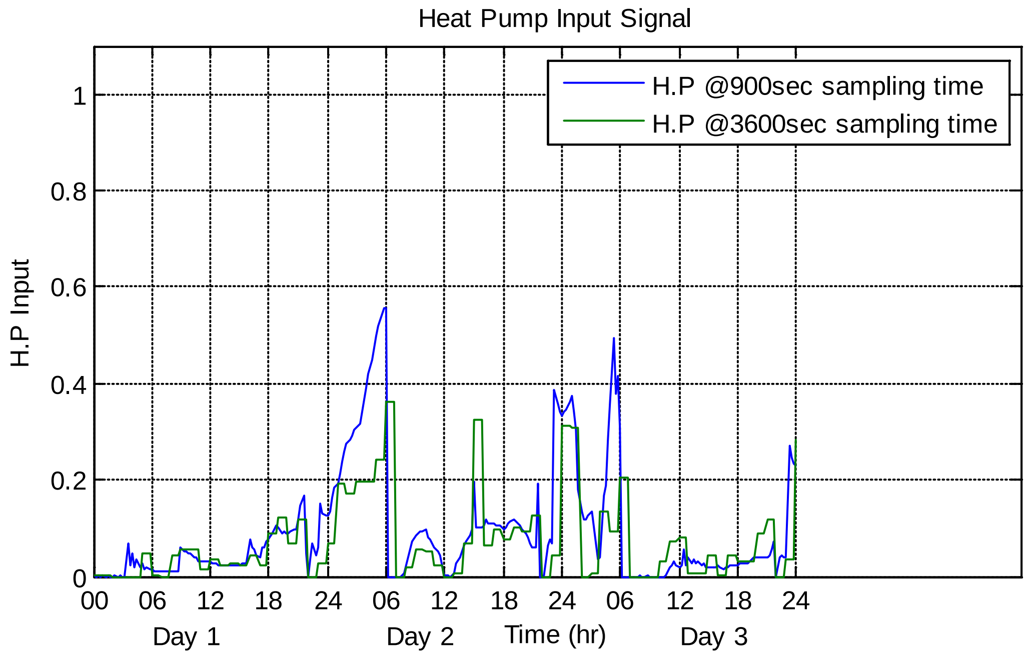


Figure 5-15: Heat pump input signal for 900 and 3600 sec sampling time

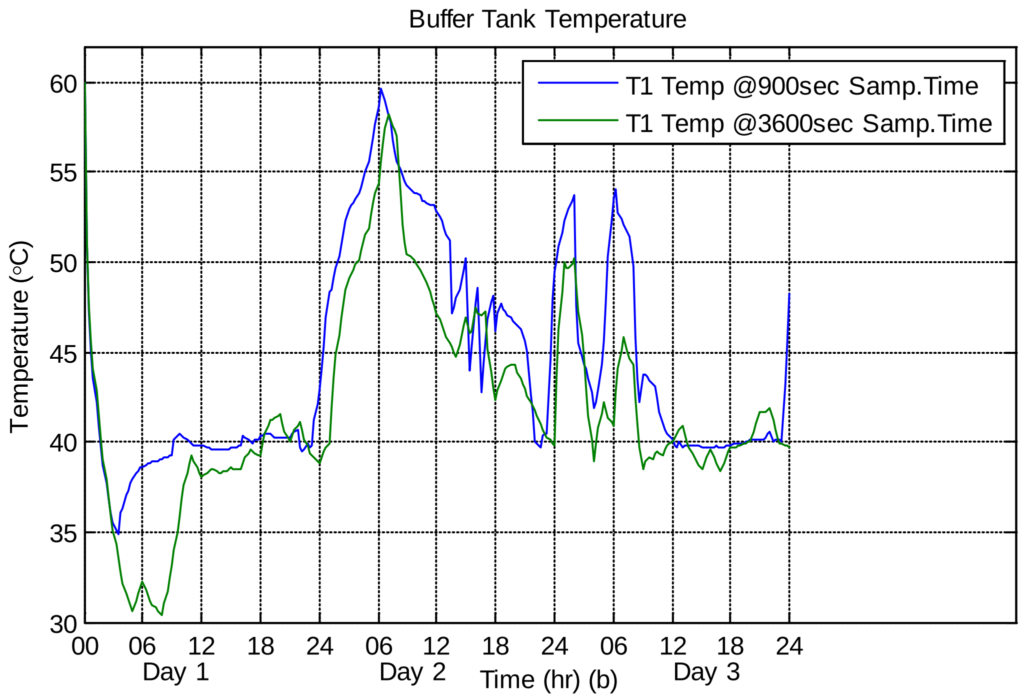


Figure 5-16: Buffer tank temperature for 900 and 3600 sec sampling time

The basic strategy of MPC explained earlier will be applied below to find out a better strategy to provide an improved thermal comfort environment to the occupants.

5.5 Results

5.5.1 Temperature based control

In the first simulation, MPC was applied to control the room air temperature. The room air temperature had a weight of 1 during the occupied period and a weight of 0 during the unoccupied period. The PMV values had a weight of 0 throughout the simulation period. This means that the model predictive controller will make more effort to keep the room air temperature to its set point during the occupied period. The heat pump signal shown in Figure 5-17(a) shows that the controller used night-time lower electricity tariffs to store the heat energy in the tanks. The rise in tank temperature during the night can be seen in the Figure 5-17(b). At the beginning of the simulation the tank 1 and tank 2 temperatures became lower than their lower limit of 40^{o}C; this is because this time was considered to be the settling time for the controller. Figure 5-18(a) indicates that the controller maintained the bedroom air temperature to 18^{o}C and the hall temperature to 22^{o}C during the occupied period. There was a rise in the hall temperature during the night before day 3. This time was the unoccupied period for the hall and this rise in the air temperature was because the controller used night-time electricity tariffs to rise the hall temperature. The PMV values were not equal to zero during the occupied period but were in the acceptable range of ±0.5.

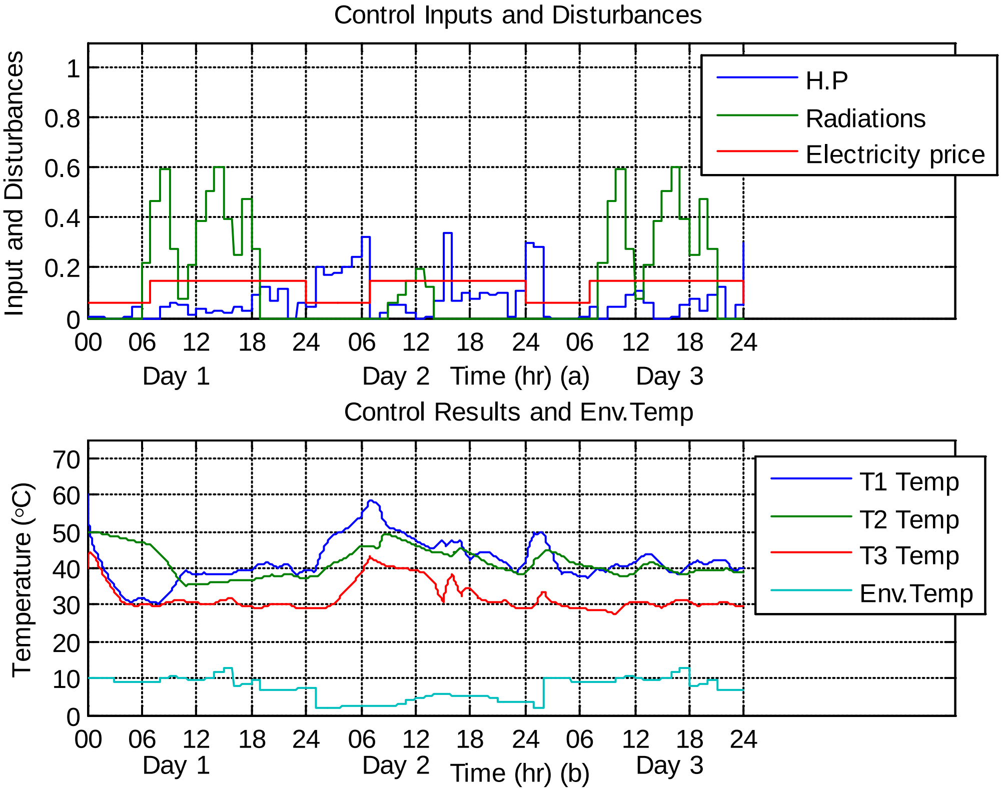


Figure 5-17: Control inputs and tank temperatures

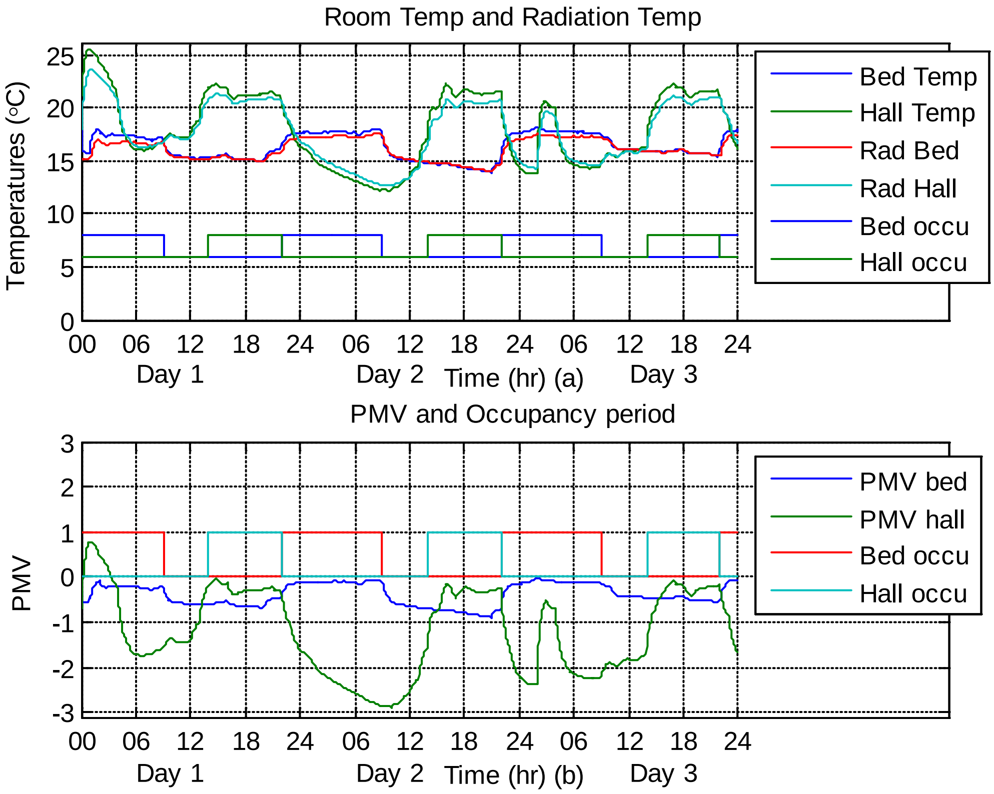


Figure 5-18: Room temperatures and PMV

5.5.2 **PMV based control**

The second case scenario was simulated by using PMV as the controllable outputs and having no penalty on room air temperatures. The PMV value had a weight of 20.64 as discussed in 5.7, which was chosen to make it comparable to the weights on room air temperature used in previous section. The controller used more night-time electricity and stored heat energy in the tanks (Figure 5-19). There was an increase in the heat pump signal at 15:00 of day 2 because the tank 3 temperature was about to violate the lower limit. So the controller decided to increase the tank temperature by using the heat pump as it was a cloudy day and having little solar radiation. The bedroom PMV (Figure 5-20b) remained very close to 0 throughout the simulation. As the hall has a window, and therefore heat losses made it more challengeable to control thermal comfort of the hall area, the controller (still) kept the hall PMV close to zero during occupancy. The rise in the PMV during the third night was because the controller used night-time electricity tariffs to increase the hall PMV and stored energy in the fabric.

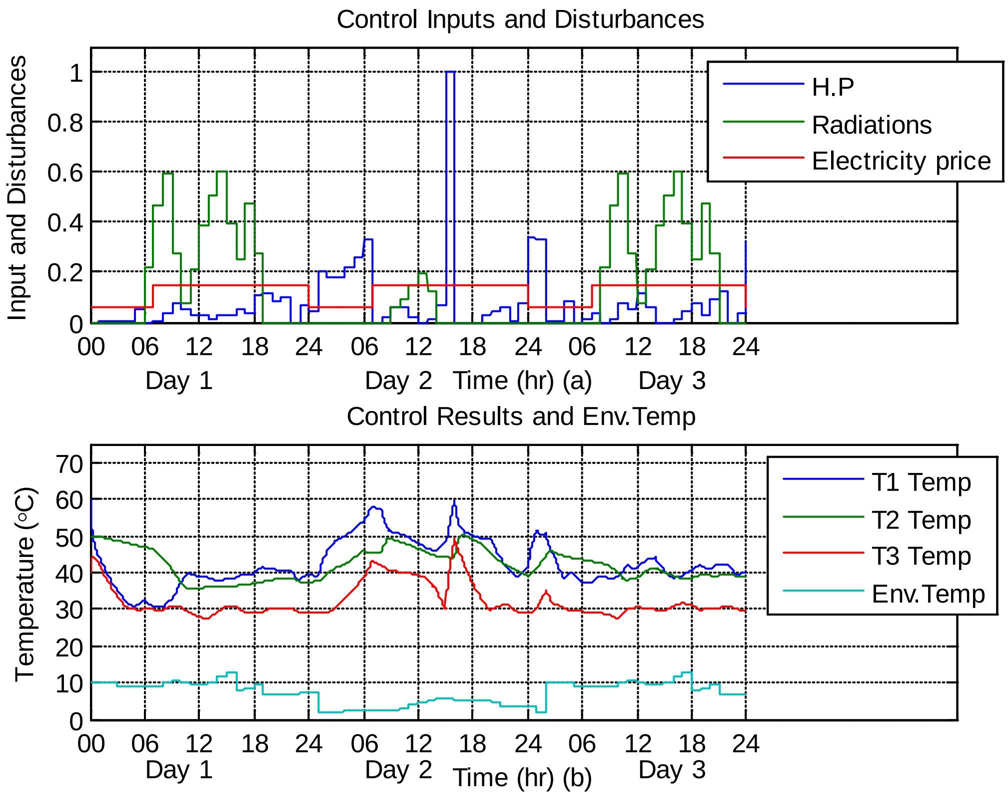


Figure 5-19: Control inputs and tank temperatures

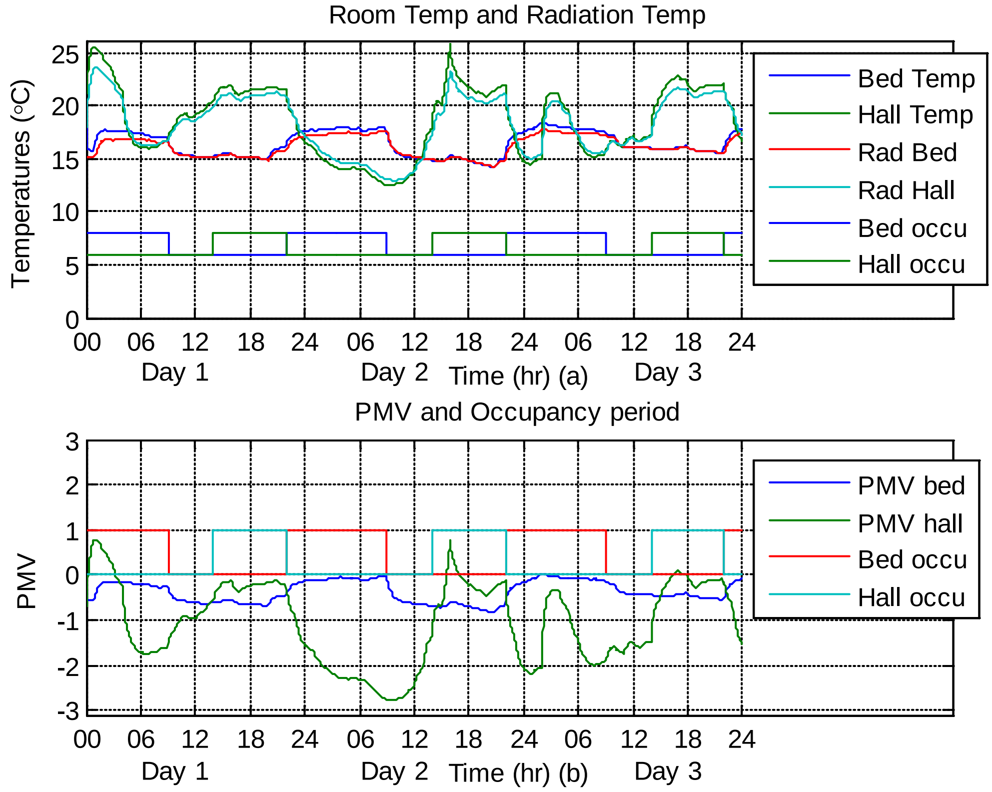


Figure 5-20:Room temperatures and PMV

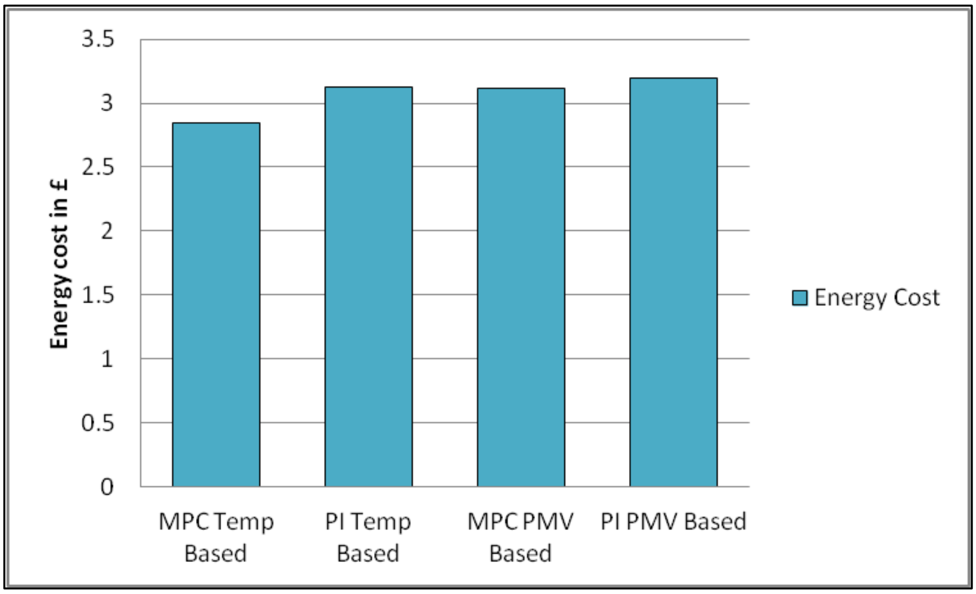


Figure 5-21: Energy price in £

5.6 Summary

In this chapter, two control strategies were developed for the space heating of a two zone building. Two scenarios were simulated for each strategy; a temperature based and a PMV based. In the PMV scenario, the comfort sensation of the occupants was quantified by a predicted mean vote and was considered as the control variable. Air radiation and air temperatures were used to calculate the predicted mean vote and the remaining four parameters were considered as constant.

Figure 5-21 shows the energy price for both the controllers and for both scenarios. The MPC has used less energy than the PI controller in both simulation cases. The control strategy based on PMV used more energy for slightly better comfort. The MPC used night-time electricity to store heat energy in the tanks. The MPC also increased the hall temperature during the night-time to get the benefit of cheap electricity and heat up the hall air. Both the control strategies satisfied the objective of maintaining a better thermal comfort environment during the occupied period.

Chapter 6 Investigation of Model and Objective function Mismatches

6.1 Introduction

This chapter focuses on the unexpected results obtained in chapter 5, especially on the situations where the MPC controller did not perform quite as well as expected. The first part of this chapter addresses the issue of model mismatch – the fact that the model used for MPC is different from reality or from the simulation model. The aim is to establish how significant this model mismatch is for the performance of the controller. The second part of the chapter explores the formulation of the objective function, and whether it should be more closely aligned with the energy consumption measure. NSGA II, a multi-criteria optimization algorithm, is used to study the difference in performance between a linear and quadratic cost function (objective function mismatch).

6.2 Linear model and nonlinear model predictive control

The model predictive controller solves an online optimization problem by relying on a model to identify optimal process inputs. At each time step, the optimization control algorithm attempts to determine the plant dynamics by finding a sequence of control inputs which satisfy the control specifications. The first step of control inputs is applied to the plant and the whole process is repeated for the next control interval.

A model can never accurately represent reality in all its details. Even the simulation model is an abstraction of reality, although it is expected to reflect the key behaviour with reasonable accuracy. The MPC approach used in this thesis is based on a linearized model derived from this simulation model. The linearized model cannot represent non-linear effects, such as the effect of temperature differences on the effectiveness on the water pumps, or the performance characteristics of the heat pump. This means that the MPC controller cannot take into account these factors.

One possible solution to this problem is to use a nonlinear plant model, however the disadvantage of using a nonlinear model is that then the optimization problem is no longer convex (having one global minimum). The loss of convexity is a serious issue for online applications since it requires much more involved algorithms to find a solution, and much longer computation times. It is therefore not considered suitable for practical applications, and even in the laboratory it would require an expert in non-linear optimization methods to implement (Camacho et al., 2004).

The approach used here to analyse the effect of model mismatch is shown in Figure 6.2. The top block diagram shows the application of the MPC controller with a linear model to the non-linear simulation model, which gives rise to the model mismatch. The easy solution is to use the existing MPC controller, but instead of applying it to the non-linear simulation model, it is applied to the very same linearized model as shown in Figure 6.1. This removes the non-linear effects completely from the simulation, and therefore eliminates the issue of model mismatch (Figure 6.2b).

Figure 6-3 shows the results of a linear plant model in the MPC controller when applied to a non-linear simulation model. This approach suffers from the model mismatch shown in Figure 6-2(a). The control results (Figure 6-3) show that the model predictive controller has used night-time electricity and also tried to raise the tank temperatures during the night-time to store heat energy (as discussed previously in Chapters 4 and 5). The problem under investigation here is to find the effect of mismatch between the model used in MPC and the model used in the simulation.

In contrast, a simulation is performed which uses the same linearized model as used in the MPC. As shown in Figure 6-2(b), this approach has no mismatch. The simulation results in Figure 6-4 are the result of a linear simulation model and there is no mismatch between the MPC model and simulation. These results are much smoother, they have no sign of non-linear effects, and the controller makes much better use of night-time electricity, increasing the tank temperatures to their upper limits. It could be said that this simulation represents a perfect scenario of maximizing load shifting to minimize energy cost. However, it has to be remembered that this simulation is using a severely simplified model, so the controller is not actually solving the same problem as before. It is conceivable that load shifting is easier in a linear system than it is in the complex non-linear heating system studied here. On the other hand the results do show that the non-linear effects are a significant problem for the MPC controller.

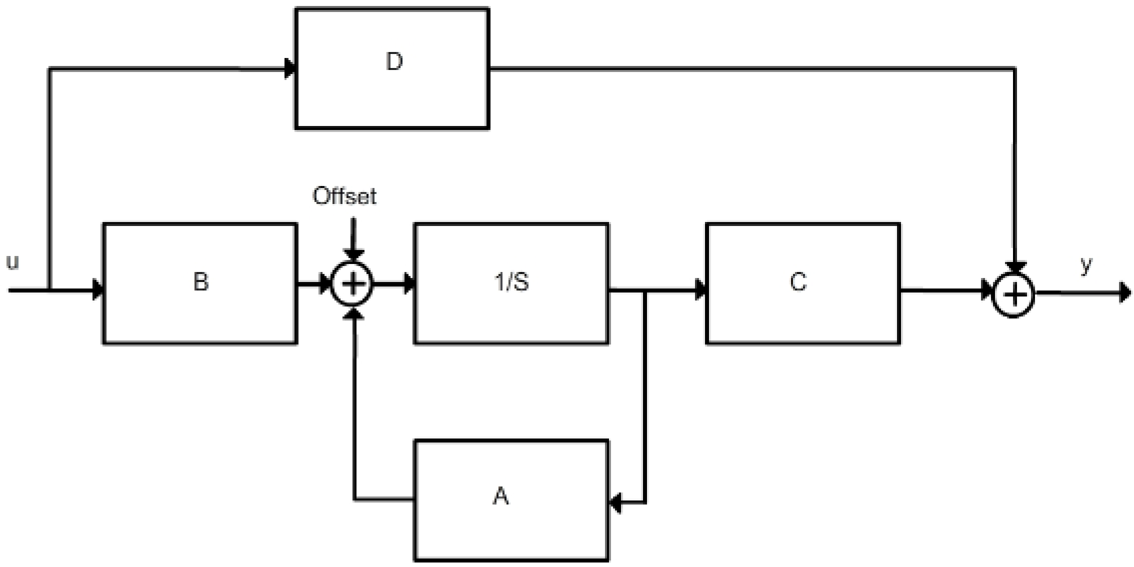


Figure 6-1: Linear plant model schematic

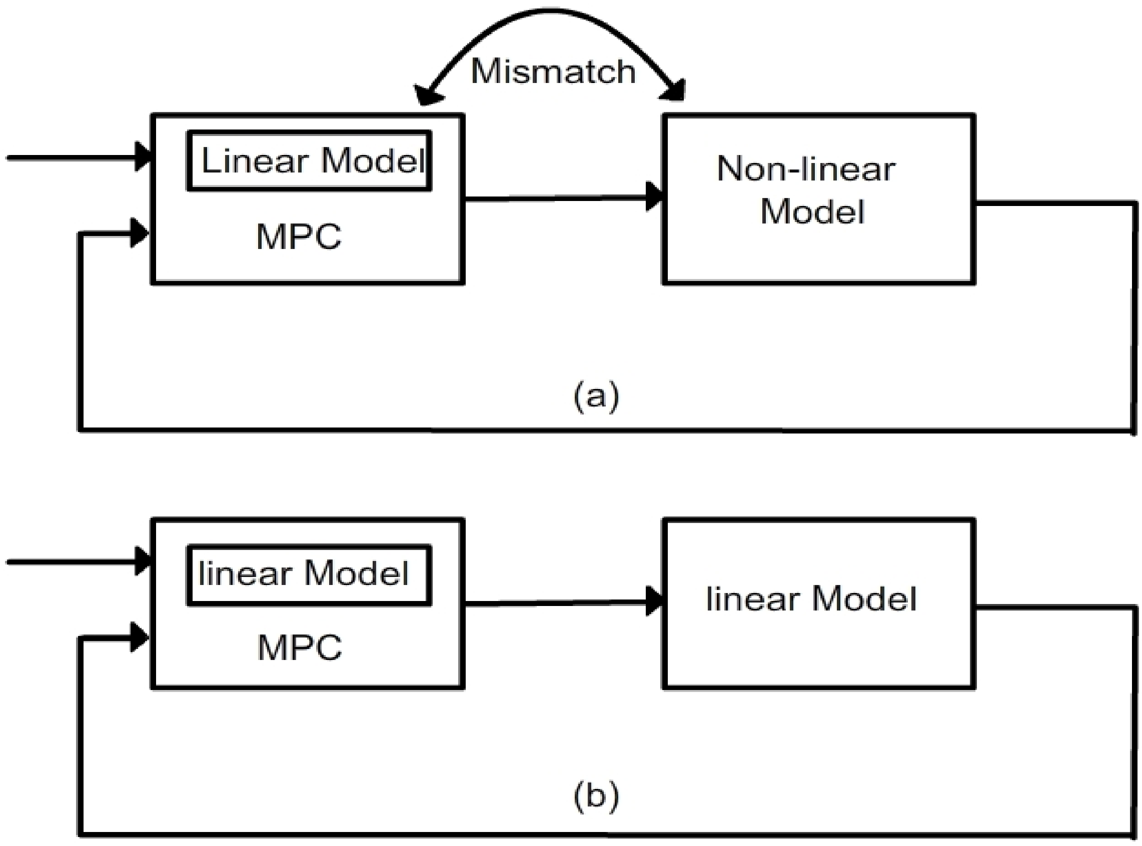


Figure 6-2: Different model setup schematics

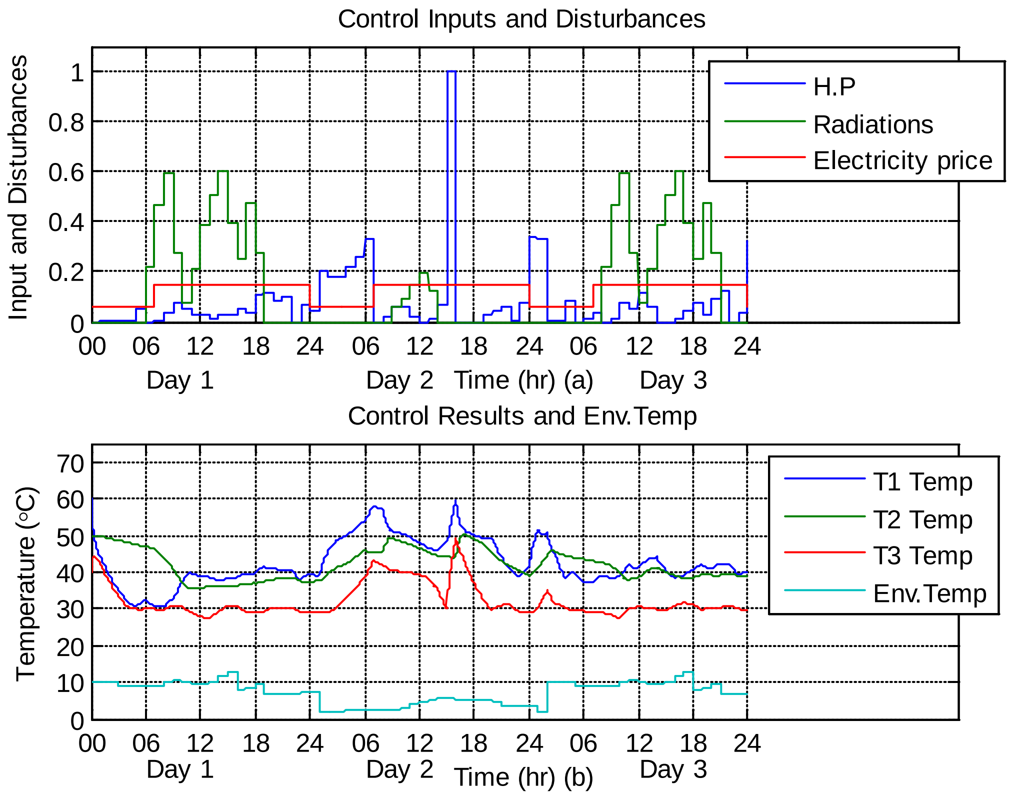


Figure 6-3: Model predictive control results with non-linear model

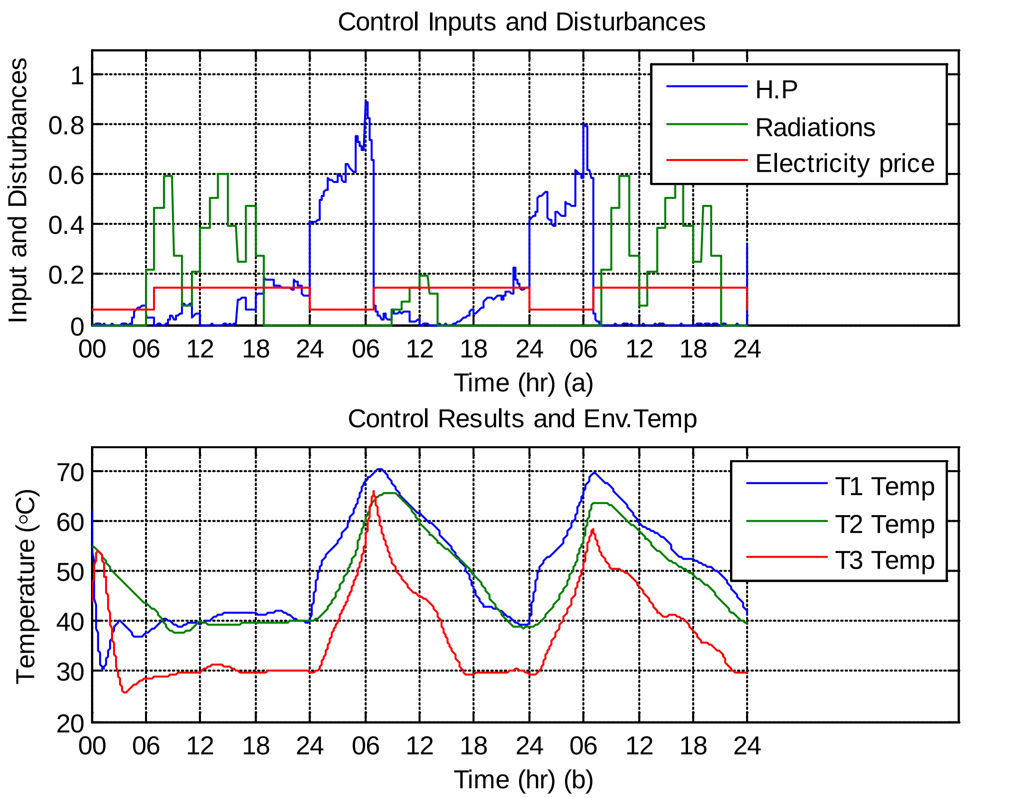


Figure 6-4: : Model predictive control results with linear model

The results given in Figure 6-5 and Figure 6-6 show the thermal comfort based control results. In Figure 6-5, during the night before day 2 the controller does not increase the hall temperature to get benefit from night-time electric tariffs. This is another result which occurs due to the non-linearities in the system. The linear MPC simulation using a linear model (Figure 6-6) shows that the control does heat up the hall air temperature on night 2. The other thing that has to be noted is that in Figure 6-6 PMV and room air temperatures are very smooth as compared to the results in Figure 6-5. The reduced control performance achieved there is again a result of the model mismatch due to non-linearites.

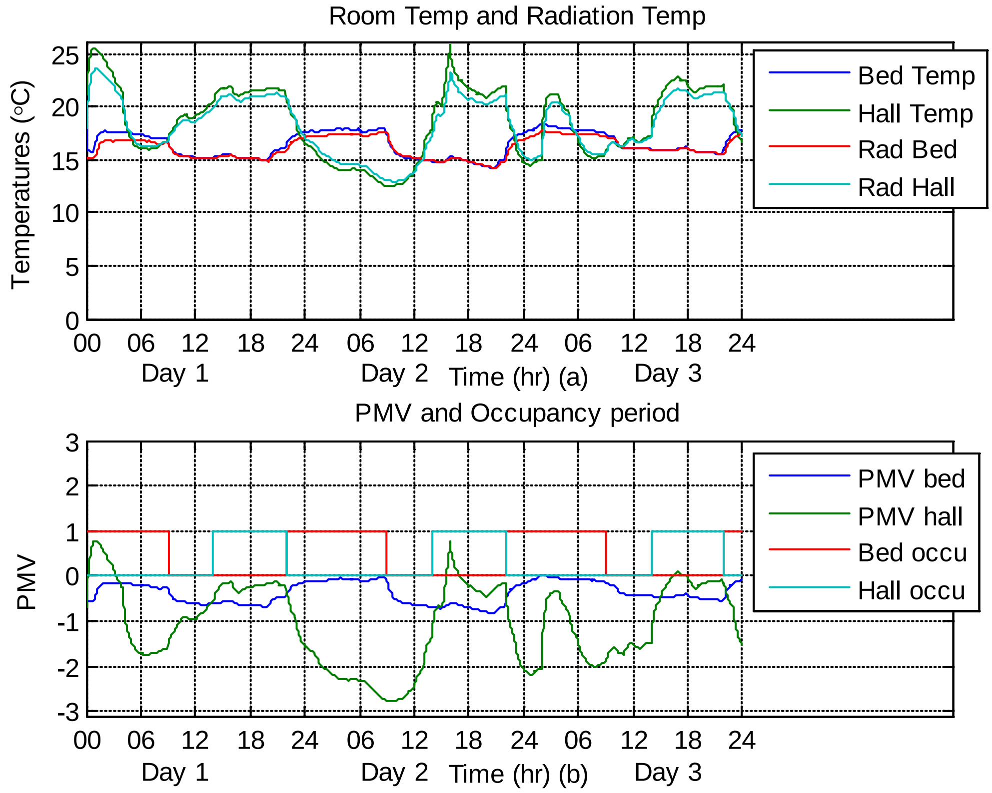


Figure 6-5: PMV and room air temperature results for non-linear model

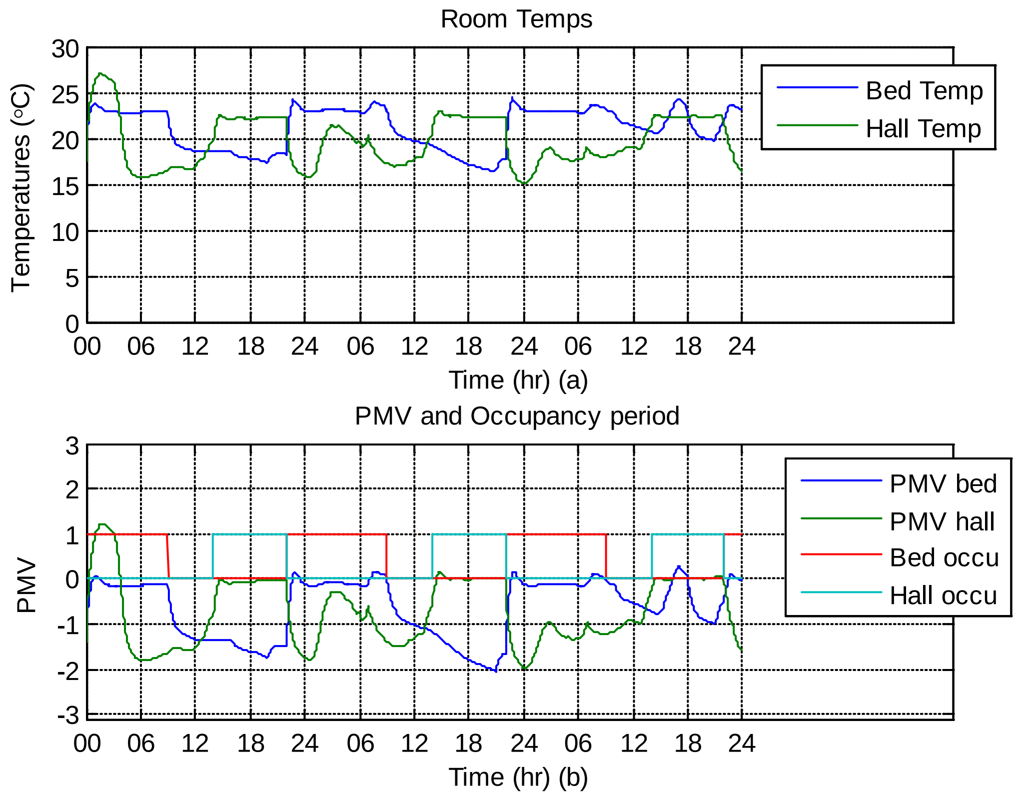


Figure 6-6: PMV and room air temperature results for linear model

Due to the use of a linear model, the MPC cannot anticipate non-linear effects, as they are not contained in the model. The evidence above demonstrates that these effects are significant, as the simulation with the linear model gives smoother and better results. The most important non-linear effects are the effectiveness of the COP of the heat pump due to changes in the tank temperature and the heat transfer depending on temperature difference.

The hall and bedroom air temperature predictions as generated by the MPC are plotted in Figure 6-7 for the linear simulation. Initially, the prediction graphs are very scattered due to the initial settling of the system and the controller. The plot also shows that the controller will always try to use the night-time electricity, and it stores some of the energy in the hall. The predicted temperatures during the occupied period converge strongly towards the set point, but they show much more variation during unoccupied periods. The reason is that the controller has a weight (penalty) during the occupied period whereas the penalty during the unoccupied period is zero and the controller has no incentive to maintain a certain temperature. Compared with Figure 6-8, which contains the predictions resulting from the non-linear simulation model, there are clear differences. Due to the model mismatch the controller is not able to predict the future behaviour accurately. This means that predictions are not realized as accurately, and they have to be changed a lot more to adjust to the simulation model. Even during the occupancy period the temperature predictions are not fully converged and this is a clear sign of model mismatch.

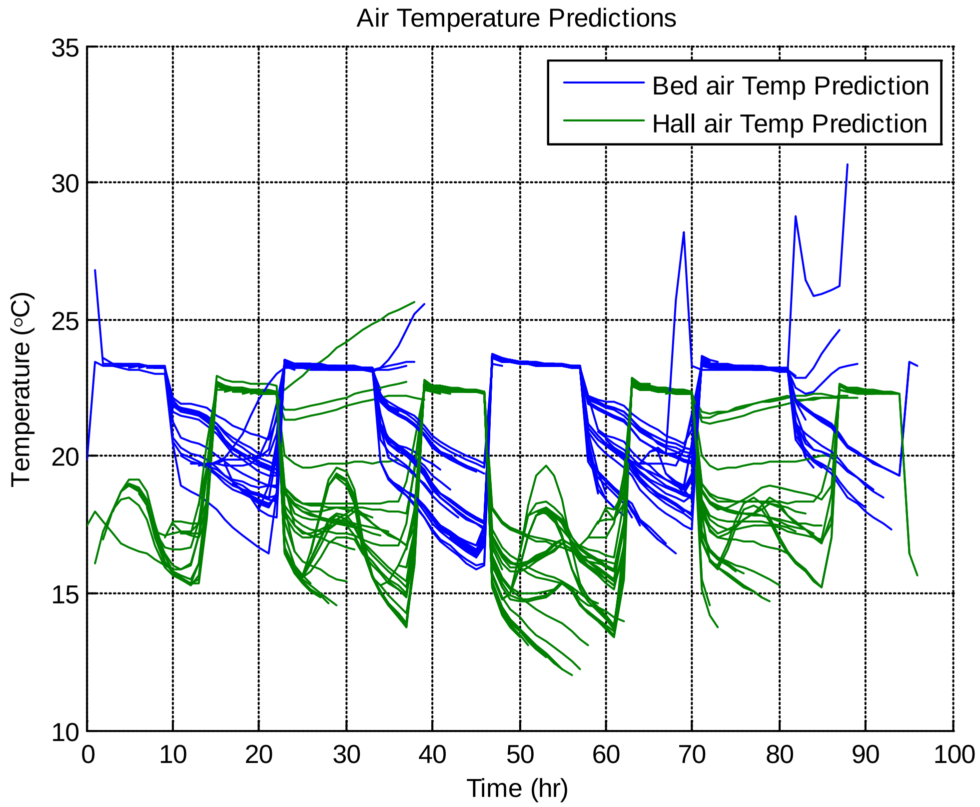


Figure 6-7: Predictions of hall air and bedroom air temperatures for linear simulation model case

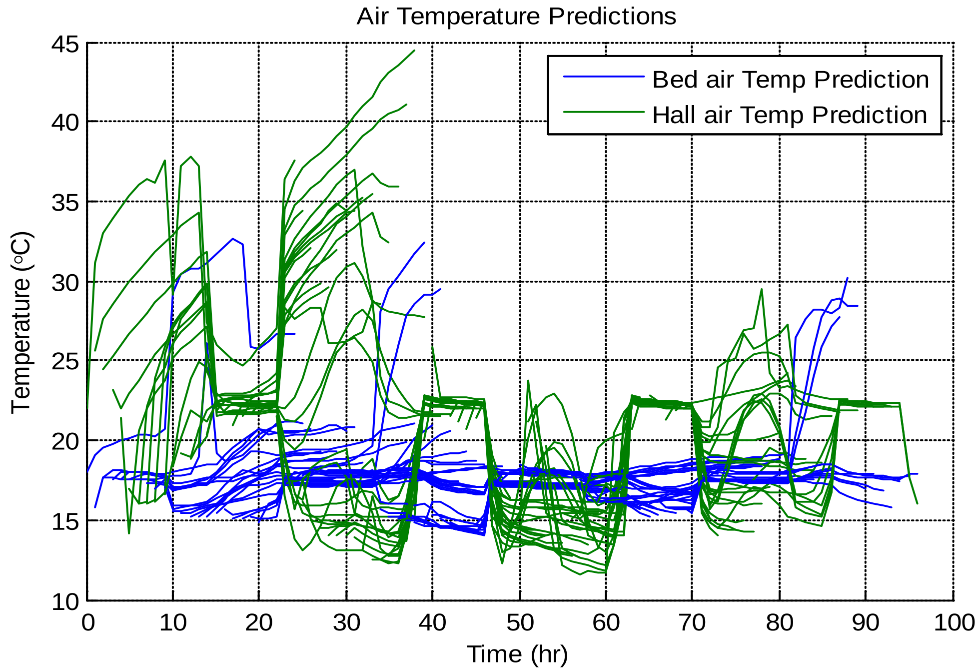


Figure 6-8: Predictions of hall air and bedroom air temperatures for non-linear simulation model case

6.3 Genetic Algorithms

To analyse the objective function mismatch further and with better comparability, a further method is investigated and was applied to the non-linear model. This problem cannot be solved using a quadratic programming algorithm as used by MPC, and instead a genetic algorithm known as a non-dominated sorting genetic algorithm (NSGA-II) is applied to the system.

