Direct Load Control for an Aggregation of Air Conditioners (ACs) Using a Setpoint Variation Control Strategy

by

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Abstract

Thermostatically controlled loads account for a significant amount of energy consumption in commercial and residential buildings[1][2]. This thesis studies the impact of controlling the thermostats of air conditioners (ACs) as a way to implement peak load shaving with consideration of end-use device performance.

A proposed system model which allows the utility to implement peak load shaving as a component of day-ahead planning for ACs in a large hotel is developed. In the experimental simulation, the results show on-peak demand reduction which is beneficial to the utility, however, the magnitude of the aggregate load that can be shifted as a contribution to peak load shaving may have a significant negative impact on customer comfort as measured by room temperature.

The research contribution includes a setpoint variation control strategy that takes into account the information from the utility and sorting of ACs to perform peak load shaving and reduce the negative impact on end-user performance.
Dedication

To God Almighty for making this a reality
Acknowledgments

Pursuing research for the first time has been challenging in various ways. Through this learning curve, I have been shaped into a better person who has identified her strength academically and personally. This wouldn’t have been possible without the help of certain people I met on this journey.

My belief in the Almighty God is the most fundamental instrument that helped me actualize this dream and scale through. I thank God for seeing me through with his favor, mercy, and grace.

I would like to appreciate my supervisors Dr. Diduch and Prof. Mary Kaye for giving me the privilege to carry out my research under their supervision. Your support, patience, encouragement, dedication and constant feedback were key features that kept me motivated throughout this period. Under your tutelage, I have indeed learned so much. I am extremely thankful, and I don’t take your kind gestures for granted.

I am grateful to my husband for his undiluted love. He constantly cheers me up during the dark days. Thank you for your support throughout this degree and helping me understand that a good man builds his woman. To my parent, siblings and friends thank you for believing in me, cheering me and constantly praying for me.
Table of Content

Abstract ................................................................................................................................. ii
Dedication ........................................................................................................................... iii
Acknowledgments ............................................................................................................... iv
Table of Content ................................................................................................................. v
List of Tables ..................................................................................................................... x
List of Figures ................................................................................................................... xi
List of Abbreviations ......................................................................................................... xvii
List of Nomenclature ......................................................................................................... xviii
Chapter 1 Introduction ...................................................................................................... 1
  1.1 Problem Statement ...................................................................................................... 1
  1.2 Why Demand Response (DR) .................................................................................... 2
     1.2.1 DR Models .......................................................................................................... 4
     1.2.2 Demand Response Benefits ............................................................................... 5
     1.2.3 Loads .................................................................................................................. 6
     1.2.4 Thermostatically Controlled Loads .................................................................... 7
        1.2.4.1 Characteristics of TCLs ............................................................................. 8
     1.3 Literature Review .................................................................................................... 9
1.4 Summary of Major Challenges Associated with Setpoint Aggregate Control of ACs

1.5 Research Objectives and Contributions

1.5.1 Research Contribution

1.5.2 Thesis Objectives

1.6 Thesis Structure

Chapter 2 Problem Statement and System Model

2.1 Formulation of the Problem

2.2 Forecast

2.2.1 Baseline Power Profile

2.2.2 Utility Demand and Regulation Signal

2.2.3 Reserve Capacity Up and Reserve Capacity Down

2.2.4 Customer Comfort Degradation Limit

2.3 Controller

2.3.1 Controller’s Mode of Operation

2.3.2 Design of Controller

2.3.3 Balance Signal

2.3.3.1 Balance Signal equal to Zero

2.3.3.2 Balance Signal greater than Zero

2.3.3.3 Balance Signal less than Zero

2.4 Air Conditioners (ACs)

2.4.1 Thermostats

2.4.2 Operation of Air Conditioner
2.4.3 Type of Air Conditioners

2.4.4.1 Mathematical Modelling of ACs

2.4.4.2 Parameters Associated with the Operational Status of First Differential

2.4.4.2.1 Ambient Temperature

2.4.4.2.2 Thermal Capacitance

2.4.4.2.3 Thermal Resistance

2.4.5 Basic Operation of a Single First-Order Differential AC

2.5 Load Control Strategy

2.5.1 Effect of Change in Setpoint Temperature of a Single AC

2.5.2 Effect of Change in Setpoint Temperature on a Population of ACs

2.6 Operation of the System Model

2.6.1 Rebound Effect

2.7 The Simulation Software

Chapter 3 Controlling Air Conditioners for Providing Peak Shaving

3.1 Introduction

3.2 Model Validation – Case Study

3.2.1 AC Parameters

3.2.2 Weather Data Acquisition

3.3 Control Framework

3.3.1 Dynamically Sorted List

3.4 Mitigation of the Rebound Effect

3.5 Setpoint Variation Control Strategy Implementation

3.6 Simulation Results for Verification of the Setpoint Control Method
3.6.1. Setpoint Control Based on ON and OFF-Peak Period ........................................ 47
3.6.2 Simulink Simulation Results .................................................................................. 48
3.6.2.1 Results for Utility Demand1 with Different Regulation Signals ................. 48
3.6.2.2 Results for Utility Demand2 with Different Regulation Signals ........... 52
3.7 Conclusion ............................................................................................................. 53

Chapter 4 Performance Evaluation of the Control Strategy ........................................... 56
4.1 Introduction ........................................................................................................... 56
4.2 Energy Conservation Evaluation ............................................................................. 56
4.2.1 Utility Demand1 ................................................................................................. 57
4.2.2 Utility Demand2 ................................................................................................. 59
4.3 Sampling Rate ....................................................................................................... 60
4.4 Comfort Limit ........................................................................................................ 62
4.4.1 Customer comfort degradation for utility demand1 and utility demand2 ...... 63
4.5 Conclusion ............................................................................................................. 66

Chapter 5 Conclusions and Future Work ..................................................................... 67
5.1 Thesis Contribution ................................................................................................. 68
5.2 Future Work ........................................................................................................... 68

Bibliography ................................................................................................................. 71

APPENDIX A .................................................................................................................... 78
A.1 Simulations Results for Different Temperature Data .............................................. 78
A.1.1 Simulation Results for Utility Demand1 ............................................................ 79
A.2. Summary ............................................................................................................... 87
APPENDIX B .................................................................................................................... 89
B.1 Simulation results using Utility Demand2 ................................................. 89
B.2 Summary.................................................................................................. 97
APPENDIX C .................................................................................................. 99
Vita
List of Tables

1.1 Properties of TCLs ................................................................. 8

3.1 Simulation Parameters .................................................................. 37

4.1 Comparison of energy consumption and cost in the controlled and uncontrolled
state for different regulation signals (utility demand1)........................................ 56

4.2 Comparison of energy consumption and cost in the controlled and uncontrolled
state for different regulation signals (utility demand2)........................................ 58

4.3 NSWIcon for different control sample rates ........................................ 59
List of Figures

1.1 Average Energy Consumption for Florida Solar Center, United States of America .......................................................... 3
1.2 Percentage of energy consumption in the United States in 2018 ................. 6
1.3 Average energy consumption for a single-family house in Florida, U.S.A .......... 8
2.1 Schematic of System Model ........................................................................ 18
2.2 Illustration of ± Preg ............................................................................. 21
2.3 Schematic view of an air conditioner ......................................................... 25
2.4 Room temperature with single AC .............................................................. 32
2.5 Power demand of a single AC .................................................................... 33
2.6 Ts changes from 21°C to 22°C at the 400th minute ......................................... 33
2.7 The indoor temperature of three ACs with a change in Ts ................................ 34
3.1 Outdoor temperature for April 1st, 2019 in Bridgetown, Barbados ................ 39
3.2 Baseline Power Profile $P_{unc}$ for April 1st, 2019 ........................................ 40
3.3 Proposed Control Framework ..................................................................... 41
3.4 Selection of ACs by the controller .............................................................. 44
3.5 Flowchart of Control Logic ........................................................................ 45
3.6 Power Demand of Barbados light and Power Distribution Company ............ 47
3.7 Generated utility demand I based on different case scenarios .................... 48
3.8 Power consumption profile for April 1st, 2019, using utility demand1 (Preg ±50kW) .........................................................49

3.9 Power consumption profile for April 1st, 2019, using utility demand1 (Preg ±100kW) .................................................................49

3.10 Power consumption profile for April 1st, 2019, using utility demand1 (Preg ±200kW) ..................................................................50

3.11 Generated utility demand2 based on different case scenarios ................50

3.12 Power consumption profile for April 1st, 2019, using utility demand1 (Preg ±50kW) ..................................................................51

3.13 Power consumption profile for April 1st, 2019, using utility demand1 (Preg ±100kW) ..................................................................51

3.14 Power consumption profile for April 1st, 2019, using utility demand1 (Preg ±200kW) ..................................................................52

4.1 Ontario Hydro TOU pricing ..............................................................................56

4.2 On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 1st, 2019 using utility demand1 .................................................................58

4.3 On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 1st, 2019 using utility demand2 ........................................................................59

4.4 Range of α and β for the 500 ACs on April 1st 2019, utility demand1 .............63

4.5 Range of α and β values for the 500 ACs on April 1st, 2019, using utility demand2 ........................................................................63

4.6 Customer comfort limit as a function of load shifting from a 4MWh forecasted on-peak energy consumption on April 1st, 2019 ......................................64
4.7 Customer comfort limit as a function of load shifting from a 3MWh forecasted on-peak energy consumption on April 1st, 2019 .................................................................65
A.1 Forecasted Baseline Power Profile using different twenty-four-hour weather data78
A.2 Generated Utility Demand1 for January 1st, 2018 based on different case ..........79
A.3 Power consumption profile on January 1st, 2018 using the proposed control strategy and different case scenarios of utility demand1 .................................................................79
A.4 On and Off-peak energy consumption difference vs daily energy consumption cost difference for January 1st, 2018 using utility demand1 ..............................................80
A.5 Range of $\alpha$ values for January 1st, 2018 and its proportionality to room percentage (utility demand1) ..........................................................................................80
A.6 Range of $\beta$ values for January 1st, 2018 and its proportionality to room percentage (utility demand1) ..........................................................................................81
A.7 Generated $P_{ud1}$ for April 8th, 2018 based on different case scenarios ............ 81
A.8 Power consumption profile on April 8th, 2018 using the proposed control strategy and different case scenarios of utility demand1 .........................................................82
A.9 On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 8th, 2018 using utility demand1 .................................................82
A.10 Range of $\alpha$ values for April 8th, 2018 and its proportionality to room percentage (utility demand1) ..........................................................................................83
A.11 Range of $\beta$ values for April 8th, 2018 and its proportionality to room percentage (utility demand1) ..........................................................................................83
A.11 Generated utility demand1 for August 1st, 2018 based on different case ..........84
A.13 Power consumption profile on August 1st, 2018 using the proposed control strategy and different case scenarios of utility demand1 ...............................................................84

A.14 On and Off-peak energy consumption difference vs daily energy consumption cost difference for August 1st, 2018 using utility demand1 ..........................................................85

A.15 Range of $\alpha$ values for August 1st, 2018 and its proportionality to room percentage (utility demand1) ..................................................................................................................85

A.16 Range of $\beta$ values for August 1st, 2018 and its proportionality to room percentage (utility demand1) ..................................................................................................................86

A.17 Customer comfort limit as a function of load shifting 2.62MWh forecasted on-peak energy consumption on January 1st, 2018 .................................................................87

A.18 Customer comfort limit as a function of load shifting 4.53MWh forecasted on-peak energy consumption on April 8th, 2018 .................................................................87

A.19 Customer comfort limit as a function of load shifting 5.2MWh forecasted on-peak energy consumption on August 1st, 2018 .................................................................88

B.1 Generated utility demand2 for January 1st, 2018 based on different case ..............89

B.2 Power consumption profile on January 1st using the proposed control strategy and different case scenarios of utility demand2 .................................................................89

B.3 On and Off-peak energy consumption difference vs daily energy consumption cost difference for January 1st, 2018 using utility demand2 .............................................90

B.4 Range of $\alpha$ values for January 1st, 2018 and its proportionality to room percentage (utility demand2) ..................................................................................................................90

B.5 Range of $\beta$ values for January 1st, 2018 and its proportionality to room percentage (utility demand2) ..................................................................................................................91
B.6 Generated utility demand for April 8th, 2018 based on different case scenarios
B.7 Power consumption profile on April 8th, 2018 using the proposed control strategy and different case scenarios of utility demand
B.8 On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 8th, 2018 using utility demand
B.9 Range of α values for April 8th, 2018 and its proportionality to room percentage (utility demand)
B.10 Range of β values for April 8th, 2018 and its proportionality to room percentage (utility demand)
B.11 Generated utility demand for August 1st, 2018 based on different case
B.12 Power consumption profile on August 1st, 2018 using the proposed control strategy and different case scenarios of utility demand
B.13 On and Off-peak energy consumption difference vs daily energy consumption cost difference for August 1st, 2018 using utility demand
B.14 Range of α values for August 1st, 2018 and its proportionality to room percentage (utility demand)
B.15 Range of β values for August 1st, 2018 and its proportionality to room percentage (utility demand)
B.16 Customer comfort limit as a function of load shifting 1.48MWh forecasted on-peak energy consumption on January 1st, 2018
B.17 Customer comfort limit as a function of load shifting from a 3.42MWh forecasted on-peak energy consumption on April 8th, 2018
Customer comfort limit as a function of load shifting from a 3.88MWh forecasted on-peak energy consumption on August 1st, 2018

B.18
## List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Air Conditioner</td>
</tr>
<tr>
<td>AMI</td>
<td>Advanced Metering Infrastructure</td>
</tr>
<tr>
<td>BPLC</td>
<td>Barbados Power and Light Company</td>
</tr>
<tr>
<td>CPP</td>
<td>Critical Peak Pricing</td>
</tr>
<tr>
<td>DR</td>
<td>Demand Response</td>
</tr>
<tr>
<td>DLC</td>
<td>Direct Load Control</td>
</tr>
<tr>
<td>EIA</td>
<td>Energy Information Administration</td>
</tr>
<tr>
<td>HVAC</td>
<td>Heating, Ventilation, and Air Conditioning</td>
</tr>
<tr>
<td>MATLAB</td>
<td>Matrix Laboratory</td>
</tr>
<tr>
<td>PCT</td>
<td>Programmable Communicating Thermostat</td>
</tr>
<tr>
<td>RTP</td>
<td>Real-Time Pricing</td>
</tr>
<tr>
<td>TCL</td>
<td>Thermostatically Controlled Load</td>
</tr>
<tr>
<td>TOU</td>
<td>Time of Use</td>
</tr>
</tbody>
</table>
List of Nomenclature

$\alpha_i$ difference between $MinTcon_i$ and $MinTunc_i$ in °C

$\beta_i$ difference between $MaxTcon_i$ and $MaxTunc_i$ in °C

$C$ thermal capacitance of the room (kWh/°C)

$C_p$ specific heat at constant pressure (J/Kg°C)

$D$ duty cycle

$Econ$ energy consumption when setpoint/external control (kWh)

$Eun$ energy consumption of an AC when no external controller is involved (kWh)

$I$ thickness of the material (m)

$K$ conductivity of the material (w/m°C)

$m$ ON/OFF state of the AC

$MaxTcon_i$ Maximum room temperature of an AC in a controlled state (°C)

$MaxTunc_i$ Maximum room temperature of an AC in an uncontrolled state (°C)

$MinTcon_i$ Minimum room temperature of an AC in a controlled state (°C)

$MinTunc_i$ Minimum room temperature of an AC in an uncontrolled state (°C)

$n$ number of ACs.

