DEMAND SIDE MANAGEMENT USING SETPOINT CONTROL AND PV SYSTEMS

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ABSTRACT

DEMAND SIDE MANAGEMENT USING SETPOINT CONTROL AND PV SYSTEMS

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The turn of the 21st century has seen a positive change in the attitude towards sustainable energy. The focus on awareness and implementation of renewable energy has improved. However, it is also important to study the energy usage. Demand Side Management (DSM) and Demand Response (DR) are not new ideas. They were introduced during the 1970s when the world was rife with energy crises. However, with population growth, increased dependence on electricity and introduction of renewable energy, these ideas are more relevant than ever. One of the biggest problems energy systems face is their efficiency. DSM and DR provide a viable solution to increase energy efficiency by reducing the peak demand and improving the demand and supply. HVAC systems generally prove to be the highest consumers of electricity. In this study, the efficiency of cooling systems is improved by setting the setpoint temperature based on an adaptive thermal comfort model in Middle East Technical University Northern Cyprus Campus and its effect on the demand is studied. The cases considered are based on the setpoint being controlled at all times, setpoint control on a schedule, setpoint control when demand peaks and setpoint control based on when demand exceeds an aggregate forecasted demand. Furthermore, this is employed in conjunction with PV systems with net metering to shift loads to periods with lower demand from the grid to improve grid stability. It is found that when setpoint is controlled at all times, energy consumption from cooling systems is cumulatively reduced by 55.7% for May, July, September and October with a minimum peak demand decrease of 1.55% for October, while when setpoint control is employed only when demand rises above the aggregate forecasted demand, the energy consumption by cooling systems is reduced by 30.3% cumulatively for May, July, September and October with a minimum peak demand decrease of 1.55% for October. Furthermore, with the cooling system improvements and PV system load shift, the peak demand reduction increases to 10.46% for October. Moreover, for winters, which have a comparatively higher rise in peaks, due to lower demand during the day, load shifting using PV decreases the peak demand by 25%, 18% and 14% for November, December and January respectively.

Keywords: DSM, Setpoint Control, PV systems

ÖZ

AYAR NOKTASI KONTROLÜ VE FOTOVOLTAİK SİSTEMLERİ KULLANARAK TALEP YÖNETİMİ

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21. yüzyıla girilen süreçte yenilenebilir enerjıye karşı sergılenen tutum olumlu yönde değışmektedir. Yenilenebilir enerjinin farkındalığına ve uygulanmasına odaklanma iyileşmiştir. Buna rağmen, enerji kullanımını incelemek de önemlidir. Talep Tarafı Yönetimi (TTY) ve Talep Yanıtı (TY) yeni fikirler değildir. 1970'lerde, dünyanın enerji krizleriyle dolu olduğu zamanlarda tanıtılmışlardır. Ancak nüfus artışı, elektriğe olan bağımlılığın artması ve yenilenebilir enerjinin kullanılmaya başlanmasıyla bu fikirler her zamankinden daha çok gündemdedir. Enerji sistemlerinin karşılaştığı en büyük sorunlardan biri verimlilikleridir. TTY ve TY, en üst sınır talebi azaltarak, talebi ve arzı iyileştirerek enerji verimliliğini artırmak için uygun bir çözüm sunar. Isıtma, Havalandırma ve Klima sistemleri genellikle en fazla elektrik tüketen sistemlerdir. Bu çalışmada, ODTÜ KKK'da uyarlanabilir bir termal konfor modeline dayalı olarak istenen değer sıcaklığı ayarlanarak soğutma sistemlerinin verimliliği artırılmış ve talebe etkisi incelenmiştir. Göz önünde bulundurulan durumlar, her zaman kontrol edilen istenen değer, bir programdaki istenen değer kontrolü, talep zirve yaptığında istenen değer kontrolü ve talebin toplam tahmini talebi aştığı zamana dayalı istenen değer kontrolüne dayanır. Ayrıca, bu, şebeke stabilitesini iyileştirmek amacıyla yükleri şebekeden daha düşük talep olan dönemlere kaydırmak için net ölçümlü Fotovoltaik sistemleri ile birlikte değerlendirilmiştir. İstenen değer her zaman kontrol edildiğinde, soğutma sistemlerinin enerji tüketiminin kümülatif olarak Mayıs, Temmuz, Eylül ve Ekim için %55,7 oranında azaldığı ve Ekim için minimum tepe talebinin %1,55 oranında düştüğü, yalnızca istenen değer kontrolü talebin toplam

öngörülen talebin üzerine çıkması durumunda kullanıldığında, soğutma sistemlerinin enerji tüketiminin Mayıs, Temmuz, Eylül ve Ekim aylarında kümülatif olarak %30,3 oranında azaldığı, Ekim için minimum tepe talebin %1,55 oranında düştüğü bulunmuştur. Ayrıca, soğutma sistemi iyileştirmeleri ve Fotovoltaik sistem yük kaymasıyla birlikte, Ekim ayı için en yüksek talep düşüşü %10,46'ya yükselmektedir. Ayrıca, gün içindeki düşük talep nedeniyle piklerin nispeten daha fazla yükseldiği kışlar için, Fotovoltaik kullanılarak yük kaydırma, pik talebini Kasım, Aralık ve Ocak için sırasıyla %25, %18 ve %14 oranında azaltmaktadır.

Anahtar Kelimeler: TTY, İstenen Değer Kontrolü, Fotovoltaik sistemleri

To my Family

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TABLE OF CONTENTS

ETHICAL DECLARATION iv

ABSTRACT v

ÖZ vii

ACKNOWLEDGEMENT x

TABLE OF CONTENTS xi

LIST OF TABLES xiii

LIST OF FIGURES xiv

LIST OF ABBREVIATIONS xviii

CHAPTER 1 INTRODUCTION 1

- 1.1. Motivation 4
- 1.2. Objectives of the Study 4

CHAPTER 2 LITERATURE REVIEW 6

- 2.1 Demand Side Managemant 6
- 2.2 DSM with PV systems 7
- 2.3 HVAC Optimization Methods 8
- 2.4 DSM in Cyprus 12
- 2.4 Gaps in the Literature 14

CHAPTER 3 THEORY AND METHODOLOGY 15

- 3.1 PV Energy Estimation 15
  - 3.1.1 Solar Geometry 15
  - 3.1.2 Solar Resources 16
- 3.2 Thermal Model of a Building 18
- 3.3 Adaptive Thermal Comfort Model 21
- 3.4 Case Study: METU NCC 23
  - 3.4.1 METU NCC Demand 24
  - 3.4.2 Building Scenario – Dormitory 1 29

3.4.3 Demand Management Strategies 31
CHAPTER 4 RESULTS AND DISCUSSION 41
4.1 Estimation of Energy Production of METU NCC PV Plant 41
4.2 Results of Demand Management Strategies 44
4.2.1 Case 1: Base Case 44
4.2.2 Case 2 – Setpoint Control Case 45
4.2.3 Case 3 - Schedule Based Case 50
4.2.4 Case 4 – Demand Monitoring Case 54
4.2.5 Case 5 – Forecasted Demand Case 58
4.2.6 Summary of Results for Cases 2, 3, 4 and 5 62
4.2.7 Sensitivity Analysis for Case 5 63
4.2.8 Case 6 - Load Shifting Analysis with Case 5 66
CHAPTER 5 CONCLUSION 71
5.1 Conclusions 71
5.2 Future Work 72
REFERENCES 74
APPENDIX 78
A.1 Simulink Diagrams 78

LIST OF TABLES

Table 3.1. Specifications of Axitech 250 W PV Module [28] 18

Table 3.2. Percentage Energy Consumption in METU NCC by Areas 30

Table 3.3. Dataset for the AC unit [48][49] 31

Table 3.4. Thermal model parameters [50] [51] 31

Table 4.1. Total Energy Consumption from cooling systems for Case 2, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 2 for the months of May, July, September and October 47

Table 4.2. Total Energy Consumption from cooling systems for Case 3, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 3 for the months of May, July, September and October 51

Table 4.3. Total Energy Consumption from cooling systems for Case 4, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 4 for the months of May, July, September and October 55

Table 4.4. Total Energy Consumption from cooling systems for Case 5, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 5 for the months of May, July, September and October 59

Table 4.5. Summary of Main Results of Case 2, 3, 4 and 5....................................... 63

Table 4.6. Change in Peak Demand through Load shifting, with Case 5 being applied 70

LIST OF FIGURES

Figure 1.1. The 6 Demand Side Management Techniques [8]....................................3

Figure 2.1. Results of annual comfort and energy consumption using Fixed Setpoint and Adaptive Control in New York [12]..9

Figure 2.2. Net HVAC Demand of the community over a 12 hour period [22] 10

Figure 3.1. Base Thermal Model in Simulink...19

Figure 3.2. Heat Loss Model in Simulink 20

Figure 3.4. Average Annual GHI for METU NCC from 2004 to 2010 [47] 24

Figure 3.6. Box plot for the load profile of METU NCC using Kibtek ‘17, ‘18 & ‘19 data averaged at each hour throughout the days of a month for a year for Winter 26

Figure 3.7. Box plot for the load profile of METU NCC using Kibtek ‘17, ‘18 & ‘19 data averaged at each hour throughout the days of a month for a year for Spring.....27

Figure 3.8. Box plot for the load profile of METU NCC using Kibtek ‘17, ‘18 & ‘19 data averaged at each hour throughout the days of a month for a year for Summer..28

Figure 3.9. Box plot for the load profile of METU NCC using Kibtek ‘17, ‘18 & ‘19 data averaged at each hour throughout the days of a month for a year for Autumn ..29

Figure 3.11. Algorithm Flowchart for Case 3 35

Figure 3.12. Case 3 implementation on Simulink...36

Figure 3.13. Algorithm Flowchart for Case 4 37

Figure 3.14. Case 4 implementation on Simulink...37

Figure 3.18. Algorithm Flowchart for Case 6 40

Figure 4.2. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Spring 42

Figure 4.3. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Summer 43

Figure 4.4. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Autumn 44

Figure 4.5. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 1 45

Figure 4.6. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 2 46

Figure 4.7. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 2 48

Figure 4.8. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 2 48

Figure 4.9. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 2.. 49

Figure 4.10. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 2.. 49

Figure 4.11. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 3 50

Figure 4.12. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 3 52

Figure 4.13. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 3 52

Figure 4.14. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 3.. 53

Figure 4.15. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 3.. 53

Figure 4.16. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 4 54

Figure 4.17. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 4 56

Figure 4.18. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 4 56

Figure 4.19. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 4 57

Figure 4.20. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 4 57

Figure 4.21. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 4 58

Figure 4.22. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 5 60

Figure 4.23. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 5 60

Figure 4.24. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 5 61

Figure 4.25. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 5 61

Figure 4.26. The sensitivity of the change in energy consumption of Case 5 compared to the Base Case with different base setpoint temperatures 64

Figure 4.28. Average Hourly Demand for the month of September with load shifting and Case 5, compared with the base demand of 2019 66

Figure 4.30. Average Hourly Demand for the month of January with load shifting, compared with the base demand of 2019 68

Figure 4.32. Average Hourly Demand for the month of December with load shifting and Case 5, compared with the base demand of 2019 69

Figure A.1. Cooling/AC Subsystem in Simulink 78

Figure A.2. Adaptive Thermal Comfort Model in Simulink 79

Figure A.3. Thermal Model with Adaptive Thermal Comfort Model in Simulink ... 79

LIST OF ABBREVIATIONS

ABBREVIATIONS

DSM	Demand Side Management
HVAC	Heating, Ventilation and Cooling
KIBTEK	Kibris Türk Elektrik Kurumu (Turkish Cyprus Electrical Instritution)
METU NCC	Middle East Technical University Northern Cyprus Campus
PMV	Percentage Mean Vote
PPD	Percentage of People Dissatisfied
PV	Photovoltaic

CHAPTER 1

INTRODUCTION

Every year, the population of the world increases by 81 million people, which amounts to a rate of 1.16% [1]. As the population increases, energy demand is also increasing when compared to the previous decades. To produce energy, fossil fuel is commonly used, and in 2011, 82% of the energy of the world was produced by fossil fuels [2]. The problem arising from burning fossil fuel for energy is the greenhouse gases emitted, which leads to global warming, causing an increase in the earth's surface temperature. Furthermore, fossil fuels are also a finite resource, therefore, it is also important to conserve these resources.

Due to the finite and hazardous nature of fossil fuels, all countries have looked for greener and more sustainable alternatives. With seemingly infinite resources, renewable energy posed as a suitable alternative to fossil fuels [3] and with technological advancements, they have become more accessible and economically feasible [4]. Following the alarming rate at which global warming was affecting the world, the United Nations enforced, through the Kyoto Protocol, to decrease emissions, causing renewable energy patents to increase [5]. Of these, implementation of PV plants have one of the highest growths, with an yearly growth rate of 60% [3].

Implementation of renewable energy with energy from fossil fuels focuses on meeting demand using supply side management, which includes efficient generation, transmission and distribution which can prove to be expensive [6]. Another way to curb this increasing demand is reducing the demand on the demand side. Development, application and assessment to modify the consumption pattern, such that the peak demand and timing of demand is affected, is called Demand Side Management (DSM) [7]. This method is heavily reliant on energy efficiency and load management, such that demand is moved to off-peak times [7]. Usually this is overlooked, since it can be complex, i.e. the number of DSM projects increase with the number of buildings to produce significant change [6]. Furthermore, human behavior is a big factor in implementing DSM projects [6]. However, DSM programs can be successful, saving between 10% to 30% energy in existing buildings [6].

DSM focuses on 6 techniques to influence the electricity consumption shown in Figure 1.1 [8]. These methods are described below :

1. Peak Clipping: Peak demand loads are reduced, such that there is a reduction in demand and the need for additional generation is removed.
2. Valley Filling: Loads which are previously run on non-electric fuels are added where electric demand is low. This causes the peak demand to be unaffected while the total consumption increases.
3. Load Shifting: Peak loads are shifted to off peak periods such that peak demand is reduced, while there is no change in total energy consumption.
4. Strategic Conservation: Reducing the end-use consumption by applying efficiency techniques, such that there is a decrease in total energy consumption and peak demand.
5. Strategic Load Growth: Conserving the load profile shape in the event of an expected growth in consumption (due to new consumers).
6. Flexible Load Shape: Interrupting loads by the utility whenever necessary, aiming to reduce the peak demand. Since this affects the reliability of service, it requires a contractual agreement with consumers.

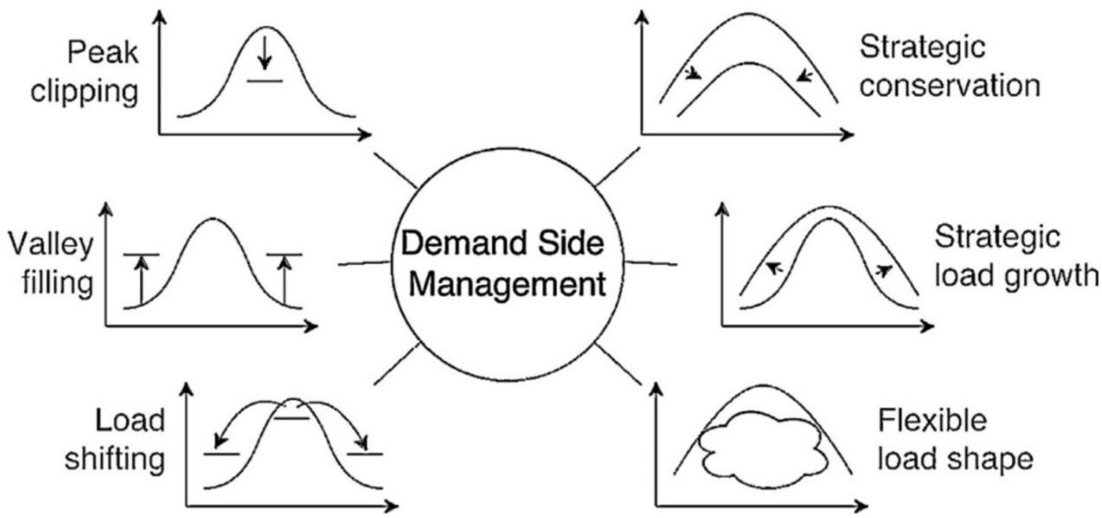

Figure 1.1. The 6 Demand Side Management Techniques [8]

The application of PV has been considered as a DSM tool previously. Using PV, it is possible to manage and reduce peak loads. Furthermore, dispatchable PV can also be used as an emergency power [9]. Hybrid PV-Battery systems are also considered, especially since PV cannot produce energy during night times, making the system more effective [10].

One of the core contributors to demand is the use of heating, ventilation and air conditioning (HVAC) systems [11]. HVAC systems are used to maintain thermal comfort, however, without active control by users, HVAC systems keep running, even when not needed [12]. Moreover, 90% of users never adjust the thermostat based on a certain programs [13]. Therefore, setpoint control of HVAC systems can prove to be vital in increasing energy efficiency. The idea behind setpoint control is to change and control the setpoint temperature in thermostats which regulate the indoor temperature. This approach varies from controlling HVAC systems to switch between on and off states, to scheduling precooling or preheating such that peak demand can be reduced by taking advantage of setpoint scheduling [14] [15].

1.1. Motivation

The rising electricity demand has imposed the need for more fossil fuel and renewable energy driven generators. This poses a concern since fossil fuel resources are diminishing, renewable sources of energy are variable and can prove to be expensive. Furthermore, addition of more fossil fuel based generators also increases the greenhouse gas emissions. DSM provides an important opportunity for sustainable and efficient energy use, such that the demand can be reduced and this can reduce the need for more electricity generation in Northern Cyprus. This approach can be employed by studying the load profile to find the possible opportunities to reduce demand. In general, HVAC systems contribute to the demand excessively and since users do not actively control these systems, this can be seen as an opportunity to reduce demand, especially in Northern Cyprus due to hot days and cooler nights. Owing to the high solar resources in Northern Cyprus, PV system installations are common. Since PV systems generate energy during the day, day time peak loads can be mitigated through PV, especially since cooling loads are high during the day due to higher outdoor temperatures. Integration of PV systems with HVAC systems setpoint control can have a significant effect on the demand of buildings in Northern Cyprus, since it has the possibility to increase the energy efficiency of the building and provides an opportunity to shift peak loads to off peak hours. However, another challenge which arises from setpoint control is making sure user comfort is maintained, which is key for HVAC systems to complete their purpose while also saving energy.

1.2. Objectives of the Study

There are three main objectives of this study which are derived from the gaps mentioned in Chapter 2. In general, the three aims of this work are based on a case study set in METU NCC.

The first objective is to determine the peak demand and the load shift opportunities in METU NCC with the current PV plant energy production. This is dependent on the load profile created from the electricity demand of METU NCC. Demand data of 2017, 2018 and 2019 are studied, and a mean hourly load profile are created to study how the demand varies between each hour. Since cooling systems are a focus in this study, the effect of the ambient temperature on the average daily demand is studied to find opportunities to reduce demand.

The second objective is to reduce the demand as a whole, on the basis of setpoint control of cooling. User comfort is also kept in mind as the setpoint temperature is controlled so that the cooling systems provide thermal comfort while being efficient. For this purpose, indoor temperatures need to be maintained based on the outdoor temperatures at a comfortable level. Furthermore, the effect of this change on the demand needs to be analyzed with two scenarios being kept in mind; setpoint control running throughout the day, and setpoint control running when energy production is low/demand is rising.

Finally, the effect of using PV with setpoint control is studied, with the goal of reducing the overall load and decrease the peak load. Using TMY data, PV production can be predicted such that this energy can be used to shift loads from peak hours to periods of lower demand while also applying setpoint control.

CHAPTER 2

LITERATURE REVIEW

In this chapter, studies concerning the current state of DSM and general strategies for DSM implementation is reviewed. Furthermore, demand reduction and peak shaving methodologies are examined. Finally, approaches to improve HVAC efficiency were also assessed.

2.1 Demand Side Managemant

As mentioned before, DSM is the design, application, and assessment of utility such that electricity consumption patterns are modified in terms of level of demand, energy and time of use. This is generally achieved by either energy saving programs, which entails encouraging consumers to switch to more energy efficient systems and decrease energy use by changing consumer behavior, or load management programs where demand peak periods are reduced to manage existing resources [7]. The main methodologies for DSM are peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shapes [7]. General methodology to implement DSM programs begins with a planning stage, followed by implementation and evaluation of the program [6][7].According to Pina, Silva and Ferrao [16], demand management strategies are important for sustainability in the long run, furthermore, load shifting can be employed to improve capacity factors of generators. Several studies discussed the emergence of DSM strategies and assessed the technical and economical feasibility of DSM for residential consumers. For instance, Mahin et al. [17] studied the impact of applying direct load control, load shifting and energy efficiency on residential load profiles numerically in Dhaka. By creating a load profile using questionnaires from residents based on daily use, they applied these demand management strategies after studying this load profile. They found that energy efficient appliances decrease average daily energy consumption by

19.76% while 1.42% of daily average energy consumption can be shifted from peak hours to off peak hours.

2.2 DSM with PV systems

With the meteoric rise of PV system technologies, numerous studies have employed PV systems as a viable DSM tool. Byrne et al. [9] examined the economic feasibility of implementing PV systems as a DSM tool. Using TMY data from Sacramento, Austin and the East Coast, they developed an economic model for the cost-benefit analysis by simulating a PV-DSM system. In their study, they found that integrating such systems offers consumers a chance to manage peak demands and are closer to being feasible commercially. Rahman and Kroposki [18] investigated the performance of PV modules as a DSM tool in Virginia, U.S.A. Using demand data and PV energy data from their test centers, they found that the academic building load peaks coincided with the PV production providing a viable option for DSM. However, on simulating energy produced by 2 axis tracking, they found that the energy generated only improved by 12.2% during the peak demand periods, meaning 2-axis tracking may not be cost effective. On the other hand, more recent studies show more promising signs due to the lower prices of PV systems. A 2017 technoeconomic analysis of PV and energy storage systems in Germany use a simulation model to study the effects of PV and energy storage systems on standard German load profiles. Owing to lower capital costs of PV and energy storage systems, price of electricity drops from 37 cents/kWh to 32 cents/kWh for standard German load profiles and had a significant effect on consumer load profiles, improving self consumption rates by 58% [19]. Phiri and Kusakana [20] studied on an energy management model based on Hybrid Optimisation Model for Energy Renewable, optimizing a hybrid Wind-PV-Battery system for an industrial load in South Africa while taking part in a time of use DSM program. finding that the developed model can significantly reduce cost of operations and can open to a possibility of selling back power to the grid. Similarly, Williams, Kelm and Binder [21] studied the effect of adding heat pumps and thermal storage systems to domestic

PV systems in Stuttgart, Germany, by simulating using numerical methods to find that self-consumption increased from 55% to 65%.

2.3 HVAC Optimization Methods

Several studies have studied optimizing HVAC systems and improving efficiencies of HVAC systems. Schibuola, Scarpa and Tambani [11] studied the introduction of variable speed drive technology in HVAC systems to match actual load requirements for a building in Venice. Using experimentally obtained data based on heating and cooling demand trends, they simulated an HVAC system which would work on the basis of diverting water flow to return when fan coils are shut based on heating and cooling needs. They achieved a global energy saving of 38.9%. Crumpler [6] followed a different approach by studying usage data and identifying unexpected energy consumption to improve HVAC systems by removing unnecessary operations in the University of Virginia. To achieve this, a Building Automation System was used to determine opportunities where energy could be saved. Once these opportunities were determined, the Building Automation System was used to improve the system, by reducing precooling and preheating, reducing air flow rate and removing humidification in summer months, and the results were metered consequently. He achieved a 42% reduction in electricity usage. In another study, Wang, Pattawi & Lee [12] employed the usage of occupancy driven thermostats to save energy for residential households. Using a building energy simulation tool, EnergyPlus, they subjected a thermostat control based on schedule and occupancy in 5 cities of America, namely, San Francisco, Miami, Pheonix, New York and Fairbanks with fixed and variable setpoints for 2020. Figure 2.1 shows the results they received for energy consumption and comfort level they achieved based on Fixed Setpoint and Adaptive Control methodologies for New York. They observed that energy usage decreased from 20 MWh to 13 MWh when HVAC systems were always on and Adaptive Control was used. Similarly, Energy usage decreased from 15 MWh to 11 MWh for schedule based case when Adaptive Control was employed.

