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Development of a holistic engineering approach for improved AC performance and energy efficiency in buildings under harsh desert climate conditions

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Résumé

La civilisation mondiale est entièrement dépendante de l'accès à de grandes quantités d'énergie tandis que la demande d'énergie continue de croître à un rythme rapide avec la croissance de la population mondiale. Les pays aux conditions météorologiques extrêmes ont tendance à avoir des demandes énergétiques plus élevées, où les principaux consommateurs d'énergie sont les systèmes de chauffage et de refroidissement. Dans les pays du Moyen-Orient et du Golfe en particulier (Qatar par exemple), il existe une forte demande pour les applications de refroidissement en raison de l'environnement désertique (chaleur, humidité et poussière), qui représente environ 60 à 70% de la consommation totale d'énergie. L'électricité en tant que forme d'énergie secondaire est principalement utilisée pour les applications de refroidissement dans ces régions, qui est générée par des processus de production d'électricité standard à base de combustibles fossiles associés à des émissions massives de carbone. La consommation typique des ménages au Qatar est dix fois plus élevée que la moyenne des ménages aux États-Unis et en Europe. De nombreuses études et techniques ont été proposées pour relever ces défis énergétiques grâce aux technologies de pointe, à l'efficacité énergétique et aux énergies renouvelables. Cependant, ils ne sont pas entièrement couronnés de succès, car beaucoup d'entre eux sont spécifiques à une région ou même à un pays, ce qui signifie que les politiques énergétiques, les concepts et la culture locaux peuvent avoir un impact sur le résultat attendu. Cette étude examine les problèmes de consommation d'énergie et d'efficacité associés aux applications de refroidissement des bâtiments et leurs implications environnementales et sanitaires dans les régions désertiques. Pour relever ces défis, une approche d'ingénierie pragmatique est proposée pour aider à résoudre les problèmes persistants de gestion de l'énergie et de charge de pointe associés aux applications de refroidissement dans les bâtiments où l'accent est mis sur la demande afin de développer des techniques de gestion de l'énergie pour plusieurs équipements de climatisation. Des schémas de contrôle optimaux et adaptatifs ont été développés avec succès pour les bâtiments afin de répondre aux demandes de refroidissement des locaux d'une manière équilibrée et harmonisée qui minimise la demande de pointe. Un autre aspect de ce travail étudie comment la poussière de l'environnement désertique environnant peut avoir un impact négatif sur les performances de la climatisation, l'efficacité énergétique et la qualité de l'air intérieur. Un algorithme d'optimisation a été développé avec succès pour guider la conception et la sélection appropriée des filtres à air pour des performances optimales du climatiseur.

Mots clés: efficacité énergétique, bâtiments, performances de refroidissement et de climatisation, réduction de la charge de pointe, filtration de l'air.

Abstract

As the world's civilization is entirely dependent on access to large amounts of energy, the energy demand continues to increase along with the rapid growth in the world's population. Countries with extreme climate conditions tend to have greater energy demand where most aggressive energy consumers are heating and cooling systems. In the middle east and Gulf countries in particular (like Qatar), there is a huge demand for Heating Ventilation & Air conditioning (HVAC) applications due to the harsh desert environment (heat, humidity & dust), which approximately accounts for 60 – 70 % of total energy consumption. Electricity as a secondary form of energy is dominantly used for cooling applications in such regions, which is usually produced via standard fossil fuel based power generation processes that are associated with massive loads of carbon emission. Typical household consumption in Qatar is ten times higher than average houses in the USA and Europe. There have been numerous studies and techniques proposed to address such energy challenges through state-of-the-art technology, energy efficiency, and renewable energy. However, they are not entirely successful, as many of which are region or even country-specific, meaning that local energy policies, regulations, and culture can always impact the expected results. This study investigates the energy consumption and efficiency challenges related to buildings' cooling applications and their environmental and health implications within areas of harsh arid climate conditions. To address these challenges, a pragmatic engineering approach is proposed to assist in tackling persistent power management and peak load issues associated with cooling applications in buildings where the focus is on demand-side to develop suitable power management techniques for multiple AC units. Optimal and adaptive control schemes were successfully developed for buildings to respond to space cooling demands in a balanced and harmonized way that significantly minimizes power peaks. Another aspect of this work investigates how dust from the surrounding desert environment can negatively impact HVAC performance, energy efficiency, and indoor air quality. An optimization algorithm was successfully developed to guide the design and proper selection of air filters for optimal HVAC performance.

Keywords: Energy efficiency, buildings, cooling & HVAC performance, Peak-load shaving, air filtration.

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Publications and scientific contributions:

Journal Paper	Al-Azba, M.; Cen, Z.; Remond, Y.; Ahzi, S. An Optimal Air-Conditioner On-Off Control Scheme under Extremely Hot Weather Conditions. *Energies* **2020**, *13*, 1021.
Journal Paper	Al-Azba, M., Cen, Z., Remond, Y., & Ahzi, S. (2017). Air-Conditioner Group Power Control Optimization for PV integrated Micro-grid Peak-shaving. *Journal of Industrial & Management Optimization*, *13*(5), 0. https://doi.org/10.3934/jimo.2020112
Poster	Development of a holistic engineering approach for improved energy efficiency in buildings under harsh desert climate conditions, JOURNÉE POSTERS, L'École Doctorale (Mathématiques, Sciences de l'information et de l'Ingénieur), le lundi 8 octobre 2018 à Télécom Physique Strasbourg - Pôle API - Illkirch
Conference paper	M. Al-Azba, Z. Cen and S. Ahzi, "Air-Conditioner On-Off optimization Control under Variant Ambient Condition," 2018 6th International Renewable and Sustainable Energy Conference (IRSEC), Rabat, Morocco, 2018, IEEE Xplore pp. 1-5, doi: 10.1109/IRSEC.2018.8703001.
Conference paper	M. Al-Azba, Z. Cen, S. Ahzi and Y. Remond, "Complex On-Off Air-Conditioning Control Strategy for Peak Demand Reduction in Desert Climate Conditions," *2019 7th International Renewable and Sustainable Energy Conference (IRSEC)*, Agadir, Morocco, 2019, pp. 1-4, doi: 10.1109/IRSEC48032.2019.9078186.
Conference Paper	Z. Cen, M. Al-Azba and S. Ahzi, "High-Power Load Management for Residential House under Desert Climate Conditions - A Case Study in Qatar," 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), Agadir, Morocco, 2019, IEEE Xplore pp. 1-5, doi: 10.1109/IRSEC48032.2019.9078287.

Table of Contents

Introduction

Energy is undeniably one of the most fundamental elements for a sustained living in our modern world. It is the backbone of modern societies and has always been the driving force for the human race civilization. Consumption of energy has drastically increased globally over the last decades while progressively exhausting earth's natural recourses and accelerating the adverse impact of climate change. As the world's industries and urbanization are entirely dependent on access to large amounts of energy of various types, the energy demand will continue to rise along with the rapid growth in the world's population.

The inevitable depletion of natural resources coupled with the increase in climate change issues and instability of energy costs has pressured governments to consider serious measures towards energy efficiency and energy conservation across all sectors. Energy efficiency measures aim to address high priority energy-related issues like energy security, climate change, and economic development. The building sector is arguably the largest consumer among the other sectors, which happens to be also perceived by decision-makers as the low-hanging fruit to achieve local and global energy efficiency targets.

Qatar and the Gulf region's (GCC countries) energy intensity is a rather complex problem that comprises multiple challenging factors like rapid growth, harsh desert climate, policies, and public awareness. Each of these issues is considered a grand challenge by itself that needs serious efforts to be appropriately addressed. With a significant share of the world's proven oil & gas reserves, GCC countries do not necessarily have issues accessing energy, but real challenges in managing it. Hence, Renewable Energy might not be the ultimate solution for such energy challenges.

With the existing Energy conservation and efficiency framework being underdeveloped, introducing new smart technologies and engineering approaches that provide practical, intelligent, and cost-effective solutions is imperative to address such complexities. Demand-side Management (DSM) systems through home automation and load management are examples of suitable solutions where power demand can be managed automatically without much involvement from consumers. Such approaches should eventually help compensate for or fill the gap caused by the lack of effective policies and consumer behavior. Within Qatar and the GCC region, the excessive use of energy is driven mainly by the domestic sector and specifically, cooling applications like standard Air conditioning (AC) and Heating, Ventilation and Air Conditioning (HVAC) systems for residential buildings. The large energy consumption for cooling applications is inevitable due to the persistent need for indoor thermal comfort and air quality within the mentioned extremely hot desert environment. Therefore, it is reasonable to focus on such a big-ticket item and target the cooling end-use with suitable energy management solutions to achieve reduced power intensity while ensuring adequate indoor comfort and air quality level.

The realm of cooling refrigeration and air conditioning is vast, comprising various technologies and applications. Air conditioning by itself is a complex process that taps into many branches of science like thermodynamics, heat transfer and fluid mechanics.

Air conditioning systems come in different types, sizes, and shapes depending on technology and intended end-use which can start from the most widely common -single unit- window or split AC up to massive district cooling facilities. The complexity of air conditioning systems typically stems from a large number of variables surrounding the cooling process that can dynamically influence the operations, efficiency and performance of such systems. In addition, a standard AC system suffers several inherent shortcomings that make them far from being optimal.

The most obvious issue with air conditioning systems is that most commonly used AC units are designed and manufactured in standard capacity size packages (e.g. 1, 1.5, 2 ton, etc.) which do not usually match real-life -highly random- room or building sizes. This fact leads most of the time to cooled space designs being either over or under designed to various extents which obviously means inefficiency.

Standard AC units operate blindly in silos without any means of communication nor interaction with each other which (in case of a multiple AC building) results in chaotic and imbalanced energy performance.

Another commonly known inherent problem with conventional air conditioning units is the notorious on-off operation mode. Despite its simplicity, on-off based AC systems cause unfavorable load fluctuations and do not provide a great advantage in terms of energy efficiency nor precise temperature control. Conventional AC systems are gradually being superseded by a newly introduced (efficient) DC Inverter technology that delivers a continuous mode of operation that overcomes the limitations of conventional ACs. Despite this fact, conventional AC units are still dominating the market and consumers' homes and it is unlikely to be displaced soon by the new technology. Thus, it is wise to deal with this sizable legacy properly with enhancement and conservation measures during the transition to the new technology.

The complexity of these AC systems requires complex and intelligent control strategies especially at the demand-side, capable of regulating and optimizing the way such sophisticated appliances work individually and part of a group in a systems approach.

Addressing the energy demand-side for the regulation of AC applications is a key step in controlling and improving the system's overall efficiency. However, other external factors that affect HVAC systems' performance need to be also addressed to ensure maximum efficiency and reliability. A prime example of such external factors is the effect of airborne dust. Within the context of desert environments, dust is a challenging factor that indirectly impacts AC efficiency and performance. The accumulation of dust particles on AC internal parts, ducts and across air filters can compromise reliability and energy efficiency. This detrimental effect goes beyond affecting equipment to impact even human beings as the failure of an AC to deliver sufficiently clean air indoors can ultimately cause serious health issues to occupants.

Air filters are the first and main line of defense against the unwelcome dust particles. Due to their crucial role and significant impact on air conditioning performance, the proper design and selection of such filter devices are of prime importance to complement the efforts of optimizing and fine-tuning the performance of air conditioning systems.

Hence, addressing the energy challenges related to cooling applications in hot desertic regions requires a holistic systems approach that evaluates and fine-tune all individual components for the objective of maximizing the overall system efficiency through the proper matching of energy supply and demand without compromising quality and in an optimal fashion.

Thesis Layout

This thesis is mainly divided into 5 chapters, some of which are self-contained research papers relating to the main topic of high consumption of energy for buildings' cooling applications in countries with harsh desert climate conditions.

- The first part (Chapter1) is an introductory chapter that sets the scene by giving a general background and insight of the energy-related challenges within the GCC desertic region with a particular focus in Qatar.
- The second part of this work (Chapter2) explores the possibility of lowering residential buildings' power demand especially during peak hours by managing the air conditioning power through a proposed AC power management load shifting technique.
- The third part (Chapter3) looks at a novel AC load management approach through designing an Optimal (predictive) Air-Conditioner On-Off Control Scheme under Extremely Hot Weather Conditions
- The fourth part (Chapter4) investigates the possibility of achieving AC group power control optimization for PV integrated Micro-grid peak-load shaving
- The fifth and last part of this thesis (Chapter5) studies the indoor air quality aspect of HVAC systems and the influence of dust on the performance and efficiency of common HVAC systems and proposes an optimal air filter selection method.

CHAPTER 1:

Background, General Literature Review, Motivation and Objectives

1.1. Background and literature review

1.1.1. Primary and secondary energy

Primary energy is the energy embodied in natural resources prior to undergoing any human-made conversions or transformations. Examples of primary energy resources include coal, crude oil, sunlight, wind, running rivers, vegetation, and uranium. When primary energy is converted to a different form like the conversion of moving air molecules to rotational energy by the rotor of a wind turbine, which in turn may be converted to electrical energy by the wind turbine generator, part of the energy from the source is converted into unusable heat energy or, loosely speaking, is “lost.” Rotors, gearboxes or generators are never 100 percent efficient because of heat losses due to friction in the bearings, or friction between air molecules. These losses are attributable to the second law of thermodynamics[1].

The Secondary type of energy is the energy generated by conversion of primary energies, e.g. electricity from gas, nuclear energy, coal, oil, fuel oil, and gasoline from mineral oil, coke and coke oven gas from coal. Secondary energy also refers to the more convenient forms of energy which are transformed from other, primary, energy sources through energy conversion processes. Examples are electricity, which is transformed from primary sources such as coal, raw oil, fuel oil, natural gas, wind, sun, streaming water, nuclear power, gasoline etc., but also refined fuels such as gasoline or synthetic fuels such as hydrogen fuels[2]. Figure 1.1 below illustrates the evolution of energy types through different conversion processes from source down to final end use.

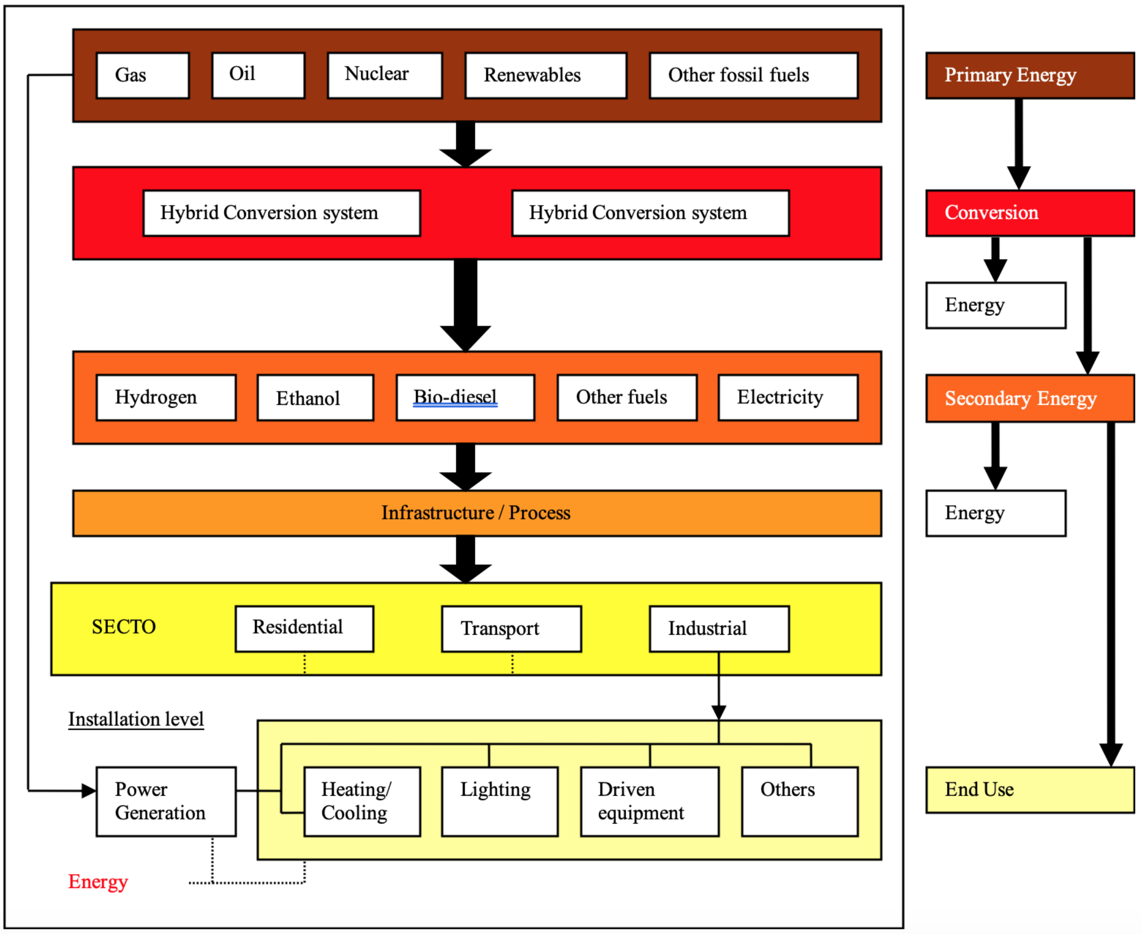


Figure 1.1. Evolution of energy and conversion processes

1.1.2. Energy and power

Power and Energy are two distinct terms that may often confused and get unconsciously used interchangeably due to their close relation (*Energy is the integral of Power over time*). While Energy generally refers to ability or capacity to do work (joules), Power denotes the rate at which such work is being done(joules/second = watt)[1].

1.1.3. Energy consumption and desert climate conditions

The largest share of Green House (GHG) emissions in the Gulf countries originates in the energy sector from electricity and heat production. Approximately 40 percent of the world's proven oil reserves and 23.6 percent of the world's proven gas reserves are located in the Gulf[3]. The majority are significant producers of oil and gas in the region and also known for the high CO2 emissions per capita[4]. Countries with extreme climate conditions generally tend to exhibit higher energy demand where most aggressive energy uses are usually for HVAC (Heating, ventilation, and Air Conditioning) systems. Arabian Gulf countries are characterized by the extremely harsh arid desert environment that is recognized by excessive heat, humidity, and dust throughout the majority of the year. Table 1.1 below shows the highest historical temperatures recorded in some countries in the GCC region.

Country	**Kuwait**	**UAE**	**KSA**	**Oman**	**Qatar**
Temp (^{O}C)	54.0	52.1	53.0	50.8	50.4
period	July 2016	July 2002	July 2017	May 2017	July 2010

Table 1.1. Maximum temperature recorded in the GCC region

The power sector in Qatar continues to grow at a rapid pace as the country continues to spend heavily on new infrastructure projects. At the same time, domestic energy consumption continues to grow despite the unstable global oil prices. Such expenditure on megaprojects is likely to remain relatively high for the upcoming years as the country prepares for the FIFA World Cup in 2022, which in turn indicates an alarming increase in power demand. Despite the ambitious plans to diversify its energy sources by the use of renewables, natural gas so far remains the primary source of energy in Qatar. While it may be considered as a clean fossil fuel, Qatar is ranked the highest globally in terms of per capita carbon emission.

#	Country	Per capita CO2 emission (Tonnes)
1	Qatar	40.1
2	Trinidad & Tobago	37.78
3	Kuwait	34.24
4	Netherlands Antilles	23.55
5	Brunei Darussalam	22.96
6	United Arab Emirates	22.31
7	Aruba	21.59
8	Luxembourg	21.34
9	Oman	20.56
10	Falkland Islands	19.56
11	Bahrain	19.18
12	United States	17.5
13	Saudi Arabia	16.92
14	Australia	16.75
15	New Caledonia	15.63

Table 1.2. Top per capita carbon emission producing countries [1]

According to the International Energy Agency (IEA) data records, the carbon emission associated with power generation in Qatar has almost doubled in size over the last ten years.

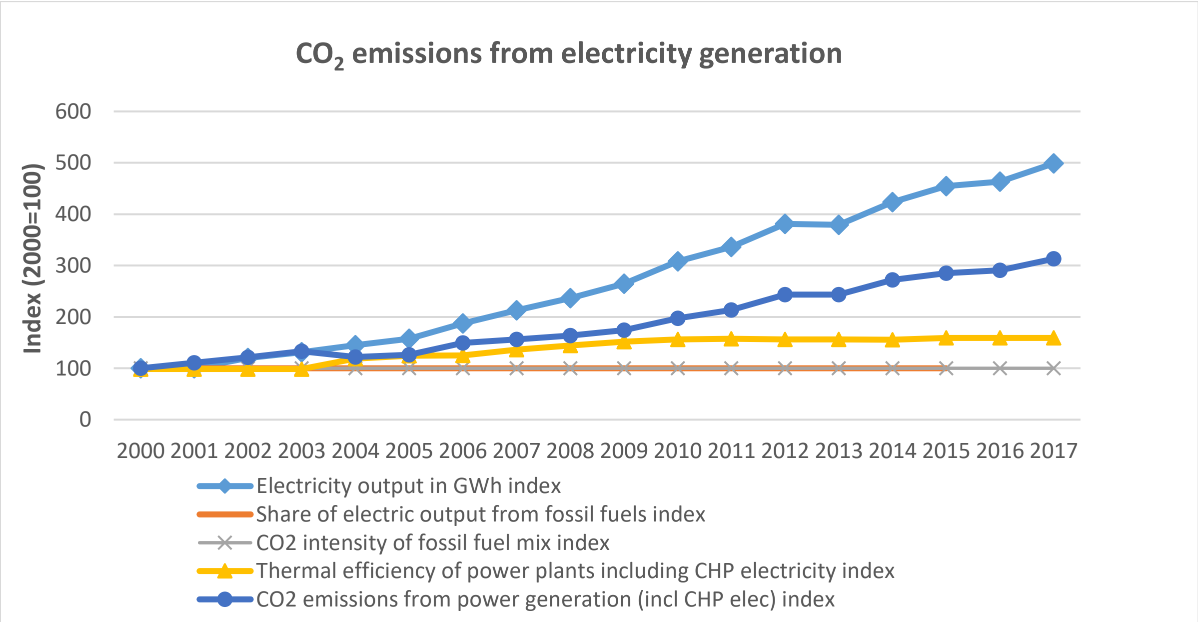


Figure 1.2. CO_2 emissions from power generation in Qatar [5]

With this fact in mind, the state of Qatar is always seeking for ways to address this challenge to help mitigate environmental risks and maintain a positive image among the global community. Qatar's National Vision 2030 puts emphasis on the support of international efforts in order to mitigate the impacts of climate change and be proactive in mitigating the negative impacts of Climate Change, especially in the Gulf region. Qatar ratified the Kyoto Protocol in 2005 and submitted an initial National Communication to the UNFCCC in 2011. In 2012, Qatar demonstrated its leadership role and support for global action on climate change action by hosting the 18th Conference of Parties (COP18) to the UNFCCC. Qatar also signed the Paris Protocol for the Climate Change of 22 April 2016 (ratified in Feb. 2017).

1.1.4. Desertification and Climate change impacts on public health

Climate change will result in thermal stress and air quality impacts in Qatar, causing increases in incidences of heat exhaustion and heat-stroke cases. Desertification and increases in the concentration of suspended particulate matter will lead to respiratory problems among children, asthmatics and the elderly. Current levels of ozone and photochemical oxidants in Qatar are already high, raising public health concerns that have the potential of worsening with climate change[3].

The relation between energy consumption and public health is quite obvious since energy is used to improve the living conditions of humans in terms of indoor comfort (heating / cooling) and air quality through HVAC systems.

1.1.5. Electric energy consumption (kWh per capita)

The production and consumption of electricity are basic indicators of the size and level of development in any country's economy. The majority of electric power production is mainly for local domestic use, while a few countries export part of the produced electric power. The growing supply of electricity to meet the ever-increasing demand for increasingly urbanized and industrialized economies without baring unacceptable social, economic, and environmental risks is one of the challenging targets facing governments in many developing countries. Modern societies are becoming increasingly dependent on reliable and secure electricity supplies to support economic growth and human prosperity.

In developing economies, growth in energy use is closely related to growth in the modern sectors - industry, motorized transport, and urban areas - but energy use also reflects climatic, geographic, and economic factors (such as the relative price of energy). Energy use has been growing rapidly in low- and middle-income economies, but high-income economies still use almost five times as much energy on a per capita basis. Governments in many countries are increasingly aware of the urgent need to make better use of the world's energy resources. Improved energy efficiency is often the most economic and readily available means of improving energy security and reducing greenhouse gas emissions[6]. The kWh per capita electric power consumption indicator measures the production of power plants and combined heat and power plants less transmission, distribution, and transformation losses and own use by heat and power plants[7]. With this indicator, Qatar falls within the top 5 countries with the highest kWh consumption per capita as shown in Table 1.3.

Country	**Electricity consumption per capita (kWh per person)**	**Year**
Iceland	51,467	2018
Norway	22,747	2018
Kuwait	19,812	2018
Bahrain	18,099	2017
Qatar	15,756	2018
Finland	14,951	2018
Canada	14,553	2018
Sweden	13,295	2018
United States	11,851	2018
United Arab Emirates	11,669	2017

Table 1.3. world top electricity consumption countries per capita[8]

As per the data published by the World Bank, Qatar has reached 15,756 kWh per capita in 2018, just below Bahrain, Kuwait, Norway and Iceland. Figure 1.3 below shows comparison graph of kWh per capita consumption in Qatar and the US and some European countries[9].

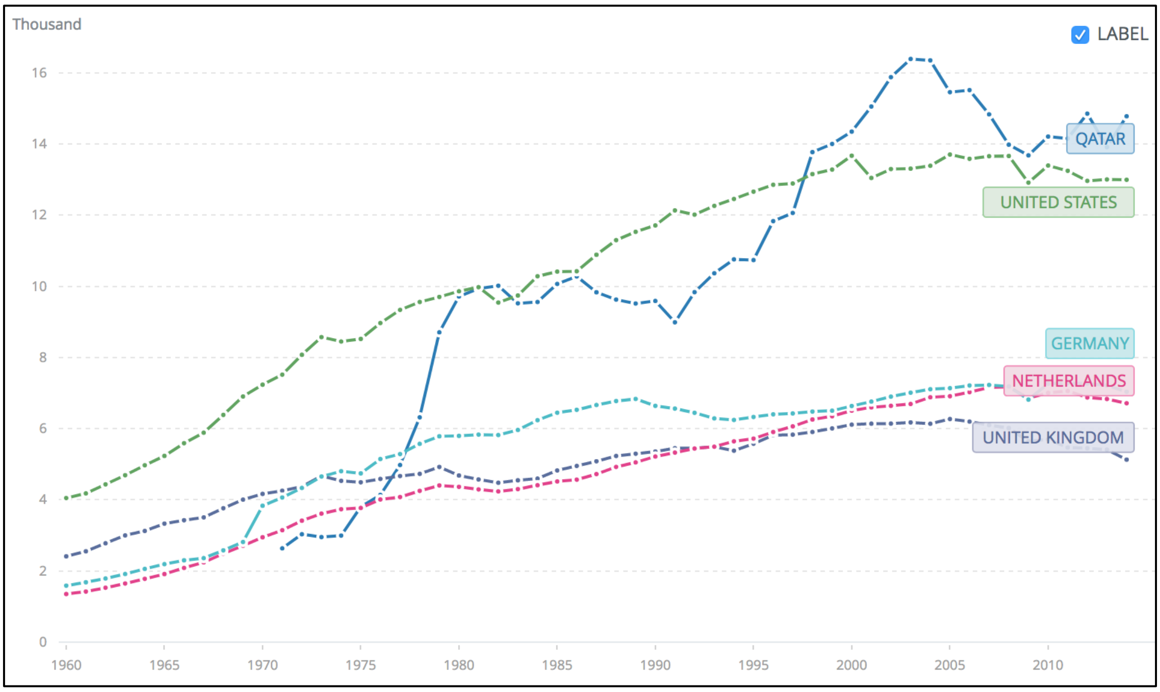


Figure 1.3. Per capita kwh comparison between Qatar, USA, UK and European countries (1960-2014)

As can be seen from Figure 1.3 above, despite the small size of Qatar compared to other countries, its consumption of energy seems very aggressive and requires serious attention.

1.1.6. Electricity consumption and demand by sector

The electricity demand has been ramping up at an annual basis in Qatar generally, however, over the last five years in particular, the demand has been raising with an average rate of ~7% and is expected to get even higher as the country approaches the planned global event of World Cup 2022.

The expansion of power capacity will essentially means building or expanding conventional gas fired power generation plants. Table 1.4 and Figure 1.4 show the maximum energy demand evolution in Qatar from 2013 to 2017.

Demand type	**2013**	**2014**	**2015**	**2016**	**2017**
System maximum demand	6000	6740	7270	7435	7855
Industrial maximum demand	1317	1648	1558	1560	1512
Domestic maximum demand	4795	5180	5905	5965	6455

Table 1.4. Maximum Demand (MW) by Sector from year 2013 to 2017[10]

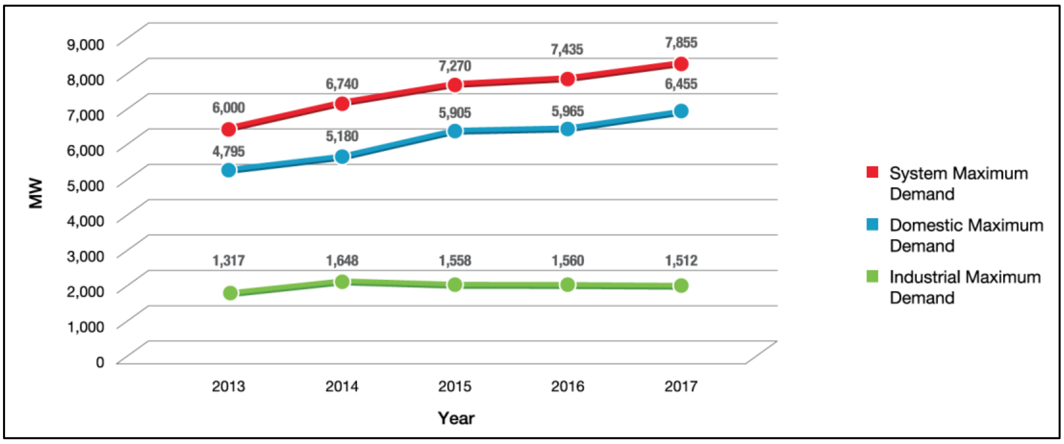


Figure 1.4. Maximum Demand (MW) by Sectors in Qatar 2013-2017[11]

In 2017, the maximum electricity demand from the grid (system maximum) was recorded in August14th with a value of 7,855 MW. The majority of this demand (~82%) is coming from the domestic sector which comprises residential, commercial and government buildings[10].It is evident from Figure 1.4 that domestic sector is the biggest consumer which needs immediate attention in order to control or slowdown the ever-increasing demand in energy. Targeting this sector for energy reduction/efficiency may present the low hanging fruits for decision-makers who need quick and cost-effective solutions.

1.1.7. Breakdown of domestic energy use

As defined earlier, the domestic sector comprises residential, commercial and government sub-sectors, and as per the IEA records (see Figure 1.5), the residential sector is the highest in terms of final electricity consumption.

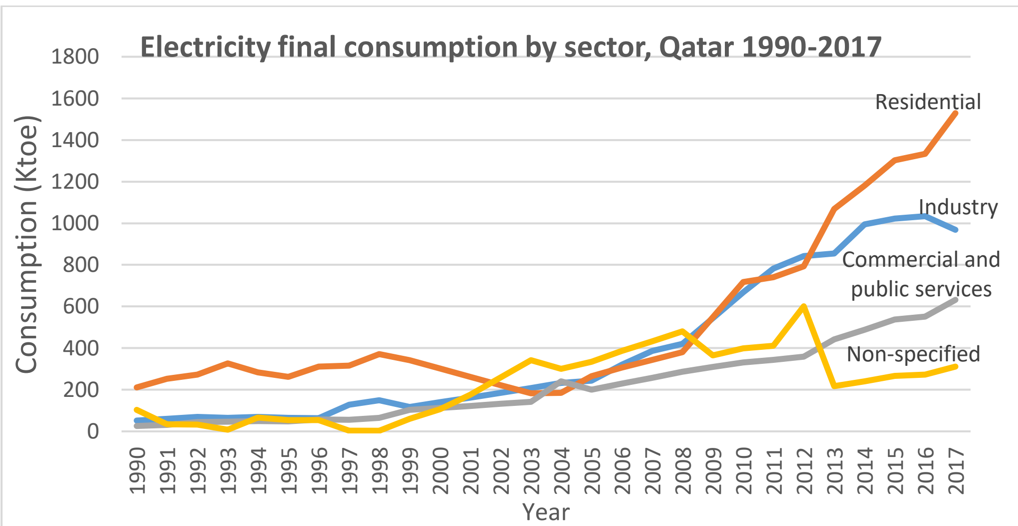


Figure 1.5. Electricity final consumption by sector in Qatar [5]

Due to the limited availability of data, breakdown of each sub-sector and final end use cannot be precisely determined. However, previous research on this topic estimated that 60%-80% of the energy of buildings is used for air conditioning throughout the year[12, 13]. The arid and hot climate throughout the majority of the year is considered the primary cause for such intense energy consumption in Qatar and similar neighboring countries within the GCC region. The consumption intensity tends to increase as the desert climatic conditions become more severe. Desert environment conditions will usually impact energy consumption in two ways, directly and indirectly. The direct way is through the increased use due to the apparent increase in cooling demand while the indirect effect comes from the adverse impact of heat, humidity, and dust on HVAC units that leads to degradation in both, system performance and energy efficiency.

District cooling technology is an efficient and cost-effective alternative to conventional air conditioning systems. However, it comes with a significant drawback, which is the high consumption of water. Despite the multiple district cooling projects implemented across the GCC region, the overall share of this technology remains marginal. In Qatar, for example, there are currently 23 operational district cooling facilities with a total cooling capacity of 665,650 Tons of refrigeration (TR) in addition to several projects that are underway [10]. The approximate share of current and planned district cooling projects is ~20%, while the remaining is conventional cooling systems.

1.1.8. Challenges and obstacles

Despite the government's strenuous endeavors to address energy and sustainability issues, the road towards achieving the planned national objectives is somewhat challenging. One of the biggest challenges in Qatar -apart from the harsh desert climate- is merely to do with the local culture and public awareness. The social acceptance and awareness are key factors that may influence the success of any introduced local measures. The lack of data is another obstacle that often hinder the possibility of making informed decisions based on advanced reports, studies and data analysis. The lack of effective energy & environmental policies is another issue that elevates the level of complexity in Qatar and other similar countries in the region.

Energy subsidies is a major obstacle which cause market distortion, namely the cost-benefit calculations by consumers/investors. With the current generous energy & water subsidies as well as absence of taxation policies, attaining sustainability targets will remain highly challenging. It is therefore imperative to identify a suitable approach to address energy challenges that fits the country's nature and specificities.

1.1.9. Ideal approach to address energy-related challenges

Governments and decision-makers worldwide are undoubtedly keen to combat climate change and address energy challenges. The type and efficacy of strategies used can -to a great extent- vary from country to country depending on many factors. This means when it comes to addressing energy-related issues, success of adopted measures is often country or region-specific. It has become an obvious trend for many countries to opt for renewable energy sources as a quick way to offset carbon emission and demonstrate sustainability as well as compliance to global environmental regulations. While this may appear as a good sign, it can be also misleading as more cost-effective solutions exist through simpler measures like Energy Conservation & Energy Efficiency.

With the perturbing per capita figures, Qatar has adopted an economy-wide renewable energy target to inject renewable energy into the national grid[3]. As a result, the country is currently investing in 800MWpeak large-scale solar PV power plant that is planned to be commissioned in 2021. Despite all the obvious benefits of adopting solar energy, it is not always a proof for efficiency as it is much more cost-efficient to save power instead of producing it even from renewable sources. According to reports by Brookings Institute, Qatar could enhance these efforts by exploring the scope for both an energy efficiency target and carbon intensity target as other advanced developing countries have done, such as China and India. For instance, an economy-wide energy efficiency target would underpin specific efforts to improve energy efficiency and incentivize investment in developing energy efficient technologies[3].

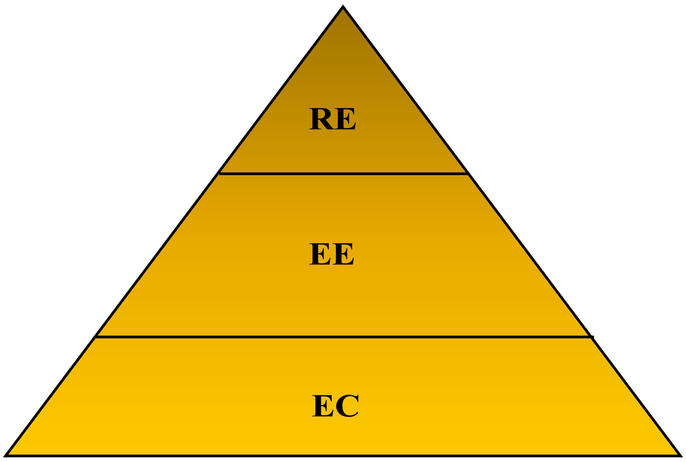


Figure 1.6. The Energy pyramid- an ideal approach of addressing energy-related issues

It is therefore important to consider energy conservation and energy efficiency whenever there is a need to address energy-related challenge before opting for renewable energy. The priority should be given in respective manner to Energy Conservation (EC), Energy Efficiency (EE), and lastly, Renewable Energy (RE). The Energy pyramid above in Figure 1.6 illustrates what could be the building blocks of a sustainable and logical approach to address energy challenges. The diagram suggests that one should first learn how to use energy wisely, then improve the efficiency at which this energy is being utilized before investing in a renewable energy source. At Qatar and other GCC countries, there are some modest energy efficiency awareness programs and initiatives being done by the governments. However, they are far away from being effective and cannot cope with the rapid increase in electricity demand.

In its simplest definitions, Energy efficiency is the use of less energy to provide the same (*or better*) service. Having established the energy conservation foundation through adequate initiatives and tools, energy efficiency can present itself to the decision-makers as the low-hanging fruit. Investing in Energy efficiency projects can be highly rewarding as it can save money for consumers by cutting energy costs. However, many of these opportunities are untapped due to the obstacles discussed in (1.1.7) which have historically reduced interest or profitability in such projects[3]. It is therefore, imperative for governments and decision-makers to lay down appropriate policies, regulations and market-based instruments to support energy efficiency initiatives.

1.1.10. Potential savings from Energy efficiency

Savings through applying energy efficiency and conservation technology & solutions can be highly significant in terms of cutting both costs and GHG emission, especially if supported by governments appropriate policies, regulations, and incentive programs. Power peak load is a daunting challenge facing many countries and utility providers, driving them to continuously expand power generation capacity to cater for the increasing demand. This is generally achieved by building more power plants; however, it can also be addressed by applying suitable energy efficiency and conservation measures that will postpone or slowdown the need for new power plants. For example, by assuming the possibility of shaving Qatar's peak load during the peak hours, this could save from 1200 to 1500 MW which is almost similar to the maximum demand from industrial sector. By considering the kWh during peak, this is equivalent to approximately 673 tons of carbon emission per hour. There are methods to realize these gains through energy efficiency and conservation technology like smart home & automation, smart grid & demand-side management programs. In addition, policies, regulations, public awareness and participation are all key factors. According to the US Environmental Protection Agency, consumers can reduce energy usage by 10-30% using schedules and temperature settings of programmable thermostats[14]. This means that by even applying simple measures to control the demand side efficiently, significant energy savings can be achieved.

1.2. Motivation

Considering both, the climate change concerns related to Gulf countries and the obstacles that hinder the implementation and realization of energy efficiency and conservation benefits in terms of cost and GHG emission reduction, such rentier states can take advantage of innovative technological and engineering approaches to bridge the gap caused by lack of effective policies. Since cooling applications for buildings are the main energy consumer, and due to encouraging potential saving figures found in literature, it is highly attractive to focus on this specific area of research to address such challenges in the most practical and cost-effective manner.

1.3. Objectives

This study aims to investigate the phenomenon of high energy consumption and issues associated with cooling applications for residential buildings at countries with harsh desert climate conditions. The following are specific targets of this work:

- Design and test an appropriate control schemes to manage the aggressive power demand for cooling systems in residential buildings
- Explore feasibility and propose a suitable solution for HVAC load management and peak shaving for microgrid applications
- Investigate the impact and Implications of dust on the HVAC systems performance and Energy Efficiency

1.4. Context of the study

The context of this study drills down to focus on a specific sub-sector and an end-use that is considered to be the low-hanging fruit for any country seeking practical & cost-effective solutions to address energy challenges. As shown in Figure 1.7 below, the boundary and focus of this study will be on air conditioning end-use for residential buildings within Qatar & GCC's desert and highly demanding climate conditions.

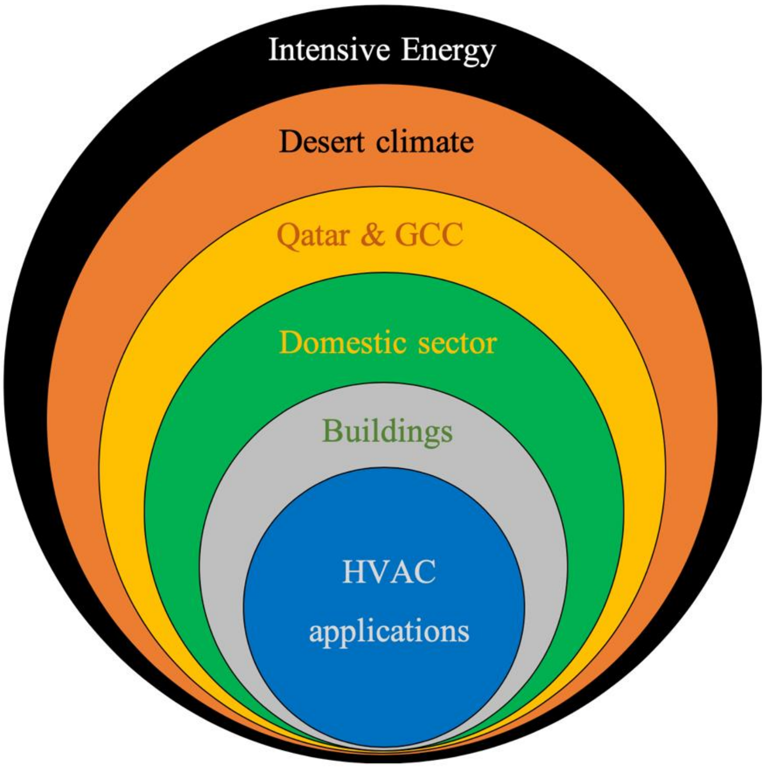


Figure 1.7.Onion diagram showing context and boundary of this study

The study shall make use of Qatar and other similar GCC countries as examples of demonstrating the energy related challenges and relevant local policies and regulations. The work is generally qualitative in nature and due to the complexity of the topic, various assumptions are made for the sake of simplicity as well as other considerations that will be highlighted in relevant section of this thesis document.

CHAPTER 2:

Complex On-Off AC Control Strategy for Peak Demand Reduction in Desert Climate Conditions

Abstract

In this chapter, a pragmatic engineering approach is proposed to assist in addressing the high-power consumption for cooling applications, specifically, peak demand issues in countries with desert climate conditions. In this approach, an improved control scheme for cooling buildings is developed to minimize load peak by responding to space cooling demands in a more holistic, organized manner rather than being randomly managed. Also, a mathematical model of a typical house cooling system is developed along with a complex multi-mode logic controller. Finally, the simulation results demonstrate the ability of the proposed control scheme to considerably reduce power peaks while maintaining an adequate level of indoor comfort.

2.1. Introduction

The most aggressive energy consumers in household applications are mainly heating and cooling systems. In the Middle East and Arabian Gulf countries with Qatar being an example case, there is a noticeably massive demand -around the year- for cooling due to the harsh desert environment (heat, humidity & dust), which approximately accounts for 60 – 70 % of total energy consumption. This can be noticed from the per capita energy consumption in Qatar which is amongst the highest worldwide and almost 3 times higher than the US. In addition to the desert climate, buildings specifications and local regulations are also factors leading to aggressive consumption and high carbon emission.

With electricity being a secondary form of energy that is being dominantly used for cooling applications in Qatar, the demand for such electric power is continuously growing, especially within the domestic sector, that frequently confronts governments and utility providers with the dreadful peak-demand issues during hot seasons. This reveals a serious power management issue that needs to be addressed on a priority basis.

There have been numerous studies and research aiming to address such energy challenges through state-of-the-art technology, energy efficiency techniques, and the use of renewable energy. While some methods have shown great success, many of them remain country-specific, meaning that local energy policy, regulations, and culture can significantly influence the expected outcome of any adopted or applied measure. There have been various studies and developed techniques to address peak load issues, where the approach usually focuses on Energy storage, where basically, energy is stored during non-peak times and release during peak hours to compensate for the shortfall [15] [16]. Also, Direct PV-battery generation is another approach, of which PV power is injected into the grid during peak time, which happens to be also around generation peak [4]. Additionally, Demand Side Management is a practical approach for peak-load reduction, which comprises arrangements between consumers and utility providers in terms of when and how energy should be used to ensure optimum efficiency [17].

In this study, an engineering approach is proposed to assist in addressing the high-power consumption for cooling and address peak demand issues. The focus will be on the development of a suitable control scheme for buildings' ACs to respond to space cooling demand while maintaining the peak load at a minimum effectively.

2.1.1. The power management problem

The main energy-related challenge in Qatar is managing the increasing power demand, especially in hot seasons. Figure 2.1 below shows the minimum and the maximum power demand recorded in 2018. The difference between the two points is massive, with a value of approximately 5GW, which is equivalent to half of the total power generation capacity in Qatar. The aggressive demand increase in hot seasons indicates that catering for cooling applications requires twice the power needed offseason. It can also be noticed that the maximum load point was recorded on August 14th at 13:30. The peak load in the summer season is approximately 1.8 GW that is equivalent to the demand of the industrial sector with a value that is comparable to a mid-size power plant. If not appropriately addressed, governments will have no choice but to bear the cost of additional power capacities in the form of expansions or new power plants. The associated carbon footprint and emission is also something that is unfavorable.

There are many energy cost avoidance strategies and topics that can be considered like cogeneration, on-site power generation, building energy cost control, utility DSM programs and deregulation, energy efficiency and peak demand reduction, commercial business energy cost control, industrial plant operation improvement, reducing environmental emissions, improving product quality, improving plant productivity and energy audits[18].

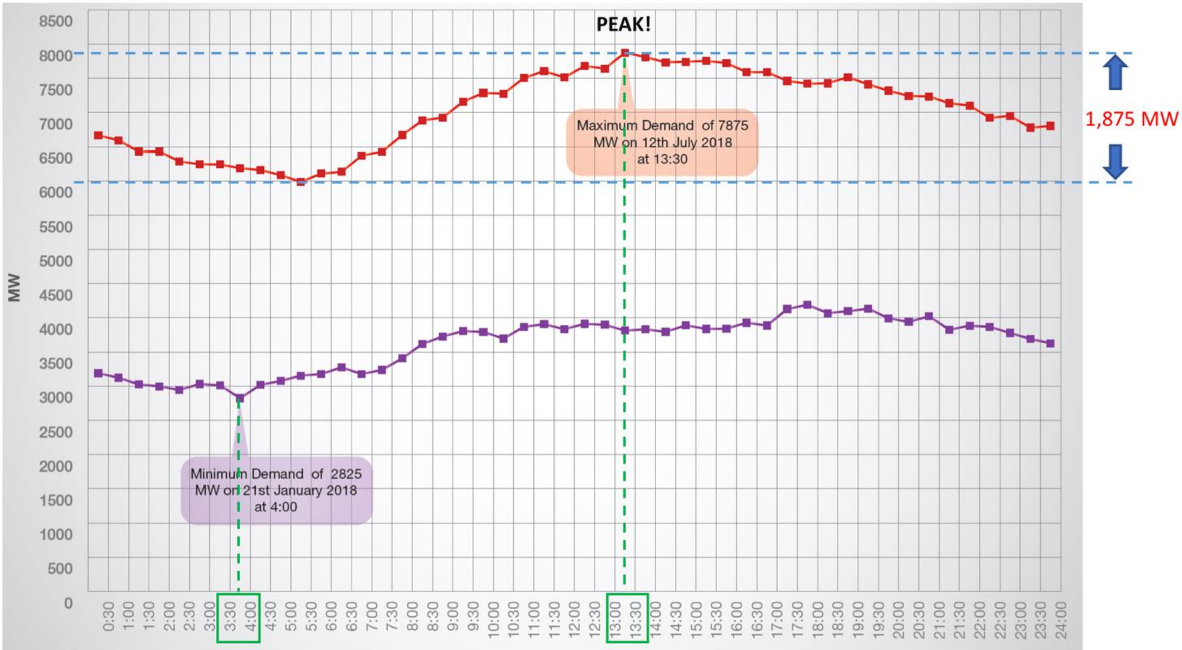


Figure 2.1. Maximum and Minimum Demand (MW)in Qatar, Half Hourly Load Curve in 2018[11]

The power generation capacity in Qatar has been growing over the last few years, with an average rate of ~ 5 %. This increase is a natural response by government and utility providers to cater for additional consumers and manage seasonal load peaks. This is achieved by the expansion of the generation capacity (either by upgrading existing or building new plants) to ensure enough power margin. Table 2.1 below illustrates the progressive annual growth between 2013 and 2018.

Demand type	2013	2014	2015	2016	2017	2018
No. of customers	293,604	310,107	329,310	344,445	364,597	376,636
Annual Growth (%)	1.6%	5.7%	6.2%	4.6%	5.9%	3.3%

Table 2.1. Annual growth of electricity generation and consumers in Qatar (2013-2018)[11]

Without controlling this growth, the need for building new power plants will continue. Such additional plants will definitely come with a whopping bill of capital cost along with the inevitable increase in fuel consumption and carbon emission.

In order to control the accelerating growth in electricity demand, governments and utility providers need to consider managing the demand side via energy conservation and efficiency measures. Such measures should help in minimizing power intensity and hence, slow down the construction of new power generation facilities.

When applying Energy Conservation/Energy Efficiency measures, it is crucial to target the source of the energy problem, which will usually stand out as the low-hanging fruits. In the case of Qatar, the big-ticket items are cooling applications within the domestic sector. Successful implementation of Energy Conservation/Energy Efficiency measures can potentially solve peak load issues through the effective management of demand-side.

2.1.2. Key sectors and final energy use

By observing electricity consumption records and statistical reports, it is evident that the domestic sector in Qatar is dominating the energy consumption and residential building more specifically.

As can be seen from Figure 2.2 below, the power demand magnitude of domestic sector (*residential + commercial +government buildings*) in 2018 was found 4 times higher than the industrial sector.