$Nbalanceoff$ Number of ACs required to change state from ON to OFF to fulfill balancing signal -$Pbs$. 
$N_{balanceon}$  Number of ACs required to change state from OFF to ON to fulfill balancing signal $+P_{bs}$.

$N_{needed}$  Number of ACs required to change state to shift demand by $P_{bs}$

$N_{presently_on}$  Number of ACs presently ON during the control sampling rate

$N_{presently_off}$  Number of ACs presently OFF during the control sampling rate

$N_{utility_demand_on}$  Number of ACs required to be ON which is required to fulfill utility demand.

$N_{utility_demand_off}$  Number of ACs required to be OFF to fulfill utility demand

$N_{SWI_{con}}$  total number of new setpoint of all ACs during the control time horizon

$p$  density (kg/m$^3$)

$P_{agg}$  aggregate power consumption of the ACs (kW)

$\pm P_{bs}$  load balancing signal in (kW)

$P$  power rating of the air conditioner (kW).

$P_{reg}$  regulation signal power required to generate the utility demand (kW).

$P_{ud}$  utility demand (kW)

$P_{unc}$  forecasted aggregate power consumption of the population of ACs (kW)

$R$  thermal resistance of the room in ($^\circ$C/kW)

$randn$  function in MATLAB that generates random values which are normally distributed

$T$  indoor room temperature ($^\circ$C)

$T_+$  upper limit of indoor temperature ($^\circ$C)

$T_-$  lower limit of indoor temperature ($^\circ$C)

$T_a$  outside temperature ($^\circ$C)

$T_c$  Time taken for AC to cool down
\( \tau_h \quad \text{Time taken for AC to heat up} \\
\Tsnew \quad \text{New Setpoint assigned by controller (°C)} \\
\Tsnew^+ \quad \text{upper deadband of new setpoint (°C)} \\
\Tsnew^- \quad \text{lower deadband of new setpoint (°C)} \\
\Ts \quad \text{setpoint of the AC’s thermostat (°C)} \\
\Tslow \quad \text{lower deadband of the setpoint temperature (°C)} \\
\Tsupp \quad \text{upper deadband of the setpoint temperature (°C)} \\
\eta \quad \text{Coefficient of performance} \\
V \quad \text{volume (m}^3\text{)} \\
\Delta T \quad \text{value needed to change the setpoint of the selected AC to } \Tsnew \text{ (°C)}
Chapter 1

Introduction

1.1 Problem Statement

In [3] the authors state that 45% of loads used by customers are thermostatically controlled loads (TCLs), which include air conditioners and water heaters. This percentage of loads is seen as a significant contributor to the high electricity demand consumption and this raises a concern as to how electricity supply will match the recent increase in demand worldwide. It is necessary that generated power matches demand consumption otherwise the reliability of the electricity grid can be reduced. Conventional methods have implemented non-selective and selective load shedding to curb this issue. Energy storage devices and real-time responding generators are also used as a means to ensure power system energy balance and stability. Major constraints of energy storage devices in power systems including capacity, proper sizing and maintenance are currently being addressed to ensure customer’s demands are met during peak hours [4][5][6]. With the increase in the deployment of thermostatically controlled loads worldwide, research involving energy-efficient technologies for TCLs are currently being investigated[7][8][9]. Demand response (DR) has been suggested as one of the technologies proposed to achieve peak shaving which helps in balancing energy supply and demand [10][11]. To achieve peak
shaving, load shifting can be applied to loads where some load consumption during the on-peak period is moved to the off-peak period [12]. Adoption of DR to mitigate the imbalance in generation and demand caused by renewable energy intermittency is studied in [13][14]. Most demand response methods implemented require the active participation of the consumer to be effective. Also, in a situation where there is an emergency requiring a load shedding, the customer's response might be slower than necessary to maintain power system reliability. An effective way to apply demand response to a group of TCLs is to intelligently control the TCLs such that the aggregated power tracks a scheduled load profile and at the same time maintains end-user device performance. In this respect, the development of an energy management system that includes a control strategy to perform demand response for TCLs is beneficial. The implementation of an intelligent control strategy comes with many issues such as the need to achieve energy balance and peak shaving while maintaining customer’s comfort. Various research has gone into studying control strategies for TCLs. A background of the control strategies for TCLs by different researchers appears in section 1.3.

1.2 Why Demand Response (DR)

According to the US department of energy [15], demand response is defined as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to include lower electricity use in times of high wholesale market prices or when system reliability is jeopardized”.
To comprehend the necessity of demand response, Fig.1.1, which highlights peak periods in winter and summer illustrates an average monthly residential electricity consumption for two hundred and four houses in central Florida, which is a southern climate.

![Average Energy Consumption from Florida Solar Center, United States of America][1]

It is observed that in central Florida, a peak electricity demand consumption exists during the summer and winter seasons due to the extremes of the outside temperature. This outside temperature increases the collective use of heating and cooling devices such as furnaces, air conditioners, water heaters, and refrigerators which contributes to peak periods. To accommodate these peak periods which occur periodically during the year, it is necessary to ensure that the power system has the capacity to supply the required peak demand without interrupting the power supply. The high cost of guaranteeing this has resulted in the adoption of demand response to control loads to reduce the cost associated with additional generation.

To implement demand response, a smart grid system is necessary. A smart grid system has been defined by [15] as an “electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated
fashion across electricity generation, transmission, substations, distribution and consumption to achieve a system that is clean, safe, secure, reliable, resilient, efficient, and sustainable”. The two-way communication system in the smart grid gives consumers and utility the ability to have better monitoring of electricity usage. Presently some real-time communication technologies have been suggested. On the customer’s side, technologies such as Advanced Metering Infrastructure, (AMIs) are currently being installed to transfer real-time data from the consumer to the utility and vice versa via a communication link[16]. To implement the advanced metering, the consumer end must have smart devices which aid the bidirectional flow of data between the utility and the consumer. Such technology gives the utility the ability to determine electricity price based on consumption. It also gives the consumers the flexibility to manually control their consumption and determine how much electricity they are willing to buy based on the price of electricity provided by the utility/system’s operator.

1.2.1 DR Models

Typically, DR can be classified based on price structure and incentive structure.

- **Price Based DR:** This model is based on the “changes in electric usage by end-use customers from normal consumption patterns in response to changes in the price of electricity over time”[17]. Various pricing options have been adopted and are classified into three main methods which are real-time pricing (RTP)[18][53], critical peak pricing (CPP) and time of use pricing (TOU)[54].

- **Incentive-Based DR:** This DR program encourages customer’s participation by providing incentives to customers that allow control of their energy consumption
in the event of a reliability issue such as a drop-in generation or peak load reduction. The utility is given permission by customers beforehand to have control of loads. Different programs under the incentive-based DR include direct load control and Interruptible/Curtailed Programs. Most times the direct control method involves the utility/system operator sending a signal which prompts a load controller or aggregator to alter loads at a specific time [18][19]. The load controller/aggregator which acts an interface between the utility and the consumers sends a control signal that alters the operation cycle of the load. This control signal could be a variation of a parameter associated with the appliance. The aggregator or controller acts based on forecasted data or real-time information received from the utility. The forecasted information includes anticipated power consumption, rating of appliances, operational status, control period, weather data and flexibility of the appliances. Based on this information, the controller broadcasts a signal to all customers’ loads to control power consumption. The major way to implement direct load control (DLC) involves consumers agreeing to an alteration in their nominal baseline power consumption at a designated time of the day. The setpoint temperature variation control strategy used in this research work is a direct load control method, however analysis of the transactional agreement between the utility and customer is not covered in the scope of this research.

1.2.2 Demand Response Benefits

Demand response (DR) comes with numerous benefits to system operators and consumers especially the cost reduction associated with power system expansion. These
benefits can be summarized below[20][21]:

- Enhanced system reliability: DR provides a medium to ensure that the demand profile matches the electricity generation profile that has a significant impact on grid system stability and reduces system damages such as damage at the transmission and the distribution level, faults, and overloading of the grid.

- Better economic efficiency: DR is economically significant to both the utility and consumers. The consumers can enjoy reduced electricity cost due to load shifting during peak hours and the utility avoids the extra cost of expanding the grid.

1.2.3 Loads

Most loads in a power system are classified as industrial, commercial and residential loads. Figure 1.2 depicts the distribution of energy power consumption in the United States of America obtained from the US energy information administration (EIA).

![Figure 1.2: Percentage of energy consumption in the United States in 2018][50]
The industry used 31\% of the total energy in the country, followed by transportation at 28\%, then residential at 22\% and commercial at 19\% [50]. Industrial loads are key players in the high demand for electricity when compared to other loads because the power rating of most industrial loads is large when compared to commercial and residential loads. Control of these loads is a critical way to adjust demand consumption but due to their specific startup and shutdown, they require procedures carried out explicitly by experts in their field. Residential and commercial loads are less complex and easier to control. Although the total energy conserved in adjusting a group of residential or commercial loads might not match up to controlling large loads, the similarity in the rating of the devices in residential and commercial buildings makes control simplistic. A group of loads in a residential and commercial building that offer flexibility in their mode of operation is termed thermostatically controlled loads. These loads include water heaters, refrigerators, and air conditioners. They offer easy access for control making them available to provide peak shaving and energy balance in the power system.

1.2.4 Thermostatically Controlled Loads
Thermostatically Controlled Loads (TCLs) have two states, the ON and OFF state. The switching between the two states is controlled by a thermostat. The thermostat has a setpoint temperature whose deadband defines the indoor temperature boundary at which the TCL will come on or go off. The setpoint temperature is input by a user/customer and the thermostat ensures that when the defined temperature boundary is reached, a command is sent to change the state of the TCL. The uniqueness of having two distinct states governed by fixed boundaries gives these appliances an advantage for direct control.
1.2.4.1 Characteristics of TCLs

The characteristics of different types of TCLs can be seen in Table 1.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Air conditioners</th>
<th>Refrigerators</th>
<th>Water Heaters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Consumption (kW)</td>
<td>2-7</td>
<td>0.1-0.3</td>
<td>4-5</td>
</tr>
<tr>
<td>Coefficient of Performance (COP)</td>
<td>2.4-2.7</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Thermal time constant (h)</td>
<td>2.35-6.2</td>
<td>32-80</td>
<td>20-84</td>
</tr>
<tr>
<td>Energy transfer rate (kW)</td>
<td>5-19</td>
<td>0.2-1.0</td>
<td>(-5)(-4)</td>
</tr>
<tr>
<td>Service temperature (°C)</td>
<td>19-27</td>
<td>1.7-3.3</td>
<td>43-54</td>
</tr>
<tr>
<td>Dead-band (°C)</td>
<td>0.25-1.0</td>
<td>1-2</td>
<td>2-4</td>
</tr>
</tbody>
</table>

*Table 1.1: Properties of TCLs*

The fig.1.3 below illustrates average electricity consumption for a single-family house in Florida, USA where space heating, water heating and air-conditioning account for 50% of the house consumption.

*Fig.1.3: Average energy consumption for a single-family house in Florida, U.S.A[51]*
As shown in Fig. 1.3, in 2009 air conditioning accounted for 27% of the electrical energy consumed by an average household in Florida, United States during the summer season [51]. Air conditioning represents a substantial baseline load profile in hot climates due to frequent high external temperatures which account for its prominent installation across commercial and residential sites. An attempt to control an aggregate number of these loads simultaneously in a commercial building is explored in this research as a critical step to energy supply and demand balance. Interrupting the operation cycle of ACs for a short duration will not disrupt their services as compared to other appliances.

The system model in this thesis adopts an automation process which involves a variation of the user-defined setpoint of an AC to provide peak load shaving. The customer’s responsibility of manually operating their appliances is automated as a way to implement demand response. The customer’s appliance can be directly controlled based on a transactional agreement between the utility and the customer.

1.3 Literature Review

Studies have shown that to investigate the impact of controlling a large number of TCLs as a way to implement an effective demand response program, it is necessary to study the effect of TCL parameters on a large population of TCLs[22][23]. Using a stochastic difference equation the author in [22] observed that the ambient temperature parameter plays a huge role in aggregate power consumption of air conditioners (ACs) due to its direct proportionality to the internal temperature of a room. In [23] direct proportionality of ambient temperature to power consumption in a single AC and a heterogeneous population of ACs is highlighted.
Several papers have explored different control methods for TCLs. A controller that uses fuzzy logic to control ACs based on a set comfortable temperature and the brightness of the day is proposed by [24][25][26]. Optimal and predictive control strategy of TCLs takes into consideration the characteristics of a building’s model [27][28][29]. This requires developing models and mathematical computations that takes into cognition the uniqueness of different parameters in the buildings and an accurate estimation of future disturbances. The complexity involved in the optimal and predictive approach can be complicated. In [30] a decentralized control implementation of a large population of ACs was developed. The proposed method utilizes the formulation of a power consumption curve based on the signal received from the utility to control individual devices. The accuracy in the generation of the individual power consumption curve for each device model is a significant factor in ensuring the success of this strategy that makes it tedious and complicated. In [31] a mathematical model which uses manipulation of the width of the hysteresis band of ACs as a control signal to implement aggregate demand response of ACs while considering customer’s comfort is developed.