Genetic algorithms (GA) were introduced by John Holland in 1970, and they are based on the principle of evaluation modelled after the mechanics of Darwin's natural selection theory. Genetic algorithms are used as optimization tools. Unlike other approaches, genetic algorithms do not provide one exact solution, but a collection of approximate solutions, which are known as a population. This method is applied to find the best global solution to the optimization problem. Each feasible solution in the population is called an individual and is encoded by a binary string called chromosomes. The population in each iteration is called a generation. The fitness of any individual in a generation is measured by the objective function and the objective function gives an idea of how individuals have performed in the given problem domain (Caldas et al., 2003).

A genetic algorithm has three stages that are applied to each generation and solution: reproduction, crossover and mutation. These operators control the next generation to give a closer approximation of the optimal solution. The probability of an individual for reproduction depends on its fitness value. A crossover operator is used for taking two solutions (parents) and creating a new individual (child solution). Mutation is used to maintain genetic diversity from one generation to the next. It involves randomly changing gene values in a solution to look for a better solution in the solution space (Caldas et al., 2003).

Genetic Algorithms are initiated by a starting population which often consists of random solutions for a given problem, evaluates them and applies the above mentioned genetic operators. This process generates a new generation with a higher level of fitness than the previous generation. This cycle is repeated for a number of generations which are set by the user. The number of generations depends on the complexity of the problem (Sahu et al., 2012). The GA's operation and its basic operators are shown in Figure 6-9. In recent years elaborate versions of these operators are available but the basic idea remains the same.

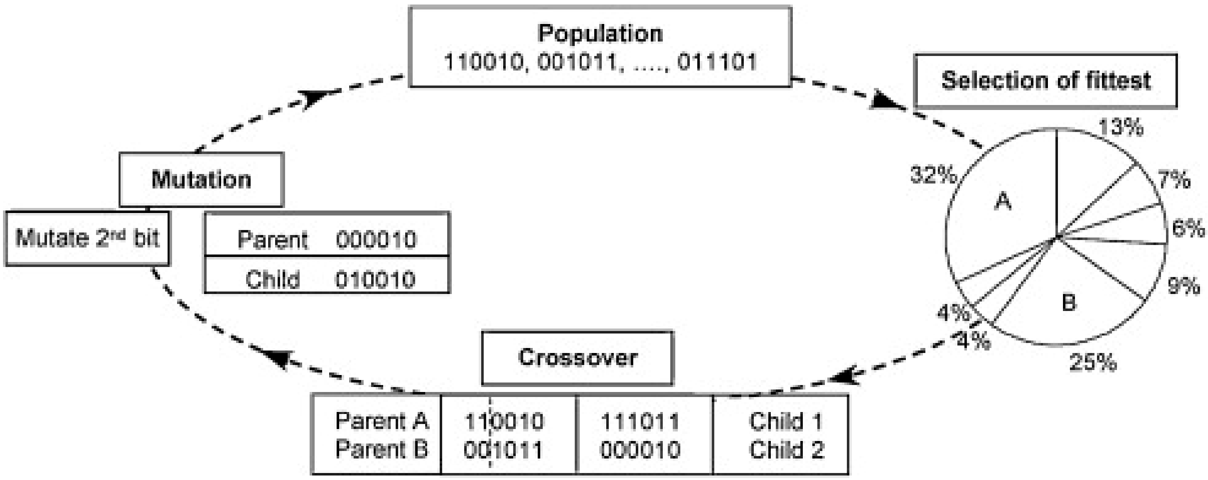


Figure 6-9: Basic GA operation and its operators Source: Sahu et al., 2012

A multi-objective GA is applied here to the problem to find an optimal solution for the problem. Below the focus is on the NSGA II description and its application to the control problem.

6.3.1 NSGA II

NSGA II is applied to find the best global solution to the optimization problem. NSGA II is used for multi-objective optimization problems and the control problem here has two objectives to meet i.e. energy consumption and thermal comfort. The key stage of NSGA II is the selection process, which takes into account more than one objective function. Also it finds the optimal solution over a pareto curve to find a compromise between the objectives. For these reasons NSGA II is more feasible for this problem. The NSGA II was first developed by Deb et al., 2002.

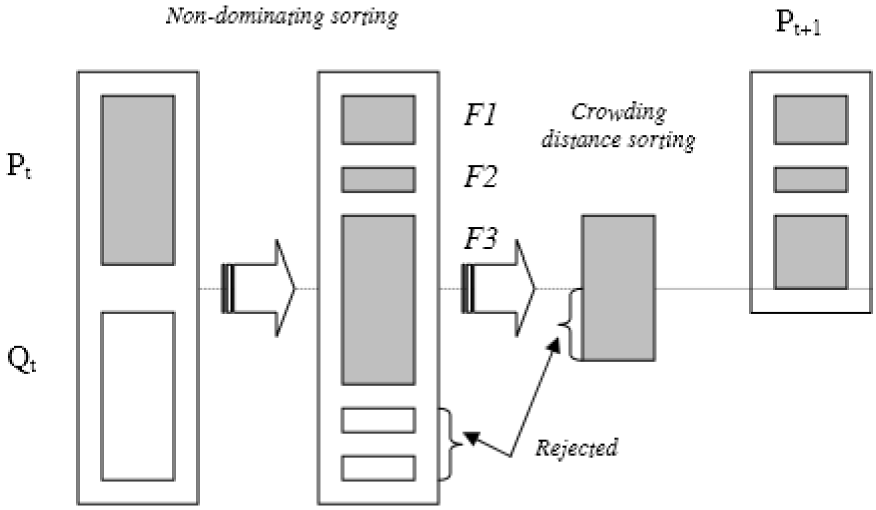


Figure 6-10: NSGA-II procedure (Source: Deb et al., 2002)

The procedure NSGA II uses to find population generation P_{t+1} from P_t is shown in Figure 6-10. Initially, a combined population of parents and offsprings (by recombination and mutation) is formed ($R_t = P_t + Q_t$). The size of R_t is equal to $P_t \cup Q_t$ and is of size $2N$. The population R_t is sorted based on non-domination. The elitism is ensured by including all the previous and current populations in the R_t. The resulting solution F1 is the best among all other solutions and is emphasized more than any other solution in the combined population. If the resulting solution F1 has a size smaller than N, then for next population P_{t+1}, all members of F1 are selected and the remaining members are selected from the subsequent non-dominated fronts in the order of their rankings. The sorting of the last solution which is to be accommodated e.g. F3 in above is done by using the crowded-comparison operator. The crowding distance is measured as the distance of the biggest cuboid containing the two solutions, which are neighbours to each other of the same non-dominating front in the objective space. The solution with higher crowding distance is selected for the next solution. The next step is to apply crossover and mutation to generate an offspring solution. The new generated population P_{t+1} is now used for selection, crossover and mutation to create a new generation.

For this current problem by using the system model, the deviations in temperatures and energy cost are determined. A pareto curve for NSGA II is shown in Figure 6-11. NSGA II tool gives a well spread out result on the pareto curve. A penalty is imposed on the cost outputs, in this case penalties of 0.1 and 1 are used for tank temperatures and room air temperature respectively. After the calculation of all objective functions of all strings, the solutions are classified into various non-dominated fronts. The crowded tournament selection operator is used to compare two solutions and return the winner of the tournament according to two characteristics: a non-dominated front in the population and a local crowding distance. The first attribute makes sure that the chosen solution lies on a better local crowding distance whereas, the second attribute ensures a better spread among the solution (Deb et al., 2002).

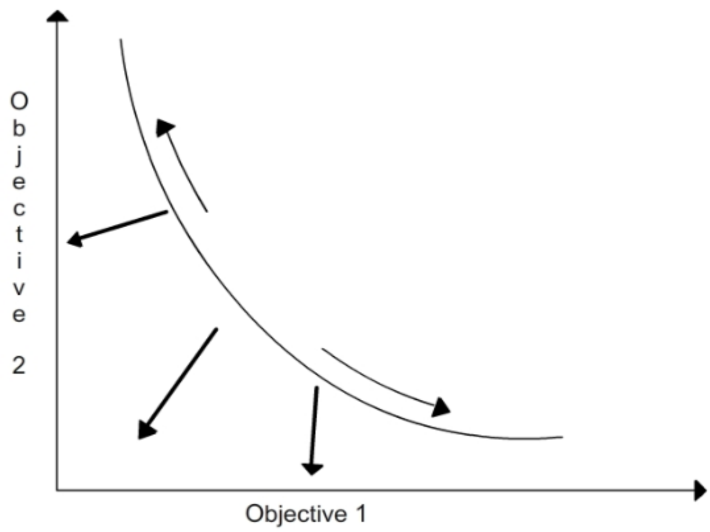


Figure 6-11: NSGA II pareto curve

6.4 Quadratic vs Linear Objective Function

NSGA-II also offers the opportunity to study a wider range of objective functions. The objective function used in this thesis is a quadratic one, because the solution algorithm depends on quadratic programming. The objective function of the quadratic programming is given in

$$J(k) = \sum_{i=N_1}^{N_2} Q(i)\big(y(k+i|k) - y_r(k+i|k)\big)^2 + \sum_{i=1}^{N_u} R(k)\big(u(k+i|k)\big)^2 \tag{6.1}$$

where N_1 and N_2 are the minimum and maximum cost horizons and N_u is the control horizon. The Q and R are the weights for outputs and inputs respectively. The terms in the objective $\big(u(k+i|k)\big)^2$ is the energy cost and $\big(y(k+i|k) - y_r(k+i|k)\big)^2$ is the thermal comfort. An alternative version of the MPC problem uses a linear objective function. The linear objective function is much more efficient than the quadratic function. The objective function for linear programming is now

$$J(k) = \sum_{i=N_1}^{N_2} Q(i)|y(k+i|k) - y_r(k+i|k)| + \sum_{i=1}^{N_u} R(k)|u(k+i|k)| \tag{6.2}$$

In the above objective function, the absolute values of the output error and the absolute values of the control increments are taken instead of their square values. The behaviour of both the objective functions is illustrated in Figure 6-12. This figure shows a problem with two decision variables x_1 and x_2 and the thick lines show the linear inequality constraints with the feasible solution being the interior of the region bounded by these lines. The dashed lines are the constant cost contours. For the linear objective function problem the cost increases as one moves upwards in the figure, whereas for quadratic case the cost increases as one moves out of the centre of the ellipse. The optimal solution for the linear objective function problems always lies on at least one constraint; it is expected to lie on the intersection of two constraints as shown in the figure. For the quadratic objective function problem the optimal solution behaves differently. The optimal solution is on one of the constraints. In a situation when the centre of the ellipse lies within the feasible solution then the optimal solution will not be on any constraints, rather it will be in the centre of ellipse. (Maciejowski, 2002).

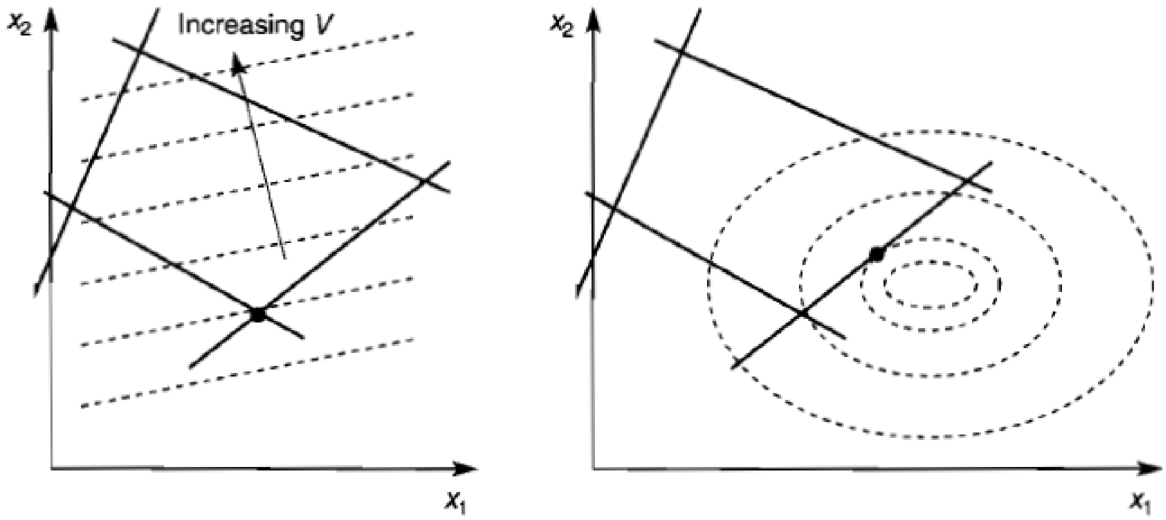


Figure 6-12: Constraints and cost contours for linear objective function (left) and quadratic objective function (right) problems. Source Maciejowski, J. 2002

The method used to solve linear objective function problems is called linear programming (LP) whereas for quadratic function problems the method used is known as quadratic programming (QP). The one reason for using the linear objective is that it can be solved more quickly than the quadratic objective function and there is more experience in solving linear objective problems both in commercial and industrial environments. However, with the advancement in computers and software, the importance of this reason is decreasing rapidly (Maciejowski, 2002). The use of the linear objective function for load function is feasible as it will give more load shifting during the night-time, but for thermal comfort it will give more temperature deviations which is not a requirement of the given control problem. The larger deviations in room air temperature are undesirable because occupants will complain about the indoor environment. For thermal comfort the quadratic objective is a good choice. This is demonstrated in Figure 6-13.

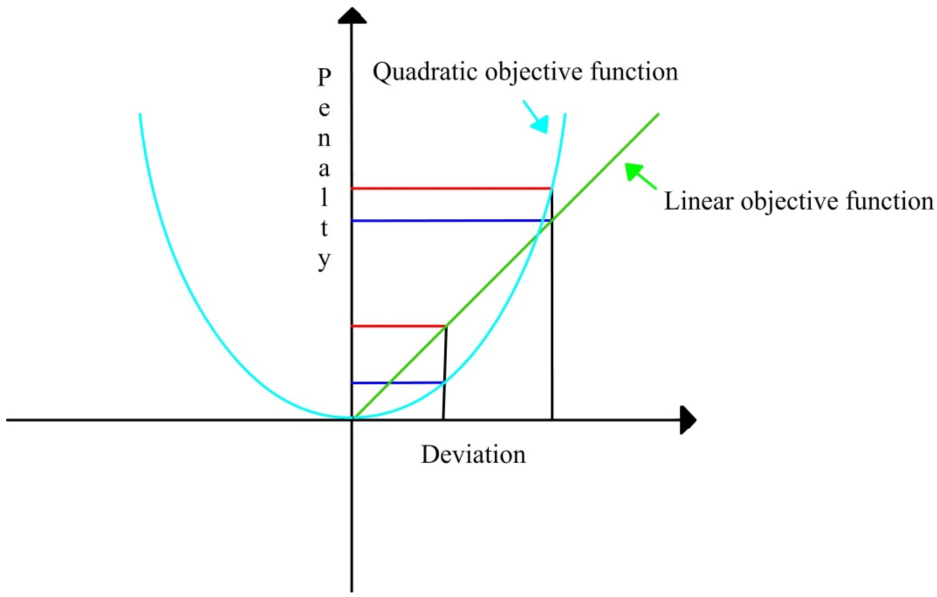


Figure 6-13: Linear and quadratic objective functions

The other reason for using LP programming in predictive control is that the resulting behaviour of the controller is different from the QP. The LP problems always find a solution at the intersection of the constraints. In the case of QP problems the solution can be off constraints, on a single constraint and sometimes, which is very rare, it can be at an intersection of constraints (Maciejowski, 2002).

Both programming methods have their own merits. In the case where it is more profitable to run a system with the plant at the intersection of several constraints and the system model is reasonably accurate, then the use of an LP method is more appropriate than the quadratic programming. However it is not advisable to hold the plant at the real constraints. There should always be some margin for unavoidable violation of constraints. Such constraint violations can arise due to errors in the model and measurement and/or unexpected disturbances. For such cases the QP solution will be more feasible to use. The disadvantage of LP is that it is only used when the system has constraints, for unconstraint problems the LP would not be able to find the solution and the solution can be at infinity (Maciejowski, 2002).

MATLAB MPC tool box does not support the linear objective function whereas the NSGA II does support any objective function that can be implemented. The domain objectives are a mix of both forms – the energy cost is a linear sum of the heat pump use, while the PMV is reflected accurately by a quadratic measure of the temperature deviation. This means a more practical objective function would be a combination of both:

$$J(k) = \sum_{i=N_1}^{N_2} Q(i)\big(y(k+i|k) - y_r(k+i|k)\big)^2 + \sum_{i=1}^{N_u} R(k)|u(k+i|k)| \tag{6.2}$$

A quadratic objective is used for the temperature deviations and for energy cost a linear weight is used.

6.4.1 Results

Figure 6-14 shows the results obtained by taking energy cost as the linear objective function. It shows that the linear cost have a pareto curve which can give the same temperature deviation but with less energy cost. The energy cost difference is small but by using the linear objective function it does help in reducing the energy cost. The mean temperature deviation plot is shown in Figure 6-15. This figure shows how much it will cost if someone decides to reduce the mean temperature deviation or how much it will save by increasing the temperature deviations.

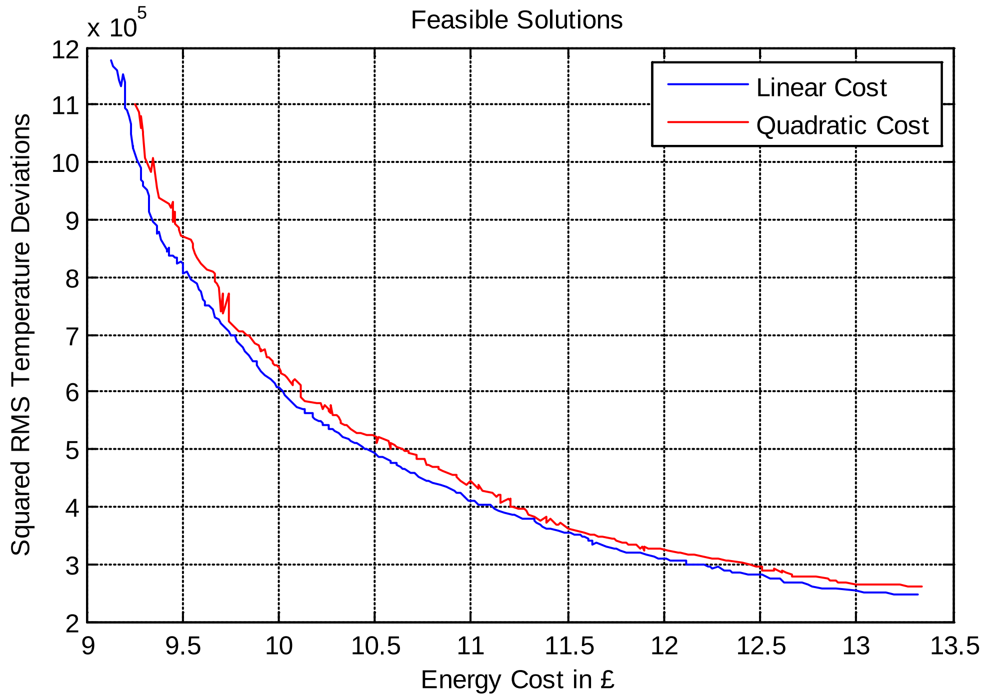


Figure 6-14: Feasible solution obtained after 200 generations for LP and QP

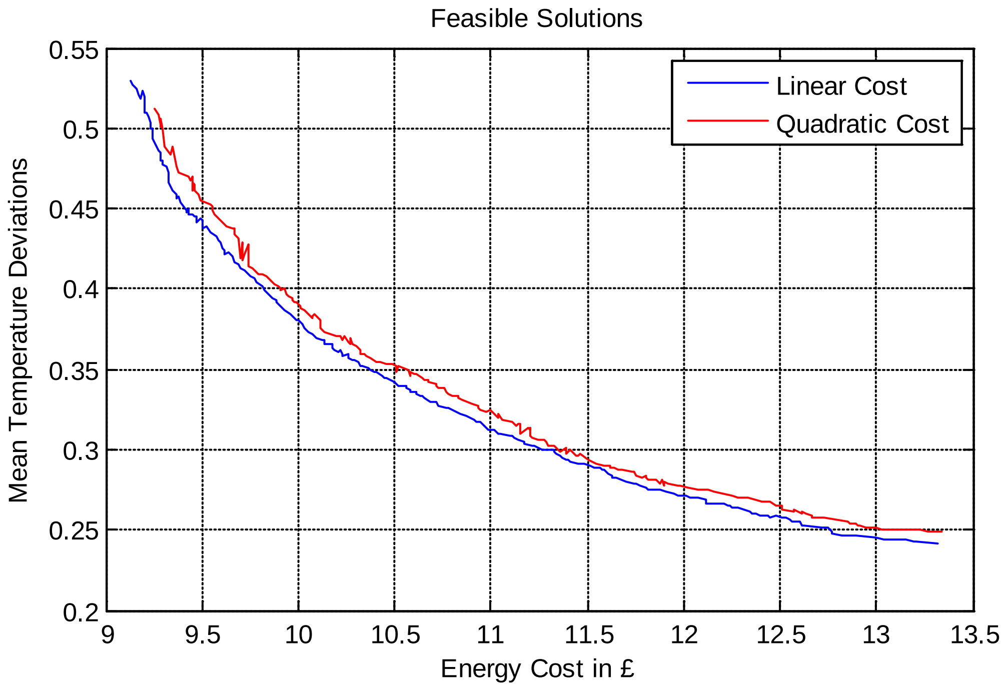


Figure 6-15: Mean temperature deviations and energy cost for linear and quadratic costs

6.5 Summary

In this chapter a comparison has been made to find out the effects of mismatch between the linear model and non-linear model. The simulations were performed by using a linear MPC applied to a non-linear system model and the same MPC to a linear system model. It was found out the MPC with the linear system model has used more night-time electricity and has also increased the tank temperatures to their maximum limits during the night. As all processes do contain non-linearities, the non-linear model performed less efficiently as compared to the linear case, but considering all the non-linearities this non-linear system model also performed well. The difference between quadratic and linear programming was also highlighted in this chapter by using a genetic algorithm called NSGA II. It was shown that the linear objective function has a slightly lower cost than the one from quadratic objective function. However, the QP solution was smoother than the LP solution.

Chapter 7 Conclusion and future work

7.1 Summary and conclusions

In the developed countries, energy consumption in buildings accounts for 20-40% of the final energy consumption. It has been increasing at a rate of 0.5-5% per annum. In 2004, the proportion of energy consumption in UK buildings was 39%, which is significant amount of energy (Pérez-Lombard et al., 2008). In order to reduce this energy consumption, the UK government is also committed to generating 15% of the country's energy from renewable energy. Different studies were conducted to find out the energy consumption cost of heat pump systems and it was found out that the electricity consumption price was cheaper than the conventional boiler system. The use of solar thermal collectors is also gaining popularity and they are used in combination with heat pumps. Although much of the work has been done to study the cost benefit of such systems, very little research has been done on the control of such systems. The control system is an important part of any HVAC or renewable energy system and is an important component of low energy buildings.

It was found in the literature that the solar collectors alone were unable to meet the heating requirement of dwellings and therefore an additional energy source was always needed. In this research different control strategies of a solar heating system combined with a heat pump were studied. The heating system of a building is challenging to control due to variations in the outside environmental conditions and indoor thermal comfort demands. The aim of the study was to develop an optimal control strategy for the mentioned system. A building consisting of two zones was considered and the wall, roof and floor were modelled by considering capacitance and resistances. This method took into account the time-varying effect of the building. The heat pump was modelled by using three different methods. The first method was to model the heat pump by using basic thermodynamic laws. The obtained model did not give promising results when compared with the limited available data from the manufacturer. It was also concluded that the response of the system was very fast as compared to the other elements of the system e.g. building model. This appeared to slow down the simulation by forcing a short time step for the global integration algorithm. The second method was to calculate the COP of the heat pump by considering four factors; thermal efficiency of the compressor, heat recovery of losses into heat, thermal coefficient on condenser side and thermal coefficient on evaporator side. It was found that the curve created by plotting the inverse of the ideal COP and the manufacturer's COP gave better results and was used as a heat pump model. The solar collector was modelled by using a single mathematical equation which is known as "Hottel-Whillier-Bliss equation".

Two conventional control strategies (PI and on-off controllers) and model predictive controller were applied to the system. Four different scenarios were simulated to analyse how these controllers behaved under different conditions. The PI and on-off controllers irrespective of disturbances performed well to maintain the tank temperatures and room air temperatures to their required set points. However, these control strategies did not consider the lower night-time electricity tariffs and so did not store energy during the off-peak demand period. The MPC performed well and used night-time electricity and also stored energy into the tanks during the night and used it during the day. The overall energy cost of the MPC was lower than the other two controllers, but the total energy consumption was slightly higher. The simulations were performed by using a linear internal model for MPC to control a non-linear model of the system.

It was also pointed out that a longer control horizon step was making the simulation slow down on a powerful computer. System limits also contributed to the longer time taken to perform a simulation scenario. This means that a longer control horizon step at this stage of the computing era is not feasible but in the next 10 years this could be possible to implement.

Comfort affects the quality of building and it is necessary to provide comfort to building occupants. To provide comfort in indoor environment, it is often compulsory to increase energy cost. Therefore a smart control system is needed which can save energy cost and can also provide better indoor environment. Control strategies for the space heating of a building in which the thermal comfort, as quantified by predicted mean vote (PMV) as a control variable, were also developed. PI and model predictive controller were used to control the room air temperature and also PMV of the occupants. The model predictive controller dealt well with the disturbances and was able to predict the occupancy pattern. The MPC performed smartly and heated the hall area during the night-time to store heat energy in the fabric even when there was no occupancy, by using night-time electricity.

Most real processes would contain some form of non-linearities and effects that may not be captured in a model. This issue was analysed and it was found that the controller works much better with a linear model than with the more accurate non-linear model. This is evident from the results in Figure 6-7 and Figure 6-8, which shows that the MPC was able to predict well and accurately when there was no mismatch between the models, and the model mismatch was clearly reducing the performance during the non-linear simulation model. The non-linear model is very close to the real system considered here, while the linear model is a significant simplification. In the absence of the model mismatch the MPC used more night-time electricity to increase the tank temperatures.

A genetic algorithm called NSGA II was used to analyse the mismatch caused by using different objective functions. The linear objective function did reduce the energy cost of the system but the quadratic objective function gave much smoother results.

The system is most suitable for residential market and the results highlight the importance of advanced controls for combined solar and heat pump systems in order for the system to operate efficiently and maintain good thermal comfort in the building. As the energy prices are predicted to increase significantly there is need for better comfort with lower energy consumption.

In summary, the investigation of performance of Model Predictive Control, and in particular its application to a solar heating system combined with heat pump, led to two conclusions. As the model of the plant used for control purpose was a non-linear one it cannot be recommended to be applied by the non-control engineers due to complex system dynamics. Secondly, for a simple linear plant model, MPC proved to be a strong and effective solution. The model predictive controller was able to tackle all the disturbances and was also predicting the occupancy well. However, It was not able to use lower night-time electricity tariffs to its full potential, and this shortfall can be explained by the model mismatch caused by the linearization.

7.2 Limitations of the research

Although this research work has looked into the developing and simulating model predictive controller and benchmarking with conventional controllers, there are some limitations. As discussed in headings 4.7.4, 4.7.5 and 5.4.2, the MPC used more computational time and using longer horizon was a serious limitation. This means the developed controller has to be implemented by using a powerful computer/hardware.

The model used in MPC was a linearized model of the system. The linearized model was unable to represent the non-linear effects and therefore causing model mismatch. This issue was discussed in detail in heading 6.2. This linear model requirement did not match the heat transfer between the tanks. The error increases as the tank temperature deviate from the nominal values used for linearization, and the effect on temperature stability is exacerbated by the long cycle time of the MPC controller. It may be possible to reduce this issue by using energy transfer rate rather than mass flow rate as a control input. Alternatively, an underlying control structure with faster response time could limit the effect on room temperatures. The use of right form of objective function was another limitation of this research. It was found that linear objective was more suitable for energy cost than the quadratic cost. This limitation was addressed by using NSGA II in heading 6.4.

7.3 Future work

- A method to predict the future disturbances should be developed so that these can be used to address disturbances in real time.
- The study investigated thermal comfort based control by considering only two variables to calculate the PMV of the system while keeping the other four factors constant. For thermal comfort control these four factors i.e. air humidity, occupant's activity, clothing and room air velocity should be embedded into the control algorithm.
- An improved linearization approach should be investigated. The linearization around a given point cannot guarantee the correct prediction of the system when the operating point digresses greatly. The effect was seen when the temperature of tank become outside the range covered by COP model. Therefore, the controller does not try to keep the tank temperature low unless

this goal is explicitly included in the cost function. One of the main limitations of MPC was found to be the use of a linear model requirement which did not match the heat transfer between the tanks. The error increases as the tank temperature deviates from the nominal values used for linearization, and the effect on temperature stability is exacerbated by the long cycle time of the MPC controller. It might be possible to reduce this issue by using energy transfer rate rather than mass flow rate as a control input. Alternatively, an underlying control structure with faster response time should be analysed that could limit the effect on room temperatures.

- It is expected that a simple model of building should have been helpful to reduce the time taken by the simulation and also for getting the same or even better results. Future work needs to be done with a simple building model with the wall having two material layers.
- The MATLAB toolbox only supports the quadratic objective function, therefore another toolbox should be used to quantify the benefits that can be achieved by using linear objective functions. The other toolbox should use the linear objective function into the MPC algorithm.
- A cascaded control scheme should be investigated that may give better control and can use the benefits of both modern controllers (MPC) and conventional controllers (PI).

References

AGRAWAL, N. & S., B. 2007. "Studies on a two-stage transcritical carbon dioxide heat pump cycle with flash intercooling." *Applied Thermal Engineering,* 27**,** 299-305.

ALLWRIGHT, J. C. 1994. "Advances in model-based Predictive Control. Chapter on min-max Model-Based Predictive Control." *Oxford University Press*.

ASCHER, U. M. & PETZOLD, L. R. 1998. "*Computer methods for ordinary differential equations and differential-algebric equations "*, The Society for Industrial and Applied Mathematics.

ASHRAE55 1992. "Thermal environment conditions for human occupancy, American Society of Heating." *Ventilating and Air Conditioning Engineers*.

ASHRAE 1989. "Thermal environmental conditions for human occupancy." *ANSI/ASHRAE standard, Atlanta*.

ASHRAE 2005. "ASHRAE Handbook – Fundamentals." *Refrigerating American Society of Heating and Air-Conditioning Engineers*.

ASHVE 1924. "Thermal comfort conditions." *ASHVE standard*.

AYOMPE, L. M. & DUFFY, A. 2013. "Analysis of the thermal performance of a solar water heating system with flat plate collectors in a temperate climate." *Applied Thermal Engineering,* 58**,** 447-454.

BEDFORD, T. 1936. "The warmth factor in comfort at work: A physiological study of heating and ventilation." *Industrial Health Research Board Report No.76, London: HMSO*.

BHATIA, A. 2012. *Fundamental of HVAC Controls* [Online]. Available: http://www.cs.berkeley.edu/~culler/cs294-f09/m197content.pdf [Accessed 07/08 2013].

BITMEAD, R. R., GEVERS, M. & & WERTZ, V. 1990. "Adaptive Optimal control. The thinking Man's GPC." *Prentice-Hall*.

BRAGER, G. S. & DE DEAR, R. J. 1998. "Thermal adaptation in the built environment: a literature review." *Energy and Buildings,* 27**,** 83-96.

BRAUN, J. E., KLEIN, S. A., MITCHELL, J. W. & BECKMAN, W. A. 1989. "Methodologies for optimal control to chilled water systems without storage." *ASHRAE Transactions,* 95**,** 652-662.

BRE 2009. "Clearline Solar Thermal Test Report – Average Household Simulation." *Client Report Number 251175 Viridian Solar*.

BRECSU. 1996. "General Information Report No. 40: Heating systems and their control. Energy Efficiency Best Practice Programme, DETR.".

BRUANT, M., GUARRACINO, G. & MICHEL, P. 2001. "DESIGN AND TUNING OF A FUZZY CONTROLLER FOR INDOOR AIR QUALITY AND THERMAL COMFORT MANAGEMENT." *International Journal of Solar Energy,* 21**,** 81-109.

CALDAS, L. G. & NORFORD, L. K. 2003. "Genetic algorithms for optimization of building envelopes and the design and control of HVAC systems." *Journal of Solar Energy Engineering,* 125**,** 343-351.

CAMACHO, E. F. & BORDONS, C. 2004. "Model Predictve Control." *Springer-Verlag, London*.

CAMPO, P. J. & MORARI, M. 1987. "Robust Model Predictive Control." *American Control Conference, 1987***,** 1021-1026.

CASTILLA, M., ÁLVAREZ, J. D., BERENGUEL, M., RODRÍGUEZ, F., GUZMÁN, J. L. & PÉREZ, M. 2011. "A comparison of thermal comfort predictive control strategies." *Energy and Buildings,* 43**,** 2737-2746.

CHEN, T. Y. 2002. "Application of adaptive predictive control to a floor heating system with a large thermal lag." *Energy and Buildings,* 34**,** 45-51.

CHI, J. & DIDION, D. 1982. "A simulation model of the transient performance of a heat pump." *International Journal of Refrigeration,* 5**,** 176-184.

CHO, S. H. & ZAHEER-UDDIN, M. 2003. "Predictive control of intermittently operated radiant floor heating systems." *Energy Conversion and Management,* 44**,** 1333-1342.

CIBSE 1986. "Environmental criteria for design, Section A1, CIBSE Guide, Vol A." *London: The Chartered Institute of Building Services Engineers*.

CIGLER, J., PRÍVARA, S., VÁŇA, Z., ŽÁČEKOVÁ, E. & FERKL, L. 2012. "Optimization of Predicted Mean Vote index within Model Predictive Control framework: Computationally tractable solution." *Energy and Buildings,* 52**,** 39-49.

CLARKE, D. W., MOHTADI, C. & TUFFS, P. S. 1987. "Generalized predictive control—Part I. The basic algorithm." *Automatica,* 23**,** 137-148.

CLARKE, D. W. & SCATTOLINI, R. 1991. "Constrained receding-horizon predictive control." *Control Theory and Applications, IEE Proceedings D,* 138**,** 347-354.

CLARKE, J. A., COCKROFT, J., CONNER, S., HAND, J. W., KELLY, N. J., MOORE, R., O'BRIEN, T. & STRACHAN, P. 2002. "Simulation-assisted control in building energy management systems." *Energy and Buildings,* 34**,** 933-940.

COFFEY, B., HAGHIGHAT, F., MOROFSKY, E. & KUTROWSKI, E. 2010. "A software framework for model predictive control with GenOpt." *Energy and Buildings,* 42**,** 1084-1092.

CRABB, J. A., MURDOCH, N. & PENMAN, J. M. 1987. "A simplified thermal response model." *Building Services Engineering Research & Technology,* 8**,** 13-19.

CRAWFORD, R. H. & TRELOAR, G. J. 2004. "Net energy analysis of solar and conventional domestic hot water systems in Melbourne, Australia." *Solar Energy,* 76**,** 159-163.

CROWN 2008. " The Environment in your Pocket." *Defra, Department of Environemnt, Food and Rural Affairs.*

CUTLER, C. R. & RAMBARKER, B. C. 1980. "dynamic matrix control- A computer control Algorithm." *In proceeding of Automatic Control conference, San Francisco.* .

DCLG. 2006. *Code for Sustainable Homes - A step-change in sustainable home building practice* [Online]. Available: http://www.planningportal.gov.uk/uploads/code_for_sust_homes.pdf [Accessed Oct 2012].

DE DEAR, R. & BRAGER, G. S. 1998. Developing an adaptive model of thermal comfort and preference.

DE DEAR, R. & BRAGER, G. S. 2001. "The adaptive model of thermal comfort and energy conservation in the built environment." *International Journal of Biometeorology,* 45**,** 100-108.

DEB, K., PRATAP, A., AGARWAL, S. & MEYARIVAN, T. 2002. "A fast and elitist multiobjective genetic algorithm: NSGA-II." *Evolutionary Computation, IEEE Transactions on,* 6**,** 182-197.

DECC. 2010a. *UK energy in brief 2010* [Online]. Available: http://www.decc.gov.uk/assets/decc/statistics/publications/brief/190-uk-energy-in-brief-2010.pdf [Accessed Oct 2012].

DECC. 2011b. *Renewable Heat Incentive* [Online]. Available: http://www.decc.gov.uk/assets/decc/what%20we%20do/uk%20energy%20supply/energy%20mix/renewable%20energy/policy/renewableheat/1387-renewable-heat-incentive.pdf [Accessed Oct 2012].

DEFRA 2008. "Measurement of domestic hot water consumption in dwellings." *Copyright Crown.*

DEWSON, T., DAY, B. & IRVING, A. D. 1993. "Least squares parameter estimation od a reduced order thermal model of an eperimental building." *Building and Environment,* 28 (2)**,** 127-137.

DOUNIS, A. I. & CARAISCOS, C. 2009. "Advanced control systems engineering for energy and comfort management in a building environment—A review." *Renewable and Sustainable Energy Reviews,* 13**,** 1246-1261.

DOUNIS, A. I., SANTAMOURIS, M. J. & LEFAS, C. C. 1992. "Implementation of artificial intelligence techniques in thermal comfort control for passive solar buildings." *Energy Conversion and Management,* 33**,** 175-182.

DOVRTEL, K. & MEDVED, S. 2012. "Multi-objective optimization of a building free cooling system, based on weather prediction." *Energy and Buildings,* 52**,** 99-106.

DTI 2001. "UK National Report 2001: Progress in energy efficiency indicators for the UK—An analysis based on the ODYSSEE Database. Ref: ED21330/R2." *Department of Trade and Industry, UK*.

DTI 2006. "The Energy Challenge, Department of Trade and Industry, London."

DTI 2007. "Meeting the Energy Challenge, Department of Trade and Industry, London."

DUFfiE, J. & BECKMAN, W. 1991. " Solar engineering of thermal processes. New York: Wiley."

DUFTON, A. F. 1929. "The eupatheostat." *Journal of Scientific Instruments,* 6**,** 249-251.

DUFTON, A. F. 1936. "The equivalent temperature of a warmed room." *JIHVE,* 4**,** 227-229.

EFTEKHARI, M. M. & MARJANOVIC, L. D. 2003. "Application of fuzzy control in naturally ventilated buildings for summer conditions." *Energy and Buildings,* 35**,** 645-655.

EL-DEEN, M. M. G. N. 2002. *Adaptive fuzzy logic control for solar buildings.* PhD Thesis, University of Northumbria, UK.

ENGLANDER, S. L. & NORFORD, L. K. 1992. "Saving fan energy in VAV systems, Part 2: Supply fan control for static pressure minimization using DDC zone feedback." *ASHRAE Transactions,* 98**,** 19-32.

EU 2006. "European Union Climate Change Programme, Brussles, EU ".

FANGER, P. O. 1970. "Thermal comfort." *Copenhagen:Danish Technical press*.

FARKAS, I. & VAJK, I. 2005. "Internal model-based controller for solar plant operation." *Computers and Electronics in Agriculture,* 49**,** 407-418.

FERREIRA, P. M., RUANO, A. E., SILVA, S. & CONCEIÇÃO, E. Z. E. "Neural networks based predictive control for thermal comfort and energy savings in public buildings." *Energy and Buildings, [In press: Online] 2012. Available from: http://dx.doi.org/10.1016/j.enbuild.2012.08.002 [Accessed Oct 2012]*.

FREIRE, R. Z., OLIVEIRA, G. H. C. & MENDES, N. 2008. "Predictive controllers for thermal comfort optimization and energy savings." *Energy and Buildings,* 40**,** 1353-1365.

FURBO, S., ANDERSEN, E., KNUDSEN, S., VEJEN, N. K. & SHAH, L. J. 2005. "Smart solar tanks for small solar domestic hot water systems." *Solar Energy,* 78**,** 269-279.

GAGGE, A. P., BURTON, A. C. & BAZETT, H. C. 1941. "A practical system of units for the description of the heat exchange of man with his environment." *Science,* 94**,** 428.

GRÜNENFELDER, W. & TÖDTLI, J. 1985. "The use of weather predictions and dynamic programming in the control of solar domestic hot water systems." *Proc. of Mediterranean Electrotechnical Conference (Melecon), Madrid, Spain*.

GUSTAFSSON, J., DELSING, J. & VAN DEVENTER, J. 2008. "Thermodynamic Simulation of a Detached House with District Heating Subcentral." *Systems Conference, 2nd Annual IEEE***,** 1-8.

HAINES, R. W. 1988. "HVAC system design handbook." *TAB Books,USA.*

HENZE, G., FELSMAAN, C. & KNABE, G. 2004. "Impact of forecasting accuracy on predictive optimal control of active and passive building thermal storage inventory." *International Journal of HVAC & Research,* 10 153–178.

HENZE, G., KALZ, D., LIU, S. & FELSMAAN, C. 2005. "Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory." *International Journal of HVAC & Research,* 11 189–214.

HERRING, H., HARDCASTLE, R. & PHILLIPSON, R. 1998. "Energy use and energy efficiency in UK commercial and public buildings up to the year 2000." *Energy Efficiency Series, Energy Efficiency Office, UK. ISBN 0-11-412903-7*.

HOUGHTON, F. C. & YAGLOGLOU, C. P. 1923. "Determining equal comfort lines." *Journal of ASHVE,* 29**,** 165-176.

HOUGHTON, F. C. & YAGLOGLOU, C. P. 1924. "Cooling effect on human beings produced by various air velocities." *Journal of ASHVE,* 30**,** 193.

HOUSE, J. M. & SMITH, T. F. 1995. "A system approach to optimal control for HVAC and building systems." *ASHRAE Transactions,* 101**,** 647-660.

HOUSE, J. M., SMITH, T. F. & ARORA, J. S. 1991. "Optimal control of a thermal system." *ASHRAE Transactions,* 97**,** 991-1001.

HUANG, B. J., LEE, J. P. & CHYNG, J. P. 2005. "Heat-pipe enhanced solar-assisted heat pump water heater." *Solar Energy,* 78**,** 375-381.

HUANG, G., WANG, S. & XU, X. 2009. "A robust model predictive control strategy for improving the control performance of air-conditioning systems." *Energy Conversion and Management,* 50**,** 2650-2658.

HULME, M., JENKINS,G.J., LU,X., TURNPENNY,J.R., MITCHELL,T.D., JONES,R.G., LOWE,J., MURPHY,J.M., HASSELL,D., BOORMAN,P., MCDONALD,R. AND HILL,S. 2002. Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report, Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK. 120pp.

HWI-BEOM, S. & JONG-GYU, P. 2012. "Anti-Windup PID Controller With Integral State Predictor for Variable-Speed Motor Drives." *Industrial Electronics, IEEE Transactions on,* 59**,** 1509-1516.

IEA 2008. "Energy Efficiency Requirements in Building Codes – Energy Efficiency Policies for New Buildings."