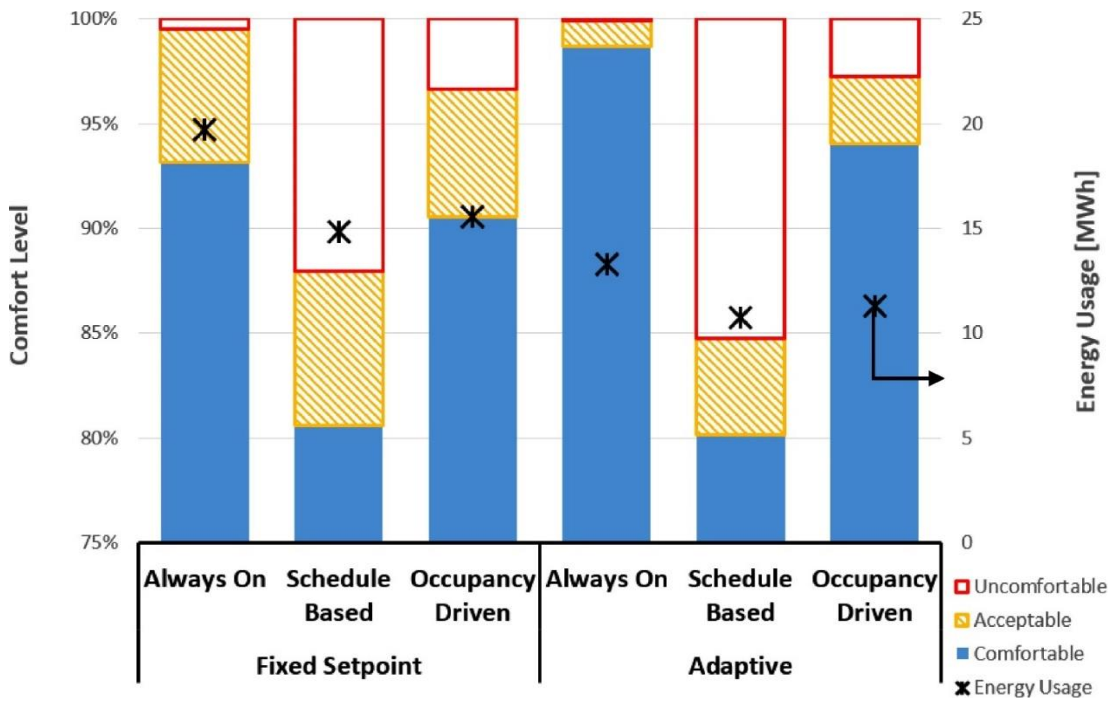

Figure 2.1. Results of annual comfort and energy consumption using Fixed Setpoint and Adaptive Control in New York [12]

Ghofrani, Nazemi and Jafari [22] produced a methodology to define HVAC operation such that they save energy and level the load. They studied on US based buildings such as offices, hotels and supermarkets as a community. Using numerical methods, their work was based on thermal inertia such that the temperature setpoints were variable across time to keep air conditioning in human comfort zone. Their design controlled the setpoint such that it alternated between 23°C and 25°C in a sinusoid showing 12.5% savings in electricity consumption and a reduction of 10% in peak demand. This can be seen in Figure 2.2.

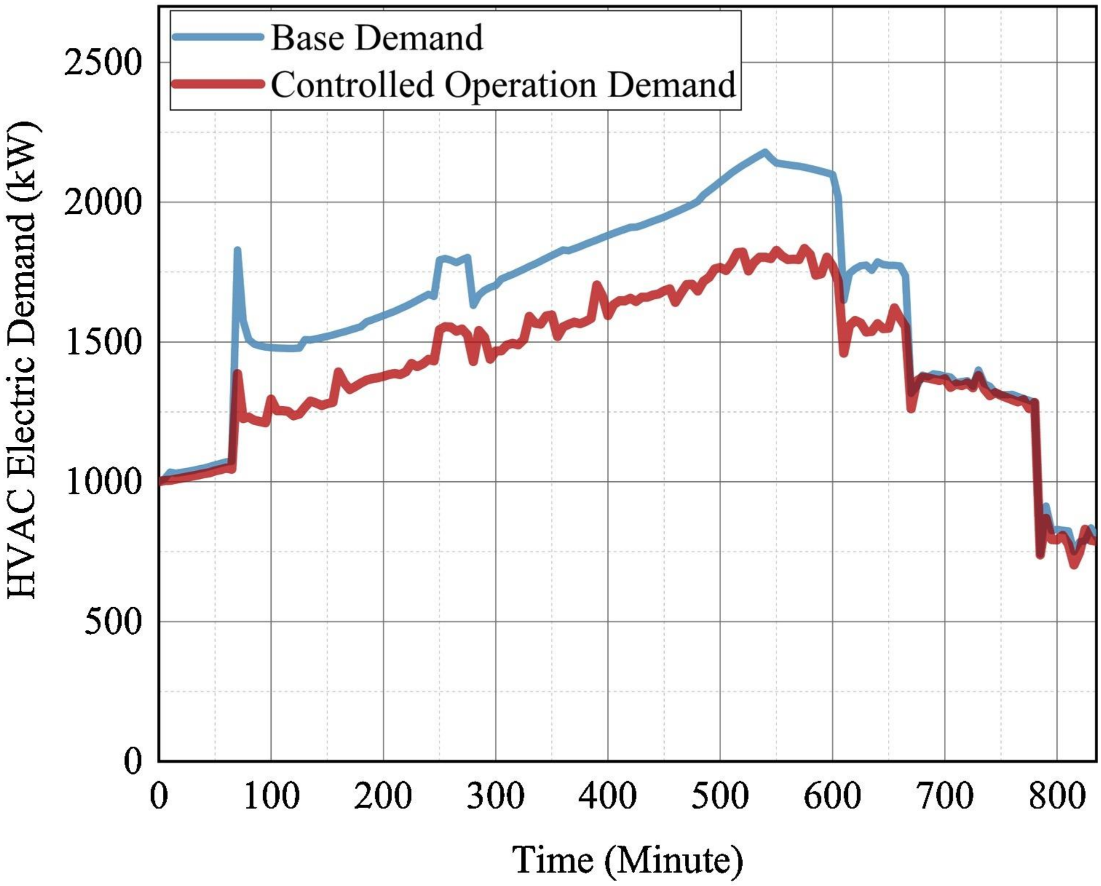

Figure 2.2. Net HVAC Demand of the community over a 12 hour period [22]

Dejvises and Tanthanuch [31] numerically modelled the performance of a cooling system in a room in Thailand, and experimentally compared these simulation results using a data logger and digital power meter. They compared two scenarios; an always on approach and the switching off the system for 15 minutes. Figure 2.3 shows the comparison between the experimental and model outputs which shows similar behavior between the experimental and simulated model. However, the power estimated by the model is overestimated by 20%.

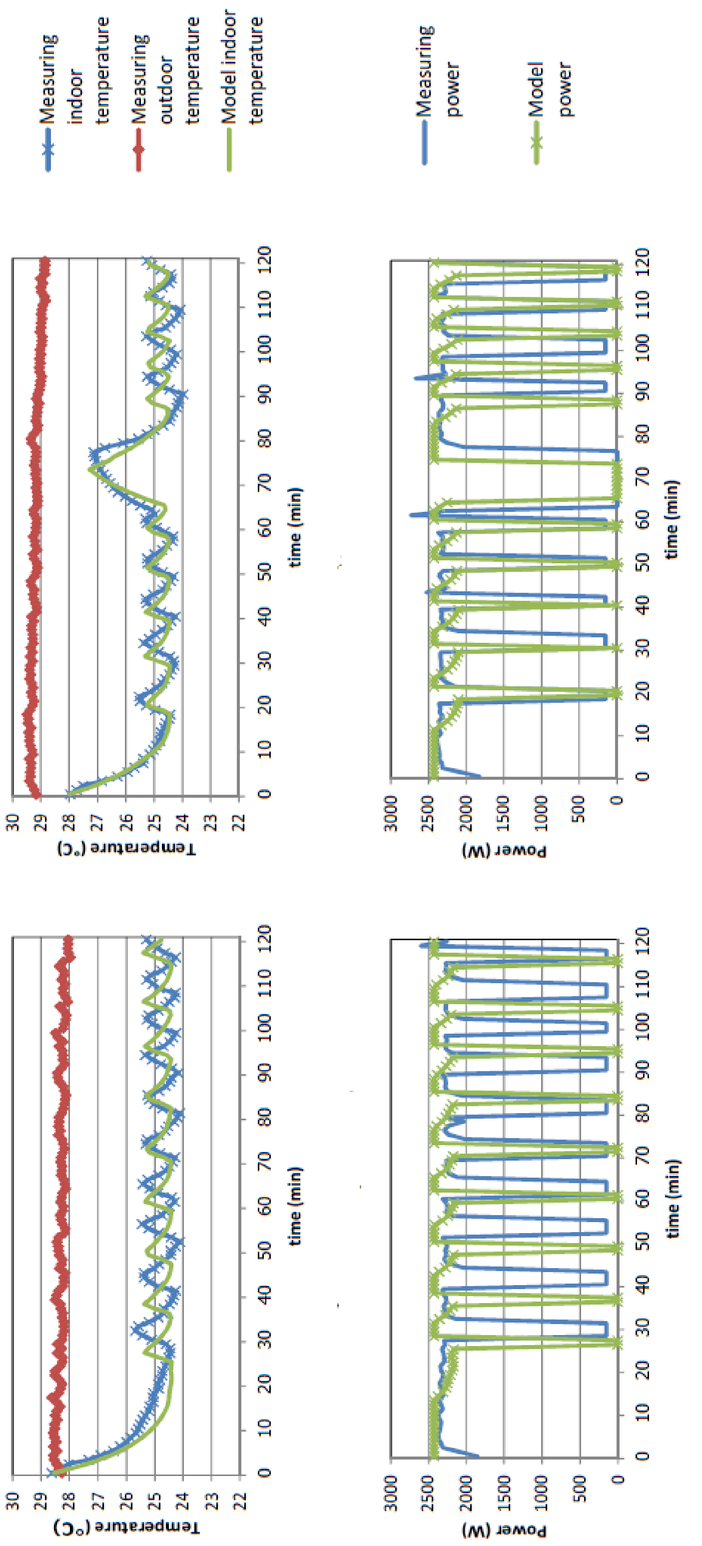

Figure 2.3. Comparison of Simulated and Experimental Model by Dejvises and Tanthanuch [23]

2.4 DSM in Cyprus

Several studies have explored PV systems and hybrid energy systems in Cyprus, however, they have not been explored as a DSM tool. Sadati et al. [24] conducted a study on the application of PV/wind hybrid systems with battery storage for Northern Cyprus, finding that a 2 MW PV, 3.75 MW wind system with a 1 MWh battery system is 0.02 cents/kWh cheaper than compared to a system without a battery system. Furthermore, İlkan and Çırak [25] discuss the importance of energy education in Northern Cyprus and the significance of the implementation of DSM programs in Northern Cyprus. Arfaei [26] discussed the importance of important energy regulations which are not being implemented in North Cyprus and studied the base of energy efficient design suggesting regulations for the case of Northern Cyprus. He found that the US regulations would be suitable for Northern Cyprus owing to the regulations being adaptable to different climate conditions. Atikol, Dagbasi and Güven [27] suggested a method to show residential end-use load analysis by conducting surveys to produce a residential load profile. They also found that DSM plans could reduce the peak demand by 53 MW in winter, assuming the current peak is 110 MW based on their DSM options which included promotion of storage space heaters, implementation of fluorescent lamps, preset timers for water heaters and selling of electric water heaters. Dakyen, Dagbasi & Murat Özdenefe [28] developed residential reference building energy models by modelling 5 different types of residential reference buildings for Northern Cyprus. They found the thermal energy required to keep buildings at a cooling setpoint of 25°C and a heating setpoint of 20°C as shown in Figure 2.3. As shown a residence with 8 dwellings and 4 floors has an annual thermal energy requirement of 54000 kWh/year of while the cooling thermal energy required is almost 28000 kWh/year.

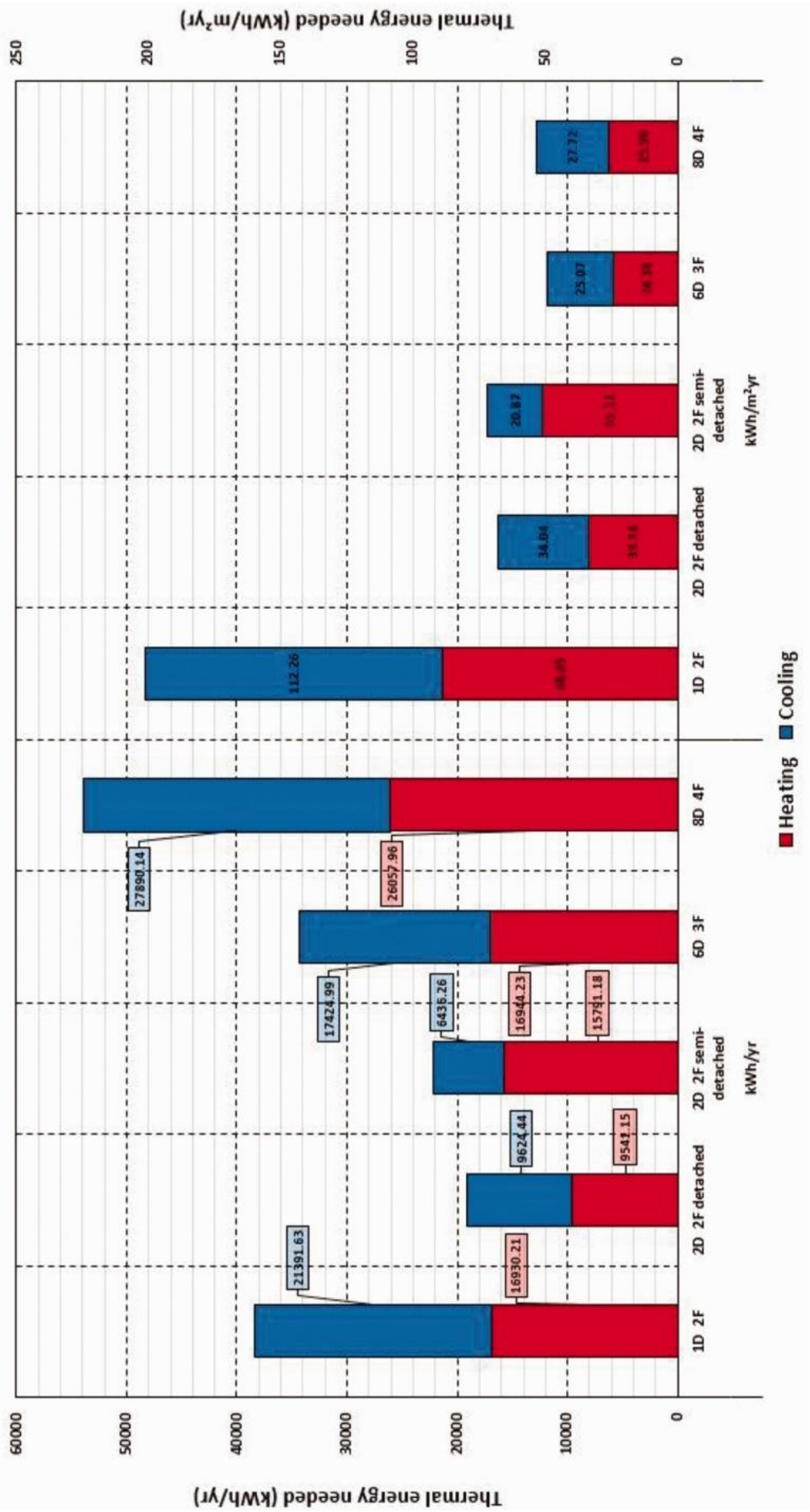

Figure 2.4. Thermal energy required to keep residential buildings with existing exterior wall configuration at a heating setpoint of 20°C and cooling setpoint of 25°C [28]

2.4 Gaps in the Literature

One of the most important aspects of planning for DSM studies is acquiring a load profile to identify opportunities to reach energy efficiency and shaving peaks. The literature lacks load profile based on metered data in Northern Cyprus. Furthermore, there is the lack of literature for operation of DSM programs in Northern Cyprus, with HVAC improvements in conjunction with PV systems.

CHAPTER 3

THEORY AND METHODOLOGY

3.1 PV Energy Estimation

3.1.1 Solar Geometry

To begin with energy from the currently installed PV needs to be estimated. For this purpose it is important to calculate the amount of solar radiation on the tilted panel. This can be done by finding the incident angle of the solar radiation. Since the angle of this incidence changes throughout the day, the amount of solar radiation falling on the panel changes with respect to the location on Earth and time across the year. This time is known as the solar time, which is the apparent angular motion of the sun. To simplify it, it shows the position of the sun in the sky. Solar time is used for geometric solar relations rather than the standard time. Solar time is dependent on the longitude, time zone and equation of time, where, the first two constants are based on the location. The equation of time changes with the day of the year such that it ranges between 1 and 365. The equation of time, E, can be found using Equations 3.1 and 3.2 while solar time, t_s, can be found through Equation 3.3 [29].

$$B = \frac{(n-1)360}{365} \tag{3.1}$$

$$E = 229.2(0.0000075 + 0.001868\cos(B) - 0.032077\sin(B) - 0.014615\cos(2B) - 0.04089\sin(2B)) \tag{3.2}$$

$$t_s = t_{std} + \frac{4(L_{std} - L_{loc}) + E}{60} \tag{3.3}$$

where, n is the day number, t_{std} is the standard time, L_{loc} is the longitude and L_{st} is the time zone, of the position in question.

The angular position of the sun and the equatior is known as the declination angle, δ, where North is assumed to be positive, ranging between +23.45º and -23.45º. The declination angle can be found using Equation 3.4 [29].

$$\delta = 23.45\sin\left(360\left(\frac{284+n}{365}\right)\right) \tag{3.4}$$

The angle describing the angle between South and the projection of the normal on a horizontal to the surface is known as the surface azimuth angle, γ. It ranges from +180º to -180º where positive values are in the West, while negative values are in the East. Hour angle, ω, is the representation of solar time in an angular form as shown in Equation 3.5 [29].

$$\omega = (t_s - 12) \times 15 \tag{3.5}$$

The zenith angle, θ_z, is the angle between the beam radiation and zenith. It can be found from Equation 3.6 [29].

$$\cos(\theta_z) = \cos(\phi)\cos(\delta)\cos(\omega) + \sin(\phi)\sin(\delta) \tag{3.6}$$

where ϕ is the latitude of the position in question.

The solar azimuth angle is the angle between the projection of the beam radiation on a horizontal surface and South. Solar azimuth angle, γ_s, ranges from +180º to -180º, like the surface azimuth angle. It can be found using Equation 3.9 [29].

$$sign(\omega) = \begin{cases} -1, & \omega < 0 \\ 1, & \omega \geq 0 \end{cases} \tag{3.7}$$

$$\gamma_s' = \begin{cases} \dfrac{\cos(\theta_z)\sin(\phi) - \sin(\delta)}{\sin(\theta_z)\cos(\phi)}, & \theta_z \neq 0 \\ 1, & \theta_z = 0 \end{cases} \tag{3.8}$$

$$\gamma_s = \begin{cases} sign(\omega)|\cos^{-1}(\gamma_s')|\,, & \gamma_s' \neq 1 \\ 0, & \gamma_s' = 1 \end{cases} \tag{3.9}$$

The angle at which the beam radiation lands on the surface is known as the angle of incidence, θ, and to maximize this, panels are usually tilted, known as the tilt angle, β. The angles described above are used to find the angle of incidence shown in Equation 3.10 [29].

$$\cos(\theta) = \cos(\theta_z)\cos(\beta) + \sin(\theta_z)\sin(\beta)\cos(\gamma_s - \gamma) \tag{3.10}$$

3.1.2 Solar Resources

The three components of insolation that fall on a tilted PV panel are known as beam, diffuse and reflected. In this analysis, reflected insolation is neglected. Using TMY data, hourly beam, *DNI*, and diffuse insolation, I_d, was found. Through these values, the beam insolation on a tilted surface, $I_{b,T}$, is found using Equation 3.11 and diffuse insolation on a tilted surface, $I_{d,T}$, using Equation 3.12 asssuming the isotropic sky model. Consequently, the total insolation on a tilted surface, I_T, can be found as shown in Equation 3.13 [29].

$$I_{b,T} = DNI\cos(\theta) \tag{3.11}$$

$$I_{d,T} = \frac{I_d(\cos(\beta) + 1)}{2} \tag{3.12}$$

$$I_T = I_{b,T} + I_{d,T} \tag{3.13}$$

The type of PV module is also important in this estimation as the energy produced is dependent on the peak power and efficiency of the panel. The efficiency is dependent on the cell temperature, and hence the ambient temperature. The performance of a PV panel is dependent on many external factors such as the ambient temperature, Tamb, and hence the cell temperature, T_{cell}. The normal operating cell temperature, *NOCT*, is the cell temperature when a PV cell is tested at the NOCT irradiance, $G_{ref,\,NOCT}$, at an ambient temperature, $T_{ref,\,NOCT}$, and wind speed of 1 m/s under no load. The temperature coefficient, β_{ref}, demonstrates how the maximum power and efficiency, η_{PV}, changes as the cell temperature changes by 1 degree Celsius. These are reported at standard test conditions of cell temperature, T_{STC}, and irradiance, G_{STC}. The efficiency at STC is $\eta_{PV,\,ref}$. Using the ambient temperature from the TMY dataset, the cell temperature is found as shown in Equation 3.14 [29].

$$T_{cell} = T_{amb} + \frac{\left(NOCT - T_{ref,NOCT}\right)I}{G_{ref}} \tag{3.14}$$

The efficiency of the panel can be found through Equation 3.15 [29].

$$\eta_{PV} = \eta_{PV,ref}(1 - \beta_{ref}(T_{cell} - T_{STC})) \tag{3.15}$$

Following this, the insolation on the tilted surface, cell efficiency, Area, A_m, and number of modules, $N_{modules}$, and system efficiency factors, η_{other} (0.85% for this research [30]) are used to find the total energy generated as shown in Equation 3.16 [29].

$$E_{gen} = \eta_{PV} I_T A_m N_{modules} \eta_{other} \tag{3.16}$$

For this campus, the PV panel used is Axitech 250W. Its specifications are shown in Table 1 [31].

Table 3.1. Specifications of Axitech 250 W PV Module [28]

$\eta_{PV,ref}$	0.1537
Area (m^2)	1.63
Peak Power (W)	250
G_{STC} (W/m^2)	1000
T_{STC} (°C)	25
NOCT (°C)	45
$G_{ref, NOCT}$ (W/m^2)	800
$T_{ref, NOCT}$ (°C)	20
β_{ref} (1/K)	0.0042

3.2 Thermal Model of a Building

In houses and buildings, thermal processes can be modelled, such that they can be seen as a resistor-capactor network, where heat transfer and temperature are modelled as current and voltage respectively. Resistances are dependent on the thermal conductivity of the walls and window, while capacitances indicate the thermal inertia of the material [32]. For this case study, only cooling systems are considered since heating systems are gas powered. Figure 3.1 shows the base thermal model of the building on MATLAB with the thermostat, AC and Building Subsystems. Here, the base setpoint is set as 20°C and the outdoor temperature comes from the TMY dataset and it outputs the energy consumption, indoor and outdoor temperatures.

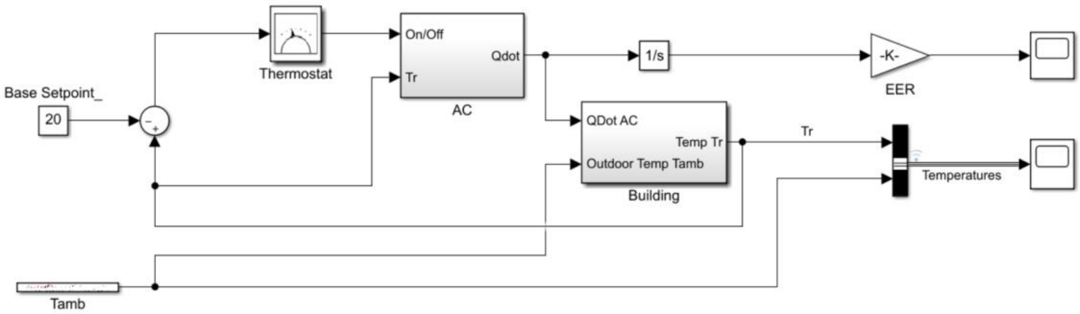

Figure 3.1. Base Thermal Model in Simulink

The basic idea of an air conditioning system is to make sure that the indoor air temperature is kept at a set temperature, known as the setpoint temperature, T_s. This is regulated by a thermostat. This is given as one of the inputs to the system such that the indoor temperature can be regulated accordingly. The heat removed by the air conditioner, dQ_{AC}/dT, can be described as shown in Equation 3.17 where, T_r is the indoor temperature, T_c is the cooler air temperature, $\dot{m}$ is the mass flow rate of air and c is the specific heat capacity of air at constant pressure [23]. The initial condition set is for temperature of the room to be 20°C.

$$\frac{dQ_{AC}}{dt} = (T_r(t) - T_c(t)) \cdot \dot{m} \cdot c \qquad (3.17)$$

Finding the indoor temperature variations requires the equivalent resistances from the thermal conductivity, such that the change in heat lost to the surroundings, $(dQ_{gain})/dt$, can be found as shown in Equation 3.18. Following this, the change in the temperature of the room, $(dT_r)/dt$, can be found as shown in Equation 3.19, where M_{air} is the mass of air in the room [23].

$$\frac{dQ_{gain}}{dt} = \frac{(T_{amb}(t) - T_r(t))}{R_{eq}} \qquad (3.18)$$

$$\frac{dT_r}{dt} = \left(\frac{dQ_{gain}}{dt} - \frac{dQ_{AC}}{dt}\right) \cdot \frac{1}{M_{air} \cdot c} \qquad (3.19)$$

where, T_{amb} is the ambient temperature, R_{eq} is the equivalent thermal resistance for composite materials or composite material configurations. The thermal resistance for a material and equivalent thermal resistance is found through Equation 3.20 and 3.21 [33].

$$R_{x_m} = \frac{1}{h_{in}A} + \frac{l_1}{k_1 A_1} \dots + \frac{l_n}{k_n A_n} + \frac{1}{h_{out}A} \tag{3.20}$$

$$\frac{1}{R_{eq}} = \frac{1}{R_{x_1}} + \cdots + \frac{1}{R_{x_m}} \tag{3.21}$$

where A is the area of the surface, h_{in} is the indoor convective heat transfer coefficient, h_{out} is the outdoor convective heat transfer coefficient, k_n is the thermal conductivity of the nth material and l_n is the thickness of the nth material. These parameters are dependent on the building properties which are given in Section 3.4.2 in Table 3.4.