In [32] modeling of a large group of TCLs can be seen and the oscillatory issue of TCLs after control is discussed. The authors observed that a period of power supply interruption in a large population of TCLs causes switching off a majority of the TCLs. This leads to large oscillations in the power system at the end of the interruption which are referred to as cold pickup or rebound effect. These oscillations occur because when power supply is restored, a large percentage of TCLs start at the same time and this can be a challenge to the stability of the power system. The magnitude and duration of this cold pickup is dependent on the diversity of rooms, duration of control period and outside
temperature, hence it is necessary to take this into consideration when controlling TCLs for demand response. The strategy of global setpoint change by $\pm 1^\circ C$ as a way to control the aggregate power consumption of TCLs is proposed in [33][34]. It is observed that manipulating the user-defined setpoint of a TCL load by $1^\circ C$ instantly changes the state of such load. In [35], the authors proposed modeling and control of a homogeneous population of TCLs using setpoint variation. Increasing the set point temperature of a large population of ACs by a small fixed change, led to a sudden and a sharp drop in aggregated power consumed, whereas a decrease in setpoint temperature to its initial value led to an increase in the power consumed. In this method, due to the assumed homogeneity and collective control of all TCLs at the same time, a large interruption in customer’s thermal comfort during the control period will be observed. Also, power surge oscillations were observed to be high and encountered for a long period after the control period. In [36] a mathematical model is used to design a controller that uses a setpoint variation feedback control strategy for aggregate load regulation. The controller carries out setpoint control for a given peak period, by broadcasting the same setpoint value to all TCLs until aggregate power consumption is lower than the normal steady-state consumption throughout the control period. When air conditioners are brought back to their initial set point before control, simulation results showed that a high load demand that causes large oscillations occurs due to a very high rise in internal room temperature during the control period. To offset these oscillations, the author suggests control of the population of air-conditioners in clusters, where different control signal is assigned to each cluster. The work [37] proposed a method that uses the heterogeneity of a large population of ACs to derive a mathematical formula that reduces power and temperature oscillation after setpoint control. Aggregate power
consumption is regulated by a simplified second-order linear time-invariant transfer function model which uses a closed-loop setpoint variation control strategy. [37] suggests further control of the large population of loads beyond the control period as a means to reduce the oscillations that occur after control. The application of set point variation as a control method is studied in [38][39], where setpoints of a large population of TCLs are increased to a value such that, throughout the peak period, the loads are switched off. High oscillations were observed at the end of these control periods when the set points were returned to their initial values. Preheating, precooling and reduction of a set point back to its initial value in steps was suggested to reduce these oscillations. The results for the suggested solutions proved to be valuable in reducing oscillations. The work [40] proposed a solution to reduce the oscillation problem and thermal discomfort in aggregate load control. The proposed solution minimizes the number of loads controlled by using the switching ON/OFF of feeders as a control strategy. A boundary load level and maximum and minimum ON/OFF time are specified for each feeder. A constraint is placed on the maximum average internal room temperature of each customer, which if exceeded determines that the feeder must be switched ON or OFF. The results proved to be effective in controlling demand during peak hours and reducing customer’s inconvenience.

Regulating the aggregated power consumption of thermostatically controlled loads using the setpoint change methods can also be done through a programmable communicating thermostat (PCT) as suggested in [41] [42] but presently the cost associated with the installation of each TCL device with PCT is high. Centralized control of HVAC units was presented in, [43][44]. The work [43] used a simulation of the aggregate baseline load consumption of a large number of HVACs to develop a load forecast utilized by the
controller to provide ancillary services through ON/OFF control of the HVACs. To consider the customer’s comfort, the control of ACs was done according to temperature priority and a stipulated time was assigned for the control of each device. In [44] set point variation is done using a centralized controller based on two methods. These methods use stored database information of each AC to compute a new setpoint value. In the first method, a new setpoint value for each AC is computed based on a stored user-defined setpoint and no criteria for utility/system operator’s requirements. In the second method a new setpoint value for all ACs is computed based on database information that consists of target demand, ambient temperature, the cooling capacity of each AC and floor area. In these methods, the control strategies take into account thermal comfort through the method used to assign new setpoint values however the ACs are all controlled at the same time. The work in [45] proposes an algorithm which considers thermal comfort of residents. It uses the zone of each AC in a building to compute a new setpoint value. This requires the modeling of each building as a necessary condition to carry out setpoint variation control, therefore, making it complex.

1.4 Summary of Major Challenges Associated with Setpoint Aggregate Control of ACs

- Assigning large setpoint value to ACs that ensures they maintain a fixed on or off state throughout the control period can often result in a large thermal discomfort which can be discouraging to customers.
Using the conventional method of switching off ACs during control time interval results in high oscillations when the ACs are returned to a steady state. These oscillations referred to as cold pickup or rebound effect are not peculiar to the conventional method of control alone but are also prevalent in setpoint variation control. In the modeling of a homogenous population of ACs using large setpoint variations, the aggregate power consumption did not return to steady-state after control[46]. High oscillations were also observed because of homogeneity in the manner of operation of all the ACs.

1. 5 Research Objectives and Contributions

1.5.1 Research Contribution

The contribution of the present thesis research work is the development of an aggregator system model that uses an intelligent setpoint variation control strategy supporting peak load shaving by aggregated control of air conditioners in a large hotel. The control of ACs is done from a centralized setpoint variation controller and it demonstrated peak shaving of the aggregate power consumption of the ACs. Also, the setpoint control strategy presented in this research work takes into consideration the rebound effect. The control of ACs reduces the rebound effect issue by implementing a strategy of further control of ACs after the control time interval as suggested in [37].

In [47] an energy management system that uses setpoint variation of ACs to reduce energy consumption and consider customer comfort is designed. It is observed that the setpoint temperature of ACs is manipulated within [(user-defined setpoint+2°C) - 27°C]. To consider customers comfort, the condition that room temperature equals setpoint
temperature is assumed as the only criteria to be fulfilled before the controller can change the setpoint temperature of an AC. Also, an assumption is made that a maximum time is given for the control of each AC to prevent consumer’s discomfort. This research work differs as the condition to control an AC depends on a scheduled day ahead forecasted utility profile and a setpoint temperature list of all ACs.

In this thesis, the thermal/customer’s comfort of a room can be defined as a customer’s desirable room temperature. This room temperature is defined by the customers-defined thermostat setpoint temperature. In some of the studies reviewed above such as [38] [44] the new setpoint values assigned to an aggregate number of ACs is done in such a way that these ACs are switched off/on throughout the control period but in this research work, the setpoint of ACs selected to be controlled are varied in small steps. This reduces the deviation expected in customer’s indoor room temperature when a complete shutdown of the ACs throughout the control period is done or a large population of ACs are assigned setpoint values such that they maintain a constant off or on state throughout the control period.

1.5.2 Thesis Objectives

The objectives highlighted below are achieved in this thesis:

- To propose an intelligent setpoint temperature variation-based control strategy for an aggregator that can implement peak shaving by regulating a population of air conditioner loads.
- To analyze the impact of the proposed DR methodology on the aggregated power consumption of ACs and end-use device performance.
To show how the analysis that relates daily ambient temperature profiles to capacity for shifting and end-use device performance may be used to inform interaction between the controller and the system operator.

1. 6 Thesis Structure

The thesis is composed of the following chapters. Chapter 2 describes an overview of the design of the proposed system model with a setpoint variation control strategy. Chapter 3 describes the modeling of the control strategy algorithm used in this thesis along with a case study to show validation of the setpoint variation control. Simulation results are also presented. Chapter 4 presents the performance evaluation of the proposed control strategy with an objective to illustrate peak load shaving and reduced residents’ discomfort. Chapter 5 summarizes the research, contributions and proposes future recommendations.
Chapter 2

Problem Statement and System Model

This chapter gives an overview of the necessary techniques used to design the proposed system model.

2.1 Formulation of the Problem

Controlling AC loads to reduce the high power demand during the peak periods of the day has an economic advantage to the utility because utilization of generation is increased. However, this may negatively impact customer comfort if ACs are switched off throughout the control period. In this research work, the problem is to develop a controller that adjusts individual thermostat setpoints of a large number of ACs such that the aggregated power tracks a utility demand signal that results in peak load shaving. It is hypothesized that customer comfort depends on the magnitude of the change in aggregated power from baseline operation. To manage customer comfort when ACs are controlled, the controller engages in a transaction with the system operator by specifying upper and lower limits on the change in aggregated power that can be acted on by the controller. The upper limit is referred to as reserve capacity up and the lower limit is referred to as reserve capacity down. The system operator in response specifies a feasible regulation signal input,
constrained in magnitude within the limits specified by the reserve capacity. The reserve capacity is determined by the controller and depends on the baseline aggregated power (that in turn depends on ambient exterior temperature) and the level of degradation in customer comfort that will be tolerated.

In Fig 2.1 the controller generates a baseline power profile of ACs which depends on the outside temperature. The baseline power profile defines the maximum limit on upward and downward shift. Although there is a maximum capacity for shifting up and down, it may be appropriate to constrain the amount of loads to be shifted below the maximum limit to ensure customer comfort is not significantly degraded. The controller communicates this indirectly to the system operator, by specifying the reserve capacity up and the reserve capacity down. This ensures i) the regulation signal provided by the system operator is feasible and can be acted upon by the controller and ii) bounds on the expected change in customer comfort are known to the controller.

Assumptions used in the system model includes:

- All ACs are simulated by a non-linear differential equation.
- There is a diversity in the thermal parameters of each room where an AC is installed.
- Thermostat setpoint is the control signal used by the controller to turn AC loads ON or OFF
- ACs used in the system model all have the same power rating value.
- A day ahead’s outside temperature is assumed as the forecasted weather data used by the controller to establish the magnitude of shifting that can be accommodated and its impact on customer comfort.
The controller provides day ahead information which is indirectly communicated to the system’s operator to be used as component for planning. The sections below describes the various parts of the proposed system model in Fig. 2.1.

2.2 Forecast

2.2.1 Baseline Power Profile (Punc)

The baseline operation of an air conditioner can be referred to as the normal operation of the air conditioner without any form of external control. A forecasted baseline profile can
be established with the knowledge of the outside weather data/ambient temperature where the proposed control strategy will be implemented. It is necessary to have accurate information on the ambient temperature of the environment to forecast a baseline power profile of the AC \( P_{\text{unc}} \). A knowledge of the baseline power profile allows the maximum capacity to shift load up and the maximum capacity to shift load down to be determined. This ensures that the number of loads scheduled by the utility to be switched on or off can be met by the controller. This thesis considers ambient temperature data profiles for Barbados in testing the control strategy algorithm however the control strategy algorithm can be applied in any weather climate.

### 2.2.2 Utility Demand and Regulation Signal

The utility demand \( P_{\text{ud}} \), refers to an anticipated hourly scheduled and desirable load profile which the aggregate AC load profile should track during a planned control time horizon. In this research work, this load profile is generated by adding or subtracting a regulation signal \( P_{\text{reg}} \), to the aggregated baseline power consumption profile \( P_{\text{unc}} \), as seen in equation 2.1.

\[
P_{\text{ud}}(t) = P_{\text{unc}}(t) \pm P_{\text{reg}}(t)
\]

where \( P_{\text{ud}} \) is the utility demand at the time, \( t \) in kW.

\( P_{\text{unc}} \) is the forecasted baseline aggregate power consumption of the population of ACs at time \( t \).

\( P_{\text{reg}} \) is amount of power in kW required to generate the utility demand.
Fig. 2.2 illustrates a graphical explanation of equation 2.1 and how it is applied in the control strategy. For example at a given time $t$, during the off-peak period $t_0$ to $t_1$, which is the time of the day when there is anticipated low energy demand, the forecasted baseline profile is increased by $P_{reg}$ while during the on-peak period $t_1$ to $t_2$, which refers to the time of the day when there is anticipated high energy demand, the baseline power profile is decreased by $P_{reg}$.

![Fig. 2.2: Illustration of Preg](image)

2.2.3 Reserve Capacity Up and Reserve Capacity Down

The reserve capacity refers to the upper and lower limits of aggregate ACs load that may be shifted. This will ensure that the system’s operator planned scheduled load profile is bounded by this limits.

2.2.4 Customer Comfort Degradation Limit

In the system model, the customer comfort degradation limit informs the utility on end-use device performance and the extent to which the magnitude of load shifted can
affect customer’s comfort. In this research work, it is measured by the deviation in room temperature from the user setpoint.

2.2 Controller

An insight is given on how the controller works to schedule the aggregated power consumption profile of the ACs to track the anticipated utility demand.

2.3.1 Controller’s Mode of Operation

There are three possible modes of operation to carry out demand response programs which can be classified as automated, semi-automated and manual. The direct load control method proposed utilizes an automated mode of operation in carrying out the research work. Automated mode of operation is mostly carried out to control cooling and heating appliances, where the appliances optimize their operation cycle at an individual level by automatically responding to a received input/control signal sent by the controller.

2.3.2 Design of Controller

The controller can be a centralized or decentralized type. In decentralized control, the devices are controlled independently by different controllers. An advantage of using decentralized control is that the controllers can be located close to their devices and the cost in relation to communication infrastructure for centralized control is reduced. Each device has its own autonomous control. As seen in [48] the decentralized control provides a faster response due to fewer delays and data losses when compared to centralized control however it has much more complicated predictability. In centralized control, the controller is situated in one location and is connected to every single device designated for control.
The controller collects information on the behavior of each device and communicates control decisions from a central location. The cost of having individual controllers for each device is reduced, however, technical challenges such as transferring a large amount of data, limited bandwidth, delays, and loss of data are a limitation on the centralized control. Nevertheless, it provides better linear predictability between control decisions and more simplistic load reduction than the decentralized control[48]. This thesis adopts DR in the form of centralized control in presenting the proposed control strategy.

### 2.2.3 Balance Signal

A technique is used by the controller to ensure aggregate AC loads tracks the utility demand. This technique prevents controlling all ACs at the same time during the control interval of the day. The controller does this by comparing the utility demand $P_{ud}$, at each point in time to the real-time aggregate power consumption of the ACs. A balance signal $P_{bs}$, which is the difference between the utility demand $P_{ud}$ and real-time aggregate power consumption is generated as seen in equation 2.2.

$$P_{bs}(t) = P_{ud}(t) - P_{agg}(t)$$

(2.2)

where, $P_{bs}$= load balancing signal in kW.

$P_{ud}$= scheduled demand by the utility in kW.

$P_{agg}$=aggregate power consumption of the ACs in kW.

Based on the value of the balance signal, the controller selects ACs in such a way that their aggregate power consumption is equal to the balance signal. The balance signal which could be zero, negative or positive is explained below.
2.3.3.1 Balance Signal equal to Zero

In a scenario where the balance signal is zero, no AC’s are required to have their setpoint manipulated by the controller and therefore the state of every AC will be left unchanged.

2.3.3.2 Balance Signal greater than Zero

A positive balance signal refers to an upward balance (i.e. some ACs are needed to be switched ON) to meet the scheduled load profile from the utility.

2.3.3.3 Balance Signal less than Zero

A negative balance signal refers to a downward balance (i.e. some ACs are needed to be switched OFF) to fulfill scheduled utility load profile.

2.4 Air Conditioners (ACs)

Air conditioning can be described as the removal of heat from an enclosed and occupied environment and releasing cool air into the environment. The aim of air conditioning is to ensure residents in an enclosed space are comfortable and, in the process, aid to cool some devices that emit heat. The possibility of performing load shifting on air conditioners is analyzed and illustrated in the rest of the chapters.