INTERNATIONALENERGYAGENCY 2006. Key world Energy Statistics.

ISO7730 1994. "Moderate thermal environment – determination of the PMV and PPD indices and specification of the conditions for thermal comfort." *International Organisation for Standardisation*.

ISO7730 2005. "Moderate thermal environments - determination of the PMV and PPD indices and specification of the conditions for thermal comfort." *Geneva: International Standards Organization*.

KALOGIROU, S. A. 2004. "Solar thermal collectors and applications." *Progress in Energy and Combustion Science,* 30**,** 231-295.

KE, Y.-P. & MUMMA, S. A. 1997. "Optimized supply-air temperature (SAT) in variable-air-volume (VAV) systems." *Energy,* 22**,** 601-614.

KERSLAKE, D. M. 1972. "The stress of hot environment." *Cambridge: Cambridge university press*.

KHALID, M. & SAVKIN, A. V. 2010. "A model predictive control approach to the problem of wind power smoothing with controlled battery storage." *Renewable Energy,* 35**,** 1520-1526.

KOLOKOTSA, D., POULIEZOS, A., STAVRAKAKIS, G. & LAZOS, C. 2009. "Predictive control techniques for energy and indoor environmental quality management in buildings." *Building and Environment,* 44**,** 1850-1863.

KOLOKOTSA, D., TSIAVOS, D., STAVRAKAKIS, G. S., KALAITZAKIS, K. & ANTONIDAKIS, E. 2001. "Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal–visual comfort and indoor air quality satisfaction." *Energy and Buildings,* 33**,** 531-543.

KREITH, F. & KREIDER, J. F. 1978. "*Principles of solar engineering.,"* New York: McGraw-Hill.

KUMMERT, M. & ANDRE, P. 2005a. "Simulation of a model-based optimal controller for heating systems under realistic hypotheses." *In Proceedings of the 9th International Building Performance Simulation Association (IBPSA) Conference, Montreal, Canada.*

KUMMERT, M., ANDRE, P. & ARGIGIOU, A. 2005b. "Performance comparison of heating control strategies combining simulation and experimental results." *In Proceedings of the 9th International Building Performance Simulation Association (IBPSA) Conference, Montreal, Canada.*

LEE, J. H., MORARI, M. & GARCIA, C. E. 1994. "State-space interpretation of model predictive control." *Automatica,* 30**,** 707-717.

LI, H. & YANG, H. 2010. "Study on performance of solar assisted air source heat pump systems for hot water production in Hong Kong." *Applied Energy,* 87**,** 2818-2825.

LIU, S. & HENZE, G. P. 2007. "Evaluation of reinforcement learning for optimal control of building active and passive thermal storage inventory." *Journal of Solar Energy Engineering,* 129**,** 215-225.

MA, Y., BORRELLI, F., HENCEY, B., PACKARD, A. & BORTOFF, S. 2009. "Modelpredictivecontrol of thermal energy storage in building cooling systems." *Proc. of 48th IEEE Conference on Decision and Control and 28th Chinese Control Conference, Shanghai, China*.

MACIEJOWSKI, J. M. 2002. "Predictive control with constraints." *Prentice-Hall*.

MAGNIER, L. & HAGHIGHAT, F. 2010. "Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network." *Building and Environment,* 45**,** 739-746.

MARJANOVIC, L. & EFTEKHARI, M. 2004. "Design and simulation of a fuzzy controller for naturally ventilated buildings." *Building Services Engineering Research and Technology,* 25**,** 33-53.

MATHWORKS. 2013. *PID Controller, Discrete PID Controller* [Online]. Available: http://www.mathworks.co.uk/help/simulink/slref/pidcontroller.html#br58hii-1 [Accessed January 2013].

MCINTYRE, D. A. 1980. "Indoor climate." *Essex:Applied science publishers*.

MISSENARD, A. 1935. "Théorie simplifeed Thermomètre Resultant." *Chauffage Ventilation***,** 347-352.

MISSENARD, A. 1959. "A thermique des ambiences: equivalences de passage, equivalences de séjours." *Chaleur et Industrie,* 276**,** 159–172 and 277, 189–198.

MOHTADI, C. 1986. "Advanced self-tuning algorithms." *PhD thesis, Oxford University*.

MORAN, M. J. & SHAPIRO, H. N. 2006. "Fundamentals of engineering thermodynamics, 5th edition. John Wiley & Sons, Inc.".

MORARI, M. 1994. "Advances in model-based predictive control, Chapter Model predictive control: Multivariable control Technique for choice in the 1990s?" *Oxford University Press*.

MOSCA, E., LEMOS, J. M. & ZHANG, J. Year. "Stabilizing I/O receding horizon control." *In:* Decision and Control, 1990., Proceedings of the 29th IEEE Conference on, 5-7 Dec 1990 1990. 2518-2523 vol.4.

NASSIF, N., KAJL, S. & SABOURIN, R. 2005. "Optimization of HVAC Control System Strategy Using Two-Objective Genetic Algorithm." *International Journal of HVAC & Research,* 11**,** 459-486.

NEVINS, R. G., ROHLES, F. H., SPRINGER, W. & FEYERHERM, A. M. 1966. "A temperature humidity chart for thermal comfort of seated persons." *ASHRAE Transactions,* 72**,** 283-291.

NICOL, F. & HUMPHREYS, M. 2002. "Adaptive thermal comfort and sustainable thermal standards for buildings." *Energy and Buildings,* 34**,** 563-572.

NÚÑEZ-REYES, A., NORMEY-RICO, J. E., BORDONS, C. & CAMACHO, E. F. 2005. "A Smith predictive based MPC in a solar air conditioning plant." *Journal of Process Control,* 15**,** 1-10.

NUNTAPHAN, A., CHANSENA, C. & KIATSIRIROAT, T. 2009. "Performance analysis of solar water heater combined with heat pump using refrigerant mixture." *Applied Energy,* 86**,** 748-756.

OLE FANGER, P. & TOFTUM, J. 2002. "Extension of the PMV model to non-air-conditioned buildings in warm climates." *Energy and Buildings,* 34**,** 533-536.

ONS 2009b. "Statistical Release: 2008 Green House Gas Emissions-Provisional Figures, London, Department of Energy and Climate Change."

PARIS, B., EYNARD, J., GRIEU, S., TALBERT, T. & POLIT, M. 2010. "Heating control schemes for energy management in buildings." *Energy and Buildings,* 42**,** 1908-1917.

PARSON, K. C. 2003. "Human thermal environments." *(Second ed.). London: Taylor & Francis*.

PÉREZ-LOMBARD, L., ORTIZ, J. & POUT, C. 2008. "A review on buildings energy consumption information." *Energy and Buildings,* 40**,** 394-398.

PRÍVARA, S., ŠIROKÝ, J., FERKL, L. & CIGLER, J. 2011. "Model predictive control of a building heating system: The first experience." *Energy and Buildings,* 43**,** 564-572.

PROPOI, A. I. 1963. "Use of LP methods for synthesizing sampled-data automatic systems." *Automn Remote Control,* 24.

QIN, S. J. & BADGWELL, T. A. 2003. "A survey of industrial model predictive control technology." *Control Engineering Practice,* 11**,** 733-764.

RAWLINGS, J. B. & MUSKE, K. R. 1993. "The stability of constrained receding horizon control." *Automatic Control, IEEE Transactions on,* 38**,** 1512-1516.

REN21. 2010. *Renewables 2010, global report* [Online]. Available: http://www.ren21.net/Portals/97/documents/GSR/REN21_GSR_2010_full_revised%20Sept2010.pdf [Accessed Oct 2012].

RICHALET, J., RAULT, A., TESTUD, J. L. & PAPON, J. 1978. "Model predictive heuristic control: Applications to industrial processes." *Automatica,* 14**,** 413-428.

ROHLES, F. H. 1970. "Thermal sensations of sedentary man in moderate temperature." *Institute for Environmental Research: Special Report, Kansas State University, USA.*

ROHLES, F. H. & NEVINS, R. G. 1971. "The nature of thermal comfort for sedentary man." *ASHRAE Transactions,* 77**,** 239-246.

ROSSITER, J. A. & KOUVARITAKIS, B. 1993. "Constrained stable generalised predictive control." *Control Theory and Applications, IEE Proceedings D,* 140**,** 243-254.

SAHU, M., BHATTACHARJEE, B. & KAUSHIK, S. C. 2012. "Thermal design of air-conditioned building for tropical climate using admittance method and genetic algorithm." *Energy and Buildings,* 53**,** 1-6.

SALSBURY, T. 2005. "A survey of control technologies in the building automation industry." *16th IFAC World Congress 2005*.

SCRI. 2010. *A review of the UK Domestic Energy System* [Online]. Available: http://live.scri.salford.ac.uk/wp-content/uploads/2010/12/SCRIenergyReport.pdf [Accessed Oct 2012].

TINDALE, A. 1993. "Third-order lumped-parameter simulation method." *Building Services Engineering Research & Technology,* 143(3)**,** 87-97.

TORDOROV, E. 2006. "*Optimal control theory. Bayesian brain: probabilistic approaches to neural coding.,"* The MIT Press, Cambridge, Massachusetts.

U.S.ENERGYINFORMATIONADMINISTRATION. 2011. *International Energy Outlook 2011* [Online]. Available: http://www.eia.gov/forecasts/ieo/pdf/0484(2011).pdf [Accessed 07/08 2012].

VAN DEN BOOM, T. J. J. & STROORVOGEL, A. A. 2010. "Model Predictive control." *DISC Course, Lecture Notes.*

VAN SCHIJNDEL, A. W. M. & DE WIT., M. H. 2003. "Advanced simulation of building systems and control with simulink." *In Proc. of 8th International IBPSA Conference, Eindhoven, Netherlands*, 1185-1192.

WANG, S. & JIN, X. 2000. "Model-based optimal control of VAV air-conditioning system using genetic algorithm." *Building and Environment,* 35**,** 471-487.

WANG, S. & MA, Z. 2008. "Supervisory and Optimal Control of Building HVAC Systems: A Review." *HVAC&R Research,* 14**,** 3-32.

WINSLOW, C. E. A. & HERRINGTON, L. P. 1949. "Temperature and human life." *Princeton, New jersey: Princeton university press*.

YAGLOGLOU, C. P. & MILLER, W. E. 1925. "Effective temperature with clothing." *ASHVE Transactions,* 31**,** 89.

ZADEH, L. A. & WHALEN, B. H. 1962. "On optimal control and linear programming." *IRE Trans. Auto. Control,* 7.

ZAIYI, L. & DEXTER, A. L. 2010. "An Inferential Model-Based Predictive Control Scheme for Optimizing the Operation of Boilers in Building Space-Heating Systems." *Control Systems Technology, IEEE Transactions on,* 18**,** 1092-1102.

ZERVAS, P. L., SARIMVEIS, H., PALYVOS, J. A. & MARKATOS, N. C. G. 2008. "Model-based optimal control of a hybrid power generation system consisting of photovoltaic arrays and fuel cells." *Journal of Power Sources,* 181**,** 327-338.

ZHANG, Y. & HANBY, V. I. 2006. "Model-based control of Renewable Energy systems in buildings." *HVAC&R research special issue,* 12(3a)**,** 739-760.

ZHENG, A. & MORARI, M. 1994. "Stability of model predictive Control with soft Constraints." *Internal report. California Institute of technology*.

ZHENG, G. R. & ZAHEER-UDDIN, M. 1996. "Optimization of thermal processes in a variable air volume HVAC system." *Energy,* 21**,** 407-420.

ZOGG, D., SHAFAI, E. & GEERING, H. P. Year. "A fault diagnosis system for heat pumps." *In:* IEEE Conference on Control Applications 2001 Maxico. 65-72.

Appendix A

Type		F2015-6
Delivered/supplied power* at 2/35 °C **	(kW)	5.4/1.4
Delivered/supplied power* at 7/35 °C **	(kW)	6.3/1.4
Delivered/supplied power* at -7/45 °C **	(kW)	3.7/1.6
Delivered/supplied power* at 0/45 °C **	(kW)	4.9/1.6
Delivered/supplied power* at 7/45 °C **	(kW)	6.0/1.7
Delivered/supplied power* at -7/50 °C **	(kW)	3.6/1.7
Delivered/supplied power* at 2/50 °C **	(kW)	5.0/1.8
Delivered/supplied power* at 7/50 °C **	(kW)	5.9/1.8
Delivered/supplied power* at 15/50 °C **	(kW)	7.2/1.9
Delivered/supplied power* at -15/45 °C **	(kW)	2.6/1.5
Delivered/supplied power* at 7/35 °C ***	(kW)	6.1/1.5
COP at 7/35 °C ***		4.21
Starting current	(A)	17
Motor protection setting	(A)	14
Soft-start relay		
Operating voltage		
Compressor		
Nominal flow heating medium	(l/s)	0,16
Internal pressure drop at nominal flow	(kPa)	1,3
Min-/max pressure heating medium side	(bar)	
Airflow	(m3/h)	1500
Nominal output, fan	(W)	70
Fuse	(A)	10
Enclosure class		
Max outgoing heating medium temperature (°C)		
Refrigerant volume (R407C)	(kg)	1,9

Figure A-1: Manufacturer's data for heat pump

Table A-1: Energy price, heat energy and energy consumption

Case A			
Controllers	Energy Price ($£$)	Heat Energy (kW)	Energy Consumption (kW)
On-Off	5.469	202.6	55.86
PI	5.676	208.4	57.26
MPC	4.938	203.7	58.56
Case B			
Controllers	Energy Price ($£$)	Heat Energy (kW)	Energy Consumption (kW)
On-Off	3.595	144.6	37.64
PI	3.77	148.8	38.55
MPC	3.391	144.4	38.89
Case C			
Controllers	Energy Price ($£$)	Heat Energy (kW)	Energy Consumption (kW)
On-Off	3.331	134.4	34.78
PI	3.512	139.9	36
MPC	3.13	133.7	36.46
Case D			
Controllers	Energy Price ($£$)	Heat Energy (kW)	Energy Consumption (kW)
On-Off	3.88	157.6	40.63
PI	4.028	160.9	41.24
MPC	3.872	156.7	43.05

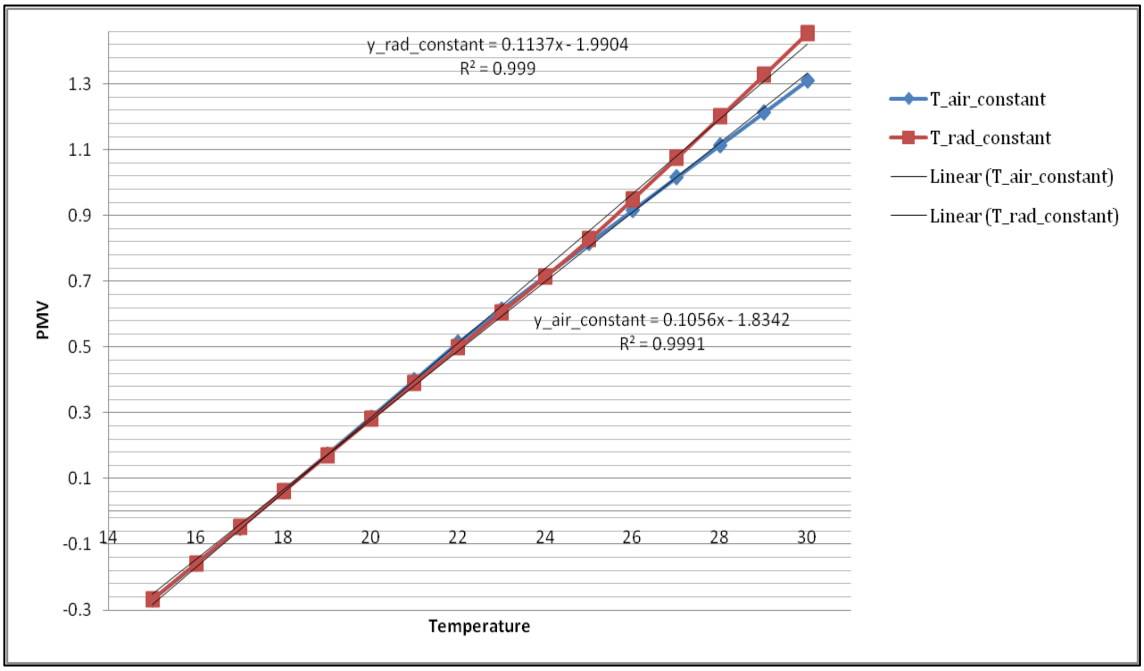


Figure A-2: PMV plot for bedroom occupant 2

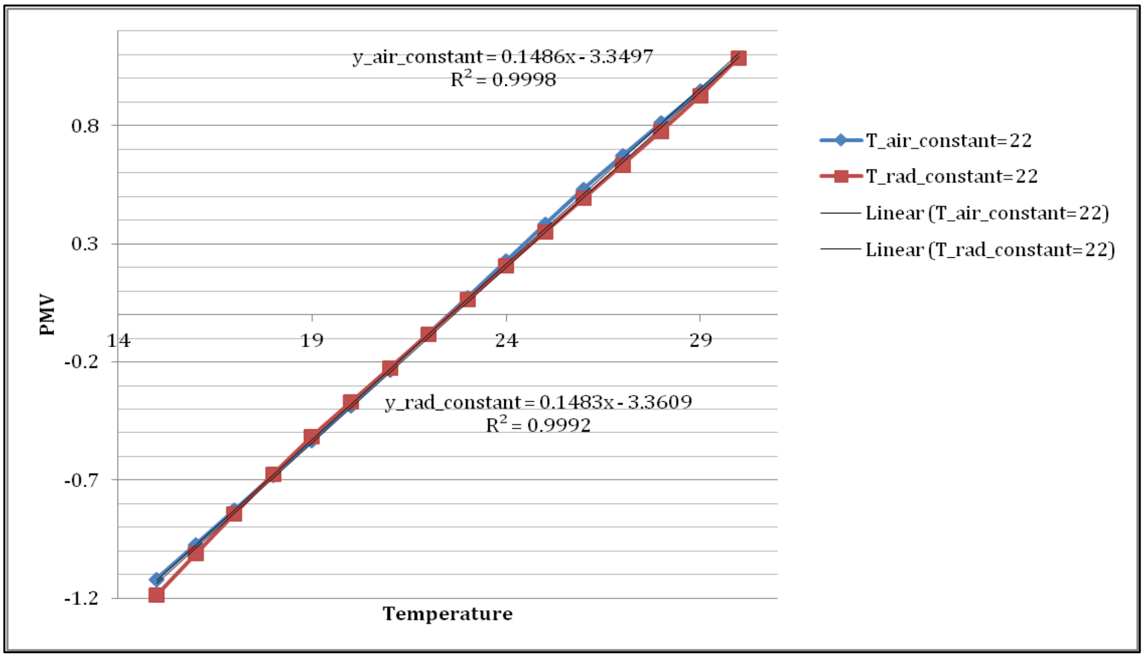


Figure A-3: PMV plot for occupant 1

Heat Pump model 1 derivation:

From equation 3.12;

$$\dot{Q}_{out} = \dot{W}COP \qquad \text{(A.1)}$$

The energy balance gives:

$$\dot{Q}_{out} = \dot{W} + \dot{Q}_{in} \tag{A.2}$$

$$\dot{Q}_{in} = \dot{W}(COP - 1) \tag{A.3}$$

the rate of heat energy gained by the evaporator from the air cycle is given by;

$$\dot{Q}_e = \dot{m}_{e1} C_r (T_{e,in} - T_{e,out}) \tag{A.4}$$

And the thermodynamics of the evaporator are

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{Q}_{in} \tag{A.5}$$

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{W}\ (COP - 1) \tag{A.6}$$

For the condenser the heat transferred in the water cycle is

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{W}\ (COP - 1) \tag{A.7}$$

$$\dot{Q}_c = \dot{m}_{c1} C_r (T_{c,out} - T_{c,in}) \tag{A.8}$$

Similarly from the dynamics of condenser,

$$C_c m_c \dot{T}_{c,out} = \dot{Q}_{out} - \dot{Q}_c \tag{A.9}$$

$$C_c m_c \dot{T}_{c,out} = \dot{W} COP - \dot{Q}_c \tag{A.10}$$

Appendix B State-Space model

$A =$

	x_1	x_2	x_3	x_4
x_1	-0.02171	0.00724	0.01214	0
x_2	0.001829	-0.002265	0	0
x_3	0.001829	0	-0.002265	0
x_4	0	0	0	-0.02177
x_5	0	0	0	0.001829
x_6	0	0	0	0.001829
x_7	7.97×10^{-6}	0	0	0
x_8	0	0	0	0
x_9	1.82×10^{-5}	0	0	2.427×10^{-5}
x_{10}	0.0008649	0	0	0
x_{11}	1.42×10^{-5}	0	0	0
x_{12}	0	$3.64E \times 10^{-5}$	0	0
x_{13}	0	0	0	0
x_{14}	0	0	3.64×10^{-5}	0
x_{15}	0	0	0	0
x_{16}	0	0	0	0.0005561
x_{17}	0	0	0	1.42×10^{-5}
x_{18}	0	0	0	0
x_{19}	0	0	0	0
x_{20}	0	0	0	0
x_{21}	0	0	0	0
x_{22}	0	0	0	0

	x_5	x_6	x_7	x_8
x_1	0	0	0.0001734	0
x_2	0	0	0	0
x_3	0	0	0	0
x_4	0.00724	0.01214	0	0
x_5	-0.002265	0	0	0
x_6	0	-0.002265	0	0
x_7	0	0	-0.0001321	2.39×10^{-5}
x_8	0	0	2.39×10^{-5}	3.19×10^{-5}
x_9	0	0	7.28×10^{-5}	6.07×10^{-6}
x_{10}	0	0	0	0
x_{11}	0	0	0	0
x_{12}	0	0	0	0
x_{13}	0	0	0	0
x_{14}	0	0	0	0
x_{15}	0	0	0	0
x_{16}	0	0	0	0

x_{17}	0	0	0	0
x_{18}	3.64×10^{-5}	0	0	0
x_{19}	0	0	0	0
x_{20}	0	3.64×10^{-5}	0	0
x_{21}	0	0	0	0
x_{22}	0	0	0	0

	x_9	x_{10}	x_{11}	x_{12}
x_1	0.0005202	0.0003374	0.000728	0
x_2	0	0	0	0.0004359
x_3	0	0	0	0
x_4	0.0006936	0	0	0
x_5	0	0	0	0
x_6	0	0	0	0
x_7	9.569×10^{-5}	0	0	0
x_8	7.974×10^{-6}	0	0	0
x_9	-0.0001333	0	0	0
x_{10}	0	-0.001309	0	0
x_{11}	0	0	-4.78×10^{-5}	0
x_{12}	0	0	0	-3.971×10^{-5}
x_{13}	0	0	0	0.0001237
x_{14}	0	0	0	0
x_{15}	0	0	0	0
x_{16}	0	0	0	0
x_{17}	0	0	0	0
x_{18}	0	0	0	0
x_{19}	0	0	0	0
x_{20}	0	0	0	0
x_{21}	0	0	0	0
x_{22}	0	8.264×10^{-5}	0	0

	x_{13}	x_{14}	x_{15}	x_{16}
x_1	0	0	0	0
x_2	0	0	0	0
x_3	0	0.0004359	0	0
x_4	0	0	0	0.000217
x_5	0	0	0	0
x_6	0	0	0	0
x_7	0	0	0	0
x_8	0	0	0	0
x_9	0	0	0	0
x_{10}	0	0	0	0
x_{11}	0	0	0	0
x_{12}	3.286×10^{-6}	0	0	0
x_{13}	-0.002382	0	0	0
x_{14}	0	-3.971×10^{-5}	3.286×10^{-6}	0
x_{15}	0	0.0001237	-0.002382	0
x_{16}	0	0	0	-0.0008539
x_{17}	0	0	0	0
x_{18}	0	0	0	0
x_{19}	0	0	0	0
x_{20}	0	0	0	0
x_{21}	0	0	0	0
x_{22}	0	0	0	5.537×10^{-5}

	$x17$	$x18$	$x19$	$x20$	$x21$	$x22$
$x1$	0	0	0	0	0	0
$x2$	0	0	0	0	0	0
$x3$	0	0	0	0	0	0
$x4$	0.000728	0	0	0	0	0
$x5$	0	0.0004359	0	0	0	0
$x6$	0	0	0	0.0004359	0	0
$x7$	0	0	0	0	0	0
$x8$	0	0	0	0	0	0
$x9$	0	0	0	0	0	0
$x10$	0	0	0	0	0	0.0004444
$x11$	0	0	0	0	0	0
$x12$	0	0	0	0	0	0
$x13$	0	0	0	0	0	0
$x14$	0	0	0	0	0	0
$x15$	0	0	0	0	0	0
$x16$	0	0	0	0	0	0.0002978
$x17$	-4.78×10^{-5}	0	0	0	0	0
$x18$	0	-3.971×10^{-5}	3.286×10^{-6}	0	0	0

$x19$	0	0.0001237	-0.002382	0	0	0
$x20$	0	0	0	-3.971×10^{-5}	3.286×10^{-6}	0
$x21$	0	0	0	0.0001237	-0.002382	0
$x22$	0	0	0	0	0	-0.000138

B=

	u_1	u_2	u_3	u_4	u_5	u_6
x_1	0	0	0	0	0.05247	0
x_2	0	0	0	0	0	0
x_3	0	0	0	0	0	0
x_4	0	0	0	0	0	0.06087
x_5	0	0	0	0	0	0
x_6	0	0	0	0	0	0
x_7	0.01137	-0.00399	-0.01196	0	0	0
x_8	0	0.003987	0	0	0	0
x_9	0	0	0.009102	-0.00019	-0.001836	-0.00213
x_{10}	0	0	0	0	0	0
x_{11}	0	0	0	0	0	0
x_{12}	0	0	0	0	0	0
x_{13}	0	0	0	0	0	0
x_{14}	0	0	0	0	0	0
x_{15}	0	0	0	0	0	0
x_{16}	0	0	0	0	0	0
x_{17}	0	0	0	0	0	0
x_{18}	0	0	0	0	0	0
x_{19}	0	0	0	0	0	0
x_{20}	0	0	0	0	0	0
x_{21}	0	0	0	0	0	0
x_{22}	0	0	0	0	0	0

	u_7	u_8	u_9	u_{10}	u_{11}	u_{12}
x_1	0.0005722	0	0	0.01734	0	0
x_2	0	0	0	0	0	0
x_3	0	0	0	0	0	0
x_4	0.0007548	0	0	0	0.01734	0
x_5	0	0	0	0	0	0
x_6	0	0	0	0	0	0
x_7	7.770×10^{-6}	0	0	0	0	0
x_8	0	-3.721×10^{-5}	0	0	0	0
x_9	1.189×10^{-5}	0	0.00165	0	0	0
x_{10}	0	0	0	0	0	0
x_{11}	3.362×10^{-5}	0	0	0	0	0
x_{12}	0	0	0	0	0	0
x_{13}	2.259×10^{-3}	0	0	0	0	0
x_{14}	0	0	0	0	0	0
x_{15}	2.259×10^{-3}	0	0	0	0	0
x_{16}	0	0	0	0	0	0
x_{17}	3.362×10^{-5}	0	0	0	0	0
x_{18}	0	0	0	0	0	0

x_{19}	2.259×10^{-3}	0	0	0	0	0
x_{20}	0	0	0	0	0	0
x_{21}	2.590×10^{-3}	0	0	0	0	0
x_{22}	0	0	0	0	0	0

$C =$

	x_1	x_2	x_3	x_4	x_5	x_6	x_7
y_1	0.1568	0.0784	0.0784	0	0	0	0
y_2	0.1554	0.078	0.078	0	0	0	0
y_3	0	0	0	0.1497	0.075	0.075	0
y_4	0	0	0	0.1483	0.0743	0.0743	0
y_5	0	0	0	0	0	0	1
y_6	0	0	0	0	0	0	0
y_7	0	0	0	0	0	0	0
y_8	1	0	0	0	0	0	0
y_9	0	0	0	1	0	0	0

	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
y_1	0	0	0	0	0	0	0
y_2	0	0	0	0	0	0	0
y_3	0	0	0	0	0	0	0
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	1	0	0	0	0	0	0
y_7	0	1	0	0	0	0	0
y_8	0	0	0	0	0	0	0
y_9	0	0	0	0	0	0	0

	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}
y_1	0	0	0	0	0	0	0
y_2	0	0	0	0	0	0	0
y_3	0	0	0	0	0	0	0
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	0	0	0	0	0	0	0
y_7	0	0	0	0	0	0	0
y_8	0	0	0	0	0	0	0
y_9	0	0	0	0	0	0	0

	x_{22}
y_1	0
y_2	0
y_3	0
y_4	0
y_5	0
y_6	0
y_7	0
y_8	0
y_9	0

$D =$

	u_1	u_2	u_3	u_4	u_5	u_6	u_7
y_1	0	0	0	0	0	0	0
y_2	0	0	0	0	0	0	0
y_3	0	0	0	0	0	0	0
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	0	0	0	0	0	0	0
y_7	0	0	0	0	0	0	0
y_8	0	0	0	0	0	0	0
y_9	0	0	0	0	0	0	0

	u_8	u_9	u_{10}	u_{11}	u_{12}
y_1	0	0	0	0	0
y_2	0	0	0	0	0
y_3	0	0	0	0	0
y_4	0	0	0	0	0
y_5	0	0	0	0	0
y_6	0	0	0	0	0
y_7	0	0	0	0	0
y_8	0	0	0	0	0
y_9	0	0	0	0	0

Input groups:

Name	Channels
Manipulated	$[u_1, u_2, u_3, u_4, u_5, u_6]$
Measured	$[u_7, u_8, u_9, u_{10}, u_{11}, u_{12}]$

Output groups:

Name	Channels
Measured	$[y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_8, y_9]$

Continuous-time state-space model.