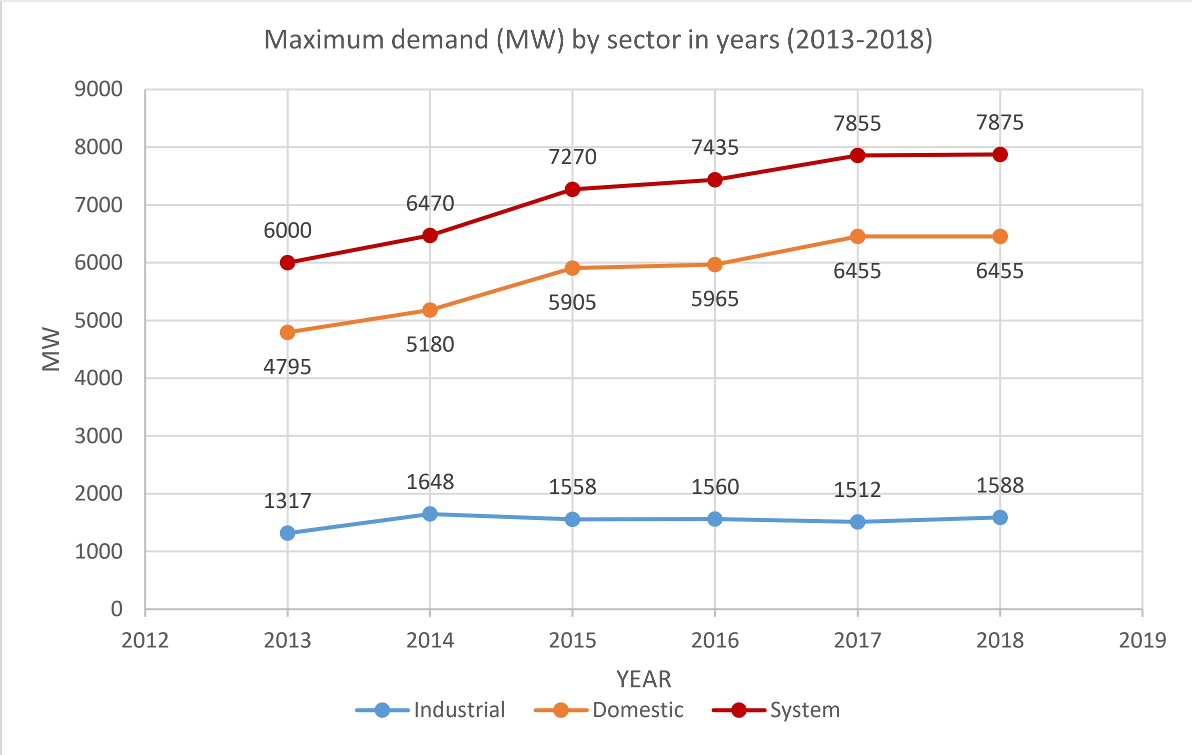


Figure 2.2. Maximum Power demand by sector in Qatar (2013-2018)[11]

Cooling applications for buildings within the domestic sector is the primary cause for such intense use of energy. Energy consumption and demand for power will continue to grow along with the growth in population, especially with the lack of stringent environment & energy policies. With such energy complexity, it is crucial to seek practical and cost-effective solutions to address these challenges to attain the country's sustainability targets. Although there are no energy access issues in Qatar, the difficulty encountered by utility providers is managing the simultaneous demand for power during peak times. The role of advanced technology, energy management techniques and the IOT is vital in facilitating new demand-side engineering approaches especially, in light of current modest policy framework.

2.1.3. Significance of Peak load issues

Peak load is a critical factor for grid stability and reliability, as it occurs occasionally and takes place only for a small percentage of the time in a day. To compensate for this peak load, many utility providers use a conventional approach which involves addition of power generation capacity. However, this approach is not economically feasible and inefficient in term of the generator's usage, since the utilities need to maintain the generation capacity that will be used only for a few hours per day. It also possesses several disadvantages, such as high fuel consumption and carbon dioxide (CO_2) emission, increase in transportation and maintenance costs and faster deterioration of equipment. Thus, peak load shaving is a preferable approach to overcome these disadvantages, associated with the capacity addition approach. From the utility perspective, peak shaving service on the grid reduces distribution power losses, increases distribution level power quality, and extends the lifetime of transformers. Thus, the utility service provider can handle more electric loads without requiring further network[15].

2.1.4. Objective

The objective of this research work is to develop a suitable control algorithm to minimize power spikes caused by running multiple AC units in a typical residential building during peak times while maintaining optimum cooling performance and indoor comfort. The success of this approach shall eventually validate the hypothesis that buildings air conditioning power loads can be manipulated in such a way to eliminate or minimize power overshoots during peak times which in turn if applied at city or country level can reduce stress on national grid significantly hence minimize or slow down the need for additional power plants.

The power spikes shaving capabilities are also of interest for off-grid applications or at a micro-grid level for resilience purposes during disruptions, where such systems would have very limited power capacities to operate at the designed comfort. However, these aspects are out of the scope of the current chapter.

2.1.5. Research approach

In order to achieve research objectives, the following approach was followed:

- Review of existing literature on the area of energy efficiency, power management and HVAC controls.
- Build and validate mathematical models for house cooling system with parameters collected from literature and manufacturer spec sheets.
- Conduct numerical simulation for a complete house cooling system with various operating conditions and analyze results.
- Develop appropriate control logic for optimum building air conditioning performance
- Validate simulation results, analyze and interpret system behavior.

2.1.6. Scope, assumptions, and limitations

The following points highlight general scope, assumptions and limitations:

- The scope of this study is to focus on targeting cooling applications in residential buildings for load shifting and peak load reduction where mainly conventional Air conditioning systems are only considered.
- Typical small-size residential building with average insulation conditions and 4 – 8 air conditioning units will be examined
- Investigation of performance during peak hours is initially targeted but will also be extended at later stage to include more operation hours.
- Several assumptions are made, and factors are neglected for simplicity purposes. This include: (eg: room size, humidity & disturbance effects)

2.2. Review of existing peak load shaving techniques

By definition, Peak load is the greatest amount of power given out or taken in by a machine or power distribution system during a given time period [1]. At a national level for example, the peak load demand usually occurs during the first few hours of a typical afternoon when residents return home from work or schools. Such peak load challenges are common globally and from utility providers' point of view it is considered an obvious bottleneck that puts significant stress on the national grid. Thus, most governments and utility providers are always striving to improve the way in which energy and peak demand is managed.

There are various studies and techniques in literature aiming to address peak load energy-related issues. The majority of these efforts are focusing on topic of "Shaving the peak".

Shaving Peak-load refers to any techniques or strategies adopted to reduce the amount of electricity (or another energy source) purchased during those periods when demand is greatest; e.g., by purchasing additional capacity when demand is low and storing it to be released when demand is high, or by shedding nonessential loads during peak periods[1]. This section gives an overview of on some the more common peak shaving techniques.

2.2.1. Peak load shaving using Energy storage

The term "Energy Storage" may refer to a wide range of energy storage technologies like battery systems, thermal, compressed air, flywheels and pumped hydroelectric storage systems. Each of these technologies has its own advantages and disadvantages depending on the intended application. For smart grid and peak shaving applications, Battery Energy Storage Systems (BESS) are common option. Battery technology can include solid state, lead-acid, Lithium-ion and Redox flow battery systems.

BESS can provide a fast, reliable and environment-friendly solution to address peak demand and help in peak load shaving. It works by charging batteries during off peak times and releasing power during peak hours when demand is high.

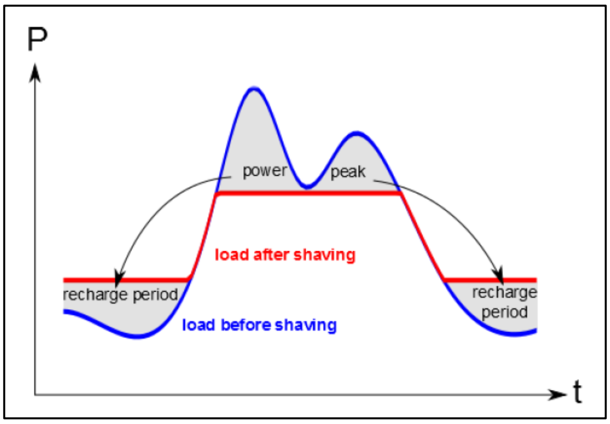


Figure 2.3. Illustration of how BESS performs peak shaving[16]

Peak shaving installations can be either owned by the electricity consumer at a household level or utility provider at power generation facility level. Households' peak loads often coincide with the peak load of the overall grid when the cost of energy is also high during these times. In such cases the benefit of peak shaving is twofold, that is reducing both the power fee and the cost of energy. Peak shaving can also be used by utilities or plants of renewable energy to increase the capacity of the existing grid infrastructure. Future transmission and distribution upgrade projects can be postponed which provides a more cost efficient upgrade path for power systems[16].

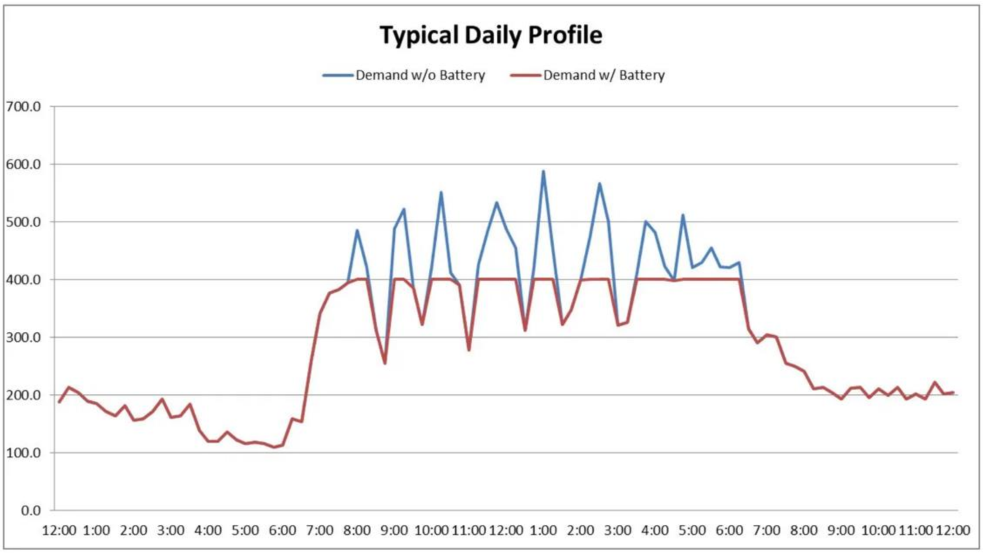


Figure 2.4. Example of house-level daily power profile with and without BESS[19]

2.2.2. Peak shaving using electric vehicles

According to Lee et al. [20], the majority of vehicles are parked during the peak load times which can present an excellent opportunity to achieve grid stability and peak load shaving. By considering EVs as energy storage units, if arranged and controlled suitably, Vehicle to Grid (V2G) connection can be established to transfer stored electricity from vehicle (battery) to grid as needed during high demand times which will consequently reduce peak load and stress on the grid. Other benefits include load leveling or valley-filling, voltage and frequency regulation, reactive power compensation, and provide spinning reserve.

2.2.3. Peak load shaving using direct PV energy supply

Solar photovoltaic technologies are dominating the market along with hydropower and wind in the realm of clean renewable energy sources. Many governments are opting for solar PV to address energy security and climate challenges. As per the International Renewable Energy Agency, the global grid-connected solar capacity reached 580.1 GW in late 2019. When combined with well sized battery storage solution, the PV systems can help in managing peak load issues where it is equally applicable at the utility and the consumer side. As per Figure 2.5 below, it is evident that Qatar's solar power generation potential is matching the peak demand profile which indicates the possibility of peak-shaving application even by direct injection to the grid.

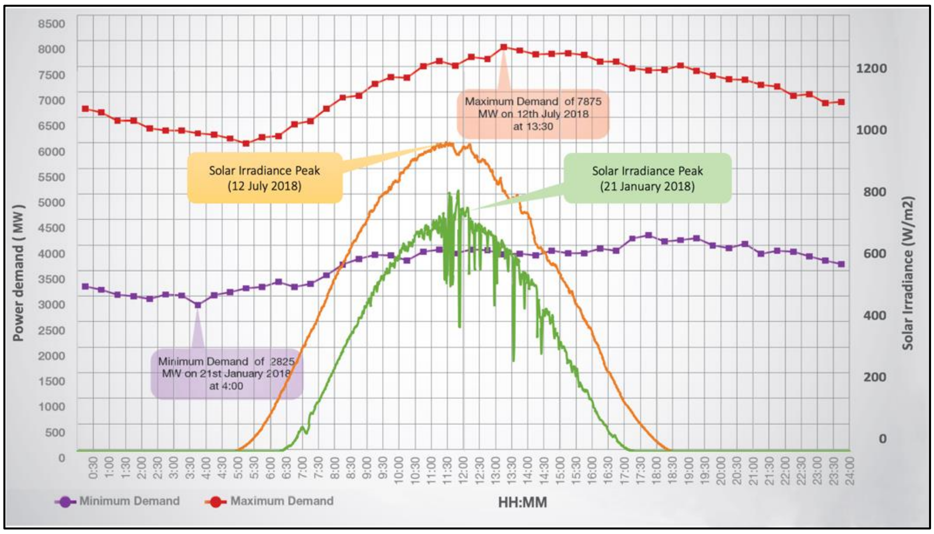


Figure 2.5. Maximum and minimum power demand vs sample solar irradiance (GHI) in Qatar

2.2.4. Demand Side Management and Demand Response

Demand-side management (DSM) is defined as the planning, implementation, and monitoring of utility activities so as to encourage customers to modify their pattern of energy usage[1]. DSM can involve all demand minimizing measures for the ultimate objective of establishing acceptable balance between energy supply and demand. The main strategies to achieve this objective is through Energy Efficiency and Demand response.

Energy Efficiency is the use less energy to provide the same (*or better*) service. It can be product wise, like efficient appliance that uses less energy or could be a measure that optimizes consumption and/or minimizes energy losses (like improved insulation). Energy Efficiency directly impacts power demand in general and peak demand in particular.

Demand response (DR) refers to incentive-based programs made by utility providers for the purpose of encouraging consumers to reduce their energy consumption during peak times in exchange of financial benefits. The result of implementing DR can aid utility providers in addressing the growing pressure on power grid especially peak demand. DR will also help in enhancing systems stability, control capital and operational costs.

2.2.5. Policy and regulations (Energy conservation and efficiency)

Governments and policymakers have increasingly used the tax code to promote energy policy targets. Long-term energy policy goals include providing a secure supply of energy, providing energy at a low cost, and ensuring that energy production and consumption is consistent with environmental objectives. There are different types policies used to promote various energy policy objectives. This includes R&D programs, mandates, and direct financial support such as tax incentives or loan guarantees[21].

Policy tools can help in shaping consumers' behavior and perception relating energy consumption and carbon footprint. Such policies can either take to form of incentive or promotional programs or regulatory framework that monitors and penalizes unfavorable behaviors through fines and taxation. Energy prices, feed-in-tariff, carbon tax and energy efficiency incentive programs are examples of policy tools used by many governments and policymakers.

The challenge with this approach is that no clear evidence of effectiveness nor guarantee of how much such policies will participate in managing / shaving power peaks since it is related to human behavior and willingness.

2.2.6. Smart grid technologies

The concept of Smart Grid involves the use of advanced sensors (*like PMUs*), 2-way communication, and computational technologies to monitor and control electricity network in such a way to enhance the overall functionality of the electric power delivery system. A conventional grid system becomes smart by sensing, communicating, applying intelligence, controlling and through feedback, continually self-adjusting[17].

Moving towards smart grid technologies modernizes the electricity infrastructure, which can significantly help in effectively facilitating the implementation of peak shaving along with other measures like energy efficiency and demand response. Smart grids can offer more benefits like resilience, improved security, stability, increased integration of renewables, and lower operational costs.

2.3. Basic Air conditioning Systems

Air conditioning (AC) or HVAC systems in general has become a highly essential component in human life at homes and buildings especially in hot regions to sustain good living conditions in terms of indoor air quality and comfort.

Air Conditioning types and technologies varies based on the intended size and application but can generally be categorized under two main types of technologies; vapor compression and absorption chillers. Absorption chillers are more energy efficient than vapor compression systems and are heavily used in industrial/commercial and district cooling applications. Nonetheless, vapor compression systems are more widely used in domestic sector with high availability in the market. This category includes many of the familiar compressor-driven types like window style ACs, portable ACs, split (ducted or non-ducted) units and Central air conditioning systems. Since they make the majority of appliance in use and because they are less efficient than chillers, they should receive special attention when addressing energy challenges.

These cooling appliances are designed to remove heat and humidity from the interior to the exterior by relying on conventional vapor compression refrigerant cycle. This basically implies a continuous process of compression and expansion of certain refrigerant through which the cooling effect is achieved.

With respect to energy consumption, the key component in the AC unit is the compressor which draws a relatively high current during compression stage. This is the main consumption point that causes the high-power demand in places where cooling is needed. The amount of energy and duration depend on various factors like compressor type, size, cooling demand, parameters, operating conditions.

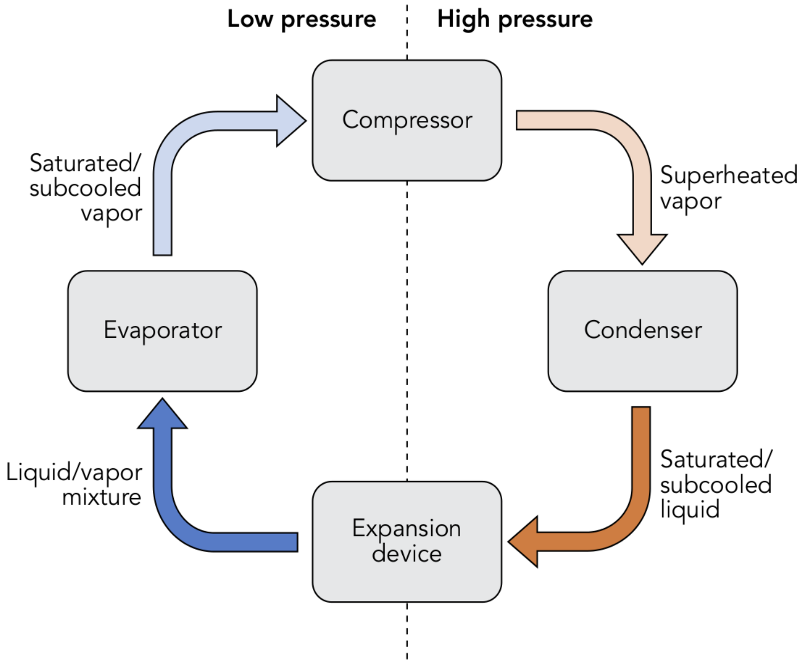


Figure 2.6. Conventional Vapor Compression Cycle[22]

The types of compressors commercially available are Reciprocating, Rotary, Screw, Scroll and Centrifugal Compressors. Also, compressors can come with either fixed speed (on-off operation to regulate temperature) or variable speed (continuous operation to regulate temperature). While the trend is now moving to modern variable speed compressors also known as inverter compressors, the majority of devices saturating the market and homes come with conventional fixed speed conventional compressors. Such fixed speed compressors are operated and controlled in a binary mode fashion in order to regulate indoor temperature at desired comfort level. That is, switching between two states (either ON 100% or OFF 0%) in order to respond to the cooling demand. This happens when compressors receive command signals from indoor thermostat sensor which triggers the compressor on and off to regulate indoor temperature around a desired setpoint.

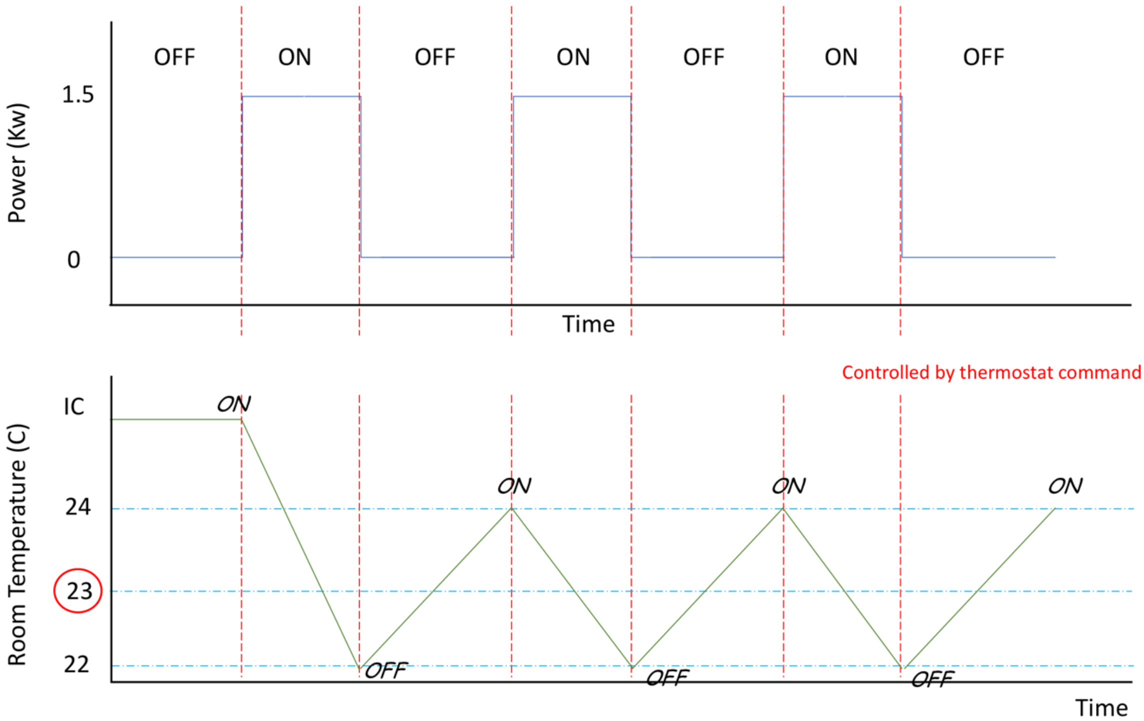


Figure 2.7. Typical operation of an air conditioning unit with fixed-speed compressor

From Figure 2.7 above, the air conditioning unit is regulating indoor temperature around 23°C by repeatedly switching the 1.5 kW compressor on and off upon crossing the control limits (±1°C)

The frequency, duration and pattern of the on-off behavior depends on many factors like, room size, insulation level, number of windows, AC size/capacity and many others. So far, there are no commercially available solutions that can offer holistic AC units' control, instead, conventional AC units work independent of each other regulating indoor temperature through on-off control system. With large number of AC units, this can be a chaotic process that leads to simultaneous or overlapping demand instances of high-power bursts that create load peaks.

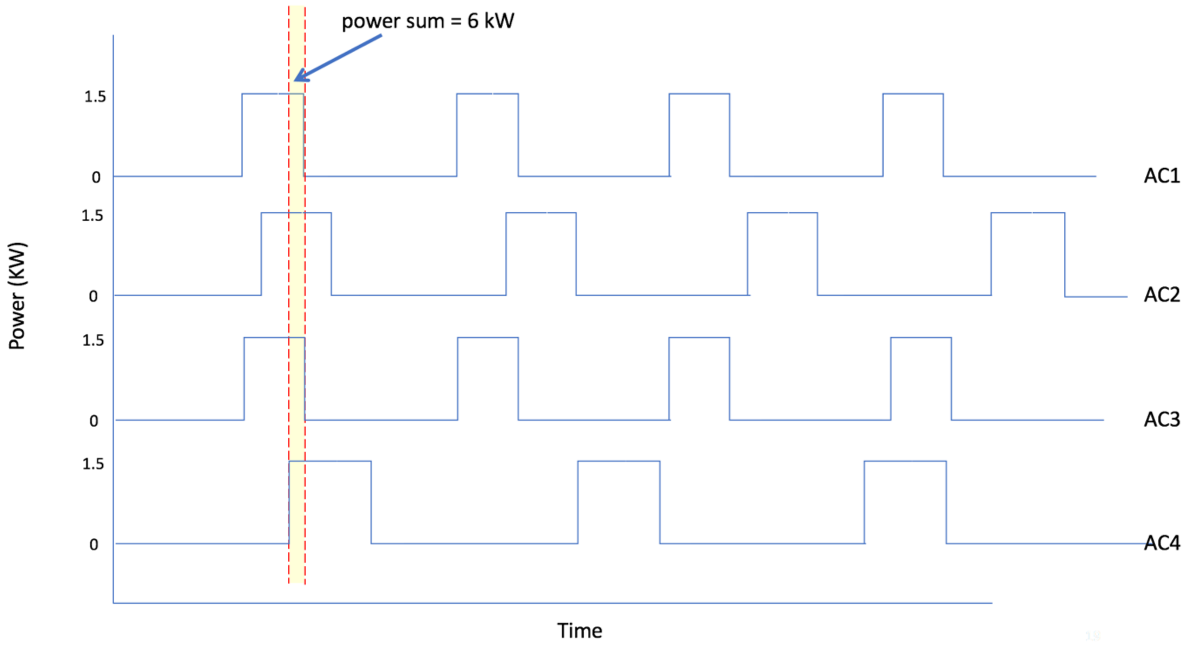


Figure 2.8.Illustration of how power overlap occurs with multiple simultaneously running AC units

Figure 2.8 above illustrates a scenario of four air conditioning units are running in parallel in a typical small size residential building (house/apartment) with 6 kW cooling load. For simplicity, it is assumed that the AC units have the same size and cooling capacities (1.5 Ton) for the cooling of 4 areas within the building.

What need to be avoided in order to minimize load peaks are the specific instances where multiple compressors are running at the same time. The situation of multiple compressors running at the same time could be the result of more than one compressor switching on at the same exact instance or simply when powered on while other compressors are already running at various points of their duty period which makes a power overlap.

2.3.1. Probability of a power overlap event

When an experiment is performed, a particular event A is said to occur if the resulting experimental outcome is contained in A. In general, exactly one simple event will occur, but many compound events will occur simultaneously[23].

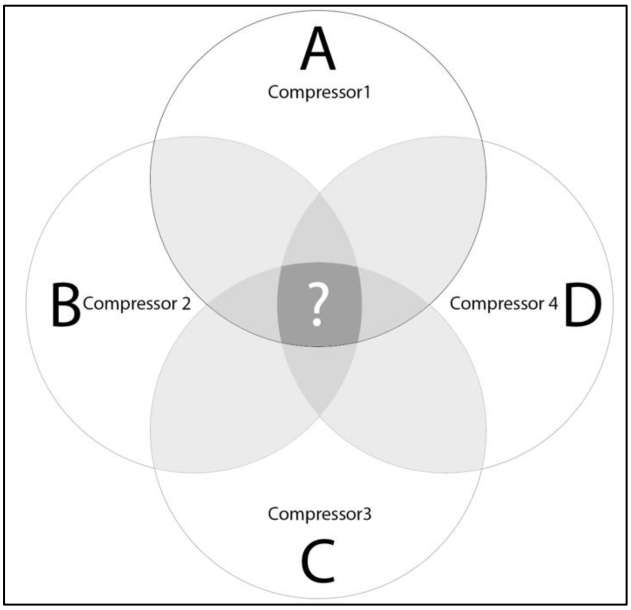


Figure 2.9. Venn diagram demonstrating probability of power overlap in 4 AC units

From probability perspective, a compressor has two states, “on” and “off” (or 1 & 0). With four compressors the total number of possible outcomes is 16. The sixteen possible outcomes combinations that comprise the sample space are as follows:

[1111,1110,1101,1100,1011,1010,1001,1000,0111,0110,0101,0100,0011,0010,0001,0000]

The worst-case scenario is when the four compressors are running at the same time, drawing maximum power. A long time after any potential simultaneous startup, the probability of this to happen can be estimated as shown below:

$$\text{Probability} = P(A \cap B \cap C \cap D) = \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} = \frac{1}{16} = 6.25\% \tag{2.1}$$

While the probability of the first “worst-case” scenario (exact switching time) might be quite low, the second scenario of, the chances for power overlap are overall fairly high and tend to get even higher with the increase in the number of AC units.

The probability of power overlap event may be quite low in small buildings, but likely to be quite high in large buildings with higher number of ACs. The case of at least 2 running at the same time then will be 11/16 ie. 68.75% chance.

2.4. Minimizing the power overlap events through load shifting

In order to avoid or at least minimize chances of power overlap, compressors' on-off triggering points need to be adjusted in a particular way that equally distributes the loads in a sequential manner. This control strategy should result in a stairs-like power distribution instead of augmented power spikes.

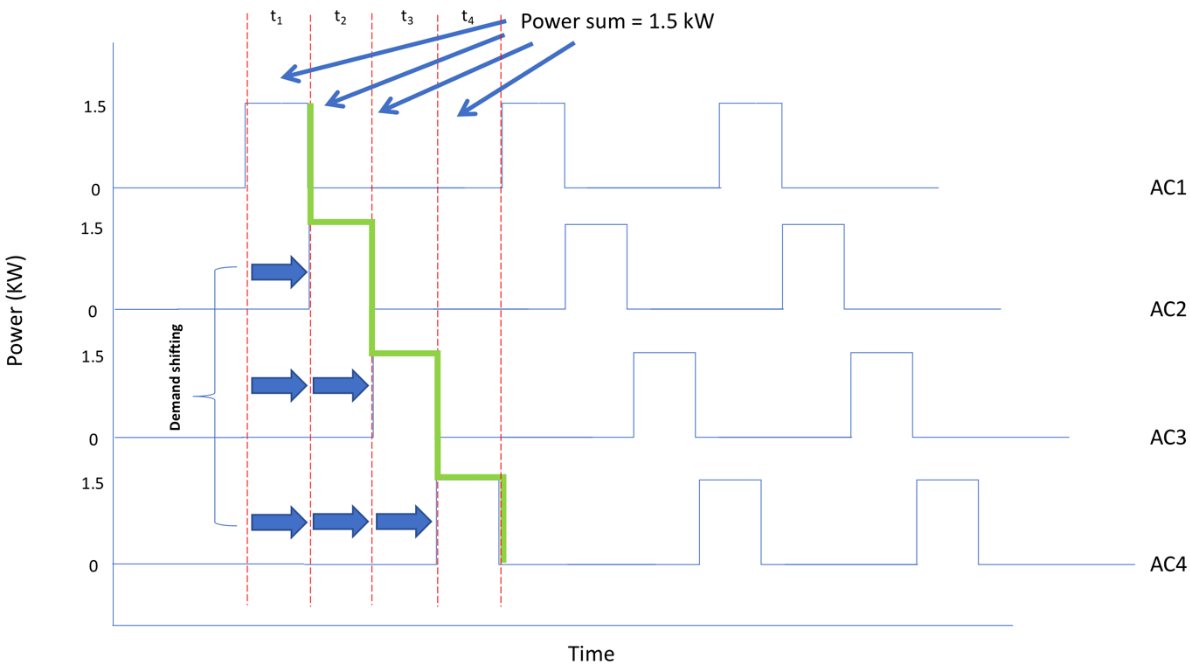


Figure 2.10. Illustration of power load-shifting for multiple AC units

For this to be achieved, a suitable control algorithm needs be designed based on a simple mathematical representation of a house cooling system. The mathematical model will capture the main required system dynamics, providing a proper platform for the design, testing, simulation and validation of appropriate control strategies.

2.5. Modeling & Simulation of a House Cooling System

Modeling and simulation tools and techniques are undoubtedly essential for researchers and engineers to address real-life issues in a safe and cost-effective manner. In this section, an attempt is made to build a simple house air conditioning system in preparation for the design work of a suitable AC load management system. It is important to build a system model that captures the essence of real system dynamics which will help in building the appropriate control mechanism. Modeling of building characteristics and envelope can involve its Heat Transfer & thermodynamics properties. This is extensively covered in the literature and can get quite sophisticated depending on the intended modeling purpose. Since the purpose of this study is mainly focused on the system control side, a simplified system model was adopted.

Figure 2.11. Illustration of a simple house cooling system

The temperature within a building is determined by its thermal properties & characteristics and the overall energy balance is governed by the laws of thermodynamics. The themal model of a room cooling system can be represented using the following relations[24]:

$$\frac{dQ}{dt} = (T_{room} - T_{aircon}).Mdot.c \tag{2.2}$$

$$(\frac{dQ}{dt})_{losses} = \frac{T_{room} - T_{out}}{Req} \tag{2.3}$$

$$\frac{dT_{room}}{dt} = \frac{1}{M_{air}.c} \cdot (\frac{dQ_{losses}}{dt} - \frac{dQ_{aircon}}{dt}) \tag{2.4}$$

where,

dQ/dt	:	the heat removal rate (J/h)
T_{room}	:	indoor temperature (°C)
T_{aircon}	:	cold air supply from AC (°C)

Mdot	:	air mass flow rate kg/h
c	:	specific heat capacity of air at constant pressure (J/kg.K)
T_{out}	:	outdoors temperature (°C)
M_{air}	:	room air mass (kg)
Req	:	room equivalent thermal resistance (K/W)

Equation (2.2) represents the rate of hot air removal from the room (cold air flow into the room) which can be converted into a simple block diagram as shown in Figure 2.12, where a cooling limit is also introduced for starting points at very high room temperatures.

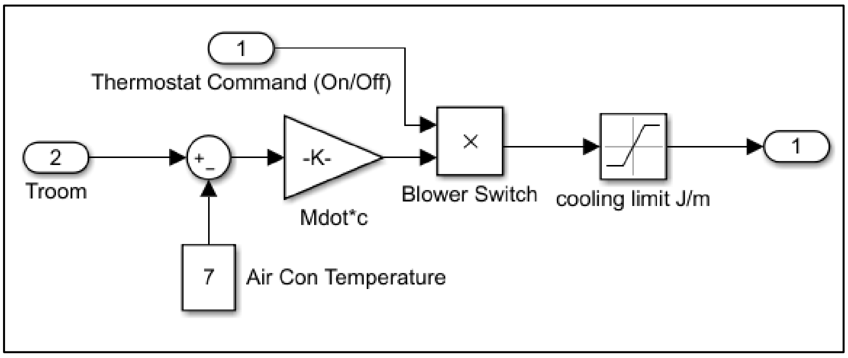


Figure 2.12. Block diagram for air conditioner part of the model

Equation (2.3) expresses system heat losses as its temperature time derivative part in Eq. (2.4), see Figure 2.13.

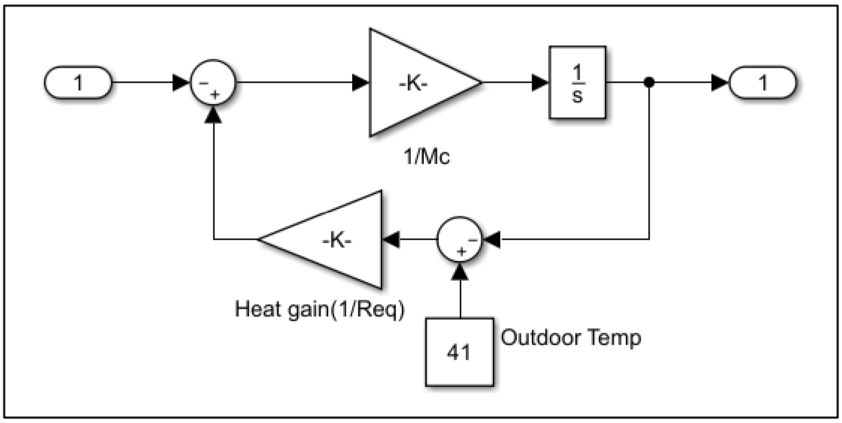


Figure 2.13.Block diagram representing the room thermodynamics aspect of the house cooling system model

By amalgamating the two equation parts (2.2) & (2.3), the overall model for one room cooling system obtained as shown in Figure 2.14 below:

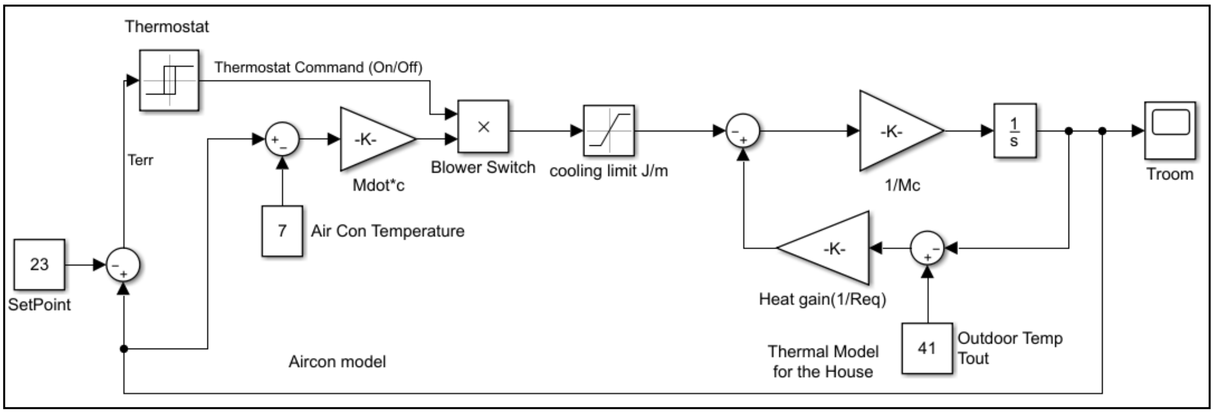


Figure 2.14. A combined block diagram model for a room cooling system

In order to finalize, test and validate the developed model, some parameters are needed to replicate real case scenarios. Such parameters should include system sizing, building's characteristics and thermal properties. Thus, assumptions and real-life parameters data are needed for both, the AC and the building side of the model.

2.5.1. General assumptions

Based on the objectives, scope and limitation of this study, the below assumptions are considered:

- Conventional air conditioning system is considered with fixed air flow and a group of 4 – 8 units is examined.
- Outdoor temperature is assumed to be fixed initially since the peak power periods' investigation is the main focus. However, temperature variation is considered at a later stage of this study.
- Effect of disturbance, humidity and building orientation is neglected.
- Other assumptions relating model thermal parameters, sizing and room geometry are only based on literature, manufacturers catalogues and nominal values.
- Based on equations, assumptions and estimated parameters, the developed mathematical model (block diagram) is updated to mimic a simple room cooling system.

2.5.2. Sizing and cooling load estimation

Cooling load estimation refers to the process of determining total heat removal requirements by an AC for a particular space to maintain the desired indoor temperature. This process is needed to determine the appropriate size of AC equipment that would deliver the needed cooling load with minimum life-cycle cost[25]. There are several sizing and load estimation methods for ACs, with different levels of complexities that can range from basic sizing charts up to extremely detailed and laborious calculation procedures. The selection of the sizing method depends on the intended application. However, commonly used methods rely either on sizing software tools or the use of rule of thumb techniques.

Engineering approaches for more exhaustive detailed sizing calculations of building zones and their cooling loads estimation can include: Transfer Function Method (TFM), Cooling Load Temperature Differential (CLTD) and/or Total Equivalent Temperature Differential (TETD). All of these advanced methods are extensively reported in literature and well supported and adopted by ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers)[26].

From the current study perspective and since the focus is on the power management side, a simple approach for the estimation cooling capacity and system sizing is adopted.

2.5.3. AC and building parameters

Based on the scope and assumptions made earlier, a hypothetical residential building is considered to generate data complementing the modeling work of this study. The key parameters that need to be identified are those impacting the building’s heat loss/gain (specifically, building thermal resistance and AC cooling capacity).

For practicality, parameters calculation for one room cooling system is performed first and then propagated to make multiple rooms (with altered parameters) within a house. Building material data and characteristics are obtained from the available literature while AC basic information gathered from manufacturers' spec sheets.

Figure 2.15 below shows the building block and baseline for the intended house cooling system which is a single 48m2 room with two windows. Based on this, the following section demonstrates the calculation steps conducted to generate appropriate parameter values to be used in the mathematical model for testing and simulation.

Figure 2.15. Illustration of a reference room used for the initial modeling (other plain walls not shown)

2.5.4. Calculation of key parameters

2.5.4.1. Room dimensions

Parameter	Abbr./sign	Value	Unit
Room length	RL	8	m
Room width	RW	6	m
Room height	RH	4	m
No. of windows	WN	2	
Windows height	WH	1	m
Windows width	WW	1	m

Table 2.2.Room geometry parameters

Windows area (A_{wind})= $$d \times e \times f \Longrightarrow 2 \times 1 \times 1 = 2\ m^2 \tag{2.5}$$

Wall area (A_{wall})= $$2 \times (RL \times RH) + 2 \times (RW \times RH) + (RL \times RW) - A_{wind} = 158\ m^2 \tag{2.6}$$

2.5.4.2. Insulation and thermal properties

Parameter	*Abbr./sign*	*Value*	*Unit*
Wall thermal conductivity	k_{wall}	*3.3*	*J/min/m/K*
Wall thickness	L	*0.3*	*m*
Windows thermal conductivity	k_{wind}	*84*	*J/min/m/K*
Windows thickness	L_{wind}	*0.06*	*m*

Table 2.3. Room thermal properties

Wall thermal resistance (R_{wall}) = $$\frac{L}{k_{wall} \times A_{wall}} \tag{2.7}$$

$$= \frac{0.3}{3.3 \times 158} = 5.75 \times 10^{-4} \quad (m^2K)/W$$

Windows thermal resistance (R_{wind}) = $$\frac{L}{k_{wind} \times A_{wind}} \tag{2.8}$$

$$= \frac{0.06}{84 \times 2} = 3.57 \times 10^{-4} \ (m^2K)/W$$

Room equivalent resistance *(Req)*= $$\frac{(R_{wall} \times R_{wind})}{(R_{wall} + R_{wind})} \tag{2.9}$$

$$= \frac{(5.75e^{-4} \times 3.57e^{-4})}{(5.75e^{-4} + 3.57e^{-4})}$$

$$= \frac{(5.75e^{-4} \times 3.57e^{-4})}{(5.75e^{-4} + 3.57e^{-4})} = 2.2 \times 10^{-4} \ (m^2K)/W$$

2.5.4.3. AC parameters

Based on initial space assumption for the $48m^2$ ($516.6ft^2$) room depicted in Figure 2.15, the cooling load estimation is obtained from online sizing tools and charts are shown in Figure 2.17 & Figure 2.20 below.

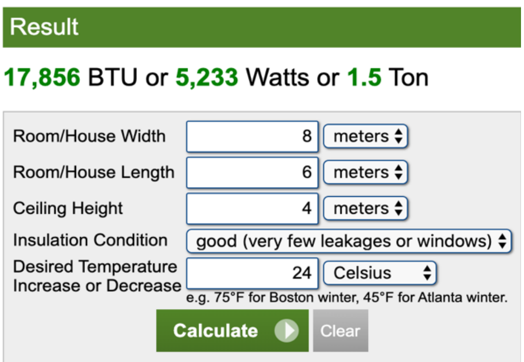
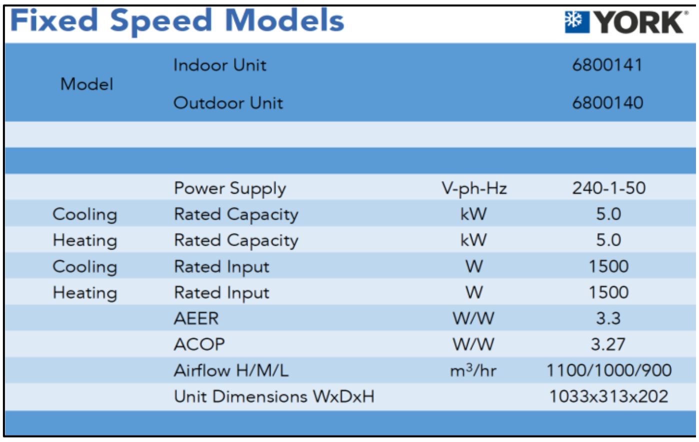


Figure 2.16. Online cooling load calculator[27]

Cooling and Heating Capacity	Area Service
9000 BTU	100 to 200 sqft
12,000 BTU	200 to 400 sqft
18,000 BTU	400 to 700 sqft
24,000 BTU	700 to 1000 sqft

Figure 2.17. Example of AC sizing charts[28]

From the available load estimation tools, it is found that for one room with assumed dimension approximately 18,000 BTU is needed, which is equivalent to ~5000 watt. This is also equivalent to 1.5 refrigeration ton which is a standard and widely spread AC capacity in the market. Figure 2.18 below shows a manufacturer spec sheet for an AC unit matching the estimated capacity. The specs are used further for modeling and simulation purposes. Figure 2.19 shows the actual measured AC outlet temperature using data logger.



Fixed Speed Models YORK

Model	Indoor Unit		6800141
	Outdoor Unit		6800140
	Power Supply	V-ph-Hz	240-1-50
Cooling	Rated Capacity	kW	5.0
Heating	Rated Capacity	kW	5.0
Cooling	Rated Input	W	1500
Heating	Rated Input	W	1500
	AEER	W/W	3.3
	ACOP	W/W	3.27
	Airflow H/M/L	m³/hr	1100/1000/900
	Unit Dimensions WxDxH		1033x313x202

Figure 2.18. Manufacturer spec sheet for 5kW AC unit (York)

Figure 2.19. AC measured Min/Max temperature

Ref.	***Parameter***	***Abbr./sign***	***Value***	***Unit***
a)	*Air specific heat capacity**	C_p	*1005.4*	*J/kg-K*
b)	*Density of air*	ρ_{air}	*1.225*	*kg/m3*
c)	*AC air Temperature (at outlet)*	T_{aircon}	*7*	*°C*

**Nominal value at 300 Kelvins (~26.85 °C)*

Table 2.4. AC parameters

Air flow rate

The AC air flow rate is assumed to be fixed for simplicity reasons. In this case and from manufacturer spec sheet the 1100 m^3/hr will be considered after conversion to kg/min as follows:

$$Air\ flow\ rate\ (Mdot) = \frac{volumetric\ flow\ rate}{60} \times \rho_{air} \tag{2.10}$$

$$= \frac{1100}{60} \times 1.225 = 22.4 \quad kg/min$$

Internal air mass (*M*)

The last parameter needed for the room cooling system model is the total internal air mass (*M*). this is simply obtained by multiplying the room volume by the density of air (ρ_{air})

$$\text{Total Internal air mass (M)} = \quad 8 \times 6 \times 4 \times 1.225 = 235.2 \ kg \tag{2.11}$$

2.5.5. Incorporation of the obtained parameters

Now that all key parameters are obtained, it is time to plug those parameters into the developed mathematical model for observation, simulation and testing. Figure 2.20 shows the block diagram for a room cooling system simplified (grouping into subsystems) and updated with the obtained parameters.

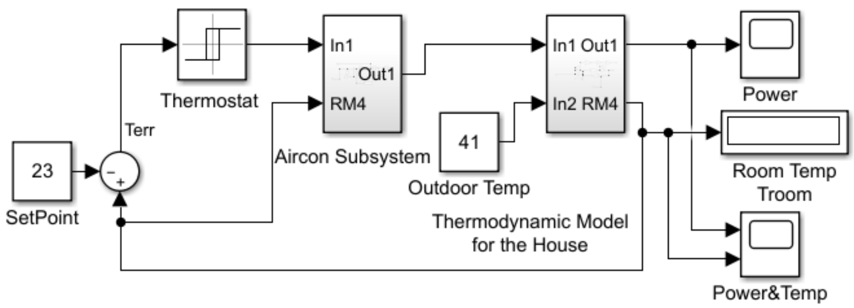


Figure 2.20 Simplified room cooling system block diagram

2.5.6. Model simulation results

By plugging the gathered parameters into the mathematical model of the room cooling system, the simulation result obtained seemed very reasonable and in line with the expected system behavior. Figure 2.21 below demonstrates the obtained simulation result.

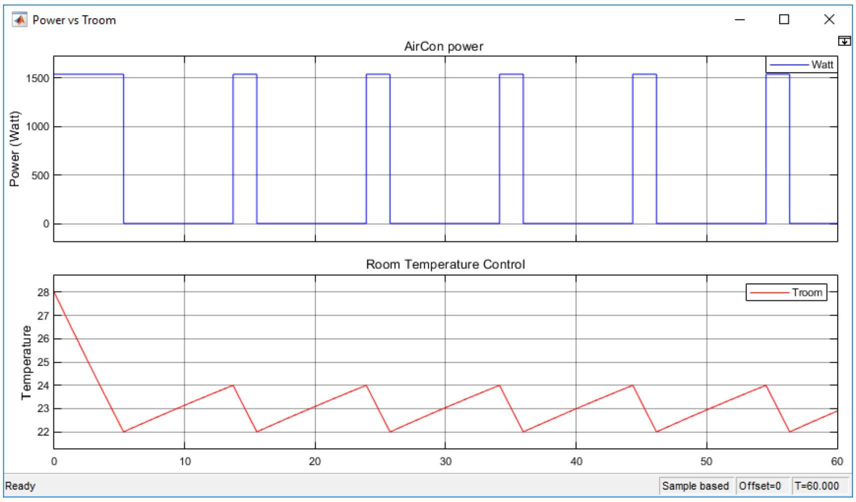


Figure 2.21. Simulation result of the initial model for a room cooling system (time axis in min)

As can be seen from Figure 2.21, the mathematical model for the room cooling system successfully is able to mimic the compressor on-off behavior, alternating between zero and maximum power value (1500 W) in attempt to regulate indoor temperature around the predetermined set point of value of 23 °C.

The initial conditions set for this simulation was 28 °C with simulated timeframe of 60 minutes. In terms of performance, the system behavior is comparable to average domestic conventional air conditioners with ~8 minutes per cycle and settling time of about 5 minutes. With this satisfactory result, the next step is to build the target house or residential building which consists of 4 rooms with separate air conditioning units.

2.5.7. Modeling of the house

Having delivered the first building block of the intended overall model, the next step now is to replicate this room cooling model to make up the 4-room house cooling system model. For simplicity, the house/residential building is assumed to be a combination of 4 individual rooms supplied with separate AC units. For illustration and to better visualize the intended setup, Figure 2.22 below shows an example 4-room residential unit (*eg. 3 bedrooms+1 living room*) that can be considered as a model baseline.

Figure 2.22. Example of 4-room residential building (house/apartment)[29]

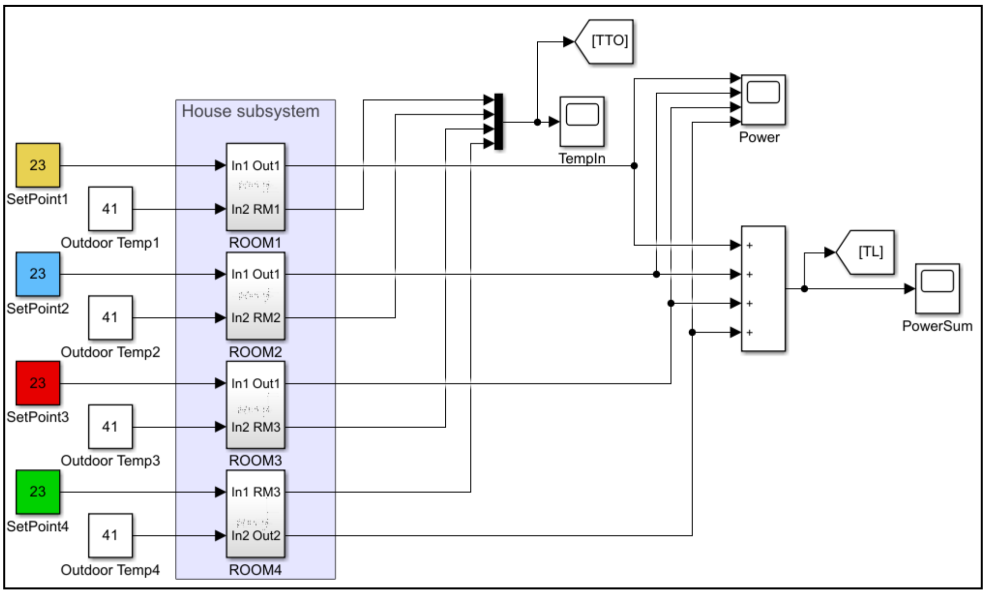


Figure 2.23. Model of the developed four-room air-conditioned house/residential building

2.5.8. Simulation of the house cooling system

As the cooled-house model is made by amalgamating four individual room cooling system models, room parameters need to be varied to avoid unrealistic model behavior (overlapping response) caused by exactly similar room parameters. Thus, to make simulation more realistic, some parameters are slightly altered for each room like room size, initial conditions and thermal resistance that could be a result of different numbers of windows and room orientation etc. These changes can give reasonable variation in individual rooms thermal performance. Below figures illustrates the house cooling system simulation results obtained after altering the rooms parameters.