Figure 3.2 shows Equations 3.18 and 3.19 in MATLAB where Q_{DotAC} signifies dQ_{AC}/dT while 1/s signifies the indoor temperature integrating over time. This subsystem finds the indoor temperature variations by taking into account the heat removed by the cooling systems and the heat gained from the surroundings.

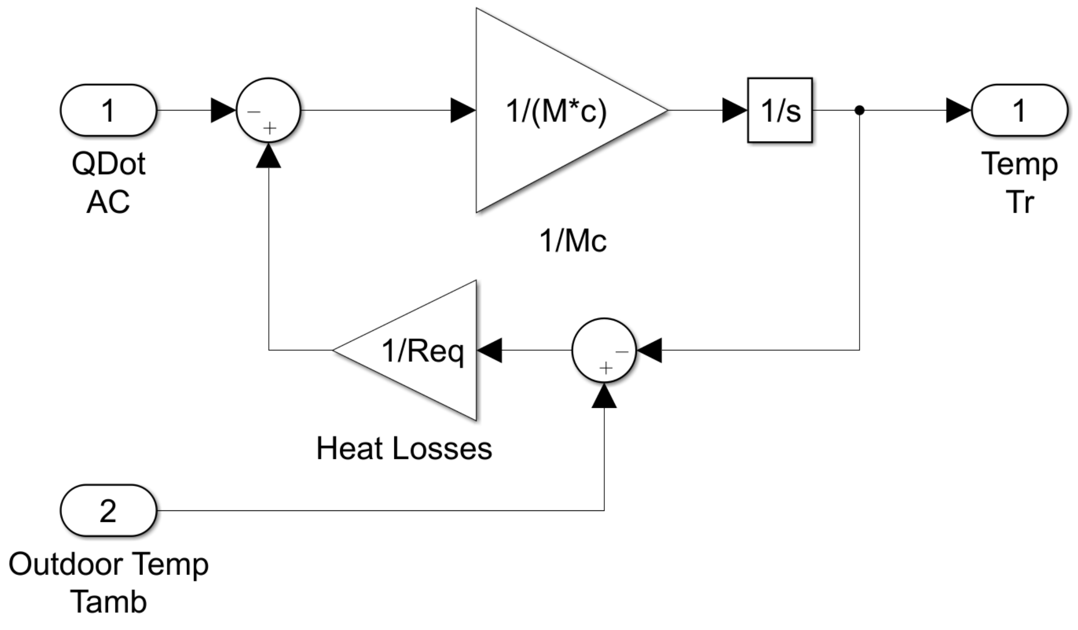

Figure 3.2. Heat Loss Model in Simulink

Using the above model, the heat removed by the cooling system from the room is calculated based on the room temperature and setpoint temperature. Using this heat removed, the energy consumed by the cooling system is calculated. The Energy Efficiency Ratio (EER) (given in Section 3.4.2) is a ratio of the output cooling energy in BTU and the energy in Wh, which is shown in Equation 3.22 [34].

$$EER = \frac{Q_{AC}}{E} \tag{3.22}$$

Consequently, the indoor temperature changes based on the heat removed by the cooling system, and the heat lost to the surroundings, which is based on the outdoor temperature, that is the ambient temperature in this case. In this model, heat gained due to radiation is not considered. There may also be heat given by appliances used in the room such as laptops and refigerators, and also by occupants inhabiting the room. Since, it is difficult to estimate the heat gains, internal heat gains from occupants and appliances is neglected. It is also assumed that heat is being removed from each room at an equal rate.

3.3 Adaptive Thermal Comfort Model

It is essential to analyze where cooling is needed to reach a thermal comfort level. This can be achieved by applying a thermal comfort model such that air conditioning systems can adjust the setpoint temperature to reduce the energy consumed. ASHRAE 55 has calculated a thermal adaptive comfort standard based on a predictive mean vote model. Based on a static model, it points towards a perspective of building occupants of thermal comfort. Built on a percentage of people dissatisfied-percentage mean vote model (PMV-PPD), it provides an empirical answer to thermal comfort needs, such that an adaptive comfort model could be defined based on the outdoor temperature. Figure 3.3 shows a detailed indoor setpoint temperature for cooling systems based on the outdoor temperature, where the blue zone shows a comfortable indoor temperature, while yellow zones show acceptable zones. It can be observed that after outdoor temperatures of 22°C, traditional setpoint may be less than what is needed [12].

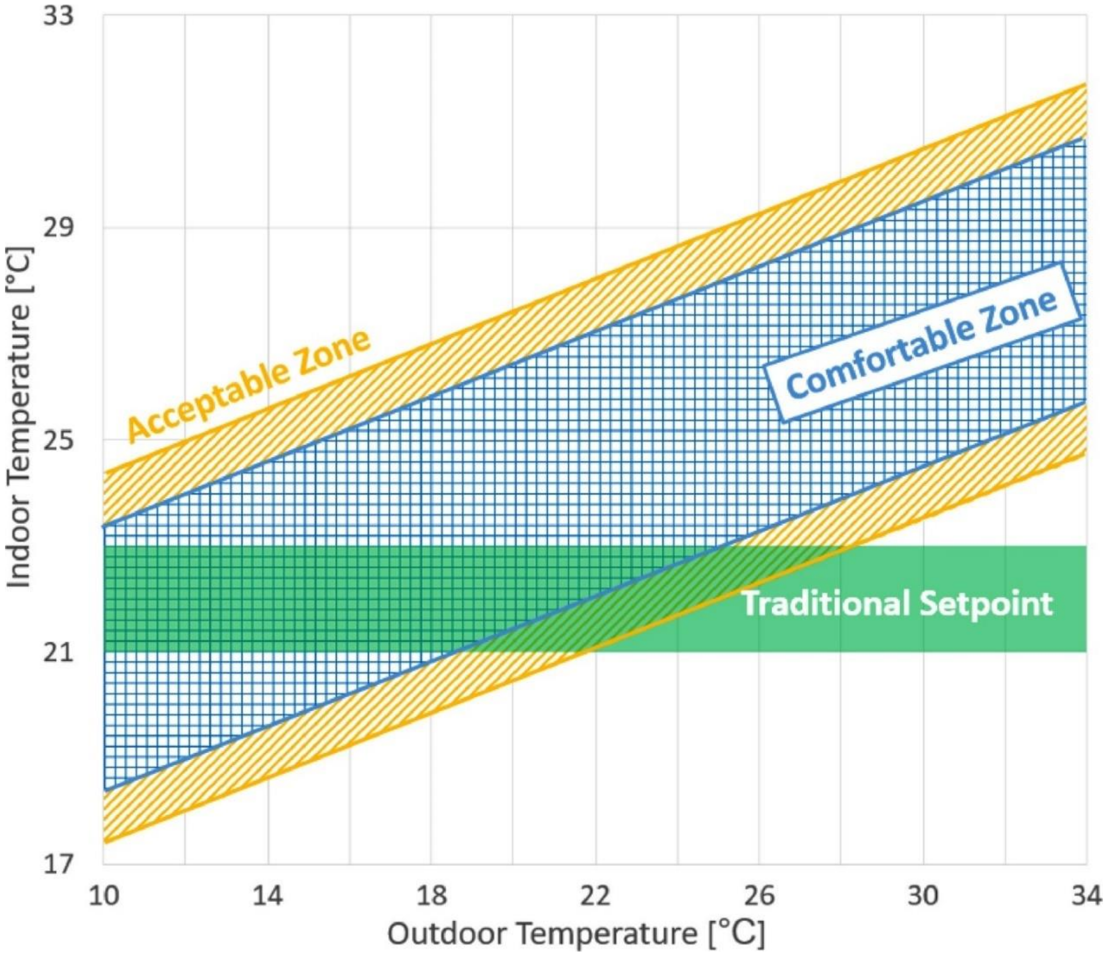

Figure 3.3. Setpoint temperature range based on outdoor temperatures defined by the ASHRAE 55 [12]

Based on this, the European thermal adaptive comfort standard BS EN15251 was calculated. The adaptive thermal comfort temperature can be calculated as shown in Equation 3.23 [35]. Therefore using this model, rather than having a fixed setpoint temperature, the setpoint temperature input varies based on the outdoor temperature, such that the heat removed by the system can be reduced. Furthermore, setpoint temperature values were limited to 25°C since temperature setpoint variation is known to add additional loads to the system [22]. Furthermore, recommended design values of BS EN15251 also suggest to keep a maximum operative temperature of 25°C-27°C [36].

$$T_s = 18.8 + 0.33 \cdot T_{amb} \tag{3.23}$$

3.4 Case Study: METU NCC

METU NCC is located in the northwest of Cyprus, a country which has typical Mediterranean climate. It is an island located between Middle East and Europe, it is the third largest island Mediterranean Sea [37]. However, since the island does not have conventional energy resources, Northern Cyprus resorts to importing fossil fuels to produce energy for the country [38]. Diesel plants at Kalecik and Teknecik make up 78.5% of energy, while Teknecik steam power plants produce 21.39% of energy in Northern Cyprus [38]. Due to this, electricity generation in Northern Cyprus results in 850 million kg of CO_2 emissions annually [39]. Moreover, it is predicted that electricity consumption will rise from 1374 GWh in 2014 to 2350 GWh by 2025 [40]. Since the island has generally sunny days, amounting upto 300 days a year, it proves to be rich in solar energy [41] [42] [43]. To reduce the dependency on fossil fuels, CO_2 emissions and demand of the country, renewable energy resources have been studied across the country in the past decade. Due to this Serhatkoy Solar PV plant was commissioned, producing 0.11% of the energy in Northern Cyprus [38]. However, DSM has only recently been implemented in the country, where KIBTEK has implemented Time of Use pricing, by increasing electricity prices at peak times [44]. This causes a behavioral change in consumers, so that users reduce electricity consumption at peak times, reducing peak loads [45]. Unfortunately, this does not affect demand in METU NCC, since Time of Use pricing does not apply to the campus and a fixed tariff rate of 0.175 $/kWh is applicable.

As mentioned before, METU NCC is located in northwest of Cyprus, in Güzelyurt (33.017°E and 35.2°W), boasting an average daily global horizontal insolation (GHI) of 5.48 kWh/m^2 per year [46]. Figure 3.4 shows the average annual GHI for METU NCC from 2004 to 2010 [46].

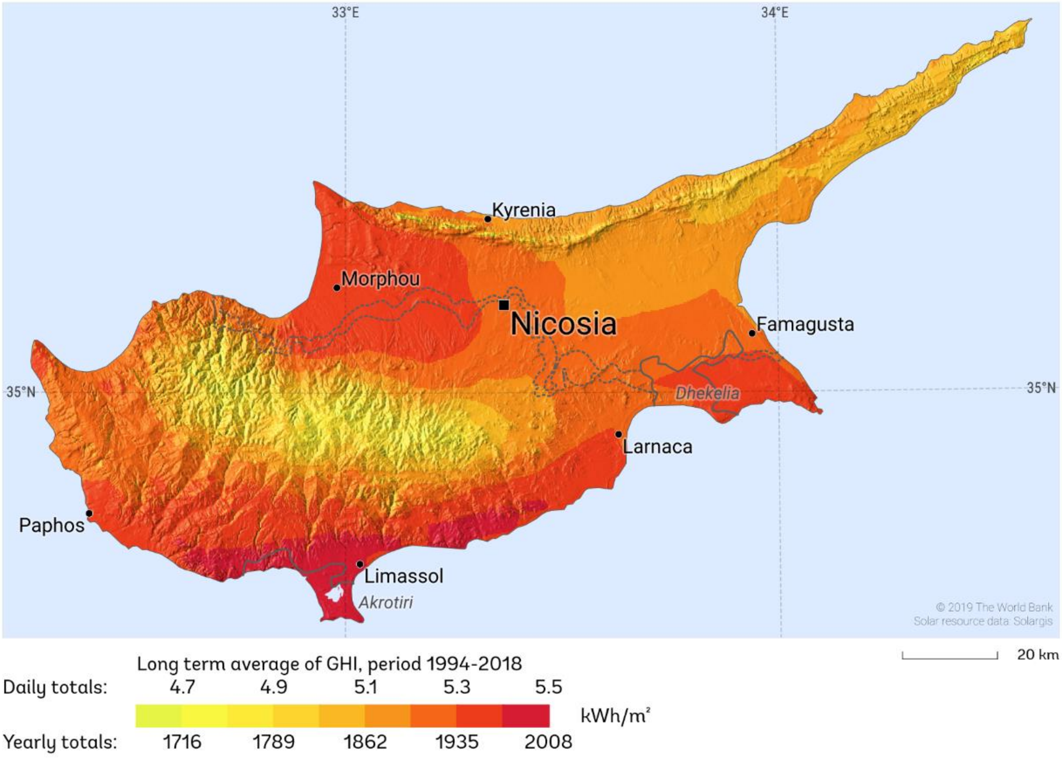

Figure 3.4. Average Annual GHI for METU NCC from 2004 to 2010 [47]

METU NCC can be considered as a community with the potential of having its own micro grid, housing almost 3000 students and staff. The campus has a significant electricity demand which was completely supplied by the grid until 2016, which is based on fuel based generators, resulting in high energy costs and greenhouse gas emissions and low energy security. Furthermore, due to an unstable grid in the northern parts of the country, blackouts are a frequent occurrence, which add expense to the campus due to diesel generators as a back-up electricity source [46]. Due to the high renewable energy resources, METU NCC has installed a 1 MW Solar PV plant in 2016.

3.4.1 METU NCC Demand

As mentioned in Section 1.2, studying the demand and load profile of the campus plays an important part in this study. Figure 3.5 shows the average daily demand of METU averaged across 2017, 2018 and 2019 and the mean monthly ambient temperature in METU NCC. The demand data comes from KIBTEK, meanwhile the mean monthly ambient temperature data comes from the TMY dataset for Güzelyurt. These data show the demand covered by the electricity utility KIBTEK, i.e., does not include the demand covered by the electricity produced by the PV plant in METU NCC. It can be seen from Figure 3.9 that the maximum demand in METU NCC is during October, the beginning of the fall semester and July, when summer school begins. This can be accounted due to the high temperatures in both months, therefore, cooling loads are at a maximum, which are run by electrical airconditioning units. On the other hand, heating loads in the colder months in larger buildings i.e. dormitories and educational facilities, are provided by heaters running on fuel. It can also be seen that there is a drop in demand during March and April since air conditioning units are closed. Meanwhile, June and August have a considerably lower demand compared to July even with comparable mean ambient temperatures due to semester break, causing students to leave METU NCC for vacations.

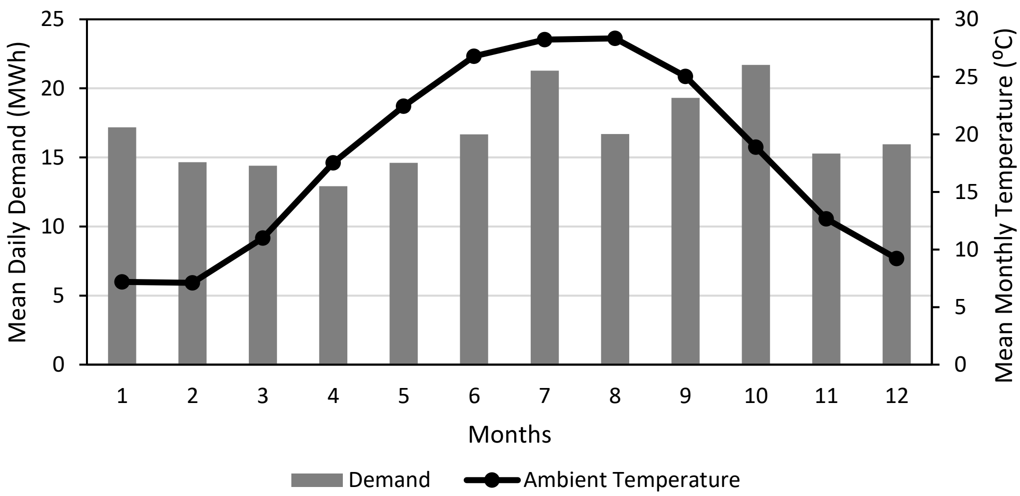

Figure 3.5. Average Daily Demand of METU NCC in in 2017, 2018 and 2019

The load profile was generated for 2017, 2018 and 2019, such that an average hourly load profile for 2017, 2018 and 2019 is shown in Figure 3.6. The load profile is shown as a box plot, averaged throughout each hour in every day of a month for the years 2017, 2018 and 2019, arranged according to seasons. Studying the load profile, opportunities to decrease HVAC loads to decrease peak loads or shift peak loads to times where loads are lower using energy produced by PV are found. From Figure 3.6, it can be seen that data from January and February are spread, meaning it contains outliers. This can be explained due to different academic calendars in the 3 years. Furthermore, a peak can be seen 6 pm and 8 pm owing to the heating loads in the campus in the campus and lack of PV production at these times.

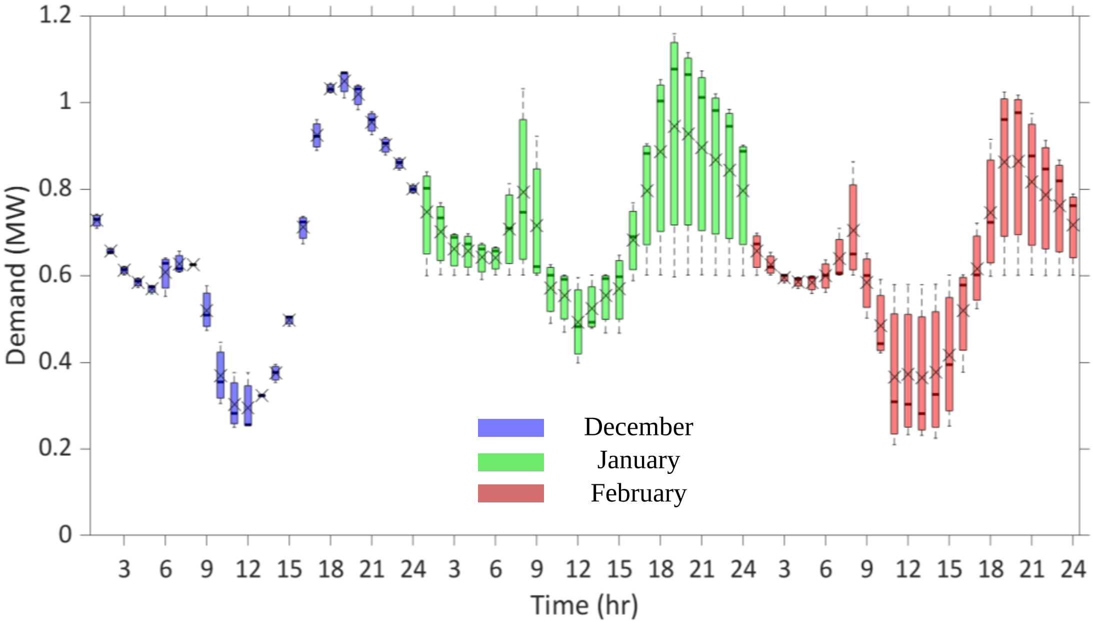

Figure 3.6. Box plot for the load profile of METU NCC using Kibtek '17, '18 & '19 data averaged at each hour throughout the days of a month for a year for Winter

Figure 3.7 shows the hourly average demand in Spring. This data contains outliers as it can be seen from the box plot. On further investigation, it was found that data for 2017 for these 3 months was incorrect since demand for each hour during these months was constant which is impossible since demand should should vary across the days. They were subsequently removed from the analysis.

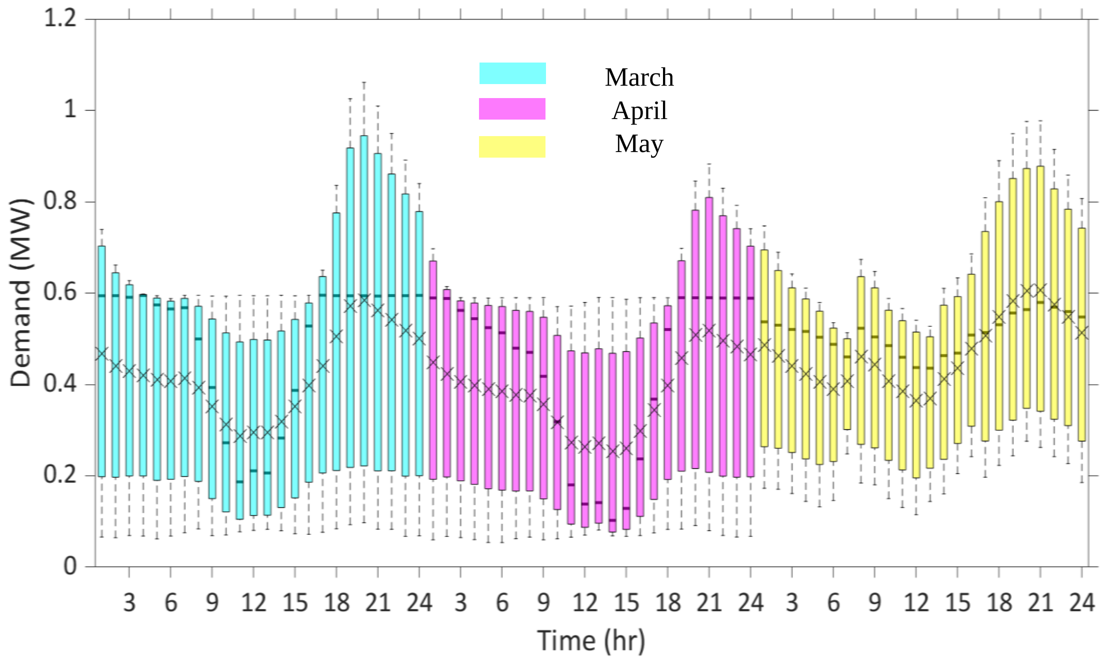

Figure 3.7. Box plot for the load profile of METU NCC using Kibtek '17, '18 & '19 data averaged at each hour throughout the days of a month for a year for Spring

Figure 3.8 shows how demand increases in the Summer months. This can be accounted to cooling loads in the campus, since air conditioners are running in dormitories. Furthermore, June and August do not have noticeable peaks, since students are not present in campus, reducing demand considerably, when compared to July which comprises of summer school. Notice that, between 8 am and 6 pm, demand is atleast 1 MW, even though, there is significant PV production. This can be accounted to the fact that cooling loads are at maximum during this time.

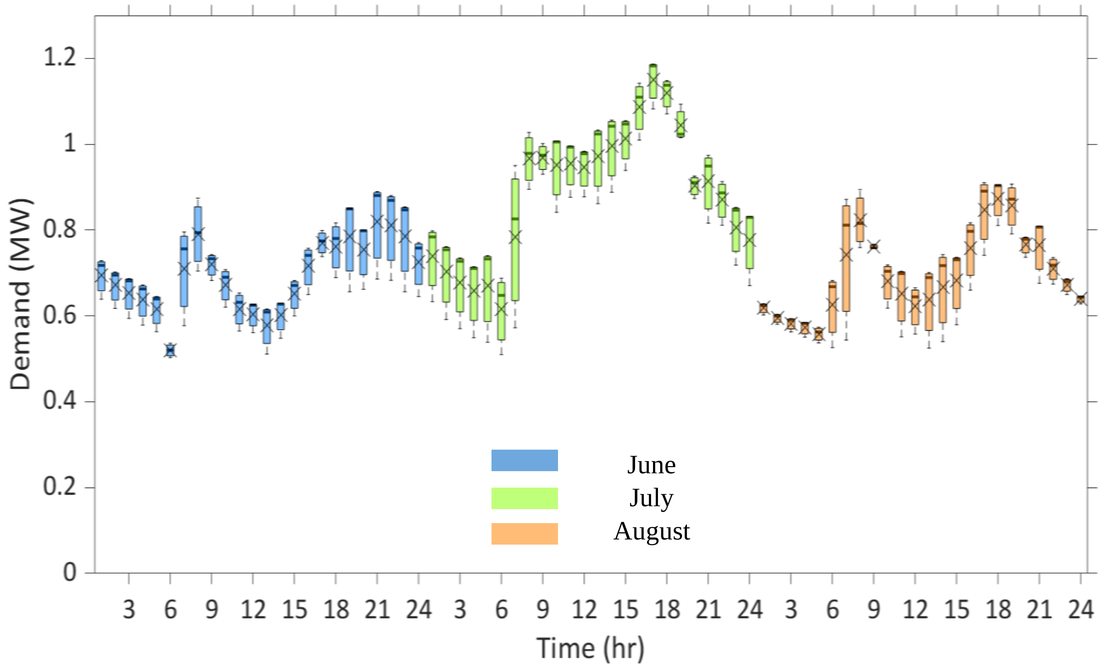

Figure 3.8. Box plot for the load profile of METU NCC using Kibtek ‘17, ‘18 & ‘19 data averaged at each hour throughout the days of a month for a year for Summer

The load profile in Autumn, shown in Figure 3.9, shows that September exhibits a bigger spread with outliers. Again, this can be accounted to the fact that academic calendars in 2017, 2018 and 2019 differ, with the academic semester starting in different periods. Notice the significant peak in October between 6 pm and 9 pm due to lack of PV production and cooling loads in the month. Similar to December, November also has a large trough followed by a high peak due to the heating loads in campus.