Appendix C   Simulink Models

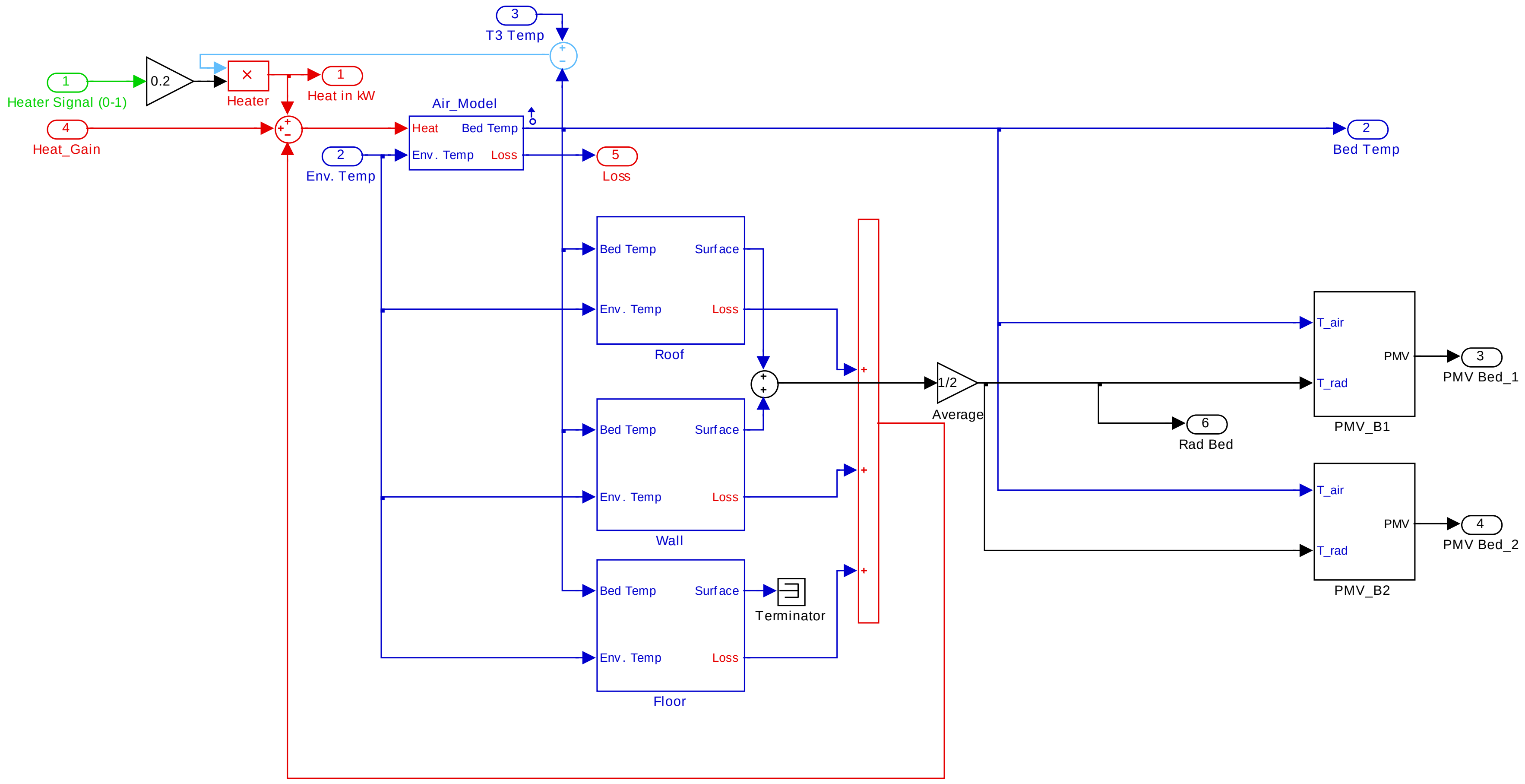


Figure C- 1: Simulink model of the bedroom

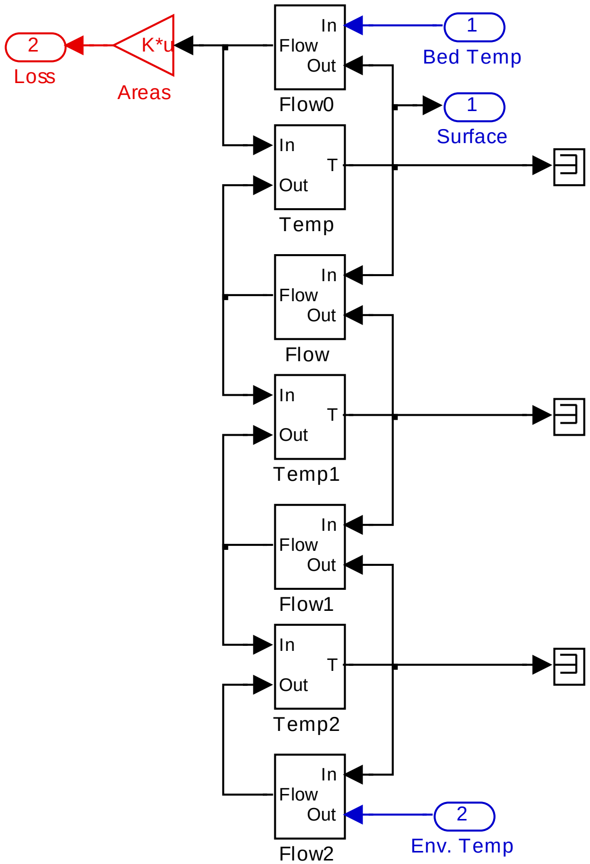


Figure C- 3: Simulink model of wall

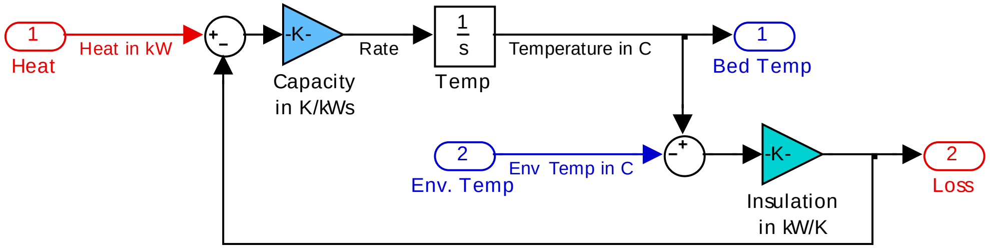


Figure C- 2: Simulink model of air

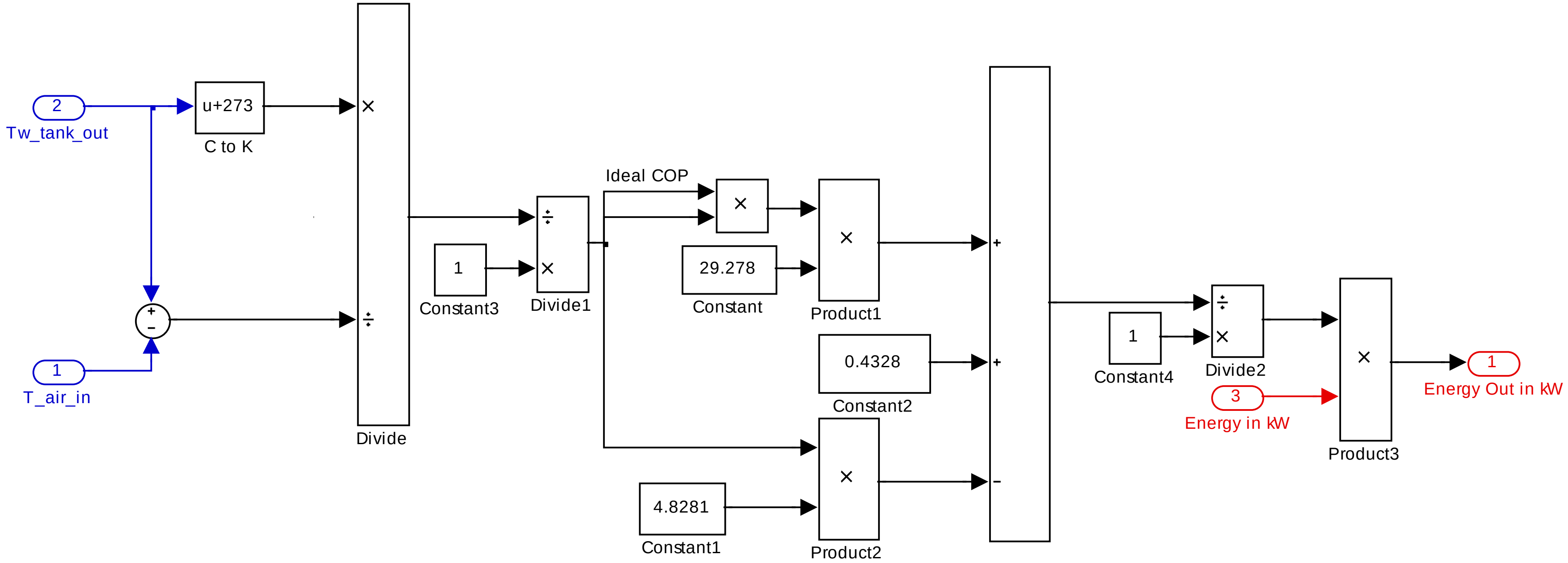


Figure C- 4: COP model of the heat pump

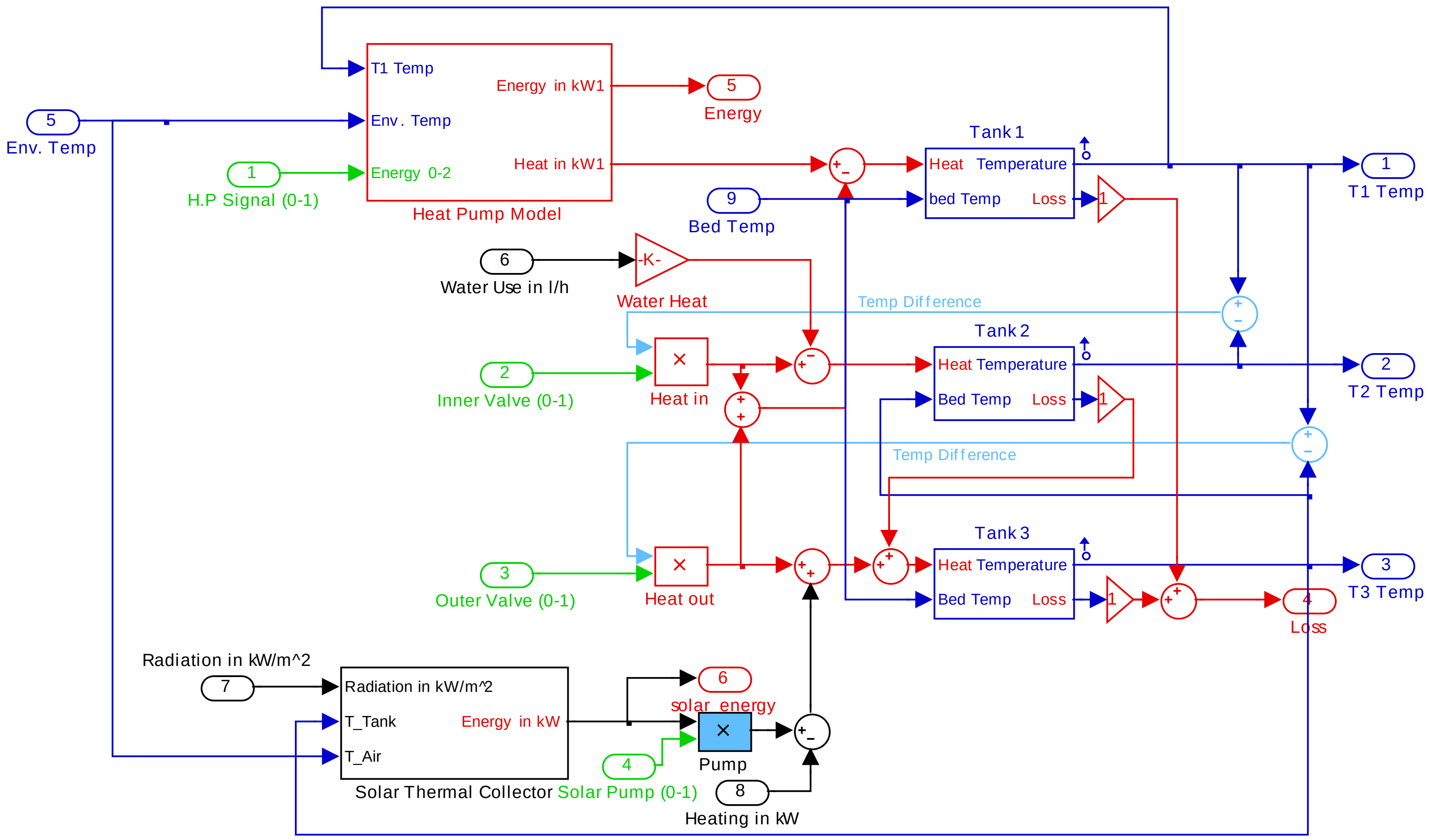


Figure C- 5: Connection between HP, solar collector and tanks

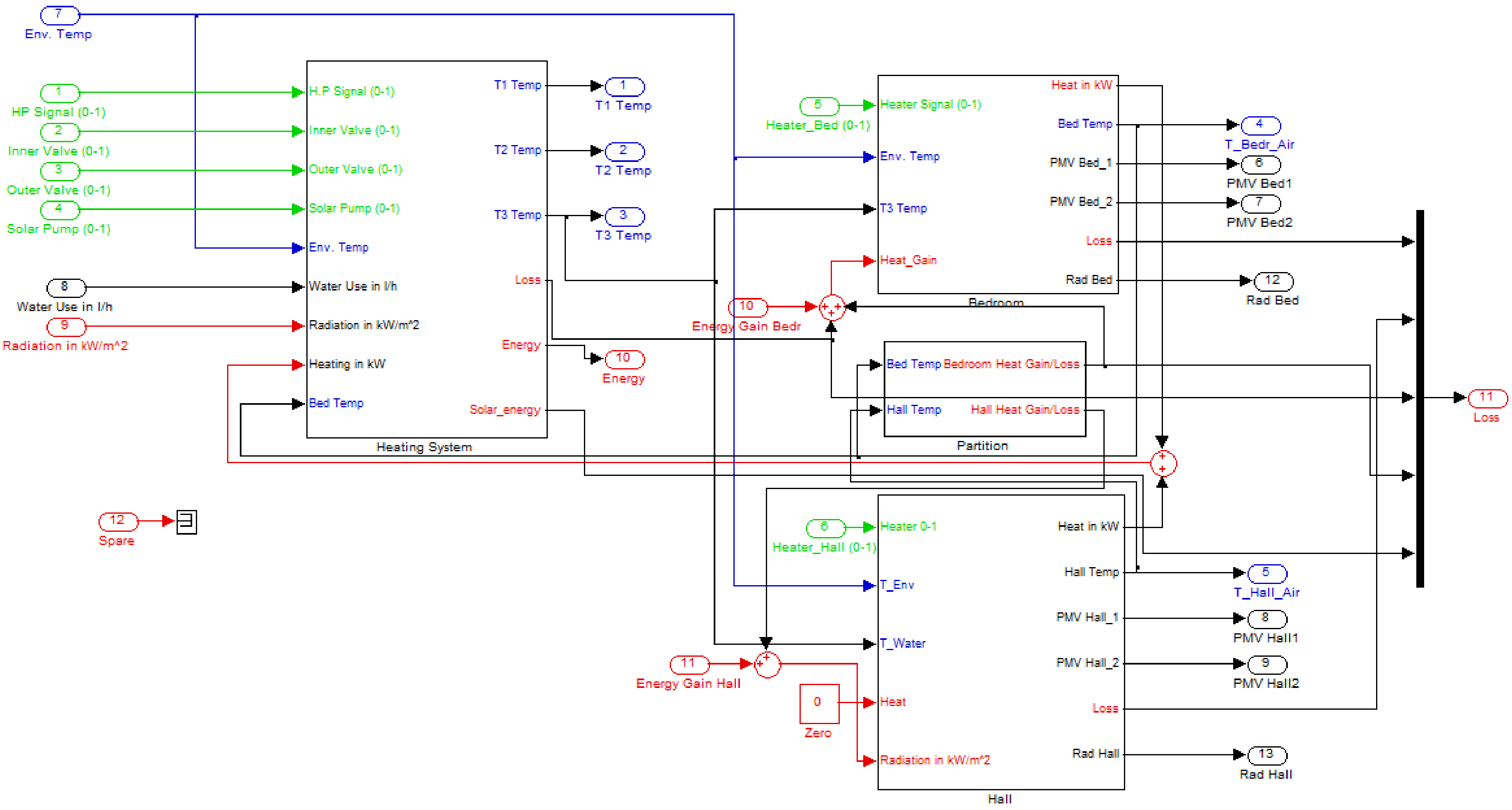


Figure C- 6: Energy flow model of heating system and living spaces

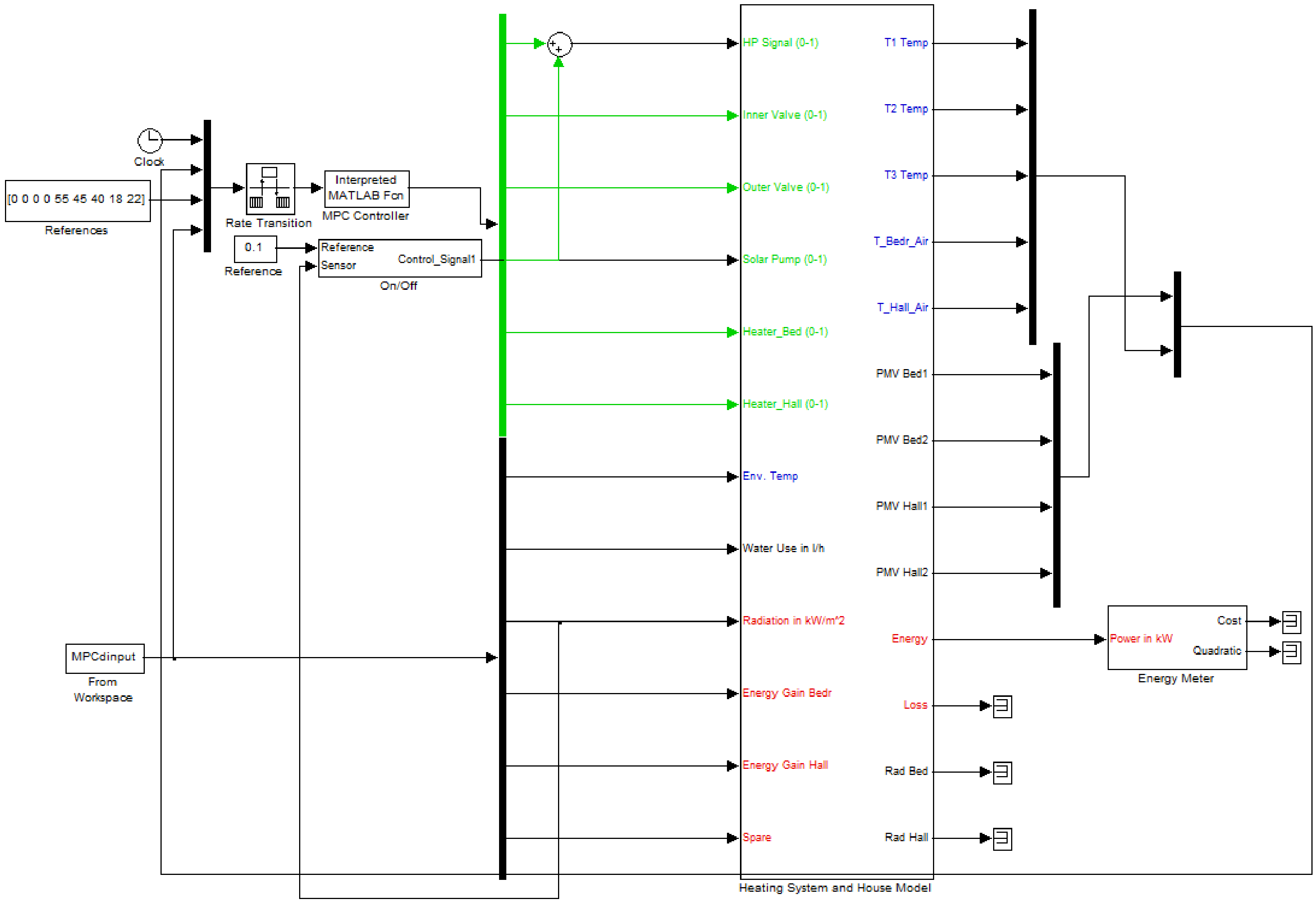
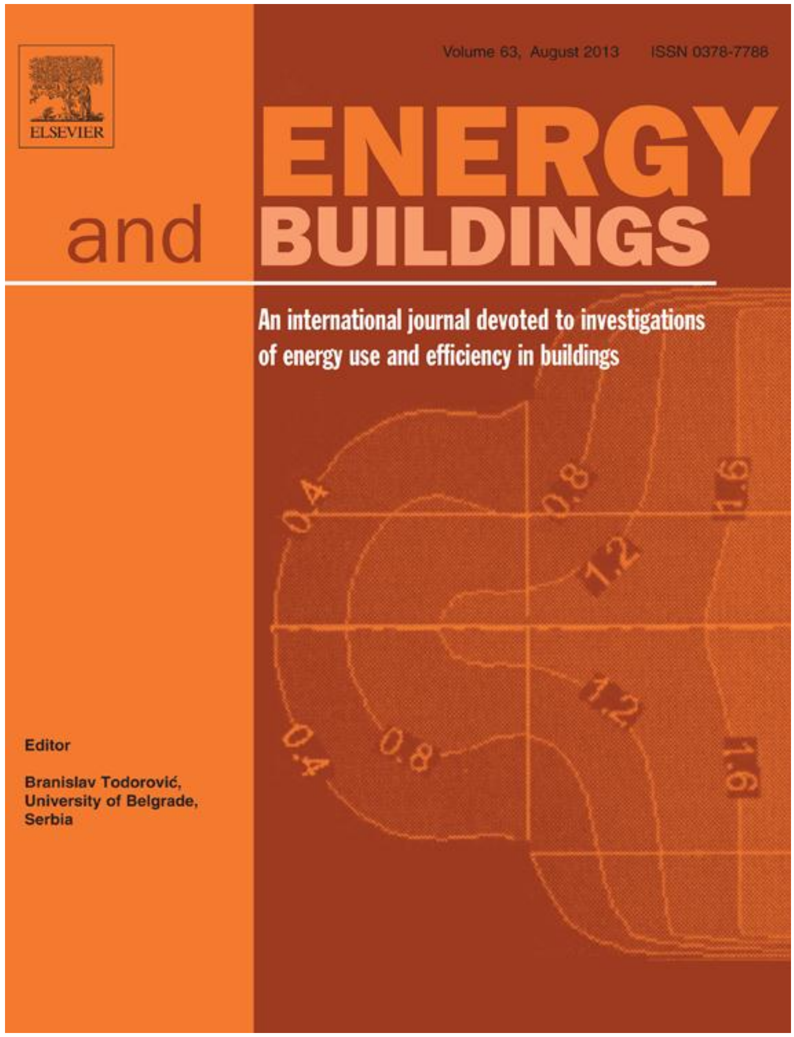


Figure C- 7: Model predictive controller with system model

Appendix D Publications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Investigating the performance of a combined solar system with heat pump for houses

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ABSTRACT

The UK government has committed to generate 20% of the country's energy from renewable sources by 2020. This paper investigates energy reduction in houses by using an innovative solar thermal collector combined with a heat pump system. The dynamic lumped parameter model for a small house is derived and the combined heating system is used to provide the typical hot water and heating requirement. The goal is to maintain thermal comfort inside the house and reduce the amount of electricity consumption used for heating and hot water. This is achieved by reducing the electricity costs through optimising the operation of the heat pump, integrating the available solar energy, and by shifting electricity consumption to the cheaper night time tariff. Models of conventional controller on–off and a multi-variable model predictive control (MPC) are developed and used for several different climatic conditions. The results showed that the model predictive controller performed best by providing better comfort, consuming less electric energy and better use of cheap night time electricity by load shifting and storing heat energy in the heating tank.

1. Introduction

According to the International Energy agency [1] the primary energy use has grown by 40% from 1994 to 2004. Overall there is an average energy and CO_2 increase of 2% and 1.8% each year respectively. The main source of energy consumption in the domestic sector is space heating, which accounted for 60% of the total domestic energy consumption in 2011. Water heating accounted for 18%, lighting 19% and cooking for a 3% [2] of a typical household bills. Currently, the use of solar thermal collectors combined with heat pump systems is becoming popular due to their low electrical cost. A heat pump is mainly used to increase the temperature of hot water generated by the solar collectors. It is acknowledged that the solar heating systems are challenging to control due to the swings in day to day and season to season energy flows and also the varying thermal comfort demands. The control system is an important component of any renewable system and is critical for increasing the performance of such systems.

The long-term performance of a combined solar collector and heat pump system was studied by Huang et al. [3] and was found that its electricity price was cheaper than conventional gas system. The performance of a solar-assisted heat pump water heating system was monitored by Hawlader et al. [4]. They showed that the performance of the system is influenced significantly by collector area, speed of the compressor, and solar irradiation. The performance of a combined solar water heater and heat pump was investigated by Nutaphan et al. [5] using a simulation program. The economical mass of hot water in the storage tank and the refrigerant mass flow for optimum operation of the system were investigated. Predictive control strategies are well known in building control research [6]. An MPC is used for chillers to optimally store the thermal energy in the tanks by using the predictions of the building load and outside weather conditions [7]. In another study a detailed building model is applied for building predictions [8]. Model predictive control has also been used for reducing peak electricity demand in building climate control [9]. Different predictive control strategies for a solar hot water system with non-predictive strategies are compared by Grünenfelder et al. [10]. It is shown in simulation that for a small storage tank, the predictive control saves energy cost when compared with non-predictive strategies. A weather predictor based on observed weather data is used by Henze et al. [11–13]. The system under study uses active and passive building thermal storage systems. Building heating systems using MPC with weather

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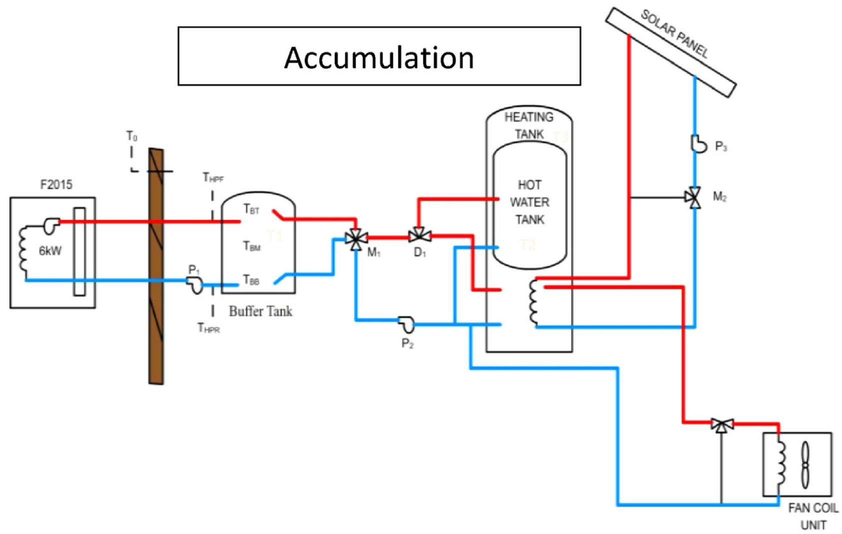

Fig. 1. Solar system combined with heat pump schematic.

prediction have shown to save between 15% and 28% of the energy consumption [14].

This paper will investigate the performance of a combined solar thermal collector and heat pump system. To control the system, a conventional (on–off) and an advanced control system (MPC) are simulated and the energy saving and load shifting of the controllers are compared. Mathematical model of the building and heating system is developed to predict the future behaviour of the whole system according to the outdoor weather conditions and occupancy pattern of the building.

2. Experimental heating system

The full size solar system and the heat pump are installed at the School of Civil and Building Engineering of Loughborough University. It consists of a solar panel, a heat pump and three accumulator tanks. The buffer tank is heated up with the help of a heat pump and when it is required this hot water is transferred into either the heating tank or the hot water tank. The heating tank is also connected to the solar thermal collector. During the night, when electric tariffs are low, the heat pump can be used to heat up all the tanks.

A general schematic diagram of the system is shown in Fig. 1. The heat pump is connected to the buffer tank.

The main components of the system are described below.

2.1. Accumulation system

The accumulation system consists of three tanks. The first tank is the buffer tank for the heat pump, and it has a capacity of 300 l. It is heated by the heat pump, and it can supply hot water to the other two tanks as required. The hot water tank is connected to the buffer tank, it has a capacity of 300l, and it is located inside the heating tank. The heating tank is of 450 l capacity, and it provides hot water to the room fan coil units for heating.

2.2. Solar collector

Solar collectors are used to collect solar radiations and to raise the water temperature of the heating tank. It is the preferred energy source of the system, because it uses only a minimal amount of electricity to power the circulation pump. The solar collector consists of 2 flat plate collectors 2 m^2 in area each, covering a total area of 4 m^2.

2.3. Heat pump

The installed system is a single stage air source heat pump. It is the only way to heat the hot water tank, and it can be used as an auxiliary energy source for the heating tank when necessary. The heat pump is directly connected to the buffer tank. The rated electric power of the heat pump is 6 kW, but the actual power consumption may be lower, and the delivered thermal power is higher due to the additional energy drawn from the heat source.

The single heat pumps are unable to modulate their output power during low load conditions, which could lead to overheating of the fluid loop. In order to solve this problem, the buffer tank is required in between the load loop and the heat pump.

3. Modelling

The system model is important for both the controller design, and for validation. The performance of a model based controller depends to a good part on the accuracy of the plant model. The nonlinear model of the whole system is implemented in Simulink, and a linearised plant model is used to formulate the optimisation problem [15,16].

The building was modelled by considering wall layers as lumped components and considering each layer as a thermal resistor and a thermal capacitor. The tanks are modelled as heat stores with a known thermal capacity. The development of heat pump model was based on curve fitting to manufacturer's data.

3.1. Building

The building under consideration is a two room building; a hall and a bedroom. However the hot water and heating energy consumption is based on a typical house [17]. The hall has a south facing and a window on the south facing window. The dimensions of both the rooms are 4.27 m × 4.57 m and they are 2.44 m high. The schematic layout of the building is shown in Fig. 2.

A typical construction element consists of different layers of different materials. All the external walls and roof are considered of the same basic construction. The model used by Gustafsson [18] is applied here. The Building materials and properties of the external walls, roof and partition wall between hall and bedroom are summarised in Table 1.

Table 1
Building model specifications.

	Thickness in m	Thermal conductivity in W/Km	Density in kg/m^3
Wall/roof			
Brick	0.1	0.84	1700
Polystyrene	0.0795	0.034	35
Concrete	0.1	0.51	1400
Plaster	0.013	0.025	900
Partition wall			
Gypsum	0.025	0.25	900
Air	0.1	0.15 (Km^2/W) (resistance)	1.204
Gypsum	0.025	0.25	900

The building construction is divided into number of layers and each layer is modelled separately. The advantage of this method is that it takes into account the time varying effect of heat moving from the inside to the outside of the building, and this is essential to model the correct response of the room air and radiation temperature to a change in heating. Solar gain was only considered in the hall area as it has the window. The fabric solar heat gain through the walls and roofs is considered as negligible because of the low thermal conductivity of the construction. Each layer of the construction is modelled separately in Simulink and considered as a single lump element. A wall with N layers can be seen in Fig. 3.

The heat transferred from indoor air to the wall can be summarised in the following equation:

$$q_{\text{conv}} = q_{\text{cond}} + q_{\text{stored}} \tag{1}$$

q_{stored} is the stored heat energy inside the wall layer or heat energy of lumped capacitance.

$$h_{in}(T_{in} - T_i) = \frac{k_i}{L_i}(T_i - T_{i+1}) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i\right) \tag{2}$$

$$\frac{dT_i}{dt} = \frac{h_i(T_{in} - T_i) - \left(k_i/L_i\right)(T_i - T_{i+1})}{c_{p,i}\rho_i L_i} \tag{3}$$

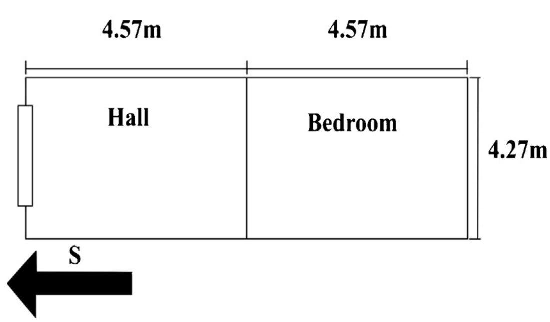

Fig. 2. Building layout.

where $i = 2, 3, \ldots, (N-1)$ $i = 1$.

For middle layers the material also has capacitance and therefore heat storage capacity of the material is taken into account. The heat balance equation is:

$$q_{\text{con},1} = q_{\text{cond},2} + q_{\text{stored}} \tag{4}$$

where $i = 2, 3, \ldots, (N-1)$.

$$\frac{k_i}{L_i}(T_{i-1} - T_i) = \frac{k_{i+1}}{L_{i+1}}(T_i - T_{i+1}) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i + c_{p,i+1}\rho_{i+1}L_{i+1}\right) \tag{5}$$

For outer layer the equation for heat energy is:

$$q_{\text{conv},N} = q_{\text{cond},N-1} + q_{\text{stored}} \tag{6}$$

$$h_{out}(T_i - T_{out}) = \frac{k_i}{L_i}(T_{i-1} - T_i) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i\right) \tag{7}$$

In the above equations it is assumed that the wall, roof and floor are divided into N layers with different properties and in Eq. (7) $i = N$.

3.2. Solar panel and water tanks

A flat plate collector is used to heat up the heating tank. The useful energy from the solar panel is calculated by using the following equation [19];

$$Q_U = F_R A_c[\tau\alpha I - U_L(T_c - T_a)] \tag{8}$$

The water tanks are modelled by assuming that the water inside the tanks mixes properly and there is no temperature stratification across the tank height. The second assumption is that the heat capacity of the tank is the heat capacity of the volume of the water inside the tank. The heat losses from the tanks are also considered and the losses from the buffer tank and the heating tank are added as the heat gain by the room air i.e. it is assumed that the tanks are placed in the bedroom. The hot water losses are added into the heat gain by the heat tank water.

3.3. Heat pump

Several models for the heat pump Coefficient of Performance (COP) were tested. Initially an existing model developed from first principles was used [20], but this model did not give a good match when its COP results were compared with the data supplied by the manufacturer.

As a second step, the dynamics of the absorber and condenser were eliminated in favour of a quasi-stationary model. This leads to a model with only four remaining factors shown in Table 2.

This leads to a quadratic equation for the effective COP:

$$(u_T + u_E)P \times \text{COP}^2 + \left(T_T - T_E - u_E P - \beta(u_T + u_E)P - \alpha u_T P\right)\text{COP}$$
$$- \alpha T_T - \beta(T_T - T_E - u_E P) = 0 \tag{9}$$

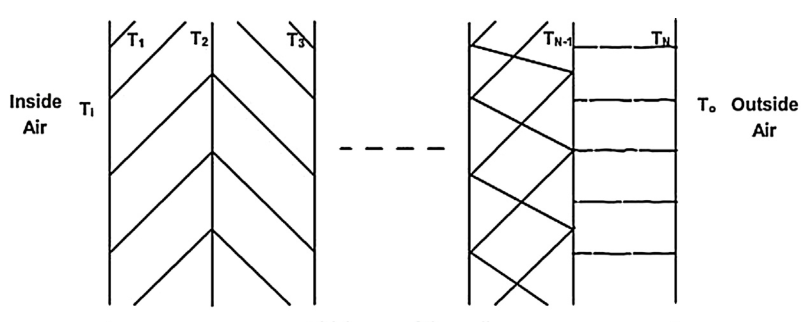

Fig. 3. Wall divisions.

Table 2
Heat pump parameters.

α	Thermal efficiency coefficient of compressor
β	Recovery share of losses into heat
$u_T P$	Thermal coefficient on condenser side
$u_E P$	Thermal coefficient on evaporator side

The above quadratic equation was then used to calculate the COP of the heat pump. Several methods were used to find the best fit to the existing data, but none of them provided a good match. It was found that plotting the inverse of the ideal COP vs the inverse of the actual COP provides a good fit. This plot was then approximated using a quadratic function:

$$y = 29.278x^2 - 4.8281x + 0.4328 \quad (10)$$

where x is the inverse of ideal COP and y is the inverse of actual (manufacturer's) COP.

It can be seen that the resulting curve gives better results than the previous methods. The plots of COP data from different methods are shown in Fig. 4 and the inverse plot of both ideal COP and manufacturer's COP is shown in the Fig. 5. The quadratic equation has an R^2 value of 0.9893, which is the coefficient of determination and is used to find out how accurate the equation will predict the future outcomes. In this case the value of R^2 is very close to 1 which means that the regression line fits the data very well. It can be concluded that this very simple model provides a good match with the experimental data, and this cannot be said for the two previous models of the heat pump.

3.4. Controllers

Below is a brief overview and comparison of the on–off and MPC strategies that are used for the experimental heating systems.

3.4.1. On–off controller

The on–off controller is the simplest type of controller. The controllable device e.g. heat pump in this case is turned on and off at certain thresholds. These are set according to a tank temperature error as given by

$$e_r = T_r - T_T \quad (11)$$

in which e_r is the error between reference temperature T_r and current tank temperature T_T. The controller output is turned on when the error e_r exceeds a positive threshold, and it remains on until e_r exceeds a negative threshold. The main advantage of the on–off controller is that it is simple and easy to implement. It is a feedback

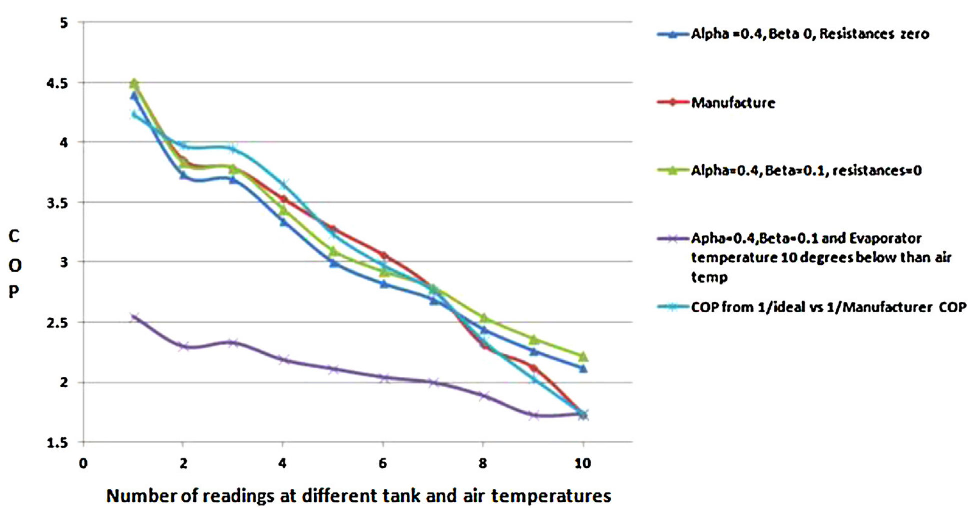

Fig. 4. COP plots from different methods.

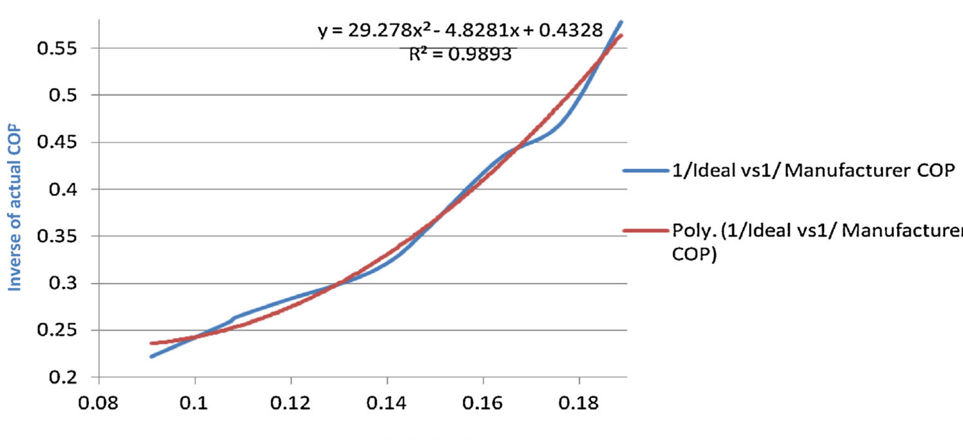

Fig. 5. Inverse plot of ideal and manufacturer COP.

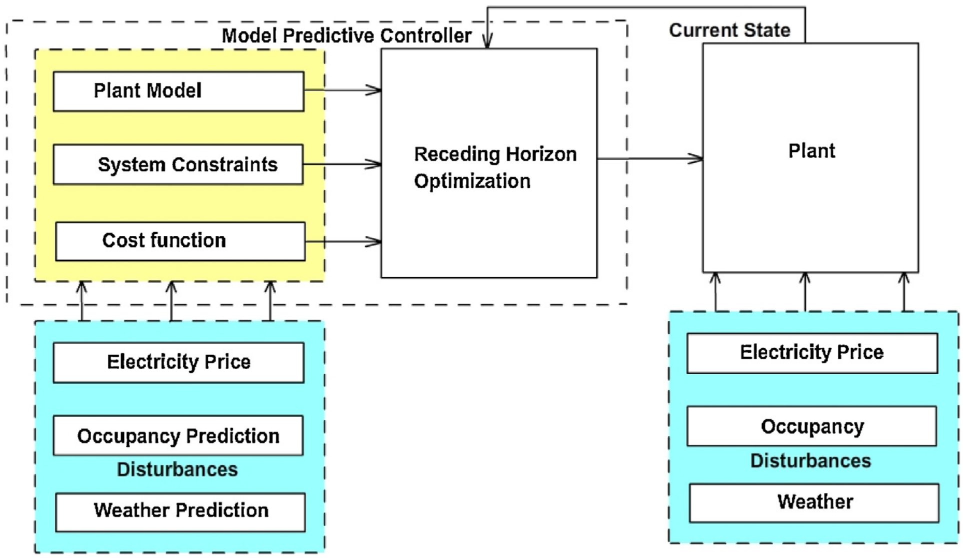

Fig. 6. Model predictive controller scheme.

controller that does not contain any information about the plant dynamics.

3.4.2. Model predictive controller (MPC)

MPC is a class of computer algorithms that utilizes process models to predict future behaviour of a plant. The control signal is obtained by minimizing an objective function in real time [21]. The main difference in the various methods is the way the problem is translated into the mathematical model, and how this is solved numerically [22]. The main ideas behind predictive control methods are,

- Explicit use of a model to predict the process output at future time instant (horizon).
- Obtaining control signal by minimizing an objective function.
- Using a receding horizon strategy, where at each time step the horizon is moved to cover the same period into the future.

In MPC the model obtains data from past inputs and past outputs and combines this data with future inputs to create a prediction of future output values. The predicted outputs are compared with a reference trajectory to determine future output errors. These future errors are then used to calculate an objective function based on control inputs and output errors. The objective function is fed into optimizer, which tries to find a cost optimal solution while still satisfying constraints on the system. The optimiser returns the optimal inputs together with the predicted behaviour and cost. Due to the receding horizon approach, only the first input is implemented, and further steps are discarded in favour of an updated optimisation results based on the additional information available at the next time step.

The ability of an MPC controller to define and predict objective function makes this control strategy one of the most advance control strategies. The model predictive control makes use of the system model to obtain the control signal as a minimisation of the objective function. The aim of the objective function is to represent the compromise between fast and strong control action, which typically increases costs, and quick and accurate following of the reference trajectory. Therefore both input values and output errors are penalized. A typical objection function of model predictive control is defined by the following equation:

$$J(k) = \sum_{i=1}^{n_y} w_{i+1}^{y}(y(k+i+1|k) - r(k+i+1|k))^2 + \sum_{i=1}^{n_u} w_i^{\Delta u}(\Delta u(k+i|k))^2 + \sum_{i=1}^{n_u} w_i^{u}\left(u(k+i|k) - u_{\text{target}}(k+i|k)\right)^2 \quad (12)$$

In the above equation, w_{i+1}^{y}, $w_i^{\Delta u}$ and w_i^{u} are non-negative weights of output, rate of change on input and input variables. The weights can be time varying, and this is used to represent changing electricity prices according to a night time electricity tariff. In the multi-variable case, non-negative (symmetric) quadratic forms can be used as weights, although many implementations only support diagonal matrices. For the simulations, the prediction horizon is set to 24 h to cover a complete cycle of daily temperature and electricity cost variations.

Fig. 6 shows the basic control scheme used for the research. The energy price, occupancy prediction and weather prediction are the time varying external conditions. Together with the temperature measurements, these form the inputs to the controller. The plant model, system constraints, cost function and objective function are defined as the parts of the MPC controller. For every time step these parameters are combined and converted into an optimization problem, which then determines the output for the next time step.

Model predictive control has the ability to include constraints into the MPC formulation. MPC constraints can be physical limitations, or they can be used to constrain the operation of the system to most efficient condition. The constraints used in this paper are linear constraints that take the following form:

$$\begin{aligned} u_{\min,k} &\le u_k \le u_{\max,k} \\ x_{\min,k} &\le x_k \le x_{\max,k} \end{aligned} \quad (13)$$

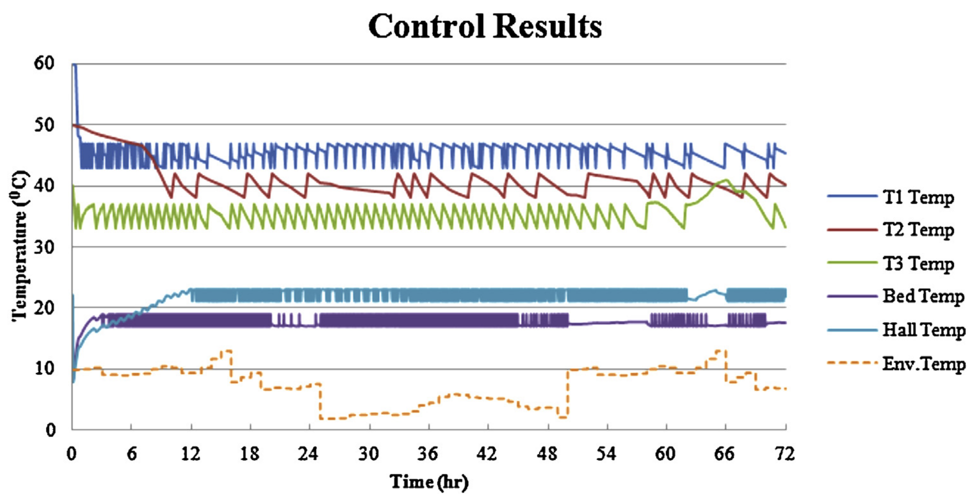

Fig. 7. On–off control results Case A.

Linear constraints are most commonly used constraints. Only simple linear weights are used here in an attempt to keep the complexity of the optimization problem manageable.

4. Simulation results

To compare the effectiveness of the MPC controller to conventional on–off control scheme, two scenarios with London location are simulated. The water consumption data is based on existing data [17]. Night time electricity price is considered from midnight to 7 am in the morning.

The water consumption, solar radiations and outside environmental temperature are considered as disturbances that are known in advance. The electricity price is also known in advance and is considered as a time varying weight.

Simulations were performed by considering one cold day in the middle of two medium temperature days (Case A) and a sunny day in between of two days having medium solar radiations (Case B). The building was simulated using Integrated Environmental Solutions (IES) in order to obtain the total indoor heat gains.

4.1. Results: Case A

The results for Case A are shown in Figs. 7 and 8. The initial air temperatures of both the bedroom and hall were 18 °C and 22 °C. The air temperatures dropped initially because the wall layers temperatures are initialised to 0 °C, and they take time to heat up. The on–off controller (Fig. 7) took 9 h to bring the hall air temperature to a steady value whereas the MPC controller (Fig. 8) took approximately 3 h to bring the air temperature to the reference temperature of 22 °C. Throughout the day with MPC better temperature control and thermal comfort in the building are also maintained.

The first objective of the control problem was to minimize the energy consumption by using night time electric tariffs, which are cheaper as compared to day time tariffs and also by using available solar energy. The model predictive controller uses more night time electricity while on–off controller uses less night time electricity. From 24:00 to 31:00 (midnight to 7:00 am day 2) MPC has used more energy than on–off by taking advantage of cheaper tariffs. MPC then switched off the heat pump when it anticipated that day time electric tariffs are coming into action as can be seen in Fig. 8. MPC also used a minimal amount of electricity to keep the tanks water temperature at desired level.

The on–off controller could not take electric tariffs into account and therefore uses more energy during the day time. After the initial settling period, the on–off controller keeps the temperatures between upper and lower limits, which lead to a typical limit cycle shown in Fig. 7.

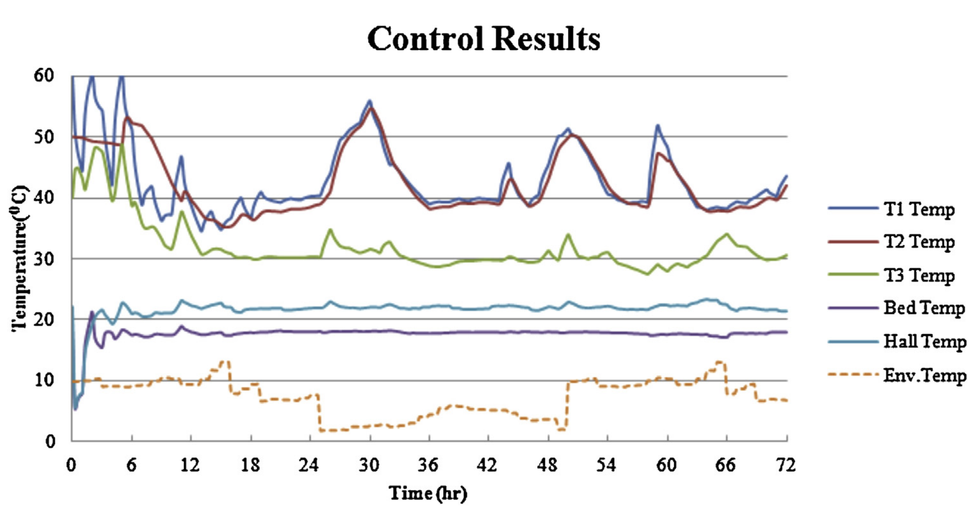

Fig. 8. MPC control results Case A.

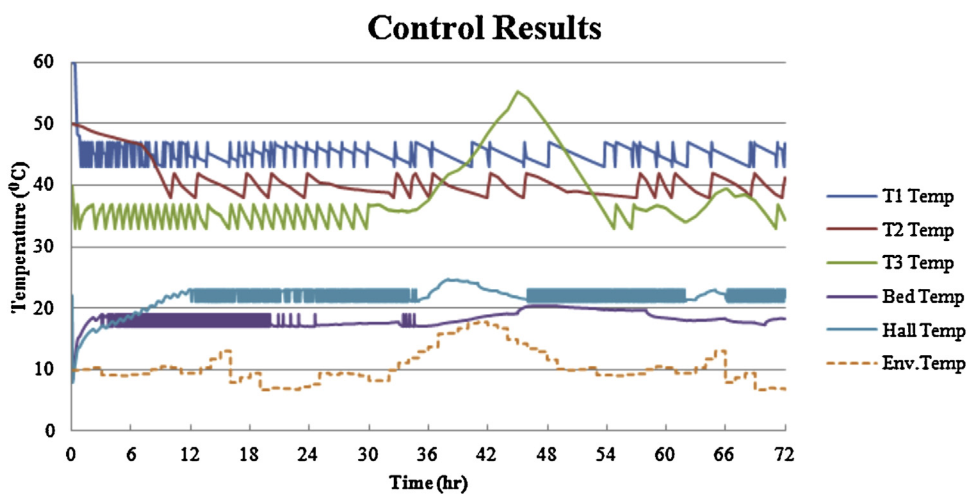

Fig. 9. On–off control results Case B.

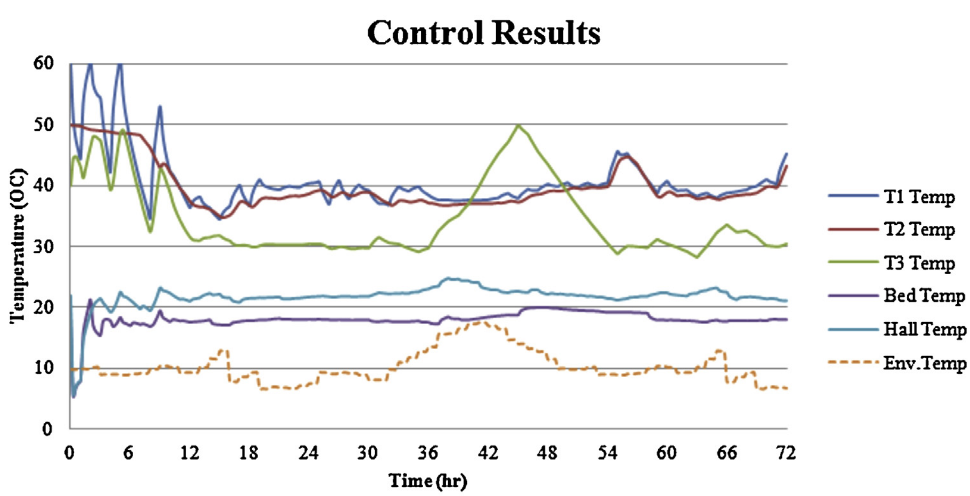

Fig. 10. MPC control results Case B.

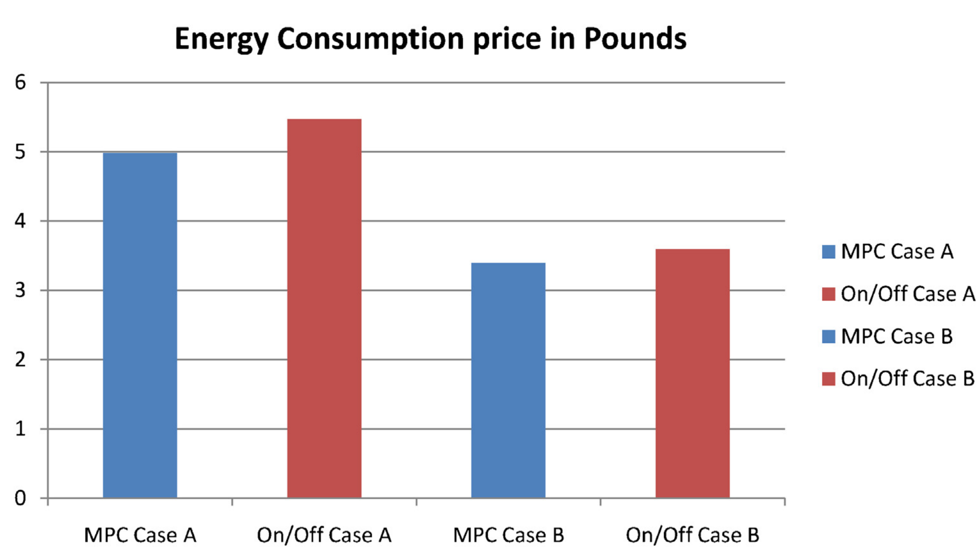

Fig. 11. Energy price in pounds per day.

The second control objective was to do load shifting by using different control strategies. The model predictive controller does load shifting as can be seen in MPC control results, Fig. 8. The MPC started storing heat energy during the night at 24:00 and raised the temperature in the buffer tank (T1) and hot water tank (T2) temperatures. The load shifting was stopped when the low electric tariffs were ended at 31:00 and 55:00 (at 7:00 am day 2 and 3) which resulted in heat pump being used at lower settings during the next days. The high buffer tank temperature at 57:00, shown in Fig. 8, is resulted from the high water consumption at that time.

The energy over time for Case A showed that the MPC achieves a lower electricity cost than the on–off controller. The MPC was able to switched off the heat pump at few points e.g. from 59:00 to 64:00 h (11 a.m. –4 p.m. day 3). The MPC used more energy at the beginning of the simulation because the room temperature became lower and controller used night time electricity. By using more energy at the beginning MPC took less time to bring room air to a steady value than the on–off controller.

4.2. Results: Case B

The second case simulations were performed by using one sunny day in the middle of two less sunny days. The results shown in Figs. 9 and 10, demonstrated that both controllers were able to maintain the temperatures at desired level. The rise in heating tank temperature (T3) at 36:00 h (12 p.m. day 2) is because of the strong solar radiation which has caused the temperature to exceed the reference temperature. Both controllers have used less energy compared to Case A, as the heating demand is less because of the sunny day.

The results for on–off controller Fig. 9 shows that tank fluctuations of the temperature in the tanks are less than the room air temperature's fluctuations, due to higher temperature range for the tanks.

The MPC has used less energy during the second day and the energy used is only to heat up the hot water tank as the heat tank has enough energy because of the solar energy as shown in Fig. 10.

The simulation results shown in Fig. 11 demonstrated that the MPC saved about 9% of the energy cost. This is mainly due to the fact that model predictive controller used cheaper night time electricity and heat pump was used at low settings or even was turned off during the day time.

The on–off strategy is the easiest to apply, as it does not require any tuning and requires essentially no computation. The MPC controller on the other hand has a number of requirements: it needs a plant model, selected weights, and it also needs measurements and predictions of external parameters.

5. Conclusions

Overall the model predictive controller proved to have a greater potential in the area of load shifting and use of renewable energy. The simulation results showed that the MPC consumed less energy than the on–off controller. The model predictive controller also used cheaper night time electricity and the heat pump was used at low settings or even was turned off during the day time. The room temperatures maintained at the desired level and the set points achieved very quickly. Overall the MPC controller maintained good thermal comfort in the building.

One of the main limitations of MPC was found to be the use of linear model requirement which did not match the heat transfer between the tanks. The error increases as the tank temperature deviate from the nominal values used for linearization, and the effect on temperature stability is exacerbated by the long cycle time of the MPC controller. It may be possible to reduce this issue by using energy transfer rate rather than mass flow rate as a control input. Alternatively, an underlying control structure with faster response time could limit the effect on room temperatures.