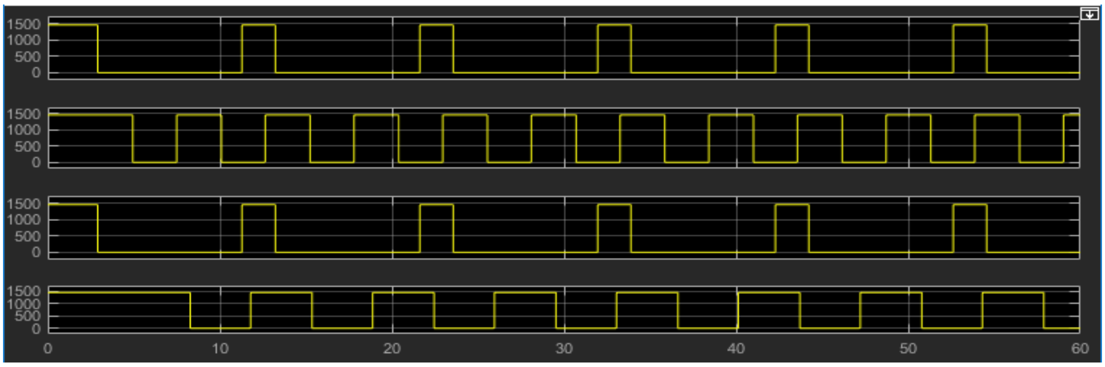


Figure 2.24. Individual AC power (Watt) of the house cooling system (time axis in min)

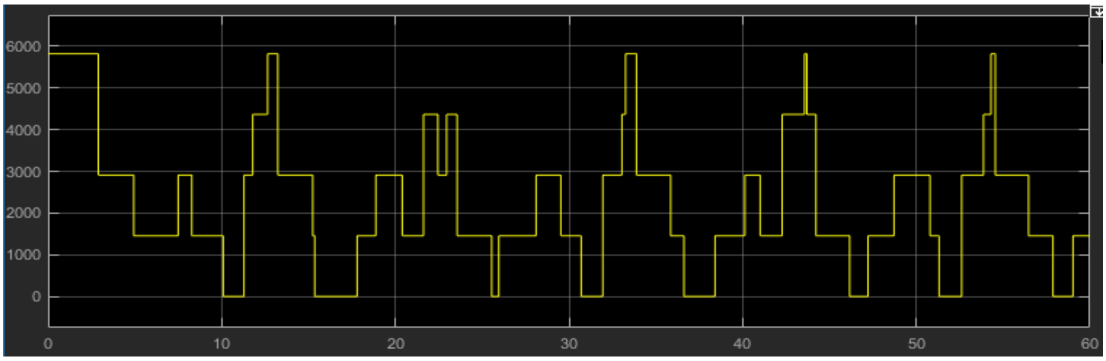


Figure 2.25.Sum of individual AC power (W) for the house cooling system (x axis in min)

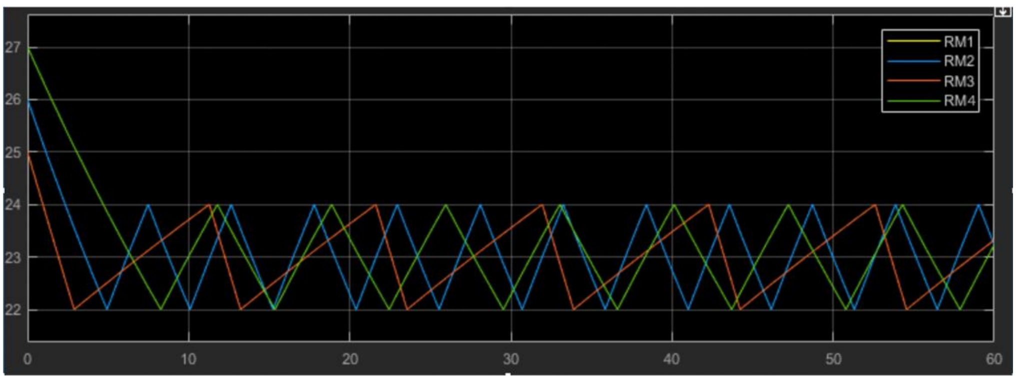


Figure 2.26. Rooms temperature regulation (°C) for the house cooling system (x axis in min)

It can be noticed from the simulation results that the house cooling model reasonably imitates the expected performance of a house with a 4 independently running AC compressor loads. There are certain instances where power overlap occurs causing noticeable power spikes. Such events tend to happen more often and for longer durations when outdoor temperature increases. Hence, the higher the outdoor temperature the more aggressive the power consumption profile will be. Figure 2.27 below shows the sum of ACs' power (Watt) at higher outdoor temperature by 5 °C compared to that of Figure 2.25 shown earlier (from 41 to 46 °C).

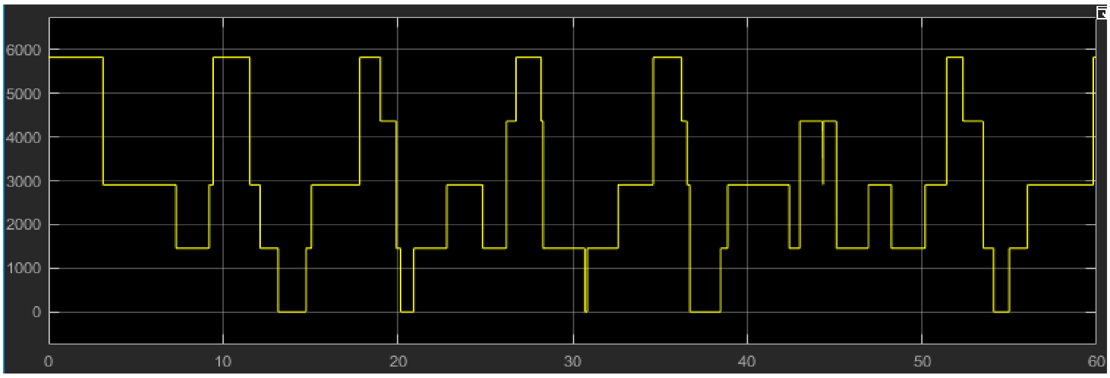


Figure 2.27. 4-room house cooling model power sum at extremely high outdoor temperature of 46 °C

In section 2.3.1, the probability of power overlap was presented from mathematical / theoretical viewpoint. With the house cooling model in hand, it is appropriate to experiment a 24-hour simulation with temperature variation to observe the frequency of overlap events by counting number of occurrences. The following figures (2.28,2.29&2.30) demonstrate respectively the events where 4, 3 and 2 compressors are running simultaneously.

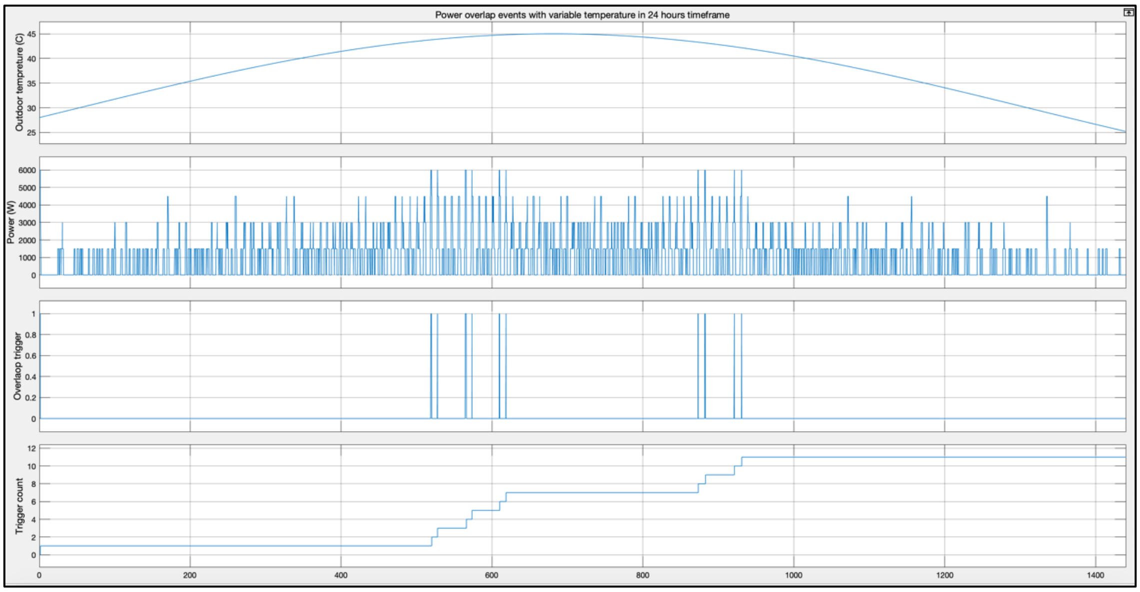


Figure 2.28. Simulation of 4 concurrent running compressors events in 24-hour variable temperature model (time scale in min)

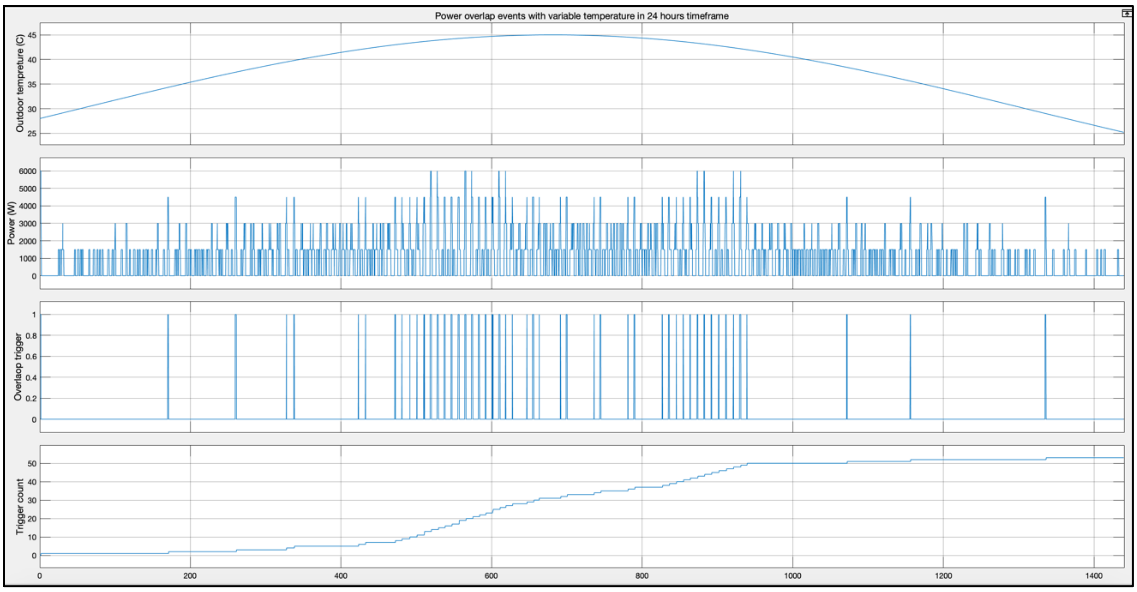


Figure 2.29. Simulation of at least 3 concurrent running compressors events in 24-hour variable temperature model (time scale in min)

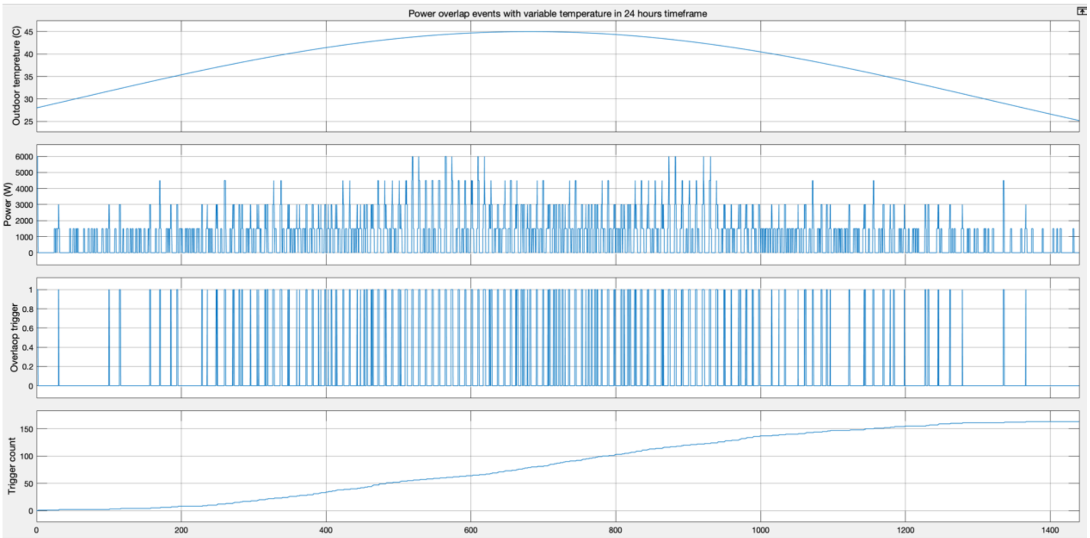


Figure 2.30. Simulation of at least 2 concurrent running compressors events in 24-hour variable temperature model (time scale in min)

	Number of concurrently running compressors	No. of recorded overlap events
Case1	4	11
Case2	3	53
Case3	2	161

Table 2.5. Summary of 24-hour observation of model simulation with temperature variation

At this stage and having demonstrated a reasonably functional house cooling system model, the next step is to design a suitable control algorithm capable of managing and minimizing the intensity of the adverse AC power spikes within residential building using the developed model.

2.6. Building the AC control system

Normally, multiple typical AC units within a building will run blindly independent of each other without interaction which will most probably lead to many instances of partial or total overlap in power demand (when compressors switch ON) resulting in power spikes. In order to solve this issue, it is necessary to control and harmonize the way in which a group of AC units work collectively within a building with the main objective of minimizing power consumption while maintaining an acceptable level of indoor comfort.

The objective of designing the AC group control system is to achieve load shifting and power leveling to minimize power peaks. This is possible by building a centralized multi-input multi-output (MIMO) control system with logic algorithm that performs load prioritization and sequencing in an optimal manner. With respect to the initial 4-room house cooling system model, the corresponding control system requirements constitutes 4 input and 4 output variables.

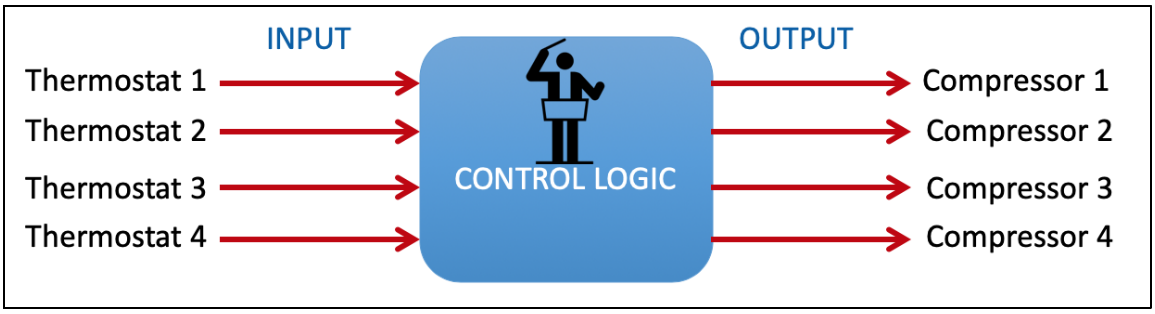


Figure 2.31. Blackbox diagram of the target group AC control system

The input variables are switching signals coming from each room's thermostat devices based on actual and desired indoor temperature. The output variables are also controller switching on/off commands that operate the AC compressors for each room based on the cooling demand. The control logic in between is where the load sequencing process occurs in a way that optimally matches the cooling supply and demand while avoiding power peaks.

The control logic is built using Matlab Stateflow® toolbox which is recognized as an environment for modeling and simulating combinatorial and sequential decision logic based on state machines and flow charts. Figure 2.32 below shows the AC load control logic using finite state machines in a bubble diagram format.

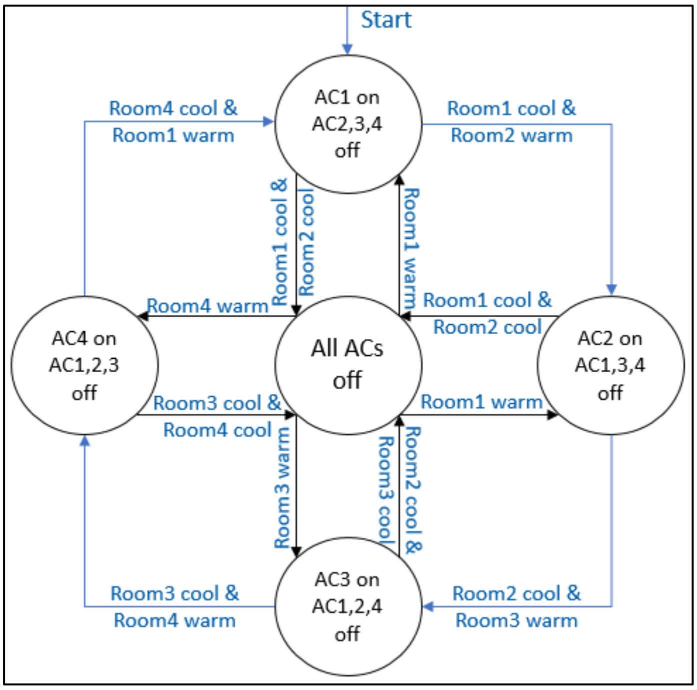


Figure 2.32 Bubble diagram of 4 AC units control logic

Note: AC on/off essentially means switching the AC compressor rather than the entire AC unit.

The above logic algorithm operates four AC units sequentially in series to avoid overlap in power demand hence minimizing power spikes that is caused by the sum of simultaneous power on demands. The logic has 5 states, four of them ensure only one AC compressor (out of four) is running at a time (based on cooling demand) and the fifth state switches all compressors off (when there is no cooling demand from any room) to avoid overcooling. The sequence starts at state 1 which switches AC 1 compressor on while keeping the other compressors switched off. As soon as desired temperature of room 1 is reached, the controller will move to the next state in the sequence by switching AC 1 compressor off and AC 2 compressor on. The sequence goes on for all AC compressors and repeat. If there is no cooling demand from all of the 4 rooms at any given moment during the operation, the controller will move into the fifth state switching all compressors off until there is a demand for cooling from any room (*in a first-come, first served basis*) and the cycle goes on. The Matlab Stateflow representation of the designed control logic is shown in Figure 2.33 below:

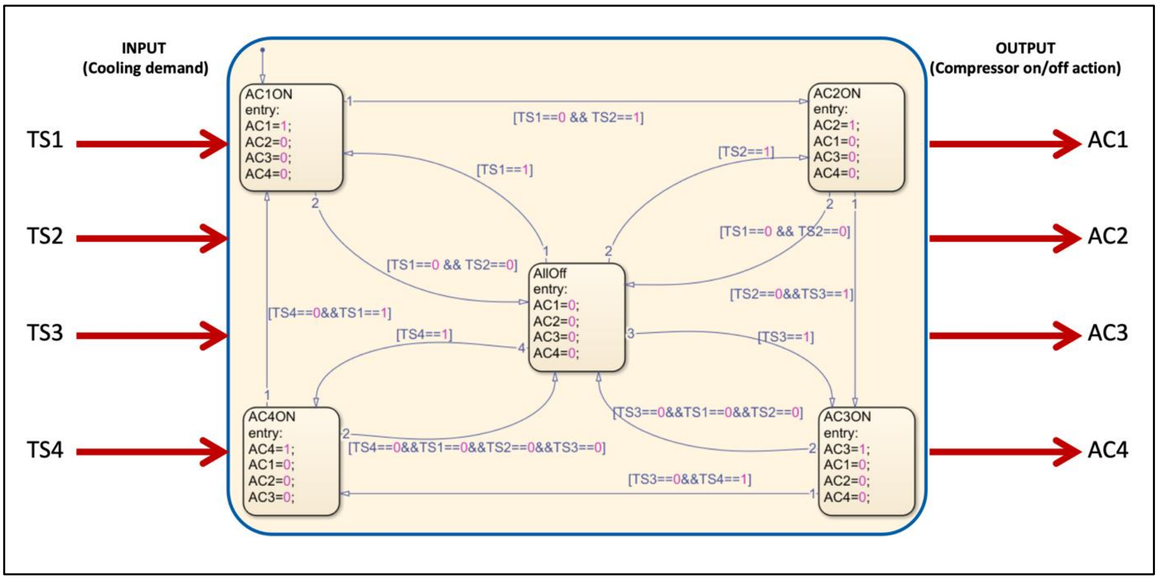


Figure 2.33. Matlab Stateflow diagram for the 4 AC control logic

2.6.1. Implementation of the designed control logic

The designed control logic has been incorporated into the house cooling system model by hooking it up to the 4 thermostats of the rooms (input) to generate and control the output signals to the 4 AC compressors.

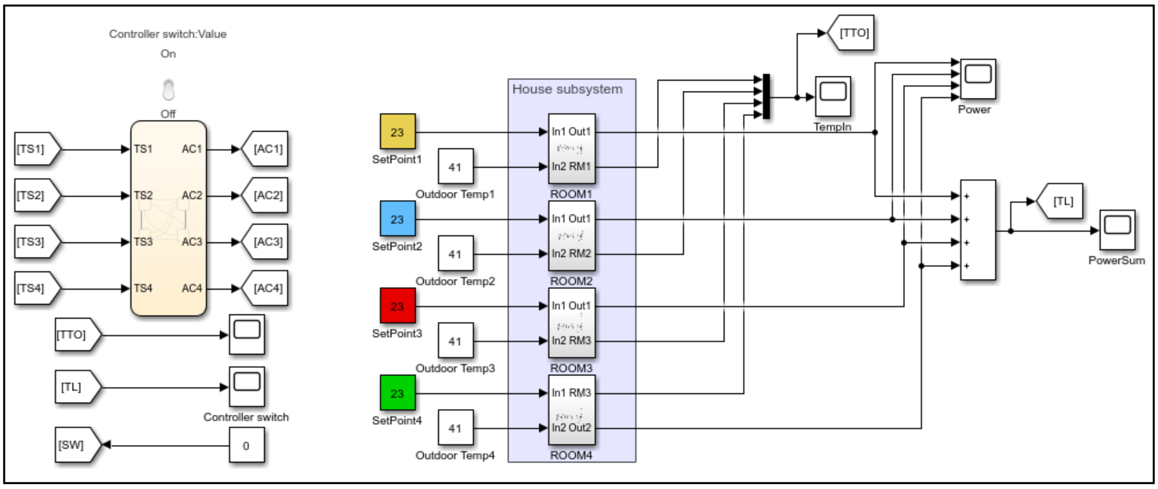


Figure 2.34. Illustration of the 4-AC control logic implementation into the house cooling system model

2.7. Implementation's Results and discussion

Applying the developed control logic into the house cooling model returned satisfactory simulation results in terms of power saving that is up to 75% reduction in power spikes with adequate level of indoor comfort.

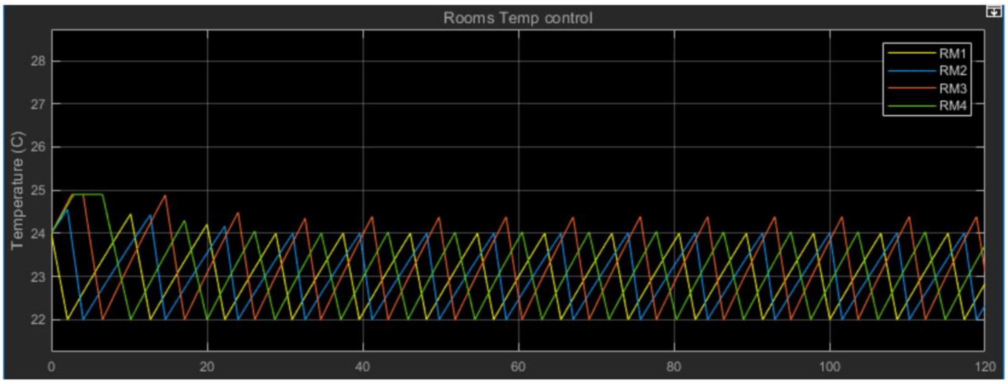


Figure 2.35.Resulting controller performance for indoor temperature control

As can be seen from Figure 2.35 , the developed controller is able to regulate the indoor temperature with fairly acceptable accuracy. The temperature is maintained around the target setpoint of 23 °C.

With respect to load-shifting, the control system has proved to be capable of distributing the cooling load in a harmonized manner to achieve optimal power peak reduction.

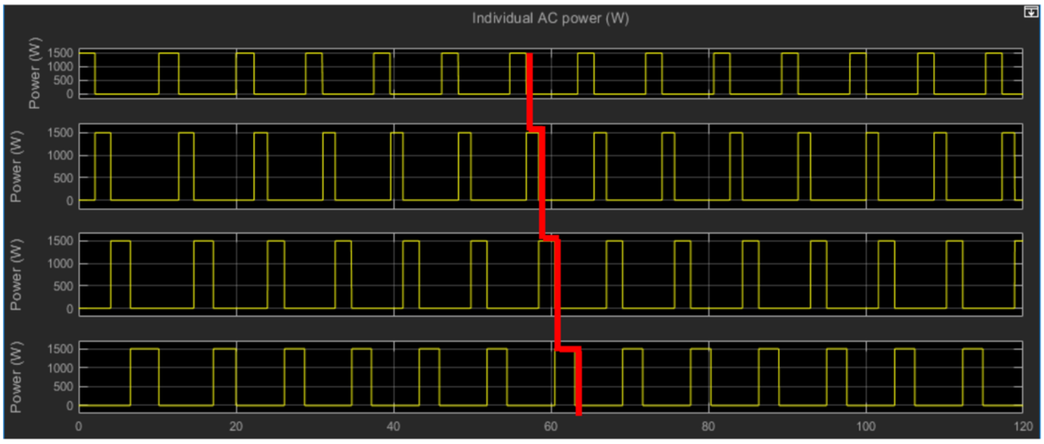


Figure 2.36.Compressor load distribution of four-room model by the designed controller

Having achieved the target load shifting and distribution functionality, the chances of power demand overlap has been eliminated resulting in a consistently shaved and spike-free power profile. Figure 2.37 below shows a comparison of the 4-AC house power performance with and without the applying the developed AC load control system.

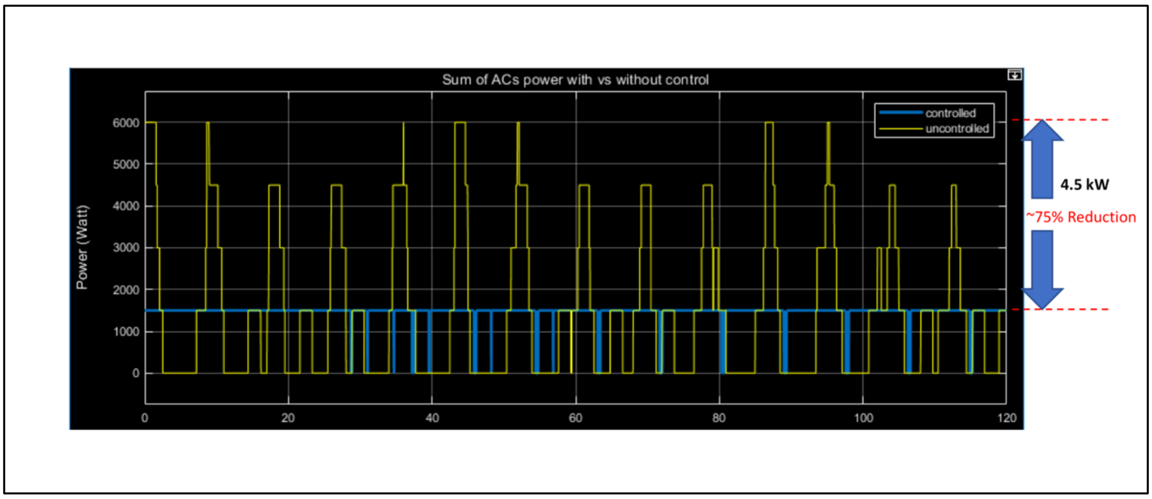


Figure 2.37. Four-AC house power sum comparison with and without the developed group load control

As can be seen from Figure 2.37 above, the developed control strategy is significantly successful in suppressing the aggressive power spikes caused by the random operation and power demand overlap of the 4 air conditioning units. This ability to orchestrate the operations of the 4 units has resulted in a massive reduction of power magnitude by approximately 4.5kW which is equivalent to ~75% of the expected maximum range. Such result reveals many promising economic, environmental and operational benefits that can be reaped by using this approach.

By considering the potential power reduction of 4.5 kW per residential building during peak hours (eg. 1 hour peak) and assuming a target of 500,000 identical residential units (*with possible power demand overlap*), the tally would be :4.5 kWh × 500,000 residential units = 2,250,000 kWh = ~2,250 MWh of potential saving.

From Figure 2.1 of this chapter and, the maximum peak demand recorded in 2018 was 1,875 MW which is approximately 83% of the potential power saving suggested by this study. That means, applying this measure will not only shave the peak but will also offer additional ~17% power reduction margin (*depending on how long the power peak lasts*) that would certainly help in minimizing power transmission losses and improve grid stability.

From capital & operational costs perspective, the 2,250 MW potential power reduction is equivalent to the generation capacity of 2 large gas-fired power plants or 4+ typical size plants (~300-500MW). The ability to achieve such power reduction translates into deferral of new power plant projects, saving the associated capital & operational costs as well as the inevitable carbon footprint and emission.

Capital cost: With respect to capital cost savings, according to the U.S Energy Information Administration (EIA), the average construction cost for natural gas power plants is $ 920/kW. Considering the aforementioned protentional power reduction and by using simple math, this equates to an approximate capital value of 920 × 2,250,000 = <u>$ 2,070,000,000.</u>

O&M cost: The average Operation &Maintenance cost of gas-fired power plants according to the IEA, is about $20 per kWh. This equates to 20 × 2,250,000kWh = <u>$45,000,000.</u>

Gas fuel: Avoiding or delaying the construction of a new power plant would result also in gas fuel savings (*as part of the O&M saving*) where such commodity can be exported instead of being consumed locally.

Carbon emission: Natural gas combustion process approximately produces 0.572 kg of CO_2 per kWh of electricity generated. With this in mind, and assuming 1 hour of continuous peak demand, the 2,250 MW of electricity generation is equivalent to 0.572 × 2,250,000 = <u>1,287</u> tons CO_2 per kWh. This equates to ~30.888 tons CO_2 per day, which is approximately <u>11,274,120</u> tons CO_2 per year. Apart from the environmental benefit, this could also present a substantial opportunity for cost-saving in countries with carbon pricing schemes depending on their carbon prices.

2.7.1. Real-life implementation

The scope of this study does not include experimental or prototype work for the proposed control scheme, however, this shall be part of future research work. The main concept of the proposed group AC control system is to make the individually randomly running AC units follow a certain pattern of operation that would result in reduced power peaks. Thus, in practice, the implementation of such system can be achieved by making use of a central digital MIMO controller that receives input signals from the thermostats of individual ACs in each room and (after processing) sends control command signals to different AC compressors. Another option involves the use of AC integration gateways, a technology that is available in the market and serve the same purpose of bi-directional monitoring and controlling of AC units. Such bi-directional, high-speed communication between the controller/interfaces and the AC units through the thermostats can take the form of any of many available wired and/or wireless communication protocols (*eg. BACnet, KNX, Modbus and WiFi*). The revolution in the electronics and telecommunication technology, the Internet of Things-IoT makes it possible for such setup to be accomplished.

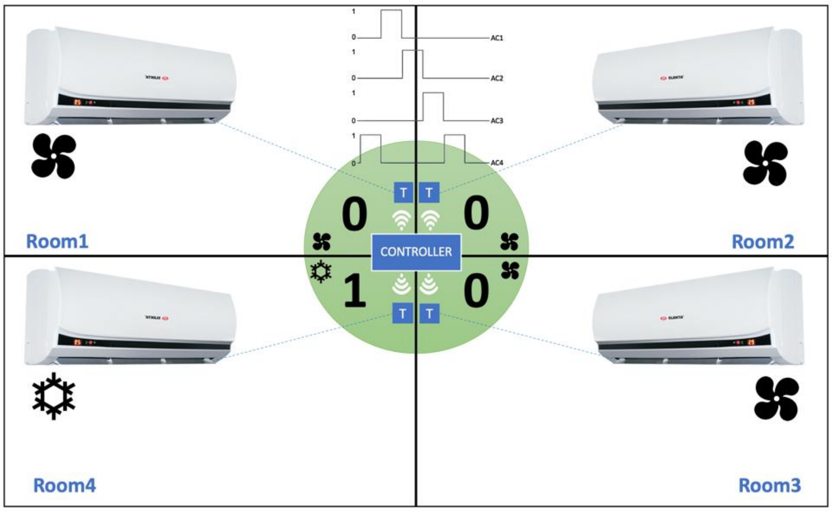


Figure 2.38. illustration of real-life group AC control setup

Many AC manufacturers offer great product flexibility by producing AC units compatible with integration gateways and/or pre-equipped with Wi-Fi communication modules to allow communication and control via internet. In addition, open-source Application Programming Interface (API) for browser-based and mobile applications is provided by some manufacturers which helps in designing customized control solutions.

2.8. Scale-up challenges, stability and system enhancements

Minimizing buildings' cooling peak demand by organizing the way in which a small group of ACs work together has been proved to be possible as established earlier within certain boundary conditions. The developed group AC control has demonstrated an acceptable performance in reducing power peaks in small residential buildings, however, system vulnerabilities appeared in cases of ultra-increase in cooling demand beyond the system's operating conditions, driven by;

1) extremely high outdoor temperature (eg. >49°C).

2) system scale up to bigger buildings with larger number of air-conditioned rooms.

In both cases, the system exhibits a sluggish or even uncontrollable performance.

In the first case, the cooling effort needed to overcome the scorching outdoor temperature is overwhelmingly high and pairing it with ambitious power reduction targets (*like 75%*) makes it impractical to be achieved. In this particular condition there are two contradicting objectives (*fighting extreme heat with minimum power consumption*) that tend to push the system beyond its working capability and outside the limits of its ideal operating conditions, the system becoming undersized.

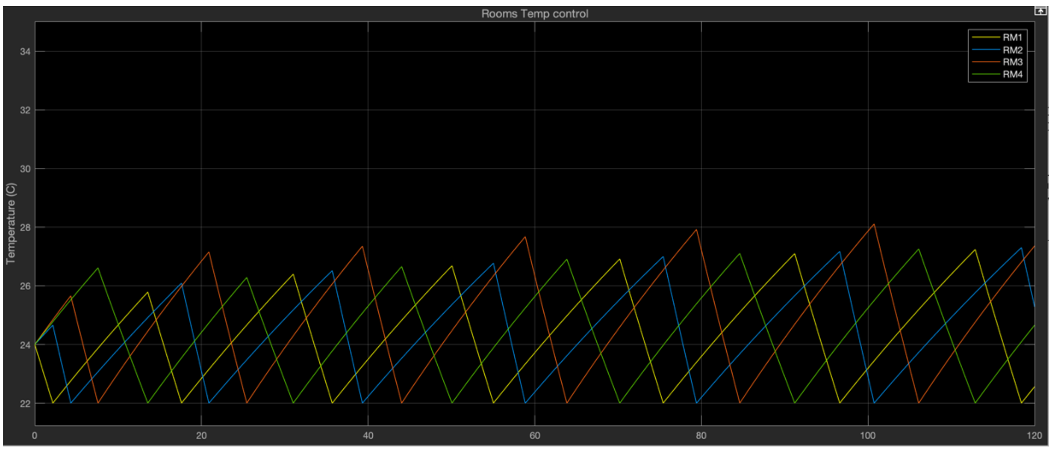


Figure 2.39. Unfavorable 4-AC system control response at extreme heat (49 °C) beyond ideal conditions

In the second case, stretching the developed (4-room) house AC control system to handle larger buildings with more AC units, combined with a range of outdoor temperature variations have shown unfavorable control results. The main reason for this shortfall is the considerable increase in the time taken by the system to complete one cooling cycle. One cooling cycle is the time between the compressor's first switch on point and the last switch off point as they are running in series. In reality, the time per cycle may change depending on factors (like temperature disturbance) that influence rooms cooling cycle time, however, an average fixed time per cycle is assumed for illustration purposes.

To further investigate and enhance the adaptability of the proposed system, the house model was extended and the control system was altered to consider an increased number of AC units (8 ACs) within a bigger building as well as to dynamically vary outdoor temperature variations (instead of fixed) during the system simulation.

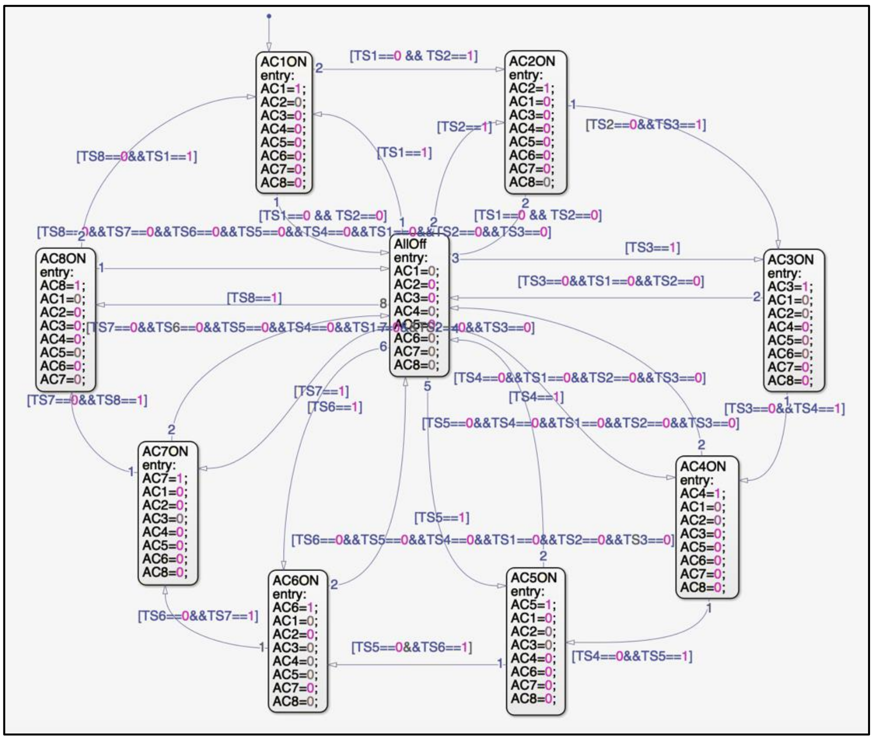


Figure 2.40. Stateflow logic diagram of 8-room group AC control

From Figure 2.40 above it is obvious that route for one sequential cycle in the case of 8-AC units building has increased in complexity and duration.

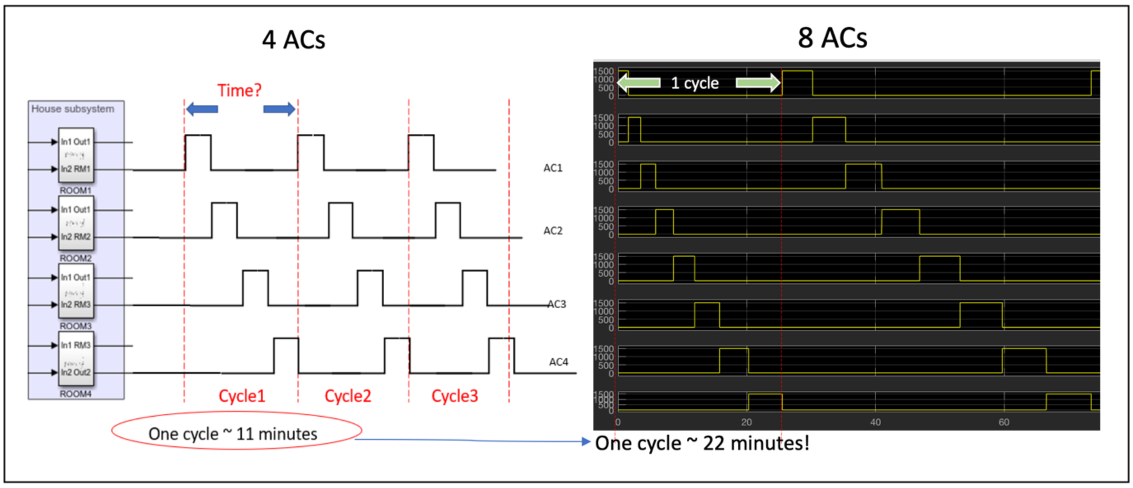


Figure 2.41. Demonstration of the difference between 4 and 8 room systems' cooling cycle durations

As can be seen in Figure 2.41, the time taken for one cooling cycle in the case of 4-AC system is approximately 11 minutes. By considering an example of a bigger house with 8-AC, the result would be doubling the time per cooling cycle which means longer idle (waiting) duration between first and last AC in the loop. This essentially creates a serious burden that hinders the system ability to cope with the immensely increasing cooling demand in a timely fashion.

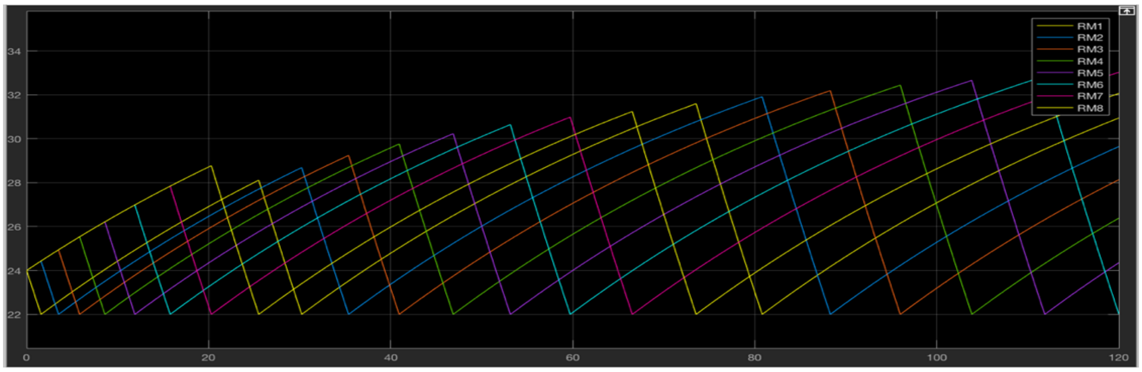


Figure 2.42.Out of control temperature response under ultra-high cooling demand beyond boundary conditions (8-AC system)

Figure 2.42 above shows an example an "out-of-control scenario" where the system is pushed outside the ideal operating conditions by attempting to control 8 rooms' internal temperature at 23 °C with outdoor temperature being fixed at 37 °C, which is frequent in Qatar. As highlighted earlier, the system exhibits similar behavior with 4-room system when outdoor temperature equals or exceeds 49 °C.

Obviously, satisfying the dual targets of power reductions and indoor comfort cannot be always achieved with this system design, especially in the ultra-high demand scenarios.

This dilemma can be addressed by simply striking a balance between power saving and indoor comfort by accepting variable power reductions (*instead of fixed*) based on cooling demand intensity (*which depends on system capacity, number of AC units and outdoor temperature*). This implies lowering the bar of power saving expectations (*eg. accepting 50% instead of 75%*) to optimally meet minimum thermal comfort requirements while securing maximum possible power peak reduction.

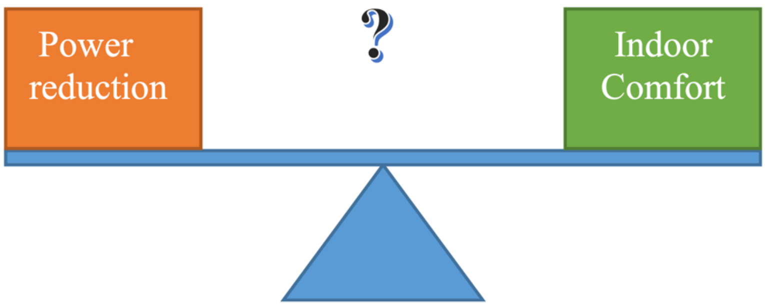


Figure 2.43.Illustration of the need for an optimal point for power reduction & comfort

2.8.1. The improved control system design

In light of thorough performance observation and analysis of the current system under various operating conditions, the control logic has been modified to include sufficient level of flexibility and adaptability that accommodates a wide range of working scenarios.

The new upgrade allows certain number of compressors (based on cooling demand) to run simultaneously in parallel as opposed to the original (baseline) system design that strictly allowed only a maximum of one compressor unit to be ON at a time. This helps in overcoming the unfavorable system control behavior under ultra-high cooling demand scenarios.

To achieve this, three power-saving modes of Min, Mod and Max are implemented in the control logic to respond to 3 cooling demand scenarios of Low, Med and High respectively.

With this added flexibility, the controller will determine based on cooling demand parameters the appropriate power saving mode to be adopted, hence the allowed number of concurrently running AC compressors. For example, in low cooling demand cases where outside temperature is low and/or in case of few AC units, then the system adopts the "Max" power saving mode where maximum power peak reduction is achieved. At the other extreme, when cooling demand is considerably high (whether due to extremely high outside temperature or/and large number of AC units) the system engages the "Min" saving mode for which an optimal number of concurrently running compressor will be allowed to maintain adequate indoor comfort. The system will expectedly adopt the Moderate ("Mod") saving mode during medium cooling demand conditions. The temperature scale reference and the threshold between each cooling demand scenario (*high, med & low*) is design-specific and determined based on model observation. Table 2.6 blow shows a summary of the 3 scenarios in an 8-AC unit system with potential power saving.

Cooling Demand	**Outdoor temperature scenario**	**Controller Saving mode**	**% Power Saving**
High	outdoor temperature >47 °C	Min	50%
Med	outdoor temperature = 36 to 47 °C	Mod	75%
Low	outdoor temperature <36 °C	Max	87.5%

Table 2.6. Multi-mode control scenarios for eight-AC units building

The outdoor temperature values depicted in Table 2.6 above are the threshold (cut-off) parameters that determine transition points from one power saving mode to another. These values are incorporated into the developed adaptive multi-mode control logic as shown in Figure 2.44. Each cut-off temperature corresponds to a loss thermal flux for the rooms that cannot be comfortably accommodated anymore through the AC system sizing that includes the lower temperatures' control system cycling period.

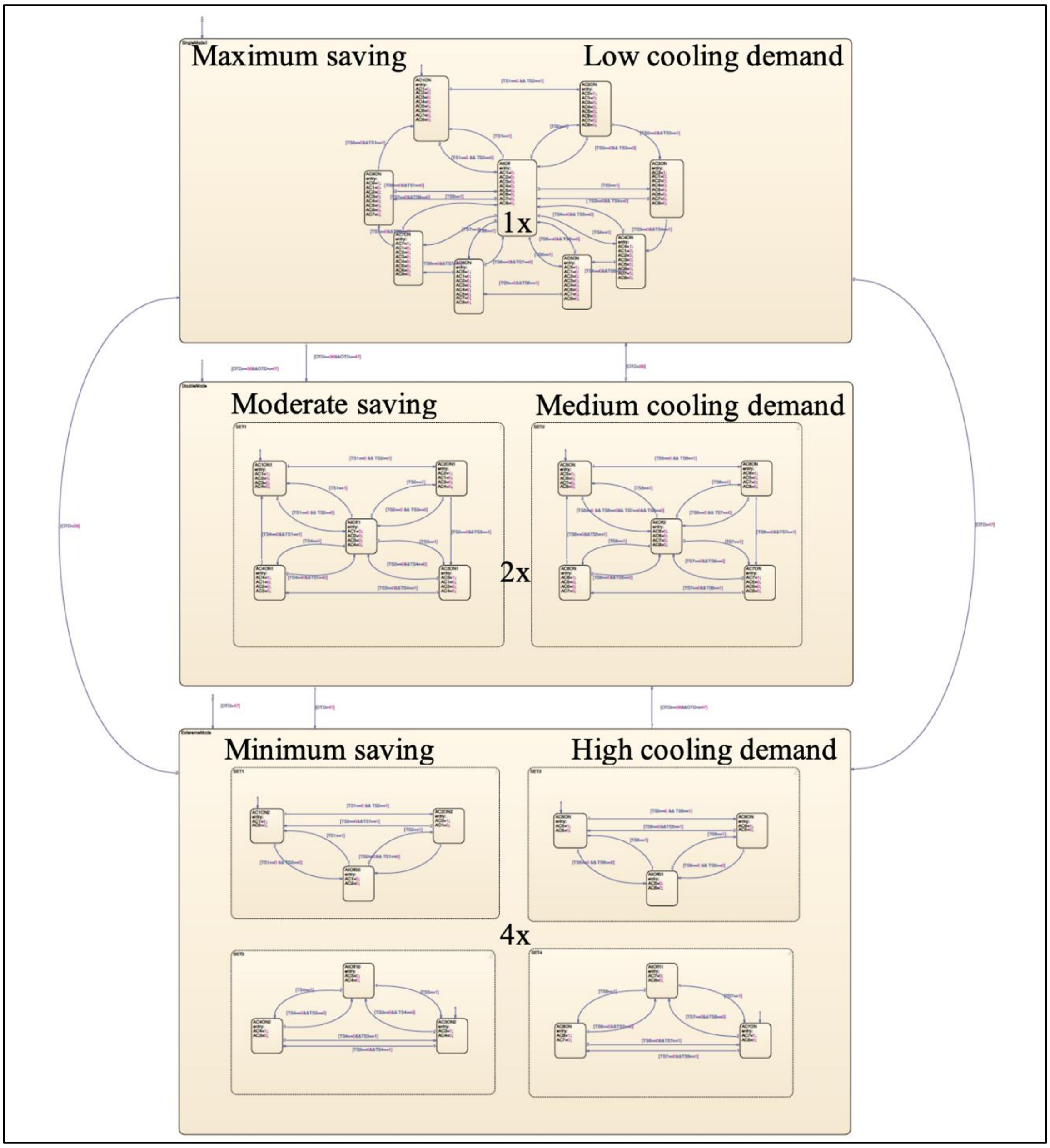


Figure 2.44.Developed adaptive multi-mode 8-AC power management logic

As shown in Figure 2.44 above, the developed multi-mode control logic has three main states (modes) corresponding to the earlier explained three cooling demand and power reduction scenarios. When the controller is turned on, one of the three modes will be engaged based on the cooling demand (outdoor temperature) and hence, will remain or transition to other control mode as cooling demand changes throughout the day based on outdoor temperature variations. With this system design, the number of allowed concurrently running compressors are either single, double or quadruple for the Max, Mod and Min power saving modes respectively. The performance of this control design is much improved as per simulation results presented in Figure 2.45.

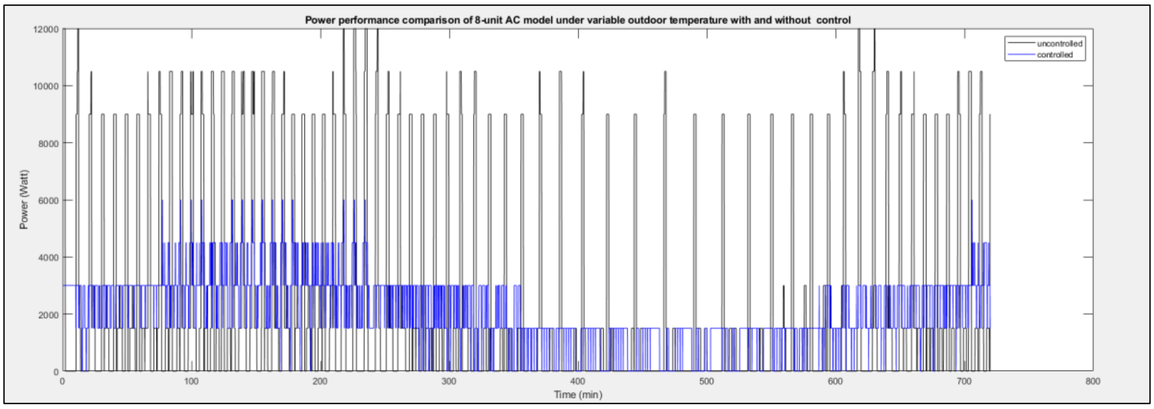


Figure 2.45. Performance of 8-AC unit system with & without adaptive control under with outdoor temperature variations

As can be seen from Figure 2.45 above, the control system is capable of reducing power intensity successfully as expected (blue color) throughout the sample 12 hours timeframe with variable outdoor temperature. The power reduction achieved is not a constant value like the initial controller design, but rather variable amount based on the cooling demand that is mainly influenced by the outdoor temperature. The power saving ranges from 50% to 87.5% from high to low cooling demand cases respectively.