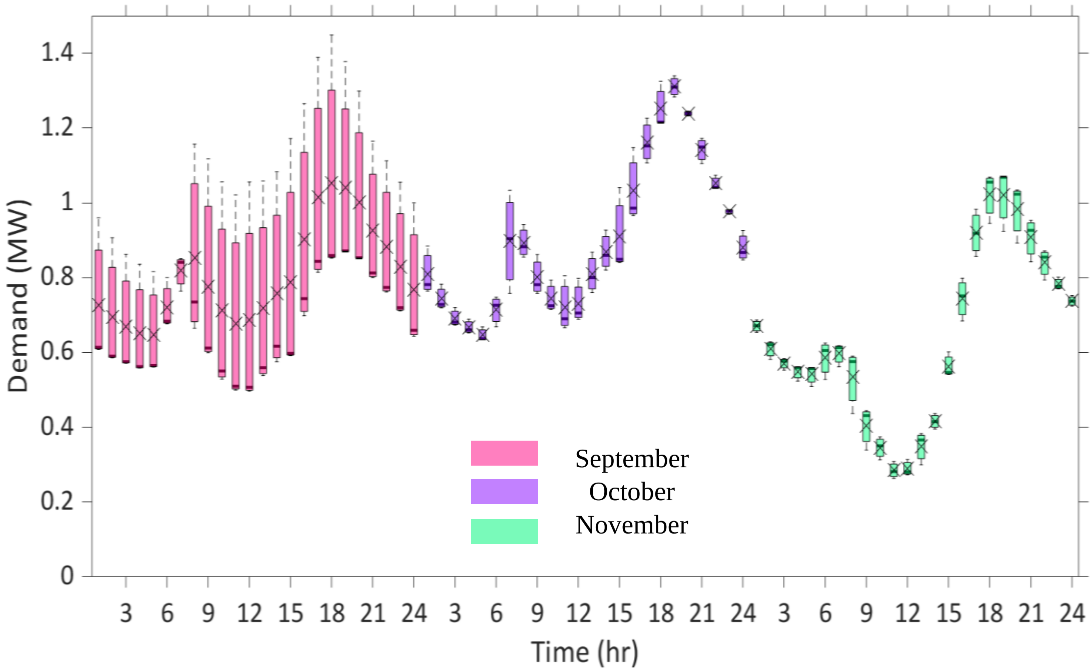

Figure 3.9. Box plot for the load profile of METU NCC using Kibtek ‘17, ‘18 & ‘19 data averaged at each hour throughout the days of a month for a year for Autumn

3.4.2 Building Scenario – Dormitory 1

In this study, it was decided to focus on one building in Campus, that is Dormitory 1. One of the reasons for this was that Dormitory 1 accounts for 18% of the energy consumption in METU NCC, which is the highest in campus as shown in Table 3.1.

Table 3.2. Percentage Energy Consumption in METU NCC by Areas

PLACES	Energy Consumption per year (%)
Dormitory 1	18
Dormitory 2	10
Dormitory 3	17
Dormitory EBİ	2
Prep School	4
Administration	6
Engineering Lab	1
R Building	4
S Building	3
GuestHouse	5
Sport Center	6
Health Center	6
IT Building	2
Residences	7
Culture Center	10

Dormitory 1 has 3 blocks, each with their own electrical central air conditioning unit that is Carrier 30RA series. This unit is only operational during the months of May, June, July, August, September and October. However, it is assumed that for the months of June and August, the system is not operational, since students are away on vacations and systems are not used. For heating purposes, a gas powered heater is used, therefore thermal adaptive comfort model will only be used for cooling purposes. Data for the Air Conditioning Unit is given in Table 3.2 [48][49].

Table 3.3. Dataset for the AC unit [48][49]

Nominal Cooling Capacity (kW)	157
Air Flow Rate (l/s)	11600
Cooler Air Temperature (ºC)	10
Energy Efficiency Ratio (EER)	9.6

Since architectural designs for Dormitory 1 are not available, the dimensions of the building is estimated using satellite images. The wall is assumed to be a concrete block and the thermal conductivities were also found to make create the thermal model. These dimensions and constants are shown in Table 3.3 [50] [51].

Table 3.4. Thermal model parameters [50] [51]

Length (m)	120
Width (m)	20
Height (m)	25
Roof Pitch (°)	30
Length and Height of Windows (m)	1
Wall thickness (m)	0.2
Window thickness (m)	0.01
Thermal Conductivity of Wall (W/m°C) [47]	0.19
Thermal Conductivity of Window (W/m°C) [47]	0.7

3.4.3 Demand Management Strategies

There were a number of strategies tested out during this study. In general, there were 5 different scenarios simulated. First, is the base case, that is the current scenario, when cooling is always on at a fixed setpoint temperature of 20°C. The second case is the setpoint control case, when the adaptive thermal comfort model adjusts the setpoint temperature at all times, such that energy is conserved regardless of the demand or PV production at that time. The third case is the schedule based case, which is defined between the times when there are instances of peak demand. The setpoint temperature is adjusted based on the adaptive thermal comfort model only during specific times during the day. The fourth case is the demand monitoring case, where the demand is monitored in real time and the setpoint is controlled based on how the demand changes. The fifth case is the forecasted demand case, where demand is forecasted on the basis of the previous days demand and accordingly, the setpoint is controlled when demand crosses a certain threshold. Finally, the sixth case is load shifting case, where setpoint control strategy will be selected on the basis of the best performing case between the 2nd, 3rd, 4th and 5th case. Figure 3.10 shows the overall Simulink Model with the thermal model of the building, adaptive thermal comfort model and the Case subsystems. Here "Go-to from" blocks are used to simplify the figure so that the inputs/outputs can be clearly seen. Therefore, for the Base Case, instead of [Case Letter], 'In' is used, for the 2nd case, 'ACTM' is used, and letters C, D and E are used for Cases 3, 4 and 5 respectively.

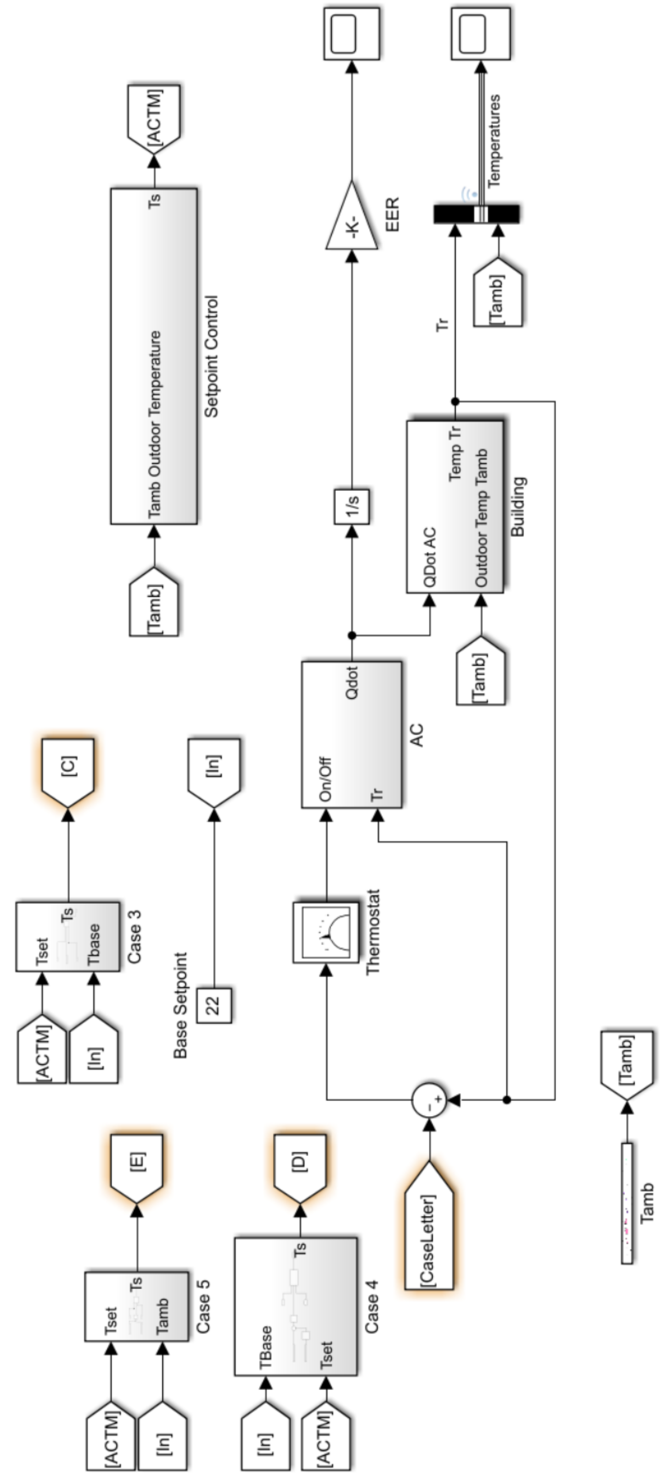

Figure 3.10. Overall Simulink Model

3.4.3.1 Case 1 – Base Case

In this case, the cooling remains on at all times, at a fixed setpoint temperature that is 20º. In Dormitory 1, currently, setpoint temperatures cannot be adjusted and stay at 20º. It assumed that the air conditioning is switched on at all times for this case.

3.4.3.2 Case 2 – Setpoint Control Case

In this case, adaptive thermal comfort model actively controls the setpoint temperature in the thermostat throughout the day based on the outdoor temperature. In the simulation, the outdoor temperature is taken from the TMY data corresponding to that hour. In a realistic scenario, this data will be taken from a sensor installed outside Dormitory 1 and fed into the system to calculate and calibrate the setpoint temperature.

3.4.3.3 Case 3 – Schedule Based Case

As seen from Figures 3.6-3.9, the demand peaks during certain times in the day due to the availability of energy from PV systems in METU NCC. Based on this, the adaptive thermal comfort model can be used during these times to reduce the demand and employ PV systems during midday to power excessive energy from cooling systems running on lower setpoint temperatures. The system decides based on the hour of the day to decide whether or not the adaptive control model should be utilized to adjust the setpoint temperature. The schedule is decided based on studying the peak demand periods based on the previously shown load profiles. As it can be seen from the load profiles, demand peaks between 06:00 and 10:00 followed by 15:00 and 20:00. Figure 3.11 shows the flowchart of Case 3 system controller.

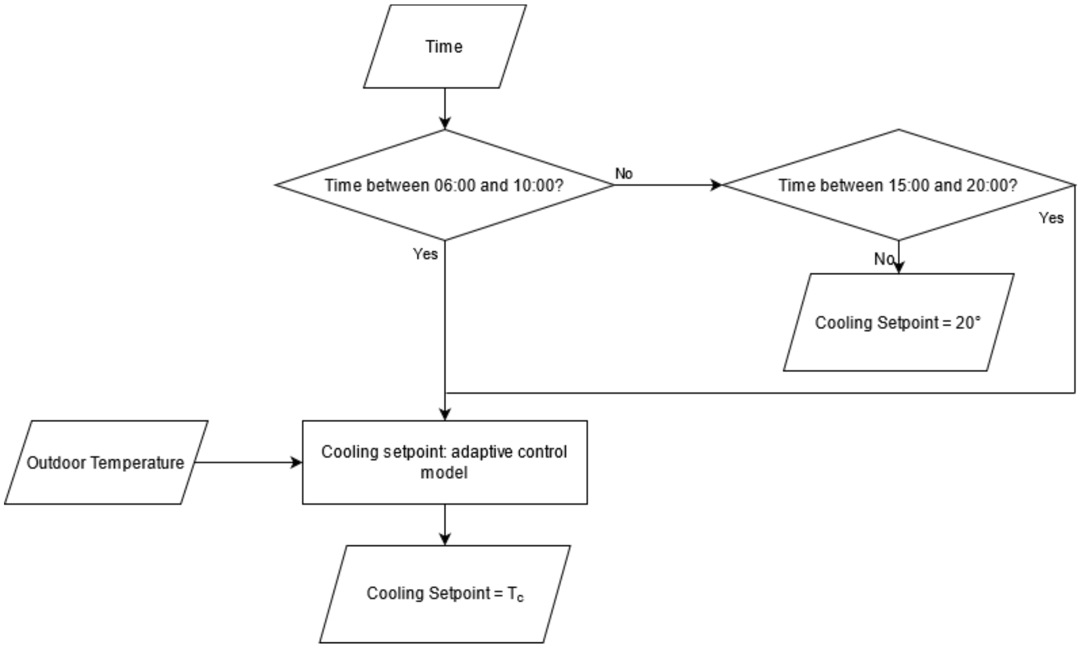

Figure 3.11. Algorithm Flowchart for Case 3

Figure 3.12 shows the algorithm shown in the figure above on Simulink. Here the Schedule block is imported from Excel where the times between 06:00-10:00 and 15:00-20:00 are set as 1 while the rest are set as 0. Here a switch is used to switch between the adaptive thermal comfort model setpoints and base setpoints, depending on what time of day it is.

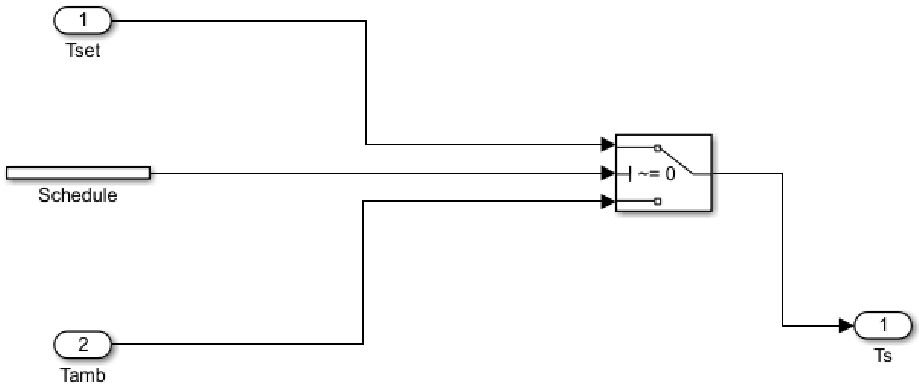

Figure 3.12. Case 3 implementation on Simulink

3.4.3.4 Case 4 – Demand Monitoring Case

Energy from PV systems installed in METU NCC create an imbalance between demand met by the grid due to which a large rise is seen in peaks, as seen in Figure 3.6-3.9. In this case, demand is actively monitored, such that if the rate of change of demand is above a certain threshold, such that incoming peak demands can be detected, setpoint temperatures are adjusted based on the outdoor temperatures to keep thermal comfort while also conserving energy. In this case, demand at time (*t*) will be compared with demand at time (*t-n*), and will be minimized. In case of the simulation, since only discrete data is available, a threshold value of 0.15 is set, based on studying the load profile. Figure 3.13 shows the flowchart of Case 4 algorithm. Figure 3.14 shows the algorithm shown above in the MATLAB Simulink environment where the threshold is set as 0.15. Using a unit delay, a scenario with previous and current demand is simulated as shown in Figure 3.14 and a switch is used to decide whether to use the base setpoint or setpoint from the adaptive thermal comfort model.

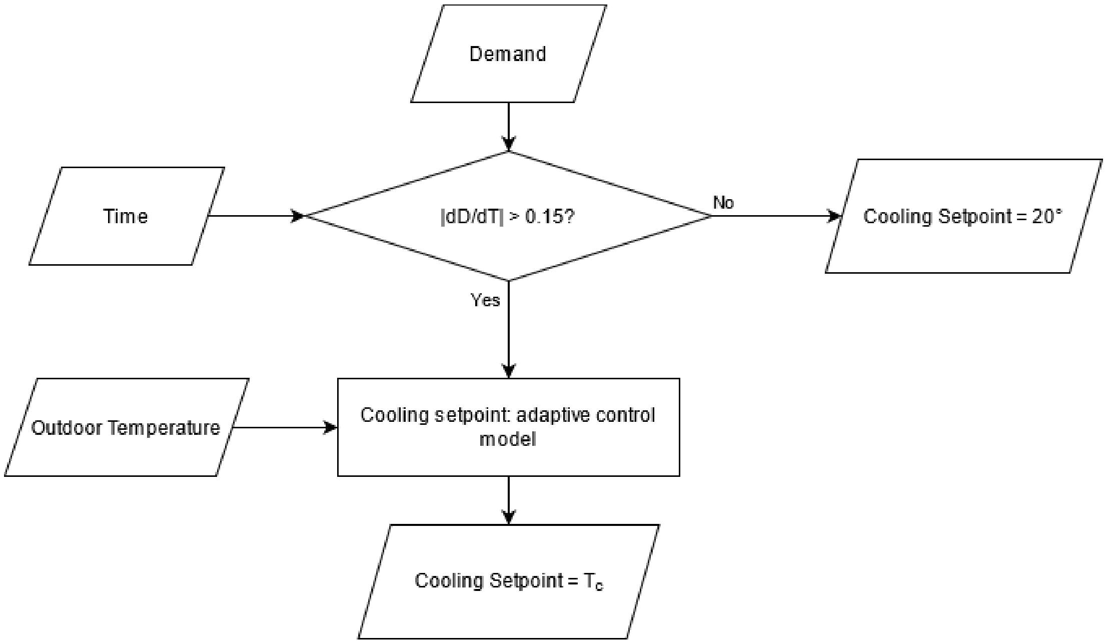

Figure 3.13. Algorithm Flowchart for Case 4

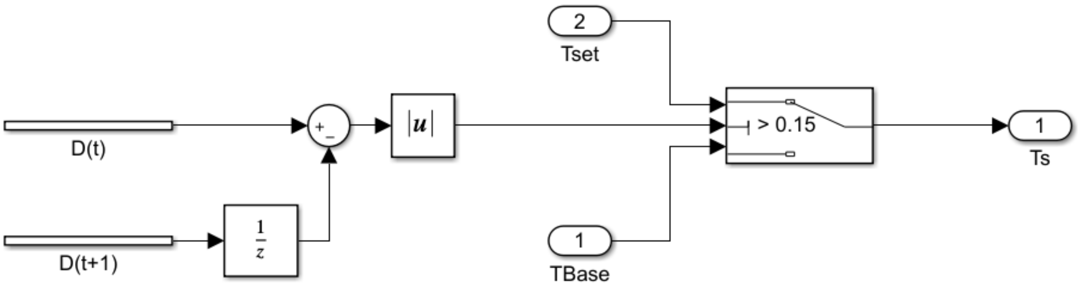

Figure 3.14. Case 4 implementation on Simulink

3.4.3.5 Case 5 – Forecasted Demand Case

In this case, the hourly demand will be forecasted based on linear regression method and based on this, calculate an aggregate demand. Based on this parameter, whenever the demand rises above the aggregate demand, the adaptive thermal comfort model will adjust the setpoint temperature to reduce the demand, incase the setpoint temperature is more than what is required. If a long term dataset was available, a better estimate could be calculated, through neural network techniques, however that is out of the scope of this study. Figure 3.16 shows flowchart of Case 5 algorithm. Figure

3.17 shows the the algorithm above in the Simulink environment on MATLAB. Here, D_{agg} is imported from MS Excel after a linear regression analysis while *D(t)* is the assumed to be the actual demand. Meanwhile, a switch is used to decide whether to use the adaptive thermal comfort model or the base setpoint depending on the demand received.

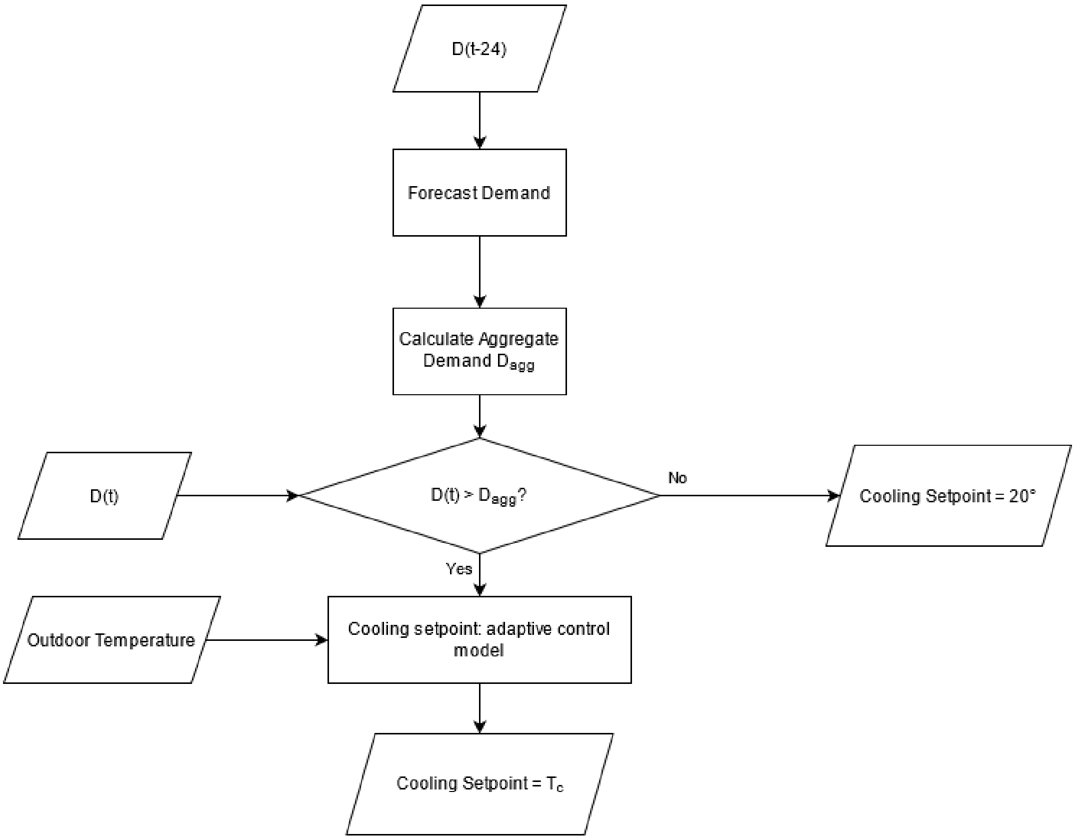

Figure 3.16. Algorithm Flowchart for Case 5

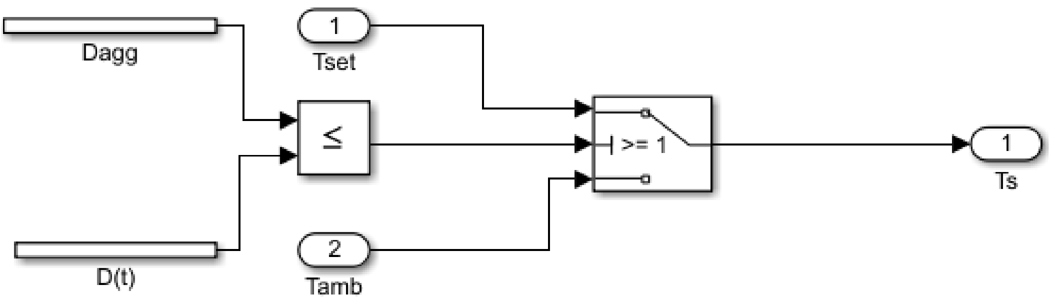

Figure 3.17. Case 5 implementation on Simulink

3.4.3.6 Case 6 – Load Shifting Case

Net Metering is an energy policy which allows consumers to export some or all of the energy they produce to the grid such that they may use this energy at any time instead of the time of generation [52]. Through this policy, the need of battery installation, which prove to be expensive, can be mitigated [52]. METU NCC can employ the net metering scheme to reduce peaks, especially peaks which are present in the Winter months, since heating systems in campus are gas powered and setpoint control cannot affect the electricity consumption in this case.

In this case, the objective is to minimize the demand peaks and use the energy produced by solar PV to shift loads where the grid acts as a battery. Through this, the current PV system can be utilized as a better demand management tool without increasing the capacity of the current PV Plant and adding batteries, since currently, PV system does not produce excess energy to be saved in batteries. As mentioned in Section 3.4.1, demand met by the grid during the day is low due to the energy produced by the PV plant, however, as solar irradiation decreases as night approaches, there is a large imbalance between the PV energy production and demand met by grid, creating a demand peak which leads to grid instability. Using the grid as a battery provides the opportunity to shift nighttime peak loads to midday, when the load on the grid is much lower. In real time, the algorithm compares the total electricity demand, $D(t)$, with previous demand met by the grid and PV, $D_s(t-1)$, such that if the total electricity demand is more, the energy from PV, $I(t)$, is dispatched such that the demand met by the grid is equal to the previous demand, while the rest is sent to the grid, G. If the energy produced from PV at that time is not enough to equal the previous demand, the energy sent to the grid is also dispatched to decrease the load. On a net basis, there is no change in the cost of energy while the peaks in the demand are reduced, which reduces the imbalances created by PV energy production, improving the grid stability. Figure 3.18 shows the algorithm for Case 6.