The second limitation was that the MPC controller could not optimise secondary (nonlinear) effects, because they are not contained in the model. The most important one is the change in effectiveness of the heat pump (COP) due to changes in the tank temperature. Therefore, the controller does not try to keep the tank temperature low unless this goal is explicitly included in the cost function.

In general, the system is most suitable for residential market and the results highlight the importance of advanced controls for combined solar and heat pump systems in order for the system to operate efficiently and maintain good thermal comfort in the building. As the energy prices are predicted to increase significantly there is need for better comfort with lower energy consumption. The MPC controller demonstrated to maintain better thermal comfort and less temperature fluctuation as well as saving over 9% energy use.

Acknowledgement

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References

[1] International-Energy-Agency, Key world Energy Statistics, 2006.
[2] http://www.decc.gov.uk/assets/decc/11/stats/publications/energy-consumption/2323-domestic-energy-consumption-factsheet.pdf, accessed November 2012.
[3] B.J. Huang, J.P. Lee, J.P. Chyng, Heatin-pipe enhanced solar-assisted heat pump water heater, Solar Energy 78 (2005) 375–381.
[4] M.N.A. Hawlader, S.K. Chou, M.Z. UIlah, The performance of a solar assisted heat pump water heating system, Applied Thermal Engineering (2001) 1049–1065.
[5] A. Nutaphan, C. Chasena, T. Kiatsiriroat, Performance analysis of solar water heater combined with heat pump using refrigerant mixture, Applied Energy 86 (2009) 748–756.
[6] http://www.opticontrol.ethz.ch/, accessed October 2012.
[7] M. Yudong, F. Borrelli, B. Hencey, A. Packard, S. Bortoff, Model Predictive Control of thermal energy storage in building cooling systems, in: Proceedings of the 48th IEEE Conference on Decision and Control, held jointly with the 28th Chinese Control Conference, 2009, pp. 392–397, http://dx.doi.org/10.1109/cdc.2009.5400677.
[8] M. Yudong, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, P. Haves, Model predictive control for the operation of building cooling systems, in: American Control Conference (ACC), 2010, pp. 5106–5111, ISSN 0743-1619.
[9] F. Oldewurtel, A. Ulbig, A. Parisio, G. Andersson, M. Morari, Reducing peak electricity demand in building climate control using real-time pricing and model predictive control, in: Conference on Decision and Control, CDC, 2010.
[10] W. Grünenfelder, J. Tödtli, The use of weather predictions and dynamic programming in the control of solar domestic hot water systems, in: Proceedings of Mediterranean Electrotechnical Conference (Melecon), Madrid, Spain, 1985.
[11] G. Henze, C. Felsmaan, G. Knabe, Evaluation of optimal control for active and passive building thermal storage, International Journal of Thermal Sciences 43 (2004) 173–183.
[12] G. Henze, C. Felsmaan, G. Knabe, Impact of forecasting accuracy on predictive optimal control of active and passive building thermal storage inventory, International Journal of HVAC and Research 10 (2004) 153–178.
[13] G. Henze, D. Kalz, S. Liu, C. Felsmaan, Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory, International Journal of HVAC and Research 11 (2005) 189–214.
[14] J. Široký, F. Oldewurtel, J. Cigler, S. Prívara, Experimental analysis of model predictive control for an energy efficient building heating system, Applied Energy 88 (9) (2011) 3079–3087.
[15] E.F. Camacho, C. Bordons, Model Predictve Control, Springer-Verlag, London, 1999.
[16] J. Maciejowski, Predictive Control with Constraints, Prentice-Hall, 2001.

[17] Defra, Measurement of domestic hot water consumption in dwellings, Copyright Crown, 2008.
[18] J. Gustafsson, J. Delsing, J. van Deventer, Thermodynamic Simulation of a Detached House with District Heating Subcentral, in: Systems Conference, 2nd Annual IEEE, 2008, pp. 1–8.
[19] J. Duffie, W. Beckman, Solar Engineering of Thermal Processes, Wiley, New York, 1991.
[20] A.W.M. Van Schijndel, M.H. De Wit, in: Proceedings of 8th International IBPSA Conference, Eindhoven, Netherlands, Advanced simulation of building systems and control with simulink (2003) 1185–1192.
[21] S.J. Qin, T.A. Badgwell, A survey of industrial model predictive control technology, Control Engineering Practice 11 (7) (2003) 733–764.
[22] T.J.J. Van Den Boom, A.A. Stroorvogel, Model Predictive control, DISC Course, Lecture Notes, 2010.

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Control Strategies for Optimum Operation of a Solar Heating System Combined with a Heat Pump

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Abstract: This paper investigates different control strategies for a solar heating and hot water system combined with a heat pump. The goal is to minimise the amount of electricity used for heating and hot water. UK buildings consume a considerable share for primary energy, and the government has committed to generate 20% of the country's energy from renewable sources by 2020. The paper considers a heating system for a small dwelling, for which a dynamic lumped parameter model is derived. The aim of the controller is to reduce electricity costs by optimising the operation of the heat pump, integrating the available solar energy, and by shifting electricity consumption to the cheaper night time tariff. Three types of controllers are tested under two different environmental conditions: a simple on-off controller, a set of classic PI controllers, and a multi-variable model based predictive control (MPC). Both on-off and proportional integral (PI) controllers were able to maintain the tanks and room temperatures to the desired set-point temperatures however did not make use of night time electricity. The results showed that the model predictive controller performed best. It reduces the energy cost and makes use of cheap night time electricity (load shifting) by storing heat energy in the heating tank.

Keywords: Model predictive control, heat pump, control strategies, load shifting, solar energy.

1 Introduction

The rapid increase in global energy consumption is a key concern of today's world. According to International Energy agency [1], the primary energy use has grown by 40% from 1994 to 2004. There is an average increase of 2% in energy and 1.8% in the CO_2 emissions. The main source of energy consumption in the domestic energy sector is space heating, which was the 60% of the total domestic energy consumption in 2011[1]. Water heating accounted for 18%, lighting 19% and cooking for a 3% [2]. Currently, the use of solar thermal collectors combined with heat pump systems is becoming popular due to their low electrical cost. A heat pump is mainly used to increase the temperature of hot water generated by the solar collectors. The control system is an important component of any heating, ventilation and air conditioning (HVAC) system and is critical for low energy buildings. It is also acknowledged that the heating systems are challenging to control, due to varying outside environmental conditions and indoor thermal comfort demands.

Different advanced control strategies are used for building control systems. A number of studies have been compiled to compare control methods for energy management and comfort in buildings [3]. A control strategy for optimal control of active and passive thermal storage inventory is presented by Liu et al [4]. It was concluded that a simulated reinforcement technique [5] can achieve 8.3% energy saving in an experiment test because the thermal storage of the building is only partially utilized. A model-free method can be used to tune a supervisory controller for a low energy building system [6].

Predictive control strategies are well studied in building control research [7]. An MPC can optimize the use of chillers by storing the thermal energy in the tanks based on predicted building load and weather conditions [8]. In another study a detailed building model is applied for building predictions [9]. Model predictive control has also been used for reducing peak electricity demand in building climate control [10].

Building heating systems using MPC with weather prediction have shown to save between 15% and 28% of the energy demand [11]. Different predictive control strategies for a solar hot water system with non-predictive strategies are compared by Grünenfelder et al [12]. It is shown in simulation that for a small storage tank, the predictive control saves energy cost when compared with non-predictive strategies. A weather predictor based on observed weather data is used by Henze et al [13-15]. The system under study uses active and passive building thermal storage systems.

An MPC strategy for an intermittently heated radiant floor heating system has been shown experimentally to save 10 % to 12 % of energy during winter period [16]. An MPC controller applied to a large university building has achieved to energy savings of 17% to 24%. [17]. It is found that a proper identification of the building model is crucial for designing a good model predictive controller.

In another study by Paris et al. (2010) [18], three control schemes are compared: a conventional PID, a combination of proportional integral and derivative controller (PID) and fuzzy logic controller (FLC), and a combination of PID and MPC. Compared to the baseline PID controller, the PID-MPC scheme saved 26.9% of fossil energy, and PID-FLC still recorded a saving of 9.8%.

This paper focuses on the control strategies for a solar heating system combined with a heat pump. A mathematical model of the system is developed to predict the future behaviour of the whole system according to the outdoor weather conditions and occupancy pattern of the building. The aim is to investigate advanced control strategies for the heating and hot water system that reduce the energy cost and make effective use of solar radiation.

2 Full size experimental heating system

The solar system and the heat pump are installed at the School of Civil and Building Engineering of Loughborough University as an experimental rig. It consists of a solar panel, a heat pump and three accumulator tanks. The buffer tank is heated up with the help of heat pump and when required this hot water is transferred either to the heating tank or to the hot water tank. The heating tank is also connected with the solar thermal collector, which provides the preferred solar energy source. The heat pump is intended to be used only if the solar energy is not sufficient, and then it is planned to use the cheaper night time electricity to heat up the tanks.
A general schematic diagram of the system is shown in Fig. 1. The heat pump is connected to the buffer tank to compensate for the intermittent operation.
The main components of the system are described below.

2.1 Accumulation system

The accumulation system consists of three tanks (Fig. 1). The buffer tank is for the heat pump, and it has a capacity of 300l. It gets heated by the heat pump, and it can supply heat to the other two tanks as required. The hot water tank is connected to the buffer tank, it has a capacity of 300l, and it is located inside the heating tank. The heating tank is 450l large, and provides hot water to the room fan coil units for heating.

2.2 Solar collectors

Solar collectors are used to collect solar radiations and to raise the temperature of the heating tank. It is the preferred energy source of the system, because it uses only a minimal amount of electricity to power the circulation pump. The solar collector consists of 2 flat plate collectors $2m^2$ in area each, covering a total area of $4m^2$.

2.3 Heat pump

The installed system is a single stage air source heat pump. It is the only way to heat the hot water tank, and it can be used as an auxiliary energy source for the heating tank when necessary. The heat pump is directly connected to the buffer tank. The rated electric power of the heat pump is 6kW, but the actual power consumption may be lower, and the delivered thermal power is higher due to the additional energy drawn from the heat source.
The heat pump is unable to reduce the output power during low load conditions. It is therefore operated intermittently, and the buffer tank is used to smooth the temperature variations caused by this mode of operation.

3 Building and system modeling

The system model is important for both the controller design, and for validation purposes. The performance of a model based controller depends to a good part on the accuracy of the plant model. The nonlinear model of the whole system is implemented in Simulink, and a linearised plant model is used to formulate the optimal control problem.
The building was modelled by considering wall layers as lumped components. Each layer is modelled as a thermal resistor and a thermal capacitor. The tanks are modelled as heat stores with a known thermal capacity. The development of heat pump model was based on curve fitting to the performance data released by the manufacturer.

3.1 Building

The building under consideration is a two room building consisting of a hall and a bedroom. The hall has a south facing wall with a window in it. The dimensions of both the rooms are 4.27m*4.57m and they are 2.44m high. The reason for selecting a two zone building is that both zones have different uses and therefore different set-point temperatures, occupancy periods and activity levels. One of the goals of the project is to determine how the control strategies respond to the demands in these two zones.
The building construction is divided into number of layers and each layer is modelled separately. The advantage of this method is that it takes into account the time varying effect of heat moving from the inside to the outside of the building, and this is essential to model the correct response of the room air and radiation temperature to a change in heating input. The building was simulated using a detailed model in the software package Integrated Environmental Solutions (IES) in order to obtain the total indoor heat gains. Solar gain was only considered in the hall area as it is the only room with a window (Fig. 2). The fabric solar heat gain through the walls and roofs is considered as negligible because of the low thermal conductivity of the construction. Each layer of the construction is modelled separately in Simulink and considered as a single lump element.

3.2 Heat Pump

Several models for the heat pump were tested. Initially an existing dynamic model developed from first principles was tried [19], but this model did not give a good match when its coefficient of performance (COP) results was compared with the data supplied by the manufacturer.
As a second step, the dynamics of the absorber and condenser were eliminated in favour of a quasi-stationary model. This leads to a model with only four remaining parameters as shown in Table 1.

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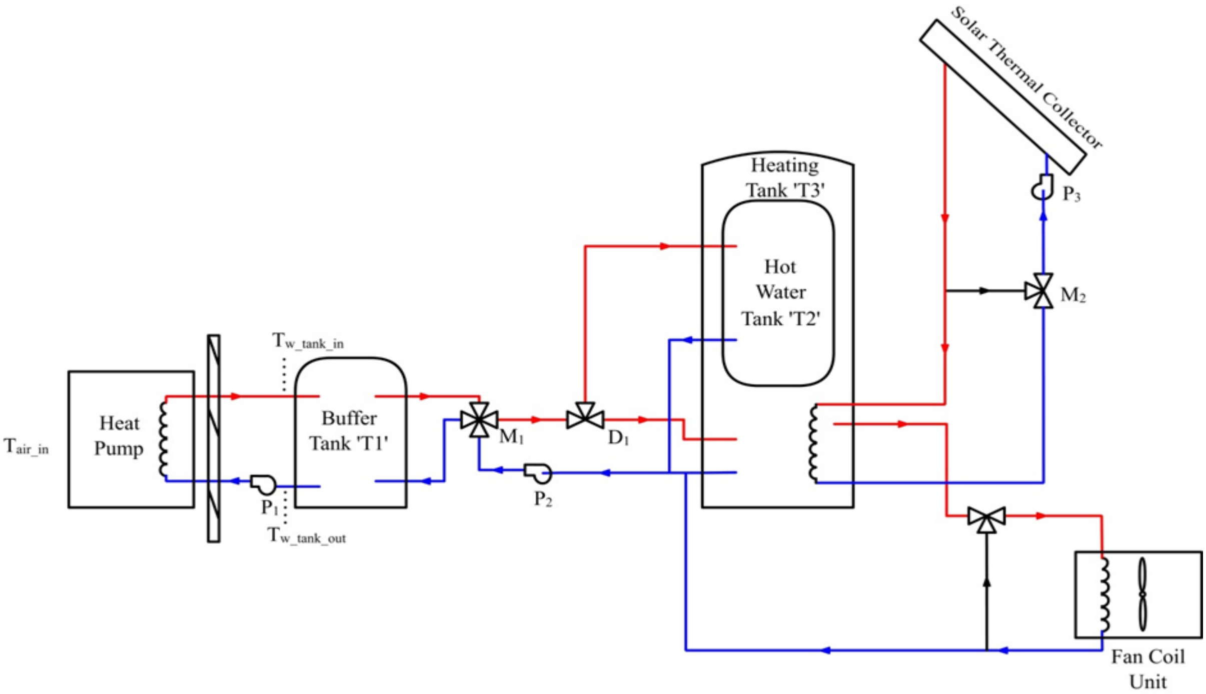

Fig. 1 Solar System Combined with Heat Pump Schematic

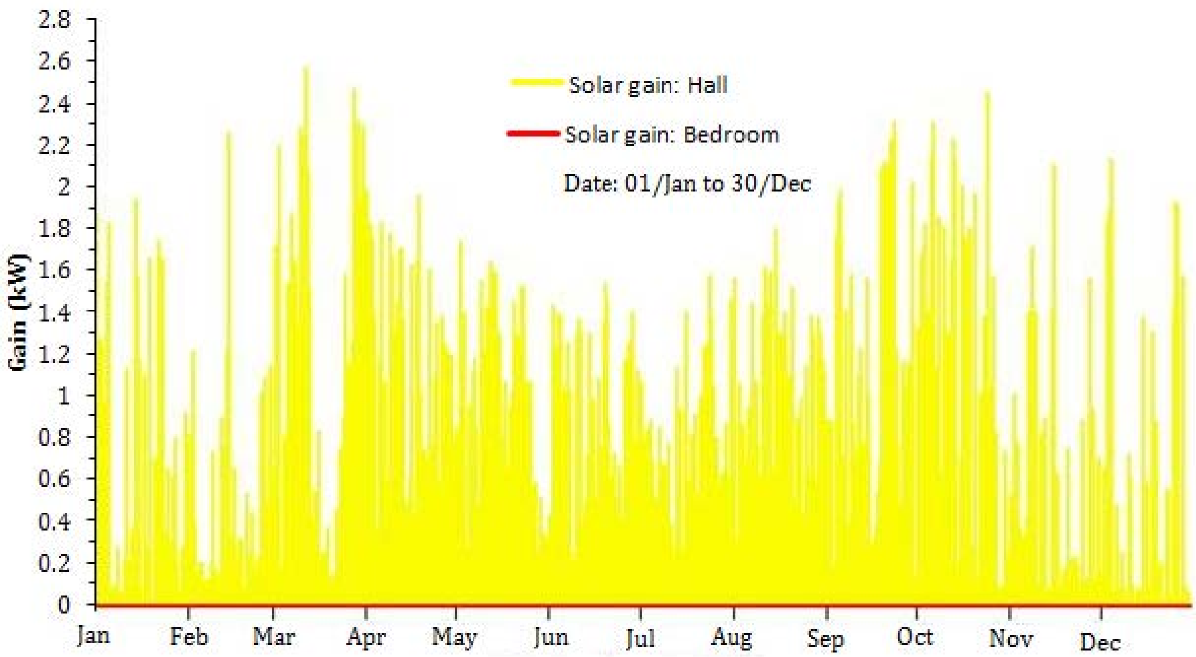

Fig. 2 Solar gains through window

Table 1 Heat pump Parameters

α	Thermal efficiency coefficient of compressor
β	Recovery share of losses into heat
$u_T\ P$	Thermal coefficient on condenser side
$u_E\ P$	Thermal coefficient on evaporator side

This approach leads to a quadratic equation for the effective COP. Different ways to fit the parameters to the available data were tried, but none of them provided a good match.

The third approach is to follow an inductive method and is based on analysis of the available data. It was found that plotting the inverse of the ideal COP vs the inverse of the actual COP provides a nearly smooth relationship. This plot was then approximated using a quadratic function:

$$y = 29.278x^2 - 4.8281x + 0.4328 \quad (1)$$

where x is the inverse of ideal COP and y is the inverse of actual (manufacturer's) COP.

3.3 Solar panel and water tanks

A flat plate collector is used to heat up the heating tank. The useful energy from the solar panel is calculated by using the following equation [20];

$$Q_U = F_R A_c\,[\tau\alpha I - U_L(T_c - T_a)] \quad (2)$$

The water tanks are modelled by assuming that the water inside the tanks mixes properly and there is no temperature stratification across the tank height. The second assumption is that the heat capacity of the tank is the heat capacity of the volume of the water inside the tank. The heat losses from the tanks are also considered and the losses from the buffer tank and the heating tank are added as the heat gain by the room air i.e. it is assumed that the tanks are placed in bedroom. The hot water losses are added into the heat gain by the heat tank water.

4 Selected control strategies

Below is a brief overview and comparison of the selected control strategies that are used for the experimental heating systems.

4.1 On-off controller

The on-off controller is the simplest type of controller. The controllable device (heat pump) is turned on and off at certain thresholds. These are set according to a tank temperature error as given by

$$e_r = T_r - T_T \quad (3)$$

in which e_r is the error between reference temperature T_r and current tank temperature T_T. The controller output is turned on when the error e_r exceeds a positive threshold, and it remains on until e_r exceeds a negative threshold. The main advantage of the on-off controller is that it is simple and easy to implement. It is a feedback controller that does not contain any information about the plant dynamics. Separate controllers of similar structures are used to control the room temperature.

4.2 PI controller

According to Haines [21] the most commonly used control for heating system is the PI controller. It provides better control of the dynamics of the system, but it requires more precise parameter selection. In this study, a discrete time PI controller is used, derived from the standard control law in the Laplace domain:

$$G(s) = k_p + \frac{k_i}{s} \quad (4)$$

k_p and k_i are the proportional and integral gain parameters, which are tuneable to the dynamics of the system under control. Given that the system demonstrates low pass behaviour, a simple PI controller tuning method can be applied.

The PI controller has a continuous power output, while the heat can only be either fully on or off. Therefore the PI controller is used to specify the average power of the heat, which will be switched on and off as required to meet the commanded power. This switching is not simulated in order to keep the simulation simple.

4.3 Model predictive controller (MPC)

Both of the above control strategies use single input and single output (SISO) controllers. A heating system is a multiple input and multiple output system (MIMO) with coupling effects between the different inputs, and these are not taken into account by a SISO approach. As a full model based MIMO approach, a model predictive control (MPC) is used here. It is easy to apply to a MIMO system, and it finds the best control strategy based on the dynamic behaviour of the system as predicted by the model.

MPC is control methodology that utilize a process model to predict future behaviour of a plant. The control signal is obtained by minimizing an objective function in real time [22]. The main difference between implementations is the way the problem is translated in to the mathematical model, and how this is solved numerically.

In MPC the model obtains data from past inputs and past outputs to find the current system state. This is combined with future inputs to create a prediction of future output values. The predicted outputs are compared with a reference trajectory to determine future output errors. These future errors are then used to calculate an objective function based on control inputs and output errors. The objective function is fed into optimizer, which tries to find a cost optimal solution while still satisfying constraints on the system. The optimiser returns the optimal inputs together with the predicted behaviour and cost. A receding horizon approach is used, which means that only the first input of the sequence is implemented, and further steps are discarded in favour of updated optimisation results based on the additional information available at the next time steps.

4.3.1 Cost function

The ability of an MPC controller to predict system behaviour and limits makes this control strategy one of the most advance control strategies. The model predictive control makes use of the system model to obtain the control signal as a minimisation of the objective function. The aim of the objective function is to represent the compromise between low effort (which is cheap, but leads to a slow response) and quick and accurate following of the reference trajectory. Therefore both input values and output errors are penalized. A typical objection function of model predictive control is defined by the following equation:

$$J(k) = \sum_{i=1}^{n_y} w_{i+1}^{y}\big(y(k+i+1|k) - r(k+i+1|k)\big)^2 + \sum_{i=1}^{n_u} w_i^{\Delta u}\big(\Delta u(k+i|k)\big)^2 + \sum_{i=1}^{n_u} w_i^{u}\Big(u(k+i|k) - u_{target}(k+i|k)\Big)^2 \quad (5)$$

In the above equation, w_{i+1}^{y}, $w_i^{\Delta u}$ and w_i^{u} are non-negative weights of output, rate of change on input and input variables. The weights can be time varying, and this is used in this application to represent changing electricity prices according to a day and night time electricity tariff For the simulations, the prediction horizon is set to 24 hours, to cover a complete cycle of daily temperature and electricity cost variations.

Fig. 3 shows the basic control scheme used for the research. The energy price, occupancy prediction and weather prediction are the time varying external conditions. Together with the temperature measurements of the tanks and within the house, these form the available information to the controller. The plant model, system constraints, cost function and objective function are defined as the parts of the MPC controller. For every time step these form an optimization problem, which then determines the control inputs for the plant at the next time step.

4.3.2 Constraints

Model predictive control has the ability to include constraints into the MPC formulation. MPC constraints can be physical limitations, or they can be used to constrain the operation of the system to the most efficient condition. The constraints used in this paper are single variable constraints that take the following form:

$$u_{min,k} \le u_k \le u_{max,k} \quad (6)$$
$$x_{min,k} \le x_k \le x_{max,k}$$

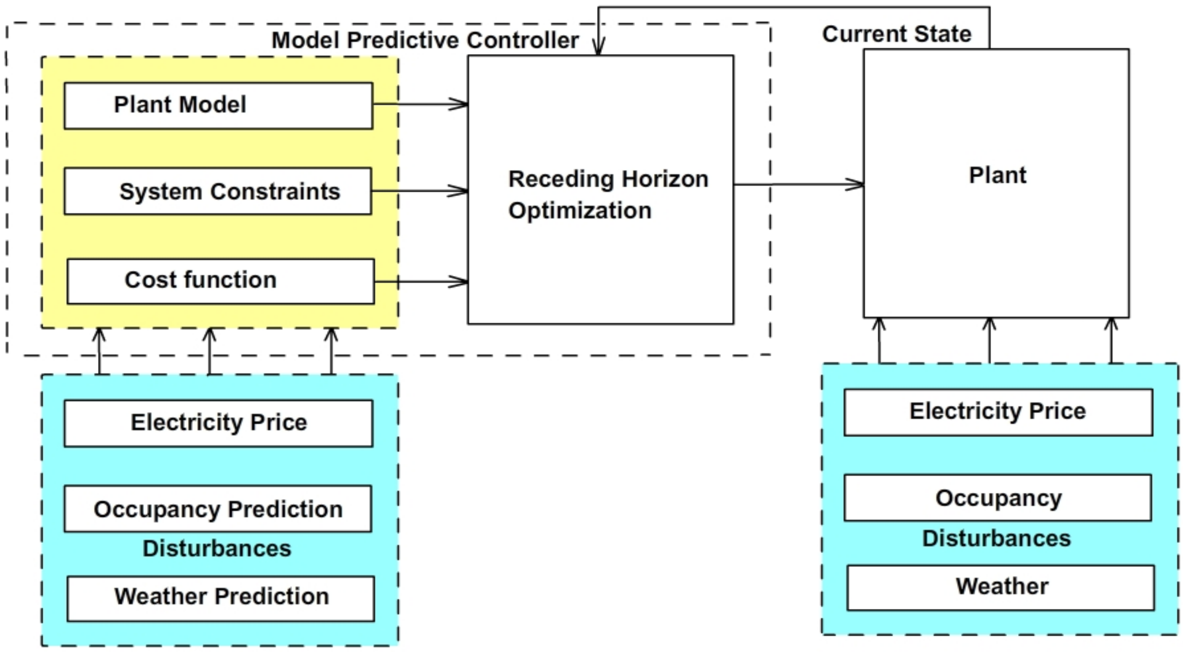

Fig. 3 Model predictive control scheme

This is the easiest form of constraints, and it is commonly used with MPC problems. More complex limits are avoided (e.g. limits that depend on twovariables at the same time) in an attempt to keep the complexity of the optimization problem manageable.

5 Selected control strategies

To compare the effectiveness of the advanced MPC controller to the simpler alternatives, two scenarios are simulated. The weather data is for London. Water consumption data is based on existing data taken from Defra [23]. The lower electricity price is assumed to be in effect for 7 hours from midnight to 6am in the morning (this is in slight variation of the E7 tariff, which promises a 7 hour period, but does not specify the exact timing).

The water consumption, solar radiations and outside environmental temperature are considered as disturbances that are known in advance. The electricity price is a time varying weight, and since it is regular it is also known in advance.

Two scenarios are simulated. In case A, one cold day is considered in the middle of two mild days. The second scenario (case B) is a sunny day in between of two mild days. The middle day is changed to investigate the effect of the weather on the temperature distribution of the system, and to show the effect of the prediction element included in the MPC controller. The use of different weather scenarios is to analyse how different controller behaves with change in weather data.

5.1 Results: Case A

The results for Case A are shown in Figs. 4-6. The labels T1, T2 and T3 denote buffer tank, hot water tank and heating tank temperatures. The initial air temperatures of both the bedroom and hall were 18^{o}C and 22^{o}C. The air temperatures dropped initially because the wall layers temperatures are initialised to 0^{o}C, and they take time to heat up. Both PI (Fig. 4) and on-off controller (Fig. 6) took 9 hours to bring the hall air temperature to a steady value whereas the MPC controller (Fig. 5) took approximately 3 hours to bring the air temperature to the reference temperature of 22^{o}C.

One objective of the control problem was to minimize the energy cost by using night time electric tariffs which are cheaper as compare to day time tariffs. The model predictive controller uses more night time electricity while the PI controller uses much less night time electricity. From midnight of day 1 to 6:00 of day 2, the MPC controller has used more energy than the PI controller, taking advantage of cheaper tariff. This leads to a significant increase in the tank temperatures during the night, a strong sign of energy being stored. The MPC controller then switched off the heat pump when the higher day time electric tariff comes into action as can be seen control input graph of Fig. 5. It mainly relies on the energy stored in the tanks, using only a minimal amount of electricity to keep the tank temperatures above the lower limit. One deviation from this objective is the strong use of the heat pump for a short period at 10:00 on day 3. Closer investigation of the optimisation reveals that this is applied in order to avoid the lower limit on T3, which is encountered unexpectedly due to model errors between the linear model used on the controller and the non-linear model used for the simulation.

Neither the PI controller nor the on-off controller takes electric tariffs into account (which is in line with their simple design). As a consequence, they use more energy during the day time. After the initial settling period, the PI controller maintains very steady temperatures throughout the system. The on-off controller keeps the temperatures between upper and lower limits, which lead to the typical limit cycle characteristic of a switching controller.

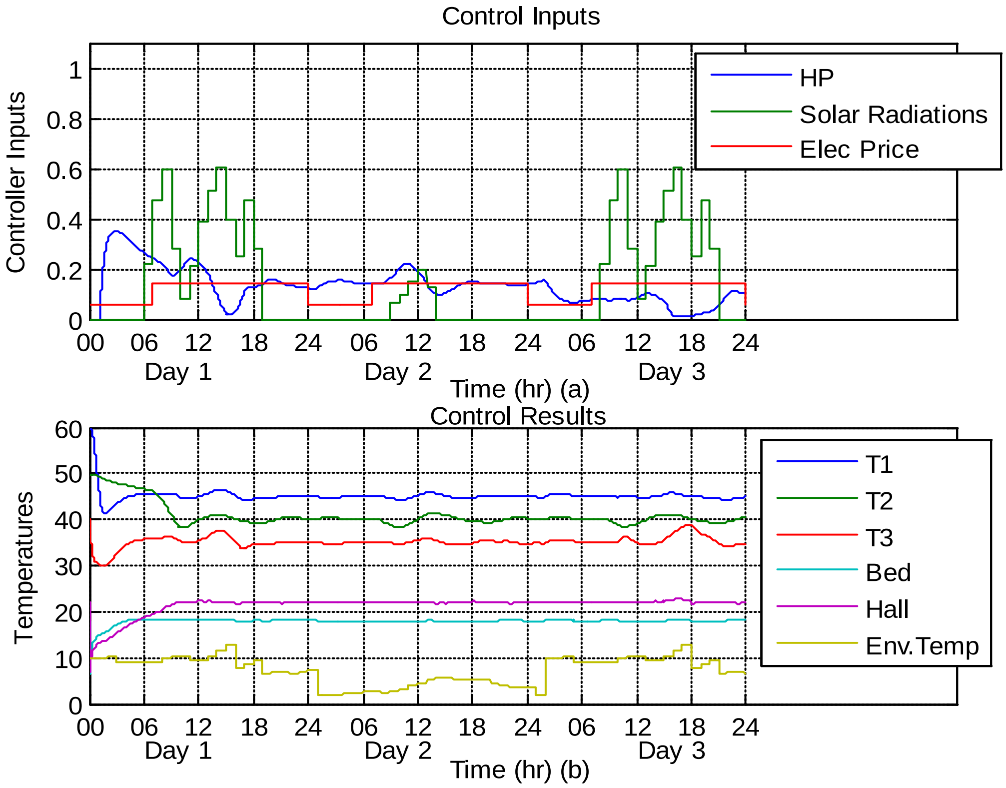

Fig. 4 PI control results Case A

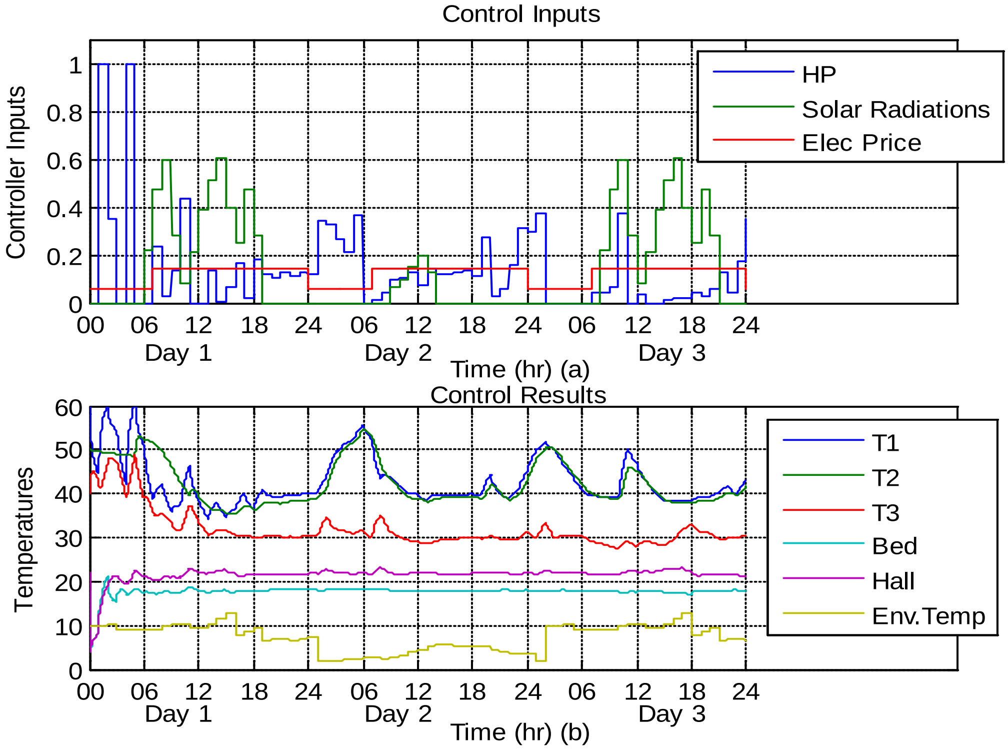

Fig. 5 MPC control results Case A

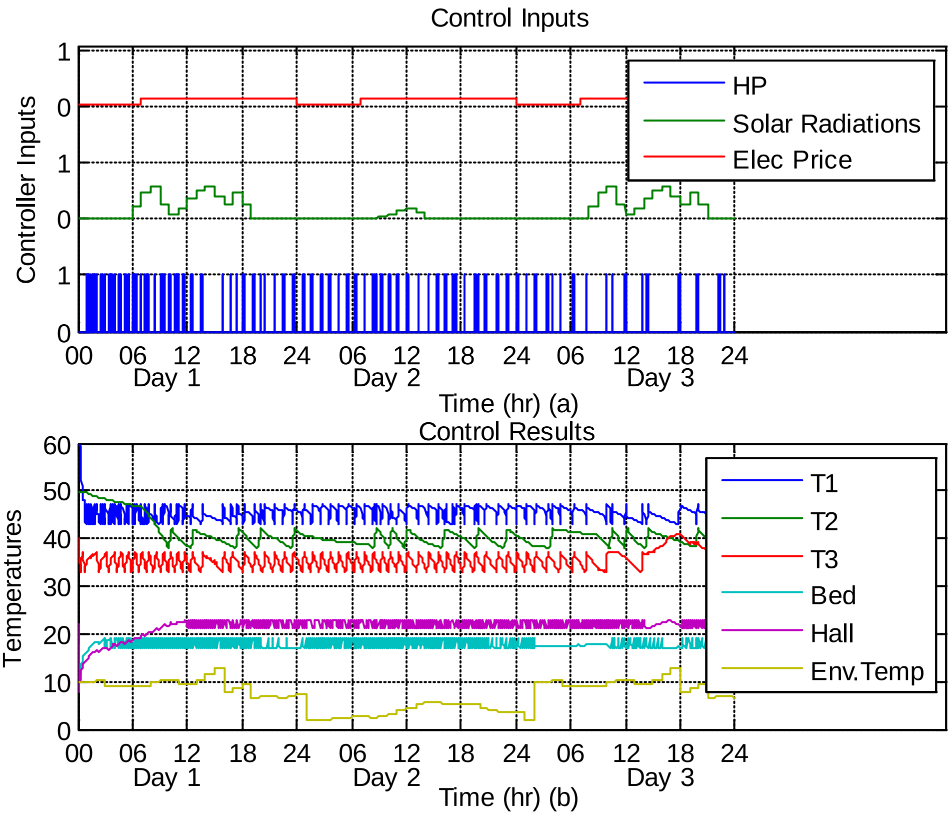

Fig. 6 On-off control results Case A

5.2 Results: Case B

The second scenario simulates a particularly sunny day in the middle of two mild days. It is used to judge how effective a control strategy is at making use of solar radiation in order to reduce the electrical consumption. The results for all controllers are shown in Figs. 7-9, and they all maintain the room temperatures at the desired level. All simulations show a rise in the temperature of tank 3 and a rise of the hall temperature during day 2 – this is caused directly by the strong solar radiation (in a typical use the occupant would use natural ventilation to reduce the temperature based on comfort level). All controllers compensate for this by cutting the heating input to the minimum required for maintaining hot water, and this means that the energy cost is significantly reduced compared to the previous scenario.

There are a few interesting differences in the details. It would be expected that the MPC controller would use to the prediction of the weather to proactively cool the rooms just before the high solar input, but this does not seem to be happening. Only a small difference is noticeable in the bedroom, but it is not very pronounced. Secondly, it would be physically possible to circulate the hot water from the heating tank back into the buffer tank and from there into the hot water tank. None of the controllers achieve this– the simple controllers because they are not designed to do so, and the MPC controller because the linear model does not account for reverse heat flow. So this is an interesting opportunity to enhance the controller in order to manage further energy savings.

Still, MPC uses slightly less energy than the other two controllers during the second day. This energy is used only to heat up the hot water tank as the heat tank has enough energy because of the solar energy as shown in Fig. 8. The results for on-off controller Fig. 9 shows that tank temperature's fluctuations are less than the room air temperature's fluctuations, due to higher temperature range for the tanks.

The energy cost analysis showed that the MPC has a lower energy cost than the PI and on-off controllers. The model predictive controller achieves this by using more electricity at night, making use of the cheaper night time tariff and using low power settings during the day time. For case A, the MPC energy cost was 12.24% less than the PI controller and 8.92% less than the on-off controller. During case B simulations, the MPC energy cost was 10.05% and 5.674% less than the PI and on-off controller. In Fig. 10 it is shown that for Case A simulations, the MPC has used more night time electricity than the other two controllers.

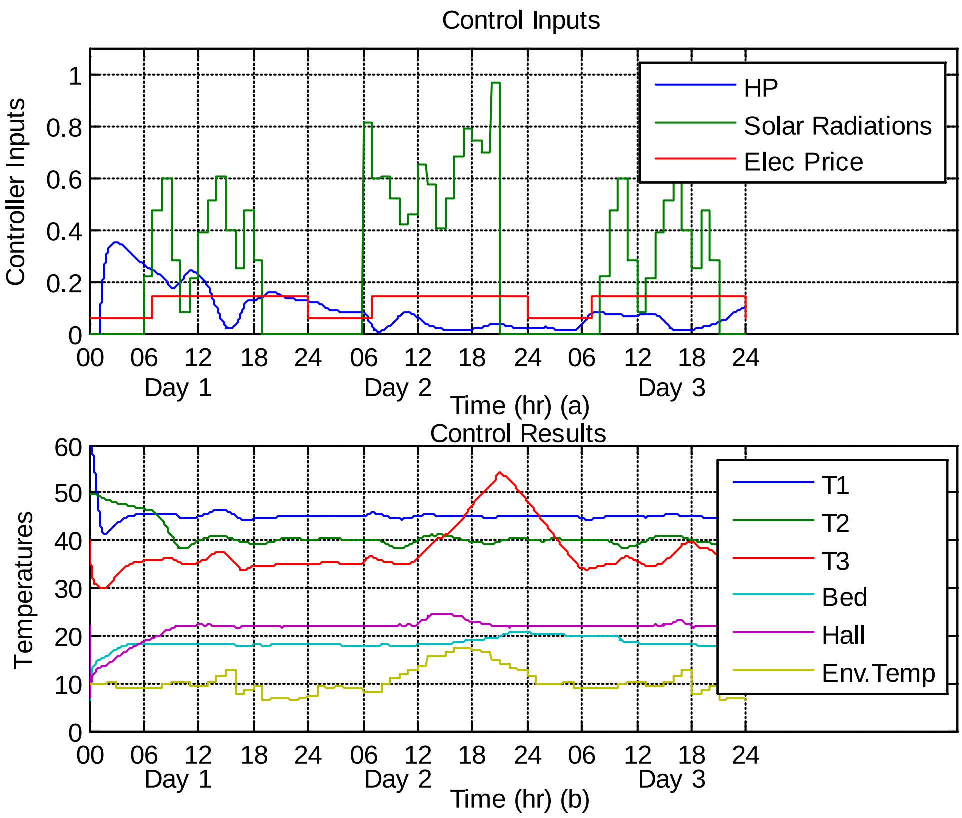

Fig. 7 PI control results Case B

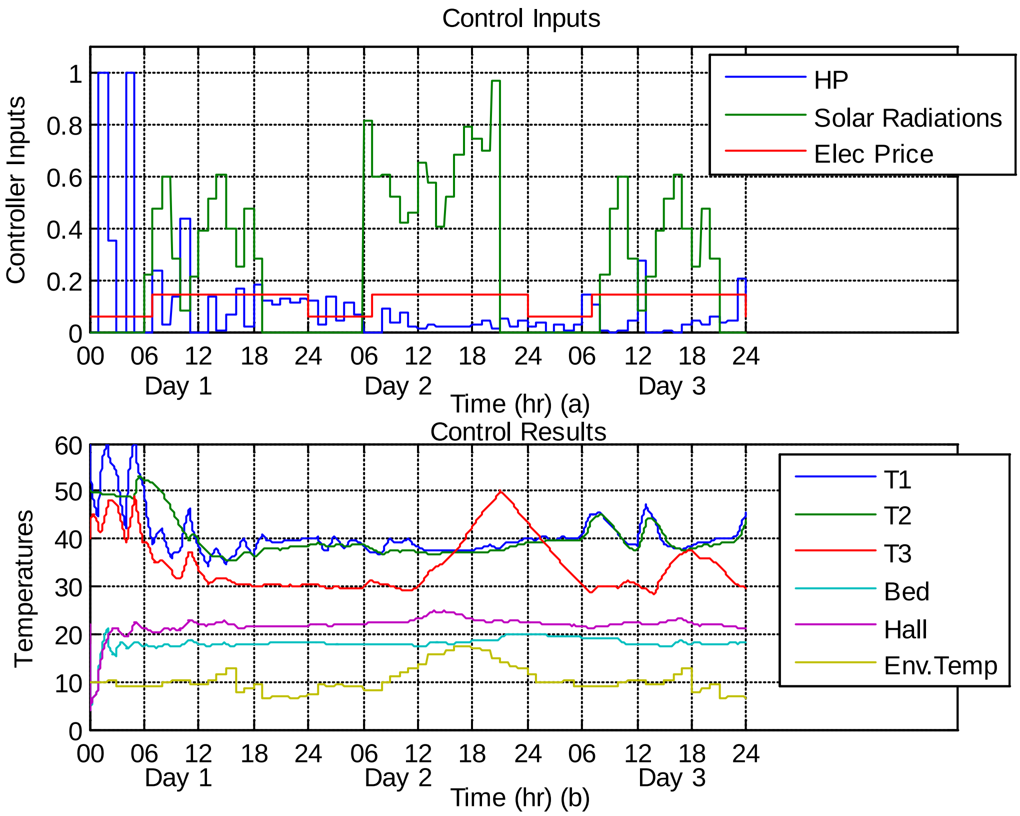

Fig. 8 MPC control results Case B

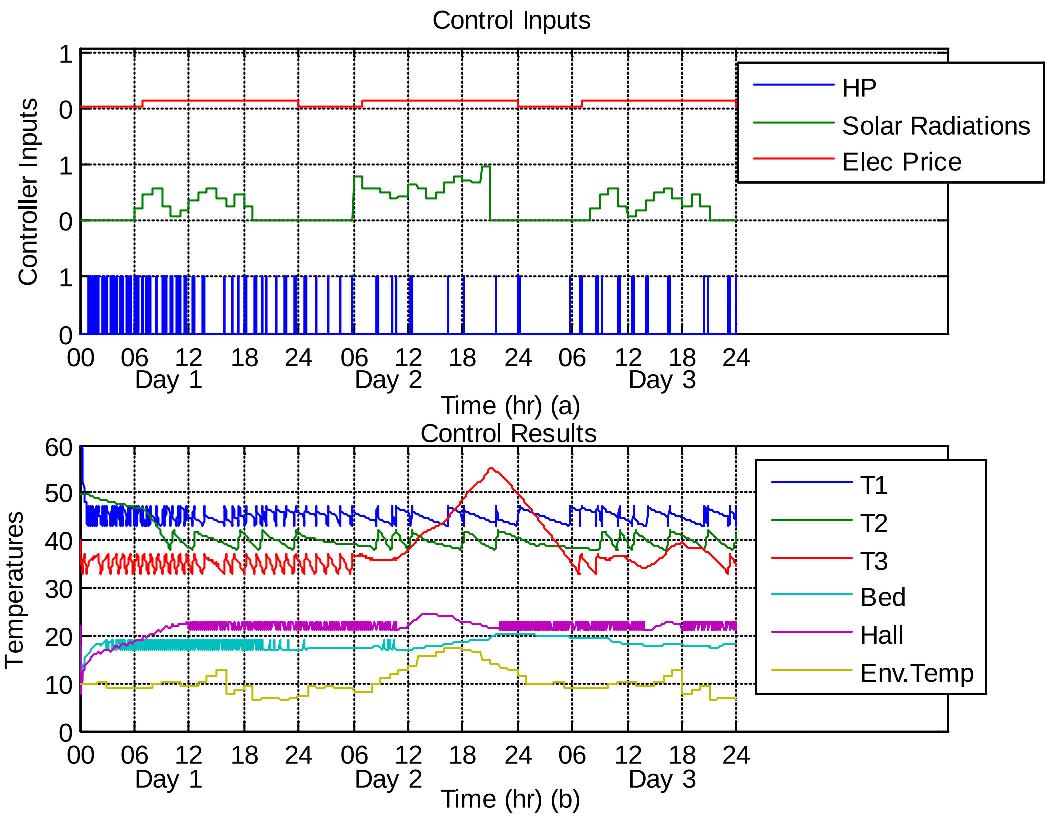

Fig. 9 On-off control results Case B

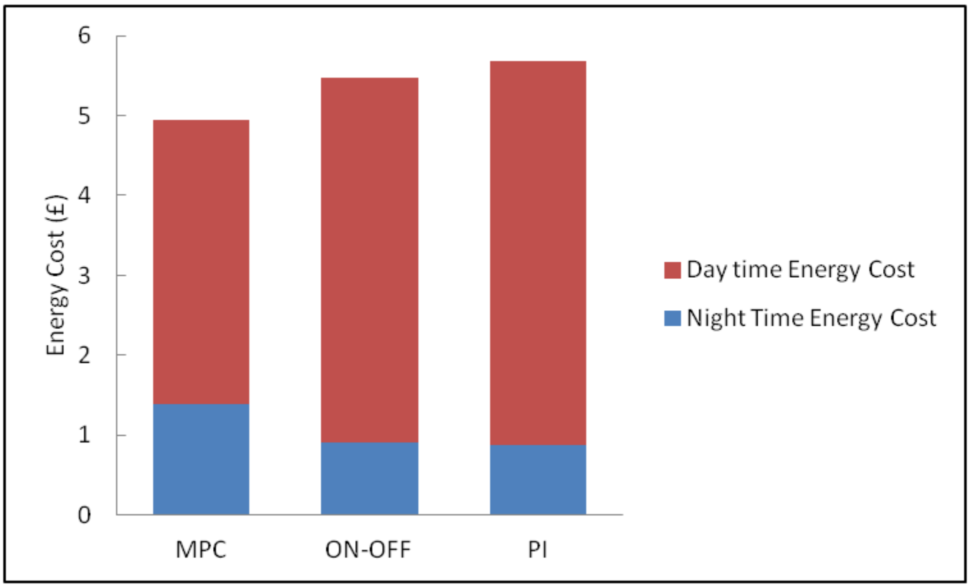

Fig. 10 Night time energy price in pounds

6 Conclusions

The simulation results showed that the MPC controller is able to perform load shifting by using the heat pump predominantly during the night time period. This means the MPC energy cost is 9.8% less than the PI and on-off controllers. The model predictive controller also used cheaper night time electricity and heat pump was used at low settings or even was turned off during the day time. Fig. 10 shows that for case A, the MPC has used more night time electricity than the PI and on-off controllers.