In terms of indoor temperature control, the system has also proved to be perfectly capable of regulating indoor temperature as anticipated to meet the desired indoor temperature despite the variable outdoor conditions.

Figure 2.46 below displays a 3-window multi plot of a 12-hour simulation of system performance for power reduction and indoor temperature control with variable outdoor temperature.

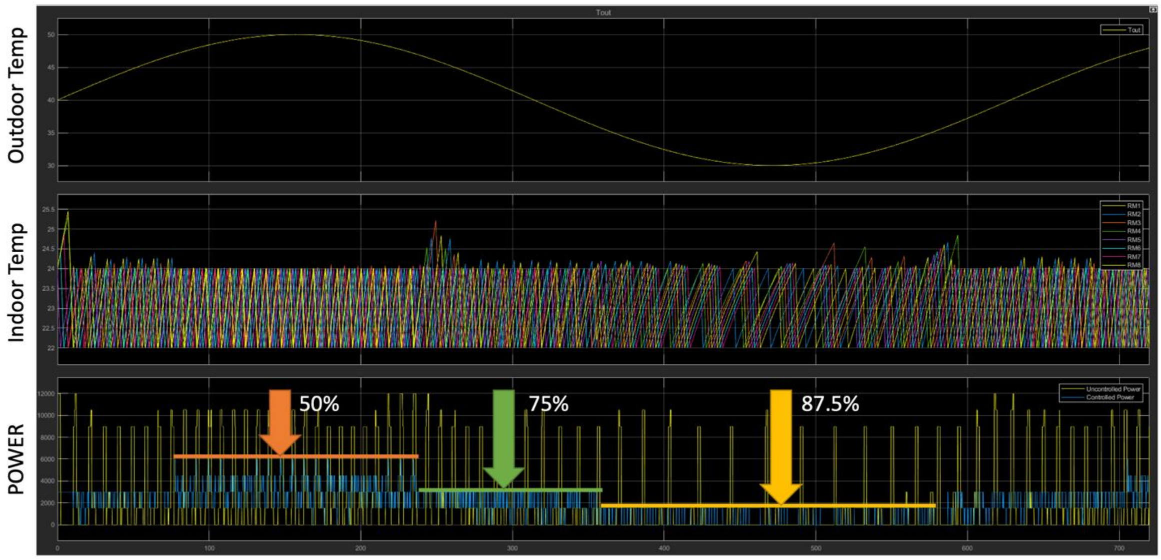


Figure 2.46. 12-hour simulation result for 8-AC control system under outdoor temperature variations

As can be seen from Figure 2.46 above, the proposed enhanced control system is capable of lowering power intensity of the example 8 unit building at various rates throughout the day while maintaining indoor temperature at the desired comfort levels. The maximum reduction (87.5%) takes place during low system load when outdoor temperature is low(<36°C). Moderate-high reduction in power spikes (75%) occur during moderate conditions with outdoor temperature in the range of 36 to 47°C. The minimum reduction of 50% is achieved in the worst-case scenario where external temperature exceeds the 47°C barrier.

The flexibility offered by this system helps in striking the right balance between indoor comfort and reasonable and practical levels of power intensity reduction.

2.9. Conclusion

This chapter examines and addresses high power consumption issues related to buildings' space cooling applications within a desert climate context. Being a key challenge, the study focuses on power peak demand issues for possible solutions by targeting residential buildings' air conditioning systems for power reduction. For this purpose, a group AC power management system was proposed initially for 4-room small size residential buildings. The initial power reduction control solution showed a good performance in cutting down power intensities caused by the operation of multiple ACs by up to 75% while maintaining adequate indoor comfort under moderately hot climate conditions. This was achieved by means of organizing the way in which multiple ACs are working together using a systems approach. The initial system design however, showed an unfavorable performance at extreme outdoor temperatures exceeding 49 °C. Similarly, issues emerged when attempting to scale up the system to accommodate more AC units as the idle (waiting) durations between individual AC operations is increased, resulting in longer time per cooling cycle. As a consequence, an improved version of the initially proposed control system was developed to include extra flexibility and adaptability. The enhanced control system offers robustness to successfully handle a wider range of variables like number of ACs and varying outdoor temperature while always ensuring optimal power reduction, indoor thermal comfort and control stability.

Future work will focus on developing the current proposed control strategy further by including control modes threshold self-calculation and explore the experimental and implementation aspects of this control strategy.

CHAPTER 3:

An Optimal Air-Conditioner On-Off Control Scheme under Extremely Hot Weather Conditions

Abstract

Countries characterized by harsh desert climate conditions like Qatar and the GCC area are heavily reliant on air conditioning systems throughout the majority of the year. Apart from the environmental issues related to the excessive use of such energy-intensive appliances, durability, reliability and cost-effectiveness are also serious source of concern. Conventional air conditioning systems are inherently feeble due to the On-Off compressors' incessant fluctuations which tend to pose high maintenance costs and shorter life spans. To address these challenges, this chapter investigates an optimal On-Off control strategy to improve and optimize the way in which typical ACs operate by minimizing such fluctuations. To overcome the computation complexities of online optimization, an off-line Elman Neural Networks (NN)-based estimator is proposed to forecast real values of the outdoor temperature and compute optimum control values off-line. By looking up the optimum values solved by the off-line optimization tool, the proposed control solutions can adaptively regulate the indoor temperature regardless of outdoor temperature variations. In addition, a multiple objectives cost function that considers both Coefficient of Performance (COP), and AC compressor weariness (caused by On-Off oscillation) is designed for the optimization target of minimum cost. Unlike conventional On-Off control methodologies, the proposed enhanced On-Off control technique can respond adaptively to match large-range (up to 20 °C) ambient temperature variations while overcoming the shortcomings of online optimization due to heavy computational load. Finally, the Elman NN based outdoor temperature estimator is validated with an acceptable accuracy and various validations for AC control optimization under Qatar's real (hot season) outdoor temperature conditions. The results demonstrate the effectiveness and robustness of the proposed optimal On-Off control strategy.

3.1. Introduction

Famous for its unique geographic location between desert and sea, Qatar has significant desert climate and extremely hot weather conditions with a high temperature, humidity, and sandstorms. The Air Conditioning (AC) systems are highly essential for humans' daily indoor comfort in this region. The local weather has some significance of representing a unique desert and coastline climate which attracts research interests in various fields such as building efficiency, health, urban environment, and renewable energy[12, 30-40]. In GCC countries such as Saudi Arabia, more than 60% of the electricity consumed by local buildings goes to AC systems[31]. This is particularly valid for other GCC countries like Qatar, which is reliant on AC throughout the majority of the year. Due to the persistent heavy cooling load caused by high temperature weather conditions and desert climate, heating, ventilation, and Air Conditioning (HVAC) equipment degrades faster compared to HVAC facilities in other areas of the world. In addition, such high cooling demand necessitates higher reliability energy efficiency while ensuring adequate levels of indoor air quality and comfort.

A conventional AC system is made up of a compressor as key part, and other parts such as a condenser and an evaporator, where the air conditioning capacity depends on the compressor power.

In space cooling scenarios, the indoor temperature will normally oscillate around a predetermined set-point value due to the way in which on-off compressors operate[41]. The component responsible for implementing this On-Off control philosophy is the temperature controller or thermoset. Thus, the On-Off compressor works by either switching ON or OFF depending on the set-point boundary and the measured indoor temperature. Usually, there is a dead-band range of 1.5 °C to 2.0 °C to prevent the too frequent On-Off fluctuations of the compressor that could lead to a reduced lifespan. The combined adverse situation of harsh climate conditions, continuous operation and heavy cooling load could accelerate the degradation of AC systems, especially if a very slight tracking error is imposed. Due to its simplicity, On-Off control is widely applied for temperature regulation application scenarios. However, On-Off control also has some eminent drawbacks, which include temperature oscillation and non-optimal operation which negatively impacts the AC moving parts and its energy consumption[41-49].

Currently, a body of research work has been reported in the literature in response to challenges around HVAC control optimization. Several research works have been proposed to optimize building HVAC system[50, 51], and address On-Off control issues under different constraints. The related research works can be summarized as two approaches: low-complexity (greedy) optimization, and dynamic optimization. In low-complexity optimization approaches, hysteresis controllers and Pulse Width Modulation (PWM) are widely utilized[41, 52]. A hysteresis controller has a simple structure to implement in practice, so it is widely used in HVAC applications. Because the AC systems by hysteresis control work under fixed hysteresis conditions/parameters (with a set-point temperature boundary), the hysteresis controller does not perform well if ambient parameters/working conditions change. PWM control is usually used in PWM actuated split air conditioners. The PWM controller tunes the duty ratio of the AC On-Off control signal in a continuous way to allow dynamic change of the manipulated variable. It can accommodate some work conditions change based on its fast feedback control, which is similar to Proportional-Integral-Derivative (PID) control. However, a PWM controller has to change under very fast switching frequency at the initial stage of the control process or scenarios of large variations in the working conditions. This fast change could degrade the AC compressor faster, and it has also been proven not to be optimal for all the HVAC control cases. Both of these optimized controllers handle process control in time horizon windows like one day, one week, one month or one year. Thus, the full process control relies on the temperature profile of an entire period and controller parameters which can only be set and tuned in advance. For instance, the hysteresis control parameters are pre-set with a hysteresis result under certain working conditions. The controllers cannot accommodate ambient temperature variations in an adaptive way.

As a dynamic optimization approach, Model-Predictive Control (MPC) is employed to accommodate disturbances and variations of the operating conditions such as time-variant parameters and targets[42, 52, 53]. The MPC's optimization performance is subjected to the prediction horizon length. In theory, a longer prediction horizon can result in solutions closer to the global optimum; therefore, it needs more computational power and resources. However, a proper prediction horizon is difficult to determine in practice, and MPC optimization will consume a lot of online computation loads. As such, online and offline optimization need to be combined in an integrated and balanced manner for an optimum trade-off between the computational load and AC control adaptiveness. In Ref. [54], a scheme of AC On-Off control and optimization is proposed for variant ambient conditions, however, the transition between off-line optimization and online control is not integrated. In addition, the outdoor temperature prediction part is missing as it is based on assumptions.

Motivated by the heavy cooling demand and the associated HVAC components wearing issues under harsh weather conditions in desert countries such as Qatar, an optimal AC On-Off Control Scheme is proposed to improve AC performance under heavy cooling load scenarios. In this scheme, the optimization process is performed offline to generate the optimal solutions under certain conditions and range of outdoor temperatures, and then, a static data table of optimized parameters is generated. Based on the proposed lookup algorithm of online optimization, On-Off control parameters are tuned online to accommodate outdoor temperatures variation. As opposed to the existing AC hysteresis On-Off control schemes, the proposed On-Off control and optimization scheme can process more complex cooling scenarios such as large range and fast temperature variations. This is due to the controller ability to adaptively accommodate the variations by tuning the parameters optimization online. Compared to the MPC control, the proposed control scheme performs optimization work offline which does not require a huge computational power in real-time like the online optimization technique.

3.2. Problem formulation

Due to Qatar's geographical location, the outdoor environment is characterized by a unique and extremely hot desert climate. According to the data from local weather records, the average outdoor temperature varies from 15 °C to 46 °C throughout the four seasons. The daily temperature variation range could be up to 20°C during autumn or spring. This huge range of temperature variation necessitates the study of thermal dynamics of a typical building with the local outdoor temperature profile analysis.

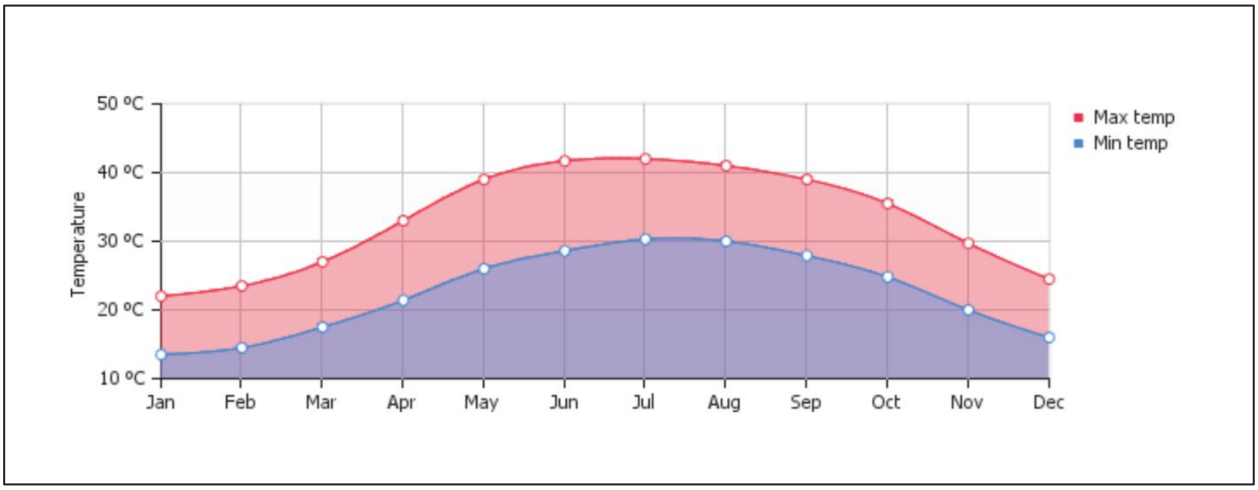


Figure 3.1.Average Min and Max Temperatures in Doha, Qatar for 2018

3.2.1. Outdoor Temperature Measurement under Qatar Weather Conditions

A three-day outdoor temperature profile that represents typical weather characteristics of Qatar, is measured in real time using thermal sensors at the outdoor test facilities of Qatar Environment and Energy Research Institute (QEERI). The daily outdoor temperature variations in the month October 2017, shown in Figure 3.3, has a very uniform probability distribution, which means that the weather prediction can be performed with higher accuracy. In practice, one day ahead prediction horizon is possible for the outdoor temperature prediction based on existing weather measurement and prediction technologies. Thus, it is feasible to have enough time to do offline optimization in advance based on predicted weather conditions, which can prevent the complexities of online optimization.

Figure 3.2.QEERI Outdoor Test facilities

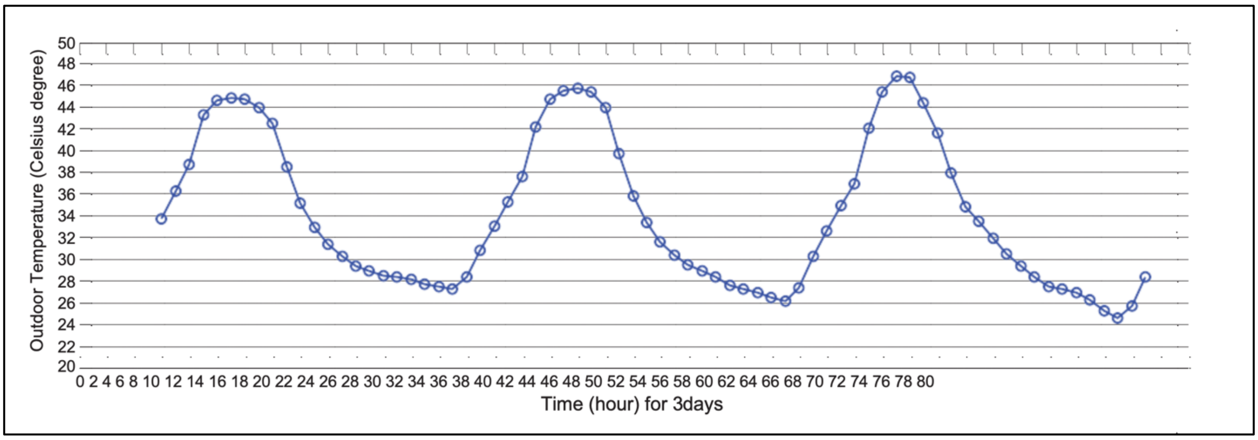


Figure 3.3.Three-day outdoor ambient temperature profile in October of 2017 at the outdoor test facilities

3.2.2. House thermal model

To mimic the thermal dynamics of a house, a simple air-conditioned building with heat exchange is considered as per diagram shown in Figure 3.4 [32]. The model thermal dynamics related equations can be denoted as follows:

$$\frac{dT_{indoor}}{dt} = \frac{\dot{Q}_d - \dot{Q}_e}{C_p m} \tag{3.1}$$

$$\dot{Q}_d = \frac{T_{outdoor} - T_{indoor}}{R} \tag{3.2}$$

By combining Equations (1) and (2), the house thermal dynamics are derived as follows:

$$\frac{dT_{indoor}}{dt} = \frac{-1}{C_p m R} T_{indoor} + \frac{-1}{C_p m} \dot{Q}_e + \frac{1}{C_p m R} T_{amb} \tag{3.3}$$

The parameters in the above equations are defined in reference to the Table1 of [54]. For simplicity, several assumptions need to be clarified to formulate the HVAC control problem. These assumptions are

- The AC system works only in cooling mode, which removes heat from the room;
- The AC house is modelled as a first-order state-space physical system;
- Only heat flux transferred from the outdoors is considered;

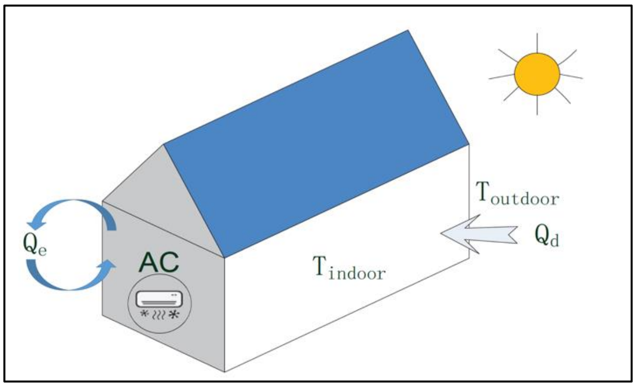


Figure 3.4.Thermal model of a house.

Remark 1. The assumption of only cooling mode fits Qatar's weather conditions because for most of the year (three hot seasons), the daytime outdoor temperature is over 25 ◦C, and only AC cooling is needed. The last two assumptions are general for

AC control and optimization studies, but it could be different in parameter setting for representing various application scenarios. For example, the indicator for extremely hot weather outdoor temperatures are considered as time-variant in the studied house model.

Based on the assumptions mentioned above, the house thermal model can be reformulated as a state-space model structure shown in Figure 3.5 below.

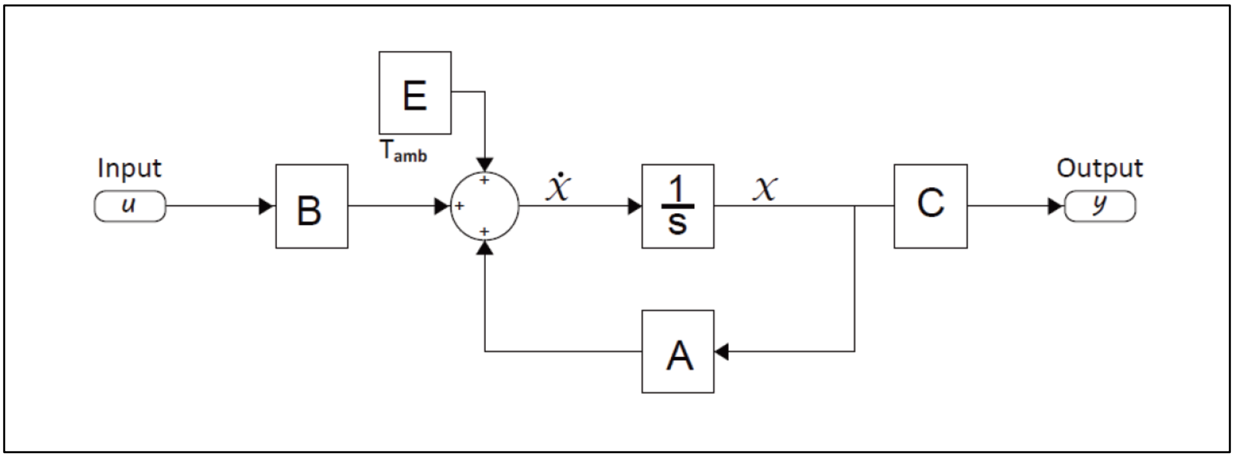


Figure 3.5.Block diagram representation of state space model

The mathematical format of the state-space model shown in Figure 3.5 can be represented as follows:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + E \\ y(t) &= Cx(t) \end{aligned} \tag{3.4}$$

In Equation (3.4), the variables and parameters have the following physical meaning: x is the vector of the state, $\dot{x}$ is the corresponding time derivative, u and y are the input and the output vectors respectively. A, B,C and E are the corresponding state-space coefficient matrixes. Vector x represents the state T_{indoor}, which is measurable, and therefore C = 1. If P_{AC} denotes the rated power consumed by the AC when the status is ON, u represents the On-Off control input $u = \dot{Q}_e = P_{AC}$, which can be denoted as:

$$u = \begin{cases} P_{AC} & t \in T_{on} \\ 0 & t \in T_{off} \end{cases} \tag{3.5}$$

By converting Equation (3.3) into the format of equations (3.4), the coefficients A,B and E can be expressed as follows:

$$\begin{cases} A = \dfrac{-1}{C_p m R} \\ B = \dfrac{-1}{C_p m} \\ E = \dfrac{1}{C_p m R} T_{amb} \end{cases} \tag{3.6}$$

In Equation (3.6), the term E is a function of T_{amb}, which means that if T_{amb} is changes as a variable and is not constant, the state-space model of Equation (3.4) could be more complex, hence the dynamics in Equation (3.4) will be changed as first-order state-space model with time-variant parameters. Therefore, the control input (u) needs to adaptively accommodate the disturbance E due to time-varying outdoor temperature. Moreover, with a full consideration on both comfort level and On-Off switch weariness, complex optimization iterations and variable tuning are needed to improve the control strategy to achieve an optimal solution for multiple objectives.

3.2.3. Optimal On-Off Control for Time-Variant Outdoor Temperature

In this section, an optimal AC On-Off control methodology is presented for stabilizing the room temperature regardless of the outdoor temperature variations. The optimal control scheme can be divided into offline and online phases. The offline phase is to solve optimum solutions by corresponding solvers for multiple objectives, while the online phase is to regulate the indoor temperature by tuning the controller with the updated parameters from the offline optimization tool.

3.2.3.1. Offline multiple objective Optimization

Dynamics subjected to On-Off control

As the control variable u in Equation (3.4) indicates On-Off binary variables, the solution of Equation (3.4) is different from the analytical solution of the standard state-space equation. The time-domain analytical solution can be written as follows:

$$
\begin{cases}
x_1(t) = \frac{Bu_{on}(t)+E}{-A} + (x_{1,init} + \frac{Bu_{on}(t)+E}{A})e^{At} \\
x_2(t) = \frac{Bu_{off}(t)+E}{-A} + (x_{1,end} + \frac{Bu_{off}(t)+E}{A})e^{A(t-\alpha T)}
\end{cases}
\tag{3.7}
$$

where, α is duty ratio, T is oscillation period.

Figure 3.6 illustrates the variables and parameters derivation by a diagram of oscillation period dynamics. Based on the temporal relationship the oscillation parameters can be defined as follow:

$$
\begin{cases}
x_{1,end} = x_{2,init} \\
x_{1,init} = x_{2,end} \\
T = T_{on} + T_{off} \\
T_{on} = \alpha T
\end{cases}
\tag{3.8}
$$

It should be noted that $x_{1,init}$ and $x_{1,end}$ can be derived from Equation (3.7) under t = 0, $t = \alpha T$, and $t = T$. The solution is shown as follows:

$$
\begin{cases}
x_{1,init} = \dfrac{\frac{Bu_{on}+E}{-A} + \frac{Bu_{on}-Bu_{off}}{-A}e^{A.T_{off}} + \frac{Bu_{on}+E}{A}e^{A.T}}{1-e^{A.T}} \\
x_{1,end} = \dfrac{\frac{Bu_{on}+E}{-A} + \frac{Bu_{off}+E}{A}e^{A.T} + \frac{Bu_{on}-Bu_{off}}{A}.e^{A.T_{on}}}{1-e^{A.T}}
\end{cases}
\tag{3.9}
$$

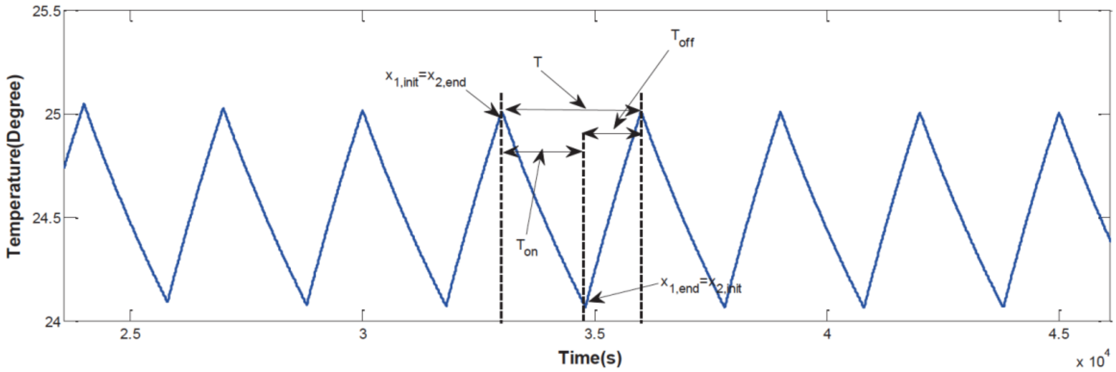


Figure 3.6.Diagram of oscillation period dynamics

Cost function for multiple objective optimization

By considering weariness cost minimization due to AC On-Off switching while maintaining maximum possible level of comfort through the Coefficient of Performance (COP) value, the cost function can be defined as follows:

$$J(T_{on}, T_{off}) = \frac{Q \cdot \int_0^{T_{on}} \left(x_1 - x_{ref}\right)^2 dt Q \cdot \int_{T_{on}}^{T_{on}+T_{off}} \left(x_1 - x_{ref}\right)^2 dt}{T_{on} + T_{off}} + \frac{RJ_{sw}}{T_{on} + T_{off}} \tag{3.10}$$

where J denotes the cost of one period of oscillation in one cycle and J_{sw} denotes the switching cost that leads to weariness and is assumed to be constant. Q and R denote the weight coefficients of the COP cost and the switching cost. x_{ref} is the target indoor temperature. To convert this optimization to a convex optimization method, the optimization variables of T_{on}, T_{off} can be converted into T & α, where their boundary conditions hold:

$$\begin{cases} T \in [100, 10000] \\ \alpha \in [0, 1] \end{cases} \tag{3.11}$$

The optimization process leads to the following optimal solution:

$$[T_{opt}, \alpha_{opt}] = \arg\min_{T,\alpha} J \tag{3.12}$$

Optimization Result lookup table generation

With the proposed cost function in Equation (3.10) constrained by the search space in Equations (3.11), an offline optimization algorithm is designed to generate the optimum parameters for online adaptive On-Off Control. The flow chart of the offline optimization is shown in Figure 3.7[54].

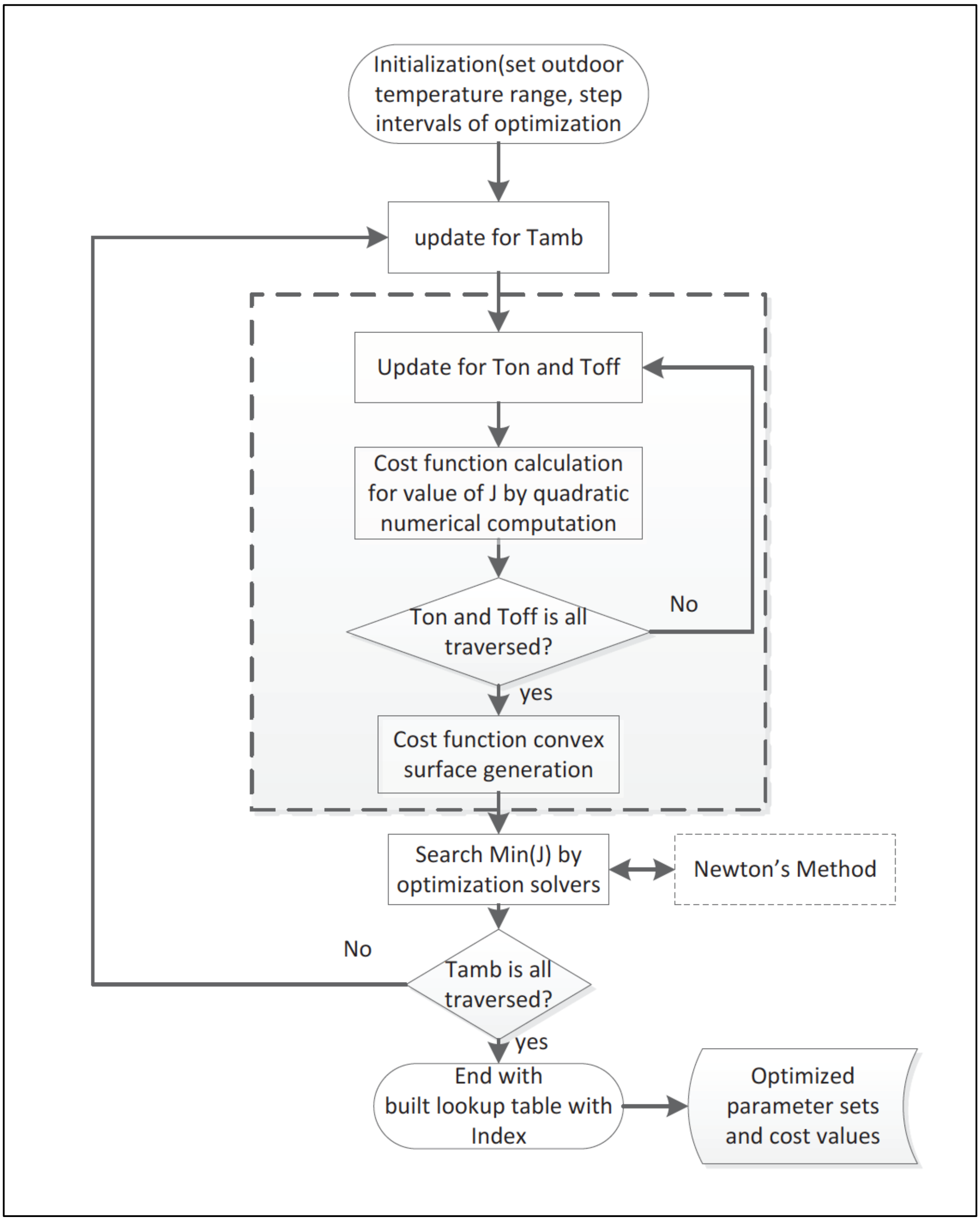


Figure 3.7. Flow chart of offline optimization

3.2.3.2. Online adaptive control for variable outdoor temperature

By looking up the optimum parameters generated by the offline optimizations tool, the online control scheme can adaptively accommodate outdoor temperature variations with a light computational load. The online control scheme is comprised of three parts: outdoor temperature profile discretion, online adaptive control, and Outdoor temperature prediction.

Temperature profile discretion

Normally, the outdoor temperature is recorded by one-hour intervals. However, if we analyze the temperature profile of Qatar, it shows slow variation properties. Thus, variation within one hour might not be notable. Moreover, it is not necessary to use hourly outdoor weather data as more hour points in a day means more duplicate or similar optimization procedures are needed. Therefore, to simplify the proposed online control scheme, the one-hour temperature profile needs to be discretized as longer intervals such as 2-hrs interval or 4-hrs interval. For a simplified implementation of system discretion, some interpolation algorithms such as nearest neighbor and linear interpolation can be applied. Interpolation results for the example of a 3-day profile with different intervals are shown in Figure 3.8below.

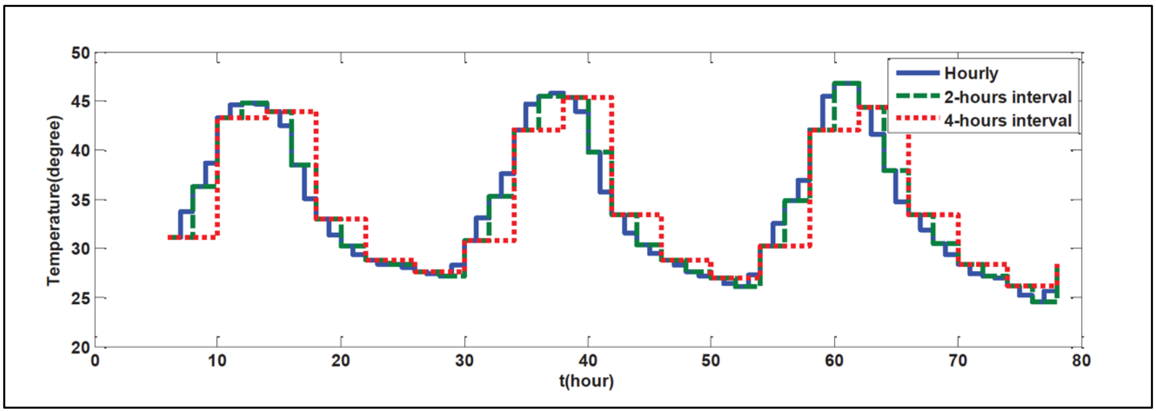


Figure 3.8.Temperature profile discretization

Online adaptive control scheme

After discretizing the outdoor temperature profile, the online adaptive control scheme is employed to stabilize the indoor temperature and accommodate the temperature variations adaptively. Figure 3.9 shows a flowchart of the proposed online AC control scheme. When triggered, the normal On-Off control is initiated to enable the AC system to converge into the target temperature range. Subsequently, two cascaded control loops are executed. The outer control loop works to tune the On-Off controller parameters with the optimized solution. The inner loop works on the search for optimum parameters set by the index in a lookup table that is previously generated online in one horizon period. Finally, the cycle ends if all the time horizon of a full day is scanned.

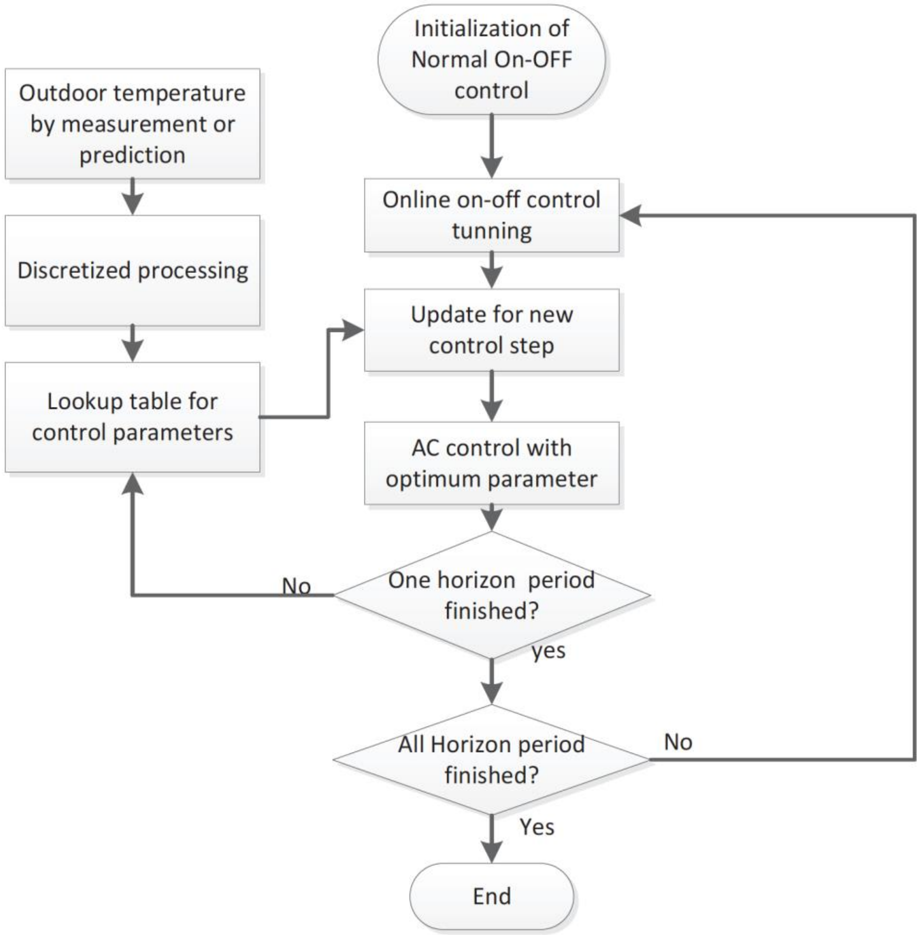


Figure 3.9.Online AC control flowchart

Outdoor temperature prediction

Temperature prediction is an important element of the AC optimization control process due to the way in which the optimization objectives cover periodic controlled steps. In the studied optimal control scenarios, at least 2-hours ahead prediction is mandatory for the online control process. With the consideration of a trade-off between the prediction accuracy and computational complexities, a typical Elman Neural Network (NN) model shown in Figure 3.10 is considered as an estimator for outdoor temperature prediction.

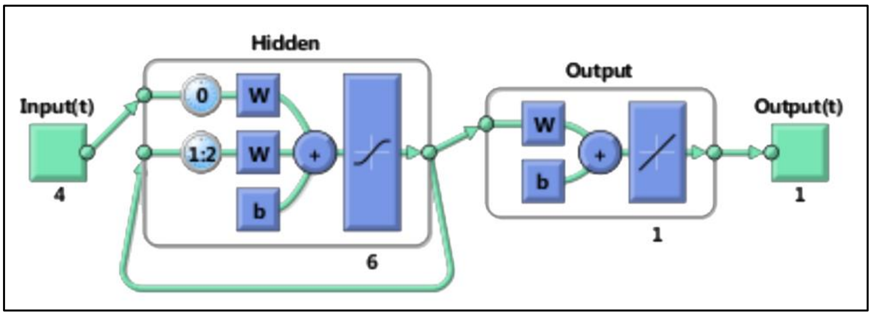


Figure 3.10.Proposed Elman Neural Network Model structure

To represent the prediction process, the outdoor temperature series can be denoted as follows:

$$T_{amb}(i), (i = 1, \ldots, N_P) \tag{3.13}$$

Due to the temporal relativity of the outdoor temperature in the time domain, the outdoor temperature variation process can be denoted as follows:

$$T_{amb}(k) = F(T_{amb}(k-1), \ldots, T_{amb}(k-1-M)) \tag{3.14}$$

where $T_{amb}(k)$ denotes the outdoor temperature at current instant k, $F(.)$ is the function between $T_{amb}(k)$ and the temperature series at previous instants $k-1, \ldots,$ $k-1-M$. For temperature time series prediction, a mapping model needs to be built firstly for approximating the mapping function $F(.)$. In this study, a two-layer (second order) Elman neural network model in Figure 3.10 is proposed to approximate the mapping function $F(.)$. The mathematical representation of Elman network can be denoted as follows:

$$\begin{cases} h_t = \sigma_h(W_h x_t + \sum_{i=1}^{N_d} W_{t,i} h_{t-i} + b_h) \\ y_t = \sigma_y(W_y h_t + b_y) \end{cases} \tag{3.15}$$

where W_h, $W_{t,i}(i = 1, \ldots, N_d)$, W_y are weight coefficients, b_h & b_y are offset coefficients, σ_h & σ_y are activation functions for hidden layer output and output layer respectively. For the outdoor temperature prediction, different prediction windows configurations exist. Depending on the availability of data series length, the input data vector length (M) could be 2, 3, . . . , 24. Thus, the cascaded prediction equations can be represented as follows:

$$\begin{cases} \hat{T}_{amb}(k) = NN(T_{amb}(k-1), \\ \quad \ldots, T_{amb}(k-1-M)) \\ \qquad \vdots \\ \hat{T}_{amb}(k+N_L) = NN(T_{amb}(k-1), \\ \ldots, T_{amb}(k-1-M)) \end{cases} \tag{3.16}$$

Here, $\hat{T}_{amb}$ (k) denotes the outdoor temperature value predicted or estimated by the Elman NN model, N_L denotes the prediction step number based on M existing temperature serial data. To get an effective and high-accuracy estimation model, the Elman NN offline training based on a set of sample data is essential and needs to be done in advance. Thus, the training problems of the Elman NN can be denoted a set of sample dataset as follows:

$$TrainingSet(T_{amb}(in), T_{amb}(out)) \tag{3.17}$$

Through the selected training algorithms, the Elman NN model parameters such as W_h, $W_{t,i}$(i = 1, . . . , N_d), W_y, b_h &b_y can be determined based on the following criteria:

$$\begin{aligned} &\exists parameterset(W, b) \\ &T_{amb}(out) \doteq \hat{T}_{amb}(out) = NN(T_{amb}(in)) \end{aligned} \tag{3.18}$$

3.3. Validation results

To validate the proposed On-Off control and optimization scheme, the studied house model parameters are referred from [41], except the AC power is changed to 1500 W (not 300W) as it is a more reasonable figure due to the specific hot climate and standard AC cooling capacities in Qatar. Normally, HVAC facilities in Qatar are prone to faster degradation and failure which normally implies higher maintenance costs. Considering the fact that the AC weariness under hot climate is more serious, the weight factors of Q in Equation (3.10) is reduced to reflect the importance of such cost impact. The updated parameters are shown in Table 3.1.

Based on the AC parameter model list in Table 3.1, the proposed control and optimization scheme is demonstrated, which includes offline optimization and online AC control performance, in different cooling scenarios.

Parameter	**A**	**B**	**E**	**R (°C/W)**	***JSW***	**Cp (J/kg°C)**	**m(kg)**	**Q**
Value	$-2.00123e^{-4}$	$4.4028e^{-6}$	0.002	0.022	2	1005	222	300

Table 3.1. Parameters values of the thermal model and optimization

3.3.1. Offline optimization results

To verify the offline optimization performance, a simplified AC cooling scenario is considered for comparison in a quantitative way. In this cooling scenario, the indoor temperature is expected to be 24 °C by different controller parameter settings with the outdoor temperature set as 34 °C. For comparison, the temperature profiles subjected to three types of controller settings are shown in Figure 3.11, and the corresponding COP values are compared. In Figure 3.11, it is shown that the COP value of the proposed optimum control is the lowest at $J = 1.5416$. Based on the cost value comparison, the optimum case has lower cost value, which means that it achieves better multiple-objective optimizations than other control scenarios. The cost-saving performance among the three cooling scenarios is presented in Table 3.2. As shown in Table 3.2, 30.16% can be saved from the case under outdoor temperature 29 °C while 55.45% can be saved from the case under outdoor temperature 38 °C by comparing with the optimum case.

AC cooling strategy	**Initial temperature**	**Period**	**Cost value**	**Cost saving**
Case1	*38*	1595	3.4606	55.45%
Case2	*29*	300	2.2074	30.16%
Optimum case	*34*	595	1.5416	N/A

Table 3.2. Performance comparison by cost-saving

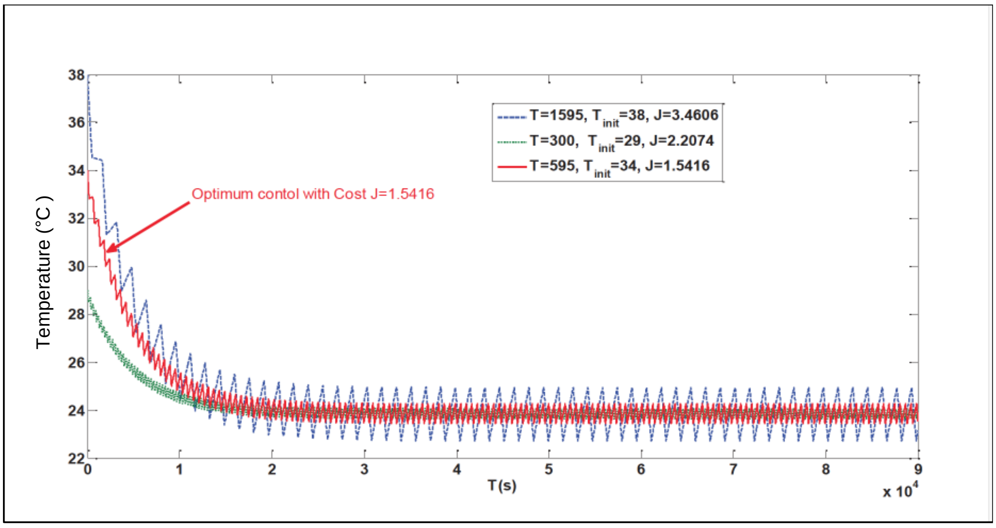


Figure 3.11.Cooling control profile comparison for different controller parameters settings

To verify the effectiveness of offline optimization under different ambient temperature scenarios, a set of offline optimizations subjected to outdoor temperature ranging between 30 °C and 44 °C was performed. The target indoor temperature is expected to 24 °C. The offline optimization parameters are shown in Table 3.3 and the optimization convex surface results are shown in Figure 3.12, which presents eight subfigures for eight temperature profiles with 2 ˚C intervals. As can be seen from Figure 3.12, all the optimization surfaces are convex, which means that the global optimum, unique and only one solution for the studied case exists. Due to the impact of the ambient temperature, the optimization surface shapes & cost values vary in a wide range. As an input for the online adaptive control, the corresponding optimization control parameters are also generated in a list of a lookup table.

Outdoor temperature	**Minimum cost (J)**	**Period (T)**	**Duty Ratio (α)**
28	0.8585	1585	0.1090
30	0.5927	2400	0.2780
32	2.1917	595	0.2575
34	1.5416	595	0.3070
36	1.4318	595	0.3565
38	1.9049	595	0.4060
40	3.0049	595	0.4555
42	3.8368	595	0.5545
44	3.0705	595	0.6040

Table 3.3. Optimization control parameters.

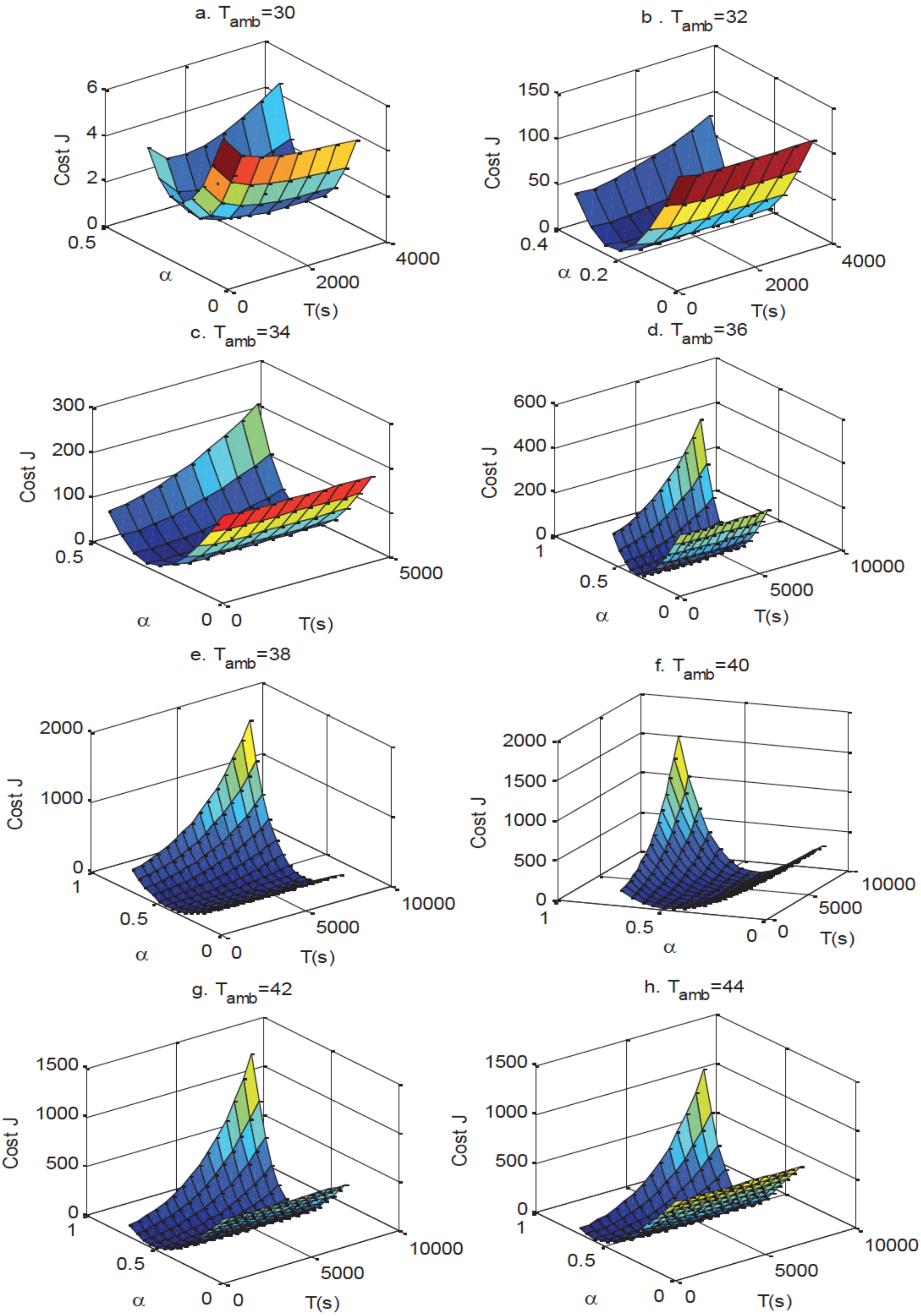


Figure 3.12.Offline optimization results under different outdoor temperatures.

3.3.2. Outdoor Temperature Prediction Results

To validate the effectiveness of the proposed outdoor temperature prediction model, the 3-day temperature profile shown in Figure 3.3 is used for Elman NN model training and testing. The 3-day profile has 72 points of hourly temperature readings. The prediction window is set as 4, hence, the total number of data points for NN test set is $72 - 4 = 68$, and it is divided into two groups, 34 points each. After selecting the proper values for the Elman Training algorithm, the training results can be obtained as in Figure 3.13a,b. From Figure 3.13a it can be seen that the output value of Elman model is very close to the true value by the training procedure regression. From Figure 3.13b, it can be seen that the error is less than 0.6 degree, which means the model regression accuracy is very high. To test the generalization ability of the proposed Elman NN model, the other data group of 34 points is used for validation, and the results are shown in Figure 3.13c,d. From Figure 3.13c, it is evident that the estimated value is also very close to the real value. Also, from Figure 3.13d it can be observed that the error estimation is within the acceptable range (< 2 degrees) although it is a little higher than training error. Based on the training regression and test validation results, it can be concluded that the Elman NN model can generate an effective prediction of outdoor temperatures.