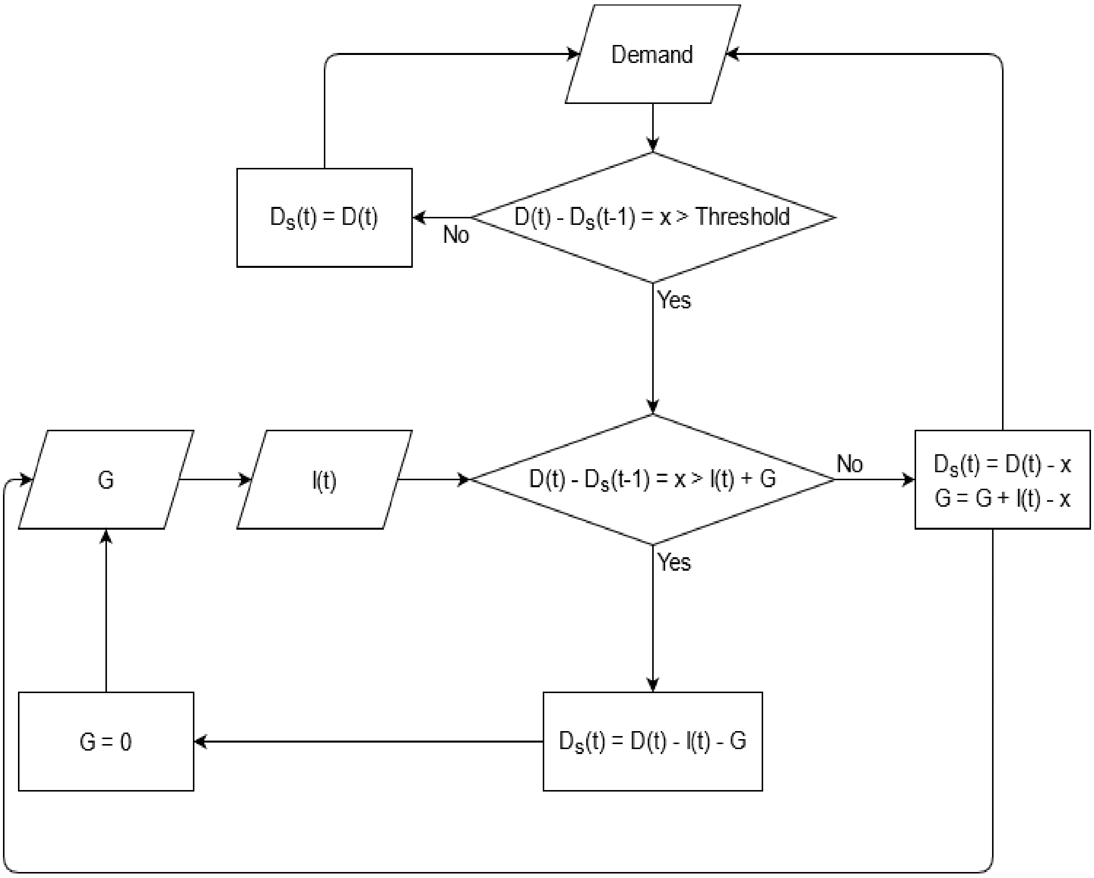

Figure 3.18. Algorithm Flowchart for Case 6

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Estimation of Energy Production of METU NCC PV Plant

The METU NCC PV Plant was installed on the campus to partially meet the electrical demand of the campus [46]. Since the renewable resources change over seasons, it is important to study the changes of the production of the PV plant over time. Figures 4.1-4.4, shows the estimated seasonal energy produced from PV using TMY data of Güzelyurt statistically obtained at each hour in each month for a year. It can be seen in Figure 4.1 that months in the winter have a narrower dome comparatively, due to shorter days. Furthermore, the electricity generation peaks at 0.5 MW, producing energy between 07:00 and 17:00. Referring to Figure 3.6, it is observed why the demand decreases after 09:00 and increases after 15:00 since the PV production is low during these times.

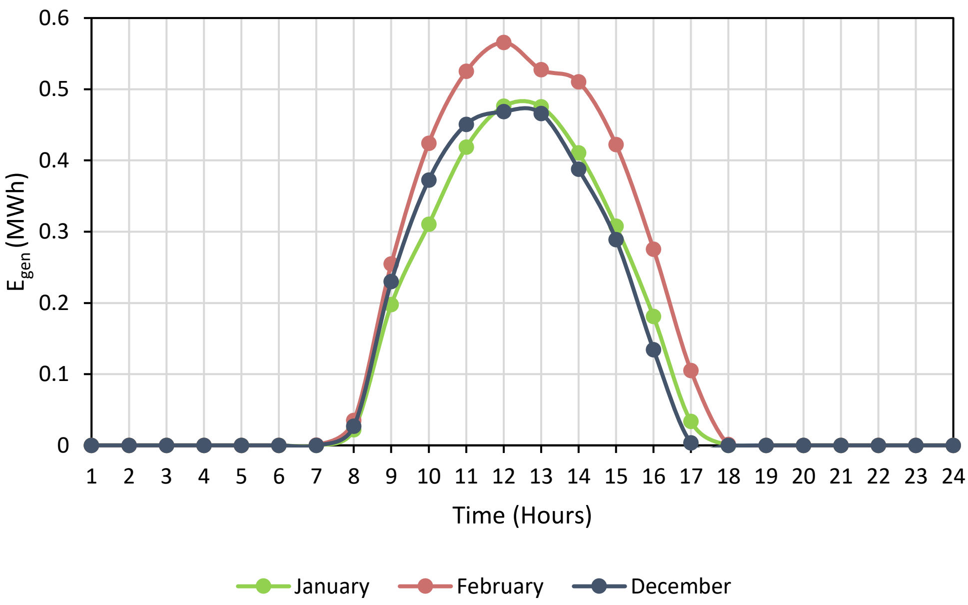

Figure 4.1. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Winter

Figure 4.2 shows the estimated PV electricity generation in Spring. As Spring approaches, the days get longer, hence PV produces energy between 06:00 and 18:00. Furthermore, the energy generation from the plant increases to 0.65 MWh.

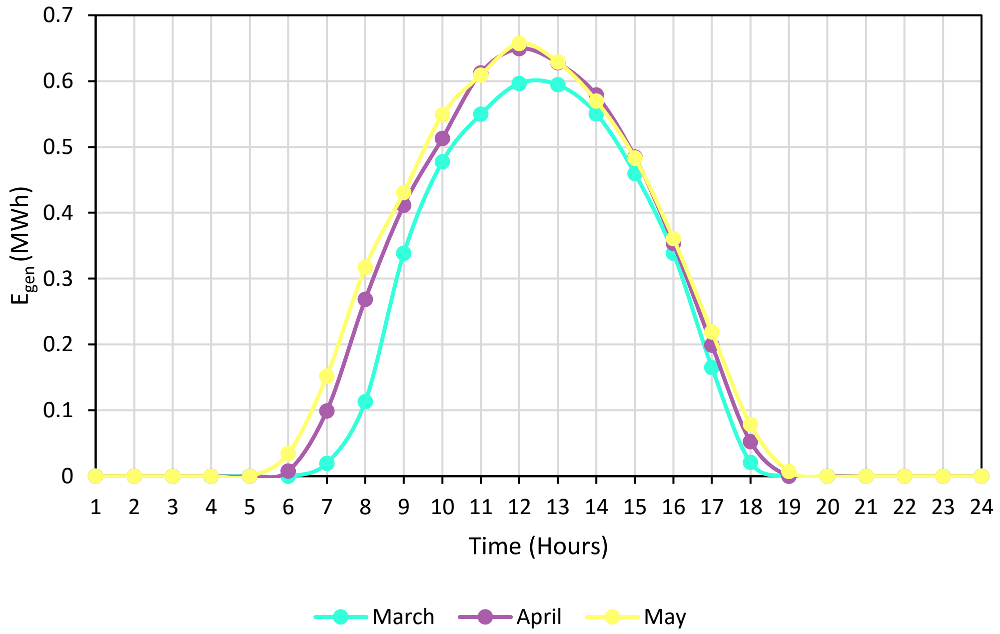

Figure 4.2. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Spring

Figure 4.3 shows that in summer days are the longest and PV produces electricity between 06:00 and 19:00 with energy generation peaking at 0.7 MWh. Referring to Figure 3.8 it can be seen that without PV energy production, the peak demand would reach 1.4 MWh for the months of June and August. Meanwhile, for the month of July the peak demand would rise to almost 1.7 MWh.

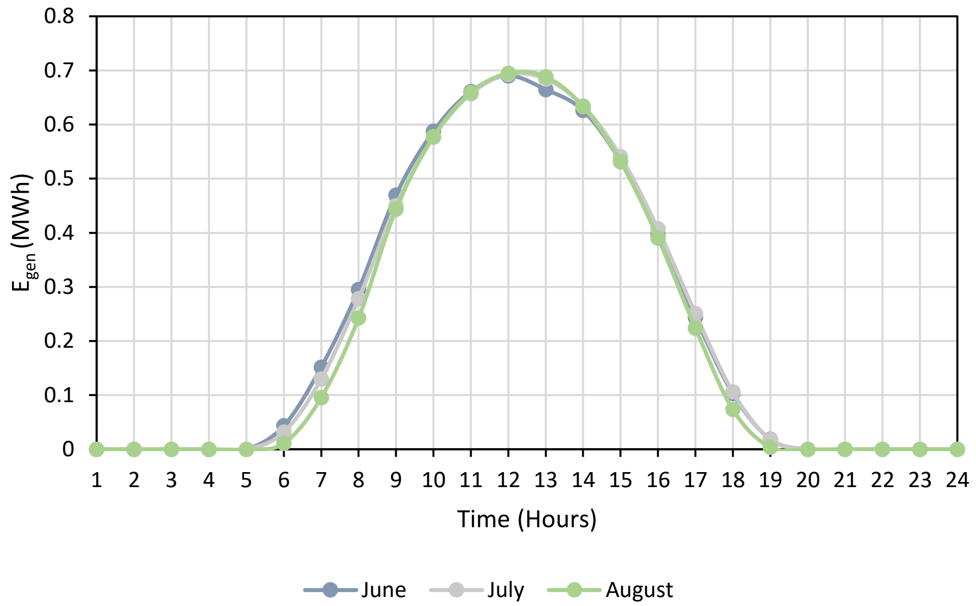

Figure 4.3. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Summer

Figure 4.4 shows the estimated energy production from PV in Autumn. It can be seen that the peak production reduces from 0.7 MWh in September to 0.6 MWh in October as the solar irradiation decreases at solar noon. As the days get smaller in October and November, PV energy is only produced from 07:00 to 17:00. This explains why the demand rises after 15:00 for the months of October and November when referring to Figure 3.9.

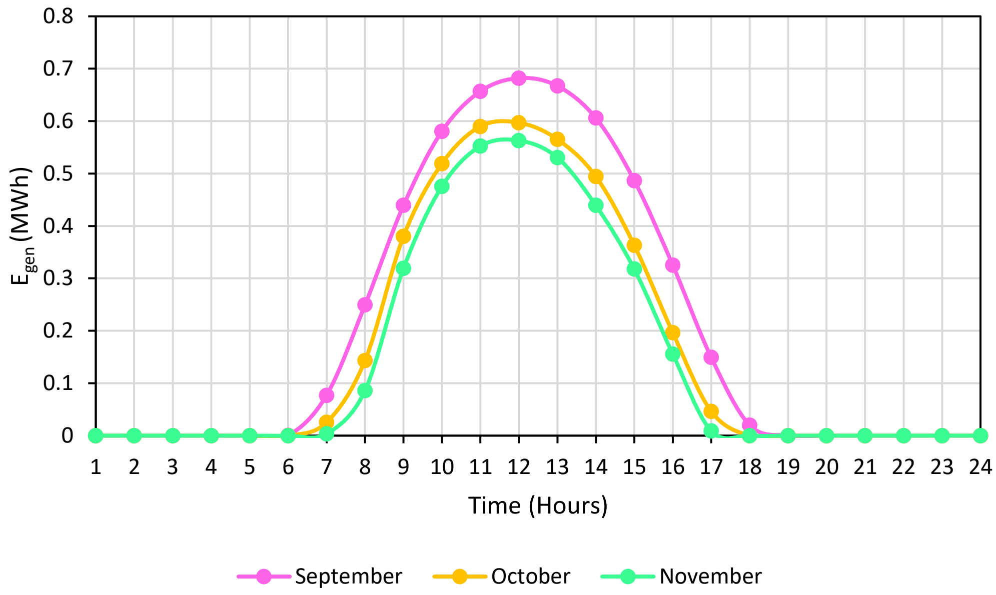

Figure 4.4. PV Production estimation using TMY Data of Güzelyurt (2004-2018) averaged at each hour throughout the days of a month for a year for Autumn

4.2 Results of Demand Management Strategies

4.2.1 Case 1: Base Case

The results for the base case show the behavior of the estimated demand from the HVAC systems based on the current scenario in Dormitory 1. Figure 4.5 shows the estimated demand from the HVAC systems on 15th July, a typically hot day with cooling on, with the outdoor temperature for Case 1. Since the setpoint temperature is set at 20°C with a ΔT of ±1.5°C, the indoor temperature fluctuates across this temperature; however, from the period between 7 am and 8 pm, HVAC systems are being used constantly. This can be corelated with the fact that temperature outdoors starts rising over 25°C, therefore, the building gains heat from outdoors, since there is a higher temperature gradient causing the system to run continuously to maintain a temperature of 20°C. Another important observation also explains why demand is so excessive in July is due to the fact that HVAC systems seem to be running consistently during the day, causing the the load curve to be over 1.2 MWh excluding the demand met by PV as shown in Figure 4.1. Furthermore, during night when the temperature falls, a higher setpoint can be used to conserve energy, which presents an opportunity to decrease the loads, especially since load peaks are generally visible between 15:00 and 22:00.

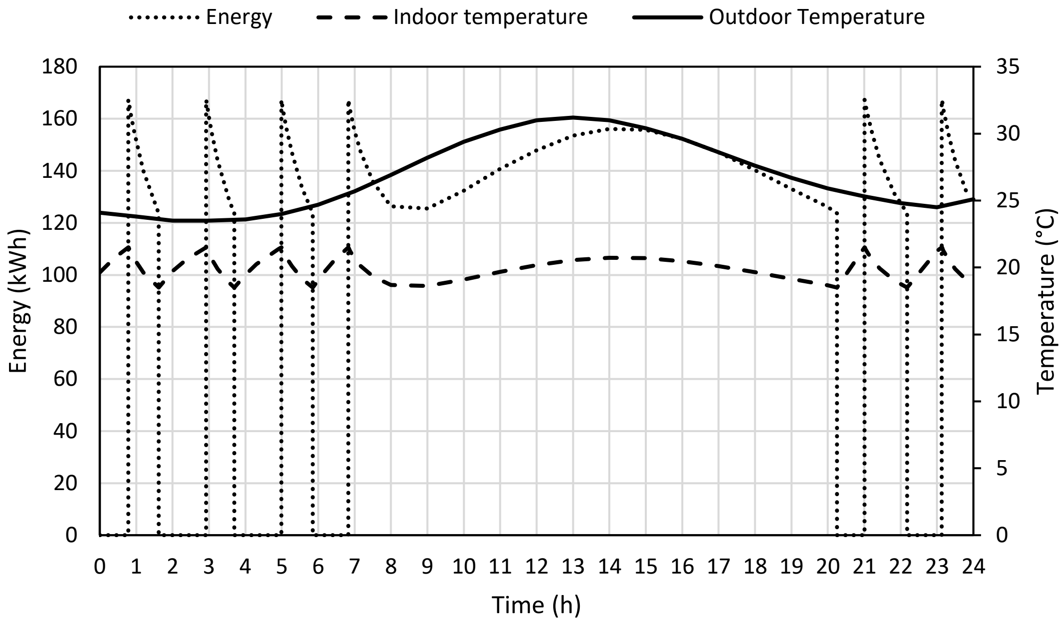

Figure 4.5. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 1

4.2.2 Case 2 – Setpoint Control Case

Case 2 controls the setpoint at all times, regardless of the demand at that time. It can be seen that energy is only consumed during the day. Figure 4.6 shows the estimated demand from the HVAC systems on 15th July, a typically hot day with cooling on, with the outdoor temperature for Case 2. This plays a significant improvement in reducing the demand peaks formed between 19:00 and 22:00. Furthermore, the system does not work in between intervals, from 19:00 to 08:00. Therefore, the overall consumption reduces. During this time, instead of indoor temperature fluctuating around 20°C, temperature fluctuates between 22.5°C and 25.5°C, which keeps the temperature comfortable on the basis of BS EN15251, while also conserving energy.

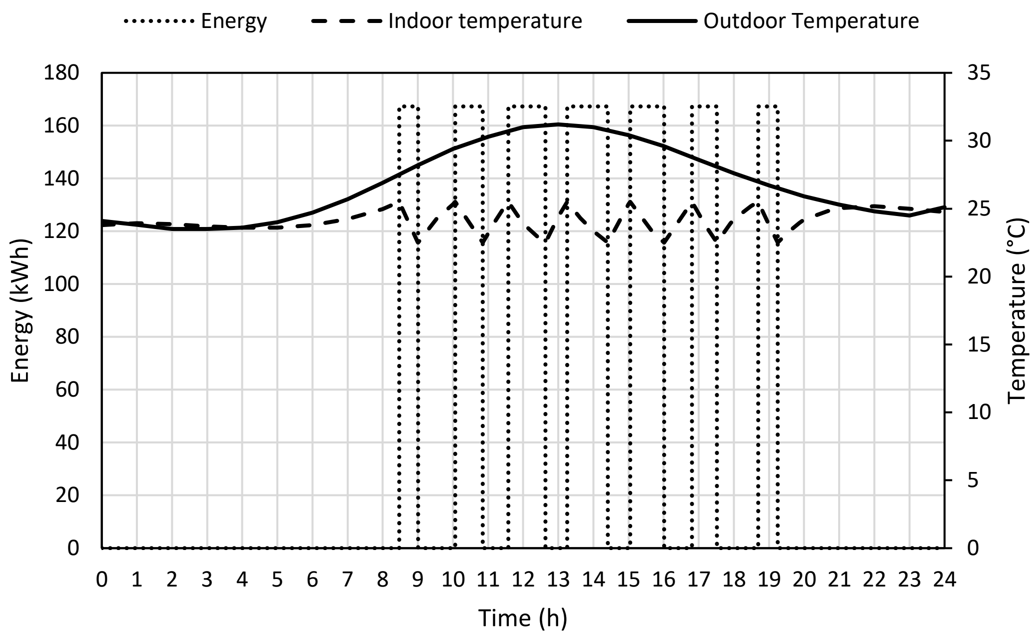

Figure 4.6. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 2

On a macroscale, when considering the monthly energy consumption for cooling, July has the highest energy consumed for the base case which is 88.11 MWh. This can be explained due to the higher mean outdoor temperature of 28.23°C, which translates to the need for cooling systems for longer periods of time. Table 4.1 shows these results. On the other hand, May and October have considerably lower energy consumption of 32.55 MWh and 26.76 MWh, since the mean monthly temperature is lower compared to the other two months. As seen from Figure 4.2, it was expected that the energy consumption would be lower than the base case, and it can be seen that especially for the months of May and October, the onsets of summer and winter respectively, the energy consumption is 73% and 67% lower compared to the base case. This can be accounted to the fact that these two months have lower night time temperatures and this can be used to conserve energy. On the other hand, in July, there is a 47% reduction in energy consumption, and this change is lower compared to the other months owing to the higher temperatures in the month.

Table 4.1. Total Energy Consumption from cooling systems for Case 2, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 2 for the months of May, July, September and October

Month	May	July	Sept.	Oct.
Energy Consumption (MWh)	8.48	45.96	27.50	8.84
Temperature (°C)	22.47	28.23	25.05	18.89
Base Energy Consumption (MWh)	32.55	88.11	57.57	26.76
Change in Energy Consumption (%)	-73.93	-47.84	-52.24	-66.96
Economic Savings ($)	4211.03	7375.77	5262.89	3135.34

Based on the previous findings, one can expect lower demand when considering the overall demand. Figures 4.7-4.10 show the average hourly demand across the months of May, July, September and October for Case 2. As seen in Figures 4.3-4.6, Case 2 exhibits a lower demand when compared to Case 1 in general. When considering the month of May, periods between 23:00-07:00 show no change in demand due to lower nighttime temperatures, meaning cooling systems do not use much energy at these times, however, from 08:00 to 20:00, the demand reduces with a magnitude between 0.05 MWh and 0.1 MWh. Although not flattening the peaks, the efficiency during this period improves. For July, due to higher outdoor temperatures even at night, the demand profile completely offets by a minimum of 0.02 MWh, while significantly decreasing the peak from 07:00 to 08:00 by 0.11 MWh. Although, this provides a more efficient cooling system, the rate of change of demand remains the same. A similar trend is seen when observing the demand profile of the month of September, albeit, a smaller offset of 0.05 MWh. Similar to May, October exhibits similar demand profile between 20:00-09:00, however decreases the peak demand by 1.55%. Notice that during this month, the mean outdoor temperature falls to 18.89°C, meaning that at nighttime there are lower temperature, which is why not much difference is seen in the load profile after 20:00.