The plant model used in this research is a lumped non-linear model, but the MPC controller uses a linearized version of it. This causes a model mismatch between the controller and the real model, leading to some suboptimal controller action. The error increases as the tank temperature deviate from the nominal values used for linearization, and the effect on temperature stability is exacerbated by the long cycle time (1h) used for the MPC controller. It may be possible to reduce this issue by controlling energy transfer rate rather than mass flow rate, or by implementing an underlying control layer. However, both solutions significantly complicate the modelling of system limits for the MPC controller.

The second limitation was that because the MPC controller only has a linear model of the plant, it cannot use non-linear effects for load shifting. This limits for example the use of solar energy, because it does not get transferred back into the other tanks.

However, despite these two limitations of MPC, overall the model predictive controller proved to have a greater potential in the area of load shifting and use of renewable energy. The computational complexity is reasonably low, and it is even suitable for online implementation on affordable embedded control hardware.

References

[1] International-Energy-Agency: 'Key world Energy Statistics.', 2006.

[2] http://www.decc.gov.uk/assets/decc/11/stats/publications/energy-consumption/2323-domestic-energy-consumption-factsheet.pdf, accessed November 2012

[3] A.I. Dounis, C. Caraiscos. Advanced control systems engineering for energy and comfort management in a building environment—A review. Renewable and Sustainable Energy Reviews. vol. 13, no. 6–7, pp. 1246-1261, 2009.

[4] S. Liu, G.P. Henze. Experimental analysis of simulated reinforcement learning control for active and passive building thermal storage inventory: Part 1. Theoretical foundation. Energy and Buildings. vol. 38, no. 2, pp. 142-147, 2006.

[5] S.Liu, G.P. Henze. Experimental analysis of simulated reinforcement learning control for active and passive building thermal storage inventory: Part 2: Results and analysis. Energy and Buildings, vol. 38, no2, pp. 148-161, 2006.

[6] Z.Yu, A.Dexter. Online tuning of a supervisory fuzzy controller for low-energy building system using reinforcement learnin. Control Engineering Practice, vol. 18, no. 5, pp. 532-539, 2010.

[7] http://www.opticontrol.ethz.ch/, accessed October 2012

[8] M. Yudong, F. Borrelli, B. Hencey, A. Packard, S. Bortoff. Model Predictive Control of thermal energy storage in building cooling systems. In Proceedings of the 48th IEEE Conference on Decision and Control, held jointly with the 28th Chinese Control Conference, doi:10.1109/cdc.2009.5400677. pp. 392-397, 2009.

[9] M. Yudong, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, P. Haves. Model predictive control for the operation of building cooling systems. In Proceeding of American control conference (ACC). ISSN 0743-1619, pp. 5106-5111, 2010.

[10] F. Oldewurtel, A. Ulbig, A. Parisio, G. Andersson, M. Morari. Reducing peak electricity demand in building climate control using real-time pricing and model predictive control. In Proceedings of Conference on decision and control, CDC. 2010.

[11] J. Široký, F. Oldewurtel, J. Cigler, S. Prívara. Experimental analysis of model predictive control for an energy efficient building heating system. Applied Energy, vol. 88, no. 9, pp. 3079-3087, 2011.

[12] W. Grünenfelder, J. Tödtli. The use of weather predictions and dynamic programming in the control of solar domestic hot water systems. In Proceeedings of Mediterranean Electrotechnical Conference (Melecon), Madrid, Spain. 1985.

[13] G. Henze, C. Felsmaan, G. Knabe. Evaluation of optimal control for active and passive building thermal storage. International Journal of thermal sciences, vol. 43, pp. 173–183, 2004.

[14] G. Henze, C. Felsmaan, G. Knabe. Impact of forecasting accuracy on predictive optimal control of active and passive building thermal storage inventory. International Journal of HVAC & Research, vol. 10, pp. 153–178, 2004.

[15] G. Henze, D. Kalz, S. Liu, C. Felsmaan. Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory. International Journal of HVAC & Research, vol. 11, pp. 189–214, 2005.

[16] S.H. Cho, M. Zaheer-uddin. Predictive control of intermittently operated radiant floor heating systems. Energy Conversion and Management., vol. 44, no. 8, pp. 1333-1342. 2003.

[17] S. Prívara, J. Široký, L. Ferkl, J. Cigler. Model predictive control of a building heating system: The first experience. Energy and Buildings, vol. 43, no. 2–3, pp. 564-572, 2011.

[18] B. Paris, J. Eynard, S. Grieu, T. Talbert, M. Polit. Heating control schemes for energy management in buildings. Energy and Buildings, vol. 42, pp. 1908-1917, 2010.

[19] A.W.M. Van Schijndel, M.H. De Wit. Advanced simulation of building systems and control with Simulink. In Proceedings of 8th International IBPSA Conference, Eindhoven, Netherlands, pp. 1185-1192, 2003.

[20] J. Duffie, W. Beckman. Solar engineering of thermal processes. New York: Wiley. 1991.

[21] R.W. Haines. HVAC system design handbook. TAB Books, USA, 1988.

[22] S.J. Qin, T.A. Badgwell. A survey of industrial model predictive control technology. Control Engineering Practice, vol. 11, no. 7, pp. 733-764, 2003.

[23] Defra. Measurement of domestic hot water consumption in dwellings. Copyright Crown, 2008.

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Appendix

Nomenclature

F_R	collector heat removal factor
Q_U	useful energy gain, W
T_c	collector average temperature, ℃
T_a	ambient temperature, ℃
α	absorption factor of solar collector
τ	transmittance factor of solar collector
A_c	area of solar collector, m^2
I	solar radiation intensity, W/m^2
U_L	collector overall heat loss coefficient, W/m^2
MPC	model predictive control
PID	proportional integral and derivative controller
FLC	fuzzy logic controller
$HVAC$	heating, ventilation and air conditioning
COP	coefficient of performance

State space model

$A =$

	x_1	x_2	x_3	x_4
x_1	-0.02171	0.00724	0.01214	0
x_2	0.001829	-0.002265	0	0
x_3	0.001829	0	-0.002265	0
x_4	0	0	0	-0.02177
x_5	0	0	0	0.001829
x_6	0	0	0	0.001829
x_7	7.97×10^{-6}	0	0	0
x_8	0	0	0	0
x_9	1.82×10^{-5}	0	0	2.427×10^{-5}
x_{10}	0.0008649	0	0	0
x_{11}	1.42×10^{-5}	0	0	0
x_{12}	0	$3.64E \times 10^{-5}$	0	0
x_{13}	0	0	0	0
x_{14}	0	0	3.64×10^{-5}	0
x_{15}	0	0	0	0
x_{16}	0	0	0	0.0005561
x_{17}	0	0	0	1.42×10^{-5}
x_{18}	0	0	0	0
x_{19}	0	0	0	0
x_{20}	0	0	0	0
x_{21}	0	0	0	0
x_{22}	0	0	0	0

	x_5	x_6	x_7	x_8
x_1	0	0	0.0001734	0
x_2	0	0	0	0
x_3	0	0	0	0
x_4	0.00724	0.01214	0	0
x_5	-0.002265	0	0	0
x_6	0	-0.002265	0	0
x_7	0	0	-0.0001321	2.39×10^{-5}
x_8	0	0	2.39×10^{-5}	3.19×10^{-5}
x_9	0	0	7.28×10^{-5}	6.07×10^{-6}
x_{10}	0	0	0	0
x_{11}	0	0	0	0
x_{12}	0	0	0	0
x_{13}	0	0	0	0
x_{14}	0	0	0	0
x_{15}	0	0	0	0
x_{16}	0	0	0	0

x_{17}	0	0	0	0
x_{18}	3.64×10^{-5}	0	0	0
x_{19}	0	0	0	0
x_{20}	0	3.64×10^{-5}	0	0
x_{21}	0	0	0	0
x_{22}	0	0	0	0

	x_9	x_{10}	x_{11}	x_{12}
x_1	0.0005202	0.0003374	0.000728	0
x_2	0	0	0	0.0004359
x_3	0	0	0	0
x_4	0.0006936	0	0	0
x_5	0	0	0	0
x_6	0	0	0	0
x_7	9.569×10^{-5}	0	0	0
x_8	7.974×10^{-6}	0	0	0
x_9	-0.0001333	0	0	0
x_{10}	0	-0.001309	0	0
x_{11}	0	0	-4.78×10^{-5}	0
x_{12}	0	0	0	-3.971×10^{-5}
x_{13}	0	0	0	0.0001237
x_{14}	0	0	0	0
x_{15}	0	0	0	0
x_{16}	0	0	0	0
x_{17}	0	0	0	0
x_{18}	0	0	0	0
x_{19}	0	0	0	0
x_{20}	0	0	0	0
x_{21}	0	0	0	0
x_{22}	0	8.264×10^{-5}	0	0

	x_{13}	x_{14}	x_{15}	x_{16}
x_1	0	0	0	0
x_2	0	0	0	0
x_3	0	0.0004359	0	0
x_4	0	0	0	0.000217
x_5	0	0	0	0
x_6	0	0	0	0
x_7	0	0	0	0
x_8	0	0	0	0
x_9	0	0	0	0
x_{10}	0	0	0	0
x_{11}	0	0	0	0
x_{12}	3.286×10^{-6}	0	0	0
x_{13}	-0.002382	0	0	0
x_{14}	0	-3.971×10^{-5}	3.286×10^{-6}	0
x_{15}	0	0.0001237	-0.002382	0
x_{16}	0	0	0	-0.0008539
x_{17}	0	0	0	0
x_{18}	0	0	0	0
x_{19}	0	0	0	0
x_{20}	0	0	0	0
x_{21}	0	0	0	0
x_{22}	0	0	0	5.537×10^{-5}

	$x17$	$x18$	$x19$	$x20$	$x21$	$x22$
$x1$	0	0	0	0	0	0
$x2$	0	0	0	0	0	0
$x3$	0	0	0	0	0	0
$x4$	0.000728	0	0	0	0	0
$x5$	0	0.0004359	0	0	0	0
$x6$	0	0	0	0.0004359	0	0
$x7$	0	0	0	0	0	0
$x8$	0	0	0	0	0	0
$x9$	0	0	0	0	0	0
$x10$	0	0	0	0	0	0.0004444
$x11$	0	0	0	0	0	0
$x12$	0	0	0	0	0	0
$x13$	0	0	0	0	0	0
$x14$	0	0	0	0	0	0
$x15$	0	0	0	0	0	0
$x16$	0	0	0	0	0	0.0002978
$x17$	-4.78×10^{-5}	0	0	0	0	0
$x18$	0	-3.971×10^{-5}	3.286×10^{-6}	0	0	0

$x19$	0	0.0001237	-0.002382	0	0	0
$x20$	0	0	0	-3.971×10^{-5}	3.286×10^{-6}	0
$x21$	0	0	0	0.0001237	-0.002382	0
$x22$	0	0	0	0	0	-0.000138

B=

	u_1	u_2	u_3	u_4	u_5	u_6
x_1	0	0	0	0	0.05247	0
x_2	0	0	0	0	0	0
x_3	0	0	0	0	0	0
x_4	0	0	0	0	0	0.06087
x_5	0	0	0	0	0	0
x_6	0	0	0	0	0	0
x_7	0.01137	-0.00399	-0.01196	0	0	0
x_8	0	0.003987	0	0	0	0
x_9	0	0	0.009102	-0.00019	-0.001836	-0.00213
x_{10}	0	0	0	0	0	0
x_{11}	0	0	0	0	0	0
x_{12}	0	0	0	0	0	0
x_{13}	0	0	0	0	0	0
x_{14}	0	0	0	0	0	0
x_{15}	0	0	0	0	0	0
x_{16}	0	0	0	0	0	0
x_{17}	0	0	0	0	0	0
x_{18}	0	0	0	0	0	0
x_{19}	0	0	0	0	0	0
x_{20}	0	0	0	0	0	0
x_{21}	0	0	0	0	0	0
x_{22}	0	0	0	0	0	0

	u_7	u_8	u_9	u_{10}	u_{11}	u_{12}
x_1	0.0005722	0	0	0.01734	0	0
x_2	0	0	0	0	0	0
x_3	0	0	0	0	0	0
x_4	0.0007548	0	0	0	0.01734	0
x_5	0	0	0	0	0	0
x_6	0	0	0	0	0	0
x_7	7.770×10^{-6}	0	0	0	0	0
x_8	0	-3.721×10^{-5}	0	0	0	0
x_9	1.189×10^{-5}	0	0.00165	0	0	0
x_{10}	0	0	0	0	0	0
x_{11}	3.362×10^{-5}	0	0	0	0	0
x_{12}	0	0	0	0	0	0
x_{13}	2.259×10^{-3}	0	0	0	0	0
x_{14}	0	0	0	0	0	0
x_{15}	2.259×10^{-3}	0	0	0	0	0
x_{16}	0	0	0	0	0	0
x_{17}	3.362×10^{-5}	0	0	0	0	0
x_{18}	0	0	0	0	0	0

x_{19}	2.259×10^{-3}	0	0	0	0	0
x_{20}	0	0	0	0	0	0
x_{21}	2.590×10^{-3}	0	0	0	0	0
x_{22}	0	0	0	0	0	0

$C =$

	x_1	x_2	x_3	x_4	x_5	x_6	x_7
y_1	0.1568	0.0784	0.0784	0	0	0	0
y_2	0.1554	0.078	0.078	0	0	0	0
y_3	0	0	0	0.1497	0.075	0.075	0
y_4	0	0	0	0.1483	0.0743	0.0743	0
y_5	0	0	0	0	0	0	1
y_6	0	0	0	0	0	0	0
y_7	0	0	0	0	0	0	0
y_8	1	0	0	0	0	0	0
y_9	0	0	0	1	0	0	0

	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
y_1	0	0	0	0	0	0	0
y_2	0	0	0	0	0	0	0
y_3	0	0	0	0	0	0	0
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	1	0	0	0	0	0	0
y_7	0	1	0	0	0	0	0
y_8	0	0	0	0	0	0	0
y_9	0	0	0	0	0	0	0

	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}
y_1	0	0	0	0	0	0	0
y_2	0	0	0	0	0	0	0
y_3	0	0	0	0	0	0	0
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	0	0	0	0	0	0	0
y_7	0	0	0	0	0	0	0
y_8	0	0	0	0	0	0	0
y_9	0	0	0	0	0	0	0

	x_{22}
y_1	0
y_2	0
y_3	0
y_4	0
y_5	0
y_6	0
y_7	0
y_8	0
y_9	0

$D =$

	u_1	u_2	u_3	u_4	u_5	u_6	u_7
y_1	0	0	0	0	0	0	0
y_2	0	0	0	0	0	0	0
y_3	0	0	0	0	0	0	0
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	0	0	0	0	0	0	0
y_7	0	0	0	0	0	0	0
y_8	0	0	0	0	0	0	0
y_9	0	0	0	0	0	0	0

	u_8	u_9	u_{10}	u_{11}	u_{12}
y_1	0	0	0	0	0
y_2	0	0	0	0	0
y_3	0	0	0	0	0
y_4	0	0	0	0	0
y_5	0	0	0	0	0
y_6	0	0	0	0	0
y_7	0	0	0	0	0
y_8	0	0	0	0	0
y_9	0	0	0	0	0

Input groups:

Name	Channels
Manipulated	$[u_1, u_2, u_3, u_4, u_5, u_6]$
Measured	$[u_7, u_8, u_9, u_{10}, u_{11}, u_{12}]$

Output groups:

Name	Channels
Measured	$[y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_8, y_9]$

Continuous-time state-space model.

Model predictive control and Simulation of a Solar water heating system with an ON/OFF controller

M. W. Ahmad*[,a], M .Eftekhari[b], J. Deng[c]

Abstract—This paper presents a simple simulation of solar water heating system. This system is controlled by a simple ON/OFF controller. The simulations were performed in TRNSYS environment. This paper also addresses the application of model predictive control (MPC) to control the temperature of a solar heating system combined with heat pump. The main objective of this work will be to maximize the use of solar energy collected by solar collector. The controller will reject disturbances caused by solar radiations.

Keywords— Model predictive control; solar radiations; solar heating system; heat pump

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I. Introduction

THE limited reserves of oil and interests of environment protection and energy efficiency have led the research direction towards renewable energy resources (RES). Energy is considered as a primary source of wealth generation and is also a significant factor of economic growth of any country. The energy resources can be divided into three categories (i) Fossil fuels, (ii) Renewable Energy resources and (iii) Nuclear resources (Demirbas, 2000). Kalogirou (2004) mentioned Renewable energy resources (RES) as alternative sources of energy. In last two decades a significant research has been carried out in the field of RES and systems. By the end of 2001 the total capacity of installed of RE (Renewable Energy) system was 9% of the total electricity generation (Sayigh, 2001).

Model predictive control has gained a considerable attention in last few decades, both within the industry and the research (Camacho et al, 1999).

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Model predictive control:

MPC originated in the late seventies and has developed very considerably. MPC is a class of computer algorithms that utilize process model to predict future outcome/response of a plant. The control signal is obtained by minimizing objective function (Qin et al, 2002) .Camacho et al (1999) mentioned the main ideas behind predictive control methods as;

- Explicit use of a model to predict the process output at future time instant (horizon).
- Obtaining control signal by minimizing an objective function.
- Using receding strategy, at each instant the horizon is moved towards the future.

MPC is a methodology rather than a single technique. The main difference in the various methods is the way the problem is translated in to the mathematical model. MPC technology is used in different areas; including chemical industry, food processing, power plants, petroleum, automotive, and aerospace (Van den boom et al, 2010). MPC is referred as a member of controller's family, which uses explicit and identifiable model. The main reason of MPC popularity is its ability to give high performance control systems, which are capable of operating without expert supervision for long time (Garcia et al, 1989).

II. Plant Description:

The plant is located at Civil and Building Engineering laboratories, Loughborough University, UK. The system consisted of solar collector, two buffers storage tanks and a heat pump. The general scheme of the plant is shown in figure (1). The system is arranged in parallel arrangement. The reason for installing this system as parallel system is that Freeman et al (1979), Chandrashekar et al (1982), Mitchell et al (1978), Marvin et al (1976) and Hatheway et al (1981) studied the performance of different solar assisted heat pump systems and it is shown that parallel systems are better in performance from series systems and also parallel systems is slightly better than dual system.

(a) Solar Collector:

The main source of energy is solar radiation. Solar collector is used to collect solar heat energy.

(b) Buffer tanks:
The system has two storage tanks. One tank is attached to solar collector loop while the second one is the load tank.
(c) Heat Pump

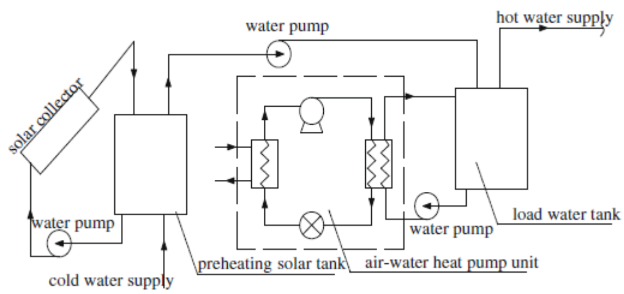

Figure 1: Solar assisted air source heat pump (Source: Li et al, 2009)

The system shown in figure 1 is solar assisted air source heat pump (SA-ASHP). The main source of energy is through solar radiations. On cloudy and during night time when there is not enough solar radiation then heat pump is used for auxiliary energy.

III. Model development:

Duffie et al (1991) calculated the useful energy from solar collector

$$q_s = A_c[I_T F_R(\alpha\tau) - F_R U_L(T_{st} - T_a)] \quad (1)$$

Heat balance on storage tank:
The heat balance heat equation on pre heating solar loop storage tank is given by following equation;

Heat stored in storage tank= Heat added –heat removed

$\rho C_p V_{st}\ dT_{st}/d_t$=Solar energy+ buffer tank energy – to radiators (load)- heat loss
The energy supplied to radiators is given by;
Energy to radiators= $q_{Ls} = m_L C_p (T_{st} - T_R)$ (2)

The heat loss from tank to environment;
Heat loss to environment= $q_{stl} = U_{st} A_{st} (T_{st} - T_a)$ (3)

Kulkarni et al (2007) proved that for cylindrical tanks the surface area of tank can be related to its volume, height and diameter.

$$A_{st} = 1.845\,(2 + h/d)\, V_{st}^{2/3} \quad (4)$$

By combining equations 1, 2, 3 and 4, the heat stored by the preheating storage tank is given by;

$$\rho C_p V_{st}\, dT_{st}/d_t = A_c[I_T F_R(\alpha\tau) - F_R U_L(T_{st} - T_a)] - m_L C_p (T_{st} - T_R) - U_{st} A_{st} (T_{st} - T_a) \quad (5)$$

Heat pump equations:

Li et al (2009) noted that the thermal energy absorbed by the water is equal to the heat released by the condenser as: $Qc = Q_{water} = C_p m_w (T_{wout} - T_{win})$ (6)

Kaygusuz (1995) estimated the relationship between heat released by condenser by heat pump and ambient temperature by using manufacturer's data;

$$Qc = 18.45 - 0.101T_a + 6.508 \times 10^{-5} T_a^2 - 5.044 \times 10^{-7} T_a^3 \quad (7)$$

By putting value of Qc from equation from 7 in to equation 6, T_{wout} by changing volume flow rate,
As

$$m_w = \rho V \quad (8)$$

IV. Trnsys:

Trnsys is a transient system simulation program. Trnsys stands for "transient simulation program". It was developed by the University of Wisconsin (Klein, 1996). Trnsys is written in fortan-77. After identifying system components, these components are connected. Each component in trnsys is represented by a box; this box requires a number of constant parameters, inputs (which are time dependent) and outputs (time dependants).
In this paper a simple simulation was run in trnsys environment. A system used for solar water heating was modeled and simulated. The system was consisted of a solar collector, a storage tank, pump, an ON/OFF controller, diverters and tee joints, load profile type. The connection between these components is shown in figure 2. Birmingham (UK) weather data was selected for this case and simulations were performed for the months of May, June and July. The radiations received by solar thermal collector are shown in figure 3. The controller used in this case study was a simple ON/OFF feedback controller. The outlet temperature from storage tank is shown in figure 4. It was found that the temperature varied between 57 ^{O}C to 100 ^{O}C.

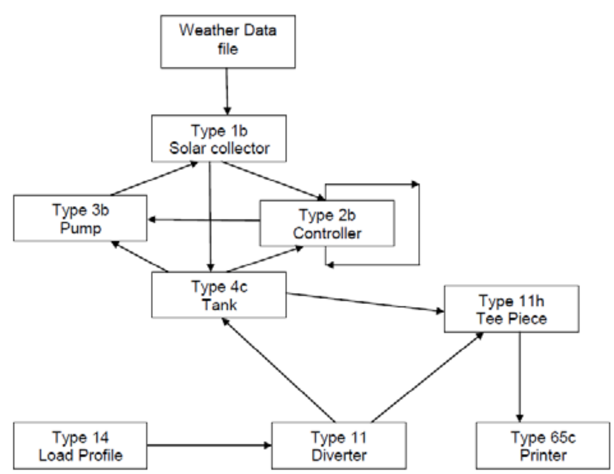

Figure 2: Flow diagram of solar heating system

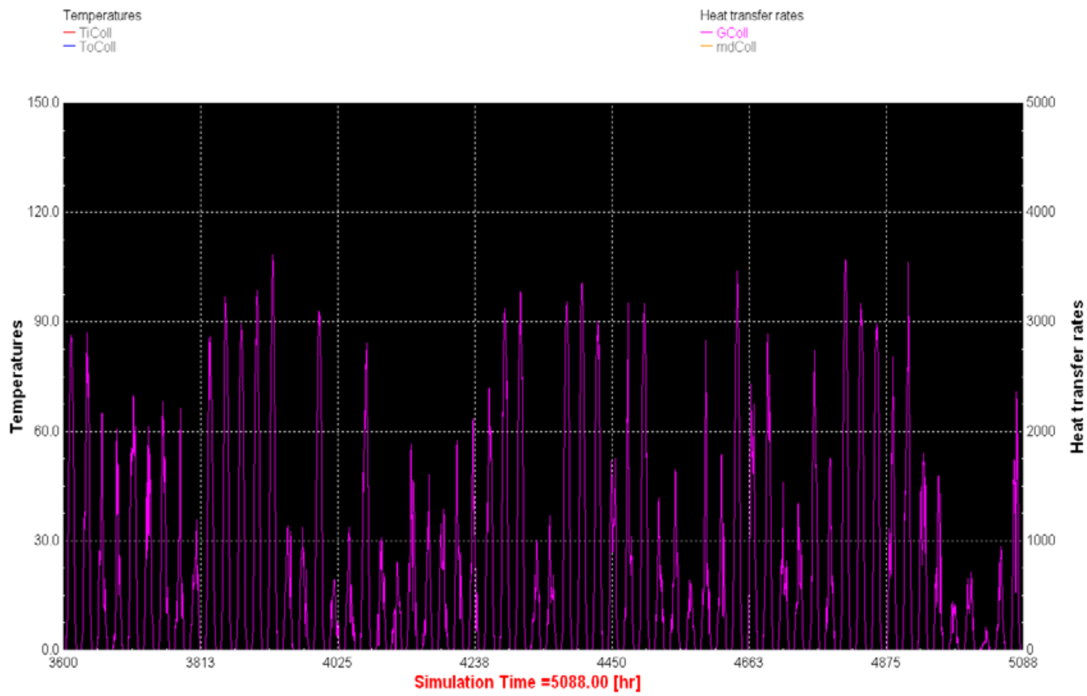

Figure 3: Radiations received by solar collector

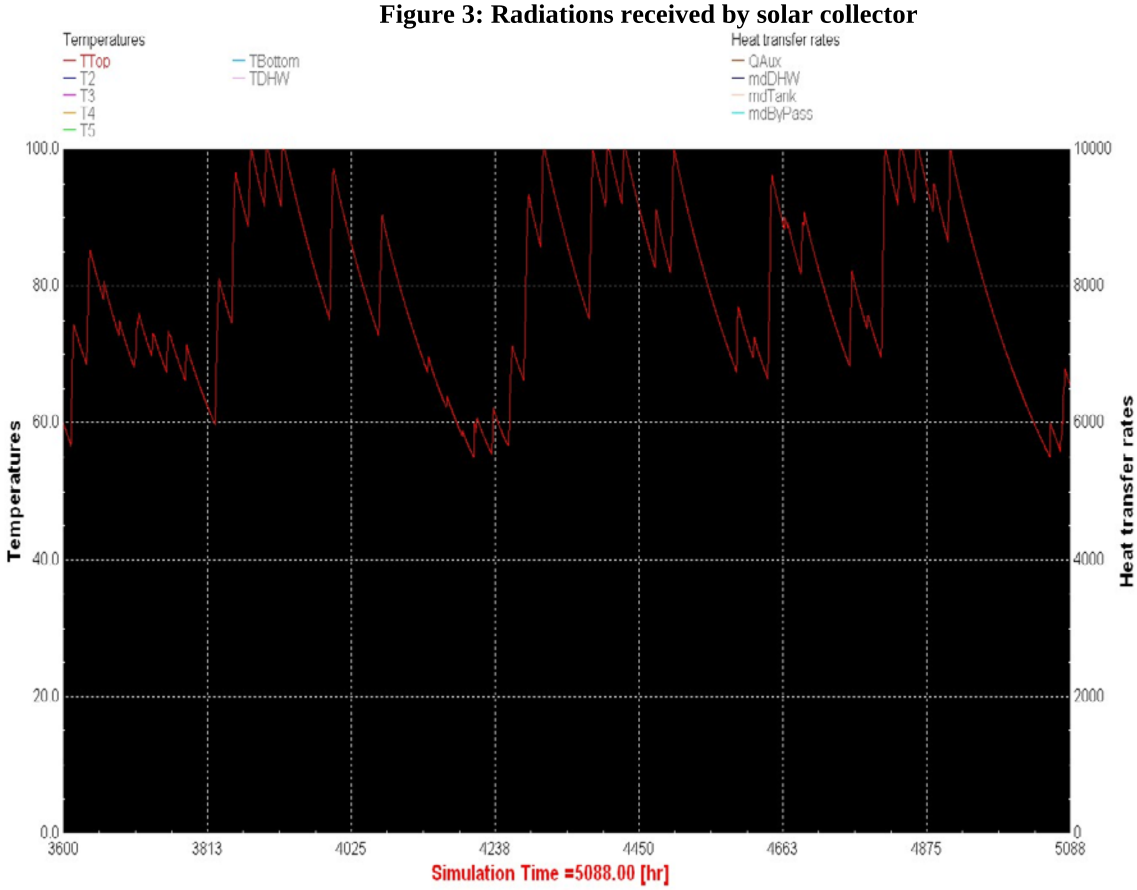

Figure 4: Outlet temperature of storage tank

V. MATLAB:

The use of Matlab is increasing in different fields. Now a days is not only used for computing/mathematical applications, it is also used in different other fields such as control engineering, fluid mechanics, mechanical vibrations, etc. in the research area of built environment its use has also been increased. Matlab/simulink is used for different applications for example pipe sizing, building energy management systems and their control strategies, indoor air quality, control of renewable energy systems and their feasibility analysis, design of controller for HVAC applications, etc.

Model Predictive control tool box™ consisted of different set of functions for designing and analyzing model predictive controller. A MPC controls a system (plant) by combining a prediction and control strategies. Constraints are always considered in designing MPC, these constraints can be e.g. opening limit of actuators. Model predictive control toolbox™ has both GUI (Graphic user interface) and command syntax to help user.

In future MPC toolbox of matlab will be used to develop and analyze model predictive control for solar assisted heat pump system and then results will be compared with the simple ON/OFF controller.

VI. COUPLING TRNSYS AND MATLAB /SIMULINK:

Riederer et al (2009) presented a paper on coupling matlab and trnsys. It was mentioned that the types in trnsys are implemented as DLL files. This means that trnsys component can be implemented using any programming language which is capable to compile DLLs. Trnsys components can be imported in to simulink. The connection between simulink block represents the connection between trnsys types.

Trnsys and Matlab will be coupled to model water heating system and model predictive controller.

VII. CONCLUSION:

It has been concluded that the system give us good results as for as temperature is concerned, the average output temperature was around 70^{O}C. The main problem was that the temperature varied much. Therefore in future MPC controller will be designed and analyzed to overcome this problem.

VIII. FUTURE WORK:

In future different renewable systems have to be modeled in trnsys environment and then these models will be transferred into simulink. MPC controller will be developed in simulink and then different systems will be analyzed on the basis on energy consumption and thermal comfort requirements. After designing and analyzing model predictive control this control will be implemented on a test rig in the department of Civil and Building Engineering, Loughborough University, Loughborough, UK.

IX. ACKNOWLEDGMENT

We would like to thanks ESPRC for funding this project. This project is multi disciplinary project and brings together five different universities of UK; Brunel, Bath, City, De Montfort and Loughborough.

X. REFERENCES:

- Camacho, E.F. and Bordons, C. (1999) Model Predictive control. Springer Verlag, London.
- Chandrashekar, M. Le, N. Sunllivan, H. Hollands, KGT. (1982) A comparative study of solar assisted heat-pump systems for Canadian locations. Solar Energy, 28, 217–26.
- Demirbas, A. (2002) Recent advances in biomass conversion technologies. Energy, Education, Science and Technology, 6, 19–40.
- Duffie, J.A. and Beckman, W.A. (1991) Solar engineering of thermal processes. New York, Wiley, 686-732.
- Freeman, T.L., Mitchell, J.W. and Audit, T.E. (1979) Performance of combined solar heat-pump systems. Solar Energy, 22, 125–35.
- Garcia, C.E., Prett, D.M. and Morari, M. (1989) Model predictive control: Theory and Practice- A Survey. Automatica, 25(3), 335-348.
- Hatheway, F.M. and Converse, A.O. (1981) Economic comparison of solar assisted heat pumps. Sol Energy, 27, 561.
- Kaygusuz, K. (1995) Performance of Solar-Assisted heat pump systems. Applied Energy, 51, 93-109.
- Kulkarni, G.N. Kedare, S.B. and Bandyopadhyay, S. (2007) Determination of design space and optimization of solar water heating systems. Sol Energy, 81, 958–68.
- Li, H. and Yang, H. (2009) Study on performance of solar assisted air source heat pump systems for hot water production in Hong Kong. Applied energy, doi:10.1016/j.apenergy.2009.06.023 (Article in press).
- Marvin, W.C. and Mumma, S.A. (1976) Optimum combination of solar energy and the heat pump for residential heating. Proceedings of Joint Conference Am Sect ISES and SES of Canada, 3, 321–324.
- Mitchell, J.W. Freeman, T.L. and Beckman, W.A. (1978) Heat pumps. Sol Age, 3(7), 20.
- Qin, S.J. and Badgwell, T.A. (2002) A survey of industrial model predictive control technology. Control engineering practice, 11, 733-764.
- Riederer, P. Keilholz, W. and Ducreux, V. (2009) Coupling of TRNSYS with Simulink-A method to Automatically export and use TRNSYS models

within Simulink and vice versa. Proceedings of Eleventh International IBPSA conference, Glasgow.
- S.A. Klein *et al.*, TRNSYS 14.2, *A Transient Simulation and Program*, Solar Energy Laboratory, University of Wisconsin, Madison (WI) (1996).
- Van den boom, T.J.J. and Stoorvogel, A.A. (2010) Model predictive control, DISC Course, Lecture Notes.

Nomenclature:

A_c solar collector area (m^2)
A_{st} surface area of preheating solar tank (m^2)
C_p specific heat of water (J/kg ^OC)
d diameter of preheating solar tank (m)
F_R heat removal factor of solar collector
h height of preheating solar tank (m)
I_T solar radiation intensity on tilted surface (W/m^2)
m_L load mass flow rate (kg/s)
m_w circulation water flow rate (kg/s)
q_{Ls} load met by solar energy (W)
q_s useful solar heat gain (W)
q_{stl} storage heat loss of preheating solar tank (W)
Q_c heat discharged by condenser (W)
Q_w heat absorbed by hot water (W)
T_a ambient air temperature (^OC)
T_R cold water temperature (^OC)
T_{st} hot water temperature in preheating solar tank (^OC)
T_w water temperature (^OC)
U_L overall heat loss coefficient of solar collector (W/m^2 ^OC)
U_{st} heat loss coefficient of preheating solar tank (W/m^2 ^OC)
V_{st} storage volume of preheating solar tank (m^3)
V_w storage volume of load water tank (m^3)

Greek symbols
$\alpha\tau$ product of transmittance and absorptance
ρ water density (kg/m^3)

Model predictive control for Airport terminals-A review

M. W. Ahmad*[,a], M .Eftekhari[b], J. Deng[c]

Abstract—This paper presents an overview of climate conditions and Government policies for renewable energy systems for reducing green house gas emissions. A detailed literature review of Model predictive control is also carried out. It is found out that no research has been made to control solar assisted heat pump by using Model predictive control (MPC). It is also found out that Phase Change Materials (PCM) can show positive effect on the performance of Building and building's energy consumption. The active phase change systems are controlled by conventional control systems. However in order to enhance PCM system's performance MPC can be used and will be analysed in near future.

Keywords— Model predictive control; Phase Change materials; Solar assisted heat pump.

I. Introduction

In general, the major environmental concerns of many airport buildings have been noise, air quality, soil and water quality, sustainability and impact on habitat and wild life management (Oh, 2006). However, in recent years, the emissions of Green house gases and their impact on environment has gained equal attention as one of the main environmental concerns. According to Pejovic et al (2008) aviation industry contributes to Green house gases (GHG) emissions from aircraft in air and on ground and also through the energy used in airport buildings. It was estimated that in 2005 the total UK emissions from aviations industry were 37.5 million tones of CO_2 representing 6.3% of U.K's total emissions. Climate change is a global problem and is one of the very silent issues of the world. Now a days climate change and air quality are the main concerns of UK government. Hulme et al (2002) mentioned in their report on UK climate impact program (UKCIP) that climate is referred as the average weather that is experienced over a long period of time, typically 30 years. In response to natural causes, the world's climate has changed a lot. Global climate is affected both by human and natural factors. Human can affect global climate by releasing green house gases –like methane and CO_2- into the atmosphere. These gases absorb heat that is radiated from the Earth's surfaces and thus global temperature is increased by warming atmosphere. Natural causes include volcanic eruption, changes in the Earth's orbit and interaction between the oceans and the atmosphere.

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This increase in green house gases emission and global temperature has made the government to focus on using renewable energy systems.

In 2008, Commission of the European Communities set two key targets;

a) Greenhouse gases emission has to be reduced by at least 20 percent by 2020.

b) 20 percent of energy has to be produced from renewable energy sources by 2020.

This can be achieved by using renewable energy system and integrating them with Phase change materials and controlling these systems in a better way.

Model predictive control:

Model predictive control has gained a considerable attention in last few decades, both within the industry and the research (Camacho et al, 1999).

MPC originated in the late seventies and has developed very considerably. MPC is a class of computer algorithms that utilize process model to predict future outcome/response of a plant. The control signal is obtained by minimizing objective function (Qin et al, 2002) .Camacho et al (1999) mentioned the main ideas behind predictive control methods as;

- Explicit use of a model to predict the process output at future time instant (horizon).
- Obtaining control signal by minimizing an objective function.
- Using receding strategy, at each instant the horizon is moved towards the future.

MPC is a methodology rather than a single technique. The main difference in the various methods is the way the problem is translated in to the mathematical model. MPC technology is used in different areas; including chemical industry, food processing, power plants, petroleum, automotive, and aerospace (Van den boom et al, 2010). MPC is referred as a member of controller's family, which uses explicit and identifiable model. The main reason of MPC popularity is its ability to give high performance control systems, which are capable of operating without expert supervision for long time (Garcia et al, 1989).

II. History of Model predictive control

The history of model predictive control can be traced back to 1970's. Richalet et al (1978) proposed a model to control processes. They described applications of this method (Model Predictive Heuristic control). Later on this method was known as Model Algorithmic control. In 1979 two engineers (Cutler and Ramakter) from Shell came with the idea of Dynamic Matrix Control. In both of these techniques, an explicit dynamic model was used to predict effects of future outcomes on the outputs. That's why it is known as Model predictive control.

The above two researches were very closely related to minimum time optimal control and to linear programming. This relation was recognised by Zadeh et al (1962). The core of all MPC algorithms is known as moving horizon principle; this principle was proposed by Propoi (1963). In 1978 and 1979, MPC became very popular in chemical process industries. Different work has been done on adaptive control ideas. It was tried to keep future value close to the reference. Generalized predictive control was developed by Clarke et al (1987). This method uses ideas from generalized minimum variance (GMV).

Morari (1994) formulated model predictive control in state space context. This allows to generate more complex problems e.g. systems with non-deterministic disturbances and noise in the measured variables. Lee et al (1994) developed a MPC technique, which was based on step response model. In this model state estimation techniques were used. It was shown that state estimation technique from stochastic optimal control can be used to predict without additional complications. Bitmead et al (1990) in their book analyzed inherent characteristics of many MPC algorithms. By using state-space relationships Mohtadi (1986) proved some stability theorems. He also studied the influence of filter polynomials on robustness improvement. The lack of stability for finite horizon receding was also pointed out. Because of this drawback new research area was focused in early nineties.

Two methods named as CRHPC by Clarke et al (1991) and SIORHC by Mosca et al (1990) were developed and were proved to be stable. The problem of stability of constrained receding horizon control problem was tackled by Rawlings et al (1993), Rossiter et al (1996) and Zheng et al (1994). New results have found by campo et al (1987) and Allwright (1994) by using robust control approaches. MPC is still a developing technique of control, still there is a lot to be developed e.g. optimization of objective functions for the worst case of the uncertainties.

III. Literature review:

Model predictive control has been used in both industries and academic research. In this section a review will be made on the application of model predictive control for different solar plants and air conditioning systems.

Zhang et al (2006) described a way to tackle supervisory control problem of different systems. This work was carried out on a prototype building, with photovoltaic array, solar air and water heating, a biomass boiler and a stratified thermal storage. The control problem was for every system to decide whether to use energy directly, store it or waste it in the environment. Different models of systems were selected and implemented in simulink®. Evolutionary Control algorithm was used to optimize control strategy. The results were compared for both BEMS and MPC. In winter using BEMS, the energy consumption was 24.8% more as compared to MPC, while in spring 47.8% more energy was consumed. In summer, this consumption of energy became more. It was concluded that MPC with evolutionary Algorithm can be used for better control.