2.4.1 Thermostats

A thermostat is a component of an air conditioner. It regulates cooling or heating based on its assigned setpoint temperature. They are commonly used in water heaters, air conditioners, HVAC system, and refrigerators and are basically divided into mechanical
and digital. The mechanical thermostats are commonly classified into two types, which are the bimetallic strips and the gas-filled strips. The digital thermostats are assumed as the thermostats to be used to implement the setpoint variation control strategy. This thermostat contains a thermistor, whose resistance value changes with temperature. When an end-user specifies a setpoint temperature, the thermostat runs a current through the thermistor and measures its resistance concurrently. As the temperature in the room changes, the resistance of the thermistor also changes. The thermostat uses the change in the resistance value of the thermistor to predict the temperature of a room. If a high temperature is indicated, the thermostat sends an indication to the air conditioner to turn it on. Once the temperature of the room drops down within the user-specified lowest temperature, another signal is sent from the thermostat to turn off the air conditioner. Some present-day digital thermostats termed programmable thermostats have a clock that allows users to configure thermostats ahead of time. End users can program the setpoint of a thermostat based on the day of the week, time of the day depending on the available parameter. This feature gives users the ability to manage their energy consumption and reduce the cost associated with heating or cooling.

2.4.2 Operation of Air Conditioner

An air conditioner consists of five basic components to carry out its operation. These components include a compressor and a condenser located at the outside part of the system, an evaporator coil located on the inside, a blower, and a chemical refrigerant.

When the thermostat receives a signal that the room temperature is above the user-specified boundary, the switch in the thermostat closes and it sends a signal to the
compressor contactor which energizes a circuit in the compressor contactor and the fan circuit. The compressor contactor closes which makes the compressor and condenser fan turn on. During this process, the blower fan also turns on and blows hot air from the room over the evaporator coils. A liquid chemical refrigerant inside the evaporator absorbs the heat in the hot air. The chemical refrigerant changes from a cool liquid to hot gas. The hot gas is then passed to the compressor, which compresses it to a state of higher pressure and temperature. The hot high pressurized gas flows through the condenser which changes the gas back to liquid by discharging heat to the surrounding environment. Afterward, the cool liquid flows through an expansion valve back into the evaporator. The entire cycle repeats itself again until the desired room temperature is achieved.

![Fig. 2.3: Schematic view of an air conditioner](image)

### 2.4.3 Type of Air Conditioners

Various types of air conditioners can be installed in a building and are majorly grouped into central and individual air-conditioning. The commercial building used as a case study for this research work is equipped with individual air conditioners. This type of
air conditioner consists of individual units that pump air for each room. They include wall air conditioners (installed in the wall of a room in a building), and window air conditioners (installed on windows that glide up and down and windows that open sideward such that the AC sits on the window and vents hot air removed from the room outside). The ACs modeled in this research work are categorized as individual ACs.

2.4.4 Load Modelling

Different models have been proposed for ACs. These models comprise of a relationship between the power consumption of ACs and its parameters such as ambient temperature, thermal resistance to determine the on and off states of the AC. The model of AC used in this research work and its basic operation is presented below.

2.4.4.1 Mathematical Modelling of ACs

A mathematical model of the AC used in this thesis is presented. Equation 2.3 states the first-order differential equation of an AC for a room widely used in the literature [23][35] [49].

\[ \dot{T}(t) = -\frac{1}{CR}(T(t) - T_a(t) + m(t)RPȠ) \]  

Equation 2.3

The variables and parameters are summarized below.

- \( R \) represents the thermal resistance of the room in (\(^{0}\)C/kW).
- \( C \) signifies the thermal capacitance of the room (kWh/\(^{0}\)C).
- \( P \) is the power rating of the air conditioner (kW).
- \( T_o \) is the outside temperature and \( m \) is the on/off state of the AC (\(^{0}\)C).
- \( T \) is the indoor room temperature (\(^{0}\)C).
\( \eta \) denotes a unitless coefficient of performance which is approximated as a linear function in [23] as

\[
\eta(T_a) = -0.14(T_a - 35) + \eta_0
\]

(2.4)

where \( \eta_0 \) is a nominal value and the ambient temperature is at a range of \( 20^\circ C \leq T_a \leq 35^\circ C \).

Equation 2.5 relates to the operational cycle of an air conditioner which depends on room temperature \( T \) and setpoint temperature \( T_s \).

\[
m(t^+) = \begin{cases} 
0, & \text{if } T(t) \leq T_s - 0.5 \\
1, & \text{if } T(t) \geq T_s + 0.5 \\
m(t), & \text{otherwise}
\end{cases}
\]

(2.5)

where \( m = \) state of AC which is ON or OFF

\( T_s = \) setpoint temperature of an AC’s thermostat

The temperature of the room, \( T \) is constrained within a 1 \( \circ C \) deadband of the setpoint temperature. This temperature range is constrained within \( T_s - 0.5(T_{slow}) \) and \( T_s + 0.5(T_{supp}) \) which refer to the lower and upper deadband of the setpoint temperature. The upper and lower deadband of the setpoint temperature also defines the upper indoor temperature limit \( T_+ \) and the lower indoor temperature limit \( T_- \).

2.4.4.2 Parameters Associated with the Operational Status of First Differential AC

The mathematical model of the air conditioner in equation 2.1 consists of parameters that can be grouped into physical parameters and other parameters.

- Physical parameters: These parameters are associated with the features of the building in which the AC is installed. They are unique to each room and assumed...
to be fixed throughout the operation of the ACs. These parameters include thermal resistance $R$ and thermal capacitance $C$.

- Other variables: These variables may be fixed and constant for all ACs or may vary from time to time during the operation of the ACs. They include ambient temperature termed $T_a$, thermostat setpoint temperature $T_s$, indoor temperature $T$, and nominal power rating $P$.

### 2.4.4.2.1 Ambient Temperature

The ambient temperature can also be defined as external weather data and is a relevant component of the system model. The ambient temperature defines the power consumption profile of an AC because the rate of the energy consumption of an AC largely depends on the temperature. For air conditioners, during the hottest period of the day, power consumption is highest because air conditioners consume more power to constantly maintain room temperature within the temperature specified by the consumer. Therefore a forecast of the ambient temperature is imperative for day ahead planning by the utility.

### 2.4.4.2.2 Thermal Capacitance

Thermal capacitance $C$ can be defined as the heat flow required to change the temperature of an enclosed space. It depends on the building where the AC is installed and is defined by the formula,

$$C = V \times p \times C_p$$  \hspace{1cm} (2.6)

where $V$ is volume in $\text{m}^3$,

$p$ is density in $\text{kg/m}^3$ and
\[ C_p \text{ is specific heat at constant pressure in J/kg}^\circ \text{C} \]

### 2.4.4.2.3 Thermal Resistance

In a building, heat flow is governed by the temperature difference across the room, the conductivity of the building material and the thickness of the building material. Thermal resistance is governed by the equation 2.7

\[ R = \frac{I}{K} \]  

(2.7)

where \( R \) is thermal resistance (\( ^\circ \text{C}/\text{kW} \)), I is thickness and \( K \) is the conductivity of the material.

### 2.4.5 Basic Operation of a Single First-Order Differential AC

The setpoint temperature of the single air conditioner model in Fig. 2.4 and Fig. 2.5 is 21\(^\circ\)C with a deadband of 1\(^\circ\)C. The room temperature \( T \), is constrained between \([T_{supp}, \ T_{slow}]\) which is 21.5\(^\circ\)C and 20.5\(^\circ\)C respectively. The values of \( R, C, Ta, P \) and \( \eta \) used for the simulation are 2, 3.6, 26, 2 and 5.46. The cooling state of the AC which entails the consumption of power is activated by the thermostat when the room’s temperature increases to 21.5\(^\circ\)C while the non-cooling state is triggered when the room temperature decreases to the lower temperature of 20.5\(^\circ\)C.

Fig. 2.4 and 2.5 illustrate the AC power consumption and room temperature change with a single AC. For the AC model defined in equation 2.3, the ON and OFF state is indicated by a binary status of 1 and 0 in Fig. 2.5. The AC comes ON and consumption of power starts when the temperature signified in Fig. 2.4 equates 21.5\(^\circ\)C. At this point, the enclosed space/room is being cooled and this cooling continues until the indoor
temperature in Fig. 2.4 drops to 20.5°C, at which time the thermostat sends a signal which turns OFF the compressor of the AC. When this happens the power consumption becomes insignificant and the temperature of the room starts increasing towards the upper bound threshold which when attained causes the compressor to come ON again.

In nominal operation, assuming the air conditioner is ON, the room temperature decreases from $T_+$ to $T$. If $T(0)= T_+$ is substituted in equation 2.3, we obtain as seen in [35]

$$T(t) = (T_a - PR)(1-e^{-t/RC}) + T_+ (e^{-t/RC})$$  \hspace{1cm} (2.8)

When the air conditioner is off, we assume the temperature of the room is increasing from $T$ to $T_+$. Assuming, the initial condition as $T(0)=T$. we obtain

$$T(t) = T_a (1-e^{-t/RC}) + T_-(e^{-t/RC})$$  \hspace{1cm} (2.9)

In equation 2.10, the time taken for an AC to cool i.e from $T_+$ to $T$. can be calculated as $T_c$

$$T_c = RC \ln \left( \frac{PR + T_+ - T_a}{PR + T_- - T_a} \right)$$  \hspace{1cm} (2.10)

Also, based on equation 2.11, the time it takes for the temperature of a room to heat up from $T$. to $T_+$ can be calculated as

$$T_h = RC \ln \left( \frac{T_a - T_+}{T_a - T_-} \right)$$  \hspace{1cm} (2.11)

The time of an air conditioner’s entire cycle is denoted by Equation 2.12a

$$T = T_c + T_h$$  \hspace{1cm} (2.12a)

The duty cycle of an air conditioner when it is on is denoted by

$$D = \frac{T_c}{T_h}$$  \hspace{1cm} (2.12b)
Therefore, the expressions for the cooling and heating time at any intermediary temperature $T_n$ is given in equation 2.13

\[ t_c (T_n) = RC \ln \left( \frac{P_R + T_+ - T_a}{P_R + T_- - T_a} \right) \]  

(2.13a)

\[ t_h (T_n) = RC \ln \left( \frac{T_a - T_+}{T_a - T_-} \right) \]  

(2.13b)

Fig.2.4: Room temperature with a single AC

Fig.2.5: Power demand of a single AC
2.5 Load Control Strategy

The control strategy defines how the controller alters the ACs aggregate power consumption \( P_{agg} \), in order to track the scheduled load profile \( P_{ud} \), while maintaining customer comfort. In this thesis, the setpoint variation control strategy is used. The effect of varying the setpoint on an ACs power consumption is presented and discussed below.

2.5.1 Effect of Change in Setpoint Temperature of a Single AC

Fig. 2.6 shows the operation of a single AC at a constant ambient temperature with a change in its setpoint. At the 400th minute, the setpoint of the AC shifts from 21°C to 22°C, which makes the upper deadband increase from 21.5 to 22.5, thereby increasing the nominal off time for this AC cycle and hence also alters the power consumption.

![SetPoint changes from 21 to 22](image)

*Fig.2.6: Ts changes from 21°C to 22°C at the 400th minute*

2.5.2 Effect of Change in Setpoint Temperature on a Population of ACs

To understand how the setpoint variation control strategy used in this research works, Fig 2.7 shows what happens to the temperature in a population of rooms when a setpoint variation is applied. The three rooms have similar thermal capacitance and resistance and a fixed setpoint of \( T_s = 21°C \) is assumed constant for the three ACs. With a
1°C deadband the upper and lower limit is [21.5°C and 20.5°C]. The initial room temperature for the rooms is 24°C, 22°C and 20°C. At the 600th minute, this setpoint is manipulated to $T_{\text{new}} = 22°C$ resulting in a new deadband [22.5°C and 21.5°C] with the constant 1°C deadband maintained. When the application of the setpoint change is done, the ACs in the ON the state are switched OFF, because the temperature of the room is less than the new lower deadband 21.5°C while the ACs that were OFF remain OFF until they satisfy the new upper deadband condition to alter their dynamics to the new deadband limit.

Therefore, for the illustration above, when the setpoint $T_s$, of a population of ACs, is manipulated to $T_{\text{new}}$, the following conclusions can be drawn:

1) ACs in the OFF state with a temperature range below $T_{\text{new}-}$ will remain OFF until they increase to $T_{\text{new}+}$.

2) ACs in the OFF state with a temperature range between $T_{\text{new}+}$ and $T_{\text{new}-}$ will remain OFF until they increase to $T_{\text{new}+}$.

3) ACs in the ON state with temperature below $T_{\text{new}-}$ will instantaneously switch OFF until they increase to $T_{\text{new}+}$.

4) ACs in the OFF state with a temperature above $T_{\text{new}+}$ will switch ON.

The value of $T_{\text{new}}$ can be linked to how much discomfort will be expected using this control strategy. In Fig. 2.7 if $T_{\text{new}}$ of an AC with the on-state is increased to 24°C instead of 22, it will take some time for the room temperature to reach the new upper deadband of 24.5°C, at which the AC switches on.
2.6 Operation of the System Model

Based on the ambient temperature forecast, a baseline power profile of the aggregate ACs is established which is used to generate a scheduled utility demand. During the scheduled control interval, a comparison is made between the aggregate power $P_{agg}$ and the desired utility demand $P_{ud}$, and a balancing signal $P_{bs}$ is computed using equation 2.2. The required balancing signal is implemented by the setpoint controller by switching on/off AC units. To provide the balancing signal, the controller sends back the control command in the form of new setpoint values for each AC through a communication channel. The new setpoint values if appropriately selected will change the state of the AC. The objective of assigning new setpoints by the controller automatically takes them off their user-defined upper and lower boundaries and instantly switches the ACs on/off. If a positive balancing signal is required, the controller lowers the setpoints of the number of ACs needed while if a negative balancing signal is required, the controller increases the setpoint of the number of ACs. A five-minute control sampling period is used in this thesis to obtain the results presented in chapter three. This implies that every five minutes
throughout the chosen control time horizon, the setpoint controller receives necessary information such as $m$, $Ts$ and $T$ from the ACs through an assumed two-way communication channel.

A time delay normally exists between when the controller samples feedback data, generates a new thermostat setpoint and sends it back. This delay should be taken into consideration in designing the control system. This will be discussed in section 4.3.