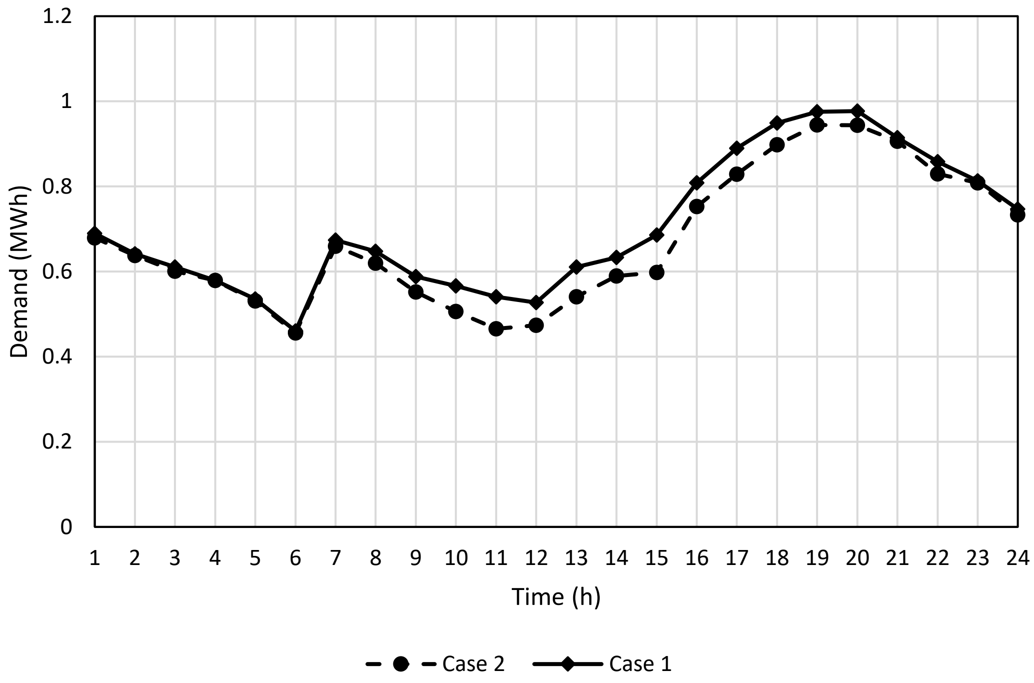

Figure 4.7. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 2

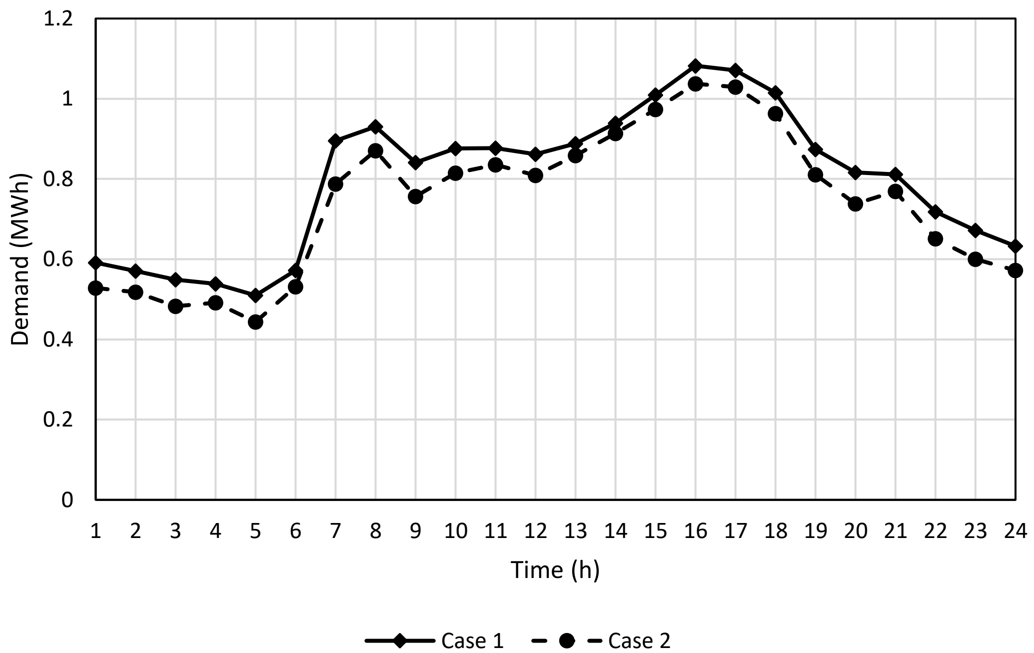

Figure 4.8. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 2

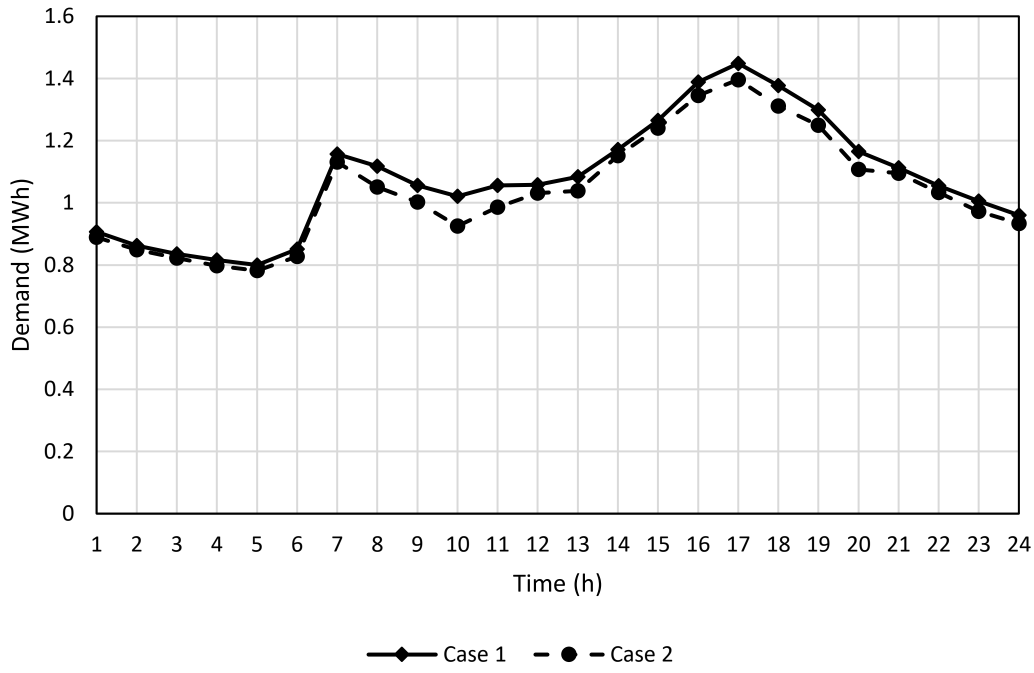

Figure 4.9. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 2

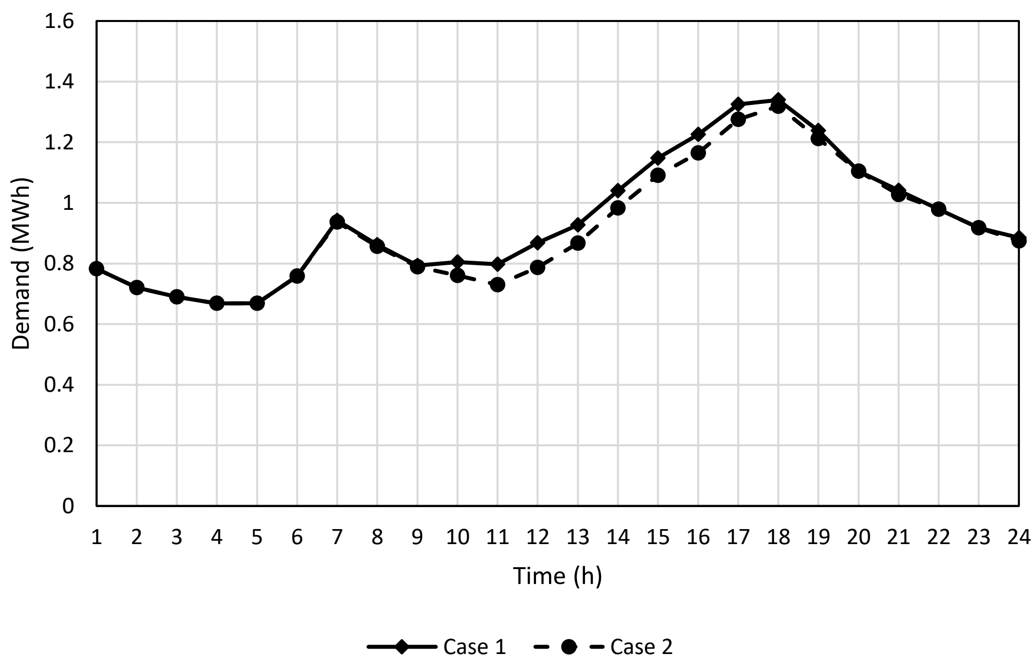

Figure 4.10. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 2

4.2.3 Case 3 - Schedule Based Case

Case 3 considers the schedule to apply BS EN15251, such that setpoint is controlled between 06:00-10:00 and 15:00-20:00 since these periods exhibit the highest demand. Figure 4.11 shows the estimated demand from the HVAC systems on 15th July , a typically hot day with cooling on, with the outdoor temperature for Case 3. One of the biggest differences, when compared to Case 1 is that the high demand between periods 06:00-10:00 and 15:00-20:00 is reduced. However after this time, since the indoor temperatures are high compared to the base setpoint, the energy consumed is more, as seen in the base case. In this case, the setpoint is controlled only for situations when the demand is usually peaking, and it can be visible from the indoor temperature that during these periods, the temperature rises to 25°C and during the periods when demand is generally low, the setpoint goes back to 20°C such that HVAC systems run at normal usage.

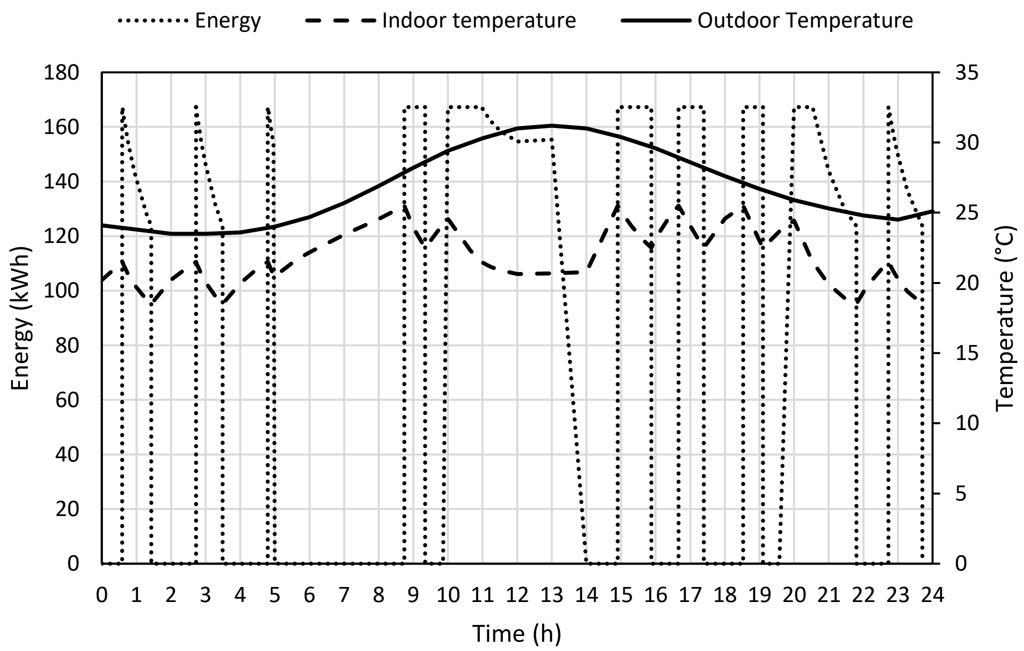

Figure 4.11. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 3

For Case 3, as seen from the previous trends, July has the highest energy consumed which is 67.68 MWh for cooling. Table 4.2 shows these results. On the other hand, May and October have considerably lower energy consumption of 20.96 MWh and 41.37 MWh, since the mean monthly temperature is lower compared to the other two months. When compared to the base case, May and October there is a reduction of 35.59 % and 36.44% in energy consumption, respectively. The reduction is attributed to the periods between the schedule decided previously. Meanwhile, in July and September which have higher outdoor temperatures, have comparatively lower change in energy consumption of 23.19% and 28.14%, respectively when compared to the Base Case.

Table 4.2. Total Energy Consumption from cooling systems for Case 3, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 3 for the months of May, July, September and October

Month	May	July	Sept.	Oct.
Energy Consumption (MWh)	20.96	67.68	41.37	17.01
Temperature (°C)	22.47	28.23	25.05	18.89
Base Energy Consumption (MWh)	32.55	88.11	57.57	26.76
Change in Energy Consumption (%)	-35.59	-23.19	-28.14	-36.44
Economic Savings ($)	2027.34	3575.61	2835.37	1706.16

On the basis of the above findings, Case 3 is expected to lower the demand in general. Figures 4.12-4.15 show the average hourly demand across the months of May, July, September and October for Case 3. Between 06:00-10:00 and 15:00-20:00, it can be seen that the demand decreases, however, at the end of the timed constraints, that is, 10:00 and 20:00, the demand rises. Especially at 8 pm, the demand rises by 0.1 MWh, 0.05 MWh, 0.1 MWh and 0.07 MWh for May, July, September and October respectively. The rise in demand at these times can be accounted to internal gains. Moreover, due to the scheduling, Case 3 causes peaks to be created at the onset of the schedules, which may create grid instability.

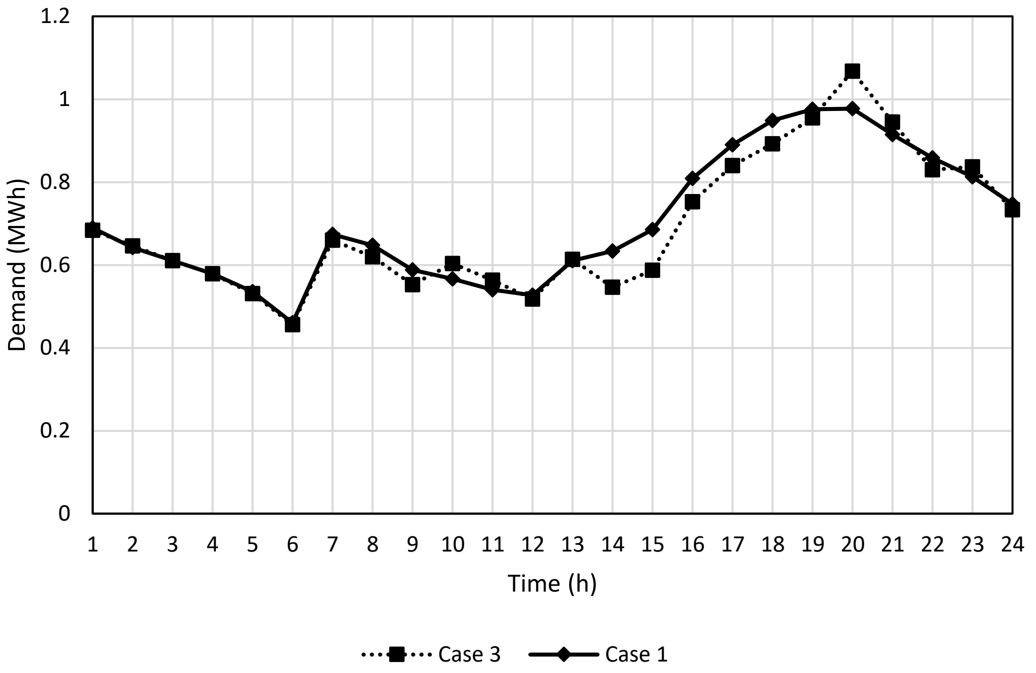

Figure 4.12. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 3

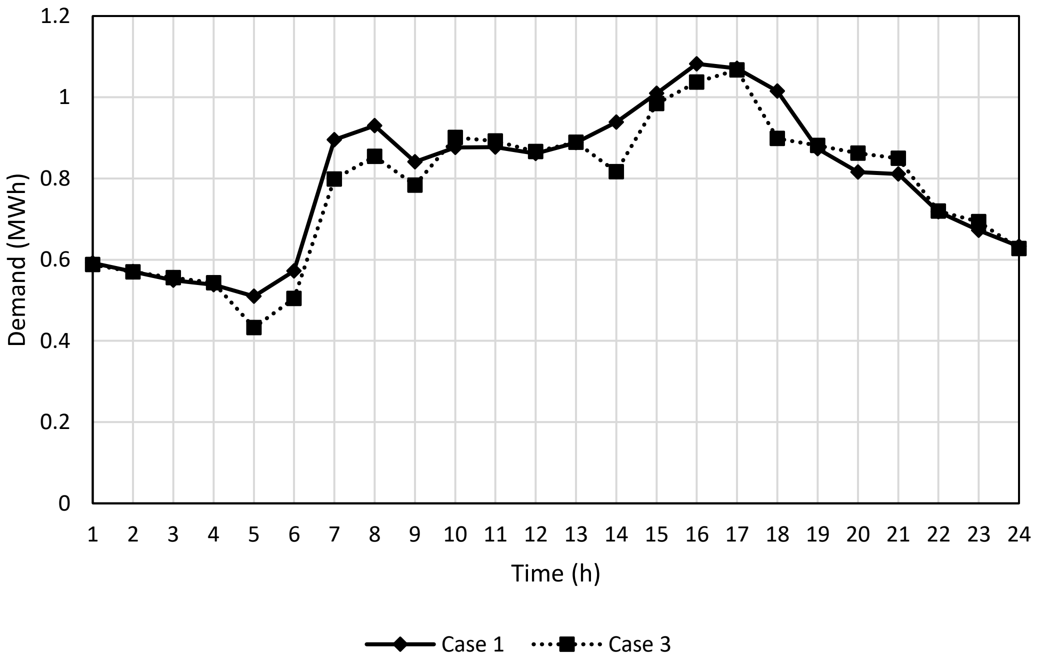

Figure 4.13. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 3

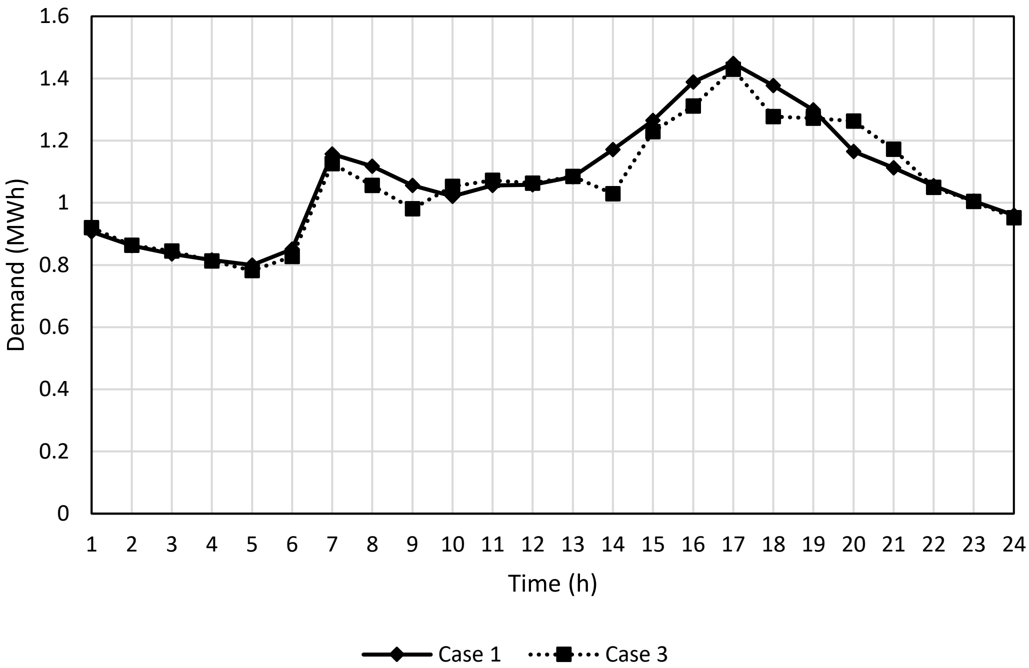

Figure 4.14. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 3

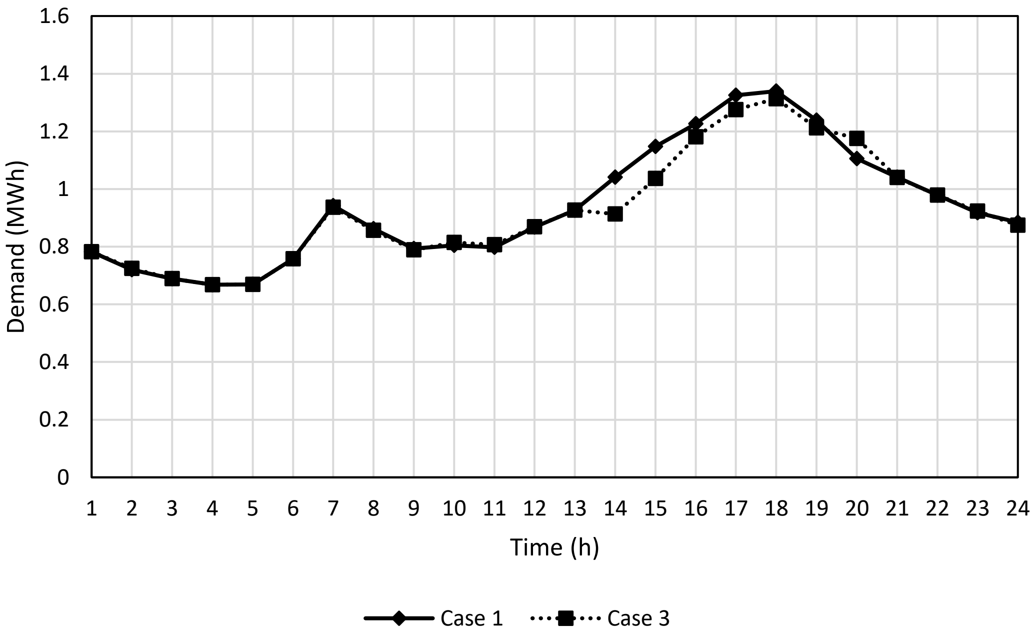

Figure 4.15. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 3

4.2.4 Case 4 – Demand Monitoring Case

Case 4 studies monitors demand such that when the demand starts to rise, setpoint is controlled to reduce the demand. Figure 4.16 shows the estimated demand from the HVAC systems on 15th July , a typically hot day with cooling on, with the outdoor temperature for Case 4. It can be seen when observing the energy between 21:00-06:00 that the demand does not rise and remains constant across these hours. Therefore, the base demand is unaffected, only the peak demand is affected. However, the issues with this case rely when the peak demand remains constant for a longer period of time. As seen between 12:00-17:00, when the peak demand stays constant, the system is unable to detect the peak, and the setpoint is not adjusted such that energy is conserved. As far as the indoor temperature is considered, it remains at a comfortable level when compared to the outdoor temperature.

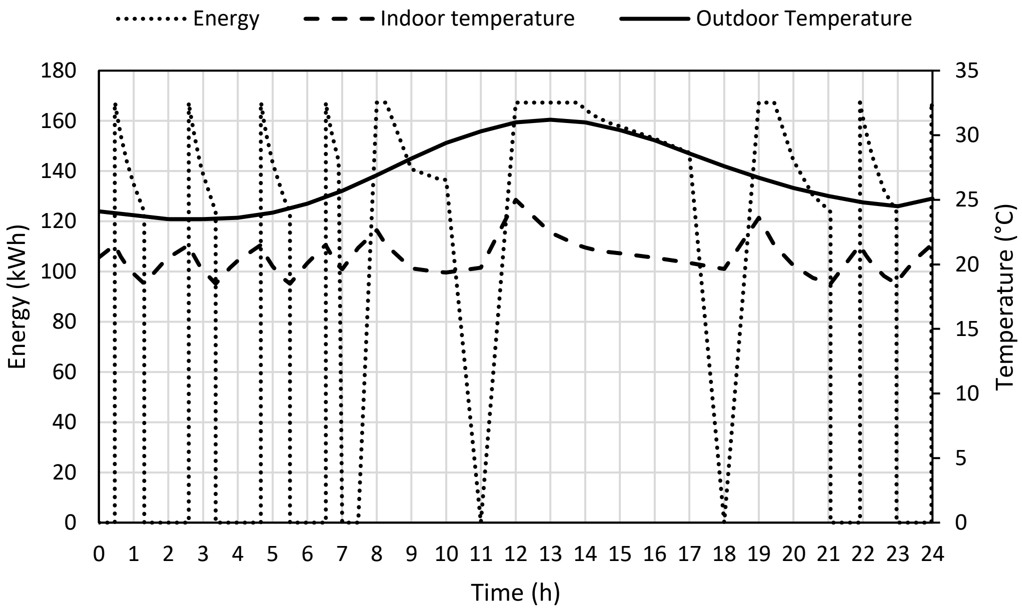

Figure 4.16. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 4

Case 4 improves on the Base Case however, does not improve the system significantly. It can be observed that the base energy consumption for cooling and energy consumption for cooling from Case 4 are almost similar. Since the demand varies daily, thresholding detects when the peak is approached, however prolonged peaks cannot be detected, causing Case 4 to behave similar to the Base Case. Table 4.3 shows these results. It can be seen that for the months of May and July, the change in consumption is about -7% since these months generally have prolonged peaks of high demand due to the high temperatures during the day. Case 4 has a better performance in September and October, with energy saved of 11% and 13.5% respectively, owing to their sharper peaks due to lower PV production.

Table 4.3. Total Energy Consumption from cooling systems for Case 4, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 4 for the months of May, July, September and October

Month	May	July	Sept.	Oct.
Energy Consumption (MWh)	30.09	81.75	51.27	23.15
Temperature (°C)	22.47	28.23	25.05	18.89
Base Energy Consumption (MWh)	32.55	88.11	57.57	26.76
Change in Energy Consumption (%)	-7.54	-7.21	-10.94	-13.49
Economic Savings ($)	429.47	1111.84	1101.70	631.55

As mentioned previously, Case 4 in general does not improve performance significantly. This is evident from Figures 4.17-4.20 showing the average hourly demand for May, July, September and October. It can be observed that the hourly demand for each month remains very similar to the base demand, and this can be accounted due to the fact that in general, sharp peaks between hours are seldom available, therefore, the system does not perform as intended. Furthermore, it also proves that setpoint control does not affect systems if applied for a short period of time. Rather it is important to run setpoint control for a considerable amount of time to see a significant effect.