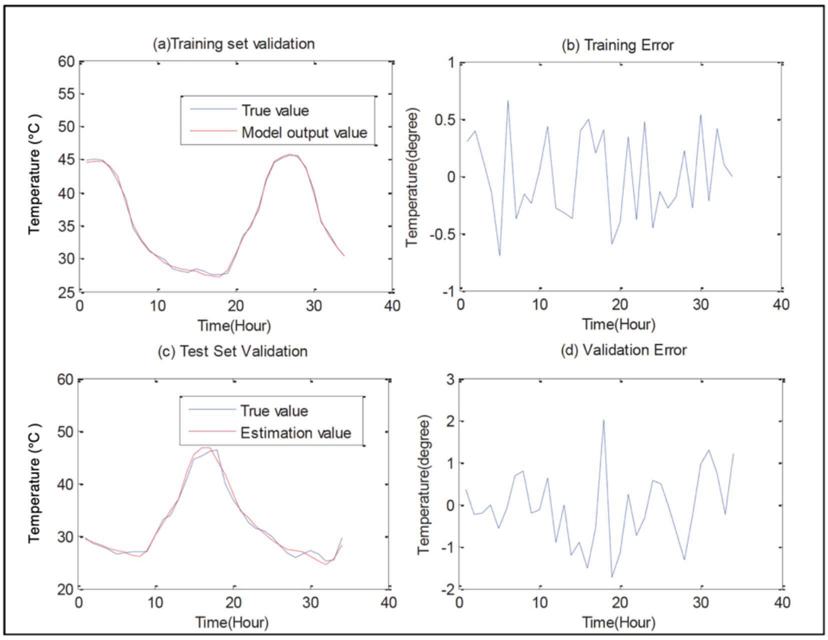


Figure 3.13. Outdoor temperature prediction results

3.4. Online adaptive control results

To validate the proposed online adaptive control scheme for the AC under Qatar climate conditions, daily indoor temperature control scenarios are considered in this section. In general, the comfort indoor temperature is set as 25 °C with an acceptable variation range of 2 °C. Due to the slow time-variant characteristics of the outdoor temperature, a two-hour interval is selected to be a reasonable time zone to evaluate the temperature within the existing weather measurement applications.

3.4.1. Scenarios A: One-day typical case in Doha of Qatar

To verify the effectiveness of the proposed scheme, the second day outdoor temperature profile in Figure 3.3, which is a typical day with large temperature variations, was selected for the data analysis. To compare the performance between the proposed optimal control and the PWM control mentioned in the literature review, comparative experiments are also conducted to re-implement the PWM control in the same house model as the proposed optimal control under same Qatar outdoor conditions. The implemented PWM control has an adjustable pulse-width based PID control structure. In this PWM control, the PWM period is constant while the duty ratio/pulse width is adjusted as a continuous control variable to avoid the fast switching in the On-Off control. In addition, a PID module is added for the tracking control to converge in a smooth manner with an acceptable oscillation error. The PWM control diagram is shown in Figure 3.14, and the time period of the PWM pulse is set to be 500 seconds which is similar to the minimum period of the optimal control. The detailed AC control and process variables are shown in Figure 3.15, while the temperature control results are presented in Figure 3.16.

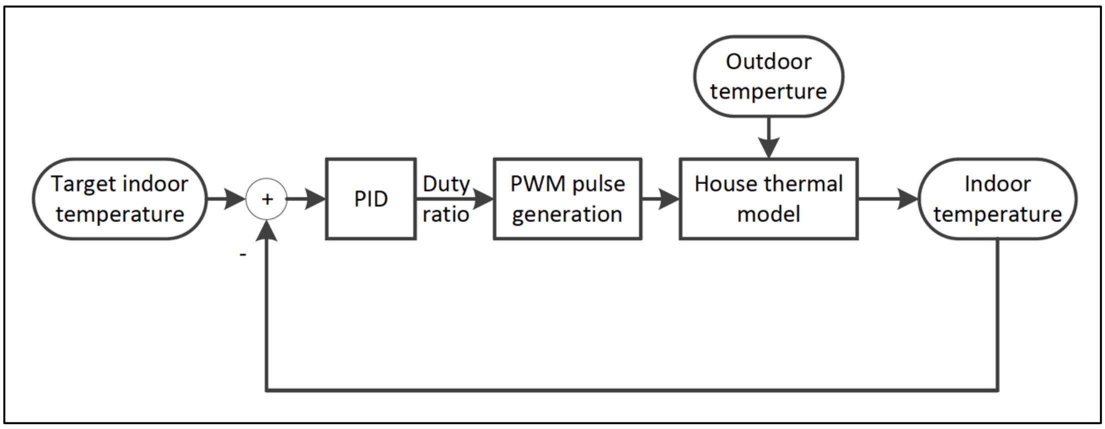


Figure 3.14.Block diagram of PWM control

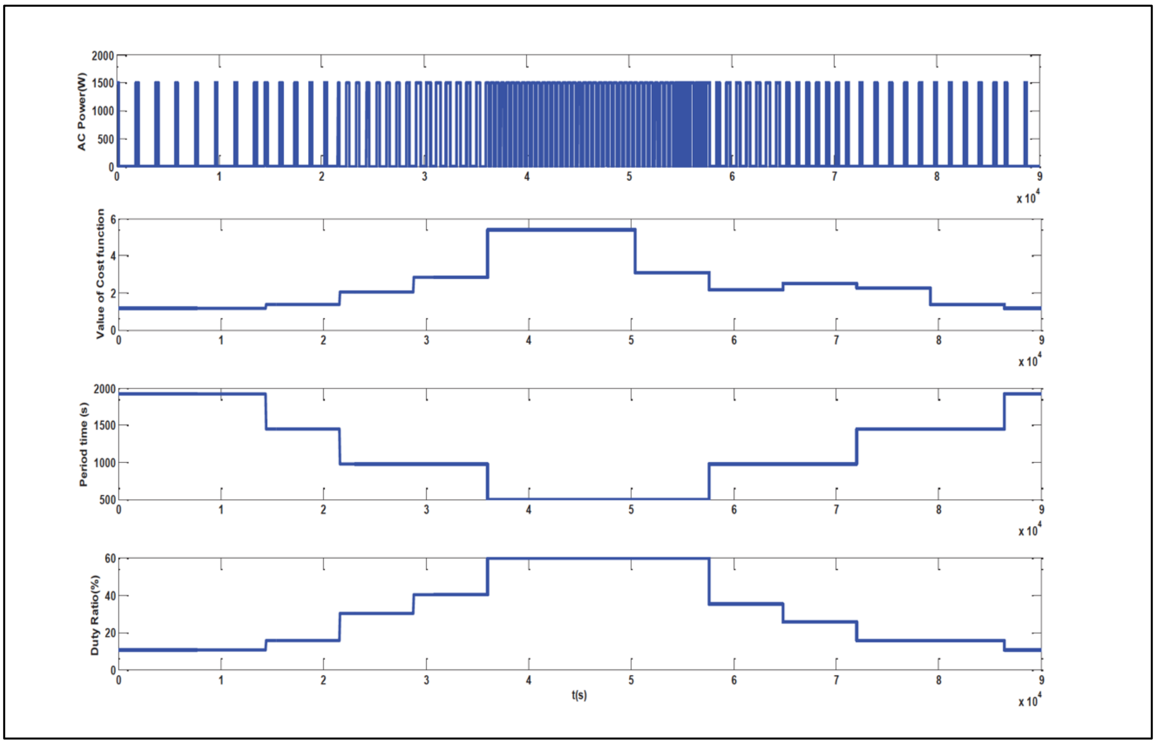


Figure 3.15.Online optimal control variables and parameters.

Figure 3.15 above shows a modulated pulse output of the AC control power, cost value, period of time, and duty ratios respectively. As can be seen from the plot of the AC power output, the AC consumption power rate is fixed at 1500 W while the pulse width is variable due to different cooling loads. The cost value plot also changes with time and shows a peak when the corresponding pulse width is the shortest. This means that a high outdoor temperature generates a heavier cooling load and more frequent AC On-Off switching action and thus, the AC cooling overall cost is higher (*the comfort part of the cost, being determined at steady state, is then with similar cost per period*). From the period plot, it can be seen that the period time shows a valley point, i.e. most frequent pulses. From the duty ratio plot it is shown that the duty ratio also reaches a peak point when the cooling load is maximum. In a summary of all the plots, the results demonstrate that the control process can track the ambient temperature change and respond with appropriate control action in a real-time manner.

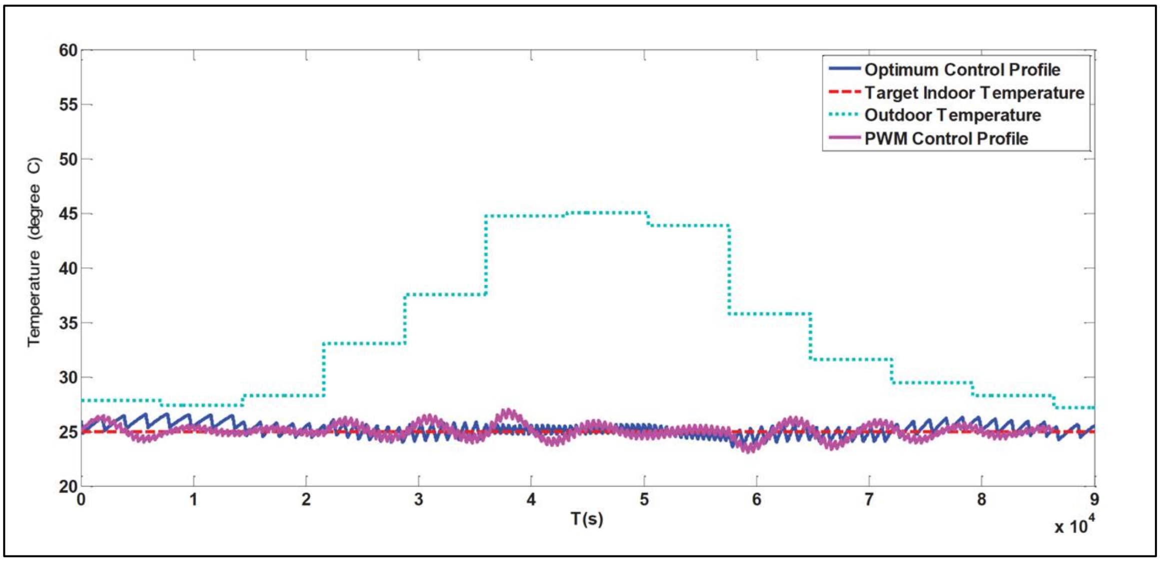


Figure 3.16. Temperature control profile in a typical day with large temperature variations

Figure 3.16 shows the optimization results AC control under a typical day in summer. From the indoor temperature profile, it can be seen that the control scheme is effective in stabilizing the indoor temperature at 25 ◦C within the temperature fluctuation range. From the outdoor temperature profile, it can be seen that the outdoor temperature changes from 27 ˚C to 46 ˚C at a gap almost 20 ˚C, but the control process can adaptively accommodate these variations by adjusting the control optimization parameters. Therefore, it is demonstrated that the proposed scheme applies for a typical large-variation scenario.

In addition, Figure 3.16 also shows the temperature profile comparison between the PWM control and the proposed optimal control. Both the PWM control and the optimal control can stabilize the target indoor temperature at 25 ˚C, despite the large daily outdoor temperature variation range of 20 ˚C. The PWM control oscillates at the transition time of the outdoor temperature's rapid change while the proposed optimal control can accommodate this rapid transition in a smoother way. Moreover, the rapid transition causes the PWM control to take a large range of oscillation (between 23 ˚C to 27 ˚C) to converge into the target indoor temperature 25 ˚C, while the optimal control can stabilize at a smaller range (between 24 ˚C to 26 ˚C). Through this comparison, it can be demonstrated that the optimal control has a better control performance over the PWM control in both aspects; stabilization accuracy and transition convergence speed.

By closely investigating the control variables of the two control approaches, the power profile for the optimal control and the PWM control is shown in Figure 3.17a,b, respectively. The duty ratio profile of the PWM control is shown in Figure 3.17c. By comparison, it can be concluded that the optimal control has fewer pulses than the PWM control, and the cost due to switching is obviously reduced. From Figure 3.17c, it can be seen that the duty ratio is a continuous variable which changes according to the outdoor temperature profile, which means that the PWM control can smooth the transition in a better way than the conventional On-Off control, although it is not the best when compared to the proposed optimum control.

Based on the fixed period value (500 s) and corresponding duty ratio sampling in each time duration, the cost in terms of COP in Equation (3.10) is calculated, and the cost comparison in the corresponding time period is shown in Table 3.4. From the table, it can be seen that the proposed optimal control has less cost than the PWM control in each time duration, which means the proposed optimal control has a better control performance for multiple objectives that considers both Coefficient of Performance and AC compressor weariness due to On-Off switching.

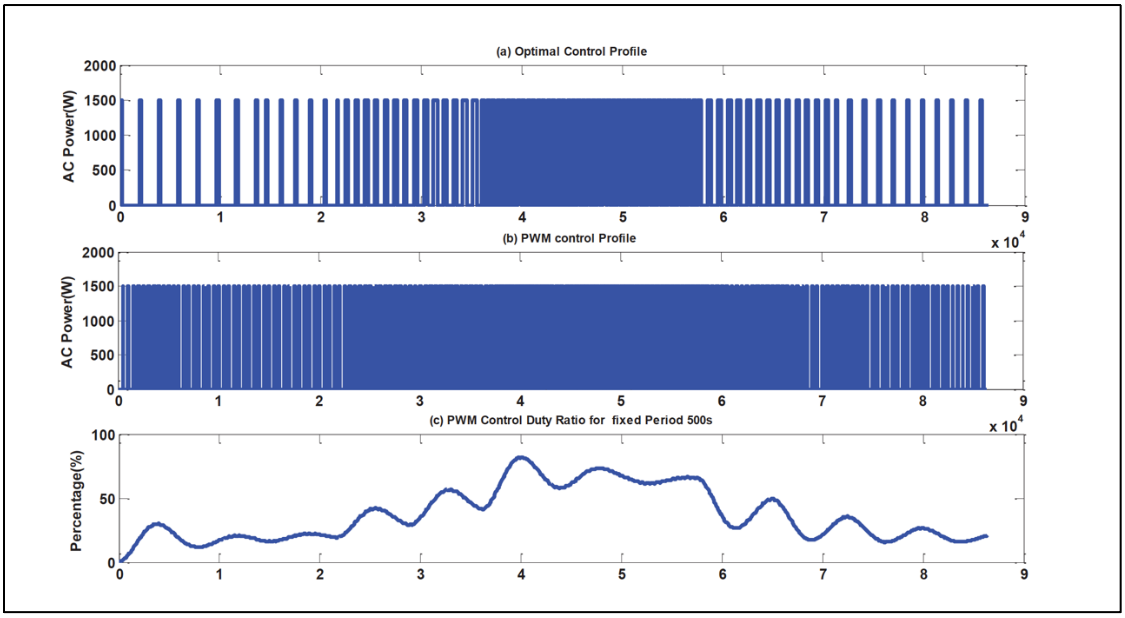


Figure 3.17. Power performance profile of Optimal and PWM control schemes.

Time duration	Duty Ratio α (%)	Cost of PWM Control	Cost of optimum Control
12 AM–2 AM	1	14.85	1.1420
2 AM–4 AM	11.76	7.77	1.1420
4 AM–6 AM	16.02	1.75	1.3436
6 AM–8 AM	37.90	4.59	2.0533
8 AM–10 AM	45.61	11.06	2.8456
10 AM–12 AM	64.68	6.26	5.3890

12 PM–2 PM	66.02	14.67	5.3890
2 PM–4 PM	61.07	112.89	3.0836
4 PM–6 PM	33.24	56.58	2.1577
6 PM–8 PM	19.01	10.07	2.5015
8 PM–10 PM	16.43	12.33	2.2423
10 PM–12 AM	17.02	29.89	1.3436

Table 3.4.Cost comparison between PWM control and proposed optimal control

3.4.2. Scenario B: Performance through three hot seasons in Qatar

To demonstrate the validity of the proposed control scheme under three hot seasons in Qatar, locally produced annual outdoor temperature data (from June of 2018 to June of 2019) is used. As can been from Figure 3.18, the outdoor temperature is either greatly or slightly over 25 degrees except from December to March. In other words, spring, summer, and autumn are all hot seasons in Qatar. Thus, air conditioning is highly essential, and this is where the proposed optimization scheme can be applied. Considering this diversity of Qatar’s desert climate, profiles of three typical days in each season (including 2019/8/6, 2018/11/6, 2019/5/6) were selected to validate the proposed scheme for the three seasons of Summer, Autumn, and Spring, respectively.

Being among the hottest months of the year in Qatar, August presents a typical harsh month for air conditioning applications due to the high outdoor temperature and humidity that result in a massive cooling demand. The validation results for the selected summer day in August are presented in Figure 3.19. The outdoor temperature profile shows that it varies from 32 ◦C to 46 ˚C in one summer day, which means that the gap between peak point and valley point is large and the AC needs to adaptively accommodate the corresponding time-variant cooling load.

From the optimum temperature control plot in Figure 3.19, it can be seen that the control oscillations is the shortest and fastest when the outdoor temperature is at peak due to the need to generate the highest cooling effort. With 2-hrs interval moving time zone, the duty ratio and time period are both set as the best optimized value by the offline optimizer. Although the profile is not always close to the central zone of the target temperature of 25 ˚C, the temperature variation range is within 1 ˚C. Despite the small control error value (±1˚C), the resulting control performance generally demonstrates the ability of the proposed AC control scheme to achieve optimal cooling effect within an acceptable level of indoor comfort.

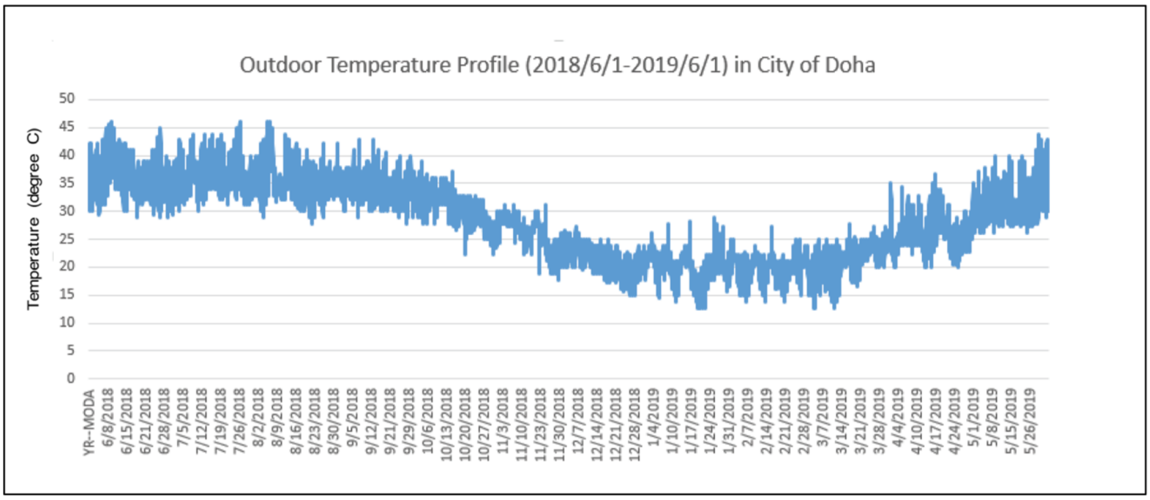


Figure 3.18. Yearly outdoor temperature profile from June 2018 to June 2019

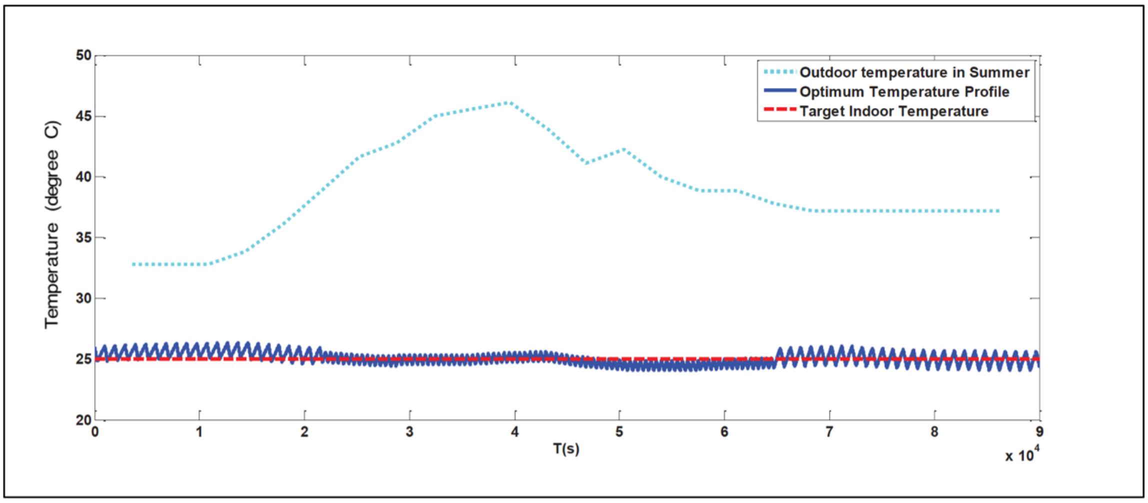


Figure 3.19. Optimal control result for a typical summer day in August 2018

The validation result for a typical autumn day, in November of 2018, is presented in Figure 3.20. As shown in the outdoor temperature profile, the temperature varies between 27 and 29 ˚C in a day which means that the demand gap during such autumn day is quite small with lighter cooling load compared to summer days. From the optimum temperature control plot, it can be noticed that the oscillation duration is longer than that of summer due to the lighter cooling load. The controlled indoor temperature is always maintained around the target 25 ˚C setpoint with a variation tolerance of ±1 ˚C. These results demonstrate the effectiveness of the proposed optimal control scheme during autumn days in Qatar.

The validation results for a typical spring day, in May of 2019, is presented in Figure 3.21. The outdoor temperature ranges from 27 to 37 ˚C in a day on average. This means the demand gap during a day in spring is smaller compared to summer days, with cooling load being quickly changing within the same day. By observing the optimum temperature control graph, it can be seen that the oscillation trend and durations is set with a different value range due to the significant and rapid change in cooling load. The temperature control profile is slightly off the target setpoint of 25 ˚C due to the large variations of AC control tuning parameter, however, it is still satisfying the comfort level by being close enough to the target 25 ◦C within 2 ˚C variation range. These results demonstrate the effectiveness of the proposed control scheme under spring season days in Qatar.

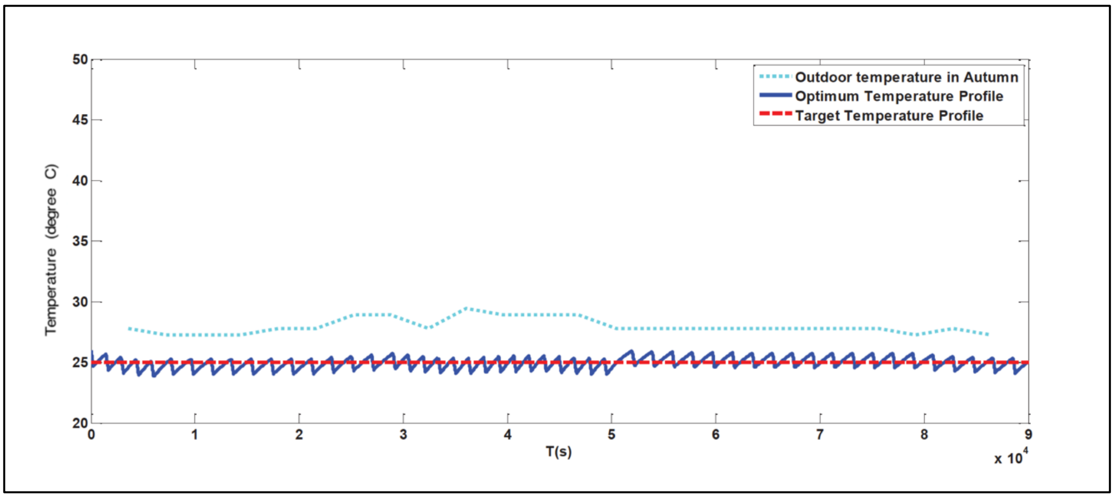


Figure 3.20. Optimal temperature control plot for a typical autumn day in November 2018

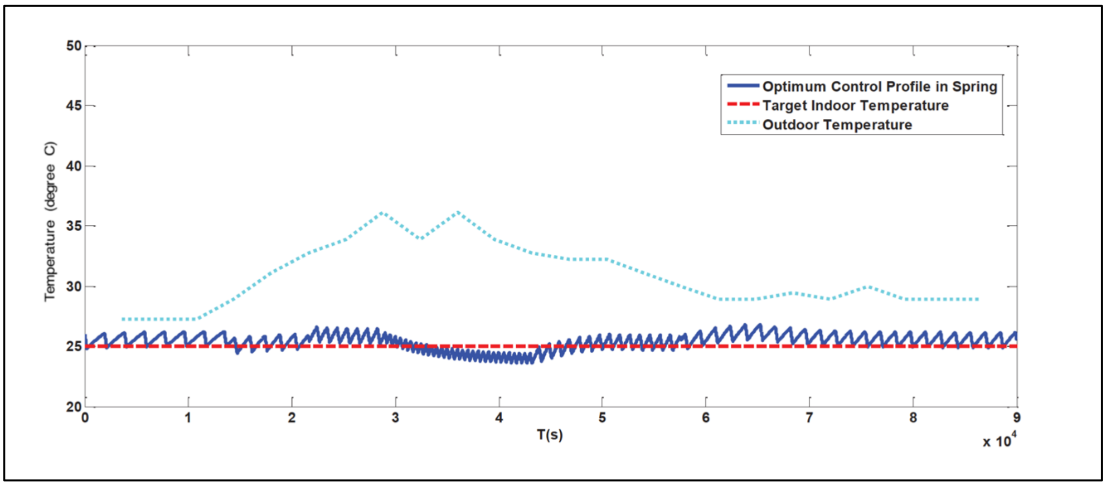


Figure 3.21.Optimal control performance in a typical spring day in Qatar (May 2019)

Due to the harsh climate conditions in Qatar and the GCC region, optimization of AC performance is very challenging, especially with issues like large daily temperature peaks, heavy cooling demand throughout the year, power consumption peaks, and consumers' behaviors which need to be all taken into consideration. To address such challenges, effective optimization solutions can be applied for multiple objectives beyond COP and switching cost. However, this ultimate optimization process can become highly complicated, and involve both of the follow: more advanced optimization theories like optimization feasible zone, and advanced computational capabilities like cloud & super-computing resources.

3.5. Conclusion

This chapter presents a novel optimal control strategy that improves the way in which existing conventional On-Off control for air conditioning operates under the harsh desert climate conditions. The optimal AC control is achieved based on an integration between off-line optimization and online adaptive control. The optimization process involves the use of a multiple objectives methodology driven by a cost function for maximum cooling efficiency expressed as Coefficient Of performance (COP) and minimized compressor weariness. This control scheme offers a practical trade-off between online and off-line optimization methods where the multiple objective optimization is achieved without excessive computational resources. By simulating several AC cooling scenarios, and based on experimental local weather data, the resulting performance is very promising. Future research work will consider more optimization objectives and factors such as sizing, number of AC units, AC power fluctuations and the impact on grid stability.

CHAPTER 4:
AC group power control optimization for PV integrated Micro-grid peak-load shaving

Abstract

Heating, Ventilation, and Air Conditioning (HVAC) systems are considered to be one of the essential applications for human comfort in modern life. Due to global warming and population growth, the demand for HVAC systems will continue to increase, especially in high demand arid countries like the Arabian Gulf region. HVAC systems' energy consumption is very high and accounts for up to 70%-80% of the total load consumption in some rapidly growing GCC countries such as Qatar. Additionally, the local extremely hot weather conditions usually lead to typical power demand peak issues that require adequate mitigation measures to ensure grid stability. In this chapter, a novel power control scheme for a large combined bulk of Air Conditioning units is proposed as a peak-shaving and power leveling strategy to address high power demand issues for PV-integrated microgrid applications. By means of local daily ambient temperature as input data, the AC group control optimization is formulated using a Mixed-Integer Quadratic Programming (MIQP) technique. Under an acceptable range of indoor temperature values, the units in the same AC group are coordinately controlled to work in accordance with the desired power performance to help in stabilizing the power curve by shaving load peaks for both, power consumption and PV generation. Finally, several simulations for the system model are performed which clearly demonstrate the effectiveness of the proposed control strategy in maintaining a smooth and stable power profile.

4.1. Introduction

Heat, Ventilation, and Air-Conditioning (HVAC) systems among the topmost blessings of modern life which provide good indoor air quality through adequate ventilation with filtration and provide necessary thermal comfort. Thus, they are inevitability essential for comfortable and healthy living conditions, especially in areas with hot climate environments such as the Arabian Gulf region. However, among the largest consumers of grid electricity, HVAC systems are the least grid-friendly and usually lack of the cost-effectiveness, especially under harsh climatic conditions. Unlike other electricity consumption loads in utility grids, the HVAC systems' profiles present a diversity of time-variant characteristics since it changes with building ambient temperature and weather conditions. This variation of power demand is not ideal for utility grid load-side demand response. This is mainly due to the uncertainty of HVAC power consumption, which can cause irregular power peaks and fluctuations. To address the irregular peaks caused by HVAC systems, utility providers need to provide a system buffer in the form of added margin of power generation capacity. For flattening the irregular fluctuations caused by HVAC systems' power demand, the grid needs to employ additional storage capacity which is not a very cost-effective nor practical solution for conventional grid regulators.

With the advancement of renewable energy technologies, renewables are increasingly considered for integration into utility grids. Higher deployment of renewable energy sources such as solar Photo-Voltaic (PV) and Wind energy means that grid power suppliers are also confronted with a diversity of time-variant characteristics. This fact makes the grid's demand response more complex and very challenging. To address this complexity, effective HVAC load management solutions are highly essential. Fortunately, an HVAC system is a type of large-inertia dynamical system due to buildings' slow thermal dynamic characteristics. Accordingly, the temperature control of a typical HVAC system is a time-delayed process. The large inertia of thermal dynamics can provide a benefit for storage applications. For example, grid voltage and frequency fluctuations can be regulated by effective HVAC control because large-inertia systems (such as flywheels) are able to absorb ultra-fast changes of grid power fluctuations. Moreover, the indoor temperature range by HVAC control has some flexibility to provide acceptable levels of comfort. For example, indoor temperature can vary between 20 and 25 ℃

as a comfortable range. Through advanced telecommunication, electronics, and control technologies, such temperature flexibility can allow the group controlled HVAC cluster to work as a virtual storage system. Modern Information and Communication Technologies (ICT) also provide tools through which the grouped HVAC systems can generate the required performance profile under different demand response scenarios. Therefore, it is promising to employ a group of HVAC units for optimal demand response by effective group control strategies, especially under smart micro-grid control applications.

Currently, some research work has been reported for HVAC-based energy efficiency optimization and grid regulation applications. For individual AC control optimizations, most of the studies focus on one or two aspects of the performance metrics to evaluate the effectiveness of their proposed controllers. In Ref.[42, 55-57], energy saving optimization of individual air conditioners is examined. In the work presented in Ref.[58], the Peak load shifting capability by HVAC control was studied. The transient response improvement studies (decrease in rise time, settling time, and peak time) were presented in Ref.[47, 48, 59, 60], and steady-state response improvement (decrease in offset error) were investigated in Ref.[46, 60]. For studies related to grouped AC control, several research works have recently been reported. Ref. [43, 61, 62] have investigated model predictive control, and augmented optimal control for buildings to compensate fluctuations in solar power generation. The demand-response-oriented HVAC control solutions are discussed in Ref.[63], which include concentrated control, distribution control, and load aggregator-based control. However, only few studies of group AC control were conducted with real case application scenarios under hot climate conditions.

The motivation of this chapter is to propose an advanced air-conditioners group power control solution based on high-performance computational intelligence and optimization tools. This can be achieved via the capability of large-scale data processing, daily-based HVAC group control optimization process under various time-scale levels. In addition, the individual ACs in one group of HVAC cluster can be coordinately controlled to generate the desired power consumption profile, which can eventually shave power peaks during both cases, load consumption and PV generation.

4.2. AC thermal model and baseline control strategy

4.2.1. Building thermal model

To mimic the characteristics of a real-world building, a thermal dynamic model of Air-conditioned room, is developed based on thermodynamics' first principle. In this model, the Air-Conditioner is simplified as a unit for transferring heat flow. Thus, the Air-Conditioned room is modeled as a first-order system, which can be represented as follows[64, 65]:

$$\frac{dT_{indoor}}{dt} = \frac{\dot{Q}_d - \dot{Q}_e}{C_p m} \tag{4.1}$$

$$\dot{Q}_d = \frac{T_{outdoor} - T_{indoor}}{R} \tag{4.2}$$

By substituting Equation (4.2) into Equation (4.1), the room model can be represented as follows:

$$\frac{dT_{indoor}}{dt} = \frac{-1}{C_p m R} T_{indoor} + \frac{-1}{C_p m} \dot{Q}_e + \frac{1}{C_p m R} T_{amb} \tag{4.3}$$

where the variables in the above expression are shown in Table 4.1 below:

Parameter	**Definition**
T_{indoor}	Indoor temperature of the building
$T_{outdoor}$	Outdoor temperature of the building
$\dot{Q}_d$	Heat flow from outdoor to the building
$\dot{Q}_e$	Cooling Energy by AC system
R	Thermal resistance from outdoor to the building
m	Mass of the indoor air
C_p	Specific heat capacity of the room air

Table 4.1. Parameters of house/building thermal model

For the controller's design, a thermal model of the building can be represented as a state-space model format as follows:

$$\dot{x}(t) = Ax(t) + Bu(t) + E$$
$$y(t) = Cx(t) \tag{4.4}$$

where x represents the state T_{indoor}, and it is measurable so that C = 1. u represents the binary on-off control input $u = \dot{Q}_e = P_{AC}$, which can be denoted as follows:

$$u = \begin{cases} P_{AC} & t \in T_{on} \\ 0 & t \in T_{off} \end{cases} \tag{4.5}$$

The coefficient A, B and E have the following expressions:

$$A = \frac{-1}{C_p m R}$$

$$B = \frac{-1}{C_p m} \tag{4.6}$$

$$E = \frac{1}{C_p m R} T_{amb}$$

It is to be noted that the variables in Equation (4.1) include the state variable T_{indoor}, and the input variable ($\dot{Q}_e$). $T_{outdoor}$ is not a constant due to the variations of the outdoor temperature, hence, it is considered to be changing with time in this study.

4.2.2. Baseline AC control strategy

The compressor is the most important component of an AC system. Due to different compressors' working principles, existing air conditioning units in the market can be classified based on compressor type into either Inverter or On-Off type. The On-Off type of compressors used to be popular in the past, but still dominates the market and mostly used for residential applications, while DC Inverter type is the latest technology in the market[66-69]. The On-Off AC operates by being either fully turned ON or totally turned OFF depending on the indoor temperature set-point and the outdoor temperature. Usually there is a dead-band range of about 1.5 °C to 2.0

°C to prevent too frequent compressor on-off switching that reduces its lifespan. In hot regions like the Middle East or Arabian Gulf area, ACs mainly work in cooling mode due to the special desert climatic weather conditions. For example, in cooling mode, the AC compressor will be turned ON when the indoor temperature is higher than the set-point temperature by 2 °C (may vary at different scenarios). It will only switch OFF when the room temperature drops below the set-point temperature. To describe the control philosophy and logic mentioned above, the baseline AC control can be described as follows:

1) *If* $T_{indoor} \geq T_{set} + \Delta T_c$, *AC compressor switches on;*

2) *If* $T_{indoor} < T_{set}$, *AC compressor switches off;*

Here, T_{set} is the set point temperature, and ΔT_c is the temperature dead-band.

For illustration purposes, an AC On-Off control temperature control plot is shown in Figure 4.1. As shown in this figure, when ON-OFF control enters a stable stage, the temperature oscillates with time between [T_{set}, $T_{set} + \Delta T_c$] and aforementioned logic applies. In practice, the oscillation frequencies and ranges can vary under different climatic conditions. Thus, the On-Off AC control has some flexibility. Also, the temperature control profile shows the system's dynamics that exhibit slow response. Both of these characteristics offer a great potential for a group of AC units to systematically work as time-shifting storage units.

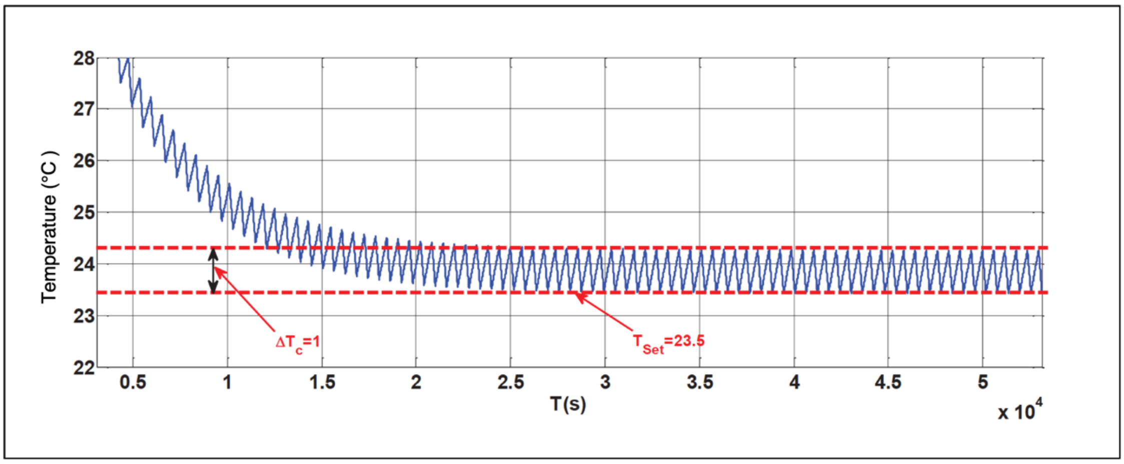


Figure 4.1. Baseline on-off AC control temperature profile

4.3. AC group control optimization problem formulation

An AC unit within a group of other ACs can be considered as a single unit with individual thermal dynamics and temperature control process. To achieve the role of time-shift applications like a storage system, a number of AC units need to be coordinately controlled to participate in achieving the desired power performance profile. In addition, the AC units' control system needs to comply with some process constraints such as required temperature-control range, and time-correlation. To implement this orchestrated control, it is feasible to monitor and control all AC units based on existing industrial control technologies such as telecommunication, smart sensing and Internet of Things (IoT). For the sake of simplicity, this chapter focuses on the elaboration of the proposed AC-group control optimization methodology.

4.3.1. Discretized AC group model

Due to the fact that On-Off control is the dominant type of controllers for conventional AC units, the Air-Conditioned rooms are considered to be controlled within certain bounds of a fixed dead-band by baseline On-Off control. Thus, a discretized On-Off control is implemented as a sampled-data based controller by employing the continuous building thermal model (see Equation (4.7)) to be discretized with sampling period ΔT, and $t_i = i\Delta T$. For the convenience of state-space model discretization, the relationship can be denoted by $\tilde{x} = x - T_{outdoors}$. Thus, Equation (4.4) can be expressed as a standard state-space model as follows:

$$\tilde{x}(t) = A\tilde{x}(t) + Bu(t) \tag{4.8}$$

Therefore, it can yield the discrete-time group AC model as follows:

$$\begin{aligned} &\tilde{x}_{k+1,j} = A_j\tilde{x}_{k,j} + B_j u_{k,j} \\ &j \in [1, N_{AC}]\,,\ k \in [0, N_T - 1] \end{aligned} \tag{4.9}$$

where the parameters A_j and B_j are expressed by:

$$
\begin{aligned}
A_j &= e^{A\Delta T} \\
B_j &= \left(\int_0^T e^{A\sigma} d\sigma\right) B
\end{aligned}
\tag{4.10}
$$

The parameter N_{AC} denotes the AC unit's number as part of a controlled group; NT denotes the time step number through a window period of control optimization. For example, if the considered time interval is ΔT = 2h, the time-step number NT = 24/2 = 12. The main objective of the group control is to generate On-Off control signals that make the AC group total power consumption follow the demand of the preferred time-shift scenarios without compromising indoor temperature comfort constrains. For load-side peak shaving scenarios, the group control target is to stabilize the total power consumption value by keeping it constant as much as possible or by making it react with slow changes in response to demand. Thus, the control target can be represented as follows:

$$
P(k) = \sum_{j=1}^{N_{AC}} u_j(k) \approx const \tag{4.11}
$$

For generation-side peak-shaving scenarios, the group control target is to make the total power consumption be almost the same as the power generation. Thus, the control target can be expressed as follows:

$$
P(k) = \sum_{j=1}^{N_{AC}} u_j(k) \approx P_G(k) \tag{4.12}
$$

4.3.2. Constraints

Due to the fact that temperature control of each AC unit has a slow thermal dynamics process, both the state and control input have constraints in this group control problem. For indoor temperature state constraint, it holds:

$$\begin{aligned} & x_{k,j} \in \left[20^{\circ}C, 25^{\circ}C\right] \\ & j \in [1, N_{AC}], k \in [0, N_T - 1] \end{aligned} \tag{4.13}$$

For the discrete On-Off control input, it should be a binary variable, which holds:

$$\begin{aligned} & u_{k,j} \in \{0, 1\} * P_{AC} \\ & j \in [1, N_{AC}], k \in [0, N_T - 1] \end{aligned} \tag{4.14}$$

where $u_{k,j}$ has only two values. If the AC unit is commanded to be turned ON, the value of $u_{k,j}$ equals the value of P_{AC}. Otherwise, if the AC unit is commanded to be turned OFF, the value of $u_{k,j}$ is 0.

4.3.3. Cost function

The cost function is a tool to evaluate the target of optimization. The group control target is peak-shaving, which essentially means minimizing the magnitude of power profile and associated spikes. By denoting the difference between total control signal and constant power signal for each time step *k*, the cost function for each step can then be expressed as follows:

$$J_u(k) = (\sum_{j=1}^{N_{AC}} u_j(k) - P_C(k))' R (\sum_{j=1}^{N_{AC}} u_j(k) - P_C(k)) \tag{4.15}$$

Here $P_C(k)$ denotes the objective power consumption at the time step *k*. If it is for load-side peak-shaving, $P_C(k)$ should be constant or piece-wise linear. However, if it is for the generation-side peak-shaving, $P_C(k)$ should have the following form:

$$P_C(k) = a \times P_{PV}(k) + b \tag{4.16}$$

where coefficients $\boldsymbol{a}$ and $\boldsymbol{b}$ denote the scalar factor and offset factor respectively.

Also, if the indoor temperature variation is considered as the performance target, then the total cost function can be expressed as follows:

$$J = \sum_{k=1}^{N_T} \left\{ (x(k) - x_{ref})' Q \left(x(k) - x_{ref}\right) + J_u(k) \right\} \tag{4.17}$$

As can be seen from (4.14) and (4.16), the control input values are binary variables in the optimization process. Thus, Mixed Integer Quadratic Programming (MIQP) is applicable for this problem. Once the cost function and constraints are defined, a solution can be obtained using existing advanced optimization solvers.

4.3.4. Model simulation

In order for the developed optimized group control system to be tested under different outdoor temperature scenarios and constraints, simulations are necessary and helpful for lab demonstrations. To build a suitable simulation environment for the AC group control, an open-source UI tool for general optimization problems (Yalmip) is used for modeling the Air-conditioning thermal dynamics problems which is compatible with Matlab simulation environment. Also, through Yalmip, commercial solvers such as Gurobi and Cplex can be integrated into Matlab environment and work together in the uniform programming language by Yalmip.

4.4. AC group control implementation

To implement the proposed group control system, the AC units need to be equipped with (bi-directional communication-enabled) smart sensors for power consumption and indoor temperature data. Additionally, open Application Programing Interface (API) is needed for remote control interface. More importantly, a remote high-performance control workstation is needed to perform data consolidation and optimization process computation. To illustrate the network structure, a diagram of the AC group control ICT hardware infrastructure topology is shown in Figure 4.2 below.

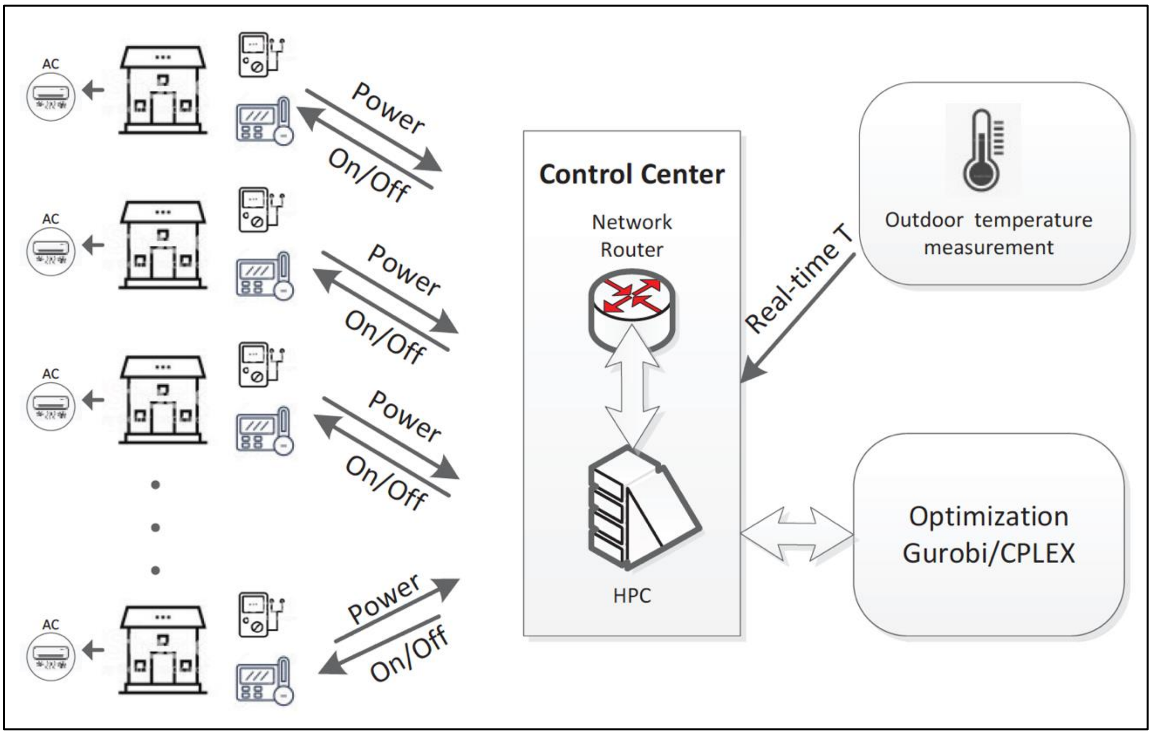


Figure 4.2. Group Control ICT hardware infrastructure diagram.

As can be seen from Figure 4.2, an air-conditioned building is additionally equipped with smart meters to monitor the power consumption, where the power metering data is sent to remote control center in real-time. The control center will consolidate all power measurement data and make appropriate calculations and decisions for individual ACs On-Off control logic action based on real-time outdoor temperature and advanced optimization solvers such as Gurobi or CPLEX. Conventionally, the optimization is a lengthy and time-consuming process that depends on many factors like optimization objective, number of variables and sparsity of solution space. However, with the aid of advanced high-performance computing, large data-processing is possible hence, the Control Center in Figure 4.2 can manage the data processing efficiently with fast response. These advantages promote the feasibility and make AC group control become more practical for implementation.

To implement the AC group control with real-time responsiveness, a flowchart for the control program is designed as depicted in Figure 4.3. As can be seen from Figure 4.3, once the AC group controller is initiated, one-day ahead forecast of outdoor temperature is estimated. This task is becoming more viable nowadays with advanced weather prediction technologies. Once completed, initial individual room target temperatures are recorded and set in the program. Based on the load peak-shaving regulation criteria, the desired power profile is generated. Along with the pre-determined constraints, all parameters and settings are then sent as input values to the optimization solver for processing. Here, the time it takes to return optimal solutions usually depends on the type of solver and computational resources being used. Upon calculations convergence, where optimal solution is found, the corresponding On-Off control signals are generated and sent to individual thermostats of each AC unit for cooling action execution. This will be repeated until one day time frame is elapsed.

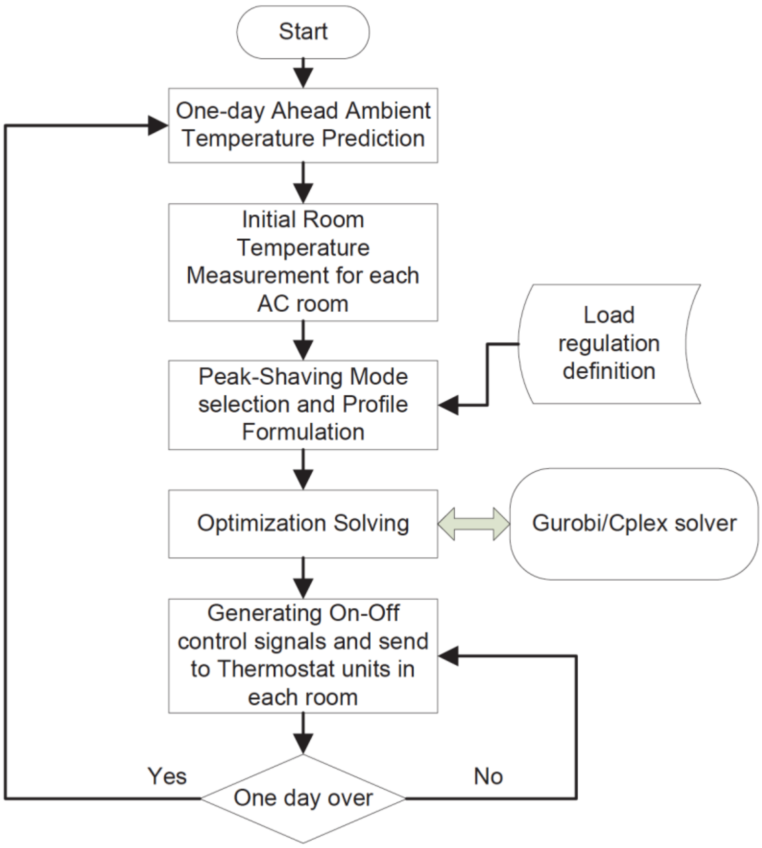


Figure 4.3. Flowchart for AC group control program.

4.5. Key simulation results

To demonstrate the proposed AC group control approach for micro-grid peak-shaving applications, typical ambient weather conditions in Qatar are considered for AC cooling cases. A real-time measurement of one-day outdoor temperature is shown in Figure 4.4. where it can be seen that the outdoor temperature profile still varies during daytime and crosses the 30 ℃ mark even in the month of November. Also, the temperature variation range is quite large, which means that the cooling energy needed for AC units will be diverse.

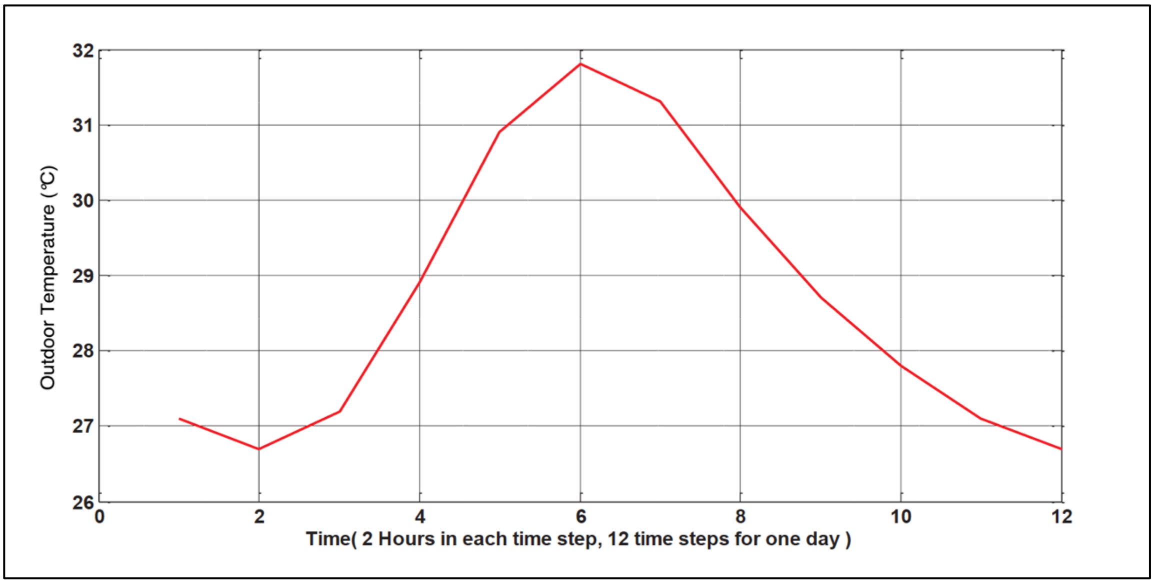


Figure 4.4. Outdoor Temperature in One day measured in Qatar (November2019)

To investigate how communication delay affects the AC control performance, a simulation scenario is designed to verify AC unit On-Off control with 3 levels of delay time:1- minutes, 5- minutes, and 10-minutes. The On-Off control power profile is shown in Figure 4.5 and the temperature profile comparison is shown in Figure 4.6. From Figure 4.5, it can be seen that the control command delay has a direct impact on the pulse width of controlled power signal; which means that the delay will be less for lower control pulse width. Also, the control power pulse signal becomes wider as the outdoor temperature becomes lower. From Figure 4.5, it is shown that 1 to 5 minutes delay has no obvious impact on the control performance, where the indoor temperature oscillates around the target range between 24 ℃ and 26 ℃. However, the 10-minute delay has a noticeable impact on the control performance as the indoor temperature tends to slightly propagate beyond the target temperature range due to control time delay. Conversely, the control stability still persists in a good way due to the effectiveness of feedback control mechanism.