### 2. 6.1 Rebound Effect

Controlling a large population of ACs using the setpoint variation changes the nominal power consumption. At the end of the control period when the setpoint of all the ACs is restored to the nominal value, a significant peak or trough in power demand may occur, triggering further oscillations. This is known as the rebound effect or payback effect. It is important to consider this rebound effect in the implementation of an aggregated control strategy by taking the necessary steps to eliminate or attenuate the rebound effect issue. As discussed in [25], the magnitude and duration of the rebound effect is dependent on ambient temperature, duration of AC control and diversity of the aggregate number of ACs. An aggregate number of ACs can be grouped into a homogenous and heterogeneous population. This grouping is a factor of variety that exists in the parameters of each AC. In the population of ACs used in this thesis, a semi-homogenous population is assumed where diversity exists in the initial indoor temperature, R and C for each AC.

### 2. 7 The Simulation Software

Several network simulation software or platforms are used by researchers for modelling
thermostatically controlled loads. Widely used software includes Energy Plus, Gridlab-D, ESP-R, and MATLAB/SIMULINK. The design of the proposed system was built in Matlab 2018a and can be seen in Appendix C. MATLAB/SIMULINK is a user-friendly software for the model of air conditioners used in this thesis.
Chapter 3

Controlling Air Conditioners for Providing Peak Shaving

3.1. Introduction

In this chapter, a detailed analysis of using the proposed system model and control strategy to perform peak load shaving in a large hotel is discussed. Simulation results are also presented.

3.2 Model Validation – Case Study

The commercial building case study used to conduct this research was a proposed hotel in Barbados. The hotel has five hundred rooms with an AC in each of the rooms. The hotel is chosen for validation of this research work due to the similarities that exist in the construction of each room hereby making it a good option for controlling the ACs from a central location. In this research work, the parameters for modeling the AC discussed in equation 2.1 are presented in subsection 3.2.1 and 3.2.2. These parameters are frequently used in modeling ACs in [23][49].
3.2.1 AC Parameters

Each AC in the hotel is modeled using the first differential model in equation 2.3. The parameters used in modeling these ACs can be seen in table 3.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>2kW</td>
<td>Power rating</td>
</tr>
<tr>
<td>$R$</td>
<td>2°C/kW</td>
<td>Thermal resistance</td>
</tr>
<tr>
<td>$C$</td>
<td>3.6kWh/°C</td>
<td>Thermal capacitance</td>
</tr>
<tr>
<td>$T_s$</td>
<td>18°C</td>
<td>Thermostat temperature setpoint</td>
</tr>
</tbody>
</table>

Table 3.1: Simulation Parameters

To create a semi-homogenous population of ACs, certain assumptions made in modeling the ACs in the five hundred room hotel are seen below:

1. Each room has a slightly different thermal resistance and thermal capacitance.
2. The thermal resistance and capacitance are normally random distributed values generated by using equation 3.1.

\[
R = 0.2 \times \text{randn}(n,1) + 2 \quad (3.1a)
\]

\[
C = 0.2 \times \text{randn}(n,1) + 3.6 \quad (3.1b)
\]

where n= 500 ACs.

3. 100% occupancy is assumed.

4. The power rating $P$, of each AC, is the same.

5. The initial indoor temperature used to begin the simulation is grouped into three values (22°C, 21°C and 20°C). We assume 22°C degree for 160 rooms, 21°C for
180 rooms and 20°C for 160 rooms.

6. The initial setpoint of the thermostat of each AC is assumed to be 18°C.

3.2.2 Weather Data Acquisition

A temperature profile for Bridgetown Barbados for 2019/04/01 is presented in Fig.3.1. This data was collected from the weather underground website with a time resolution of 60 minutes. The lowest temperatures occurred from 9 pm to 1 am while the highest occurred at 9 am. To carry out the simulation, the temperature data was used as the forecasted ambient temperature.

![Temperature profile for April 1st, 2019 in Bridgetown, Barbados](image)

*Fig.3.1: Outdoor temperature for April 1st, 2019 in Bridgetown, Barbados*

Based on the above assumptions and forecasted ambient temperature $T_a$, the aggregate baseline power profile $P_{unc}$ was generated by the controller for the five hundred ACs, as shown in Fig.3.2. This was done by simulating the five hundred ACs using the temperature data presented in Fig.3.1. The shape of $P_{unc}$ closely tracks the temperature data and this suggests that baseline power profile is approximately proportional to ambient
temperature. Appendix A also shows forecasted baseline profile based on different temperature data.

Fig.3.2: Baseline Power Profile Punc for April 1st, 2019

3. 3 Control Framework

The proposed control framework is illustrated in Fig. 3.3. The centralized setpoint controller generates $P_{ud}$ (utility demand) based on the forecasted baseline profile. Since the utility demand $P_{ud}$ generated is based on a forecasted baseline profile $P_{unc}$ and regulation signal $P_{reg}$, the controller ensures that the balance signal $\pm P_{bs}$ that is computed is constrained within the regulation signal used to generate the load profile. The number of ACs whose setpoints needs to be changed is computed by the controller using equation 3.2:

$$N_{needed}(t) = \text{abs(round} \left( \frac{P_{bs}(t)}{P} \right) \text{)}$$  \hspace{1cm} (3.2)

where $N_{needed}$ is the number of ACs required to change state to shift demand by $P_{bs}$

$P_{bs}$ is the amount of power required to balance utility demand.

$P$ is the rated power of the AC.
Once the number of ACs required to meet the balancing signal requirement is determined, the controller chooses the specific ACs whose setpoint temperature will be adjusted. The selection depends on measurements of setpoint temperature $T_s$ and ON/OFF state $m$, of all ACs received by the controller. To choose the ACs to fulfill the balancing signal, the controller creates a dynamically sorted list of ACs which is ranked, based on the setpoint temperature $T_s$ of all ACs.

![Diagram of Proposed Control Framework](image)

**Fig.3.3: Proposed Control Framework**

### 3.3.1 Dynamically Sorted List

The procedure used by the controller to select ACs required to shift demand by $P_{bs}$ involves the update of a dynamically sorted list. The conditions for selecting an AC are
defined below:

1. Based on the balancing signal \( \pm Pbs \), the controller identifies whether a downward or upward balance is required.

2. If an upward balance \( +Pbs \) is required, then a list created and sorted by descending setpoint temperature of all ACs with off state is generated by the controller. The number of ACs required to balance the upward balance are determined by equation 3.3 and the ACs are chosen from the top of the list.

\[
N_{\text{balance on}}(t) = N_{\text{utility demand on}}(t) - N_{\text{presently on}}(t) \quad (3.3)
\]

where \( N_{\text{balance on}} \) denotes number of ACs required to change state from OFF to ON to fulfill \( +Pbs \).

\( N_{\text{utility demand on}} \) denotes number of ACs required to be ON to fulfill utility demand.

\( N_{\text{presently on}} \) denotes number of ACs presently ON.

3. If a downward balance \( Pbs \) is required, an ascending setpoint temperature array of all ACs with the on-state is generated by the controller. Equation 3.4 computes the number of ACs required to meet the downward balance. This computed number of ACs is chosen from the top of the array.

\[
N_{\text{balance off}}(t) = N_{\text{utility demand off}}(t) - N_{\text{presently off}}(t) \quad (3.4)
\]

where \( N_{\text{balance off}} \) denotes number of ACs required to change state from ON to OFF to fulfill balancing signal \( -Pbs \).

\( N_{\text{utility demand off}} \) denotes number of ACs required to be OFF to fulfill utility demand.

\( N_{\text{presently off}} \) denotes number of ACs presently OFF.
To obtain the needed balance signal, a new computation is done by the controller algorithm at each control sampling period. The process of creating and updating the priority list created by the controller also occurs at each control sampling period.

Equation 3.5 assigns the new thermostat setpoint for ACs selected from the sorted list.

\[ T_{\text{new}}(t) = T(t) \pm \Delta T(t) \]  

(3.5)

where, \( T_{\text{new}}(t) \) denotes new thermostat setpoint of the AC at time \( t \).

\( T \) denotes indoor room temperature of the AC at the time, \( t \).

\( \Delta T \) denotes value in °C needed to change the thermostat setpoint of the selected AC to \( T_{\text{new}} \)

\( \Delta T \) ensures that the new setpoint of the ACs will turn the ACs ON or OFF. A positive \( \Delta T \) ensures that an AC changes state from on to off for a downward balance, while a negative \( \Delta T \) ensures an AC changes state from OFF to ON for an upward balance. The larger the value of \( \Delta T \), the more time it takes for an AC’s room temperature \( T \) to reach the new deadband limit of \( T_{\text{new}}(t) \) which will cause the AC to change state again. \( \Delta T \) used in this thesis is 0.6°C.

Fig. 3.4 gives an illustration of how the controller makes the selection of ACs to be controlled. In selecting ACs that will be chosen from the list, the concept of arranging the setpoint in ascending/descending order as a criterion in choosing the ACs was done to ensure that all ACs are equally controlled in a fair manner. An initial approach of using the difference between the indoor temperature \( T \), and setpoint temperature \( T_s \), was also a good way for selection. This approach was also successful in achieving peak load shaving, however, an issue was observed. Observations showed that the setpoint of some ACs was more frequently changed than other ACs and this resulted in a wide diversity of the indoor
3.4 Mitigation of the Rebound Effect

The issue of the rebound effect discussed in chapter 2 is taken into consideration in the proposed control strategy algorithm. At the end of the scheduled control time horizon, the proposed control strategy adopts returning ACs back to their initial setpoints in groups. At the end of the control, the controller creates a list of ACs with setpoints higher than the initial setpoint of 18°C. This is because the ACs with new setpoints higher than the initial value are responsible for the rebound effect issue. In this control strategy, if the list consists of less than eighty ACs, group restoration is not performed but if the number of ACs in the list is greater than eighty, every twenty minutes after the control period ends, the ACs are divided into a set of four and a group of ACs will be restored back to their initial setpoint. This selection is done every twenty minutes until the number of ACs in the list is minimal. Experimental results that compare scenarios where all ACs are reinstated back to their normal setpoint after control and a scenario where ACs are restored back to their initial setpoint in groups staggered over time is presented.
3.5 Setpoint Variation Control Strategy Implementation

Fig. 3.5 illustrates the flowchart for the implementation of the setpoint variation.

The steps for the setpoint variation control strategy are summarized below:

- A forecast $P_{unc}$ is made to determine the baseline profile of the group of ACs when operated without external control and percentage bounds on the capacity for peak shaving.
• Based on this forecasted baseline profile, scheduled utility demand signal $P_{ud}$, is generated.

• At the beginning of each control time period, the external controller generates a setpoint temperature list either in ascending or descending order depending on the load balancing signal $\pm P_{bs}$.

• The ACs that meets $\pm P_{bs}$ are chosen from the top of the lists and then has their setpoints altered.

• At the end of the scheduled control interval, ACs are returned back to their setpoints in groups.

3.6 Simulation Results for Verification of the Setpoint Control Method

3.6.1. Setpoint Control Based on ON and OFF-Peak Period

The demand profile in Fig. 3.6 is used to establish the on and off-peak period used in this thesis for peak load shaving.

Based on this demand profile, two examples of the utility demand $P_{ud}$ are generated. As stated in subsection 2.2.2, the utility demand $P_{ud}$, is generated based on the forecasted mean hourly baseline power demand of the aggregate ACs. For utility demand 1, the off-peak period chosen is 2 am to 8 am where the mean aggregate baseline power demand of the population of ACs is increased by $+P_{reg}$. The on-peak period chosen is 8 am to 5 pm where the mean aggregate baseline power of the population of ACs is decreased.
by $-P_{reg}$. For utility demand2, from 2 am to 8 am, the mean aggregate baseline power of the population of ACs is increased by $+P_{reg}$, while from 8 am to 2 pm, the mean baseline aggregate power of the population of ACs is decreased by $-P_{reg}$. The utility demand2 occurs from 2 am to 2 pm and is referred to as an energy-neutral generated utility load profile. Energy neutral can be defined as a zero difference between the total baseline power demand and the utility demand2 from 2 am to 2 pm. Three regulation signals ±50kW, 100kW, and 200 kW are used to analyze the proposed control strategy. It is worth noting that each regulation signal comes with different observations.

![Power Consumption of Barbados Light and Power Distribution Company](image)

*Fig.3.6: Power Consumption of Barbados Light and Power Distribution Company [55]*

### 3.6.2 Simulink Simulation Results

The simulation results presented in this chapter are for the temperature data of April 1st, 2019. More simulation results can be found in Appendix A and B for different temperature data.

#### 3.6.2.1 Results for Utility Demand1 with Different Regulation Signals

Fig.3.7 shows the utility demand1 generated based on the different regulation signals. The results of using the setpoint variation method to achieve utility demand1 are
I. Case Scenario One: ±50kW Regulation Signal

In Fig. 3.8 (a), the mustard line represents the scheduled expected utility demand $P_{ud}$, generated based on a ±50kW regulation signal. The aggregate power consumption of all ACs is expected to track this utility demand. The blue line represents the aggregate power consumption of the population of ACs without control. The brown line represents the aggregate power which is achieved with the setpoint variation control. From figure 3.8, if the expected aggregate demand from the utility ($P_{ud}$) is zero, the controller assumes that no form of control is expected for that time horizon. During the control horizon, it is observed that the brown line closely tracks the mustard line, however, in (a), a peak is observed at 5 pm, which is the end of the control. This peak is as a result of the setpoint of every AC been brought back to their initial value before control. In order to avoid this peak, ACs are returned in groups to their initial setpoint value as described in section 3.4 and
the effect is shown in (b) where the huge peak seen in (a) is reduced. The concept used to explain ±50kW can be used for the remaining case scenarios below.

Fig. 3.8: Power consumption profile for April 1st, 2019, using utility demand 1 (Preg ±50kW)

II. Case Scenario Two: ±100kW Regulation Signal

(a): Power Consumption with rebound effect

(b): Power Consumption with rebound effect controlled
(b): Power Consumption with rebound effect controlled

Fig.3.9: Power consumption profile for April 1st, 2019, using utility demand 1 (Preg ±100kW)

III. Case Scenario Three: ±200kW Regulation Signal

(a): Power Consumption with rebound effect

(b): Power Consumption with rebound effect controlled

Fig.3.10: Power consumption profile for April 1st, 2019, using utility demand 1 (Preg ±200kW)
3.6.2.2 Results for Utility Demand2 with Different Regulation Signals

Fig. 3.11 shows the utility demand2 generated and the results of using the setpoint variation method is presented below.