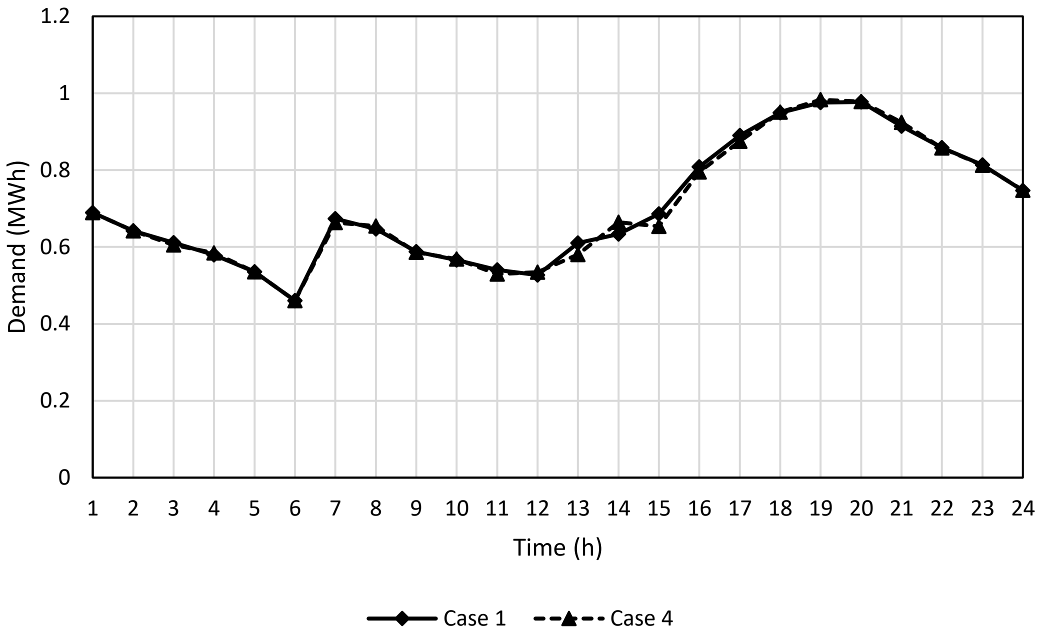

Figure 4.17. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 4

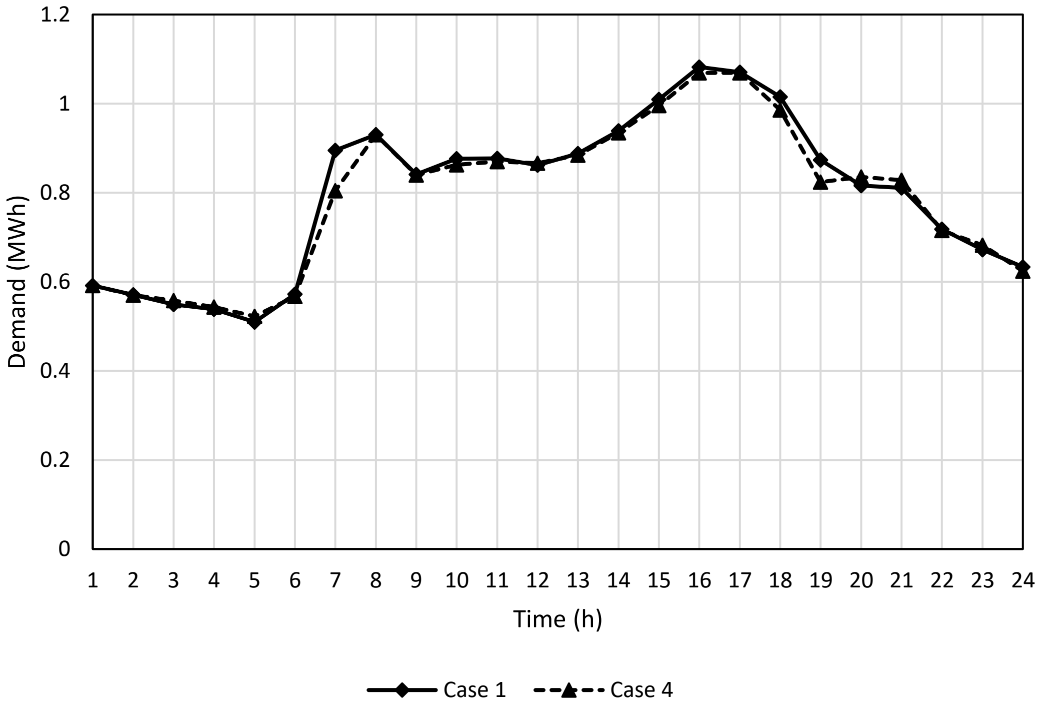

Figure 4.18. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 4

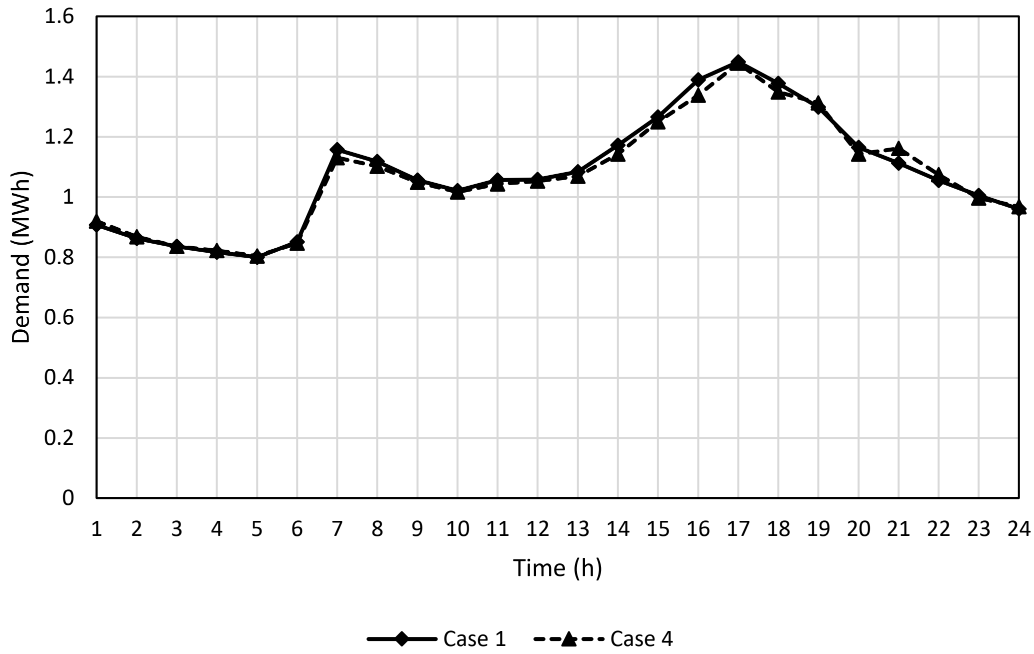

Figure 4.19. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 4

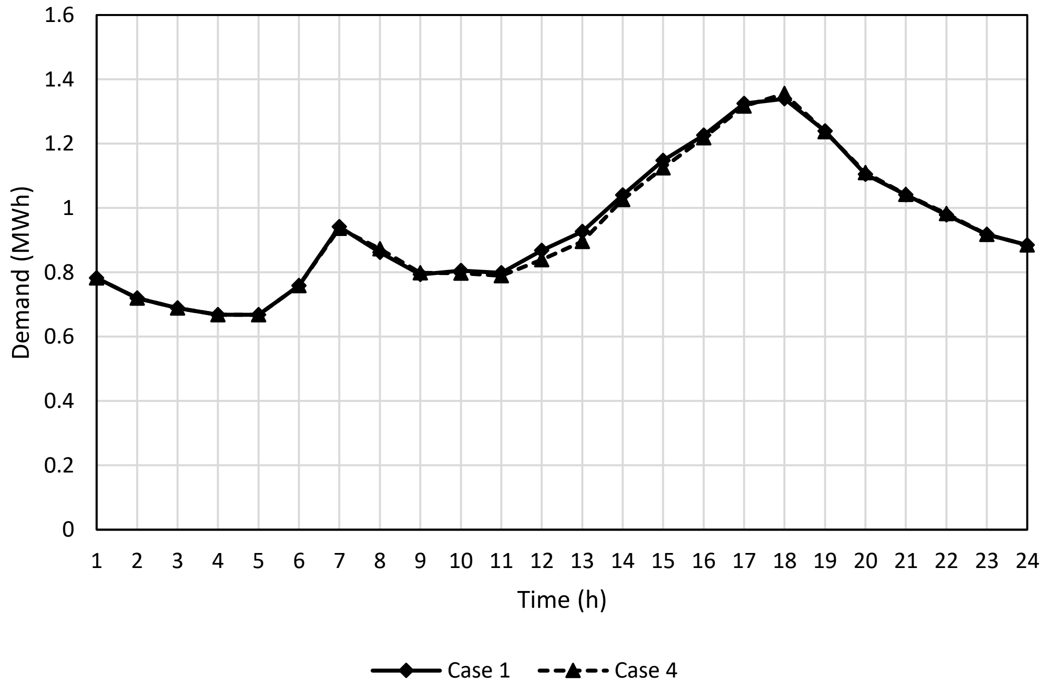

Figure 4.20. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 4

4.2.5 Case 5 – Forecasted Demand Case

Case 5 forecasts the demand, such that above the daily aggregate demand, the setpoint is controlled to reduced energy consumed from HVAC. Figure 4.21 shows the estimated demand from the HVAC systems on 15th July, a typically hot day with cooling on, with the outdoor temperature for Case 5. It can be seen in this case that during hours with base demand, HVAC systems work at base conditions, however during periods of higher demand, setpoint is controlled such that energy consumption is reduced. This can be visible when referring to Cases 1 and 2, where the energy between 09:00-18:00 is comparable to Case 2, while at other times, the behavior is similar to Case 1. Notice that more energy can be conserved between 19:00-07:00, however, that would also decrease the demand at these times, causing a peak to be created.

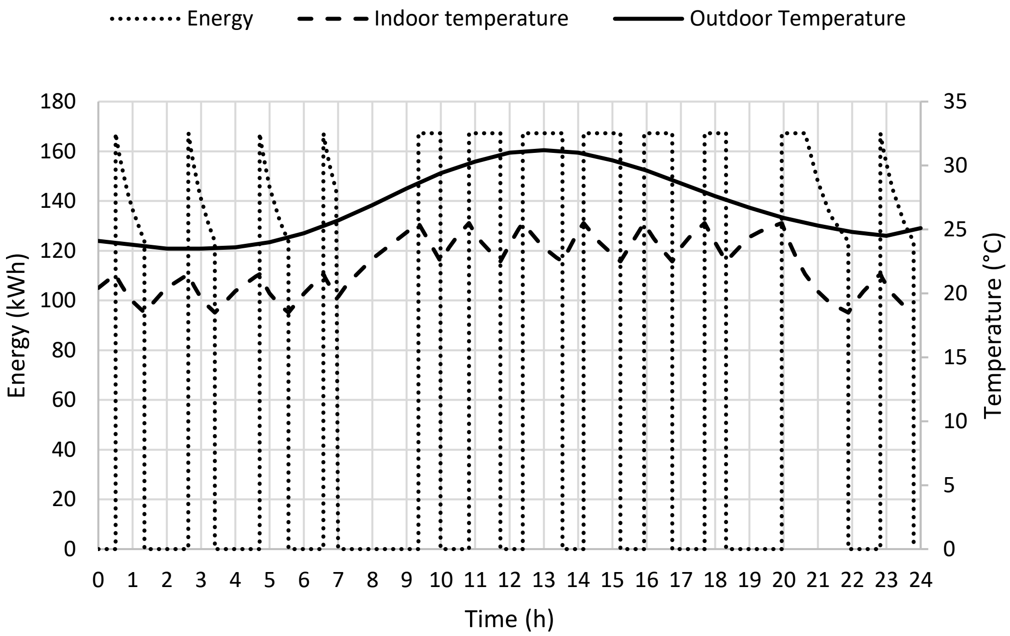

Figure 4.21. Estimated Demand from Cooling Systems on July 15th with Indoor and Outdoor temperatures for Case 4

In terms of energy consumption for cooling, Case 5 shows results similar to Case 3. Table 4.4 shows these results. The reduction in October is 44.78% which relates to the sharper peaks due to lower PV production in this month. Furthermore, the months of May and September show significant improvement over the Base Case with a reduction in energy consumption of 35% and 30% respectively. Due to the higher average outdoor temperature in July, energy consumption in July dropped by 24% compared to the other months.

Table 4.4. Total Energy Consumption from cooling systems for Case 5, Average Outdoor Temperature, Base Case Energy Consumptions from Cooling Systems and the Change in Energy Consumption between Base Case and Case 5 for the months of May, July, September and October

Month	May	July	Sept.	Oct.
Energy Consumption (MWh)	20.90	66.97	40.20	14.77
Temperature (°C)	22.47	28.23	25.05	18.89
Base Energy Consumption (MWh)	32.55	88.11	57.57	26.76
Change in Energy Consumption (%)	-35.78	-23.99	-30.17	-44.78
Economic Savings ($)	2038.08	3699.44	3039.21	2097.13

Figures 4.22-4.25 show how Case 5 affects the mean hourly demand profile. In general, it can be seen that peak demands are reduced, and the rate of change of demand is also decreased. For the month of May, it can be seen that demand during the middle of the day, i.e., the period when demand is low, has almost similar demand, however later during the day, Case 5 reduces the peak by 0.05 MWh. Similarly, for July, apart from the demand at 16:00, which is similar to the Base Case, the demand during the peak period 15:00-18:00 is reduced by 0.08 MWh. It similarly flattens the peak between 07:00-09:00. Similarly, for the month of September and October, the peaks between 16:00 and 19:00 are flattened, such that the peak demand is reduced by 0.07 MWh and 0.06 MWh respectively. During other times, cooling systems run normally, providing a cooler environment to residents.

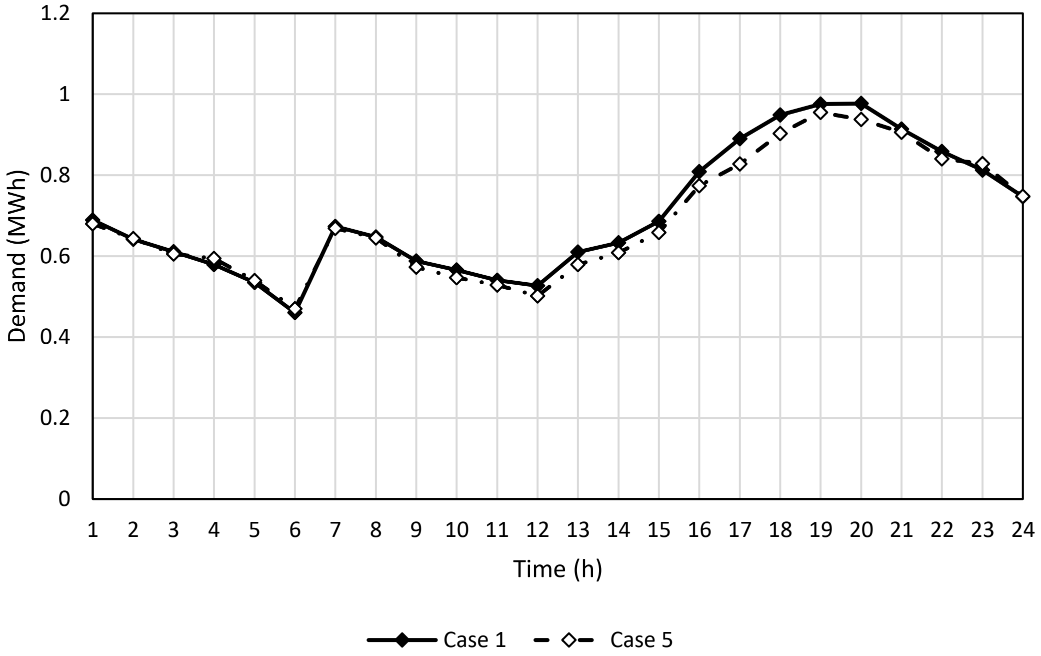

Figure 4.22. Average Hourly Demand throughout the days of the month of May for Case 1 and Case 5

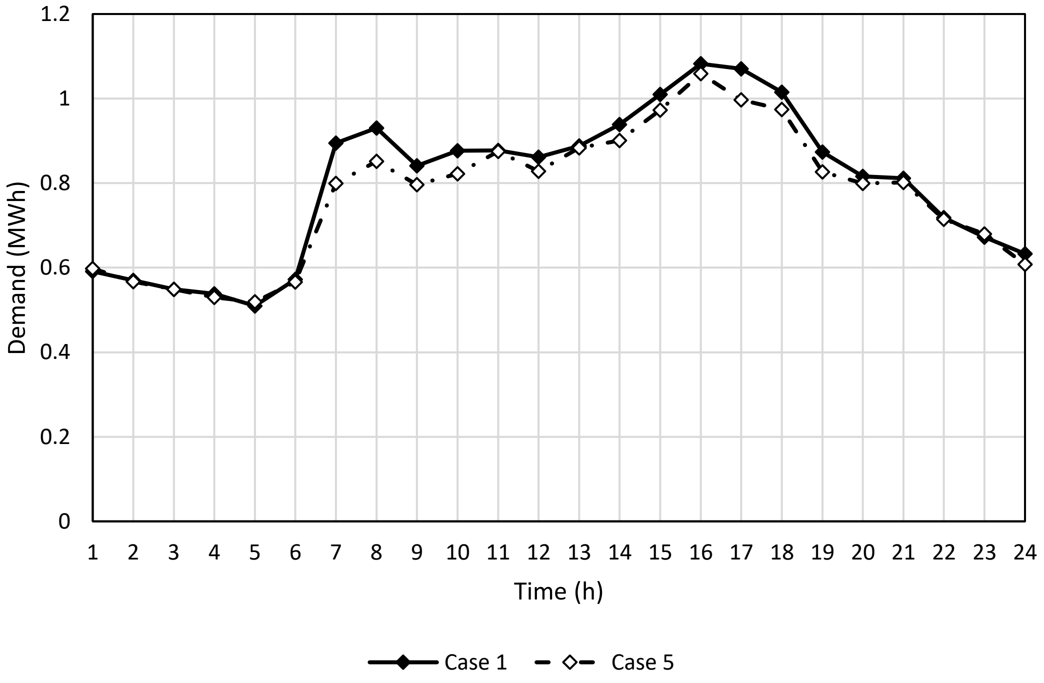

Figure 4.23. Average Hourly Demand throughout the days of the month of July for Case 1 and Case 5

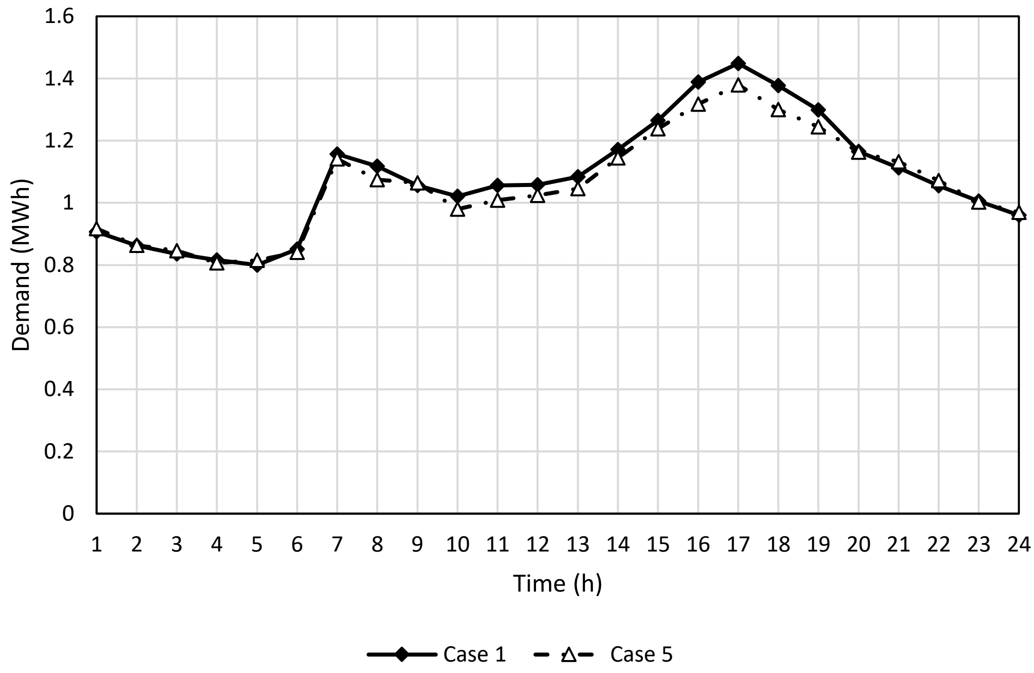

Figure 4.24. Average Hourly Demand throughout the days of the month of September for Case 1 and Case 5

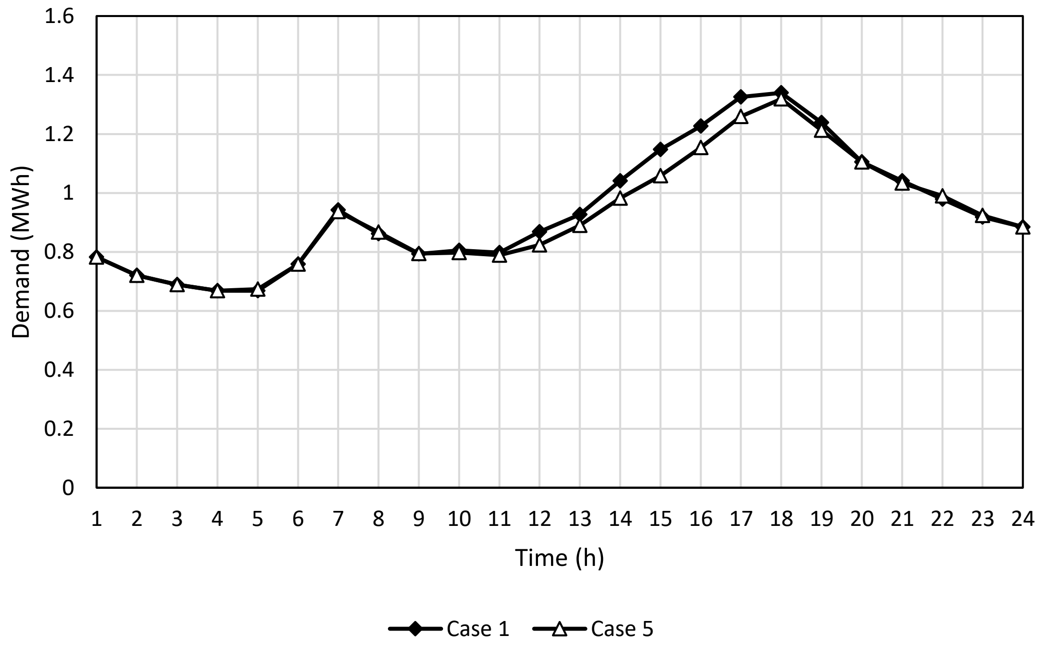

Figure 4.25. Average Hourly Demand throughout the days of the month of October for Case 1 and Case 5

4.2.6 Summary of Results for Cases 2, 3, 4 and 5

Table 4.5 show a summary of the main results of Case 2, 3, 4 and 5. It can be seen that Case 2 shows the most reduction in energy consumption of cooling systems. Meanwhile, Case 3 and 5 show comparable reduction in energy consumption of cooling systems, however, Case 5 shows better results when compared to Case 3 for the months of September and October, with 2% and 8% more reduction in consumption respectively. Furthermore, Cases 3 and 4 increase the peak demands for the month of May by 9.27% and 0.60%, respectively, which makes them ineffective especially for this month. Cases 2 and 5 display similar results in terms of peak demand reduction. Furthermore, the economic savings of Case 2 are clearly more, due to the fact that it has the least energy consumption out of all cases with a total of $19,985 saved, while Case 5 saves up to $10,873, which is over half of what Case 2 saved financially. This is expected since Case 5 has lesser energy saved compared to Case 2.

Integration of Case 2 to the current system seems improve the energy efficiency the most, however, this also keeps the indoor temperature at higher than the base of 20°C. Although based on the literature, adaptive setpoint control keeps the temperature at a comfortable level, it is still based on predictive mean vote, and residents may or may not be content with this setpoint at all times based on the hypersensitivity of occupants to changes in their living environments. On the other hand, Case 5 applies adaptive set point control only at times when the demand is expected to be higher, such that at other times, indoor temperature remains to be at a cooler 20°C especially at night time, during which comfort is of the utmost importance. Furthermore, if economics are considered, the general infrastructure is already available in METU NCC to apply such a system. Smart thermostats, with a lifetime of 10 years, cost approximately $300, the payback period should be around 5-6 years based on the economic savings shown in Table 4.5 for Case 5. Although not as energy efficient as Case 2, Case 5 gives a solution that provides an opportunity to reduce peak demand and energy consumption in cooling while also preserving comfort to residents indoors. For this reason, Case 5 is considered as the suggested configuration.

Table 4.5. Summary of Main Results of Case 2, 3, 4 and 5

	Month	May	July	Sept.	Oct.
Case 1	Energy Consumption (MWh)	32.55	88.11	57.57	26.76
Case 2	Energy Consumption (MWh)	8.48	45.96	27.5	8.84
	Change in Energy Consumption (%)	-73.93	-47.84	-52.24	-66.96
	Change In Peak Demand (%)	-3.35	-4.16	-3.62	-1.55
	Economic Savings ($)	4211.03	7375.77	5262.89	3135.34
Case 3	Energy Consumption (MWh)	20.96	67.68	41.37	17.01
	Change in Energy Consumption (%)	-35.59	-23.19	-28.14	-36.44
	Change In Peak Demand (%)	9.27	-1.37	-1.31	-1.95
	Economic Savings ($)	2027.34	3575.61	2835.37	1706.16
Case 4	Energy Consumption (MWh)	30.09	81.75	51.27	23.15
	Change in Energy Consumption (%)	-7.54	-7.21	-10.94	-13.49
	Change In Peak Demand (%)	0.60	-1.23	-0.31	1.17
	Economic Savings ($)	429.47	1111.84	1101.70	631.55
Case 5	Energy Consumption (MWh)	20.9	66.97	40.2	14.77
	Change in Energy Consumption (%)	-35.78	-23.99	-30.17	-44.78
	Change In Peak Demand (%)	-2.25	-2.16	-4.77	-1.55
	Economic Savings ($)	2038.08	3699.44	3039.21	2097.13

4.2.7 Sensitivity Analysis for Case 5

Changing the base setpoint temperature selected affects the results obtained for Case 5 in Section 4.2.5. Therefore, the sensitivity of the system with different base setpoint temperatures is investigated, such that the effect of different base setpoint temperatures on the change in energy consumption and change in peak demand compared to the Base Case can be observed.

Figure 4.26 shows the change in energy consumption in Case 5 with base setpoint temperatures ranging from 18°C to 22°C. It is clear that as the base setpoint temperature rises, the reduction in energy consumption also decreases. This is more apparent for the months with lower mean outdoor temperatures i.e., May and October. In general, when the base setpoint temperature is between 18°C and 20°C, the change in energy consumption does not vary, with the maximum variation being +1%. This does not apply to the month of May, where the energy saved decreases by 3% at every interval as the base setpoint temperature increases from 18°C to 20°C. A significant effect is seen when a base setpoint of 21°C and 22°C is applied. For the months with comparatively cooler outdoor temperatures i.e., May and October, a significant reduction in energy savings can be observed. The reduction in energy savings of 4% and 7% is seen during May and October, respectively, when the base setpoint temperature is increased from 20°C to 21°C. This can be explained due to the fact that cooler outdoor temperatures decrease the usage of cooling systems such that, lesser energy is used, when compared to lower temperatures. A similar trend is visible in the hotter months as well. In July and September, energy savings are reduced by approximately 4% and 5%, respectively, at each interval after 20°C.