Núñez-Reyes et al (2005) applied model predictive controller to control the temperature in a solar air conditioning plant. Smith predictor was used in this controller and in order to reject disturbances caused by solar radiations and the auxiliary gas heater, a feed forward control action was included in this smith predictor. Previously, a PID controller was installed to control the inlet temperature of the absorption machine. This PID controller was unable to reject the disturbance in the inlet temperature due to oscillation in the gas heater temperature. A three input and one output model was identified. The experimental results showed that smith predictor is an appropriate way to increase the robustness and its tuning is also very simple. It also achieved a good performance in both set-point tracking and rejection of disturbances. Farkas et al (2005) developed a model predictive controller for solar plant operation. This plant model was based on energy balances. The developed model was the internal part of the controller. Internal model control uses the advantages of different unconstrained MPC schemes, easy online tuning and good performance. It was showed that the internal model control performed very well with short control time and no overshooting. A study to design model predictive controller to smooth the output power from a wind farm was carried nu Khalid et al (2010). They focussed to optimize the battery storage system. Model predictive control theory was applied to combine wind power prediction system with battery storage system. This control action was consisted on two stages i.e. prediction of wind speed and direction and secondly prediction of power output. Predicted power output was obtained by converting predicted wind speed. This controller performed well under practical constraints and achieved maximum ramp rate.

A research of model-based optimal control of hybrid power generation was carried out by Zervas et al (2008). This hybrid power generation system consisted of photovoltaic arrays, electrolyser, metal hydride tanks and proton exchange membrane fuel cells. Hybrid energy systems store energy efficiently. A neural network model was used to predict the global solar irradiations and then energy produced by solar array was estimated. Finally, MPC was used to get an optimal control strategy. The fundamental rolling horizon principle of MPC was used to develop decision strategy. The proposed model was proved to be very useful tool for decision making.

A robust model predictive control strategy was developed by Huang et al (2009). This control strategy was to improve the performance of air conditioning systems. First order time-delay model with uncertain time delay and system gains were used to describe air-conditioning processes. The uncertainties in time-delay and system gains were formulated by using uncertainty prototype. A typical Variable-Air-volume (VAV) system was used for this research. LMI (Linear Matrix Inequality) was employed to design this controller. Model predictive control strategy was tested and then was compared with the performance of the conventional strategy (PI). It was found that for MPC the outlet temperature followed the supply air temperature when there was a sudden step change. In case of PI, it performed well but the output response was not very fast. Robust analysis was also performed and MPC strategy responded very quickly to the disturbances. The results showed that MPC had much more robustness than conventional PI algorithm control. Kolokotsa et al (2008) combined model predictive controller with a BEMS (Building Energy Management System). The main purpose of the overall system was to predict the indoor environmental conditions and to take appropriate actions, in order to satisfy indoor environmental conditions and minimizing energy consumption. State vector was defined as;

$x(k)=[CO_{2\,in}(k)\ RH_{in}(k)\ T_{in}(k)\ E_{in}(k)]$

where $CO_{2\,in}(k)$ is the indoor Carbon dioxide concentration, $RH_{in}(k)$ is the indoor relative humidity, $T_{in}(k)$ is the indoor temperature and $E_{in}(k)$ is the indoor illuminance.

and control vector was defined as;

$u(k)= [W(k)\ L(k)\ S(k)\ AC(k)]^T$

Where S is shading output, W is window opening, AC is air conditioning output, and L is lighting output, the variables were modeled by using bilinear approach, which is simple and an extension of linear modeling approach. The controller was designed to minimize the performance index J(k), which was aimed to keep the variable as much close as possible to the set points. It was found that system's response to the variable was very fast and stable.

IV. MODEL PREDICTIVE IN BUILDING SERVICES ENGINEERING:

Henze et al (2005a, 2005b) experimentally analyzed MPC for active and passive building thermal storage inventory. A real time experimental implementations were carried out using 24h future horizon and a 1-h controller time step. Trnsys software was used for building model and Matlab for central purposes. They noticed some technical problems, but overall this approach was very successful. In their other research (Henze et al (2004) , they also found out the importance of forecasting on model predictive controller. Determination of optimal start time for heating was addressed by researchers from Honeywell control systems Ltd and the University of Strathclyde (Clarke et al, 2002). They came with some concerns between control system and simulation tools (ESP-r) and optimizer.

Kummert et al (2005a, 2005b) studied optimal control of passive solar building with night setback. They made an attempt to minimize energy consumption. A linear S-S (steady-space) representation was used and quadratic programming was done for optimization.

V. FUTURE WORK:

Zhu et al (2009) reviewed energy performance of buildings with phase change materials (PCM). They concluded that PCM has positive effects on the performance of buildings and energy consumption. They also concluded that active PCM energy systems conventional control was used. In order to maximize the performance of PCM system optimum control has to be used.

This project is focused on airport environment. In this project investigation of Control of Phase change material energy systems for terminal buildings will be carried out. In order to implement Model predictive control on PCM energy systems, it has been decided to develop MPC for solar energy hot water system assisted with heat pump.. The layout diagram of the system is shown in figure 1.

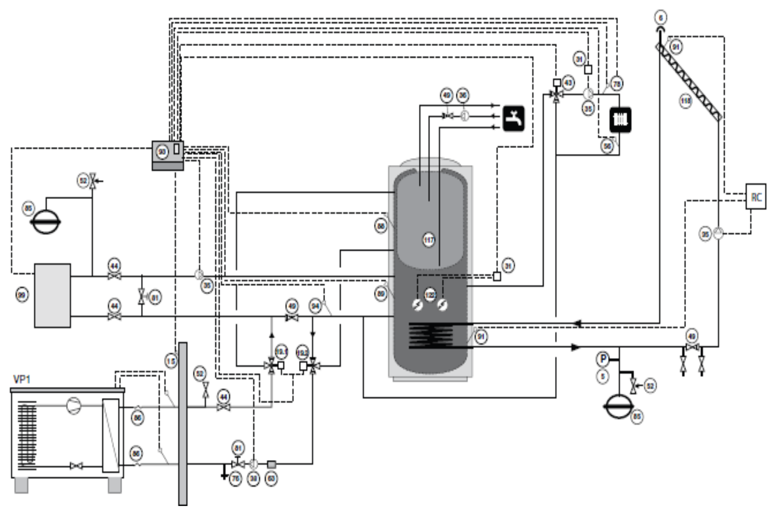

Figure 1: Layout diagram of the system

List of Components

Pos	Name
VP1	Heat pump
5	Pressure gauge
6	Venting
15	Outside temperature sensor
19.1	Three way valve
19.2	Three way valve
31	Auxiliary relay/Contactor
35	Circulation pump
36	HWC pump
38	Charge pump, hot water
43	Shunt valve
44	Shut-off valve
49	Non-return valve
52	Safety valve
56	Return temperature sensor 2
78	Flow sensor 2
81	Control valve
85	Expansion tank
86	Flexible hoses
88	Hot water temperature sensor
89	Flow sensor
91	Other boiler
93	Control box
94	Return temperature sensor
99	Immersion heater/electric boiler
117	Accumulator with water heater and solar coil
118	Solar panels
122	Immersion heater

Figure 2: Explanation of components of figure 1

The main objective of the control for above system will be to use maximum of solar energy, predicting outdoor weather conditions and load and to minimize the use of heat pump. This controller will compensate all the disturbances in outside weather. Also from literature review it has been showed that no solar system assisted with heat pump is controlled with the help of MPC.

In order to implement MPC on PCM energy system, first this controller will be designed for solar assisted heat pump for water heating. For this purpose this system will be modeled in TRNSYS and then TRNSYS model will be coupled with matlab. The controller will be designed in Matlab. The same TRNSYS model system will be experimentally installed and with the help of XPC target toolbox of Matlab this experimental setup will be controlled by Model predictive controller.

The phase change material energy system will be designed in trnsys and then MPC will be developed in Matlab. All these system will be analysed on the basis of energy consumption.

VI. Coupling TRNSYS and Matlab /Simulink:

Trnsys is a transient system simulation program. Trnsys stands for "transient simulation program". It was developed by the University of Wisconsin (Klein, 1996). Trnsys is written in fortan-77. After identifying system components, these components are connected. Each component in trnsys is represented by a box; this box requires a number of constant parameters, inputs (which are time dependent) and outputs (time dependants).

The use of Matlab is increasing in different fields. Now a days is not only used for computing/mathematical applications, it is also used in different other fields such as control engineering, fluid mechanics, mechanical vibrations, etc. in the research area of built environment its use has also been increased. Matlab/simulink is used for different applications for example pipe sizing, building energy management systems and their control strategies, indoor air quality, control of renewable energy systems and their feasibility analysis, design of controller for HVAC applications, etc.

Model Predictive control tool box™ consisted of different set of functions for designing and analyzing model predictive controller. A MPC controls a system (plant) by combining a prediction and control strategies. Constraints are always considered in designing MPC.

These two software tools will be used to carry out this research. Trnsys will be used to model solar heating system and then PCM system. These two systems will be controlled by MPC with the help of Matlab.

VII. Conclusion:

The Government goal of using renewable energy systems and reducing carbon emissions has made to think about other energy options. In this paper general view of climate condition has been sketched. Government targets of reducing carbon emissions can also be achieved by using better control of building systems. Model predictive control is a control algorithm, which is used to control very simple as well as very complex problems. This includes systems with long delay times, unstable systems**.** MPC deals multivariable problem very easily. MPC has shown very promising results in controlling different solar and air conditioning plants. MPC will be used to control solar assisted heat pump and PCM systems.

VIII. Acknowledgment

We would like to thanks ESPRC for funding this project. This project is multi disciplinary project and brings together five different universities of UK; Brunel, Bath, City, De Montfort and Loughborough.

IX. References:

- Allwright, J.C. (1994) Advances in model-based Predictive Control. Chapter on min-max Model-Based Predictive Control, Oxford University Press.
- Bitmead, R.R., Gevers, M. and Wertz,V. (1990) Adaptive Optimal control. The thinking Man's GPC. Prentice-Hall.
- Camacho, E.F. and Bordons, C. (1999) Model Predictive control. Springer Verlag, London.
- Commission of the European communities. (2008) 20 20 by 2020.Available at: http://www.energy.eu/directives/com2008_0030en01.pdf [Accessed 19/06/2010].

- Campo, P.J. and Morari, M. (1987) Robust model predictive control. American Control Conference, Minneapolis, Minnesota.
- Clarke, D.W. and Scattolini, R. (1991) Constrained Receding-horizon predictive control. Proceeding of IEE, 138(4) 347-354.
- Clarke, J., Crockroft, J., Conner, S., Hand, J., Kelly, N., Moore, R., O'Brien, T. and Strachan, P. (2002) Simulation-assisted control in building energy management systems. Energy and Buildings, 34, 933–940.
- Cutler, C.R. and Ramarker, B.C. (1980) dynamic matrix control- A computer control Algorithm. In proceeding of Automatic Control conference, San Francisco.
- Farkas,I. and Vajk, I. (2005) Internal model-based controller for solar plant operation. Computers and Electronics in Agriculture, 49, 407–418.
- Henze, G., Kalz, D., Felsmann, C. and Knabe, G. (2004) Impact of forecasting accuracy on predictive optimal control of active and passive building thermal storage inventory. HVAC&R Research, 10 (2), 153–177.
- Henze, G., Kalz, D., Liu, S. and Felsmann, C. (2005) Experimental analysis of model-based predictive optimal control for active and passive thermal storage inventory. HVAC&R Research, 11 (2), 189–213.
- Henze, G. and Krarti, M. (2005) Predictive optimal control of active and passive building thermal storage inventory. Final report, DOE Award Number: DE-FC-26-01NT41255.
- Huang, G., Wang, S/ and Xu, X. (2009) A robust model predictive control strategy for improving the control performance of air-conditioning systems. Energy Conversion and Management, 50, 2650-2658.
- Hulme, M., Jenkins, G.J., Lu.X., Turnpenny, J.R.,Mitchell, T.D., Jones, R.G., Lowe, J., Murphy, J.M., Hassell, D., Boorman, P., McDonald. and Hill, S. (2002) Climate Change Scenarios for the United Kingdom. The UKCIP02 Scientific Report, Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK, pp 120.
- Khalid, M. and Savkin, A.V. (2010) A model predictive control approach to the problem of wind power smoothing with controlled battery storage, Renewable Energy, 35, 1520–1526.
- Klein, S.A. et al, (1996) TRNSYS 14.2, A Transient Simulation and Program. Solar Energy Laboratory, University of Wisconsin, Madison (WI).
- Kolokotsa, D., Pouliezos, A., Stavrakakis, G. and Lazos, C. (2009) Predictive control techniques for energy and indoor environmental quality management in buildings. Building and Environment, 44, 1850-1863.
- Kummert, M., Andre, P. and Argigiou, A. (2005) Performance comparison of heating control strategies combining simulation and experimental results. In Proceedings of the 9th International Building Performance Simulation Association (IBPSA) Conference, Montreal, Canada.
- Kummert, M. and Andre, P. (2005) Simulation of a model-based optimal controller for heating systems under realistic hypotheses. In Proceedings of the 9th International Building Performance Simulation Association (IBPSA) Conference, Montreal, Canada.
- Lee, H.J., Morari, M. and Garcia, C.E. (1994) State-space interpretation of model predictive control. Automatica, 30(4), 707-717.
- Morari, M. (1994) Advances in model-based predictive control. Chapter Model predictive control: Multivariable control Technique for choice in the 1990s?. Oxford University Press.
- Mohtadi, C. (1986) Advanced self-tuning algorithms. PhD thesis, Oxford University.
- Mosca, E., Lemos, J.M. and Zhang, J. (1990) Stabilizing I/O Receding Horizon control. Proceedings of IEEE conference on Decision and Control.
- Nu~nez-Reyes, A., Normey-Rico, J.E., Bordons, C. and Camacho, E.F. (2005) A Smith predictive based MPC in a solar air conditioning plant. Journal of process control, 15, 1-10.
- Oh, X. (2006) Airports and Climate Change-Framing the Issues. Airports Council International, Canada.
- Pejovic, T., Noland, R. B., Williams, V. and Toumi, R. (2008) Estimates of CO2 emissions from aviation using air traffic data. Climate Change, 88, 367-384.
- Propoi, A.I. (1963) Use of LP methods for synthesizing sampled-data automatic systems. Automn remote control, 24.
- Qin, S.J. and Badgwell, T.A. (2002) A survey of industrial model predictive control technology. Control engineering practice, 11, 733-764.
- Rawlings, J. and Muske, K. (1993) The stability of Constrained Receding horizon control. IEEE transaction on Automatic Control, 38, 1512-1516.
- Richalet, J., Rault, A., Testud, J.L. and Papon, J. (1978) Model predictive heuristic control: Application to industrial processes. Automatica, 14(2), 413-428.
- Rossiter, J.A. and Kouvaritakis, B. (1993) Constrained Stable Generalized predictive control. Proceedings of IEE, Part D, 140(4).
- Van den boom, T.J.J. and Stoorvogel, A.A. (2010) Model predictive control, DISC Course, Lecture Notes.

- Zadeh, L.A. and Whalen, B.H. (1962) On optimal control and linear programming. IRE Trans. Auto. Control, 7(4).
- Zervas, P.L., Sarimveis, H., Palyvos, J.A. and Markatos, N.C.G. (2008) Model-based optimal control of a hybrid power generation system consisting of photovoltaic arrays and fuel cells. Journal of power sources, 181, 327-338.
- Zhang, Y. and Hanby, V.I. (2006) Model-based control of Renewable Energy systems in buildings, HVAC&R research special issue, 12(3a), 739-760.
- Zhu, N., Ma, Z. and Wang, S. (2009) Dynamic Characteristics and energy performance of buildings using phase change materials: A review. Energy Conversion and Management, 50, 3169-3181.

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Model development of a solar system combined with heat pump

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***Abstract*— This paper describes the setup and model of a solar panel combined with a heat pump system for domestic hot water and heating. The system has been built at the School of Civil and Building Engineering of Loughborough University. Solar collectors provide clean and renewable energy, while the heat pumps can provide energy efficient and environmentally friendly heat when necessary. This paper describes the layout of the experimental system, the model development based on first energy principles and initial simulation results. Local weather data is used to check the working of the model. The current controller controls the flow of hot water into the tanks based on current measurements only. The objective of future work is to apply model predictive control (MPC) to this system.**

Keywords- domestic heating, heat pump, solar collectors, energy modelling, model predictive control (MPC).

I. INTRODUCTION

All our energy sources are derived from solar energy. Wood, Oil and natural gas were originally produced through photosynthesis and complex chemical reactions. Fossil fuels are the result of chemical reactions in decaying vegetation under high temperatures and pressures over long periods of time [1]. The main advantage of solar energy is that it is clean and can be delivered without pollution.

Solar collectors have a wide variety of applications, such as solar water heating, space heating and cooling, solar refrigeration, solar thermal power plants, solar desalination etc. In solar water heating systems the main component is the solar collector, which absorbs energy and transfers it to the working fluid. Integrated collector systems use part of the tank as a solar collector. The disadvantage of this system is the thermal losses from the tank [2]. Solar energy systems can be used for hot water generation. In this application a heat exchanger is used between the solar collector and the hot water tank, which allows the use of antifreeze solutions in the solar collector loop [3].

Air source heat pumps are devices which transfer energy from air at low temperature to a tank at high temperature. The use of a heat pump for space heating and hot water generation is gaining popularity day by day because of its low energy consumption compared to other equipment [4], [5], [6]. The heat pump operates best at low temperature differences, when the coefficient of performance (COP) is high and the required energy low [7].

The solar radiation is not available during night times and on cloudy days. Therefore, solar collectors can be combined with a heat pump in such a way that in times of low solar radiation the heat pump is used instead. The heat pump can also benefit from cheap night time electricity when combined with a thermal storage.

II. PLANT DESCRIPTION

The solar assisted heat pump system is installed at the School of Civil and Building Engineering of Loughborough University as an experimental rig. It consists of a solar panel, a heat pump and accumulators.

Solar panels are used for heating when feasible, and the heat pump is used for heating when solar irradiation is insufficient (cloudy weather, night), and it is used for the domestic hot water purposes. The heat pump has a power capacity of 6kW.

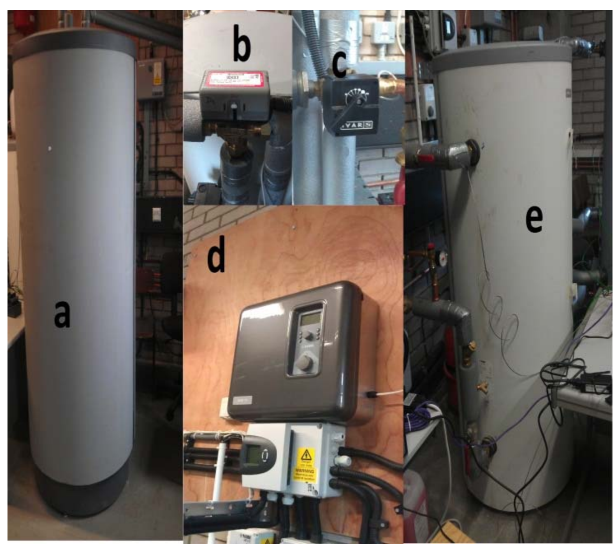

Figure 1: Heat pump combined solar system. (a) Heating Tank (b) Diverter (c) Valve (d) Controller and (e) Buffer tank

The main components of the system are shown in figure 1. In figure 1(a) the heating tank is shown, which encapsulates the hot water tank (not visible). In figure 1 (b) the diverter is shown, which diverts the flow from the buffer tank to the heating tank or the hot water tank. Figure 1(c) is the valve which regulates the flow from the buffer tank to the other two tanks. Figure 1(d) is the current controller which controls the heat pump, diverter and valves. The figure 1(e) is the buffer tank which is connected to the heat pump.

A general schematic diagram of the plant is shown in figure 2. In figure 2 the main components of the system can be observed. The heat pump is connected to the buffer tank. The plant uses two different energy sources: the solar collector and the electric air source heat pump. Both of these can be used together or separately for the heating tank.

The mixing valve M_1 allows water to flow from the buffer tank (heat pump tank) into the heating tank or hot water tank, while the diverter D_1 diverts the flow to either or both of these tanks. The valve M_2 allows water to bring energy into the heating tank or to take it back to the solar collectors.

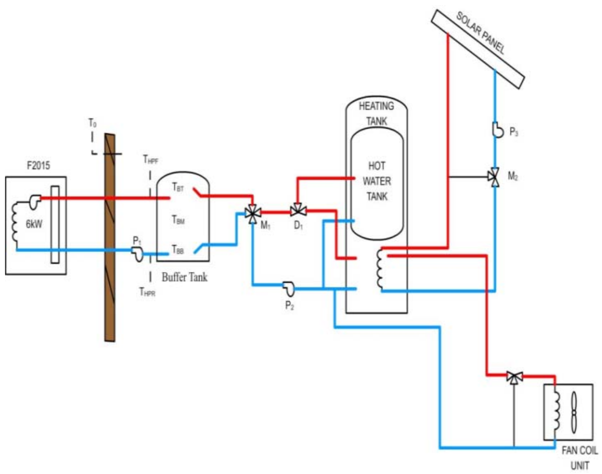

Figure 2: Plant Scheme

Table 1: Tank capacity

Tank Sizes	
Buffer Tank	300litres
Hot water Tank	300litres
Heating Tank	450litres

The objective for the system is to supply hot water for heating and domestic hot water at the required temperatures. The control object is to minimize the cost of electric energy for the heat pump. If the solar irradiation is low the heat pump can be used, but the desired solution is to operate the heat pump during the night when the energy tariffs are low. The preferred energy is of course solar energy. Since the solar radiation cannot be controlled, it is considered as a measured disturbance here.

III. SYSTEM DESCRIPTION

The main components of the system are described here.

A. Accumulation system:

The accumulation system consists of three tanks. The hot water tank is inside the heating tank. The heating tank is 450L and hot water tank is 300L of capacity. The third tank is the buffer tank and is 300L. It is connected to the heat pump and supplies hot water to other two tanks when it is required.

B. Solar Collector:

Solar collectors are used to collect sole radiations and to raise the temperature of water of the heating tank. It uses solar energy to raise the water temperature and is the primary energy source of the system. It consists of 2 flat plate collectors $2m^2$ in area each.

C. Heat Pump:

The installed heat pump uses air as a heat source. It is the auxiliary source of the energy for the heating tank, but it is the main (only) energy source for the hot water tank. The heat pump is directly connected to the buffer tank. The rated electric power of the heat pump is 6kW.

The system variables are shown in figure 3 and are explained below;

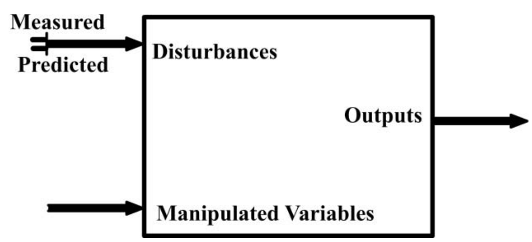

Figure 3: Inputs, Disturbances and Outputs

D. Manipulated variables:

- M1 allows the connection between buffer tank and other two tanks.
- M2 allows the heating tank and solar collector.
- D1 diverts flow to either hot water tank or heating tank
- Heat pump On/Off switch
- Heater On/Off Switch to heat the indoor environment.

E. Output Variables:

- All tank temperatures
- Solar collector output temperature or useful energy from the collector.
- Energy consumed by the heat pump

F. System disturbances:

- Outside Environmental temperature
- Solar irradiations
- Domestic hot water consumption
- Tanks temperature

G. House:

The house modelled in the Simulink is a semi-detached house, which consists of lounge, kitchen, dining room, hall and three bedrooms. The design data used for the calculation of the heating load is a Birmingham location as taken from CIBSE (Chartered Institute of Building Services Engineers) guidelines. While calculating the thermal capacity, the effective capacity of the outer walls is assumed to be 50% of its total capacity. The wall is 9" in thickness and it is assumed that the average wall temperature is half way between the inside and outside temperature.

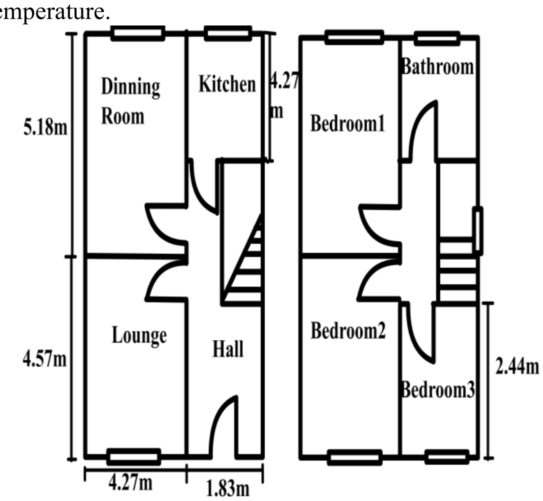

Figure 4: House plan

Table 2: House model specifications

House model specifications	
Outer walls construction	0.2286m brick
Inner walls construction	0.1143m brick
Floor	Solid concrete
Outer walls U-value	2.2 W/m^2 ^{O}C
Inner walls U-value	2.2 W/m^2 ^{O}C
Height of the walls	2.44m
Fabric loss in winter	5.880 kW
Infiltration loss	2.296 kW
Outside design conditions	-5.5 ^{O}C for Birmingham

IV. Mathematical Modelling of the System:

The mathematical model of the whole system is developed and implemented in Simulink.

A. Heat Pump:

A heat pump is a device that transfers thermal energy from a lower temperature (Source) to a higher temperature (Sink). It reverses the natural flow of thermal energy. The operating cycle of heat pump is shown in figure. It consists of four components;

- a compressor,
- a condenser,
- an expansion valve, and
- an evaporator.

The condenser is used to convert the refrigerant from its gaseous state into the liquid form, while the evaporator is used to convert the refrigerant from liquid to gaseous state. The refrigerant in its gaseous state is pressurised in the compressor. It is compressed by extra mechanical work (W_{net}). This high pressurised and high temperature fluid is then fed into condenser where it releases its heat (Q_{out}) and changes into liquid. Then, it enters into the expansion valve and changes into low pressure and low temperature liquid. In this state the refrigerant is fed into the evaporator, where it gains energy (Q_{in}) and changes it into gaseous state. Detailed information can be found in [8].

The efficiency of the heat pump is calculated by its coefficient of performance (COP). COP is the ratio of the heat transferred to the amount of the work done to the compressor.

$$COP = K * \frac{T_{c,out}}{(T_{c,out} - T_{e,out})} \qquad \text{(A)}$$

Where K is the efficiency coefficient of the compressor and is assumed as 0.4.

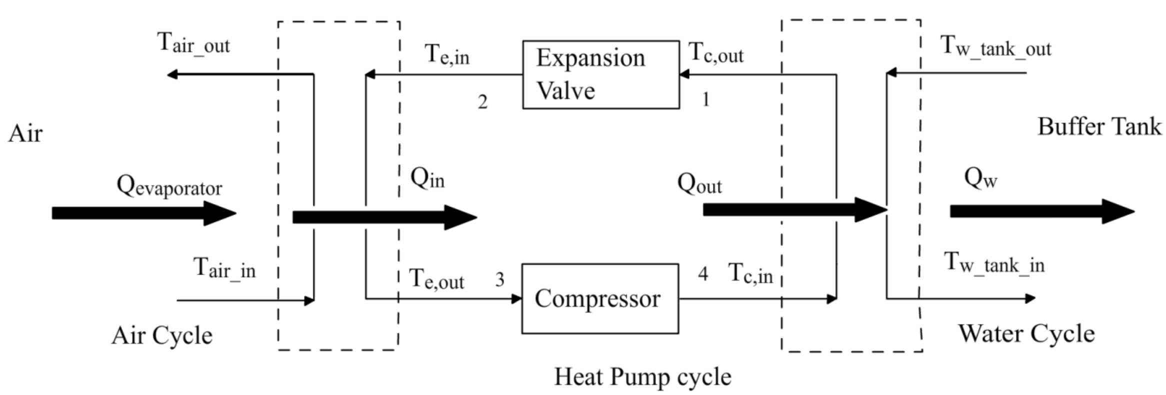

Figure 5: Schematic Diagram of heat Pump

Below the focus is on the dynamic heat pump model developed in [9]. The heat pump under study is an air source heat pump. Figure 5 shows the operating cycle and two external cycles. The air cycle is attached to the evaporator while the water cycle is attached to the condenser. It is assumed that the temperature of liquid leaving the condenser denoted as $T_{c,out}$ at point 1 is equal to the temperature of the water going into the water tank denoted as $T_{w\_tank\_in}$ (buffer tank). Similarly it is also assumed that the temperature of the refrigerant feeding into the evaporator denoted by $T_{e,in}$ at point 2 is equal to the temperature of air coming into the evaporator denoted by T_{air_in}.
On the basis of these assumptions we have;
$T_{c,out} = T_{w\_tank\_in}$ and $T_{e,in} = T_{air\_in}$
Based on equation 1, further approximation of COP has been done by [9]

$$COP = \dot{Q}_{out} / W_{net} \qquad (1)$$

From equation 1;

$$\dot{Q}_{out} = \dot{W}COP \qquad (2)$$

The energy balance gives:

$$\dot{Q}_{out} = \dot{W} + \dot{Q}_{in} \qquad (3)$$

$$\dot{Q}_{in} = \dot{W}(COP - 1) \qquad (4)$$

According to [5,1], the rate of heat energy gained by the evaporator from the air cycle is given by

$$\dot{Q}_e = \dot{m}_{e1} C_r (T_{e,in} - T_{e,out}) \qquad (5)$$

And the thermodynamics of the evaporator are

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{Q}_{in} \qquad (6)$$

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{W}\,(COP - 1) \qquad (7)$$

For the condenser the heat transferred in the water cycle is

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{W}\,(COP - 1) \qquad (8)$$

$$\dot{Q}_c = \dot{m}_{c1} C_r (T_{c,out} - T_{c,in}) \qquad (9)$$

Similarly from the dynamics of condenser,

$$C_c m_c \dot{T}_{c,out} = \dot{Q}_{out} - \dot{Q}_c \qquad (10)$$

$$C_c m_c \dot{T}_{c,out} = \dot{W}COP - \dot{Q}_c \qquad (11)$$

Rearranging these equations leads to

$$\dot{T}_{e,out=} \frac{\dot{m}_{e1} C_r T_{e,in} + \dot{m}_{e1} C_r T_{e,out} - (COP - 1)\dot{W}}{C_e m_e} \qquad \text{(B)}$$

$$\dot{T}_{c,out=} \frac{\dot{m}_{c1} C_r T_{c,in} - \dot{m}_{c1} C_r T_{c,out} + COP * \dot{W}}{C_c m_c} \qquad \text{(C)}$$

Equations A, B and C are used as a heat pump model which is implemented in Simulink.
From above it is concluded that the COP of the heat pump depends on the outside air temperature and the condenser outflow temperature. The heat pump operates between two different mediums (air and water), which have very different heat capacities. Air has less capacity than water, and for this reason the mass flow rate on the evaporator side is assumed higher than on the condenser side.

B. Solar Collector Model:

Flat plate collector is used to heat up the heating tank. The useful energy from the solar panel is calculated by using the mathematical model proposed by [3]. The model of the solar panel used in Simulink is shown below;
The energy used in the solar panel is solar energy. The solar radiation is captured by the solar panel and used to heat up water. With a solar radiation I (W/m^2) covering the solar panel of an area Ac (m^2), the energy received by the solar collector is given by;

$$Q_r = I.A_c \qquad (12)$$

Table 3: Solar collector specifications

Solar Collector data	
$U_L.F_R$	4.90(W/m^2)/^{O}C
$\tau\alpha.F_R$	0.68

It is known that not all of energy received by the solar collector is used to raise the temperature of water, since some of the radiation is reflected back in to the sky. Only part of the radiation is absorbed by the solar plate. The conversion factor τα indicates the percentage of solar radiations which is absorbed by the solar collector and transmitted into the cover of panel. Therefore the energy received by solar collector is given by;

$$Q_r = \tau\alpha(I.A_c) \qquad (13)$$

There is also an energy loss from the solar collector surface when the temperature of solar panel is higher than the surroundings. This loss is given by;

$$Q_l = U_L A_c\,(T_c - T_a) \qquad (14)$$

Therefore the rate of useful energy gained by the solar collector is given by;

$$Q_U = Q_{r-}Q_l = \tau\alpha(I.A_c) - U_L A_c\,(T_c - T_a) \qquad (15)$$

The useful energy is also measured by the amount of the energy carried by the fluid;

$$Q_U = mC_p(T_o - T_i) \qquad (16)$$

It is difficult to define the average collector temperature in equation (15), therefore a factor called "the collector heat removal factor (F_R)" is given by the following equation;

$$F_{R=}\frac{mC_p(T_o - T_i)}{A_c\,[\tau\alpha I - U_L(T_c - T_a)]} \qquad (17)$$

The useful energy from the collector is measured by multiplying F_R with Q_U. The useful energy is;

$$Q_U = F_R A_c\,[\tau\alpha I - U_L(T_c - T_a)] \qquad (18)$$

The above equation is called "Hottel-Whillier-Bliss equation" and is used as a collector model in Simulink.

C. *Energy equations:*

In this section the different heat transfer equations will be presented. The equations are based on energy balance and energy flow. By assuming an average temperature equal to T_b, T_h and T_H for buffer tank, heating tank and hot water tank respectively.

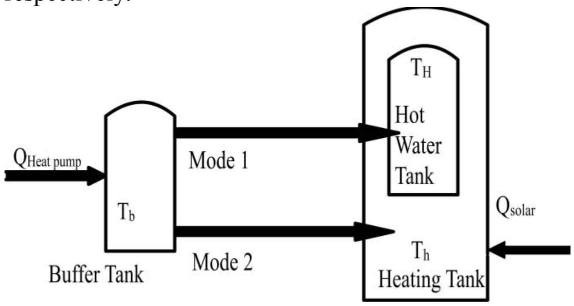

Figure 6: Modes of the system

The heat transferred from the heat pump into the buffer tank is;

$$\dot{Q}_{out} = \dot{W}COP \qquad (19)$$

Where $\dot{Q}_{out}$ is the energy output from the condenser and $\dot{W}$ is the power input. The heat transfer between buffer tank and hot water tank is given by;

$$\dot{Q} = \dot{m}C_p\,(T_b - T_H) \qquad (20)$$

There is an energy use caused by the withdrawal of hot water, as cold water is fed into the tank. It is assumed that the cold water has a temperature of 15 ^{O}C and the hot water tank temperature is 55^{O}C. The heat transfer between the buffer tank and the heating tank is;

$$\dot{Q} = \dot{m}C_p\,(T_b - T_h) \qquad (21)$$

The solar energy input in the solar tank is given in the equation 18.

V. SIMULATION RESULTS:

The simulation is performed by considering the data given in figures 8, 9 and 10. In figure 9 two COPs are shown; one is from manufacturer data and the second one is from the Simulink model. The difference between these COPs is caused by the assumption of an ideal thermodynamic process in the Simulink model (Section IV), which is compensated by a higher temperature gradient in the air heat source. A better selection of parameters should lead to a closer match.

The water consumption is considered as a measured disturbance and the data is taken from [10] and is shown in the figure 8. The environmental temperature and solar radiations are shown in figures 9 and 10. This data is collected on the roof of the School of Civil and Building Engineering and is for July month (Courtesy of Shen Wei). This data was used to test the model.

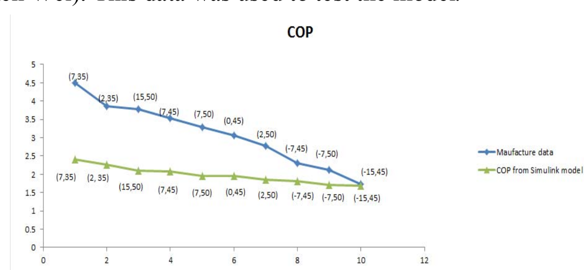

Figure 7: Coefficient of performance

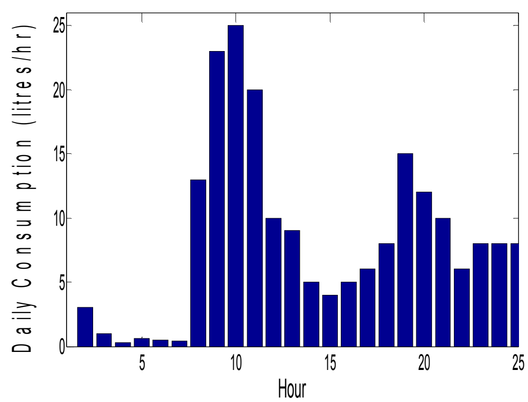

Figure 8: Water daily consumption

The simulation results are shown in figures 11 and 12. The simulation was performed by running heat pump at half of its electrical ratings (3kW), with the valve fully open, and the diverter switched to the hot water tank. It can be seen in figure 12 that the only heat the heating tank gets is the solar radiation, plus a small amount of heat lost from the hot water tank through its isolation inside the heating tank.

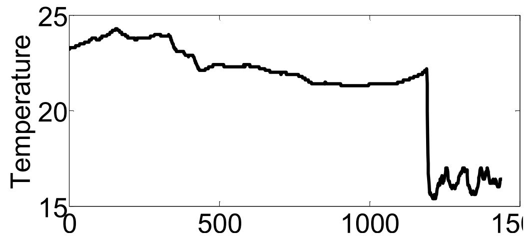

Figure 9: Outside Temperature

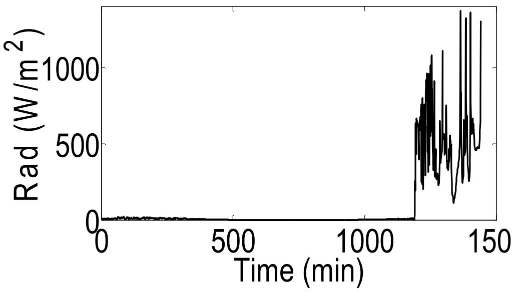

Figure 10: Solar Radiations

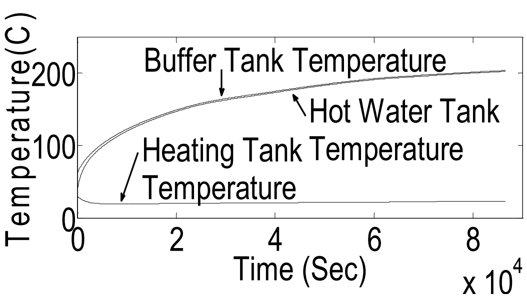

Figure 11: Tanks temperatures

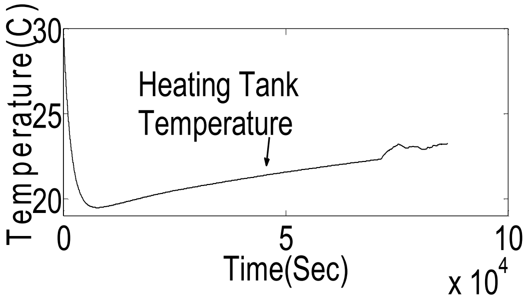

Figure 12: Heating tank Temperature

It can be seen in the figure 11 that the hot water tank temperature follows the buffer tank temperature closely. In a complementary situation with a different diverter setting, the same can be seen for the heating tank. Either way the energy is contained within the system as expected. The main energy loss in the system is through the walls into the environment.

The temperature in figure 11 touches the value of 200. This is of course unrealistic, and caused by the linear model of the tanks and the high heat pump setting. Once the system is controlled, such high temperatures can be avoided by choosing appropriate set-points.

VI. CONCLUSIONS:

A model of a heating system consisting of a heat pump and a solar panel has been developed. Initial simulations are performed using Loughborough weather data. It is concluded that the system is working according to the expectations, reflecting the energy flows between the tanks as caused by opening valve and diverter.

In future work, a model predictive controller (MPC) will be designed, which will be able to make use of predicted future weather data and changing electricity prices. The goal is to use the heat pump during the night time when the electric tariff is low, and to store the heat energy in the tanks so that it can be used throughout the day. It will also be used to predict how the solar radiation heats up the heating tank.

REFERENCES

[1] Kreith, F. and Kreider, JF. Principles of solar engineering. New York: McGraw-Hill; 1978.

[2] Kalogirou, S.A. (2004). Solar thermal collectors and applications. Progress in Energy and Combustion Science, 30(3),231-295.

[3] Duffie, JA. and Beckman, WA. Solar engineering of thermal processes. New York: Wiley; 1991.

[4] Agrawal,N.and Bhattacharyya. S.(2007). Studies on a two-stage transcritical carbon dioxide heat pump cycle with flash intercooling. Applied Thermal Engineering,27,299-305.

[5] Rakhesh,B.Venkatarathnam,G. and Murthy, S.S. (2003). Experimental studies on a heat pump operating with r22, r407c and r407a: comparison from an energy point of view. Journal of energy resources technology, 125,101-112.

[6] Sakellari, D. and Lundqvist, P. (2002) Modelling the performance of a domestic low-temperature heating system based on a heat pump. In Proc. ofthe 9th International Refrigeration and Air Conditioning Conference, West Lafayette, USA, 1, pages 65-72.

[7] Zogg,D. Shafai,E. and Geering, H.P.(2001)A fault diagnosis system for heat pumps. In Proc. of the 2001 IEEE Conference on Control Applications (CCA),Maxico,70-76.

[8] Moran, M. J.and Shapiro, H.N. (2006) Fundamentals of engineering thermodynamics, 5th edition. John Wiley & Sons, Inc.

[9] Van Schijndel, A.W.M. and De Wit., M.H. Aug (2003) Advanced simulation of building systems and control with simulink. In Proc. of 8th International IBPSA Conference, Eindhoven, Netherlands, 1185-1192.

[10] Defra. (2008) Measurement of domestic hot water consumption in dwellings. Copyright Crown.

MODEL DEVELOPMENT AND CONTROL STRATEGIES FOR A SOLAR SYSTEM COMBINED WITH HEAT PUMP

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Abstract— Buildings consume a considerable amount of energy. This paper presents a model predictive control (MPC) strategy and two conventional control strategies (On-Off and PI) for a solar system assisted by heat Pump. This type of setup is used mainly for domestic hot water and heating purpose. This research is in response to the UK government's commitment to produce 20% of country's energy from renewable sources by 2020. The aim of the controller is to reduce electric consumption and to provide better thermal comfort of the occupants. The MPC controller uses cheaper night time electricity to store heat energy in the water tanks and uses this later in the day, when it is required. The MPC controller also anticipates any future hot day and then tries to use solar radiations to heat up the water. In this paper mathematical model of the heat pump and lumped model of the building is also presented. Three control strategies i.e. MPC, PI and On-Off are compared and it is concluded that model predictive controller provided the best performance.

Keywords- Model predictive controller, Heat Pump, Thermal comfort, Conventional control strategies, Solar radiations.

I. INTRODUCTION

The rapid increase in world's energy use is one of the main concerns of today's world. This energy use has high environmental impacts such as depletion of ozone layer, global warming, climate change etc. According to IEA (International Energy Agency) the primary Energy has grown by 49% in the last two decades (1984-2004) and the CO_2 emission has been increased by 43% [1]. It was also shown by the IEA that there is an average increase of 2% in energy and 1.8% in the CO_2 emissions. All our energy sources are derived from solar energy. Wood, Oil and natural gas were originally produced through photosynthesis and complex chemical reactions. Fossil fuels are the result of chemical reactions in decaying vegetation under high temperatures and pressures over long periods of time [2]. The main advantage of solar energy is that it is clean and can be delivered without pollution.

Solar collectors have a wide variety of applications, such as solar water heating, space heating and cooling, solar refrigeration, solar thermal power plants, solar desalination etc. In solar water heating systems the main component is the solar collector, which absorbs energy and transfers it to the working fluid. Integrated collector systems use part of the tank as a solar collector. The disadvantage of this system is the thermal losses from the tank [3]. Solar energy systems can be used for hot water generation. In this application a heat exchanger is used between the solar collector and the hot water tank, which allows the use of antifreeze solutions in the solar collector loop [4].