**Fig. 3.11. Generated utility demand2 based on different case scenarios**

I. Case Scenario One: ±50kW Regulation Signal

- **(a): Power Consumption with a rebound effect**

- **(b): Power Consumption with rebound effect controlled**

**Fig. 3.12: Power consumption profile for April 1st, 2019, using utility demand2(Preg ±50kW)**
II. Case Scenario Two: ±100kW Regulation Signal

(a): Power Consumption with a rebound effect

(b): Power Consumption with rebound effect controlled

Fig. 3.13: Power consumption profile for April 1st, 2019, using utility demand2(Preg ±100kW)

III. Case Scenario Three: ±200kW Regulation Signal

(a): Power Consumption with a rebound effect
Fig. 3.14: Power consumption profile for April 1st, 2019, using utility demand $P_{ud} \pm 200kW$

3.7 Conclusion

The utility demand load profile $P_{ud}$, generated based on a forecasted baseline load profile $P_{unc}$, and regulation signal $\pm P_{reg}$, shows that the capacity to shift load up or down depends on the baseline aggregated load profile. For instance, if the utility randomly schedules a load profile without any forecasted information, the price to pay is that there is a possibility of insufficient ACs in the dynamically sorted list. For example, if only an aggregate of 600 kW is consumed by the five hundred ACs but the utility sends a load profile that requires 800 kW of load to be dropped, there will be insufficient ACs that can be switched off to meet up with the utility demand.

Instead of just assigning a large setpoint to every AC or controlling all the ACs at the same time, the proposed control strategy selects the ACs to be controlled from a dynamically sorted list and then increases or decreases the setpoint of an AC in small steps.

From the results presented in section 3.6 and Appendix A and B, the plots shows that the proposed system model uses setpoint variation to control a group of ACs in such a
way that their aggregate power consumption can effectively track the scheduled utility demand hereby achieving peak load shaving during the on-peak period.

The control strategy also reduces the rebound effect issue which occurs after setpoint variation.
Chapter 4

Performance Evaluation of the Control Strategy

4.1 Introduction

This chapter provides an analysis of the performance of the proposed control strategy. The benchmarks used to evaluate this performance are energy conservation and customer comfort degradation limit. Energy conservation here refers to how much energy consumption is reduced using the proposed control method to perform load shifting. A comparison is made between the energy consumption of the ACs in an uncontrolled state and the energy consumption of the ACs in a controlled state. The electricity savings incurred by the customer because of peak shaving is also determined. Customer comfort degradation limit refers to how much inconvenience is expected based on the research method. The minimum and maximum temperature of each room when the ACs are only controlled by their normal thermostat is compared with the minimum and maximum temperature if load shifting is carried out.

4.2 Energy Conservation Evaluation

For evaluating energy conservation, the equation below is used to determine the
percentage of energy saved due to the control strategy implementation. For instance, to obtain the energy conserved for a period of 5 hours, \( s=0, 1, 2, 3, 4 \)

\[
\%\text{difference} = \frac{\sum_{i=1}^{n=500} E_{u,n|i} - \sum_{i=1}^{n=500} E_{c,n|i}}{\sum_{i=1}^{n=500} E_{u,n|s+1}} \times 100
\] (4.1)

where \( \%\text{difference} \) is the percentage of energy consumption conserved

\( E_{u,n} \) is the energy consumption of an AC when no external controller is involved.

\( E_{c,n} \) is the energy consumption when setpoint/external control is incorporated.

Using a real-time time of use (TOU) electricity rate seen in figure 4.1, the energy cost savings for the different case scenarios is also presented below. TOU from Ontario Hydro in the summer season is used because BPLC doesn’t have an existing TOU electricity rate.

![Ontario Hydro TOU](image)

*Fig.4.1: Ontario Hydro TOU pricing*

### 4.2.1 Utility Demand1

Table 4.1 presents a comparison of energy consumption and cost of the five hundred ACs in the controlled and uncontrolled state for different regulation signals using utility demand1 on April 1st, 2019.
Table 4.1: Comparison of energy consumption and cost in controlled and uncontrolled state for different regulation signals (utility demand1)

The results presented in table 4.1 is summarized in Fig.4.2. As the magnitude of shifting increases, the cost savings also increases.

<table>
<thead>
<tr>
<th>energy consumption</th>
<th>on-Peak energy consumption (MWh)</th>
<th>off-Peak energy consumption (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>±50 kW</td>
<td>±100 kW</td>
</tr>
<tr>
<td>no control</td>
<td>9.72</td>
<td>9.72</td>
</tr>
<tr>
<td>setpoint control</td>
<td>9.77</td>
<td>9.79</td>
</tr>
<tr>
<td>%difference</td>
<td>+0.5</td>
<td>+0.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>cost (CAD)</th>
<th>no control</th>
<th>setpoint control</th>
</tr>
</thead>
<tbody>
<tr>
<td>887</td>
<td>849</td>
<td></td>
</tr>
<tr>
<td>887</td>
<td>832</td>
<td></td>
</tr>
<tr>
<td>475</td>
<td>418</td>
<td></td>
</tr>
<tr>
<td>475</td>
<td>369</td>
<td></td>
</tr>
<tr>
<td>243</td>
<td>251</td>
<td></td>
</tr>
<tr>
<td>243</td>
<td>270.6</td>
<td></td>
</tr>
<tr>
<td>243.3</td>
<td>310.2</td>
<td></td>
</tr>
<tr>
<td>%difference</td>
<td>+4.3</td>
<td>+6.2</td>
</tr>
<tr>
<td></td>
<td>+11.1</td>
<td>+11.9</td>
</tr>
<tr>
<td></td>
<td>+22.2</td>
<td>+42.1</td>
</tr>
<tr>
<td></td>
<td>-3.3</td>
<td>-11.2</td>
</tr>
<tr>
<td></td>
<td>-27.5</td>
<td></td>
</tr>
</tbody>
</table>

Fig.4.2: On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 1st, 2019 using utility demand1
4.2.2 Utility Demand2

Table 4.2 presents a comparison of energy consumption and cost of the five hundred ACs in the controlled and uncontrolled state for different regulation signals using utility demand2 on April 1st, 2019.

<table>
<thead>
<tr>
<th>energy consumption</th>
<th>daily energy consumption (MWh)</th>
<th>on-Peak energy consumption (MWh)</th>
<th>off-Peak energy consumption (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>no control</td>
<td>±30 kW</td>
<td>±100 kW</td>
<td>±200 kW</td>
</tr>
<tr>
<td></td>
<td>9.72</td>
<td>9.72</td>
<td>9.72</td>
</tr>
<tr>
<td>setpoint control</td>
<td>±30 kW</td>
<td>±100 kW</td>
<td>±200 kW</td>
</tr>
<tr>
<td></td>
<td>9.84</td>
<td>9.99</td>
<td>10.4</td>
</tr>
<tr>
<td>%difference</td>
<td>+1.2</td>
<td>+2.8</td>
<td>+6.9</td>
</tr>
<tr>
<td>cost (CAD)</td>
<td>no control</td>
<td>±30 kW</td>
<td>±100 kW</td>
</tr>
<tr>
<td></td>
<td>887</td>
<td>887</td>
<td>887</td>
</tr>
<tr>
<td>setpoint control</td>
<td>475</td>
<td>475.2</td>
<td>475.2</td>
</tr>
<tr>
<td>%difference</td>
<td>+2.3</td>
<td>+2.5</td>
<td>+5.2</td>
</tr>
</tbody>
</table>

Table 4.2: Comparison of energy consumption and cost in controlled and uncontrolled state for different regulation signals (utility demand2)

The results presented in Table 4.2 are shown graphically below. The energy cost savings for each regulation signal can be seen as almost constant because of the energy neutrality of utility demand2.
Fig. 4.3. On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 1st, 2019 using utility demand2

4.3 Sampling Rate

The effect of the setpoint controller’s sampling period is analyzed in this section of the thesis.

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>1 minute</th>
<th>5 minutes</th>
<th>10 minutes</th>
<th>15 minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSWIcon</td>
<td>3274</td>
<td>2329</td>
<td>2043</td>
<td>1755</td>
</tr>
</tbody>
</table>

*Table 4.3: NSWIcon for different control sample rates*

In table 4.3, NSWIcon stands for the total number of new setpoints assigned to all ACs during the control time horizon i.e. for instance if AC one had a setpoint change of 20, 22 and 23, the NSWIcon for the AC is three. Using ±100kW (utility demand1), the NSWIcon for 500 ACs for 1, 5, 10 and 15 minutes is presented in table 4.3. It can be observed that there is higher NSWIcon when the sampling period is one minute because the setpoint
of the ACs is changed more frequently by the controller. This frequent change is because the controller is trying to ensure the aggregated power accurately tracks the utility demand efficiently.

From the simulation results seen in section 3.6, the aggregate power doesn’t track the utility demand 100%. The tracking error is caused by the delay discussed in section 2.6 which is the time gap that exists between the setpoint controller carrying out an action based on feedback data received and the implementation of the action. The time gap results in some of the non-selected ACs from the dynamically sorted list changing their state before the implementation of the setpoint controller’s decision. This error thus prevents the aggregate power consumption of the ACs from exact tracking of $P_{ud}$. At each control sampling period, the controller notices this error and tries to rectify it by changing the setpoint of some ACs to ensure utility demand is met. If the controller’s sampling period increases, correction of the error by the setpoint controller is done less frequently. Also, with an increase in the sample period of the controller, the errors tend to become more significant.

The rectification of this error is necessary, but with a lower sampling period, we can expect increased wear and tear on the AC and degradation of AC components. To reach a tradeoff between degradation of the ACs and achieving $P_{ud}$, 5 minutes was chosen as the control sample period.
4.4 Customer Comfort Degradation Limit

In this part of the thesis, the magnitude of the shifted load’s impact on customer’s comfort is analyzed. It is observed that customer’s comfort is reduced with an increase in magnitude of shifted load.

In equation 4.2, the difference $\beta$, between the maximum temperature of an AC when externally controlled and the maximum temperature of an AC when there is no control is calculated. Also, the difference $\alpha$, between the minimum temperature of an AC when externally controlled and the minimum temperature when there is no control is calculated. $\alpha$ and $\beta$ signifies the deviation from the customer’s desired upper and lower temperature when the control action is applied.

\[ \alpha_i = MinT_{con_i} - MinT_{unc_i} \]  \hspace{1cm} (4.2a)

\[ \beta_i = MaxT_{con_i} - MaxT_{unc_i} \]  \hspace{1cm} (4.2b)

where, $i = 1, 2, 3, ..., 500$th AC,

$MinT_{con_i}$ = Minimum room temperature of an AC in a controlled state ($^\circ$C).

$MinT_{unc_i}$ = Minimum room temperature of an AC in an uncontrolled state ($^\circ$C).

$\alpha_i$ = difference between $MinT_{con_i}$ and $MinT_{unc_i}$ ($^\circ$C)

$MaxT_{con_i}$ = Maximum room temperature of an AC in a controlled state ($^\circ$C)

$MaxT_{unc_i}$ = Maximum room temperature of an AC in an uncontrolled state ($^\circ$C).

$\beta_i$ = difference between $MaxT_{con_i}$ and $MaxT_{unc_i}$ ($^\circ$C).

Since the setpoint for all ACs used during normalized operation is 18$^\circ$C, the desired maximum and minimum temperature for all ACs in an uncontrolled state will be 18.5$^\circ$C.
and 17.5°C simultaneously. Using the equation 4.2, results for $\alpha$ and $\beta$ are presented below for the different regulation signals. $\alpha$ is always a negative number while $\beta$ is a positive number.

4.4.1 Customer comfort degradation for utility demand1 and utility demand2

Figures 4.4 and 4.5 give histograms of the number of ACs operating within certain range of $\alpha$ and $\beta$ on April 1st, 2019. For instance, in Fig.4.5 (a) when ±50kW is shifted, it is observed that all five hundred rooms will have $\alpha>=-1$°C and $\beta<=1$°C while for a 100kW regulation signal, only about three hundred and eighty-six rooms will have $\alpha>=-1$°C and four seventy rooms will have $\beta<=1$°C. However as seen in Fig.4.2 and Fig.4.3, the nominal on-peak energy consumption reduction and energy savings of ±50kW is less when compared to ±100kW.

(a): Range of $\alpha$ values of all ACs using utility demand1
(b): Range of β values of all ACs using utility demand1

Fig.4.4: Range of α and β for the 500 ACs on April 1st, 2019, utility demand1

(a): Range of α values of all ACs, using utility demand2

(b): Range of β values of all ACs using utility demand2

Fig.4.5: Range of α and β values on April 1st, 2019, using utility demand2
Based on the analysis result of α and β in this chapter, Fig.4.6 and Fig.4.7 illustrates the customer comfort degradation limit as a capacity of peak shaving percentage. This limit is defined by the expected indoor temperature range for the 500 ACs when the setpoint variation control strategy is used to shift loads of different magnitude on April 1st, 2019. For instance, in Fig.4.6, reducing 10% of the on-peak hour's energy consumption (4MWh) results in indoor temperature within the range \([T_{slow-1}, T_{supp+2}]\). Better range of comfort limits result in a lower capacity for shifting.

**Fig.4.6: Customer comfort degradation limit as a function of load shifting from a 4MWh forecasted on-peak energy consumption on April 1st, 2019**

**Fig.4.7: Customer Comfort limit as a function of load shifting from a 3MWh forecasted on-peak energy consumption on April 1st, 2019**
4.5 Conclusion

In this chapter, the performance evaluation of the control strategy based on the different utility demand and regulation signal has been presented. It has shown excellence in peak load shaving however the magnitude of load shifted has an impact on customer’s comfort.

Therefore from the performance evaluation analysis result in this chapter and Appendices A and B, the following can be summarized as its relevance to the system operator/utility.

1. The daily temperature profile governs aggregated baseline power.

2. A knowledge of a day ahead forecasted temperature profile can be used by the controller to determine the forecasted aggregated baseline load profile which determines the capacity to shift load up and down.

3. Based on the evaluation analysis, the controller can generate a reserve capacity up and down bounded by expected customer comfort degradation limit. This is communicated to the utility/system operator for a day ahead planning. This ensures that the system’s operator will take into consideration customer comfort in planning the magnitude of load to be shifted.
Chapter 5

Conclusions and Future Work

5.1 Thesis Contribution

A direct load control strategy that performs peak load shaving while taking into consideration customer comfort is proposed in this thesis. The control strategy involves manipulating a customer’s defined setpoint temperature to a new value such that the required utility demand is fulfilled at every point in time. Although the work has focused on peak load shaving, the workings can be applied for providing ancillary services.

The main contributions of the thesis are summarized as follows:

1. An intelligent system model using setpoint variation control strategy for aggregated loads has been developed with a case study conducted on a 500 semi-homogenous room hotel. When peak shaving is implemented with the control strategy, energy consumed during chosen on-peak hours is reduced. This reduction is necessary and beneficial to the utility because it prevents increasing power generation required to satisfy power demand. In addition, the rebound effect issue dominant in setpoint variation control strategy is reduced.