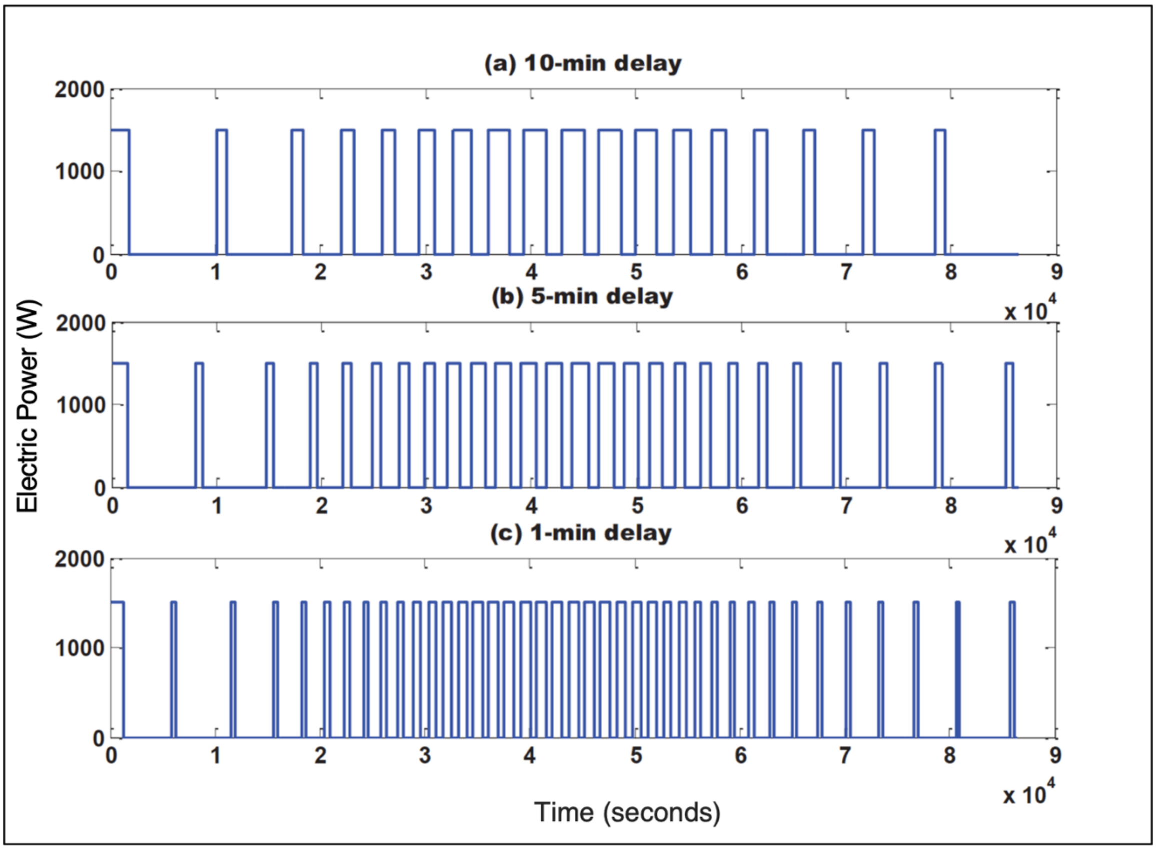


Figure 4.5. On-Off Control Power profile subjected to different time delay

In the current study, both load-side and generation-side peak-shaving scenarios are considered for demonstrating the effectiveness of the proposed AC group control methodology. The load side peak shaving aims to regulate and smoothen the power consumption profile by controlling the multiple AC units as a group in a system's approach. The generation-side peak shaving control aims to absorb the power generated from the PV arrays by managing the power demand of all AC units, that is constrained by an acceptable range of indoor temperature. Compared with the load-side peak shaving, PV generation-side peak shaving has a direct impact on energy demand & supply balance.

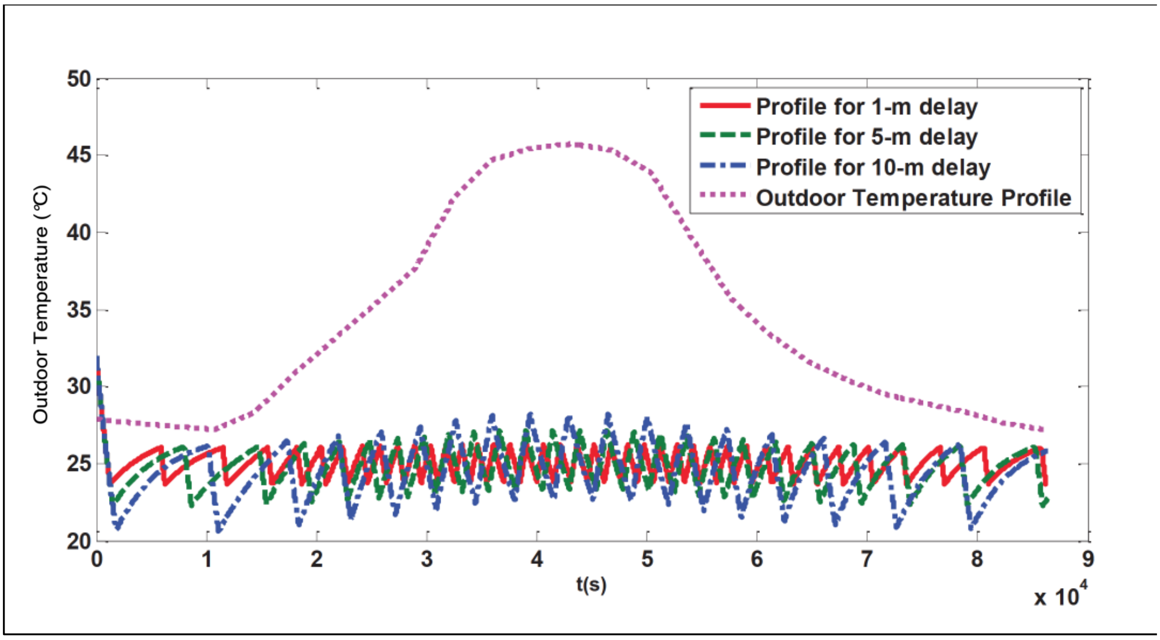


Figure 4.6. Indoor Temperature Control Profile Comparison

With the pre-determined acceptable comfort level range, the target room indoor temperature is set to be maintained between 20 ℃ and 25 ℃. A total of 40 AC units is considered to be the AC group load, and as per system design, they would work together to generate a constant power consumption profile against the variations of local outdoor ambient temperature. The parameters of the thermal model are shown below in Table 4.2.

Parameter	Value	Parameter	Value
A	-2.00123e-4	J_{SW}	2
B	4.4028e-6	Cp($J/kg°C$)	1005
E	$0.002{*}T_{ref}$	$m(kg)$	222
R($^oC/W$)	0.022	Q	300

Table 4.2. Thermal parameters of the building's model

4.5.1. Load demand Peak-Shaving

In order to simplify the optimization process, the AC On-Off control step is set to be at 2-hour intervals. The AC group control is performed for the 40 AC units over a one day timeframe. By applying the proposed harmonized control method, the indoor temperature control profiles of the 40 air-conditioned rooms are depicted in Figure 4.7. From there, it can be noticed that the temperature profiles exhibit similar peaks during noon time with the raise of outdoor temperature. However, the range of the indoor temperature is maintained within the required range.

The On-Off logic commands generated by the control system for the considered 40 AC units are displayed in Figure 4.8. To distinguish the command signals for each AC unit, the individual plots are shifted vertically at the *y*-axis to different levels that illustrates different ACs identification labels. From the control logic plot, it can be seen that the AC group demonstrates a diversity of the On-Off logic combinations throughout the process while being coordinately controlled by the proposed AC group control strategy.

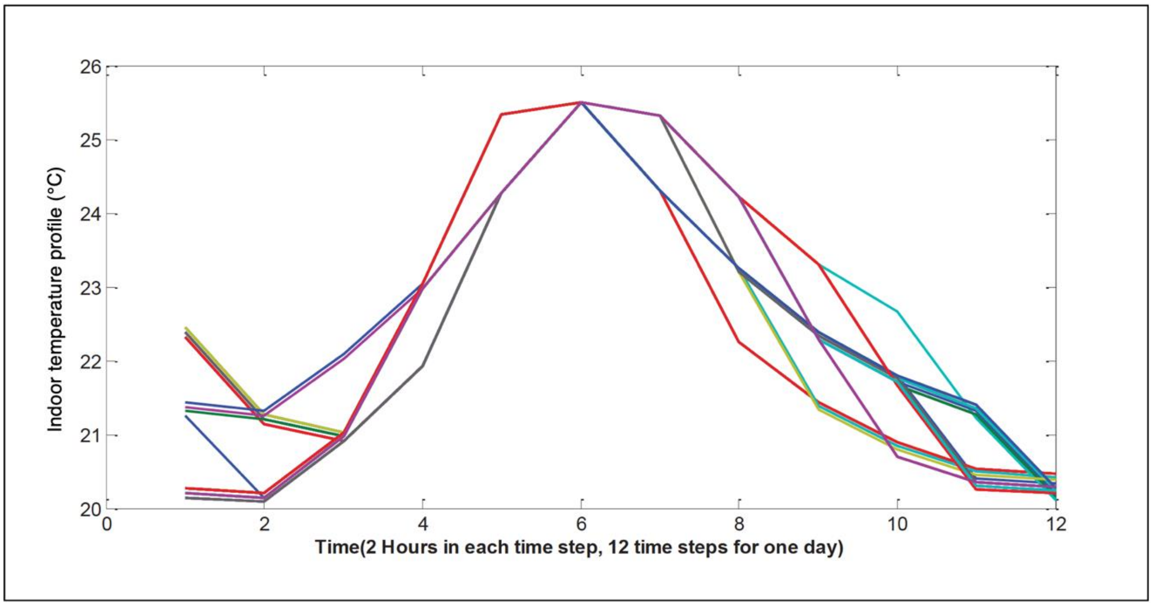


Figure 4.7. Indoor temperature profiles of load-side peak shaving (for the considered 40 AC units)

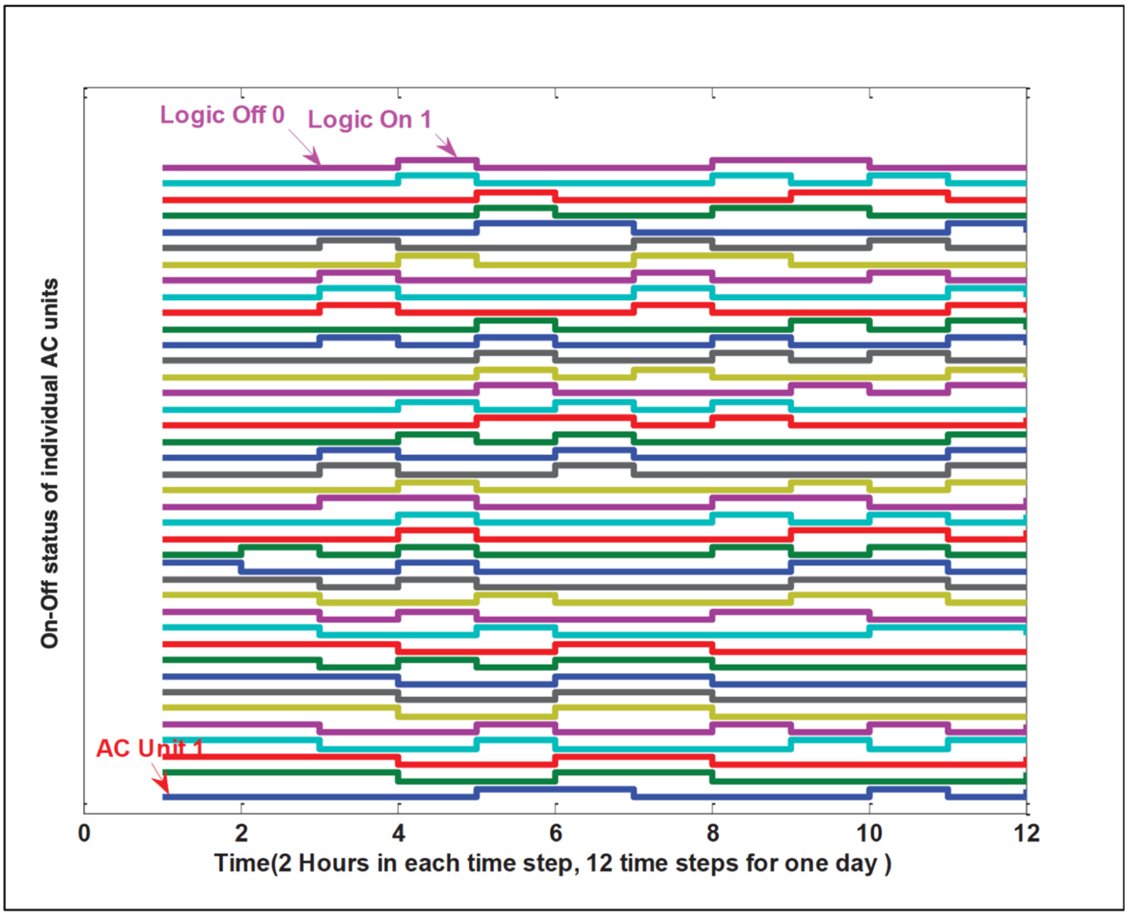


Figure 4.8. Individual AC power control logic of load-side peak shaving

Cumulative power curve

The total power consumption sum of the 40 AC units is shown in Figure 4.9. By comparing to the desired (reference) constant power line, the AC group power control performance is almost identical, with exception of a slight difference during all the durations of peak-shaving which is negligible. From this result, it can be concluded that the ACs of the considered group operate in a well-organized, harmonized and coordinately controlled manner regardless of the ambient temperature variation and despite the inconsistency of individual ACs power consumption.

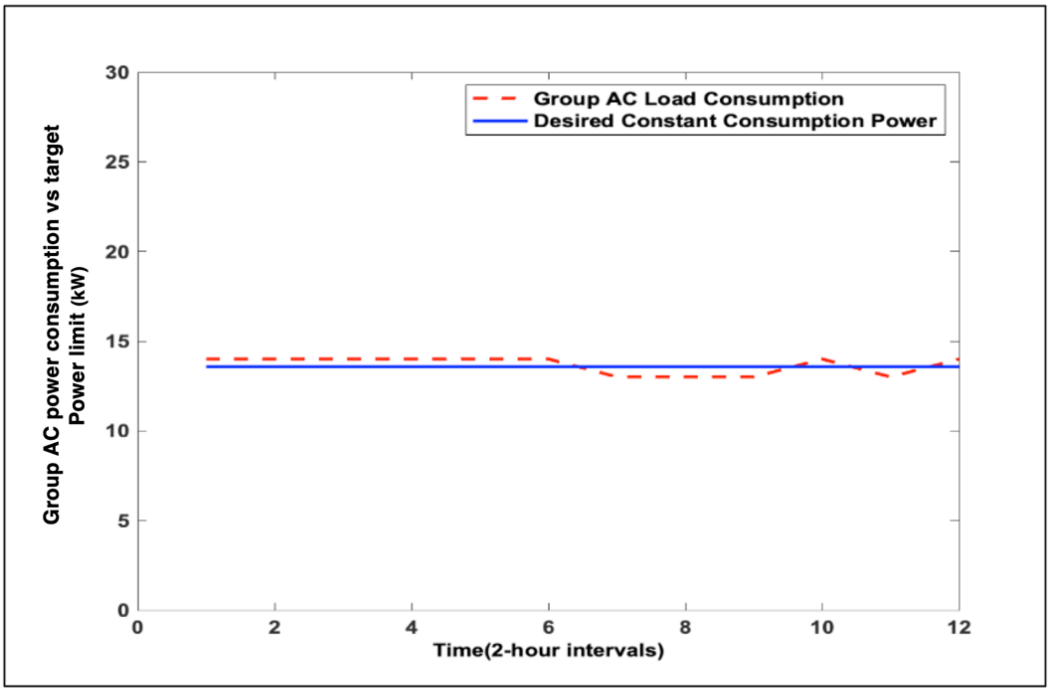


Figure 4.9. Load-side shaving by AC group control

4.5.2. PV generation peak-shaving

Compared with load peak-shaving, PV generation peak-shaving needs to generate a more time-variant power profile to balance out the PV generation and AC consumption. In doing this, the AC group control needs more control units and flexibility to satisfy the diversity of time-variant characteristics. In this section, ternary mode (on, partially-on, and off) will be considered (in case2) as opposed to the conventional binary (on-off) mode (in case1) where both modes are analyzed for improved control performance and peak-shaving results.

4.5.2.1. Case1: group AC control for PV peak-shaving with binary on-off modes

The indoor temperature profiles for PV peak shaving scenario under binary mode (0-1) control setup are shown in Figure 4.10. From the plot of the 40 air-conditioned rooms, it can be seen that all the indoor temperatures drop within the target indoor temperature range, and the curves present time-variant characteristics similar to the load peak shaving scenario. This similarity is due to the influence of the outdoor temperature. Moreover, it demonstrates that the AC group control is able achieve both, maintaining indoor comfort level and absorb the PV-generated power, hence, shave the generation peaks from PV sources.

Figure 4.11shows the individual AC units' signal command / power control logic for PV peak shaving scenario under binary mode setup, while Figure 4.12 compares the power profiles of both AC group consumption and PV power generation. By comparing Figure 4.11with Figure 4.8, the individual AC power control logic appears to be similar, but the control logic profile seem to be changing less frequently, which means less fluctuations that can help in minimizing issues of AC wearing parts. From Figure 4.12 it is shown that the PV power profile is matching the AC group consumption profile, which demonstrates the AC group control ability to achieve the target PV peak-shaving effect.

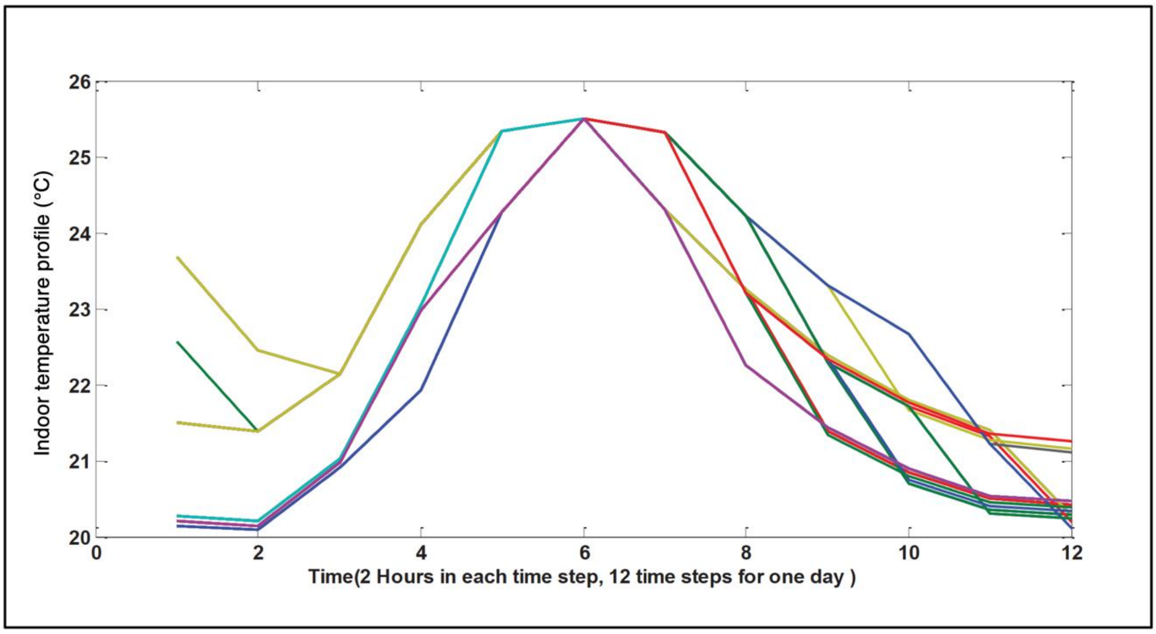


Figure 4.10.Indoor temperature profiles under binary Mode

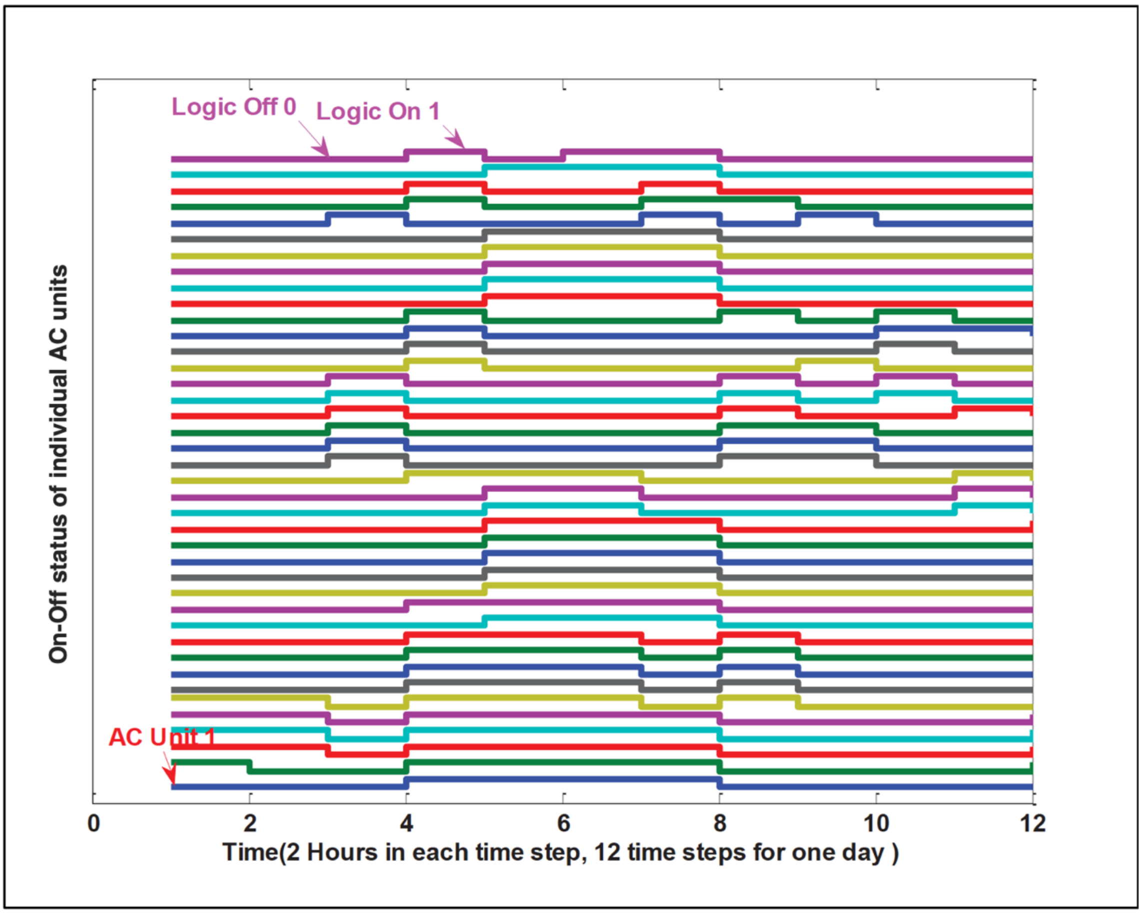


Figure 4.11. Individual AC power control logic for PV peak shaving scenario (binary mode)

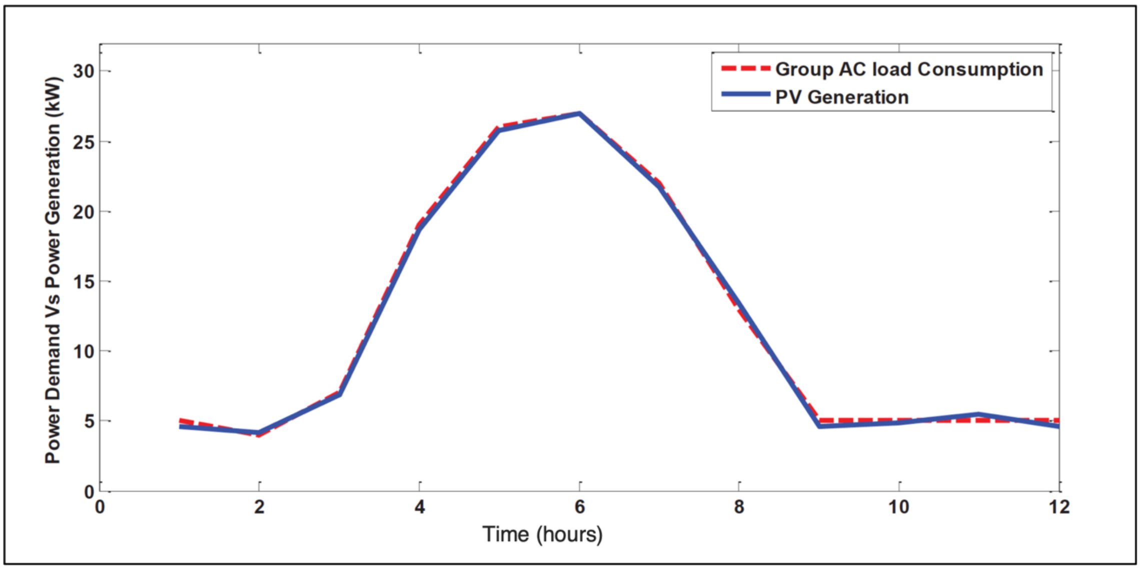


Figure 4.12. PV side Peak-shaving by AC group control (binary mode)

4.5.2.2. Case 2: group AC control for PV peak-shaving with ternary modes

As opposed to binary with 2 working states (0-1), ternary logic with 3 states (0-1-2) exist in many device applications as it can bring benefits in terms of logic flexibility and minimized computational hurdles. For this, ternary mode is considered in the AC unit work application for PV peak-shaving scenario where the 3 states of on, partially-on, and off are applied. Figure 4.13 shows the indoor temperature profiles for PV peak shaving scenario using the ternary mode setup. Different from the binary mode performance (in Figure 4.10), the ternary mode performance plot of indoor temperature control demonstrates that each AC unit has a more diverse temperature profile, resulting from more work states thus, the AC group control has more flexibility to accommodate the complex characteristics of PV power generation profiles.

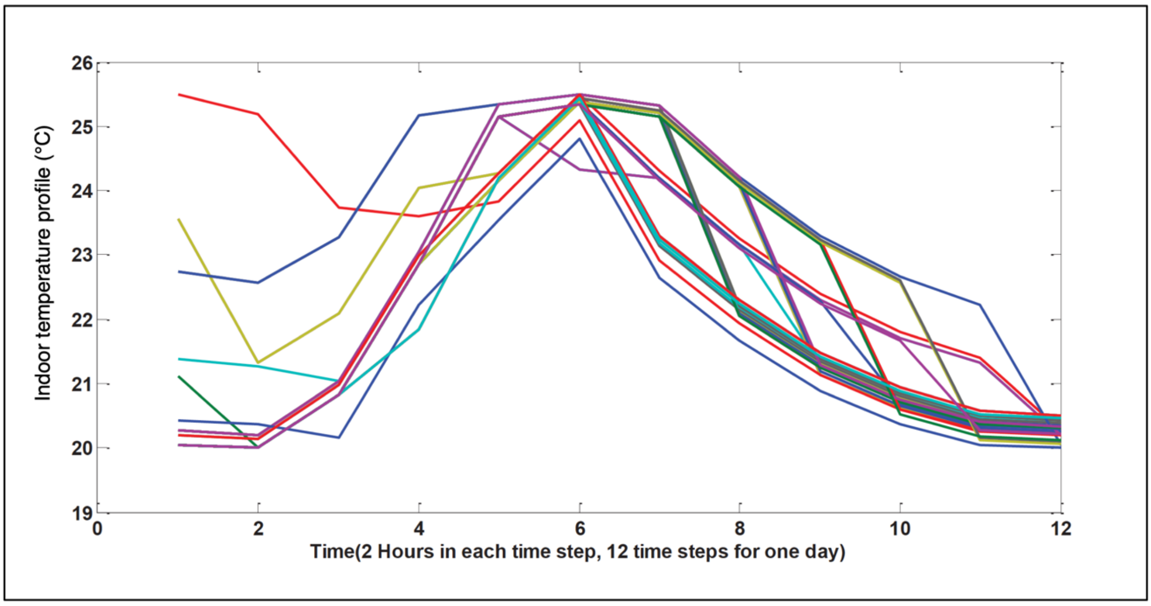


Figure 4.13. Indoor temperature profiles under Ternary Mode (0-1-2)

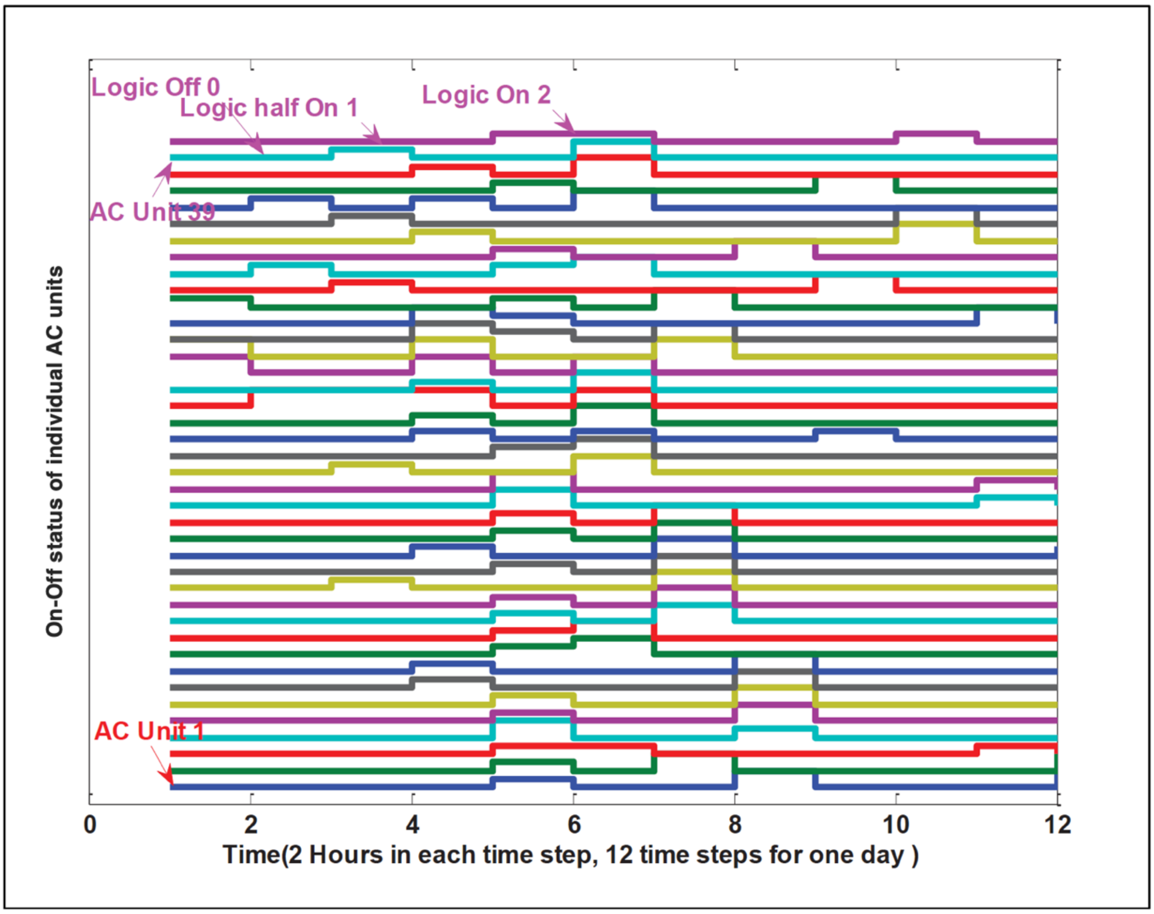


Figure 4.14. Individual AC power control logic under Ternary Mode (0-1-2)

Figure 4.14 presents the ternary control logic for PV peak shaving scenario under the ternary mode. As can be seen from the profile, the AC working states alternate among the 3 states; ON (2), OFF (0), Half ON (1) based on the criteria of AC group control. Also, the control profile between AC units is not identical and the variations in 2 hours interval are minimal.

Power profiles comparison between the AC group total consumption and PV generation is shown in Figure 4.15. There, the two curves exhibit a good fitting, which means the PV generation power can be fully absorbed by the 40 AC units under the proposed AC group control strategy. Also, by comparing Figures 4.15 &4.12, the ternary mode has a better fitting than the binary mode because of the extra control flexibility.

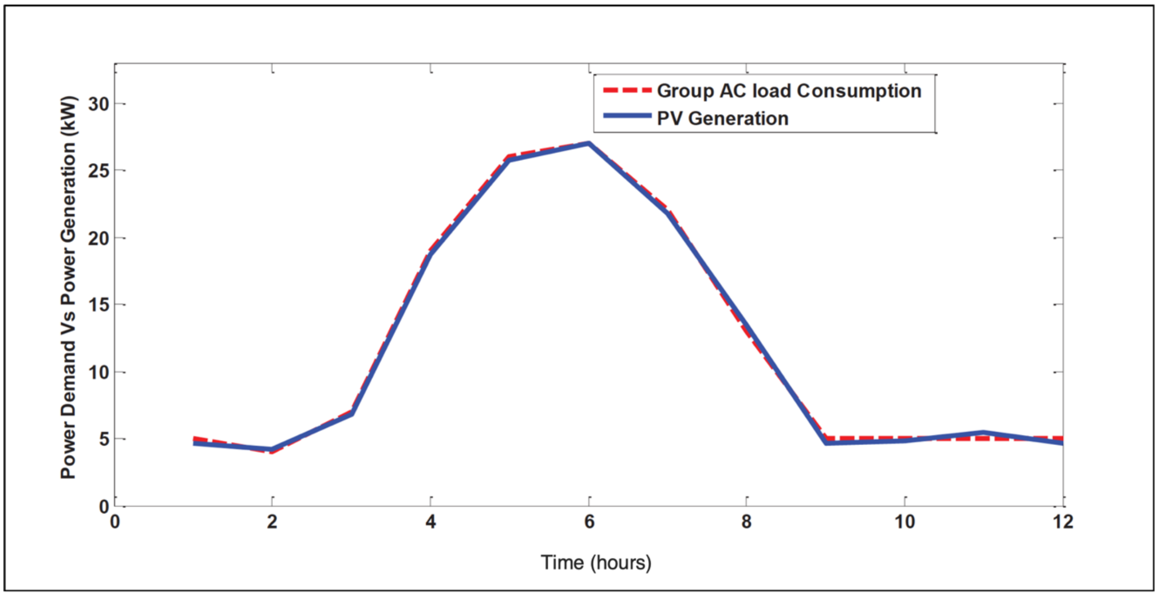


Figure 4.15. PV side Peak-shaving by AC group control with Ternary Mode (0-1-2)

It is to be noted that the AC group control flexibility depends on the diversity of AC work states. With the inevitable penetration of modern variable frequency Air-Conditioning technologies, a new technical reality is confronted which is the different working mode. With this new technology, AC compressors work continuously (*with variable load ratios*) rather than alternating between different ON and OFF states as in conventional discrete ACs. Theoretically, the proposed AC group control can handle variable-frequency based ACs with a better peak-shaving capability than traditional On-Off based. In addition, the proposed AC group control can be applied to regions with similar climate conditions, which require power management and peaking-shaving from both the demand and solar PV generations side. For other regions with different environment and climate conditions (eg. solar irradiance, ambient temperature, etc.), the load-side peak-shaving group control can be applied, however, the PV generation-side peak-shaving may not be directly applicable as it needs to be customized. That is mainly attributed to the various PV technologies in the market as well as the diverse cooling/heating demands. Hence, generic applicability of the proposed AC group control is possible but with specific constraints and criteria relevant to local environment and climate conditions.

4.6. Conclusion

This chapter introduces an AC Group control approach for micro-grid peak-shaving applications. the feasibility of making use the AC systems' dynamics and the way in which a cluster of air conditioning units work together to produce with guided synergy a favorable, smooth and stable power performance curve is examined via leveling and peak shaving (*from both demand &supply sides*) is examined. An optimization method for daily based AC load control is studied and addressed by means of MIQP technique. Through the use of powerful optimization solvers such as Gurobi, a group of AC units can be coordinately controlled to generate the desired power consumption profile whilst maintaining an acceptable indoor comfort level, separately from the outdoor ambient temperature variations. Finally, simulations conducted under Qatar's typical local weather conditions successfully demonstrates the effectiveness and reliability of the proposed concept in managing aggressive air conditioning power loads in a synergistical manner. Future work will focus on considering more thermal electric loads such as water heaters, refrigerators to demonstrate applicability under various seasonal desertic weather conditions.

CHAPTER 5:

Influence of dust on the performance and efficiency of common HVAC systems

Abstract

Cooling and air conditioning appliances like standard Air conditioning ACs or Heating, Ventilation, and Air conditioning (HVAC) systems are becoming necessary in modern life, especially in areas characterized by extreme heat. Apart from delivering appropriate indoor thermal comfort, HVAC systems also ought to maintain a sufficient level of indoor air quality (IAQ) through air filtration. This is especially important for countries with desert climate and/or high air pollution levels where IAQ is fundamental for sustained human health and wellness. Numerous studies have been conducted to determine the scope of particle buildup caused by the particle deposition on ventilation units, namely air filters and evaporator units, as it relates to the system's airflow, efficiency, and lifecycle cost (LCC). Usually, clogged air filters reduce airflow through the system, putting stress on fans, and increasing the energy consumption and its associated cost. This is a very challenging issue, especially in desert climates, where there are more high-temperature days and a more arid environment. Without proper system design and maintenance, such internal surfaces will accumulate particles that will both impair the key functionality of an HVAC unit and potentially cause system degradation and failure. In this chapter, the focus will be on assessing and addressing the main detrimental dust-related challenges impeding the full potential and added-value of standard HVAC systems within the context of arid desert climates. Air filters will be studied to gain an understanding of how they operate and influence the HVAC system's performance. Finally, an optimal air filter selection approach is proposed by using a multi-variable optimization technique.

5.1. Introduction

Throughout human civilization history, the need for having a safe, secure, and comfortable home has always been of prime importance to humankind. Along with technological evolution, this basic need has grown in demand and complexity over the years to include aspects of convenience and even luxury in modern homes. While this may sound logical and legitimate right, especially that we spend most of our time indoors, the associated increase in the ecological footprint is becoming a serious source of concern.

HVAC systems are one of the modern homes’ core utilities, designed to provide ideal indoor living conditions for occupants in terms of thermal comfort and IAQ. While they could be tagged as basic need (rather than convenience or luxury), especially in hot regions, they are notoriously aggressive consumers of energy and well-recognized big-ticket items when it comes to building investment. Moreover, these systems are vulnerable to harsh climate conditions where the combination of extreme heat and dust has a detrimental impact on the system’s performance and lifespan.

Global warming is a well-established fact that is caused by adverse human activities and inevitably leading to a dreadful Climate Change[70]. Additionally, around 300 million people worldwide suffer from asthma and the number is expected to rise towards 400 million by 2025[71]. Without appropriate control measures, the result will most likely be a dilemma with propagating increase of HVAC systems demand and its related environmental impact. These make a very challenging predicament facing governments and authorities who are continuously stretching efforts to cope with their nations' ever-growing demands while striving to pave concrete pathways that lead to sustainability.

Addressing these complex challenges might not be an easy task. However, some basic strategies can definitely help to make the situation less severe, like measures aiming for system optimization, Energy Efficiency, and maximizing added value. Since HVAC's energy/power management aspects are covered in previous chapters of this thesis, the following sections of this chapter will focus on the adverse impact of dust on HVAC systems' performance and possible ways to address this phenomenon in the context of buildings within harsh climate conditions.

5.2. Dust, Aerosols and Particulate Matter

The simple definition of dust is “the solid aerosol particles formed by mechanical disintegration of their parent materials”[72]. Such fine, solid matter particles usually borne in the air and settle onto surfaces. According to the ISO 4225: 1994; dust is defined as “small solid particles, conventionally taken as those particles below 75 µm in diameter, which settle out under their own weight, but which may remain suspended for some time[73].

Aerosols generally refer to liquid or solid particles suspended in air (Tellier 2009; Judson 2019). They can be visible, like fog, but are most often invisible, like dust or pollen.

Particulate matter (PM) is the sum of all solid and liquid particles suspended in air many of which are hazardous. This complex mixture includes both organic and inorganic particles, such as dust, pollen, soot, smoke, and liquid droplets. These particles vary greatly in size, shape, and origin. The composition of these PM can be either organic or inorganic, simple or complex comprising hundreds of different chemicals[73].

Some of these PM be is visible to the naked eye like dust, dirt, soot, or smoke, while others are so small, they can only be detected using a suitable microscope.

The main two categories of PM are:

- **PM_{10}** : are those inhalable particles, with diameters of 10 micrometers and smaller; and
- **$PM_{2.5}$** : are fine inhalable particles, with diameters of 2.5 micrometers and smaller. Normally, average human hair is about 70 micrometers in diameter – which makes it 30 times larger than the largest fine particle.

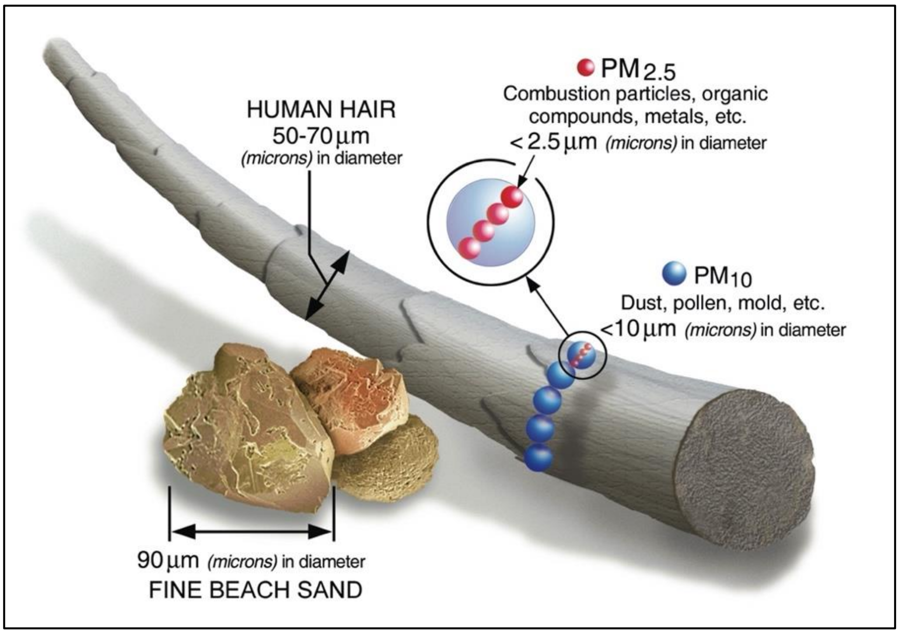


Figure 5.1 Particulate Matter (PM) size comparison[74]

5.2.1. Health effects

Particulate matter generally comprises microscopic solids or liquid droplets that can be inhaled and lead to serious health issues. Particles that are smaller than 10 μm in diameter (PM_{10}) can penetrate deep into the lungs and some may even reach bloodstream. Fine particles, 2.5 μm or less in diameter ($PM_{2.5}$), pose the greatest risk to human health. Numerous scientific studies have linked particle pollution exposure to a variety of problems, including; premature death of people with heart or lung disease, acute asthma, decreased lung or respiratory functions. People with heart or lung diseases, children, and older adults are the most likely to be affected by particle pollution exposure. There are certain regulations set by the EPA for inhalable particles, however, sand and large dust particles > 10 μm, are not regulated by EPA[74].

In the GCC region, Saudi Arabia is on the top of the list with most asthma cases where about 24% of the population has asthma. Qatar and Kuwait follow, with case rates of 19.8% and 16.8% respectively. This is followed by the UAE with 13% and Oman with 10%. These numbers are considerably high when compared to other countries. For example, and as per the CDC, 15.2% in the US are suffering Asthma.

Given the size difference between countries, it can be noticed that countries with desert climate are more susceptible to respiratory diseases.

Globally, there are more than 300 million people worldwide suffering from asthma which if not managed and controlled can lead to fatalities. Incidences of asthma diagnosis are continuing to increase each year – especially among children. It is predicted that by 2025 around 400 million people will have asthma[71].

5.2.2. Environmental Effects

The world's continents and oceans atmosphere are connected to what can be described as a global dust ecosystem. Studies show that approximately 3 billion tons of dust move across the earth's atmosphere every year[75]. This dust migration phenomenon usually occurs along global climate effects. Thus, dust particles travel long distances by wind and then settle on ground or water. While some countries benefit from this this phenomenon in the form of soil imports, others have to deal with the negative effects which (depending on the chemical composition) may include materials damage, causing to acid rain effects, depleting the nutrients in soil and damaging sensitive forests and farm crops.

Inherently, dust is a warming agent that absorbs sunlight hence, it becomes a substance that can both collect and clog HVAC ventilation systems. A 2012 NASA study clarified that dust is actually a collection of particulate matter, which combine to absorb solar radiation and warm the surrounding atmosphere. Subsequent analysis determined that approximately half of dust's potential cooling effect is countered by its propensity to absorb and reflect sunlight [76]. To clarify, sunlight is comprised of shorter wavelengths known as short waves. However, dust can absorb the longer wavelengths known as long wave radiation and more specifically, the effect of dust warming can counter half of the cooling effect created by the air conditioning unit[76, 77].

5.2.3. Effects of dust on HVAC systems performance

The combination of extreme heat, humidity, dust and dust storms makes harsh weather conditions that negatively impact both humans and assets. For HVAC systems, the size of particles that settle on air-conditioning duct bends and internal components are decisive culprits responsible for compromised HVAC units. In fact, particulate buildup is among the most common causes of HVAC unit failure, causing permanent and potentially serious damage to the HVAC system[78]. Examples of dust-related issues affecting the performance of HVAC systems include icing, airflow blockage, and reduced efficiency due to clogged air filters.

Dust accumulation on coils and evaporator units can lead to the formation of ice that eventually blocks airflow and causes serious stress on compressor and air handler units.

Figure 5.2.Ice formation on HVAC evaporator unit due to improper maintenance & dust accumulation

The accumulation of dust also clogs the system's filters restricting the airflow and hampering the system's ability to deliver the needed cooling load while drawing high power in attempt to compensate for the gap in cooling demand.

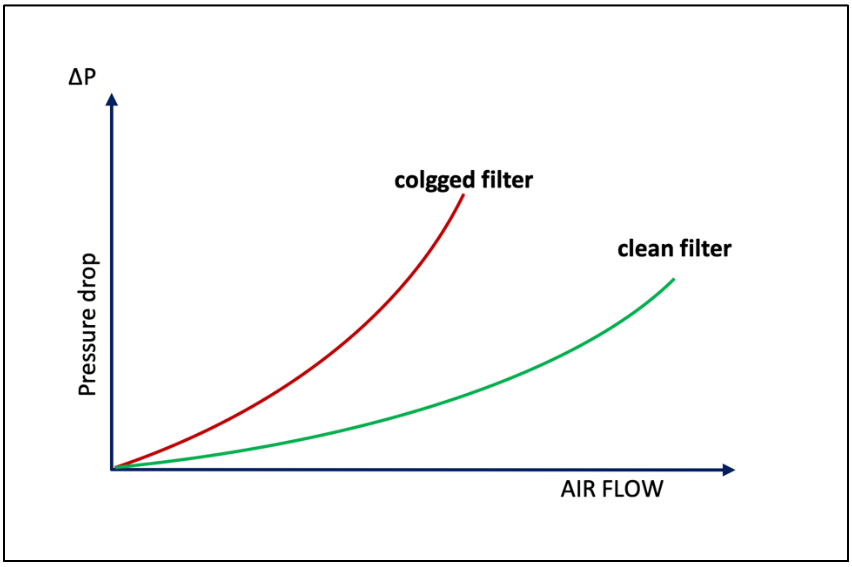


Figure 5.3. HVAC fan performance comparison with clean and loaded filters

The way different HVAC or air conditioning systems respond to airflow restriction due to filter blockage differs based on many factors like the type and size of system motors, filters as well as system design, specification, and the severity of the filter blockage.

With modern HVAC systems' controls, the fan or motor is maintained automatically at a certain speed to deliver specific airflow rates regardless of pressure drop. This is made possible by the modern Electronically Commutated Motors (ECMs), which adjust airflow rates to compensate for pressure drop changes. However, a higher pressure drop will generally lead to an increase in energy consumption[79].

Routine HVAC maintenance remains a vital measure in combating the issues of dust deposition. The complexity and intervals of maintenance activities vary based on many factors. Geographical location and climate have a direct influence on how often maintenance is needed and how fast filters become loaded with dust particles.

Gaining a good understanding of dust particles' composition and sources can undoubtedly help improve the system performance by selecting reliable filters and adopting appropriate and site-relevant maintenance programs.

5.3. Dust composition

5.3.1. Dust particles in desertic GCC region

In GCC countries, the major contributor to indoor air pollution include particulate matters (PMs), carbon monoxide (CO), carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen dioxide (NO_2) and heavy metals. Causes of such indoor air pollution in most cities in the GCC region is attributed to the infiltration of ambient air pollutants into residential buildings, poor ventilations, burning of biomasses (Arabian incense), and overcrowding.

Qatar as a GCC member was recently rated as the second among the top globally air polluters with PM in specifically that is caused by both anthropogenic and natural sources. Moreover, ongoing massive construction activities in the country are clearly becoming an important source of air pollution, that is steadily increasing as Qatar is approaching the big event of hosting the FIFA World Cup in 2022. The infiltration of PM from outdoor to indoor and entry through windows and building cracks are the main sources of $PM_{2.5}$ comprising of crystal matter(31.5%), nitrates (17.7%), sulfates (16.5%), organic carbon (7.6%)[80].

Qatar's harsh weather conditions features a high temperature range that is up to 45 °C and massive dust loading through atmospheric deposition of about 200 mg/m^3 which makes it second highest globally[81].

Designing sustainable buildings to suit the unique weather conditions is important in controlling built-up indoor air pollutants. The design of appropriate HVAC systems and air filtration units is a key element in attaining the overall sustainable building design for optimum efficiency and IAQ.