Air source heat pumps are devices which transfer energy from air at low temperature to a tank at high temperature. The use of a heat pump for space heating and hot water generation is gaining popularity day by day because of its low energy consumption compared to other equipment [5], [6], [7]. The heat pump operates best at low temperature differences, when the coefficient of performance (COP) is high and the required energy low [8].

The solar radiation is not available during night times and on cloudy days. Therefore, solar collectors can be combined with a heat pump in such a way that in times of low solar radiation the heat pump is used instead. The heat pump can also benefit from cheap night time electricity when combined with a thermal storage. The main idea behind using model predictive control in this work is that this control strategy can predict outside weather conditions and occupancy pattern in the building. This strategy also predict any future hot sunny day and then can use maximum free energy during the day i.e. solar energy and also can predict the electricity prices and uses electricity during the night.

Model predictive control (MPC) originated in the late seventies and has developed very considerably. MPC is a class of computer algorithms that utilize process model to predict future outcome/response of a plant. The basic structure of MPC is shown in figure 1. The model gets data from past input and past outputs and combines this data with future inputs. The model then gives predicted output for the time step. This predicted output is combined with reference trajectory to give future errors to the systems. These future errors are then fed into optimizer, which enforces constraints on future predicted outputs and also minimizes the operating cost functions. Optimizers gives future predicted inputs which are fed back into main model. A generic framework of MPC problem in finite-horizon is given by following problem:

$$J(x_o) = \min_{u_0,\ldots\ldots,u_{N-1}} \sum_{k=0}^{N-1} l_k\,(x_k, u_k) \quad \text{Cost Function} \qquad \text{(i)}$$

The above equation is the cost function of the problem and is subject to following;

$$(x_k, u_k) \in X_k * U_k \qquad \text{Constarints} \qquad \text{(ii)}$$

$$x_o = x \qquad \text{Current state} \qquad \text{(iii)}$$

$$x_{k+1} = f(x_k, u_k) \qquad \text{(iv)}$$

In the above equations N is the prediction horizon, X_k and U_k are the sets of constriants for state x_k and inouts u_k respectively at time step k. The cost funtion and constraints are the main components of model predictive control design. The controller uses current state as the initial state for prediction of the future inputs.

II. PLANT DESCRIPTION

The solar assisted heat pump system is installed at the School of Civil and Building Engineering of Loughborough University as an experimental rig. It consists of a solar panel, a heat pump and accumulators.

Solar panels are used for heating when feasible, and the heat pump is used for heating when solar irradiation is insufficient (cloudy weather, night), and it is used for the domestic hot water purposes. The heat pump has a power capacity of 6kW.

The main components of the system are shown in figure 2. In figure 2(a) the heating tank is shown, which encapsulates the hot water tank (not visible). In figure 2(b) the diverter is shown, which diverts the flow from the buffer tank to the heating tank or the hot water tank. Figure 2(c) is the valve which regulates the flow from the buffer tank to the other two tanks. Figure 2(d) is the current controller which controls the heat pump, diverter and valves. The figure 2(e) is the buffer tank which is connected to the heat pump.

A general schematic diagram of the plant is shown in figure 3. In figure 3 the main components of the system can be observed. The heat pump is connected to the buffer tank. The plant uses two different energy sources: the solar collector and the electric air source heat pump. Both of these can be used together or separately for the heating tank.

The mixing valve M1 allows water to flow from the buffer tank (heat pump tank) into the heating tank or hot water tank, while the diverter D1 diverts the flow to either or both of these tanks. The valve M2 allows water to bring energy into the heating tank or to take it back to the solar collectors.

The objective for the system is to supply hot water for heating and domestic hot water at the required temperatures. The control object is to minimize the cost of electric energy for the heat pump. If the solar irradiation is low the heat pump can be used, but the desired solution is to operate the heat pump during the night when the energy tariffs are low. The preferred energy is of course solar energy. Since the solar radiation cannot be controlled, it is considered as a measured disturbance here.

III. SYSTEM DESCRIPTION

The main components of the system are described here.

A. Accumulation system:

The accumulation system consists of three tanks. The hot water tank is inside the heating tank. The heating tank is 450L and hot water tank is 300L of capacity. The third tank is the buffer tank and is 300L. It is connected to the heat pump and supplies hot water to other two tanks when it is required.

B. Solar Collector:

Solar collectors are used to collect sole radiations and to raise the temperature of water of the heating tank. It uses solar energy to raise the water temperature and is the primary energy source of the system. It consists of 2 flat plate collectors 2m^2 in area each.

C. Heat Pump:

The installed heat pump uses air as a heat source. It is the auxiliary source of the energy for the heating tank, but it is the main (only) energy source for the hot water tank. The heat pump is directly connected to the buffer tank. The rated electric power of the heat pump is 6kW.
The system variables are shown in figure 4.

D. Manipulated variables:

- M1 allows the connection between buffer tank and other two tanks.
- M2 allows the heating tank and solar collector.
- D1 diverts flow to either hot water tank or heating tank
- Heat pump On/Off switch
- Heater On/Off Switch to heat the indoor environment.

E. Output Variables:

- All tank temperatures
- Solar collector output temperature or useful energy from the collector.
- Energy consumed by the heat pump

F. System disturbances:

- Outside Environmental temperature
- Solar irradiations
- Domestic hot water consumption
- Tanks temperature

G. Building:

The building under consideration is a two rooms building; a hall and a bedroom. The hall has a south facing and a window on the south face. The dimensions of both the rooms are 4.27*4.57 and 2.44m high. The schematic layout of the building is shown in figure 5. The design data for the location of Birmingham is used for the calculation of the heating load and is taken from CIBSE (Chartered Institute of Building Services Engineers) guidelines. The building schematic and properties of the construction are given in figure 5 and table 1 respectively.

IV. MATHEMATICAL MODELLING OF THE SYSTEM:

The mathematical model of the whole system is developed and implemented in Simulink.

A. Heat Pump:

A heat pump is a device that transfers thermal energy from a lower temperature (Source) to a higher temperature (Sink). It reverses the natural flow of thermal energy. The operating cycle of heat pump is shown in figure. It consists of four components;

- a compressor,
- a condenser,

- an expansion valve, and
- an evaporator.

The condenser is used to convert the refrigerant from its gaseous state into the liquid form, while the evaporator is used to convert the refrigerant from liquid to gaseous state. The refrigerant in its gaseous state is pressurised in the compressor. It is compressed by extra mechanical work (W_{net}). This high pressurised and high temperature fluid is then fed into condenser where it releases its heat (Q_{out}) and changes into liquid. Then, it enters into the expansion valve and changes into low pressure and low temperature liquid. In this state the refrigerant is fed into the evaporator, where it gains energy (Q_{in}) and changes it into gaseous state. Detailed information can be found in [9].

The efficiency of the heat pump is calculated by its coefficient of performance (COP). COP is the ratio of the heat transferred to the amount of the work done to the compressor.

$$\mathrm{COP} = \mathrm{K} * \frac{\mathrm{T_{c,out}}}{(\mathrm{T_{c,out}} - \mathrm{T_{e,out}})} \qquad \text{(A)}$$

Where K is the efficiency coefficient of the compressor and is assumed as 0.4.

Below the focus is on the dynamic heat pump model developed in [10]. The heat pump under study is an air source heat pump. Figure 6 shows the operating cycle and two external cycles. The air cycle is attached to the evaporator while the water cycle is attached to the condenser. It is assumed that the temperature of liquid leaving the condenser denoted as $T_{c,out}$ at point 1 is equal to the temperature of the water going into the water tank denoted as $T_{w\_tank\_in}$ (buffer tank). Similarly it is also assumed that the temperature of the refrigerant feeding into the evaporator denoted by $T_{e,in}$ at point 2 is equal to the temperature of air coming into the evaporator denoted by Tair_in.

On the basis of these assumptions we have;

$T_{c,out} = T_{w\_tank\_in}$ and $T_{e,in} = T_{air\_in}$

Based on equation 1, further approximation of COP has been done by [9].

$$\mathrm{COP} = \dot{\mathrm{Q}}_{\mathrm{out}} / \mathrm{W}_{\mathrm{net}} \qquad (1)$$

From equation 1;

$$\dot{\mathrm{Q}}_{\mathrm{out}} = \dot{\mathrm{W}}\mathrm{COP} \qquad (2)$$

The energy balance gives:

$$\dot{\mathrm{Q}}_{\mathrm{out}} = \dot{\mathrm{W}} + \dot{\mathrm{Q}}_{\mathrm{in}} \qquad (3)$$

$$\dot{\mathrm{Q}}_{\mathrm{in}} = \dot{\mathrm{W}}(\mathrm{COP} - 1) \qquad (4)$$

The rate of heat energy gained by the evaporator from the air cycle is given by [11];

$$\dot{Q}_e = \dot{m}_{e1} C_r (T_{e,in} - T_{e,out}) \qquad (5)$$

And the thermodynamics of the evaporator are

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{Q}_{in} \qquad (6)$$

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{W}\,(COP - 1) \qquad (7)$$

For the condenser the heat transferred in the water cycle is

$$C_e m_e \dot{T}_{e,out} = \dot{Q}_e - \dot{W}\,(COP - 1) \qquad (8)$$

$$\dot{Q}_c = \dot{m}_{c1} C_r (T_{c,out} - T_{c,in}) \qquad (9)$$

Similarly from the dynamics of condenser,

$$C_c m_c \dot{T}_{c,out} = \dot{Q}_{out} - \dot{Q}_c \qquad (10)$$

$$C_c m_c \dot{T}_{c,out} = \dot{W}COP - \dot{Q}_c \qquad (11)$$

Rearranging these equations leads to

$$\dot{T}_{e,out=} \frac{\dot{m}_{e1} C_r T_{e,in} - \dot{m}_{e1} C_r T_{e,out} - (COP - 1)\dot{W}}{C_e m_e} \qquad (B)$$

$$\dot{T}_{c,out=} \frac{\dot{m}_{c1} C_r T_{c,in} - \dot{m}_{c1} C_r T_{c,out} + COP * \dot{W}}{C_c m_c} \qquad (C)$$

Equations A, B and C are used as a heat pump model which is implemented in Simulink.
From above equations it can be concluded that the COP of the heat pump depends on the outside air temperature and the condenser outflow temperature. The heat pump operates between two different mediums (air and water), which have very different heat capacities. Air has less capacity than water, and for this reason the mass flow rate on the evaporator side is assumed higher than on the condenser side. The COP results found from the above equation did not match with the limited data that was available from the manufacturer as shown in the figure 7. Therefore the above model of heat pump was not suitable for this study.
In the second method to calculate the COP of the heat pump four other factors are considered i.e. α, β, $u_T P$ and $u_E P$. Whereas α thermal efficiency coefficient of compressor, β is the recovery of losses into heat, $u_T P$ is the thermal coefficient on condenser side and $u_E P$ is the thermal coefficient on evaporator side. $u_T P$ and $u_E P$ incorporates the resistances of air and water on cold and hot mediums of the heat pump. The COP equation will be given by following equations;

$$\mathrm{COP} = \alpha\left(\frac{T_H}{T_H - T_C}\right) + \beta \quad (12)$$

By taking air and water resistances into account;

$$\mathrm{T_H - T_C = T_T - T_E + (u_T + u_E)P * COP - u_E P} \quad (13)$$

By Simplifying the above equation we have;

$$\mathrm{(u_T + u_E)P * COP^2 + (T_T - T_E - u_E P - \beta(u_T + u_E)P - \alpha u_T P)COP - \alpha T_T - \beta(T_T - T_E - u_E P) = 0} \quad (14)$$

The above quadratic equation can be solved for COP. In the figure 8 different calculations are shown with different values of α, β and $\mathrm{u_E P}$ and one calculation by taking inverse of ideal COP and manufacture's COP and plotting them against each other. The results given by plot of inverse of ideal COP and manufacture's COP gives better results than the others and is considered as the heat pump model.

B. Solar Collector Model:

Flat plate collector is used to heat up the heating tank. The useful energy from the solar panel is calculated by using the mathematical model proposed by [4]. The energy used in the solar panel is solar energy. The solar radiation is captured by the solar panel and used to heat up water. With a solar radiation I (W/m^2) covering the solar panel of an area Ac (m^2), the energy received by the solar collector is given by;

$$\mathrm{Q_r = I.A_c} \quad (15)$$

It is known that not all of energy received by the solar collector is used to raise the temperature of water, since some of the radiation is reflected back in to the sky. Only part of the radiation is absorbed by the solar plate. The conversion factor τα indicates the percentage of solar radiations which is absorbed by the solar collector and transmitted into the cover of panel. Therefore the energy received by solar collector is given by;

$$\mathrm{Q_r = \tau\alpha(I.A_c)} \quad (16)$$

There is also an energy loss from the solar collector surface when the temperature of solar panel is higher than the surroundings. This loss is given by;

$$\mathrm{Q_l = U_L A_c\,(T_c - T_a)} \quad (17)$$

Therefore the rate of useful energy gained by the solar collector is given by;

$$\mathrm{Q_U = Q_r - Q_l = \tau\alpha(I.A_c) - U_L A_c\,(T_c - T_a)} \quad (18)$$

The useful energy is also measured by the amount of the energy carried by the fluid;

$$\mathrm{Q_U = mC_p(T_o - T_i)} \quad (19)$$

It is difficult to define the average collector temperature in equation (15), therefore a factor called "the collector heat removal factor (F_R)" is given by the following equation;

$$F_R = \frac{mC_p(T_o - T_i)}{A_c\,[\tau\alpha I - U_L(T_c - T_a)]} \qquad (20)$$

The useful energy from the collector is measured by multiplying F_R with Q_U. The useful energy is;

$$Q_U = F_R A_c\,[\tau\alpha I - U_L(T_c - T_a)] \qquad (21)$$

The above equation is called "Hottel-Whillier-Bliss equation" and is used as a collector model in Simulink. The values of F_R* τα is taken as 0.68 and value of $F_R U_L$ is 4.90 (W/m2)/^{O}C.

C. Energy equations:

In this section the different heat transfer equations will be presented. The equations are based on energy balance and energy flow. By assuming an average temperature equal to T_b, T_h and T_H for buffer tank, heating tank and hot water tank respectively.

The heat transferred from the heat pump into the buffer tank is;

$$\dot{Q}_{out} = \dot{W}COP \qquad (22)$$

Where $\dot{Q}_{out}$ is the energy output from the condenser and $\dot{W}$ is the power input. The heat transfer between buffer tank and hot water tank is given by;

$$\dot{Q} = \dot{m}C_p\,(T_b - T_H) \qquad (23)$$

There is an energy use caused by the withdrawal of hot water, as cold water is fed into the tank. It is assumed that the cold water has a temperature of 15 ^{O}C and the hot water tank temperature is 55^{O}C. The heat transfer between the buffer tank and the heating tank is;

$$\dot{Q} = \dot{m}C_p\,(T_b - T_h) \qquad (24)$$

The solar energy input in the solar tank is given in the equation 21.

D. Building Modelling:

Following is the modelling of the building using Simulink and equations used to develop the building model. All the external walls and roof are considered of same construction. The building is modelled as lumps because it takes into account the time changing behaviour of the building.

It is assumed that there are two modes of heat transfer to and through the wall i.e. one dimensional conduction and convection. The 1-D conduction heat transfer can be derived by using Fourier's law given by equation 25.

$$q_{cond} = -kA\frac{dT}{dt} \qquad (25)$$

In above equation $\frac{dT}{dt}$ is the rate of change of temperature, k is the thermal conductivity and A is the area of the heat transfer section.

The heat transfer between solid and gas or liquid is known as convection and can be described by the equation 26.

$$q_{conv} = hA(T_1 - T_2) \tag{26}$$

In figure 9 a typical wall divisions are shown, Ti is the inside temperature, T1 is the temperature of first layer, ………,T_N is of the N^{th} layer and T_o is the outside temperature.

The heat transferred from indoor air to the wall can be summarized in the following equation;

$$q_{conv} = q_{cond} + q_{stored} \tag{27}$$

q_{stored} is the stored heat energy inside the wall layer or heat energy of lumped capacitance.

$$\frac{dT_i}{dt} = \frac{h_i(T_{in} - T_i) - \frac{k_i}{L_i}(T_i - T_{i+1})}{c_{p,i}\rho_i L_i} \tag{28}$$

$$\text{in above equation } i = 1$$

For middle layers;

$$\frac{k_i}{L_i}(T_{i-1} - T_i) = \frac{k_{i+1}}{L_{i+1}}(T_i - T_{i+1}) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i + c_{p,i+1}\rho_{i+1}L_{i+1}\right) \tag{29}$$

$$\text{where } i = 2, 3, \ldots\ldots, (N-1)$$

For outer layer the equation will be;

$$h_{out}(T_i - T_{out}) = \frac{k_i}{L_i}(T_{i-1} - T_i) + \frac{dT_i}{dt}\left(c_{p,i}\rho_i L_i\right) \tag{30}$$

Each wall layer is modelled separately in Simulink.

V. SIMULATION RESULTS:

The water consumption is considered as a measured disturbance, which can be predicted in advance by using model predictive control. The data is taken from [12] and is shown in the figure 10. The figure 11 shows the temperature of tank 1 (Buffer tank). The reference signal is a step signal and it is set as to use night time electricity and to store the heat energy during night. As can be seen that the model predictive controller gives better results. The MPC performance tracking of the reference signal is superior than the PI and on-off controllers. The model predictive controller takes less time to reach to the set point than other two control strategies, also there is less fluctuations in the MPC controlled temperature readings.

The second simulation was performed to find out whether the heat pump is using the night time electricity when the electricity cost is lower. Three days were simulated, two with low radiation rates and the third day with high radiation level. In figure 12 the red graph is the radiations in kW/m^2 and heat pump signal is shown by blue curve. It is evident that controller was shifting the load to the night. The first two days are cloudy days with low radiation level. In the first two days the controller has used the heat pump during the day to meet the hot water and heating demand of the building. In the third day the controller has predicted a very hot sunny day and the heat pump use during the day is almost zero and the heat pump was switched off during most of the third day. The heat pump was used during the night and also on the third day when the radiations level was high the controller did not switched ON the heat pump and the energy was supplied through the solar thermal collector. Another simulation was performed with one cold day and two hot days i.e. low solar radiations day and high solar radiations day respectively. This simulation was performed to find out the weather prediction ability of the model predictive controller. In the figure 13 the heat pump is using more electricity during the first day and very little on day two and three. It does uses more electrical energy during the night. The controller predicts the upcoming hot days and it can be seen that at the beginning of day 2 and 3 the use of heat pump is minimized by the controller. it can be concluded that the controller did predicted the weather changes and used very less electrical energy on two hot days as compared to the cold day.

VI. CONCLUSIONS:

A model of a heating and hot water system consisting of a heat pump and a solar panel has been developed. Initial simulations are performed using Loughborough weather data. It is concluded that model the system is working according to the expectations and a good match of the heat pump is also found. A detailed building model is also presented.

Model predictive control proved to have good performance than the other control strategies. From this paper it is also concluded that model predictive gave better reference tracking capability and also uses night time electricity efficiently. Model predictive control also shifted load to the night to save some energy and store heat energy during the night. However, the model predictive control needs some extra effort and getting the accurate model of the system is the crucial part of the controller. Once the model of the system is found, the controller tuning is much easier than the PI controller.

In future these three control strategies will be tested for different environmental conditions and energy consumption will be analysed. All these control strategies will be implemented to on the basis of thermal comfort of the indoor environment. The cost function used in this paper is a quadratic cost function and did not used the heat pump during the night time as it was expected. In future a linear weight for this formulation will be analysed. The linear programming (LP) gives totally different results than the quadratic programming problem (QP). The LP method always gives solutions at the intersection of the constraints whereas QP solutions can be on intersection of constraints, on a single constraint or off constraints. It is expected that for this problem LP method is more suitable to get better use of heat pump and to shift the building heating and hot water loads to the night. Model predictive control strategy also depends on the right selection of input and output weights i.e. how much to penalized the input or output of the system if it deviates from the limits or set point. The effect of different weights will be analysed in near future.

ACKNOWLEDGMENT

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REFERENCES

[1] International Energy Agency 2006. Key world Energy Statistics.

[2] Kreith, F. and Kreider, JF. Principles of solar engineering. New York: McGraw-Hill; 1978.

[3] Kalogirou, S.A. (2004). Solar thermal collectors and applications. Progress in Energy and Combustion Science, 30(3),231-295.

[4] Duffie, JA. and Beckman, WA. Solar engineering of thermal processes. New York: Wiley; 1991.

[5] Agrawal,N.and Bhattacharyya. S.(2007). Studies on a two-stage transcritical carbon dioxide heat pump cycle with flash intercooling. Applied Thermal Engineering,27,299-305.

[6] Rakhesh,B.Venkatarathnam,G. and Murthy, S.S. (2003). Experimental studies on a heat pump operating with r22, r407c and r407a: comparison from an energy point of view. Journal of energy resources technology, 125,101-112.

[7] Sakellari, D. and Lundqvist, P. (2002) Modelling the performance of a domestic low-temperature heating system based on a heat pump. In Proc. ofthe 9th International Refrigeration and Air Conditioning Conference, West Lafayette, USA, 1, pages 65-72.

[8] Zogg,D. Shafai,E. and Geering, H.P.(2001)A fault diagnosis system for heat pumps. In Proc. of the 2001 IEEE Conference on Control Applications (CCA),Maxico,70-76.

[9] Moran, M. J.and Shapiro, H.N. (2006) Fundamentals of engineering thermodynamics, 5th edition. John Wiley & Sons, Inc.

[10] Van Schijndel, A.W.M. and De Wit., M.H. Aug (2003) Advanced simulation of building systems and control with simulink. In Proc. of 8th International IBPSA Conference, Eindhoven, Netherlands, 1185-1192.

[11] Yang, Z. Pedersen, G.K.M. Larsen, L.F.S and Thybo. H. Nov (2007) Modeling and Control of Indoor Climate Using a Heat Pump Based Floor Heating System. In Proc. Of 33rd Annual Conference of the IEEE Industrial Electronics Society (IECON), Taipei, Taiwan.

[12] Defra. (2008) Measurement of domestic hot water consumption in dwellings. Copyright Crown.

[13] Camacho, E. F. & Bordons, C. 1999. "Model Predictve Control." Springer-Verlag, London.

FIGURES AND TABLES:

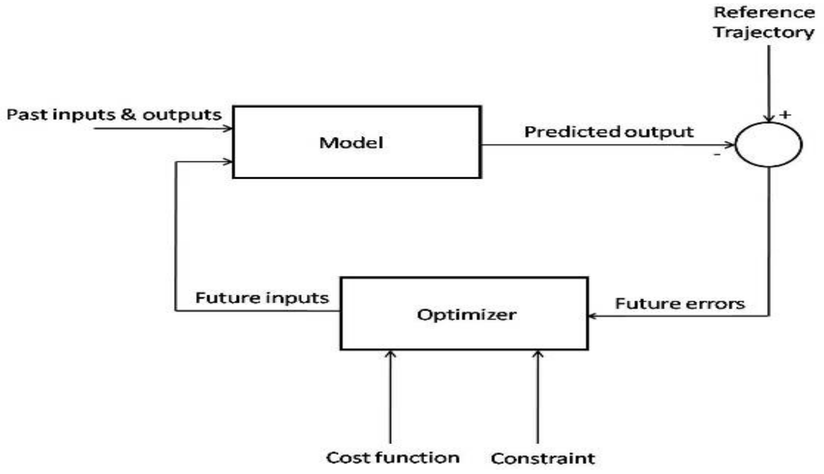

Figure 1: Basic Structure of MPC (Source Camacho et al., 1998 [13])

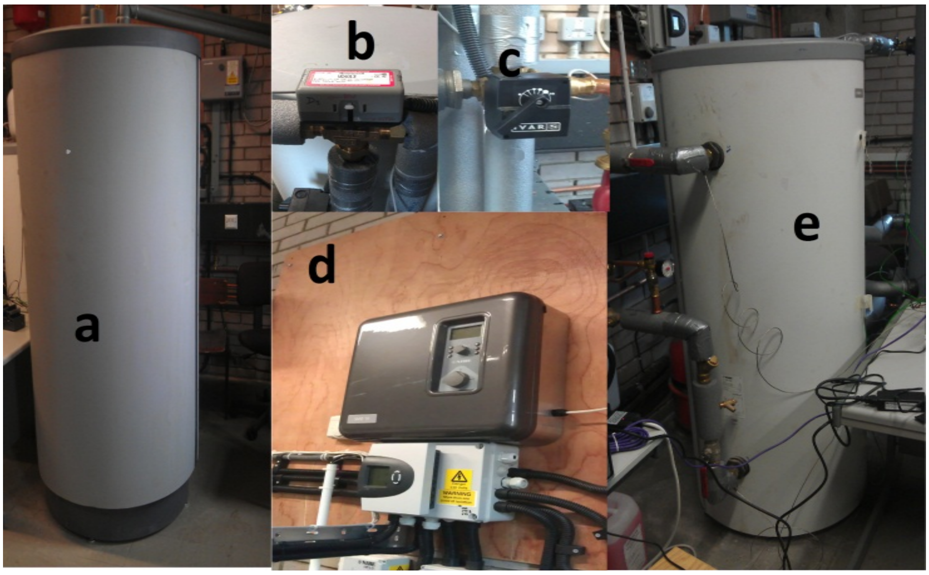

Figure 2: Heat pump combined solar system. (a) Heating Tank (b) Diverter (c) Valve (d) Controller and (e) Buffer tank

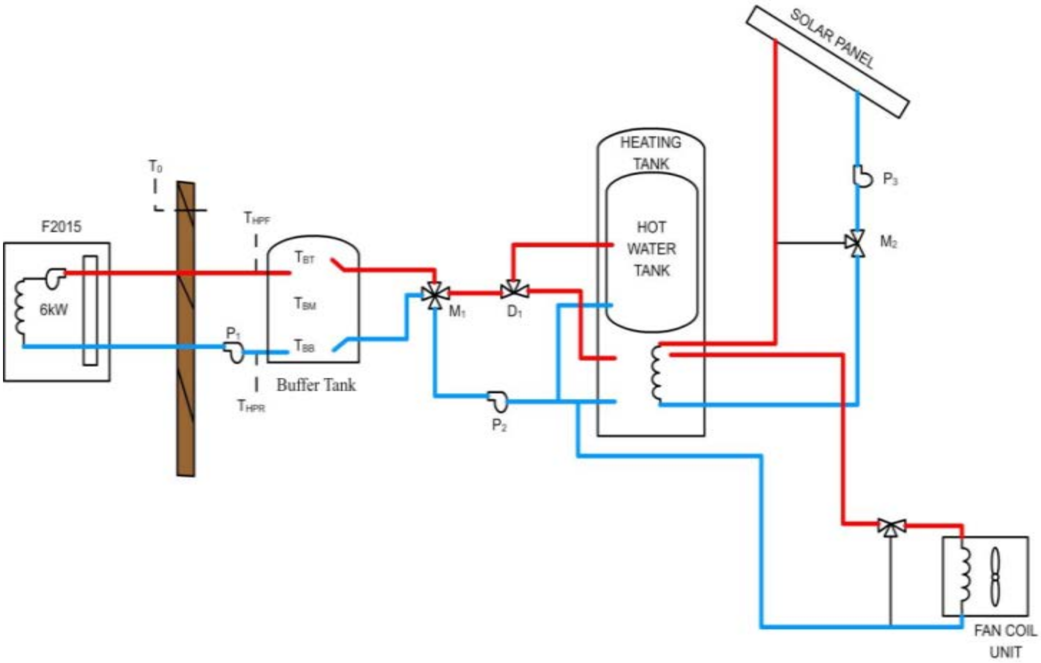

Figure 3: Plant Scheme

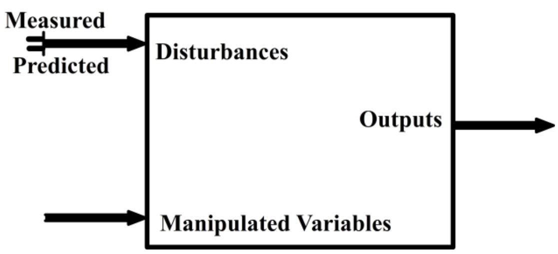

Figure 4: Inputs, Disturbances and Outputs

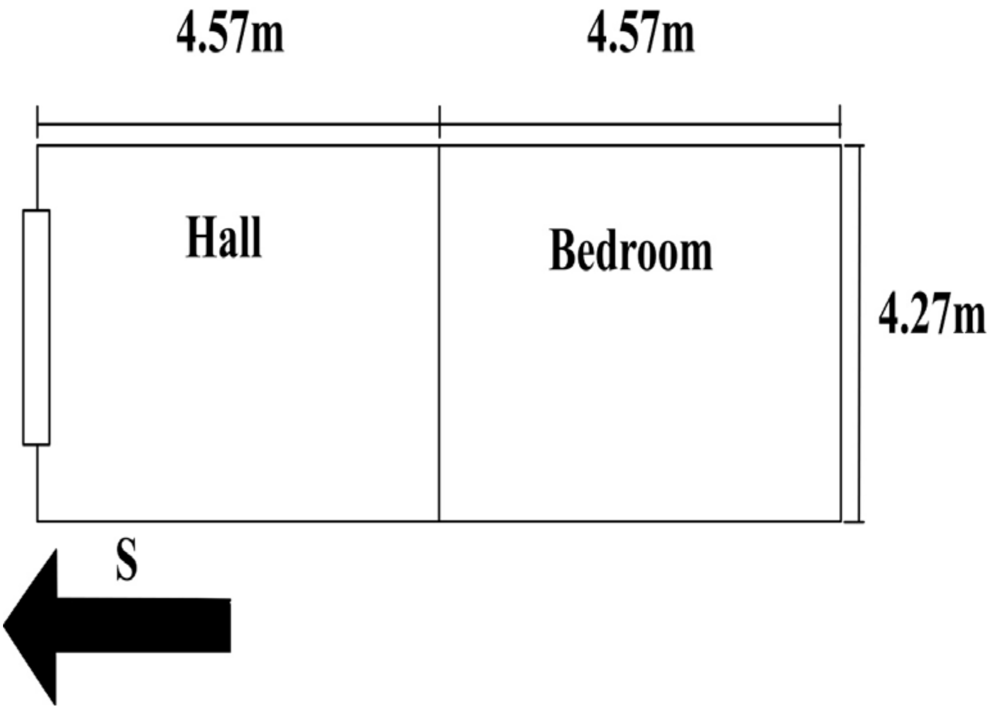

Figure 5: House plan

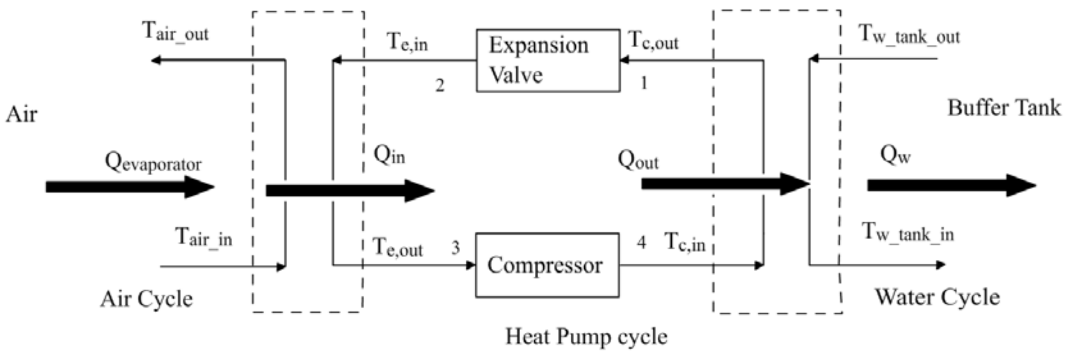

Figure 6: Schematic Diagram of heat Pump

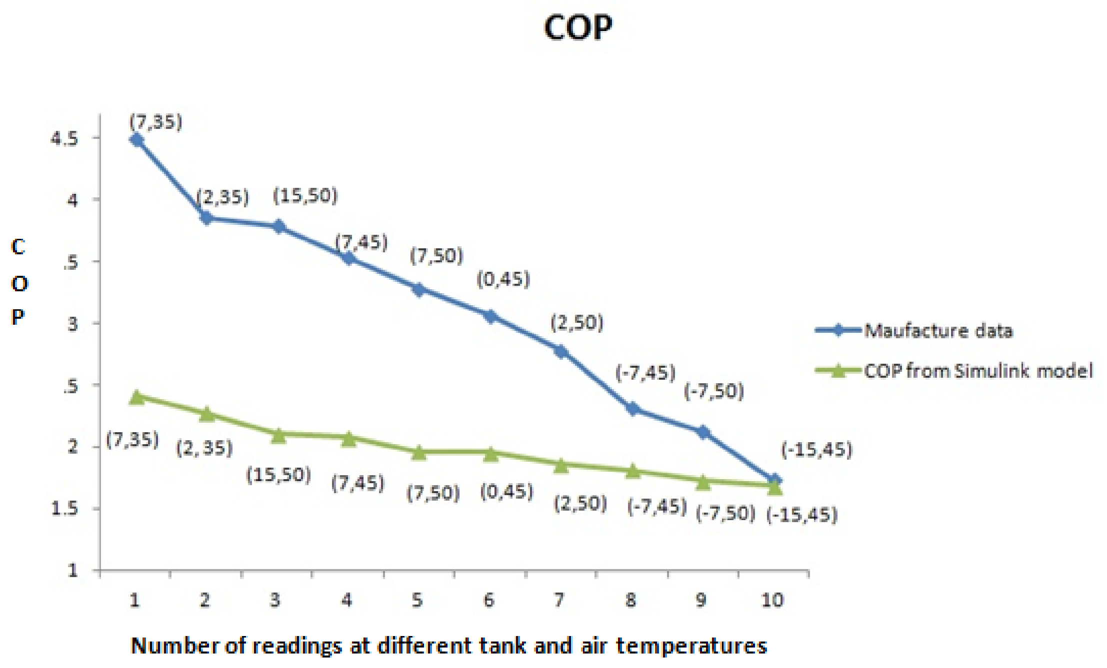

Figure 7: Heat Pump COP Model 1

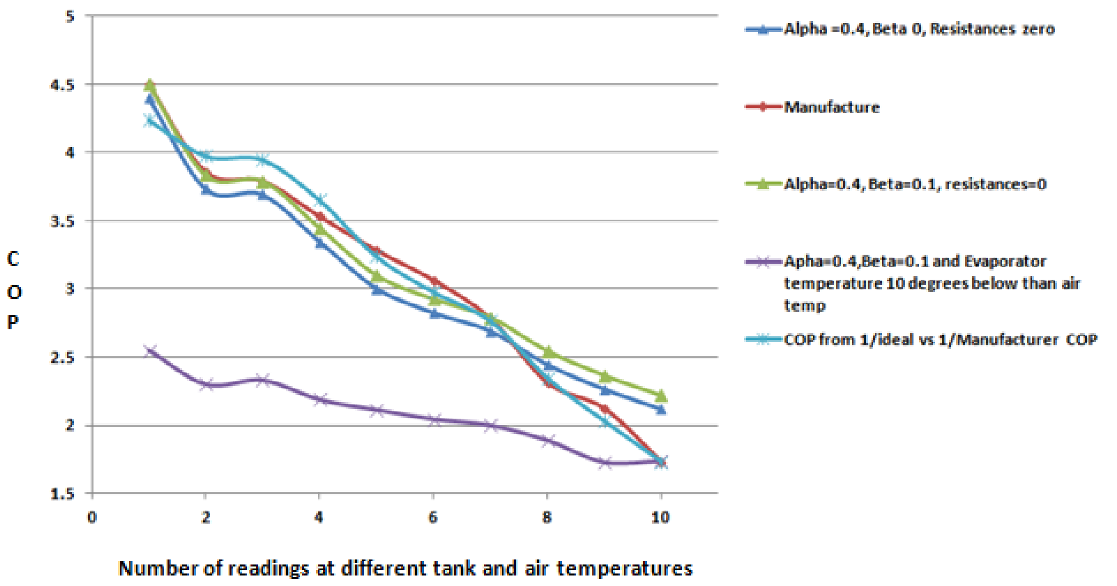

Figure 8: Heat Pump COP Model

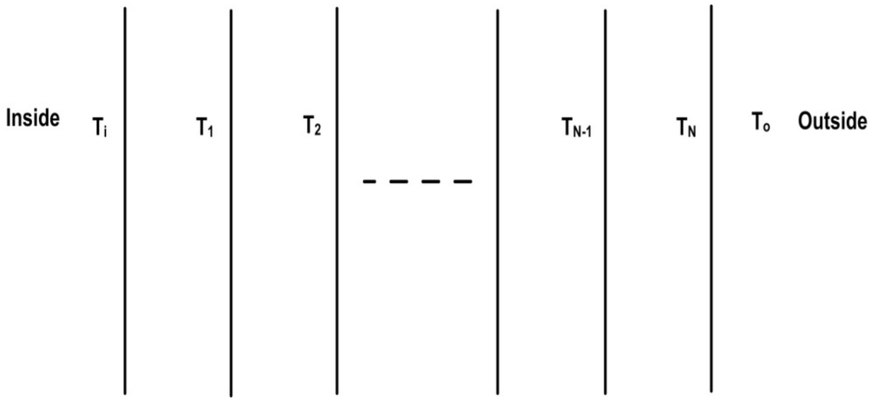

Figure 9: Wall divisions

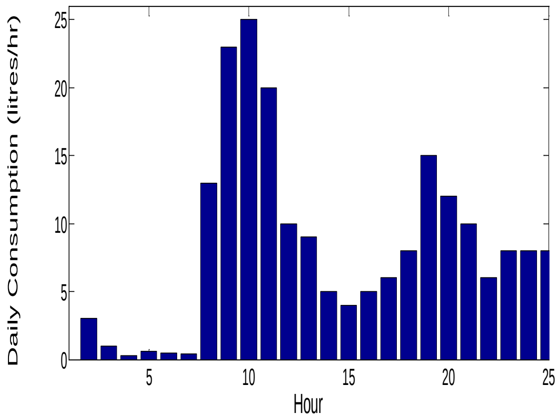

Figure 10: Water daily consumption

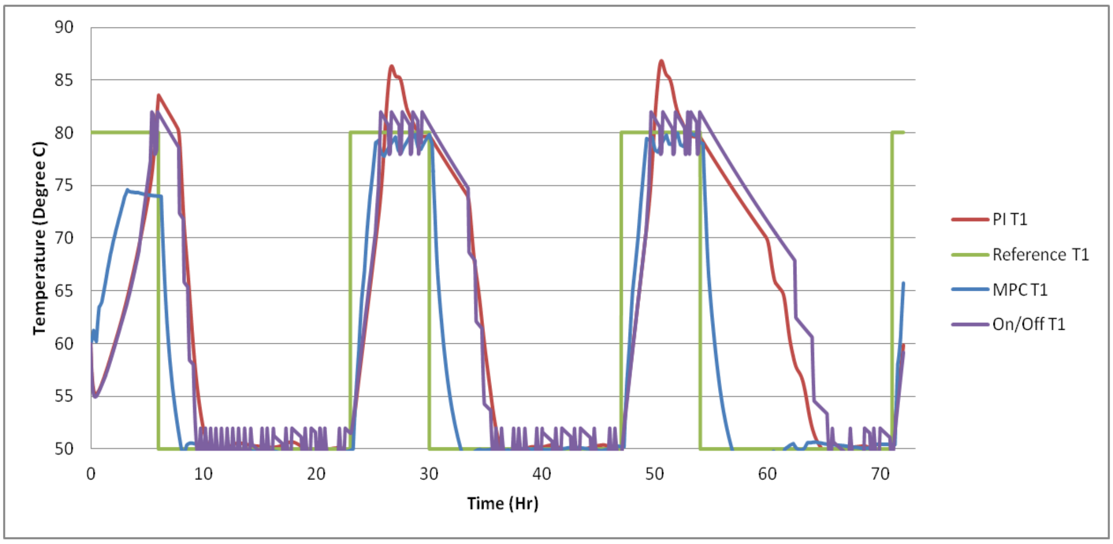

Figure 11: Step response of the controller for buffer tank

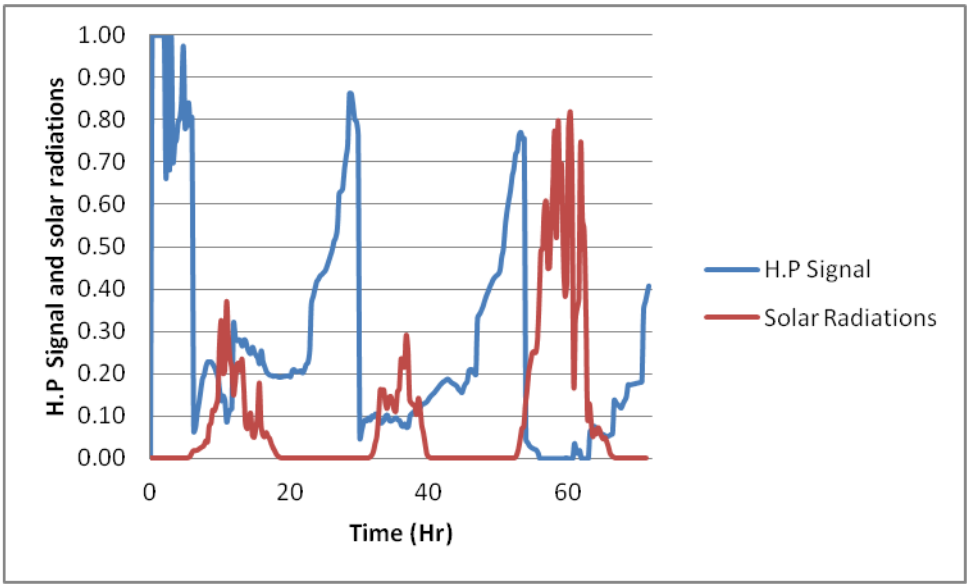

Figure 12: Use of night time electricity

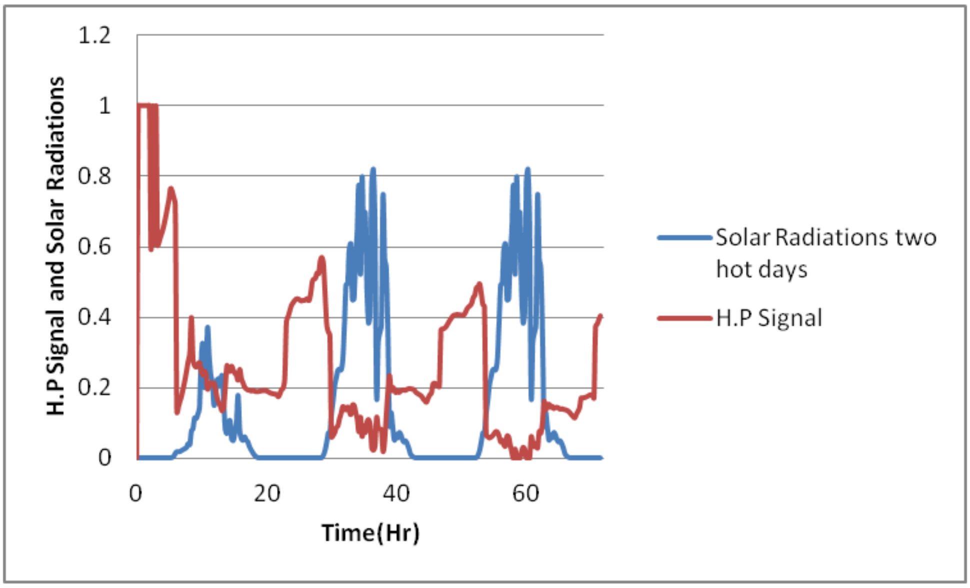

Figure 13: Weather prediction

Wall/Roof		Thickness (m)	Thermal conductivity (W/m.K)	Density (kg/m^3)
	Brick	0.1	0.84	1700
	Polystyrene	0.0795	0.034	35
	Concrete	0.1	0.51	1400
	Plaster	0.013	0.025	900
Partition Wall				
	Gypsum	0.025	0.25	900
	Air	0.1	0.15 (Resistance) m^{2}K/W	1.204
	Gypsum	0.025	0.25	900

Table 1: House model specifications