2. The controller can provide a day ahead information to the system’s operator on the reserve capacity to shift up and down and the expected customer comfort degradation
limits. This enables the system’s operator to select a regulation signal that takes into consideration customer’s comfort.

3. The controller selects ACs to be controlled based on a forecasted utility load profile and a dynamically sorted list of ACs. To ensure that discomfort is accommodated the setpoint temperature of the selected ACs are varied in small steps preventing a complete shutdown of the ACs throughout the control period, hence the deviation expected in customer’s room temperature can be reduced.

5.2 Future Work

This research work demonstrated strong results with the proposed control strategy but nevertheless, it is recommended that further improvements be applied for better results. The recommendations for future work are presented below:

1. In chapter 3, an occupancy assumption has been made. This might not accurately depict a real-world scenario. Therefore, it is necessary that for implementation of this control strategy in any real-world situation, precise occupancy can be as a way to select ACs to be controlled. Taking this into consideration can ensure that $\pm \Delta T$, defined in chapter 3 as the amount by which setpoint temperature of an AC is increased or decreased can be much larger for unoccupied rooms than occupied rooms.

2. The proposed control strategy had an assumption of a communication channel. The effect of this assumption can be seen in the time gap between the setpoint controller decision and thermostat implementation which results in accurate tracking of utility demand. This time gap in the simulations was seen to be about 0.0002
seconds. However, in a real-world implementation, this time can be much more due to package losses, delays or misinterpretation of the broadcast signal. It is, therefore, necessary to give an allowance that takes into consideration these issues in real-world implementation to ensure good results.

3. The control strategy can be studied for different ancillary services and also extended to different TCL loads i.e. the population of loads controlled should be diversified with TCLs that include water heaters, ACs, refrigerators and similar loads. This ensures that a single controller is maximized in a building rather than having different controllers for different groups of TCLs.

4. From the results presented, it can be observed that the proposed control strategy achieves rebound effect mitigation but the peak after the control period is seen to be higher with an increase in regulation signal. This is because more ACs have their setpoint higher than the initial value of 18°C. It can, therefore, be suggested that with an increase in regulation signal, the rebound effect can be further reduced by increasing the set of ACs in the list discussed in section 3.4 from four to a higher number or to increase the time interval (twenty minutes) when ACs are returned back to setpoint.

5. An interesting area to explore for future research is to have a definite structure that defines thermal discomfort. This may be done in a qualitative survey by implementing the control strategy with different regulation signals for a real-world scenario. Feedbacks should be gotten from customers’ on how the deviation from their defined temperature affects them.
6. Using the AC model in this research work, an interesting area to explore for future research is to take into assumption the location of each controlled room as a method in the decision making of the ACs to be manipulated by the controller. This simply means that if we have two rooms A and B in a building and room A has one window and room B two windows. This can be a consideration when creating the sorted list to fulfill $\pm Pbs$. This will ensure that the participating ACs are selected in such a way that thermal comfort will be better improved.
Bibliography


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APPENDIX A

This chapter shows further simulation results that highlight the success of the proposed control strategy. As seen in fig. A.1, different forecasted baseline power profile of the 500 ACs is generated based on the three different temperature data. The three daily weather used are retrieved from weather underground website for the days 01/01/2018, 8/04/2018 and 01/08/2018. The concept of the setpoint variation control strategy concept explained in chapter three is applied to perform load shifting on the forecasted baseline power profile. Based on the weather data, five different regulation signals are used to highlight expected energy savings, on-peak power consumption reduction, and expected discomfort. The results of utility demand1 and utility demand2 is presented in Appendix A and Appendix B

The five regulation signals used are ±50kW, ±100kW, ±200kW, ±250kW, ±300kW

A.1 Simulations Results for Different Temperature Data

In figure A.1, the orange line represents the outside temperature for a period of twenty hours and this can be read on the right y-axis, while the blue line which can be read on the left y-axis represents corresponding aggregate power consumption of the 500ACs due to the outside temperature. It can be seen that the shape of aggregate power consumption of the ACs closely tracks the shape of the outside temperature. This gives an
indication that the outside temperature is approximately proportional to the aggregate power profile.

(a): Forecasted Baseline Power Profile for January 1st, 2018

(b): Forecasted Baseline Power Profile for April 8th, 2018

(c): Forecasted Baseline Power Profile for August 1st, 2018

Fig. A.1: Forecasted Baseline Power Profile using different twenty-four-hour weather data
A.1.1 Simulation Results for Utility Demand

Fig. A.2: Generated utility demand for January 1st, 2018 based on different case scenarios

Fig. A.3: Power consumption profile on January 1st, 2018 using the proposed control strategy and different case scenarios of utility demand
Fig. A.4:  On and Off-peak energy consumption difference vs daily energy consumption cost difference for January 1st, 2018 using utility demand1

Fig. A.5:  Range of $\alpha$ values for January 1st, 2018 and its proportionality to room percentage (utility demand1)
Fig. A.6: Range of $\beta$ values for January 1st, 2018 and its proportionality to room percentage (utility demand1)

Fig. A.7: Generated utility demand1 for April 8th, 2018 based on different case scenarios
Fig. A.8: Power consumption profile on April 8th, 2018 using the proposed control strategy and different case scenarios of utility demand1

Fig.A.9: On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 8th, 2018 using utility demand1
**Fig.A.10:** Range of $\alpha$ values for April 8th, 2018 and its proportionality to room percentage (utility demand1)

**Fig.A.11:** Range of $\beta$ values for April 8th, 2018 and its proportionality to room percentage (utility demand1)
Fig. A.12: Generated utility demand for August 1st, 2018 based on different case scenarios

Fig. A.13: Power consumption profile on August 1st, 2018 using the proposed control strategy and different case scenarios of utility demand
Fig. A.14: On and Off-peak energy consumption difference vs daily energy consumption cost difference for August 1st, 2018 using utility demand1

Fig. A.15: Range of α values for August 1st, 2018 and its proportionality to room percentage (utility demand1)
Fig.A.16: Range of $\beta$ values for August 1st, 2018 and its proportionality to room percentage (utility demand1)

A.2. Summary

In figure A.17 –A. 19, the plots gives a summary of the percentage of shifted load during peak hours with the expected comfort limit for the different outside temperature presented in A.1. It can be summarized that a knowledge of the outside temperature gives an indication of the capacity for shifting within a comfort limit which is relevant to the utility/system’s operator.
Fig.A.17: Customer comfort limit as a function of load shifting 2.62MWh forecasted on-peak energy consumption on January 1st, 2018

Fig.A.18: Customer comfort limit as a function of load shifting 4.53MWh forecasted on-peak energy consumption on April 8th, 2018
Fig.A.19: Customer comfort limit as a function of load shifting 5.2MWh forecasted on-peak energy consumption on August 1st, 2018.
APPENDIX B

The results of utility demand2 is presented below. Each result is based on the weather data and forecasted baseline profile presented in A.1.

B.1 Simulation results using Utility Demand2

Fig. B.1: Generated Utility Demand2 for January 1st, 2018 based on different case scenarios

Fig. B.2: Power consumption profile of January 1st using the proposed control strategy and different case scenarios of utility demand2
Fig.B.3: On and Off-peak energy consumption difference vs daily energy consumption cost difference for January 1st, 2018 using utility demand2

Fig.B.4: Range of $\alpha$ values for January 1st, 2018 and its proportionality to room percentage (utility demand2)
Fig. B.5: Range of $\beta$ values for January 1st, 2018 and its proportionality to room percentage (utility demand2)

Fig. B.6: Generated utility demand2 for April 8th, 2018 based on different case scenarios
Fig. B.7: Power consumption profile on April 8th, 2018 using the proposed control strategy and different case scenarios of utility demand2

Fig. B.8: On and Off-peak energy consumption difference vs daily energy consumption cost difference for April 8th, 2018 using utility demand2
Fig. B.9: Range of $\alpha$ values for April 8th, 2018 and its proportionality to room percentage (utility demand2)

Fig. B.10: Range of $\beta$ values for April 8th, 2018 and its proportionality to room percentage (utility demand2)
Fig. B.11: Generated utility demand for August 1st, 2018 based on different case scenarios.

Fig. B.12: Power consumption profile on August 1st, 2018 using the proposed control strategy and different case scenarios of utility demand.
Fig. B.13: On and Off-peak energy consumption difference vs daily energy consumption cost difference for August 1st, 2018 using utility demand2

Fig. B.14: Range of $\alpha$ values for August 1st, 2018 and its proportionality to room percentage (utility demand2)
**Fig.B.15:** Range of $\beta$ values for August 1st, 2018 and its proportionality to room percentage (utility demand2)

**B.2 Summary**

In figure B.16 –B.18, the plots gives a summary of the percentage of shifted load during peak hours with the expected comfort limit for the different outside temperature presented in A.1. It can be summarized that a knowledge of the outside temperature gives an indication of the capacity for shifting within a comfort limit which is relevant to the utility/system’s operator.
Fig.B.16: Customer comfort limit as a function of load shifting 1.48MWh forecasted on-peak energy consumption on January 1st, 2018

Fig.B.17: Customer comfort limit as a function of load shifting 3.42MWh forecasted on-peak energy consumption on April 8th, 2018
Fig.B.18: Customer comfort limit as a function of load shifting 3.88MWh forecasted on-peak energy consumption on August 1st, 2018
APPENDIX C

This section presents the Matlab codes used to run and generate the simulation results.

SIMULINK FILE NAMED ONANDOFF500

%% Outside Weather Data Code for generating the outside temperature load profile. This can be seen as an startfcn in the Simulink file onandoff500 for the block called climate

Name of file: ReadExcel %generated by Eberechukwu Ezemaduka, please note I used a weather profil of 48 hours but it is for one day. This simply mean a 24 hour weather data for aprilst was repeated twice to make it 48. The code called plotresults500basic extracts data only for the last 24 hours. I did this because if you use ony 24hours, the baseline profile plots show that the ACs are under transient situation for most of the time.
Ta = xlsread('april1st.xlsx', 'F2: F49');
Ta=[0:48; [Ta' Ta(1)]];
savefile = 'Climate.mat';
save(savefile, 'Ta')

%% Generating R and C values, This function can be seen in the simulink file named onandoff500

Name of file: Random RC %generated by Eberechukwu Ezemaduka

function [rnR, rnC]= fcn(rnr,rnc)
    rnR=rnr;
    rnC=rnc;

function CR  = fcn(R,C)
    C = double(C);
    R = double(R);
    CR=[C;R];

%%Thermostat code for changing state of AC from off to on and vice versa. This function can be seen in the simulink file named onandoff500

Name of file: Boundary %generated by Eberechukwu Ezemaduka

function m = fcn(mPrev,Tempdiff)
    m=mPrev;
    m(Tempdiff >= 0.5)=1;
    m(Tempdiff<= -0.5)=0;

Name of file: mwithtimestep %generated by Eberechukwu Ezemaduka
function mt = fcn(m, t, mPrevStep)

if mod(t, 1/3600) == 0
    mt = m;
else
    mt = mPrevStep;
end

% Codes used to read output of on and off 500 Simulink and generate plots and data. It is the stopfcn
Name: Plotresultsbasic500 % generated by Eberechukwu Ezemaduka

%C&R
y = out.signals.values;
C = transpose(y(1, 1:500)); % change from columns to rows
R = transpose(y(1, 501:1000));
C = [3.6; C]; % change to rows
R = [2; R];
savefile = 'C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500 rooms\SetPointControl\C.mat';
save(savefile, 'C')
savefile = 'C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500 rooms\SetPointControl\R.mat';
save(savefile, 'R')

%%
%% t = out.time;
t = duration(0:(5/60):24, 0, 0, 'Format', 'hh:mm'); % plot time like 00:00 01:00
P = y(:, 1001:1500); % power data
T = y(:, 1501:2000); % Temp data

% calculate power consumption

% for i = 1:size(P, 1)
for i = 1:289 % changed from leng to size because length returns the highest size either row or col, we have 289x300 here
    % the highest matrix here is 300 column (each column is for an ac)
    if i is 1:300, the code sum should be cal for rows(i, :) but we have only 289 rows, the code % will be wrong becos i said i=1:300 but in reality we have
        % only 289
        a = P(289:577, :); % reads the last 24 hours
        power(i) = sum(a(i,:));
        powerr = transpose(power);
end
xlswrite('C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500 rooms\OnOffControl\powerweather4.xls',[powerr]);

% plot power
figure; plot(t, power) % baseline power profile
xlabel('Time (hour)');
ylabel('Power Consumption (kW)');
mean power for each hour which is a summation of power in each step divided by no of steps
step=5/(60); %signifies 5 minutes sample period
meanPower(1)=sum(power(1:((1/step))))*step;
% for i=1:46 This is for a 48 hours weather
for i=1:23 %This is for a 24 hour weather and we used it cos we ran 48hrs (two weather data of april1st) to ignore initial transient but we took the result for the second
    meanPower(i+1)=sum(power(((i/step)+1):(((i+1)/step))))*step;
end
M1= transpose(meanPower);
xlswrite('C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500 rooms\OnOffControl\M1.xls',[M1]);
for i=1:2:46
    ppower(i:i+1)=meanPower((i+1)/2)*ones(1,2);
    tt(i:i+1)=[((i+1)/2 )]-1+0.001;(i+1)/2];
end
hold on;plot(tt,ppower,'g')
legend('Power consumption','mean power');
hold off

plot Temperature of all ACs
c=500;
for i=1:c
    plot(t, T(289:577,i)) % plot(t, T(:,i))This plots the T of individual ACs as long as
time
    hold on;
end
xlabel('Time (hour)');
ylabel('Temp (°C)');

ENERGY CONSUMPTION CALCULATION FOR DAILY, ON/OFF PEAK PERIOD IN UNCONTROLLED STATE
MeanPower1=sum(power(((0/step)+1):((24/step))))*((5/60));
MeanPower2=sum(power(((8/step)+1):((17/step))))*((5/60));
MeanPower3=sum(power(((2/step)+1):((8/step))))*((5/60));
MeanPower4=sum(power(((8/step)+1):((14/step))))*((5/60));
meanpowerr=[MeanPower1;MeanPower2;MeanPower3;MeanPower4];
savefile = 'meanpowerr.mat';
save(savefile, 'meanpowerr');

CALCULATE ENERGY COST IN UNCONTROLLED STATE
MeanPower11=sum(power(((7/step)+1):((11/step))))*((5/60)))*(0.094);
MeanPower21=sum(power(((11/step)+1):((17/step))))*((5/60))*(0.134);
MeanPower31=sum(power(((17/step)+1):((19/step))))*((5/60))*(0.094);
MeanPower41=sum(power(((19/step)+1):((24/step))))*((5/60))*(0.065);
MeanPower51 = sum(power(((0/step)+1):((7/step))))*((5/60))*(0.065);
meanpowerr1=[MeanPower11;MeanPower21;MeanPower31;MeanPower41;MeanPower51];
savefile = 'meanpowerr1.mat';
save(savefile,'meanpowerr1');
M = sum(meanpowerr1);

**SIMULINK FILE NAMED TESTING3**

%% Outside Weather Data Code for generating the outside temperature load profile. This can be seen as an startfcn in the Simulink file testing3 for the block called climate

Name of file: ReadExcel %generated by Eberechukwu Ezemaduka, please note I used a weather profilr of 48 hours but it is for one day. This simply mean a 24 hour weather data for aprilst was repeated twice to make it 48. The code called plotresults500basic extracts data only for the last 24 hours. I did this because if you use ony 24hours, the baseline profile plots show that the ACs are under transient situation for most of the time.