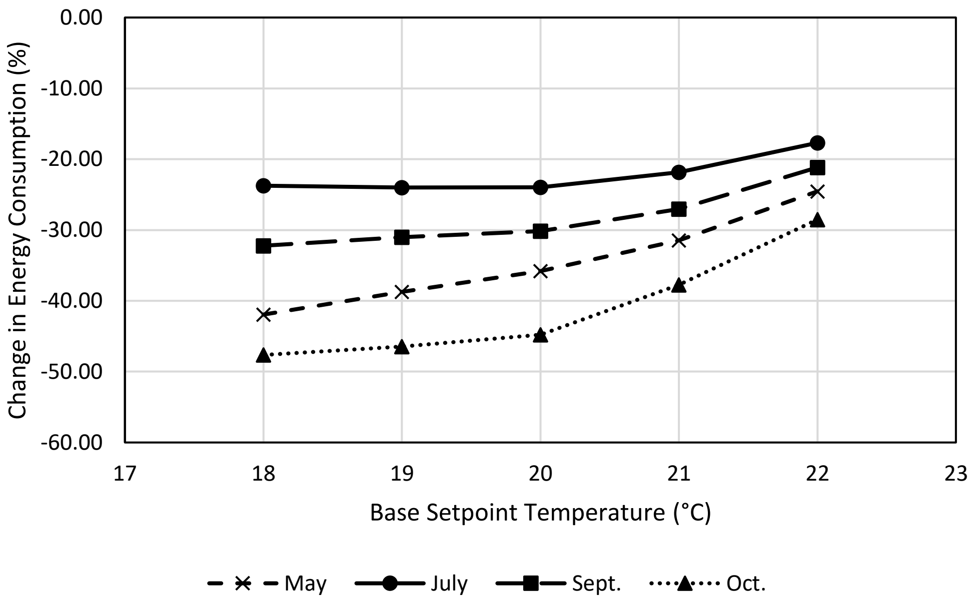

Figure 4.26. The sensitivity of the change in energy consumption of Case 5 compared to the Base Case with different base setpoint temperatures

Figure 4.27 shows the change in peak demand when base setpoint temperatures ranging from 18°C to 22°C are used. One of the core observations from Figure 4.27 is that the decrease in peak demand between each month does not follow a trend similar to the one in Figure 4.26. This is due to the fact that each month exhibits its own demand pattern. However, at a base setpoint temperature of 22°C, the change in peak demand reduces to values between 0% to -1%. This correlates to the fact that peak demand usually occurs during night time when cooler outdoor temperatures are observed. Therefore, if a base setpoint temperature of 22°C is used, it becomes more difficult to improve peak demands. In general, however, reduction in peak demand decreases as the base setpoint temperature increases for the months of May, July and October. For the month of September, however, the change in peak demand does not change from a base setpoint temperature range of 18°C to 21°C. From Figure 4.24 it can be seen that a peak is observed at 17:00 which coincides with lack of solar irradiation when outdoor temperature is low and the same amount of energy is consumed by cooling systems is the Base scenario between the range of 18°C-21°C, causing a similar effect between base setpoint temperatures from 18°C to 21°C.

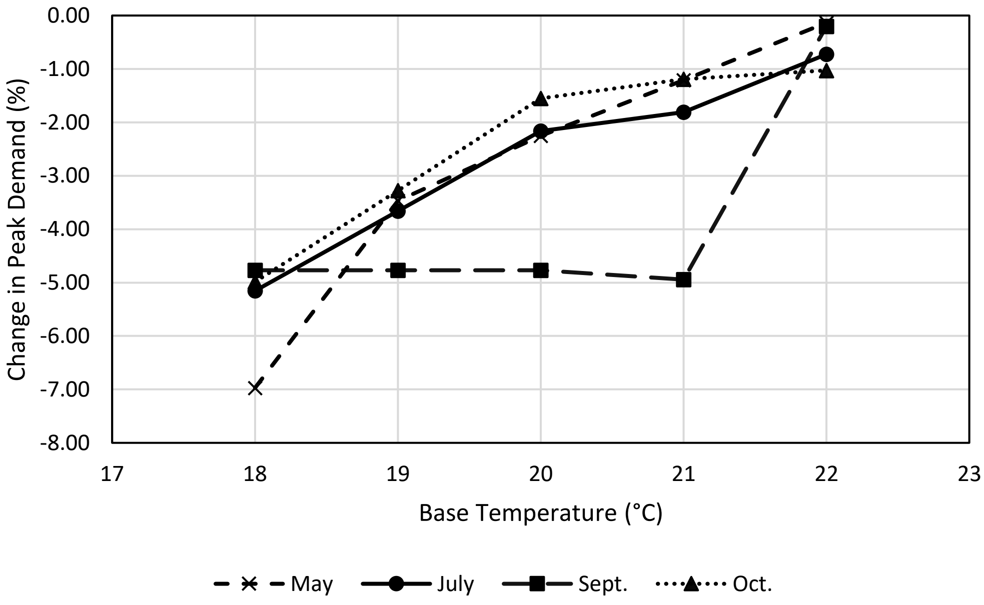

Figure 4.27. The sensitivity of the change in peak demand of Case 5 compared to the Base Case with different base setpoint temperatures

4.2.8 Case 6 - Load Shifting Analysis with Case 5

The changes to current cooling systems causes the peak demands to reduce; however, using the PV plant installed, the peaks between 17:00 and 21:00 can be further reduced. Furthermore, for the winter months, when heating is sourced from gas powered supplies in Dormitories, load shifting helps to reduce the peak demand. Using net metering, energy from PV can be supplied to the grid to be used later, when PV may not be available and the demand is higher.

Figures 4.28 and 4.29 show the average hourly demand of September and October 2019, comparing it with the average hourly demand of September and October after shifting the load using PV and applying HVAC adjustments. From Figure 4.23, it can be seen that the base demand of 2019 peaks between 16:00 and 21:00 while a trough is observed between 08:00 and 15:00. As seen in the figure, the peak demand of 1.45 MW is decreased to 1.3 MW by shifting the load to the trough formed between the trough. This stabilizes the demand at this peak. Similarly, from Figure 4.24, it can be seen that the peak demand of 1.34 MW in October reduces to 1.2 MWh.

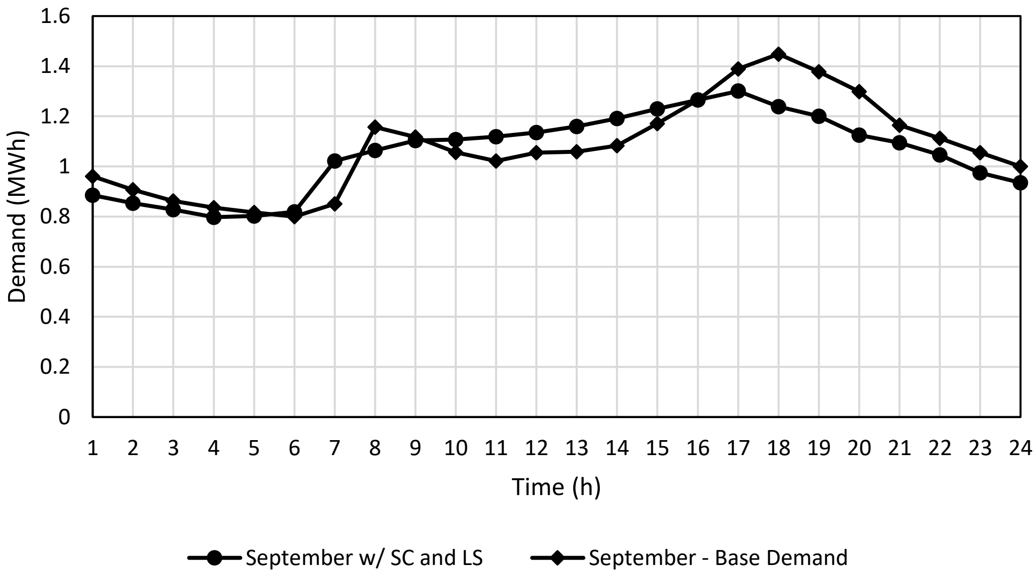

Figure 4.28. Average Hourly Demand for the month of September with load shifting and Case 5, compared with the base demand of 2019

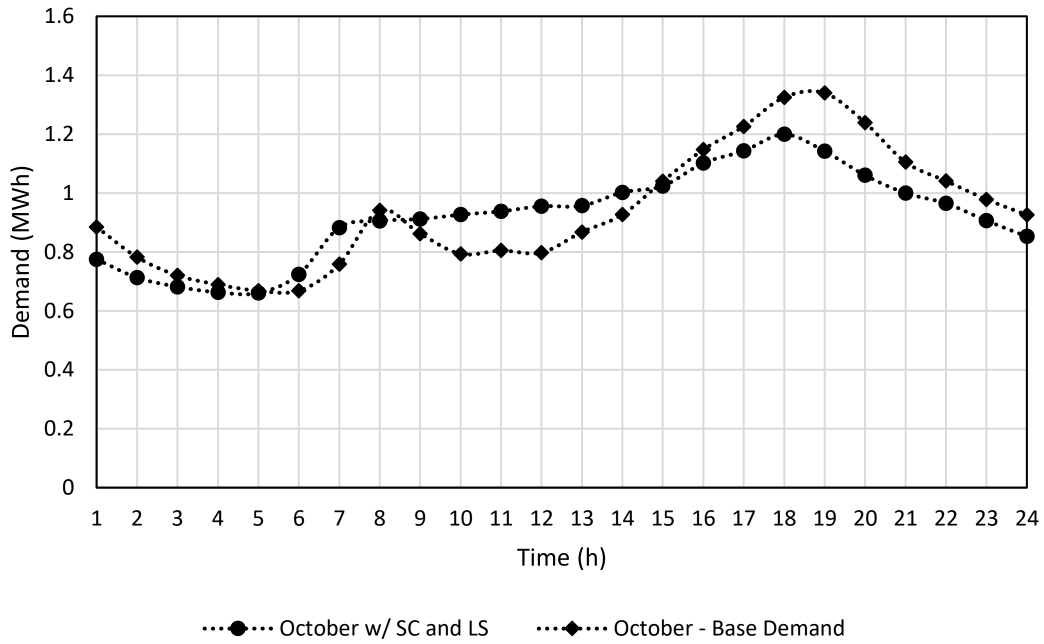

Figure 4.29. Average Hourly Demand for the month of October with load shifting and Case 5, compared with the base demand of 2019

On the other hand, Figures 4.30-4.32 show average hourly demand of 2019 for the months of January, November and December. It can be seen that load shifting significantly improves the load profile. The peak demand at 19:00 decreases by 0.4 MWh due to the load shift in January. However, due to the lack of solar resources, it can be seen that the peak rises to 0.95 MWh by 22:00. In contrast, demand in November with load shifting remains stable, with the demand peaking at 0.68 MWh. It is also seen that the peak demand at 18:00 decreases from 0.94 MWh to 0.6 MWh. In December, the demand after load shifting exhibits a similar behavior to demand after load shifting in January, since there is a lack in solar resources. However, it decreases the peak demand at 18:00 by 0.4 MWh.

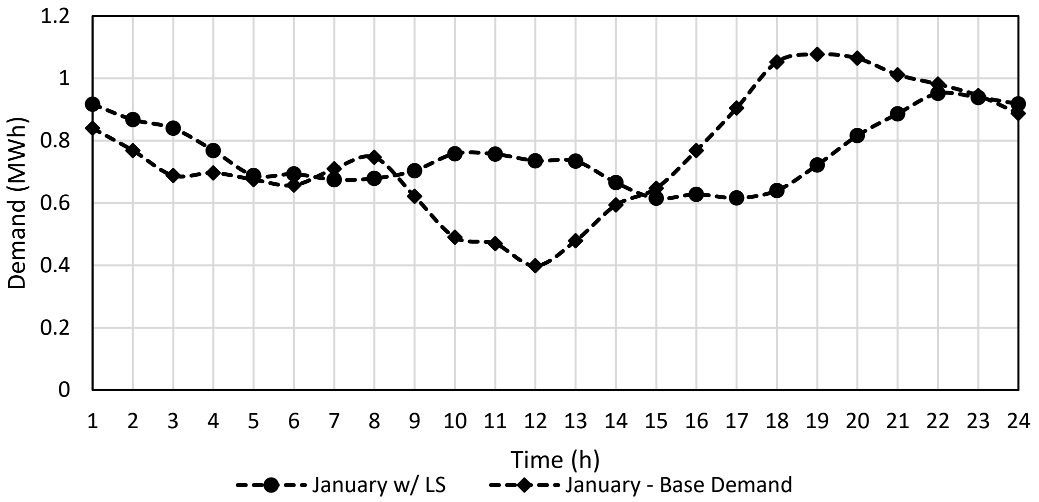

Figure 4.30. Average Hourly Demand for the month of January with load shifting, compared with the base demand of 2019

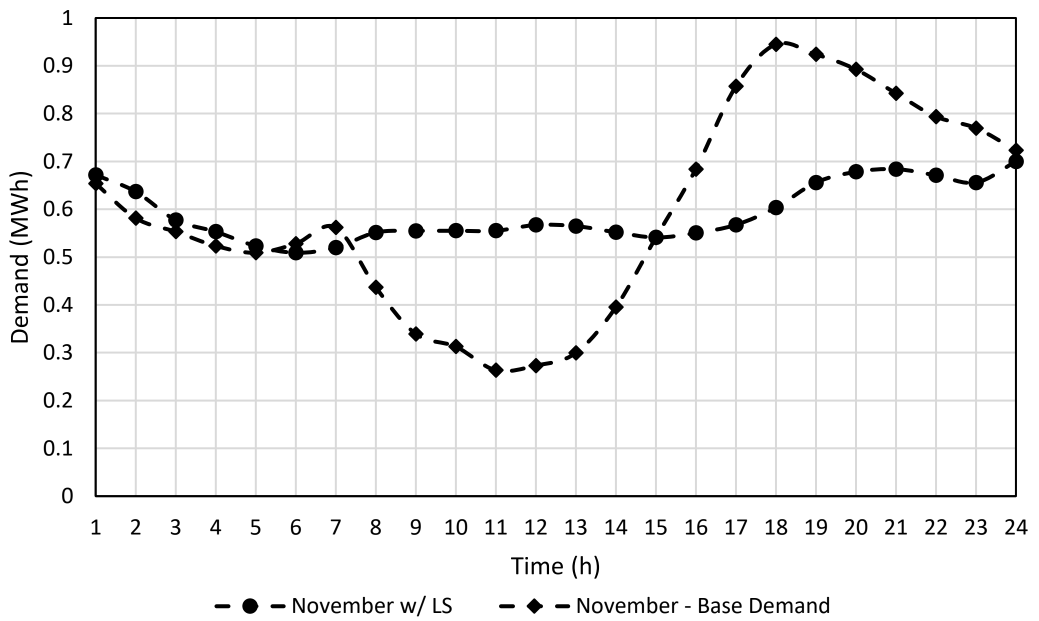

Figure 4.31. Average Hourly Demand for the month of November with load shifting, compared with the base demand of 2019

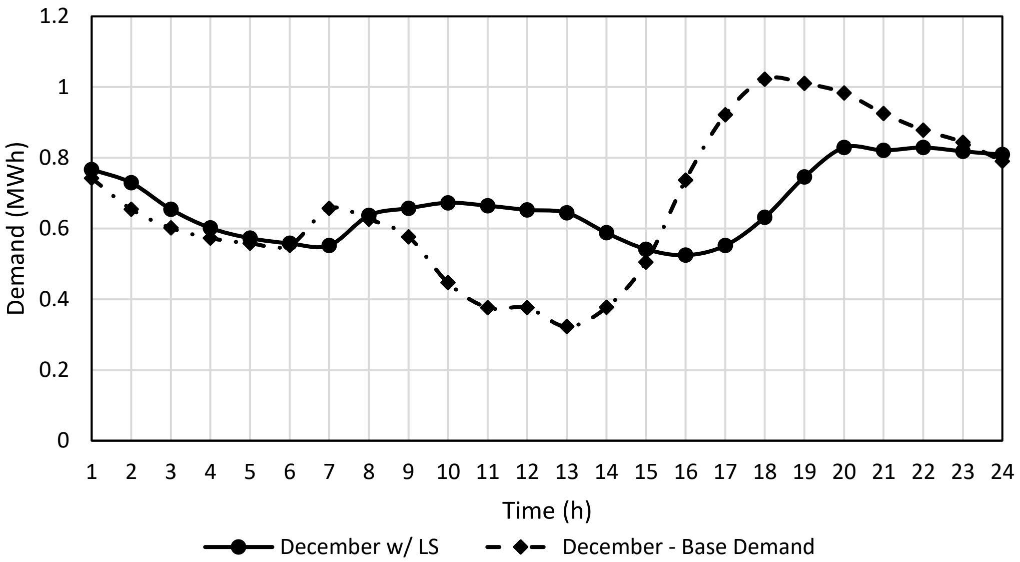

Figure 4.32. Average Hourly Demand for the month of December with load shifting and Case 5, compared with the base demand of 2019

Table 4.6 shows how the peak demand changes in each month for the load shifting with Case 5. It can be seen that in general, the peak decreases for each month. Notice that summer months exhibit the least reduction in Peak demand. This can be attributed to the fact that though solar resources are high, the demand is also high during the day, which means that most of the electrical energy from solar is used during the day. In August, since students and faculty are away for vacations, the demand is lower, therefore this trend is not followed in this month.

Table 4.6. Change in Peak Demand through Load shifting, with Case 5 being applied

Month	**Change in Peak Demand (%)**
January	-13.67
February	-25.26
March	-31.85
April	-36.95
May	-19.61
June	-2.83
July	-6.87
August	-11.78
September	-10.21
October	-10.46
November	-24.96
December	-18.11

CHAPTER 5

CONCLUSION

5.1 Conclusions

Several studies have looked at the effect of setpoint control as a method of demand reduction; however, none of these studies are based in Northern Cyprus and neither they integrate the systems with PV systems as a demand management tool. In this study, setpoint control is used to make cooling systems more efficient while maintaining human comfort such that demand may be reduced, especially at peak periods for METU NCC. Furthermore, the effect of using PV with net-metering and setpoint control on the demand profile of METU NCC is studied. For this purpose a load profile for METU NCC is constructed such that peak demand periods and load shifting opportunities can be found. PV production is estimated using TMY data on MS Excel, while a model is created for Dormitory 1 using MATLAB such that setpoint may be controlled based on outdoor temperatures using TMY data. Several cases are discussed such as setpoint control case, schedule based case, demand monitoring case and demand forecasting case and finally, based on their performance, the grid was used as a battery to shift loads to reduce peaks.

Based on the findings, the following can be said;

- In terms of energy, the highest energy is consumed in July. However, due to the availability of solar resources, this does not create a rise in demand from the grid. On the other hand, September and October have a significant rise in peaks due to incoming new students and lower energy resources compared to summer months. Furthermore, during the winter months, since there is a low demand during the day, and higher demand at night, there is a large rise in demand from the grid between 17:00 and 20:00.
- As the outdoor temperature increases, the demand in METU NCC rises, pertaining to the fact that cooling systems are one of the major causes of the rise in demand during the summer months.

Based on the assumptions made, this study finds that;

- If setpoint is controlled at all times (Case 2), energy consumption from cooling systems can be reduced by 55.7% cumulatively over the months of May, July, September and October. Meanwhile, if setpoint control is only applied to schedules between 06:00-10:00 and 15:00-20:00 (Case 3), the energy consumption is reduced by 28.3% cumulatively over the months of May, July, September and October. Finally, when setpoint control is applied when demand is higher that an aggregate demand based on forecasted values (Case 5), the energy consumption from cooling systems can be reduce by 30.3% cumulatively over these months.
- In terms of peak reduction, Case 3 increases the peak demand in May by 9.27%. On the other hand, Case 2 and Case 5 exhibit comparable peak reductions, ranging between 2-5%. Although, Case 2 is seen to be more efficient that Case 5 in terms of energy consumption, Case 5 exhibits a better peak reduction for the months of September and October and also keeps the indoor temperature at 20°C when the demand is low, improving the living environment for residents. Furthermore, most of the infrastructure is already present on campus for such an implementation, with excess costs being covered within a 5-6 year period. On the basis of this, Case 5 should be implemented.
- Finally, when the load is shifted, peaks for November, December and January decrease by 25%, 18% and 13.6% respectively. A significant improvement is also observed for September and October, with peaks decreasing by 10% each. Therefore, if Case 5 is coupled with a grid being used as a battery for PV, significant peak reductions can be observed, which can be implemented.

5.2 Future Work

To build on this study, one of the most important steps is to conduct studies based on the demand of the dormitories specifically, based on continuous data, furthermore, cooling systems should be metered. This provides a better understanding of the behavior of the demand in dormitories, and provides a better estimate of demand from cooling systems. Another reason why continuous data needs to be used is since outdoor temperature changes constantly across the day, and so does the demand over time, therefore, it provides a better estimate. Moreover, with long term data, electricity demand can be predicted through neural networks and provide the option of day ahead planning.

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APPENDIX

A.1 Simulink Diagrams

Figure A.1 shows Equation 3.17 in effect in MATLAB Simulink. Depending on the temperature indoors, the thermostat turns the air switch on or off. Furthermore, a saturation limit is added based on the cooler's cooling capacity.

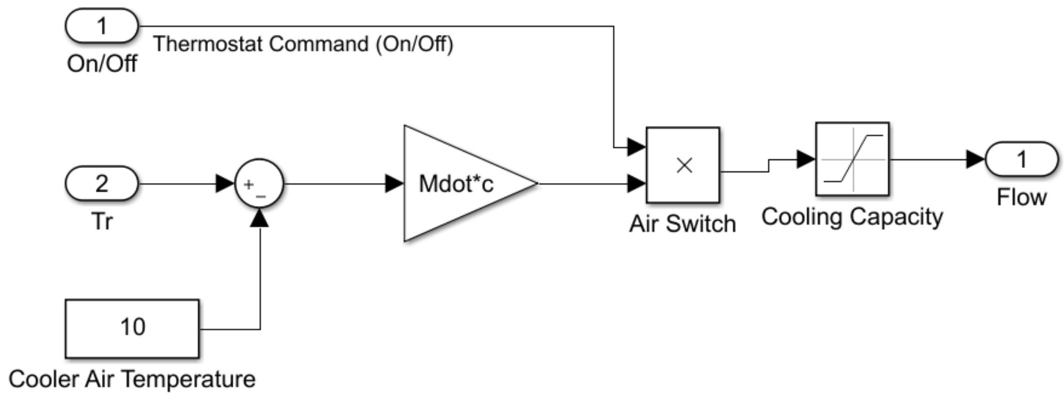

Figure A.1. Cooling/AC Subsystem in Simulink

Figure A.2 shows the application of Equation 3.22 in MATLAB. The values were capped at 25°C to avoid internal gains, to reduce demand overshoot. This is caused due to extensive temperature setpoint variation.

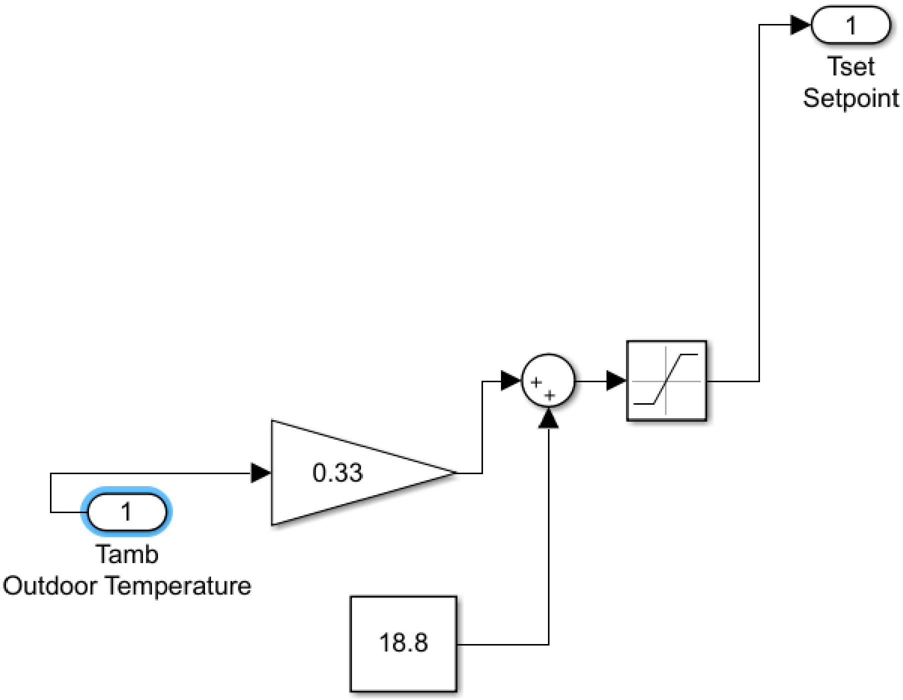

Figure A.2. Adaptive Thermal Comfort Model in Simulink

Figure A.3 shows the thermal model of the building on MATLAB with the thermostat, AC and Building Subsystems. Here, the adaptive thermal model subsystem can be seen to provide the setpoint temperatures instead of a traditional fixed setpoint.

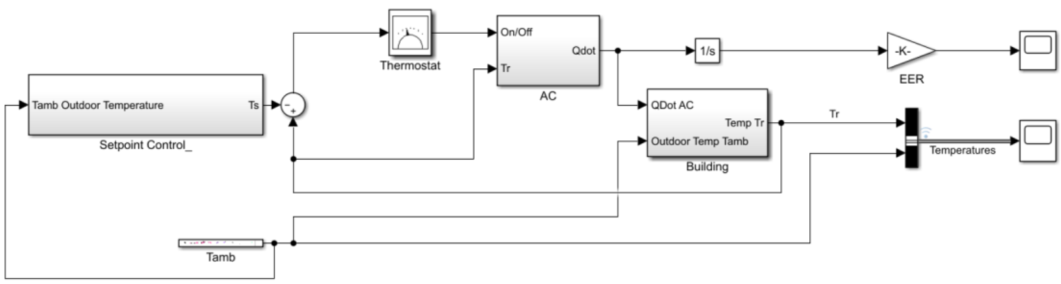

Figure A.3. Thermal Model with Adaptive Thermal Comfort Model in Simulink