5.3.2. Home HVAC filter analysis

The following section presents the experimental work results through lab analysis of an air filter sample from a typical villa HVAC system in Qatar. The lab imaging, characterization work is done in the core labs of Qatar Environment and Energy Research Institute (QEERI). The techniques used were Scanning Electron Microscopy (SEM *-FEI equipped with Bruker EDS-*), Energy Dispersive X-Ray Spectroscopy (ESD), and X-Ray Diffraction (XRD).

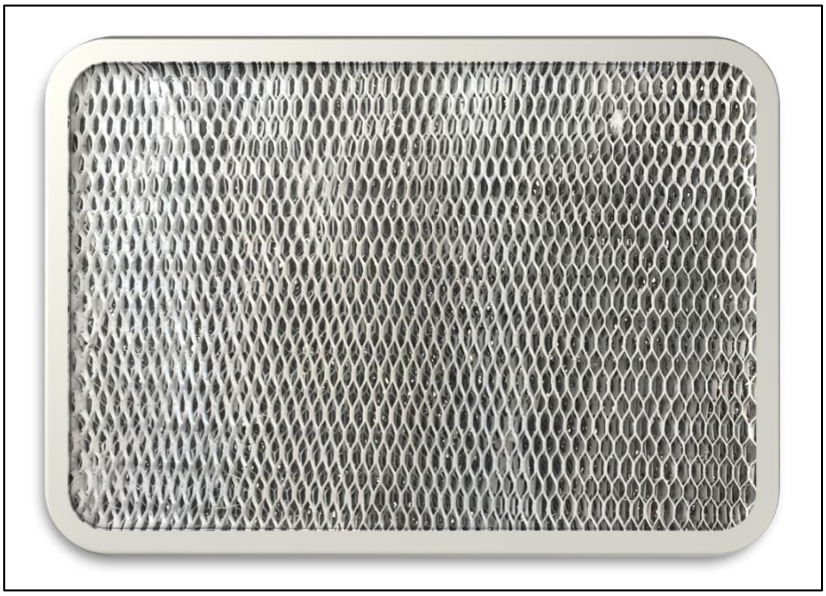
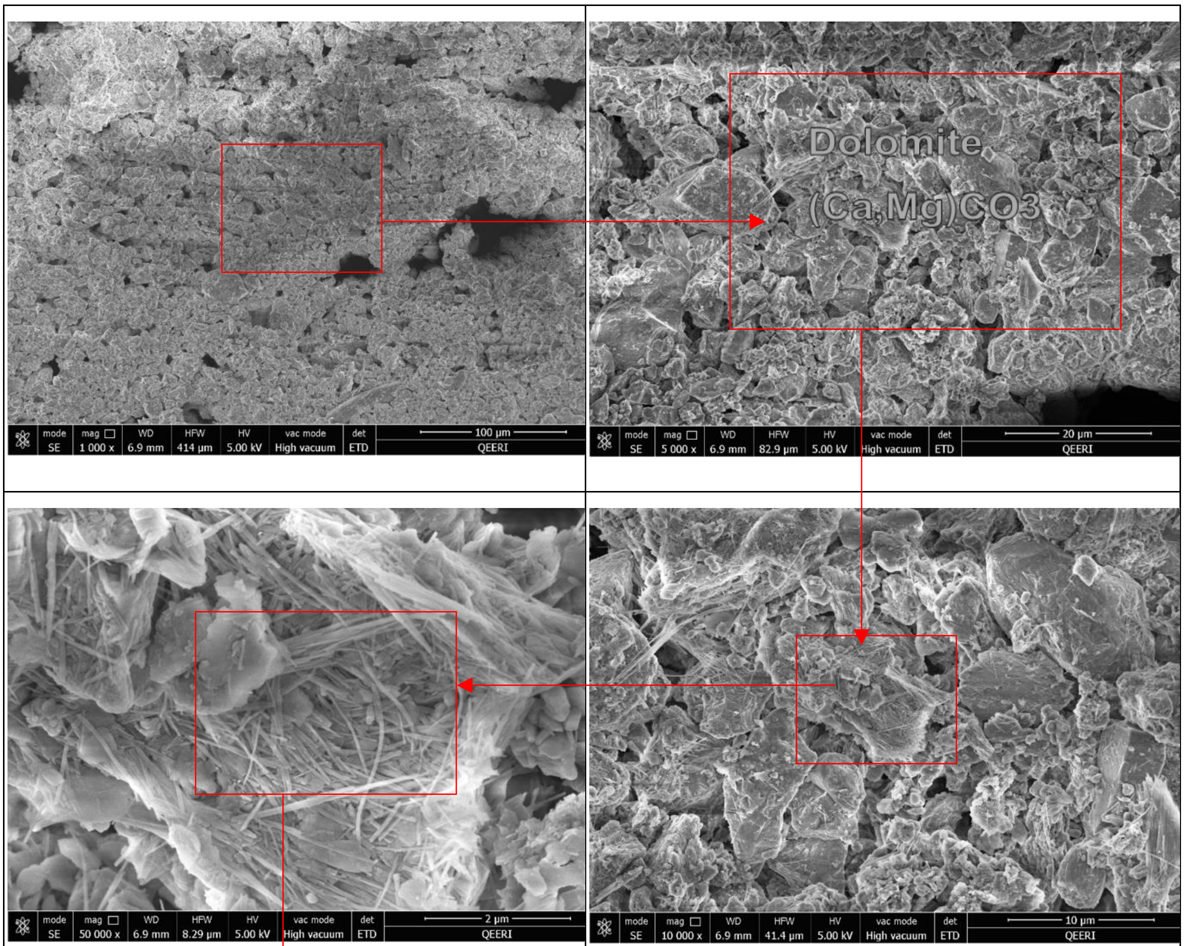


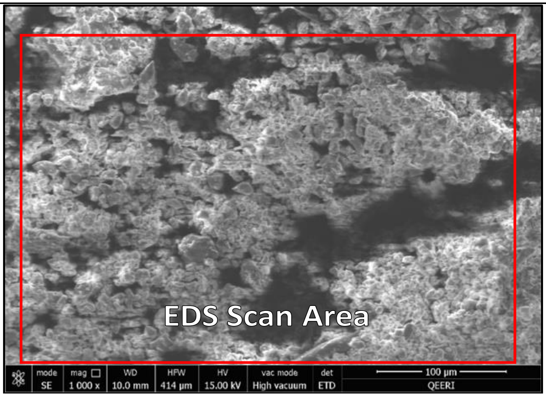
Figure 5.4. Sample (1 month loaded) washable HVAC air filter from local residential villa in Qatar

SEM analysis (Sample1, Area1)



SEM images of first sample show morphologies of filter dust at different magnifications (1000x, 5000x, 10,000x, 50,000x and 100,000x) clearly showing different morphologies indicative of different chemical species. Arrows show known dust compounds (i.e. Dolomite and Palygorskite phases). Others are present as will become clear from other images and chemical composition by EDS and X-Rays)

Figure 5.5. SEM analysis1 of sample air filter



Element	[wt.%]	N. wt.%]	N. at.%]	Compound	N. wt.%]
Carbon	7.62	8.51	14.21	CO2	8.51
Oxygen	43.10	48.12	60.31		48.12
Sodium	0.81	0.90	0.79	Na2O	0.90
Magnesium	3.07	3.42	2.82	MgO	3.42
Aluminium	2.63	2.94	2.19	Al2O3	2.94
Silicon	8.87	9.91	7.07	SiO2	9.91
Sulfur	2.05	2.28	1.43	SO3	2.28
Chlorine	0.57	0.63	0.36		0.63
Potassium	0.62	0.69	0.35	K2O	0.69
Calcium	15.70	17.53	8.77	CaO	17.53
Titanium	0.17	0.19	0.08	TiO2	0.19
Iron	1.71	1.90	0.68	FeO	1.90
Copper	2.66	2.97	0.94		2.97
	89.55	100.00	100.00		

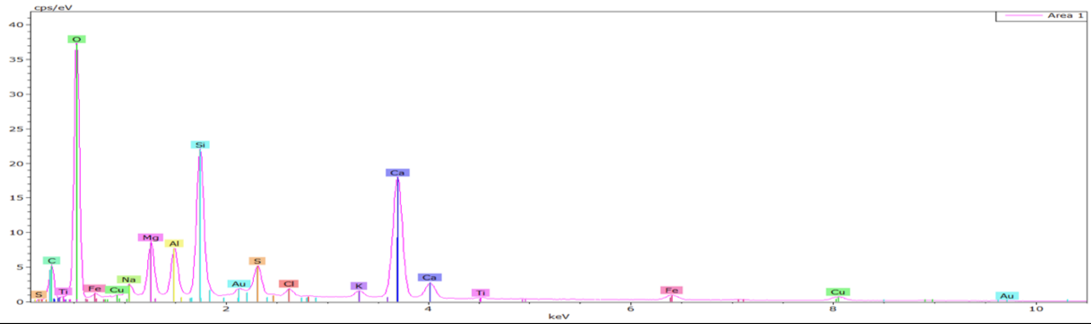


Figure 5.6. EDS analysis1 of sample air filter

Overall Chemical analysis of filter dust detected list of elements in the above table. Elements indicate a broad range of elements suggesting complicated compounds/ species which is further investigated by elemental mapping, X-ray Diffraction (XRD) and thermal analysis (TGA/MS).

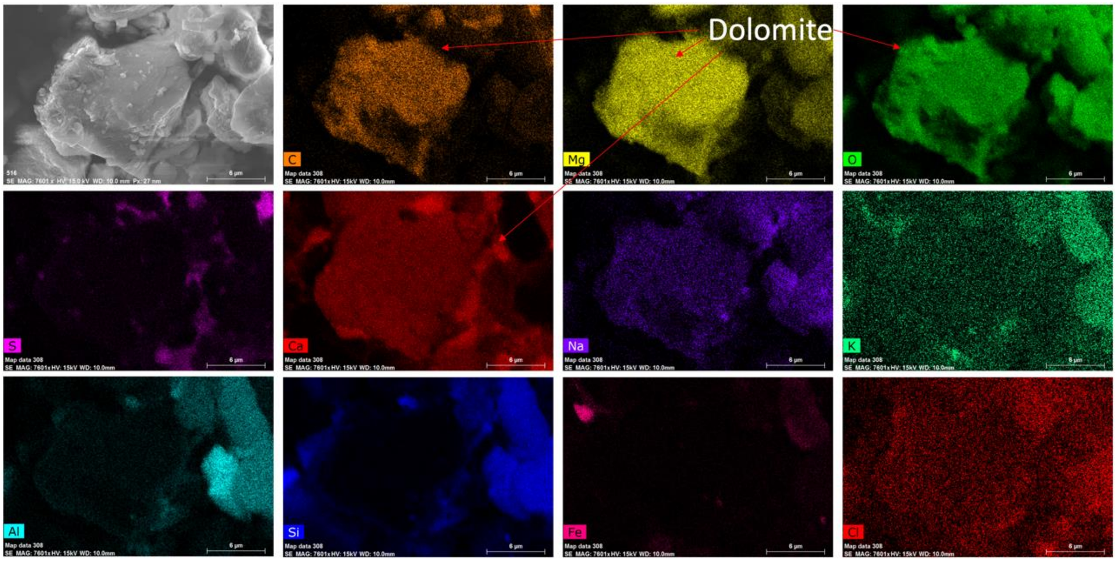
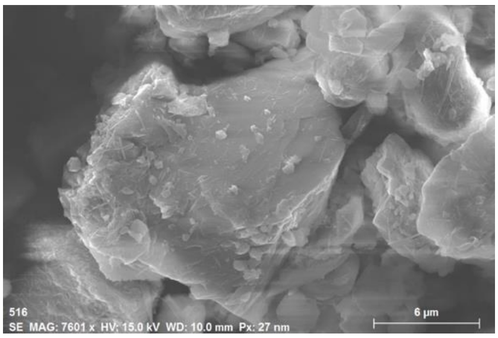


Figure 5.7. Sample EDS mapping (area1)

Different compounds based on elemental distribution were identified as mentioned below (Dolomite, Albite, Feldspar, Gypsum, Salt and Iron).



Element	[wt.%]	N. wt.%]	N. at.%]	Compound	N. wt.%]
Carbon	8.85	9.68	15.54	CO2	35.45
Oxygen	46.17	50.50	60.88		0.00
Sodium	0.64	0.70	0.59	Na2O	0.94
Magnesium	6.91	7.56	6.00	MgO	12.54
Aluminium	2.55	2.79	2.00	Al2O3	5.27
Silicon	6.45	7.05	4.84	SiO2	15.09
Sulfur	1.03	1.13	0.68	SO3	2.81
Chlorine	0.31	0.33	0.18		0.33
Potassium	0.45	0.49	0.24	K2O	0.59
Calcium	15.32	16.76	8.06	CaO	23.45
Iron	1.63	1.78	0.62	FeO	2.29
Copper	1.12	1.23	0.37		1.23
	91.41	100.00	100.00		

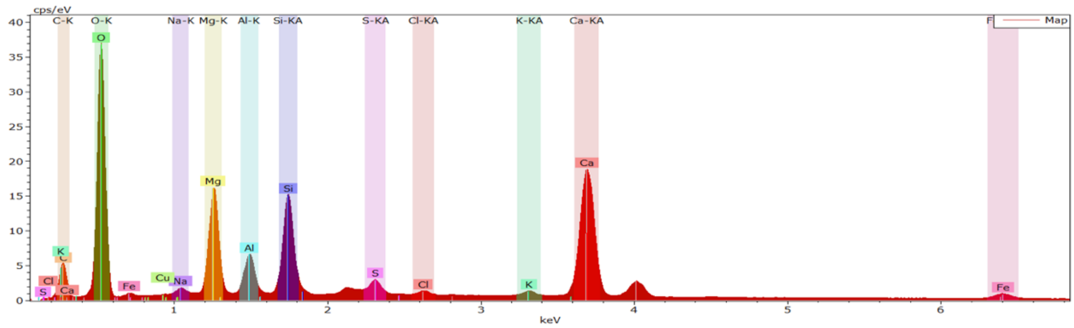


Figure 5.8 Quantification of mapping area1

Chemical analysis of a few dust particles suggested that large particle are Dolomite (Ca,Mg) CO_3. Detected elements indicate a broad range of elements suggesting complicated compounds/ species which will be further investigated by elemental mapping, X-ray Diffraction (XRD) and thermal analysis (TGA/MS).

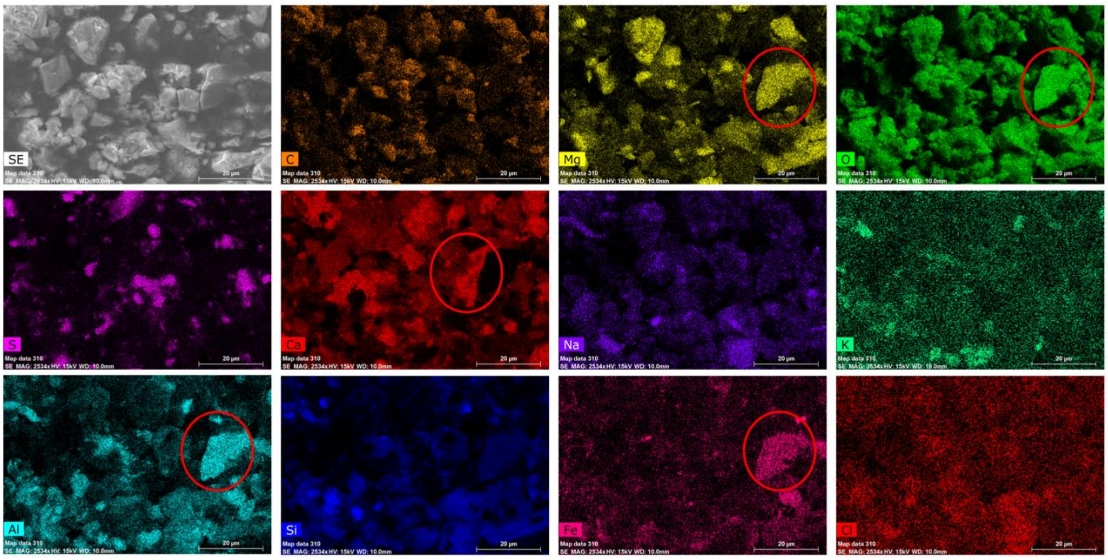


Figure 5.9. Sample ESD mapping (area 1)

Note: Red circles showing (Mg, Al, Fe)$_x$SiO4 (Alkali material).

SEM Analysis (area1, sample 2)

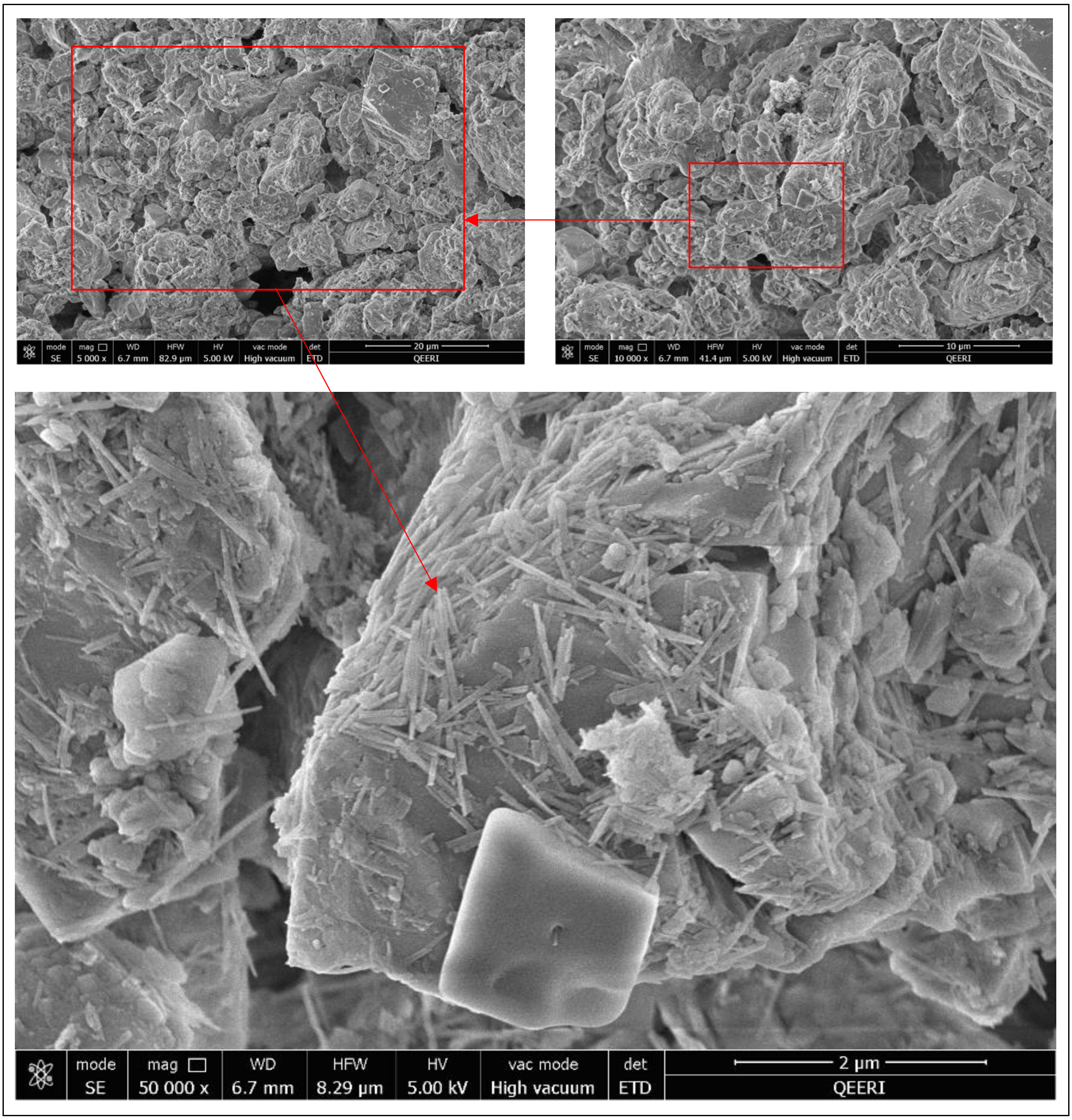


Figure 5.10. SEM analysis of sample 2 (area1)

SEM images clearly shows needle-like Palygorskite mineral and other mineral phases.

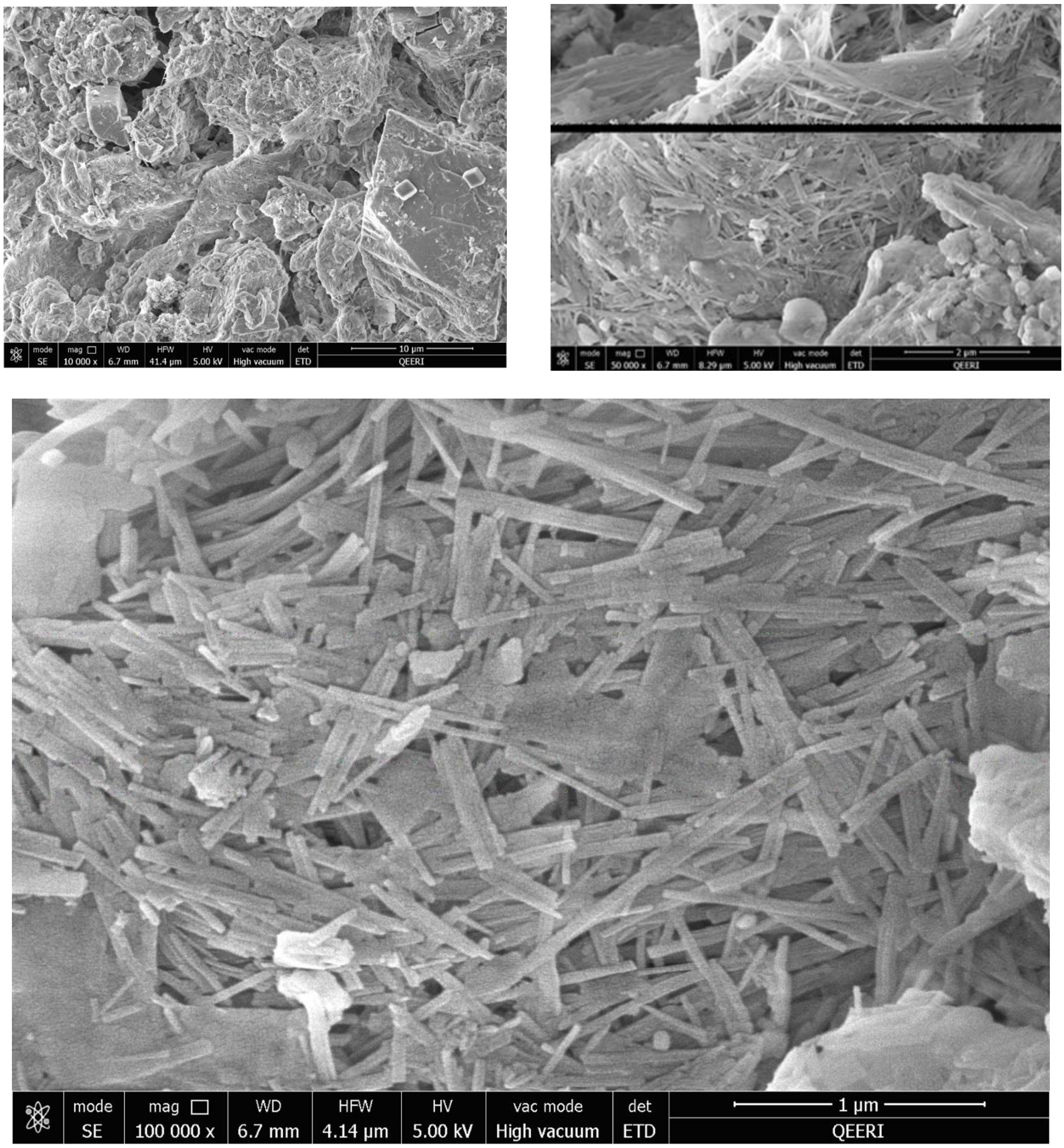


Figure 5.11. SEM analysis of sample 2 (area2)

Area3

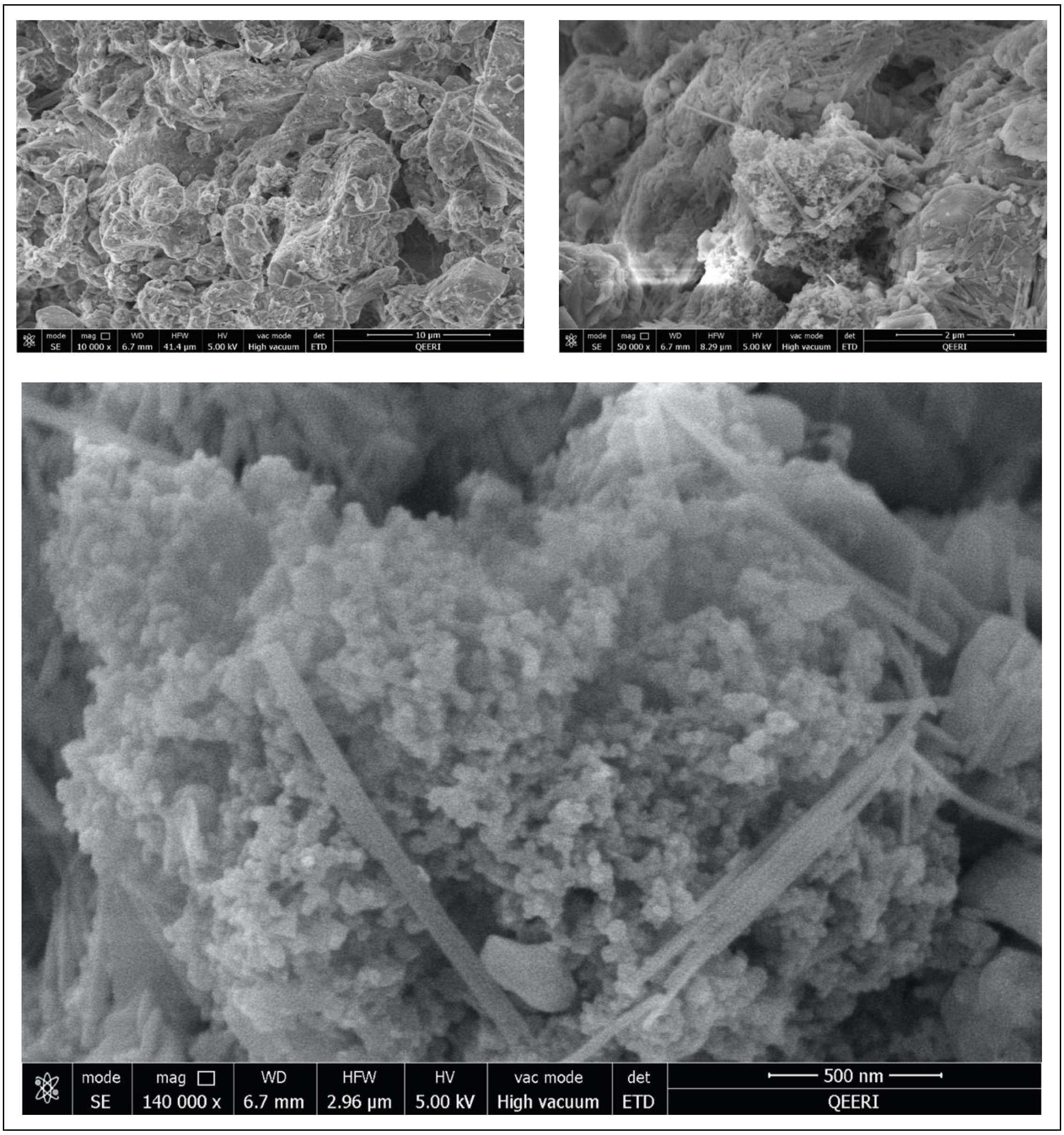
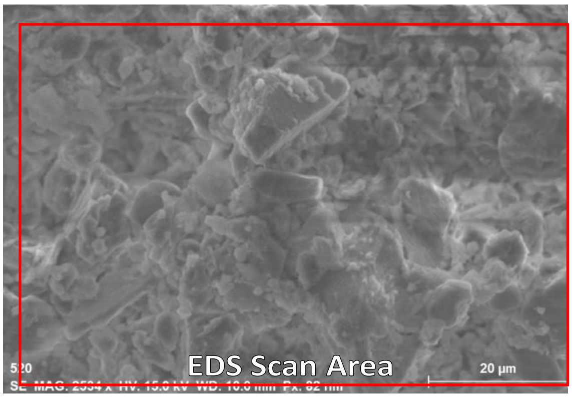


Figure 5.12. SEM analysis of sample 2 (area3)

SEM image above shows traces of organic/ biological materials that are present in the sample.

EDS analysis; Sample2



Element	[wt.%]	N. wt.%]	N. at.%]	Compound	N. wt.%
Carbon	7.19	7.63	12.82	CO2	27.9
Oxygen	45.50	48.30	60.95		0.0
Sodium	0.93	0.99	0.87	Na2O	1.3
Magnesium	3.93	4.17	3.47	MgO	6.9
Aluminium	3.10	3.29	2.46	Al2O3	6.2
Silicon	9.16	9.73	6.99	SiO2	20.8
Sulfur	2.07	2.20	1.38	SO3	5.4
Chlorine	0.48	0.51	0.29		0.5
Potassium	0.55	0.58	0.30	K2O	0.7
Calcium	16.15	17.15	8.64	CaO	23.9
Iron	2.03	2.16	0.78	FeO	2.7
Copper	3.11	3.30	1.05		3.3
	94.20	100.00	100.00		

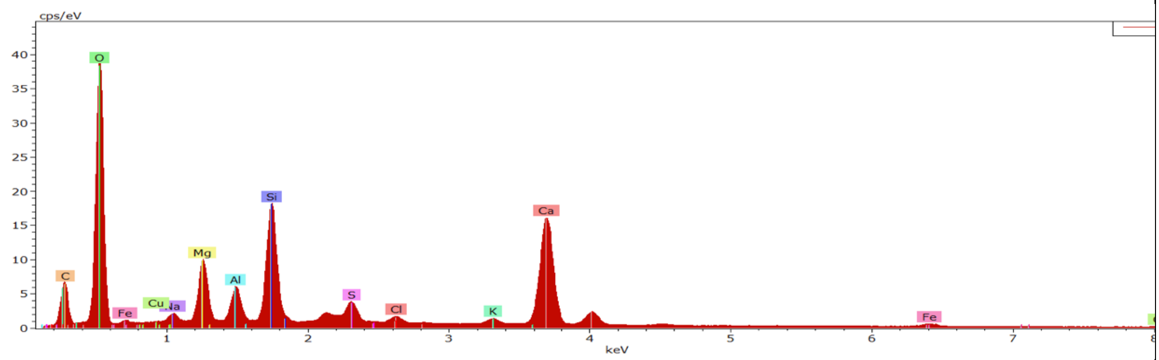


Figure 5.13. Sample 2 EDS analysis

Overall Chemical analysis of filter dust detected list of elements in above table. Elements indicate a broad range of elements suggesting complicated compounds/ species which will be further investigated by elemental mapping, X-ray Diffraction (XRD) and thermal analysis (TGA/MS)

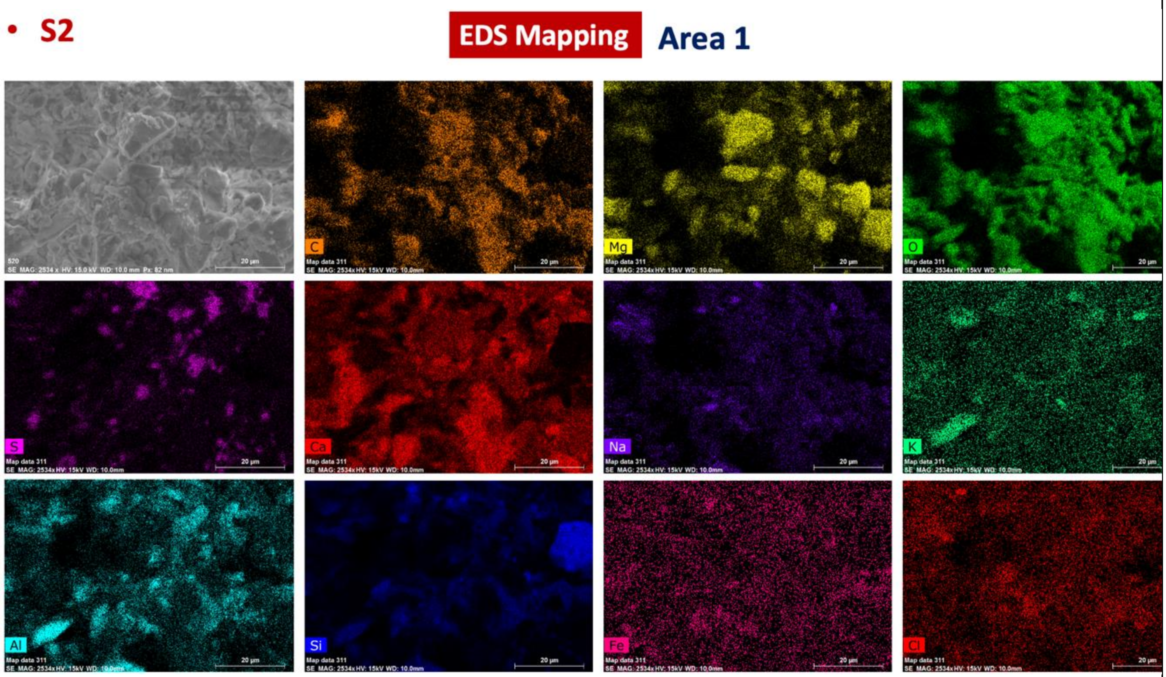


Figure 5.14. Sample 2 ESD mapping (area1)

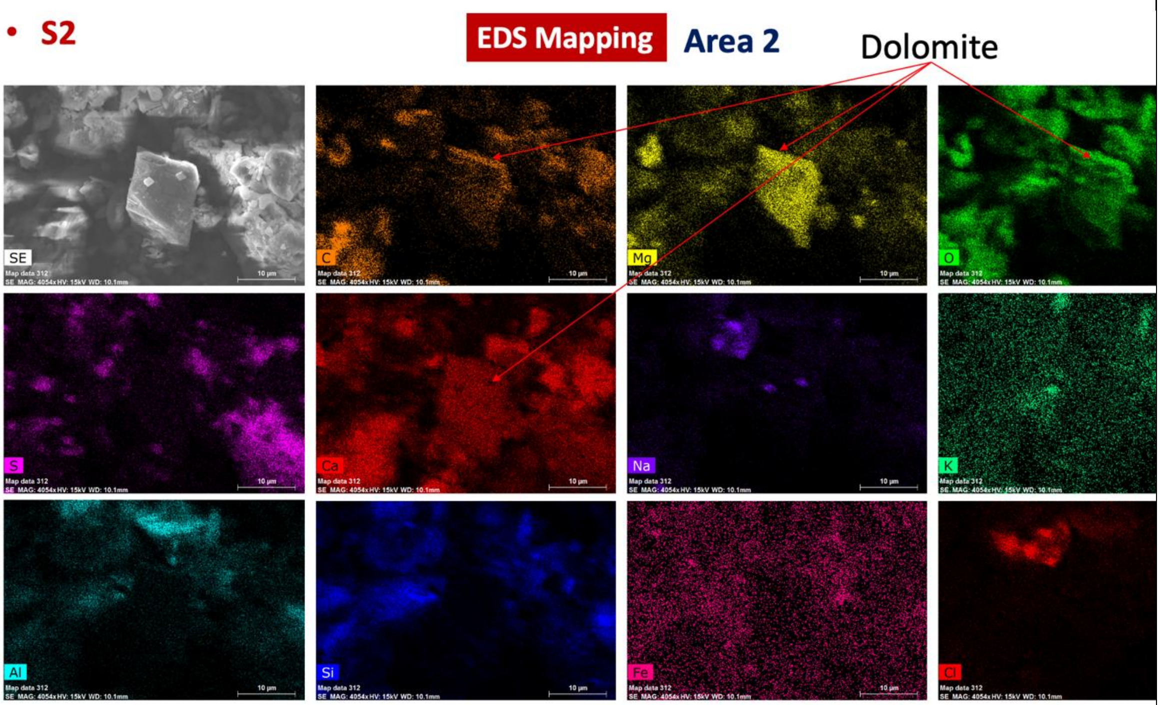
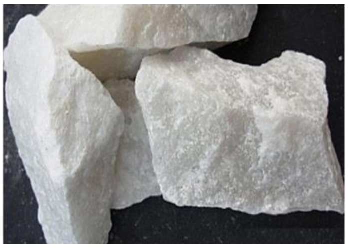


Figure 5.15. Sample 2 ESD mapping (area2)

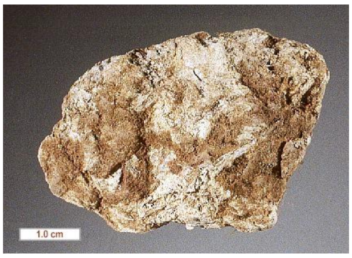
Form the conducted analysis, it is observed that the dust from the sample air filter is mainly composed of Dolomite, Palygorskite, Halloysite.

Dolomite:



is a type of limestone with carbonate fraction dominated by the mineral dolomite, calcium magnesium carbonate [$CaMg(CO_3)_2$]. It is also known as "dolostone" and "dolomite rock,". Dolomite is found in sedimentary basins worldwide.

Palygorskite:

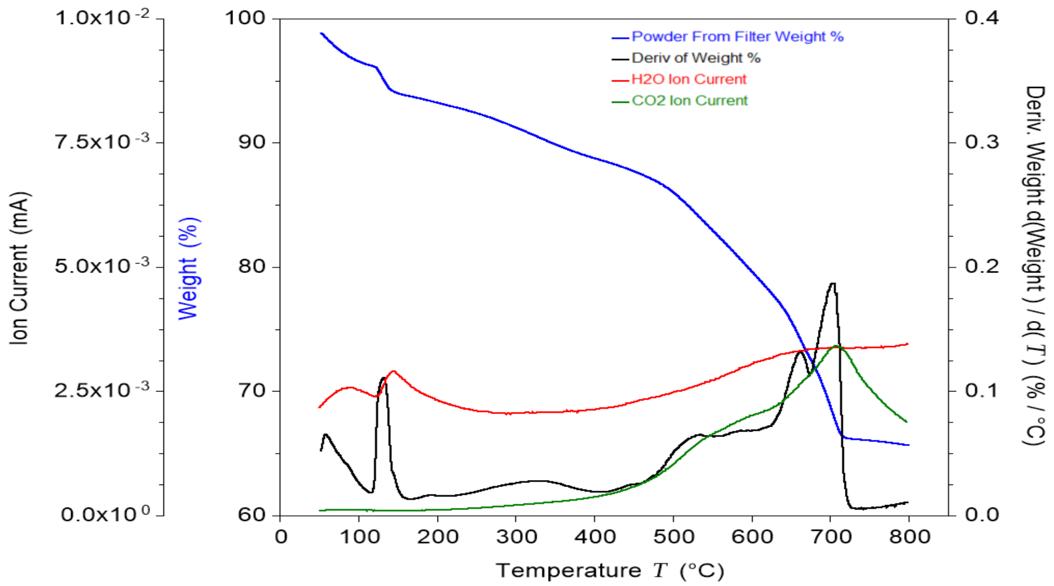


is a fibrous magnesium aluminum silicate $(Mg,Al)_2Si_4O_{10}(OH)_4H_2O$. The structure of which contains extended silicon-oxygen sheets. The mineral occurs in sediments from playa lakes and saline deposits, in desert soils, and in calcareous material.

Halloysite:

$Al_2(Si_2O_5)(OH)_4$ is an aluminosilicate clay mineral which mainly constituents oxygen (55.78%), silicon (21.76%), aluminum (20.90%), and hydrogen (1.56%). Halloysite typically forms by hydrothermal alteration of alumino-silicate minerals.

Thermal gravimetric Analysis (TGA/MS) of Dust



TGA shows weight loss of dust at temperature risen to 900 $^{\circ}$C. It shows weight loss due to water loss at about 120-150 $^{\circ}$C and continuous loss after indicative of presence of other compound including organic/ biological material at around 300°C and finally dolomite and alkaline materials decomposition in the 500- 750°C range

XRD analysis

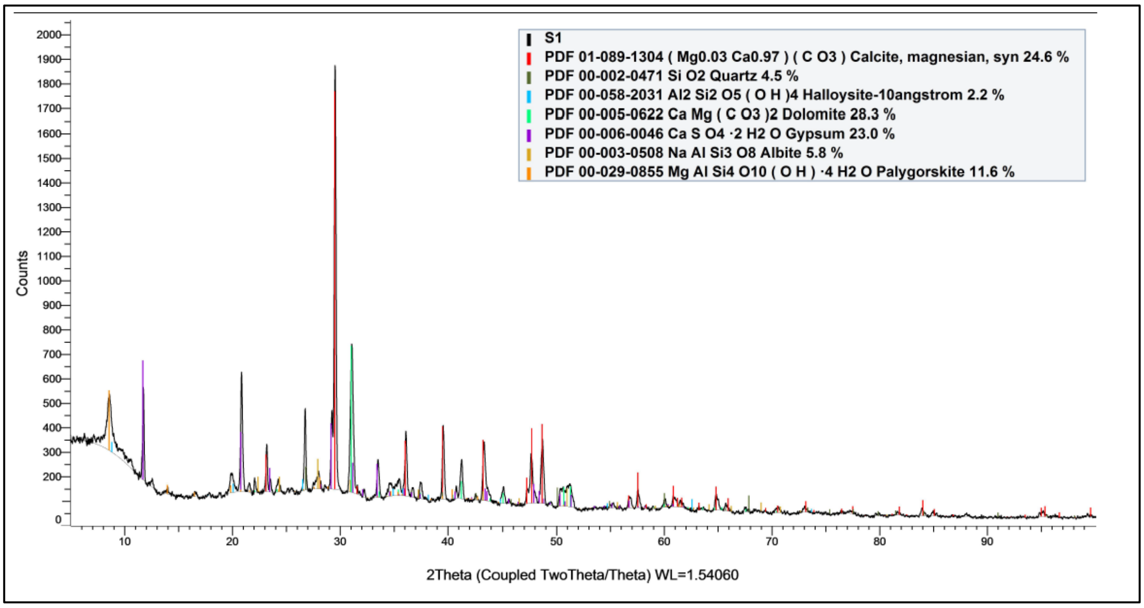
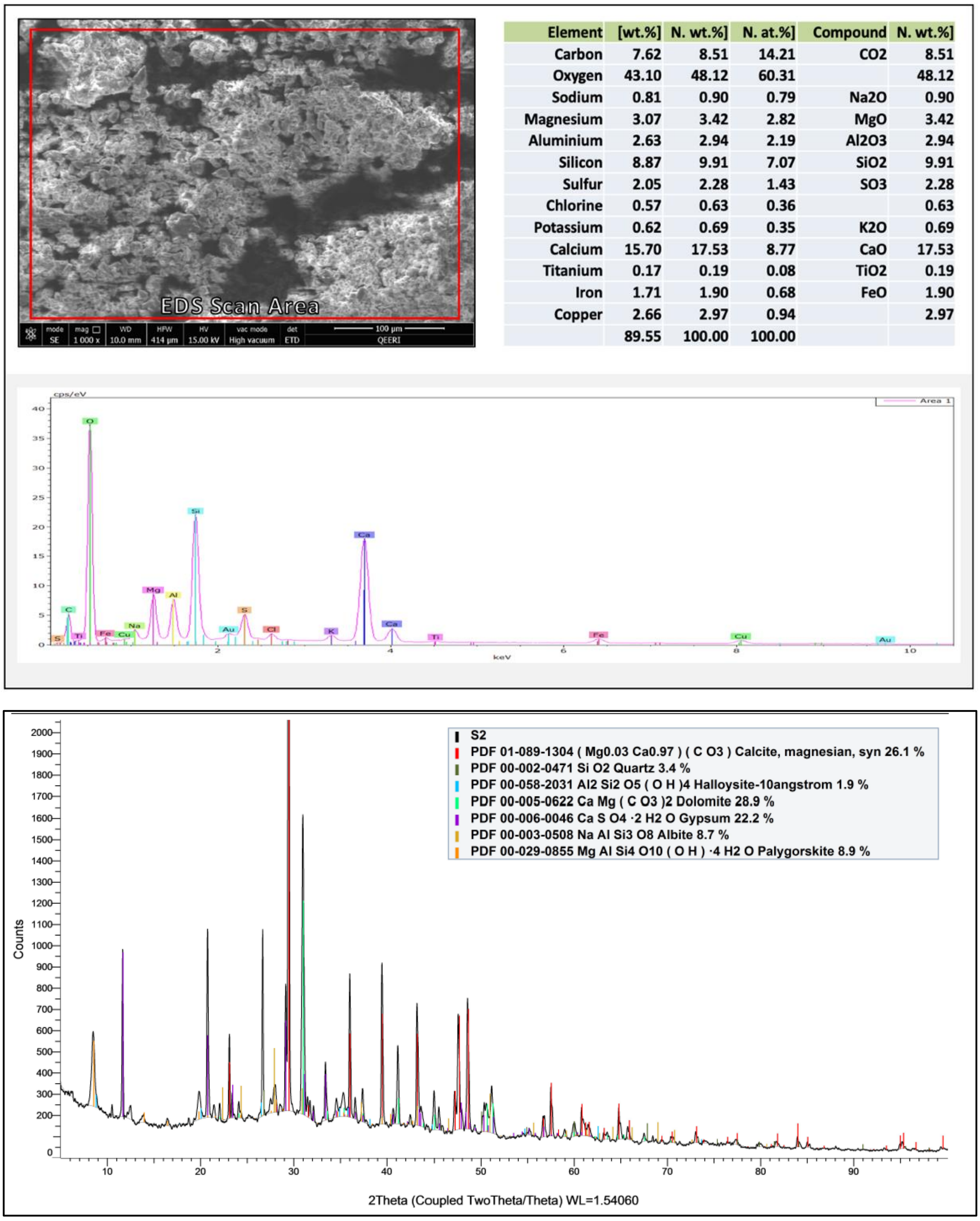


Figure 5.16. XRD analysis of sample filter (sample1)



Element	[wt.%]	N. wt.%]	N. at.%]	Compound	N. wt.%]
Carbon	7.62	8.51	14.21	CO2	8.51
Oxygen	43.10	48.12	60.31		48.12
Sodium	0.81	0.90	0.79	Na2O	0.90
Magnesium	3.07	3.42	2.82	MgO	3.42
Aluminium	2.63	2.94	2.19	Al2O3	2.94
Silicon	8.87	9.91	7.07	SiO2	9.91
Sulfur	2.05	2.28	1.43	SO3	2.28
Chlorine	0.57	0.63	0.36		0.63
Potassium	0.62	0.69	0.35	K2O	0.69
Calcium	15.70	17.53	8.77	CaO	17.53
Titanium	0.17	0.19	0.08	TiO2	0.19
Iron	1.71	1.90	0.68	FeO	1.90
Copper	2.66	2.97	0.94		2.97
	89.55	100.00	100.00		

Figure 5.17. XRD analysis of sample filter (sample2)

Phase	**S1 (%)**	**S2 (%)**
Mg0.03 Ca0.97 C O3: Calcite, magnesium oxide	24.6	26.1
Si O2: Quartz	4.5	3.4
Al2 Si2 O5 (OH)4: Halloysite	2.2	1.9
Ca Mg (C O3): Dolomite	28.3	28.9
Ca S O4 . 2 H2O: Gypsum	23.0	22.2
Na Al Si3 O8: Albite	5.8	8.7
Mg Al Si4 O10 (OH). 4H2O: Palygorskite	11.6	8.9

Table 5.1.XRD analysis quantification results of 2 samples

Observations:

The above compounds in Table 5.1 were detected by XRD showing main mineral is Ca,Mg CO3 compounds in addition to Gypsum and other earth minerals such as Palygorskite, Halloysite and Albite were all detected by elemental dot mapping. Moreover, organic/ biological materials were found. However, the nature of such organic material is not known. The detected needle shaped crystals, submicron size Palygorskite, could be harmful to respiratory system if inhaled. The excessive amounts of earth minerals did not seem to be naturally occurring from the desert environment, which lead to further investigations that resulted in the discovery of a nearby concrete batching and asphalt plant. The plant is 5 km to the north of the residential area as shown in Figure 5.18 below (*a location also compatible owing to the prevailing wind*).

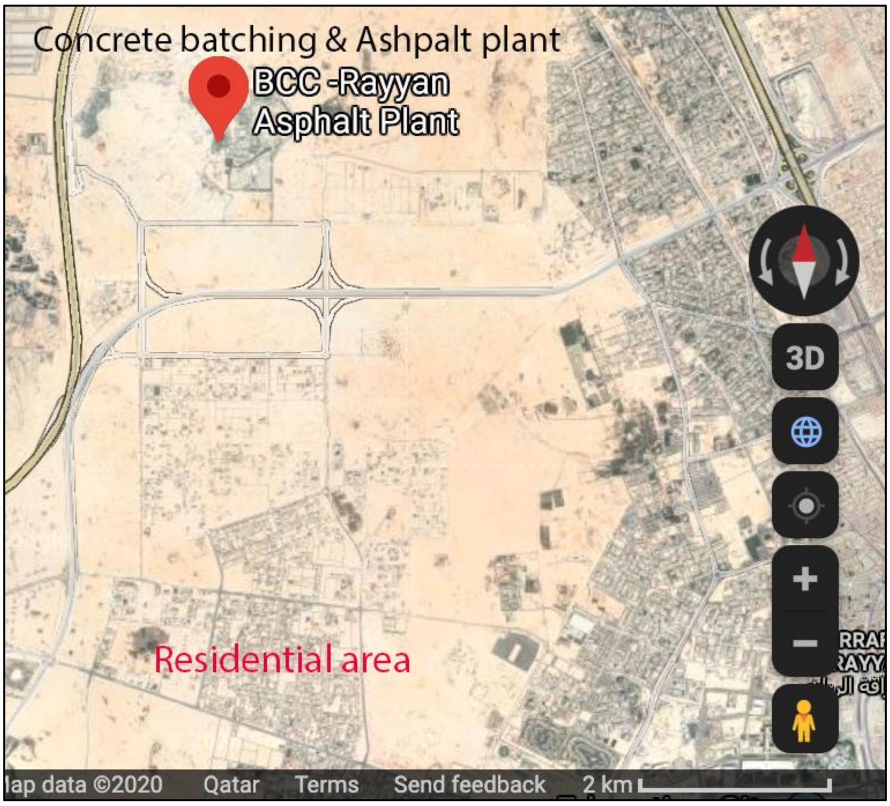


Figure 5.18. Identified source of dust close to the area of sample residential villa

5.4. Air filtration

Air filters are typically utilized to minimize exposure to dust and address multiple harmful dust-related effects on human health, environment, and equipment.

Air filters refer to devices used to detect and remove foreign particles such as powder, dust, mould, pollen, fibre germs, Volatile Organic Compounds (VOCs), and bacteria that are harmful to human health when inhaled. These devices use both chemical and physical processes to purify the air.

Air filtration technologies try to tackle an existing dilemma even with higher anxiety to innovate new sustainable techniques and filter materials to remove impurities from the air. Even though many air filtration technologies can eliminate air pollutants and eventually increase IAQ in buildings, it is often overshadowed that these air filters increase energy consumption[82].

Air filter's efficiency, energy consumption, life span, and life-cycle cost are issues that should be considered while developing or selecting air filters. Thus, the selection of an optimal and sustainable technology with maximum efficiency and highest added value remains an important topic. This section looks at the role and implications of choosing various types of filters for HVAC applications and the best ways to secure optimal results.

5.4.1. Types of Air Filters

There are many types and shapes of air filters that are commercially available on the market. Depending on the intended use, they also vary in terms of the used technology and the price tag. The most common air filter types include Fiberglass, Polyester and pleated filters, High-Efficiency Particulate Air (HEPA), and Washable air filters.