Ta = xlsread('april1st.xlsx', 'F2: F49');
Ta=[0:48; [Ta' Ta(1)]]; savefile = 'Climate.mat'; save(savefile, 'Ta')

%% block named model is ACs

note that r and c values are read from the output file derived from onandoff500

%%Thermostat code for changing state of AC from off to on and vice versa is used in this thesis. This function can be seen in the simulink file named testing 3 in the block named onoffcontroller

Name of file: Boundary %generated by Eberechukwu Ezemaduka

function m = fcn(mPrev,Tempdiff)
m=mPrev;
m(Tempdiff >= 0.5)=1;
m(Tempdiff<= -0.5)=0;

Name of file: mwithtimestep %generated by Eberechukwu Ezemaduka

function mt = fcn(m, t, mPrevStep)

if mod(t,1/3600)==0
    mt=m;
else
    mt=mPrevStep;
end

Name: Regulation signal constraint %generated by Eberechukwu Ezemaduka

function DemandKWat = fcn(ADemand,m) DemandKWat=ADemand;
c=sum(m);
if ADemand >0
a=ADemand-(2*c);
if a>=0 && a<=200
    DemandKWat=ADemand;
elseif a>200
    DemandKWat=2*sum(m)+200;
end
if a<0&& a>-
    DemandKWat=ADemand;
elseif a<-
    DemandKWat=2*sum(m)-200;
end
if ADemand <=0
    DemandKWat=ADemand;
End

%%This is the file used to generate new setpoints for AC depending on balance signal
Name: setpoint manage, seen in the block named setpointcontrol
%generated by Eberechukwu Ezemaduka
% In this Function we receive the energy value demanded by the utility to be consumed by the hotel. first priority vector is created to choose which ACs are more prior to be turned on or off.

function TsNew = fcn(DemandKWat,m, T,Ts,t)
%DemandKWat is energy value demanded by the utility to be consumed by the hotel during high and low peak.
%m is a vector with boolean elements showing the ACs on and off.
%Ts is the ACs setpoint.
%TsNew is the new setpoint adjusted for the next step.
%summ is number of ON ACs
n=500;
TsNew=Ts;
IncreaseTs=0.6; %IncreaseTs & DecreaseTs are the amounts to increase or decrease the setpoint
DecreaseTs=0.6;
manageAC=round(DemandKWat/2); %manageAc is the minn or max number of ACs expected to be working
Priority=zeros(n,1);

if mod(t,(5/60))==0 % FIVE MINUJTES CONTROL SAMPLING RATE
    if manageAC > 0 && abs(manageAC) > sum(m) %Utility wants more energy consumed. Some ACs must turn on
        addAC = abs(manageAC) - sum(m); % addAc is the number of ACs needed to be working all the time to meet the utility demand
        IndOff = find(m== 0);
        Tq=sort(Ts(IndOff),'descend');
        LP=length(IndOff);
        if LP >= addAC
            Counter = addAC;
        else
            Counter= LP;
        end
    else
        DemandKWat=ADemand;
    End
End
end
T1=Ts;
for i= 1 : Counter
    q = find(T1 == Tq(i)); %among the sorted temperatures
choose no of Acs in counter with in descending order
    Priority(i,1) = q(1); %set priority vector to this value
    T1(q(1)) = -1000; %prevents chosen Acs from being chosen
again
end
if LP < addAC
    IndOn = find(m==1);
    Tp = sort(Ts(IndOn), 'descend');
    T2=Ts;
    for i= 1 + LP: addAC %former priority was Lp, so we need
to start from 1+LP
        p = find(T2 == Tp(i));
        Priority(i,1) = p(1);
        T2(p(1)) = -1000;
    end
end
Priority=Priority(find(Priority~=0));
TsNew(Priority) = T(Priority) - DecreaseTs; % Compute the new
setpoint by reducing "DecreaseTs" according to the priority

elseif manageAC > 0 && manageAC < sum(m)

%in this part we do the same algorithm as the previous part. However,
the controller wants to turn some ACs off.
    IndOn = find(m==1);
    Tq = sort(Ts(IndOn));
    LP=length(IndOn);
    T1=Ts;
if LP >= cutAC
    Counter = cutAC;
else
    Counter= LP;
end
for i= 1 : Counter
    q = find(T1 == Tq(i));
    Priority(i,1) = q(1);
    T1(q(1)) = 1000;
end
if LP < cutAC
    IndOff = find(m==0);
    Tp = sort(Ts(IndOff));
    T2=Ts;
    for i= 1 + LP: cutAC
        p = find(T2 == Tp(i));
        Priority(i,1) = p(1);
        T2(p(1)) = 1000;
    end
end
Priority=Priority(find(Priority~=0));

TsNew(Priority) = T(Priority)+IncreaseTs;
%%This is the file used return setpoints for ACs to intial
Name: setpoint manage, seen in the block named backtosetpoint
%generated by Eberechukwu Ezemaduka
%In this function first we check the ACs with increased or decreased
setpoints to return them back to their initial setpoints.

function Tss = fcn(t,TsNew,m, DemandKWat, T)

IncreaseTs=1; %IncreaseTs & DecreaseTs are the amounts to increase
or decrease the setpoint
DecraseTs=1;
SetPoint=18;
Tss=TsNew;

if mod(t,(20/60))==0
    manageAC = round(DemandKWat/2);
    if manageAC < 0
        B2 = find(TsNew > SetPoint);
        LP=length(B2);
        if LP>80
            a=round(LP/4);
            for i=1:a
                Tss(B2(i)) = SetPoint;
            end
        elseif LP<=80
            a=round(LP);
            for i=1:a
                Tss(B2(i)) = SetPoint;
            end
        end
    end
    manageAC = round(DemandKWat/2);
    if manageAC < 0
        A2=find(TsNew<SetPoint);
        LP1=length(A2);
        a=LP1;
        for i=1:a
            Tss(A2(i)) = SetPoint;
        end
    end
    manageAC = round(DemandKWat/2);
    if manageAC == 0
        Tss(1:end)=SetPoint;
    end
    A3 = (TsNew > SetPoint+IncreaseTs) | (TsNew < SetPoint-
DecraseTs);
    Tss(A3) = SetPoint;

    Tss=Tss;

n=500;
%% t=out.time;
t = duration(0:(301/3600):24,0,0,'Format','hh:mm'); %plot time like 00:00 01:00
t1 = duration(0:(5/60):24,0,0,'Format','hh:mm');
x = rand(size(t));
y=out.signals.values;

%% Codes used to read output of testing3 Simulink and generate plots and data. It is the stopfcn
Name: Plotresults % generated by Eberechukwu Ezemaduka

% Output values from Simulink used to create plot and perform analysis
DDemandKWat=y(:,1); % utility demand
pp=y(:,2:501); % power
TTs=y(:,502:1001); % setpoint
TT=y(:,1002:1501); % Temp

% calculate aggregate power
np=size(pp,1); % size of all the rows
for i=1:288
    power(i)=sum(pp(i,:));
    a=pp(288:575,:); % reads last 24 hours data
    power(i)=sum(a(i,:)); % power achieved with setpoint variation
end

%% plot power
figure(3);
plot(t,power');
hold on;
DD=abs(DDemandKWat);
DD1=DD(288:575,:);
plot(t, (abs(DDemandKWat))', 'linewidth', 2, 'color', 'red') OLD PLOT
plot(t, (abs(DD1))', 'linewidth', 2, 'color', 'red')
import5 = xlsread('poweragg.xls'); % baseline power data
hold on
plot(t1,import5') % plots on and off uncontrolled power
hold on
uselesspower=zeros(288,1);
plot(t,uselesspower') % plotting useless power to eliminate that zero stuff
xlabel('Time (hour)')
ylabel('Power (kW)');
legend('Achieved Agg Power ','Pud ','Punc')

%% plot setpoint temperature for all rooms
figure(2);
for i=500
    plot(t, TTs(:,i));
    hold on;
end
title('Setpoint of Ac in room')
xlabel('Time (hours)')
ylabel('Set point Temperature');
%calculate NSWRcon, all the diff setpoints of an AC without counting a repeated number twice i.e first AC, if setpoint is 19,20,22,22 h=3
%Also, the row 25:204 chosen is the control horizon chosen for to run %simulation i.e (2*12:17*12)for 5min or (2*60:17*60) for 1 min for 5 min,
%288 values are outputed while 1min is 1440

gt=size(TTs,2);
for i=1:gt
  h(i)=size(unique(TTs(156:249,i)),1); %FOR ten MIN
  h(i)=size(unique(TTs(104:168,i)),1); %FOR fifteenMIN
  h(i)=size(unique(TTs(311:497,i)),1);
  swi =sum(h);
end

%%Average Power graph
z= 301/(3600); %step size
meanPower(1)=sum(power(1:((1/z))))*z;
for i=1:23
  meanPower(i+1)=sum(power(((i/z)+1):(((i+1)/z))))*z;
end

%Plot the average power as a step function
for i=1:2:46
  ppower(i:i+1)=meanPower((i+1)/2)*ones(1,2);
  tt(i:i+1)=[((i+1)/2)-1+0.001;(i+1)/2];
end
%hold on;plot(tt,ppower,'g')

hold off
% plot agg room temp
figure(4);
c=500;
rl= randperm (500, c);
for i=1:c
  plot(t, TT(:,rl(i)))
  hold on;
end
xlabel('Time ( hour)');
ylabel('Temp (°C)');
hold off
%plot aggregate room temperature for 500 ACs
for i=1:c
  plot(t, TT(288:575,i))
  % plot(t, T(:,i))This plots the T of individual ACs as long as time
% is just t.out.time
hold on;

deal('Time (hour)');
ylabel('Temp (°C)');

% plot agg setpoint for 500 ACs
c=500;
r1= randperm (500, c);
for i=1:c
  plot(t, TTs(:,r1(i)))
  hold on;
end

deal('Time (hour)');
ylabel('SetPoint (°C)');
hold off

%ENERGY CONSUMPTION CALCULATION FOR DAILY, ON/OFF PEAK PERIOD IN
CONTROLLED STATE
MeanPowermin=sum(power(((0/z)+1):((24/z))))*((301/3600));
MeanPowermax=sum(power(((8/z)+1):((17/z))))*((301/3600));
MeanPowerm=sum(power(((2/z)+1):(8/z)))*(301/3600));
MeanPowern=sum(power(((8/z)+1):((14/z))))*(301/3600));
meanpower=[MeanPowermin;MeanPowermax;MeanPowerm;MeanPowern];
savefile = 'meanpower.mat';
save(savefile, 'meanpower');

% Tp=size(TT,1); %gives the average temperature of each AC i.e results
% is temp of 500 ACs which is the average temp for each 500 throughout
% control horizon
for i=1:Tp
  TS(i)=(sum(TT(i,:)));%  end
T1=transpose(TS);
% excelwrite('C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500
rooms\SetPointControl\TS2001.xls',[T1]);
TY=TT(288:575,:);
T2=max(TY);
T22=transpose(TS2);
excelwrite('C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500
rooms\SetPointControl\maxtt501.xls',[T22]);
T3=min(TT);
T33=transpose(TS3);
xlswrite('C:\Users\eezemadu\Documents\THESIS\THESIS MATLAB\500
rooms\SetPointControl\mintt501.xls',[T33]);

%CALCULATE ENERGY COST IN CONTROLLED STATE
MeanPower111=sum(power(((7/z)+1):((11/z))))*((301/3600)))*(0.094);
MeanPower211=sum(power(((11/z)+1):((17/z))))*((301/3600)))*(0.134);
MeanPower311=sum(power(((17/z)+1):((19/z))))*((301/3600)))*(0.094);
MeanPower411=sum(power(((19/z)+1):((24/z))))*((301/3600)))*(0.065);
MeanPower511=sum(power(((0/z)+1):((7/z))))*((301/3600)))*(0.065);
meanpowerr11=[MeanPower11;MeanPower211;MeanPower311;MeanPower411;MeanPower511];
savefile = 'meanpowerr11.mat';
save(savefile, 'meanpowerr11');
N=sum(meanpowerr11);

%%code used to generate baseline and outside weather on same plot
Name: weather and baseline %generated by Eberechukwu Ezemaduka

%%plot baseline power profile and weather data

t = duration(0:(5/60):24,0,0,'Format','hh:mm');%plot time like 00;00
01;00
t1 = duration(0:(1):23,0,0,'Format','hh:mm');%plot time like 00;00
01;00
import = xlsread('powerweather1.xls');
P1=import(:,1); %aggregate baseline power
newYLim1 =[0,1000];%left y axis scale
yyaxis left
plot(t,P1);
ylim(newYLim1)
xlabel('Time (minutes)');
ylabel('Power Consumption(kW)');
Ta = xlsread('barbados weather data1.xlsx','F2: F25');%weather data
newYLim =[20,35];
plot(t1,Ta);
ylim(newYLim)
xlabel('Time (hour)');
ylabel('Temp(celsius)');
legend('P1','Ta')

%%code for generating alpha and beta anad also coming up with comfort limit
Name: roundup %generated by Eberechukwu Ezemaduka

code for generating alpha and beta
import = xlsread('MAXapr8.xls');
import1 = xlsread('MINapr8.xls');
T1=import(:,1);
T2=import1(:,1);
A1=T1-18.5;
B1=T2-17.5;
T3=round(A1,1);
T4=round(B1,1);
a=find(T3<=1.0);a1=length(a);
b=find(T3>1.0 & T3<=2);b1=length(b);
c=find(T3>2.0 & T3<=3);c1=length(c);
t=find(T3>3.0 & T3<=4);t1=length(t);
s=find(T3>4.0 & T3<=5);s1=length(s);
d=find(T4>=-1.0);d1=length(d);
e=find(T4<-1.0 & T4>=-2);e1=length(e);
f=find(T4<-2.0 & T4>=-3);f1=length(f);
g=find(T4<-3.0 & T4>=-4);g1=length(g);
h=find(T4<4.0 & T4>=5);h1=length(h);
Vita

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