Fibrous filters are the common type of filter recognized globally, but they are divided into three sub-classes with different efficiencies pre-filters, medium-filters, and "high-efficiency particulate air" (HEPA). HEPA filters are widely known for the high efficiency that reach up to 99.9% in removing 0.3 μm and above particles with minimal airflow resistance of 300 pascals[83]. Thus, for best filtration efficiency and performance HEPA filters are usually the preference.

5.4.2. Particle Capture Mechanisms

The successful filter design and selection highly relies on understanding the ability of filter media to collect particles from a gas stream passing through it. The particle capturing process occurs within the depth of a porous media as the gas follows a tortuous flow path created by the series of interconnected void spaces formed by the microfibers' structure. When the gas stream flows around the microstructure, or through a porous opening, particles deposit onto the structure primarily by several capture mechanisms as shown in Figure 5.19 below for diffusion, interception, inertial impaction and electrostatic deposition. Other mechanisms such as sieving and gravitational sedimentation are of less importance. The effectiveness of particle capturing of each mechanism is primarily dependent on the particle size, gas velocity and size of the filter structure.

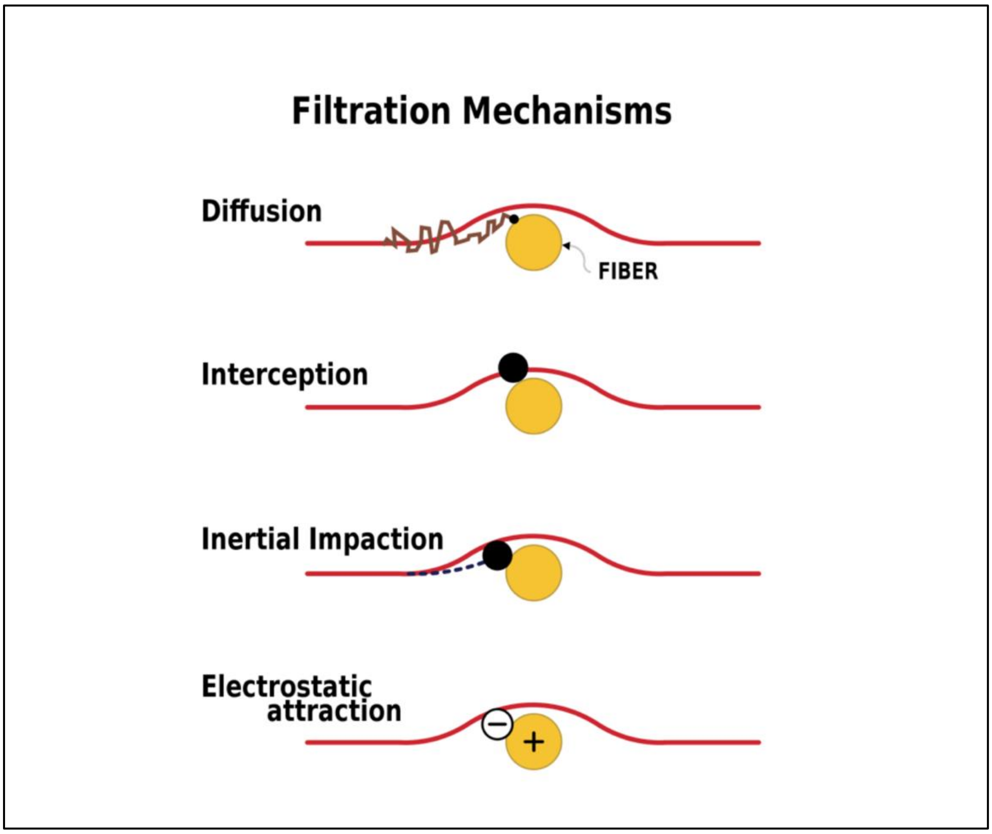


Figure 5.19. Particle deposition mechanisms on filter media

5.4.2.1. Diffusion

The deposition of particles through diffusion occurs when particles collide with the filter structure due to their random Brownian motion. This random motion occurs when small particles collide with gas molecules, thereby altering the particle trajectory around the filter structure. This motion, and hence the degree of particle capture, becomes more pronounced as the particle diameter becomes smaller, especially for particles less than 0.1 µm.

5.4.2.2. Interception

Deposition of a particle via the interception mechanism occurs if a particle of finite size is brought within one particle radius of the filter structure as it follows the flow streamlines around the filter structure. Collection via this mechanism increases with increasing particle size. Interception becomes the dominant capture mechanism for particles in the 0.1 to 1 µm and larger size range.

5.4.2.3. Inertial Impaction

Due to the mechanism of inertial impaction, larger particles collide with the filter structure, as the particles are unable to follow the curve path of the gas streamline around the filter structure. Particles deviate from their initial fluid streamline, due to their inertia (finite mass), as the gas curves to flow around the filter structure. This mechanism becomes an increasingly significant means of particle collection for larger particles (particle mass), and higher gas velocities. This mechanism becomes important for particles larger than 0.3 to 1.0 µm, depending on the gas velocity and filter structure size.

5.4.2.4. Electrostatic effects

If electrical charges on either the particle or the filter, or both are present then particles can deposit via electrostatic deposition where attractive electrostatic forces of sufficient magnitude are created to attract the particle to the filter surface.

5.4.2.5. Gravitational Sedimentation

For large particles (i.e., larger than 10 µm), at relatively low velocities, can be captured via gravitational sedimentation if sedimentation causes the particle to deviate from its original path and come into contact with the filter structure.

5.4.2.6. Sieving

Due to their larger size, particles maybe unable to pass through openings in the filter structure, and hence captured via the mechanism of sieving. While this mechanism is operable in gas filtration, particles capable of being captured via sieving usually are captured via interception or inertial impaction before they can be captured via sieving.

5.4.3. Overall particle collection performance

In practice, the capturing performance of a filter is a combined action of all particle capture mechanisms, resulting in an overall particle collection which can be represented by a curve as shown in Figure 5.20 below. The graph demonstrates the degree of particle capture through each mechanism according to the diameter of the particles. All filter materials exhibit the same basic total curve, as illustrated by the curve. However, the effectiveness of each mechanism and the resulting overall degree of particle capture can vary widely depending on the design of the filter, media characteristics, filter operation conditions, and particle size.

Diffusion and interception are the dominant particle collection mechanisms when particles in the vicinity of the Most Penetrating Particle Size (MPPS). The combination of these two mechanisms leads to an overall filter efficiency curve that first decreases with increasing particle size, and then increases with further increases in the particle size. The maximum penetration point, which is also the point of minimum particle capture efficiency, is a critical point where the corresponding particle size is referred to as the MPPS. Larger particles are still captured through the mechanisms of interception and inertial impaction. By understanding the efficiency in the vicinity of the MPPS, it can be known that the efficiency will be even higher for any other particle size.

It should be noted that filter efficiency (particle penetration) curves for all filter materials show the same basic shape as shown in the figure below, with the level of particle capture and the location of the MPPS are dependent on the filter media and its operating conditions. In general, the location of the MPPS is typically in the range of 0.1 to 0.3 µm; thus, leading to the use of the traditional 0.3 µm DOP *(Di-Octyl Phthalate)* test for filter efficiency.

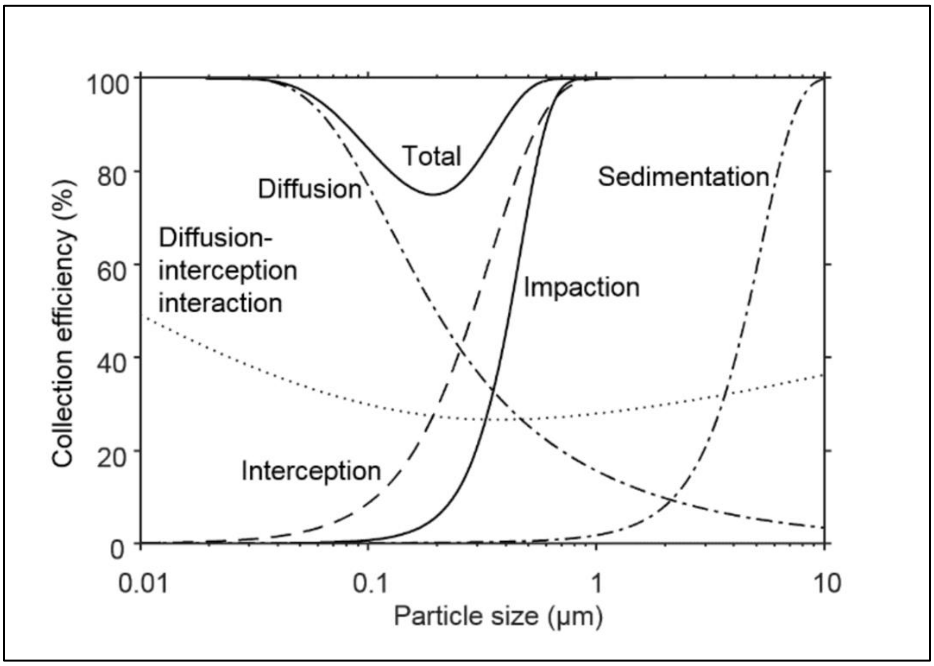


Figure 5.20. Combined effect of total particle capture mechanisms on filter efficiency[84]

5.4.4. Modeling of HEPA filter

5.4.4.1. Single fiber efficiency

The single fiber efficiency and the overall penetration of the filter are related to the following equation:

$$P = \exp\left(-\frac{4\alpha t\eta}{\pi(1-\alpha)df}\right) \tag{5.1}$$

Where:

P = filter penetration , α = medium packing density , η = single fiber efficiency t = thickness of the filter df = fiber diameter

In terms of penetration ratio as a function of concentration of particles downstream and upstream of filter, overall penetration of the filter can be given as:

$$P = \frac{[downstream]}{[upstream]} \tag{5.2}$$

Decontamination factor (D_f) is the inverse of penetration ratio:

$$D_f = \frac{1}{P} \tag{5.3}$$

The penetration as a function of the aerosol particle size is a relation that could be plotted in a graph.

5.4.4.2. Modeling of the single fiber efficiency

The total single-fiber efficiency $\boldsymbol{\eta}$ has contributions from different collection mechanisms and can be written according to Ramarao et al (1994) [85]as:

$$\eta \approx \eta_D + \eta_R + \eta_I \tag{5.4}$$

Where: η_D, η_R, η_I, represent the collection efficiency due to diffusion, interception, inertial impaction respectively.

In another way,

$$(1-\eta)=(1-\eta_D)(1-\eta_R)(1-\eta_I) \tag{5.5}$$

The total efficiency η is approximately equal to η_D when dp < 100 nm; dp is the particle diameter. The expression for η_D according to the model [86]:

$$\eta_D = 2\mathrm{Pe}^{\frac{-2}{3}} \tag{5.6}$$

where: P_e is the Peclet number which provides an indication of the relative importance of diffusion and convection. Pe is defined as:

$$\mathrm{Pe}=\frac{dfU_o}{D}=dfU_o.(\frac{3\pi n}{kTC_c})dp \tag{5.7}$$

D=diffusion coefficient, μ= viscosity of air, k= Boltzmann constant, T= temperature, C_c= slip correction factor, and U_0 = filtration velocity.

$$D=\frac{kTC_c}{3\pi\mu dp} \tag{5.8}$$

$$C_c=1+\mathrm{Kn}\left[A+B\times e^{\left(-\frac{C}{\mathrm{Kn}}\right)}\right] \tag{5.9}$$

$$\mathrm{A}=1.165, \mathrm{B}=0.483, \mathrm{C}=0.997 \quad \text{and kn(Knudsen number)} = \frac{2\lambda}{dp}$$

$$\lambda = \text{mean free path} = 6.4\times10^{-8}$$

Diffusion (η_D)

Theoretical model developed by Lee and Liu[87] adapted these experimental results as follows:

$$\eta_D=1.6\left(\frac{1-\alpha}{Hku}\right)^{\frac{1}{3}}\mathrm{Pe}^{\frac{-2}{3}} \tag{5.10}$$

where, α = medium packing density.

Interception (η_R)

The model for cylindrical assembly and continuous regime in [87], suggests the expression for collection efficiency as:

$$\eta_R = 0.6(\frac{1-\alpha}{Hku}).(\frac{R^2}{1+R}) \quad (5.11)$$

where:

$Hku = \alpha - 0.5\ln\alpha - 0.25\alpha^2 - 0.75$

$R = characteristic.Number \rightarrow R = \frac{dp}{df}$

α = medium packing density

dp = particle diameter

df = fiber diameter

$0.05 < dp < 1.3\ \mu m$

$0.0045 < R < 0.12$

$0.008 < \alpha < 0.151$

Impaction (η_I)

As per Gougeon et al.[88], the collection efficiency of impaction can be expressed as follows:

$$\eta_I = 0.0334(St)^{\frac{3}{2}} \quad (5.12)$$

where,

$$St = \text{Stokes number} = \frac{Uf.dp.2\rho_p}{18\mu df} \quad (5.13)$$

where:

uf = superficia l velocity

dp = particle diameter

ρ_p = particle density

μ = fluid dynamic viscosity

df = fibre diameter

The clean filter overall removal efficiency E is closely related to the single fiber removal efficiency η through the following relation[89-91]:

$$E = 1 - \exp(-\frac{4\alpha t\eta}{\pi(1-\alpha)df}) \quad (5.14)$$

5.4.5. Mathematical Modeling of Clean Filter

5.4.5.1. Theoretical considerations

Due to the fact that the real filter structure is relatively irregular and non-uniform, it requires the use of filter model which is amenable to mathematical analysis to obtain the solution of the flow field.

The following assumptions are needed to get the solution for a filter model:

1. A particle which collides with the fiber remains in contact and is not separated following its initial collection by the fiber.
2. The presence of particles in the gas stream and on the fibers does not change the flow pattern around the fibers.
3. The particles on the fibers are electrically charged (electrostatic) and gravitational effect is so small that the mechanism of gravity and electrical attraction can be neglected.

The HEPA filter model is built via conventional spreadsheets using the following data, parameters and assumptions:

Particle size:	from 0.05 – 5 micrometer (μm)
Glass fiber's geometric median diameter:	0.6 micrometer (μm)
Glass fiber's numerical mean diameter:	0.9 micrometer (μm)
Thickness of medium:	521 ± 31 micrometer (μm)
Weight:	92 ± 2 ($g.m^{-2}$)
Packing density:	0.071 ± 0.006
Particle density:	1500 kg/m^3
Temperature:	298 K
Air flow rate:	3400 m^3/h
Filtering Area:	36 m^2
Dynamic viscosity of air:	1.85×10^{-05} (kg/m.s)
Particle mean free path:	6.4×10^{-08}

Other assumptions:

Uniform fiber diameter size.
Screening and electrostatic forces are not considered.
Change in pressure drop is not considered.

5.4.5.2. Modeling Results

By carrying out the model simulation, all calculations for the predetermined particles size range were performed. The obtained resulted was to a great extent adequate and in line with the expected behavior. The following graphs show the resulting filtering efficiency as a function of particle size by using original parameters.

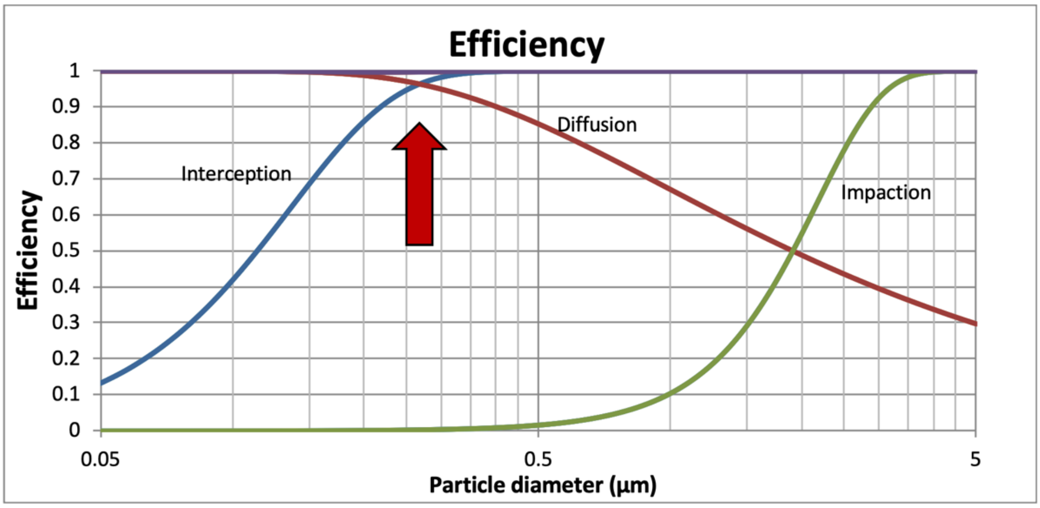


Figure 5.21. Model result for filter efficiency vs particle diameter

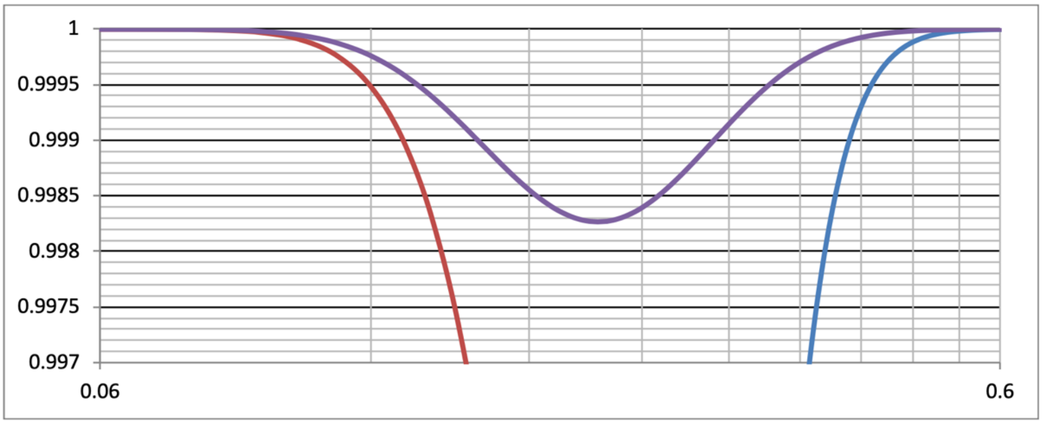


Figure 5.22. Filter efficiency vs particle diameter (zoomed in)

The above graph shows the efficiency of each of the three particle collection mechanisms Interception (η_R), Diffusion (η_d), Impaction (η_I), in addition to the overall collective global efficiency (η_G). It is evident from the above graphs that the result is in accordance with the expected filtration performance result, which validates HEPA filter model.

5.4.6. Role and Implication of choosing different air filter ratings

5.4.6.1. Ratings and standards of Air Filters

When it comes to performance ratings, air filters are generally categorized and rated in terms of efficiency based on different standards. The commonly known standards are the American ASHRAE52.2 standard, the European (*Eurovent and CEN EN*) like EN779 (*including G, M & F ratings*) and EN1822 (*for EPA, HEPA & ULPA*). ASHRAE introduced MERV (*Minimum Efficiency Reporting Value*) rating system which is on an ascending efficiency scale from 1 to 20. The European CEN scale is divided into G class and F class with HEPA and ULPA (*Ultra Low Penetration Air*) in separate classification. The rating scale goes generally from the lowest level of particle filtration performance (*MERV1 in ASHRAE or G1 in EN779*) to the ultra-high efficiency filters such as those rated for clean super rooms (*like U17 EN1822*).

The MERV ratings are given to air filters based on their efficiency in capturing particles at different air flow rates within the size ranges of: 0.3–1, 1–3, and 3–10 microns. Generally, the range of MERVs is from 1 to 16, but high-efficiency-particulate-air (HEPA) filters, which have MERVs of 17 to 20, are tested using different standards. With MERV rating system, the higher the MERV, the higher filtration efficiency become. However, the increase in filter efficiency usually comes at the expense of ideal system air flow. Air filters with MERV value of 6–8 are within the average acceptable range for reasonable HVAC operations and IAQ. MERV 6 is the recommended rating as per ASHRAE Standard for ventilation and IAQ[92].

5.4.6.2. The implications of selecting different filter ratings

Air filters selection for HVAC application is a critical step in the system design process and important factor throughout the system operation. Air filtration industry is very mature with many competitive products and technologies to choose from. Manufactures are continuously enhancing their filtration products in a way that also considers sustainability and environmental impact.

With the existing wide range of filtration technologies, styles and efficiencies HVAC systems contractors and owners should be able to select suitable air filters that can help in maintaining IAQ, reduce energy consumption and maximize the HVAC system lifespan. However, and especially when operating in a desert environment conditions, the optimal filter selection becomes a daunting task. This is mainly due to the complexities surrounding HVAC systems, and air filters and the way external environment affects their performance. For example, selecting extra high performance filters can dramatically reduce HVAC airflow which consequently reduce cooling quality and increase energy consumption. The dusty desert environment adds another layer of complexity to the selection process.

Dust accumulation across air filters and evaporator unit stifles airflow and forces HVAC system to compensate by increasing its output. This in turn results in greater energy consumption, which leads to higher energy bills. Reduced efficiency may also affect indoor air quality, as the HVAC system is no longer able to catch contaminants such as unpleasant smells, smoke particles and spores that can trigger allergies, as well as cause mold and mildew growth.

So far, the filtration process has remained the mere process of removing a fraction of pollutants filtered at any given time. Simultaneously, the operation of air filters has remained part of the causes contributing to high energy consumption. Most studies still concentrate on the development of conventional filters. Only a handful of studies lean towards developing long-term steady filters, which leads to a reduction of operation cost and crucial for lifetime service[82]. Thus, there is a need for a sustainable and practical system’s approach to selecting suitable air filters for the challenging and highly demanding desert climate based on performance and long-term cost.

5.4.6.3. Cost of ownership and Life Cycle Cost

Life Cycle Cost (LCC) is the overall compilation of an asset's ownership cost that will potentially be incurred over a specific timeframe. Such costs normally include the initial investment/purchase, installation, operations, maintenance, and disposal costs. In this method, the compiled ownership costs are discounted to present values, which can help identify (and compare) expected return on investment. The resulting outcome of this exercise is highly essential in the investment decision-making process.

LCC is particularly important and highly applicable for HVAC air filters due to the broad spectrum of available filtration products, specifications, and the complexity of selecting appropriate air filters. For example, an air filter's initial purchase cost merely represents a small fraction of the total LCC. Below is a breakdown of the typical HVAC filter LCC.

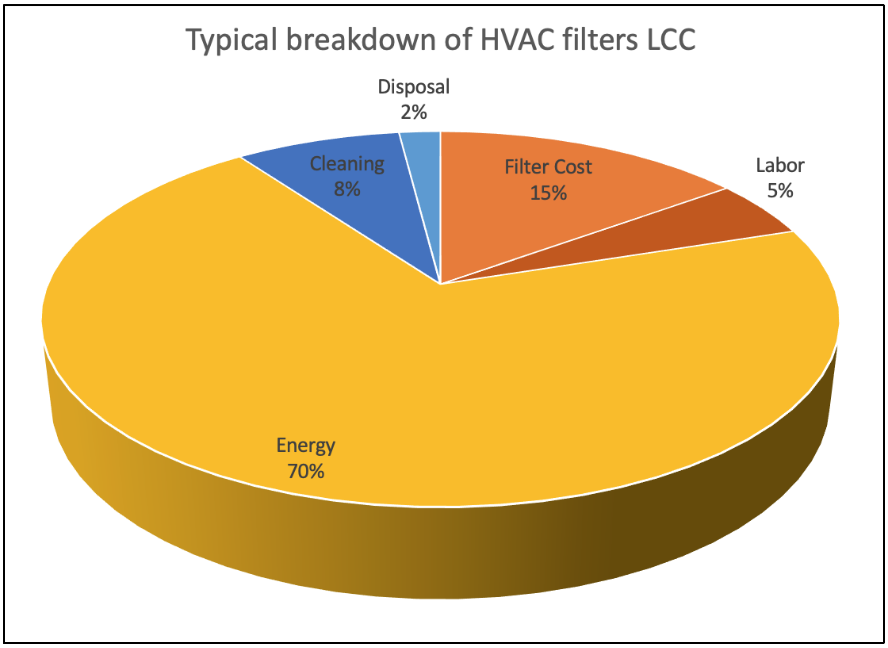


Figure 5.23. LCC components of filter's ownership cost[93]

The LCC is an adequate tool to be used for evaluating and guiding the selection of air filters since it factors in key elements governing, overall cost, filter design and its performance like pressure drop and energy consumption, etc.

LCC can be calculated by the adding up all individual lifecycle cost elements namely: Initial investment, Energy, maintenance and disposal costs.

$$LCC = I_{Investment} + LCC_{Energy} + LCC_{Maintenance} + LCC_{Disposal} \tag{5.15}$$

The investment element in the above LCC expression represent the initial purchasing cost, while the other elements of Energy, maintenance and disposal constitute total present values of these LCC elements. Part of the operation cost, Energy has the biggest impact on the filter's LCC with about 70% as illustrated in Figure 5.23 above.

The energy use of a typical air filter can be calculated using the following expression:

$$E = \frac{Q \times \Delta P \times T}{\eta \times 1000} \tag{5.16}$$

where, E is energy consumption (kWh), Q is the air flow rate (m3/s), ΔP is the pressure drop (Pa), T is the operation time (hours) and η is the fan's motor efficiency.

Calculation of present cost of LCC elements

The present cost (C_p) per element cost (C_n) that is paid through a certain number of years (n) with interest rate (i) can be calculated via the following expression:

$$\frac{C_p}{C_n} = \lfloor 1 + (i - p) \rfloor^{-n} \tag{5.17}$$

The right-hand side of the above expression represents the present value correction factor for each year. Accumulative sum of these factors returns the total discounted costs.

5.4.6.4. Example case study

The below parameters and assumptions are considered to calculate the LCC value for a filter of a hypothetical building HVAC scenario:

Parameter	value	unit	Remarks
Interest Rate:	5%		(i)
System Airflow:	1	m^3/s	($3600\ m^3/h$)
Operation time:	8760	h/year	
Fan efficiency:	0.65		
Energy cost:	0.05	$/kWh	2% annual increase (p)
Filter investment:	50	$	part and installation
Filter replacement /maint.	55	$	fixed
Filter disposal cost	1.5	$	3% annual increase
Air resistance (ΔP):	75-350	Pa	
Number of years:	10	year	lifetime of asset
Filter replacement/year	7		
Filter lifetime	1.43	year	10/7

Table 5.2. LCC parameters for an example case study

From equation (5.17 present values of LCC elements are generated as shown in Table 5.3 below:

	Correction factors per element to calculate present cost over a timeframe (10Y)											
	Energy			Maintenance					Disposal			
No of years	int rate	annual+		Filter No.	repl year	int rate	annual+		repl year	int rate	annual+	
n	i	p	Cf	FN	RY	i	p	Cf	RY	i	p	Cf
1	5%	0.02	0.97	1	0	0	0	0	1.43	5%	0.03	0.97
2	5%	0.02	0.94	2	1.43	5%	0	0.93	2.86	5%	0.03	0.94
3	5%	0.02	0.92	3	2.86	5%	0	0.87	4.29	5%	0.03	0.92
4	5%	0.02	0.89	4	4.29	5%	0	0.81	5.71	5%	0.03	0.89
5	5%	0.02	0.86	5	5.71	5%	0	0.76	7.14	5%	0.03	0.87
6	5%	0.02	0.84	6	7.14	5%	0	0.71	8.57	5%	0.03	0.84
7	5%	0.02	0.81	7	8.57	5%	0	0.66	10	5%	0.03	0.82
8	5%	0.02	0.79		10							
9	5%	0.02	0.77									
10	5%	0.02	0.74									
			8.53					**4.73**				**6.26**

Table 5.3. calculated correction factors and present costs for LCC parameters over a 10 years period

From the parameters in Table 5.2 and present values in Table 5.3, LCC can be calculated by using equation (5.15) as shown below (in USD):

			Present cost of		
LCC =	**Investment**	+	**Energy** +	**Maintenance** +	**Disposal**
	50		2011.82	260.40	9.39
LCC =	***2331.60***	$			

The value here represents the Life Cycle Cost of a particular filter with the specifications depicted in Table 5.2. Different filter specifications and system parameters yields different LCC. Among all parameters, pressure drop seems to have the most adverse effect on the final LCC. It is generally known that higher efficiency filters will generally have higher air resistance. Table 5.4 below shows ASHRAE's air filter MERV ratings and the corresponding standard filtration efficiency and pressure drop.

MERV rating	**ΔP (Pa)**	**Dust Spot efficiency**	**Capture Efficiency per PM size (Microns)**		
			0.3 to 1.0 μ	**1.0 to 3.0 μ**	**3 to 10 μ**
1	75	<20%	<20%	<20%	<20%
2	75	<20%	<20%	<20%	<20%
3	75	<20%	<20%	<20%	<20%
4	75	<20%	<20%	<20%	<20%
5	150	<20%	<20%	<20%	20% to 35%
6	150	<20%	<20%	<20%	35% to 49%
7	150	25% to 30%	<20%	<20%	50% to 69%
8	150	30% to 35%	<20%	<20%	70% to 85%
9	250	40% to 45%	<20%	<50%	>=85%
10	250	50% to 55%	<20%	50% to 64%	>=85%
11	250	60% to 65%	<20%	65% to 79%	>=85%
12	250	70% to 75%	<20%	80% to 90%	>=90%
13	350	80% to 85%	<75%	>=90%	>=90%
14	350	90% to 95%	75% to 84%	>=90%	>=90%
15	350	>95%	85% to 94%	>=95%	>=90%
16	350	n/a	>=95%	>=95%	>=90%

Table 5.4. Air filters MERV ratings and corresponding standard performance

This was confirmed by conducting several calculations with various types, categories and specifications of air filters which clearly the drastic effect air resistance and consequence pressure drop can have on the filter's LCC.

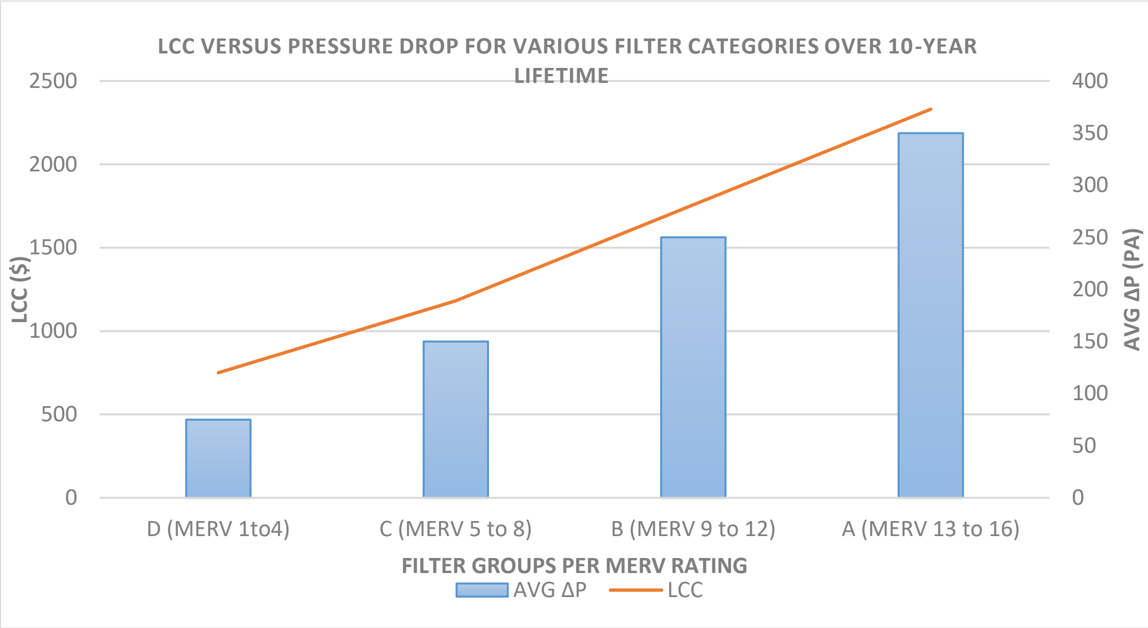


Figure 5.24. Effects of pressure drop increase on filter Life Cycle Cost (LCC)

As can be seen from Figure 5.24 above the Life cycle cost of an air filter significantly increases as filter efficiency rating (MERV) and air resistance increase

Air filter manufacturers are continuously trying to address this dilemma by striving to develop filters that can provide high filtration performance with less air resistance. While this could technically be feasible, the investment cost factor may also increase leading to similar or even worse LCC scenarios. Thus, it is important to properly design and select filters that can deliver maximum performance with minimum cost in a practically optimal fashion. This may involve the evaluation and optimization of multiple parameters that govern the overall filter LCC. To explore this aspect, optimization techniques are considered in the following section in an attempt to understand and facilitate optimal filter design and selection process.

5.5. Optimal selection of filter parameters

So far and as seen in previous sections, it is understood how air filtration is essential for human health and the integrity of cooling equipment. The benefit of high-efficiency filters is enormous; however, they usually come with a liability of high energy consumption along with the associated financial and environmental impact. Thus, selecting the best filter design is crucial to minimize such liabilities and increase benefits by striking a balance between costs and benefits in an optimal manner.

Energy cost is the dominant contributor to filters' Life Cycle Cost, as explained in the previous section. To address this issue, the appropriate filter design should target minimization of energy consumption which basically involves lowering the air resistance. This should be done in a way that does not drastically compromise filtration efficiency. Thus, suitable filter design and selection can be a daunting task that requires complex calculations, skills, and expertise. Such complexity is due to the multiple variables that govern the filters and filtration process. For this, an algorithm for finding optimal filter parameters is proposed, which can be used as a guide to identify the best combination of parameters to optimize filter performance by minimizing energy consumption and its associated cost while opting for maximum possible filtration efficiency.

There is no doubt that most industries and businesses make use of some sort of optimization techniques to assist in the design and decision-making processes. For the concerned optimal filter parameters design, Particle Swarm Optimization technique (PSO) is proposed.

5.5.1. Particle Swarm Optimization (PSO)

PSO is a stochastic, meta-heuristic population-based and nature-inspired search algorithm that mimics the movement of flock of birds or school of fish[94]. It is considered to be one of the modern and most powerful optimization techniques with proven capability of handling challenging problems in a fairly complex search space.

A PSO has a population (Swarm) that consists of numerous members (Particles) through which a given search space is explored.

The algorithm starts the search with a randomly initial points and direction in the search space. Each particle explores the search space while recording and sharing best positions with other particles of the swarm. Particles will continuously update, change and adjust position and velocity based on collectively gathered and shared information pertaining best position. This will continue until all particles converge into a global best position, which is the optimal solution. Figure 5.25 below shows a basic PSO algorithm flowchart:

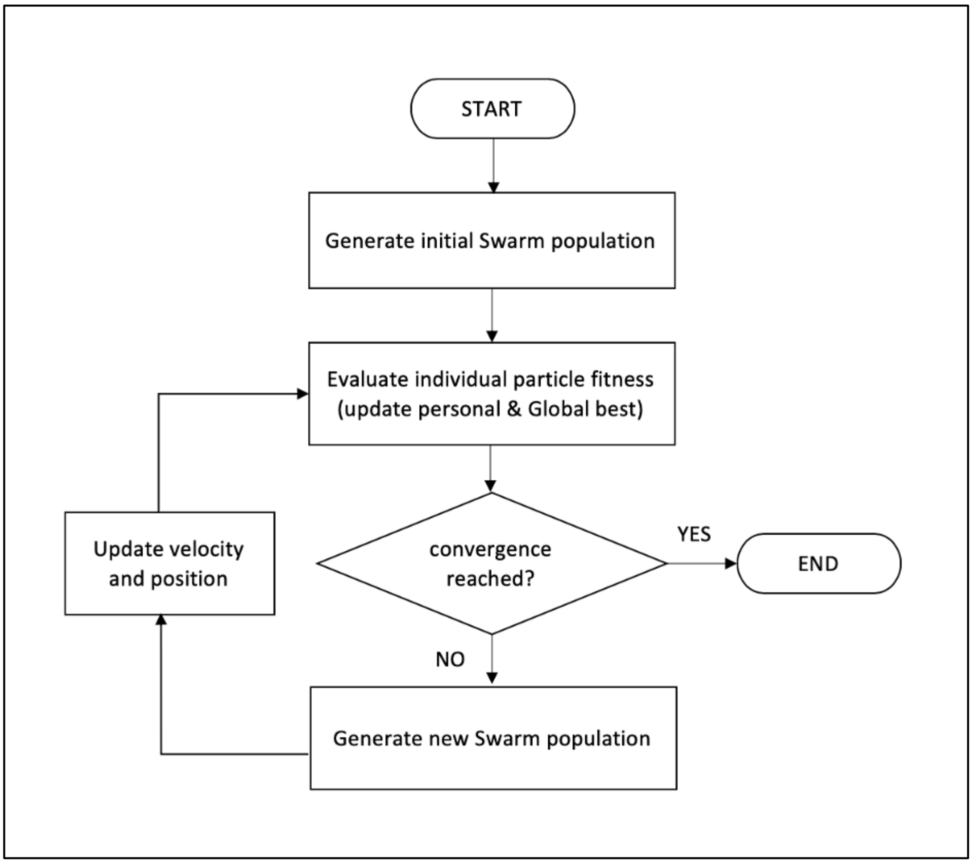


Figure 5.25. Flowchart of a basic Particle Swarm Optimization (PSO)algorithm[95, 96]

There are many advantages that make the use of PSO much more popular than other optimization methods. These include implementation simplicity, efficiency and the rapid ability to converge to optimal solutions. PSO is applicable for many complex optimization problems in the form of non-linear, non-convex continuous as well as discrete systems[97].

5.6. Optimized filter design and selection with PSO

Filter design and selection can make use of PSO's ability to perform multivariable optimization where optimal combination of filter parameters can be determined. With this in mind, what will follow is an attempt to explore the ability of PSO techniques to provide optimal design and selection guidance to what could be optimal air filter. This will be based on evaluating different combinations of 3 variables, namely air velocity (v), filter surface area (A) and pressure drop (ΔP). The resulting optimal filter parameters should facilitate the selection of filters that will provide maximum IAQ with minimum operating costs/ energy consumption/cost with maximum system(cooling) performance.

5.6.1. Problem definition:

The aim of the optimization task is to minimize the filter's energy consumption (*E*) which is mainly driven by the filter's air resistance. For this, a suitable cost (objective) function needs to be determined and optimized whilst applying relevant constraints.

From Equation (5.16), the energy consumption (E) driven by a typical air filter is approximated by the following relation:

$$E = \frac{Q \times \Delta P \times T}{\eta \times 1000}$$

Where, Q is the volumetric airflow rate, ΔP is the pressure drop across filter, T is the operation period and η is the efficiency of air handler motor.

The volumetric flow rate Q through the duct system can be expressed as follows:

$$Q = v \times A \tag{5.18}$$

Where, *v* is the fluid (air) velocity and A is the duct cross sectional area.

From (5.16) and (5.19) the objective function can be written as follows;

$$f(E) = \frac{v \times A \times \Delta P \times T}{\eta \times 1000} \tag{5.20}$$

5.6.2. Constraints

The optimization process will consider 3 variables *v*, A and ΔP while trying to minimize (E), subject to the following constraints (search space):

- *v* from 0.1 to 1.0 m/s
- *A* from 0.2 to 10 m2
- *ΔP* from 75 to 350 Pa

Thus, the optimization problem is to minimize objective function (5.20) subject to the above constraints and boundary conditions. The constraints will penalize and exclude results that are beyond search space of interest.

For simplicity, the model assumes fixed motor efficiency and fixed filter media type.

The objective function and the PSO algorithm were coded and executed in Matlab environment.

Objective function in Matlab:

```
============================================

function E = objective_function(x)
V = x(1);
A = x(2);
DP = x(3);
% Constraint

Const1 = x(1) <= 0.1 && x(1) <=1.0;
Const2 = x(2) >= 0.2 &&x(3)<= 10 ;
Const3 = x(3) > 75 && x(3)<= 350 ;
Const4 = x(1)*x(2)*x(3)>0;

if Const1==1&&Const2==1&&Const3==1&&Const4==1

    E = V*A*DP*8760/(0.65*1000);
Else
    E = (V*A*DP*8760/(0.65*1000)+25000); % Penalty
end
=================================================
```

The above filter objective function was used within a lengthy PSO algorithm code and after some fine-tuning of PSO parameters, the following solution convergence result in Figure 5.26 was obtained.

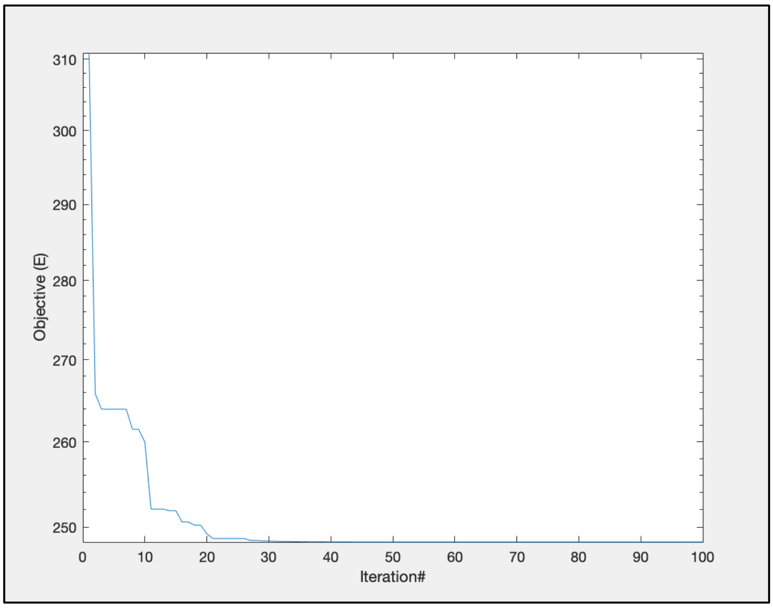


Figure 5.26. Convergence to solution result using PSO algorithm for optimal filter parameters

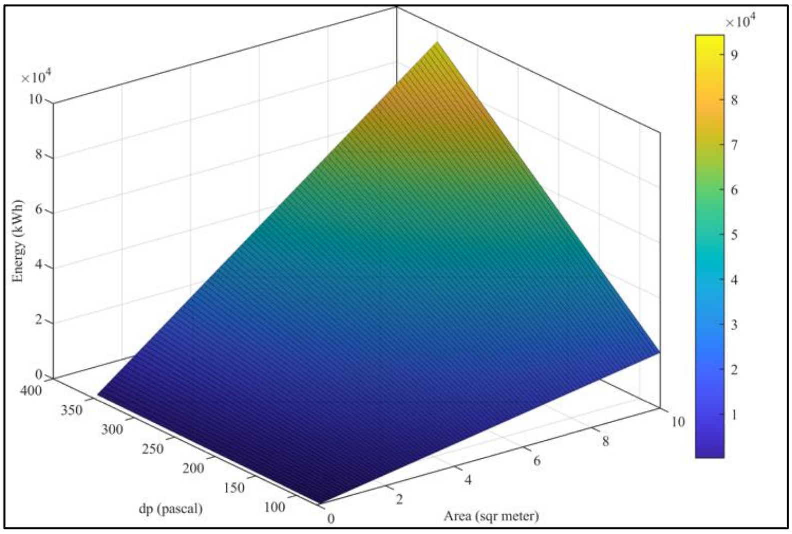


Figure 5.27. Search space for optimal air filter parameters

Figure 5.27 above shows the search space of possible combinations main filter parameters (pressure drop and surface area) and the corresponding Energy consumption value.

As can be seen also from Figure 5.26, the PSO algorithm was successful in converging to optimal solution after the 30th iteration. Below are the last 5 iterations showing optimal values for the filter parameters against the constraints and assumptions drawn:

```
Iteration 96; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 97; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 98; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 99; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 100; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
```

Different optimal results can be obtained by altering the optimization variables based on the intended design (eg. air flow, size, etc). Table 5.4 can be used as a reference to choose the filter category and rating with pressure drop value (ΔP) close to the calculated optimal value. In the above case, the optimal value for ΔP is 153.6 Pa which is approximately matching 150 Pa from ASHRAE standard that implies choosing filter with MERV rating of 5 to 8.

5.6.3. Discussion and future work

- The PSO algorithm is a simple yet powerful technique to explore Blackbox systems and return optimal solution in a relatively fast manner.
- The performance of the proposed PSO algorithm is fairly satisfactory in suggesting optimal solutions in terms of best filter parameter combinations for a reduced cost.
- One issue with PSO is that it could end up converging too soon, missing out on a better global solution.
- The simulation, however, confirms how high pressure drop negatively effects the energy consumption. Increasing the filter area is a valid and verified option to minimize pressure drop which is done by many manufacturers by means of pleated filters.
- The current work focused on minimizing Energy cost being the main contributor to air filters' Life cycle cost.
- Future research work shall expand on the existing to include optimization of the whole filter Life Cycle Cost while exploring other advanced optimization algorithms for filter design and optimization.

5.6.4. Conclusion

This chapter looked at an important aspect of cooling and air conditioning which relates to air filtration, dust accumulation and their impact on the performance and energy consumption of cooling systems. A general overview of dust phenomenon and particles composition was discussed followed by an insight into common air cleaning and filtration technologies and their theory and applications. Finally, we explored ways of enhancing awareness and decision making towards the design and selection of air filters via optimization techniques.

6. Summary and General Conclusions

This study was aimed to investigate, explore, and eventually address the issues of high intensity use of air conditioning systems in desert climates and its implications on environment, health and economy. Due to their extremely high energy consumption, the energy efficiency and performance of common air conditioning and HVAC systems were the main theme of this study with emphasis on arid countries where the demand for cooling is increasingly high.

The first chapter of this work sets the scene by shedding light on the energy-related issues and challenges especially in desertic, oil-producing regions like Qatar and the GCC where the abundance of carbon-emitting energy and high (*mainly cooling-driven*) energy demand contribute to forming such aggressive consumption profile.

The second chapter investigates the possibility of lowering household power consumption by mainly targeting peak-demand for reduction through a pragmatic load management engineering approach. The proposed AC load management approach showed a considerably significant ability to reduce power intensities in buildings.

In chapter three, an optimal air conditioner on-off control scheme is proposed to enhance system performance and reliability under the highly demanding and harsh weather conditions. The proposed optimal on-off control strategy is capable of improving and optimizing AC operation, reliability and longevity by reducing its inherent fluctuations while delivering the required cooling load with less computational burden. This is achieved by the seamless integration between off-line optimization and on-line adaptive control as well as the neural network-based temperature forecasting tool.

The fourth chapter delves into investigating the possibility to optimally manage the power of a cluster of air conditioning units, in one building, in a way that facilitate manipulation of load of effective supply and demand matching, through peak-load shaving and PV power integration in a microgrid environment. An optimization method based on MIQP technique was proposed to handle daily control of AC load in an optimal manner. Through the use of powerful optimization solvers, the optimization algorithm proved to be successful in coordinately controlling the AC cluster to generate the desired smooth and stable power consumption profile while maintaining indoor temperature variations within the acceptable limits.

The fifth and the last chapter of this thesis explores the dust phenomenon as an intrinsic feature of desert environments and how it effects the performance and energy efficiency of common air conditioning and HVAC systems. Dust particles size, composition and impact on both, human health and equipment are discussed with a brief outline of globally known air quality policies, regulations and best practices.

Air cleaning and filtration technologies were also studied, these being the way to combat dust and IAQ issues. Modeling of High Efficiency Particulate Air filter was performed in a step to gain understanding of the filtration process and dynamics. Due to the complexity of air filters' design and selection, as well as the crucial role they have on human health, equipment performance and integrity, an optimization-based decision support algorithm was proposed to guide filter design and selection process. Using Particle Swarm Optimization (PSO) technique, a constrained, multivariable filter optimization algorithm was designed in such a way that iteratively scans the search space and returns optimal combinations of filter parameters in line with the search criteria. The proposed technique shown a great ability to generate interesting results for optimal system design and performance.

Some aspects of this thesis work can be further investigated and expanded to enhance existing and/or explore other potentials to improve efficiency and performance of energy intense systems like HVAC. For example, in the case of the discussed enhanced AC on-off control strategies (chapter2,3&4), further work can consider the inclusion of other on-off operated appliances beyond air conditioning systems like electric water heaters, refrigerators, and washing machines.

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List of figures

List of tables

Résumé de thèse

Mohammed Al-Azba

La civilisation mondiale est entièrement dépendante de l'accès à de grandes quantités d'énergie, de sorte que la demande d'énergie continue de croître à un rythme rapide avec la croissance de la population mondiale. Les pays aux conditions météorologiques extrêmes ont tendance à avoir des demandes énergétiques plus élevées, où les principaux consommateurs d'énergie sont les systèmes de chauffage et de refroidissement. Dans les pays du Moyen-Orient et du Golfe en particulier (le Qatar par exemple), il existe une forte demande pour les applications de refroidissement en raison de l'environnement désertique (chaleur, humidité et poussière), qui représente environ 60 à 70% de la consommation totale d'énergie. L'électricité en tant que forme d'énergie secondaire est principalement utilisée pour les applications de refroidissement dans ces régions. Ce refroidissement est généré par des processus de production d'électricité standard à base de combustibles fossiles associés à des émissions massives de carbone. La consommation typique des ménages au Qatar est dix fois plus élevée que celle de la moyenne des ménages aux États-Unis et en Europe. De nombreuses études et techniques ont été proposées pour relever ces défis énergétiques grâce aux technologies de pointe, à l'efficacité énergétique et aux énergies renouvelables. Cependant, ils ne sont pas entièrement couronnés de succès, car beaucoup d'entre elles sont spécifiques à une région ou même à un pays, ce qui signifie que les politiques énergétiques, les concepts et la culture locale peuvent avoir un impact sur le résultat attendu. Cette étude examine les problèmes de consommation d'énergie et d'efficacité associés aux applications de refroidissement des bâtiments et leurs implications environnementales et sanitaires dans les régions désertiques. Pour relever ces défis, une approche d'ingénierie pragmatique est proposée pour aider à résoudre les problèmes persistants de gestion de l'énergie et de charge de pointe associés aux applications de refroidissement. On s’intéresse en particulier aux bâtiments où l'accent est mis sur la demande afin de développer des techniques de gestion de l'énergie pour plusieurs équipements de climatisation. Des schémas de contrôle optimaux et adaptatifs ont été développés avec succès afin de répondre aux demandes de refroidissement des locaux d'une manière équilibrée et harmonisée qui minimise la demande de pointe. Un autre aspect de ce travaille concerne la poussière de

l'environnement désertique environnant. Il peut en effet avoir un impact négatif sur les performances de la climatisation, l'efficacité énergétique et la qualité de l'air intérieur. Un algorithme d'optimisation a été développé avec succès pour guider la conception et la sélection appropriée des filtres à air pour des performances optimales du climatiseur.

Introduction

L'énergie est considérée comme un élément fondamental pour une vie durable dans notre monde moderne. C'est l'épine dorsale des sociétés actuelles et cela a toujours été la force motrice de la civilisation humaine. La consommation d'énergie a considérablement augmenté dans le monde au cours des dernières décennies tout en épuisant progressivement les ressources naturelles de la planète et en accélérant les effets néfastes du changement climatique. Étant donné que les industries et l'urbanisation mondiales dépendent entièrement de l'accès à de grandes quantités d'énergie de divers types, la demande d'énergie risque de continuer à augmenter parallèlement à la croissance rapide de la population mondiale.

L'épuisement à terme des ressources naturelles, associé à l'augmentation des problèmes de changement climatique et à l'instabilité des coûts de l'énergie, a poussé les gouvernements à envisager des mesures sérieuses en faveur de l'efficacité énergétique et de la conservation de l'énergie dans tous les secteurs. Les mesures d'efficacité énergétique visent à résoudre les problèmes énergétiques hautement prioritaires tels que la sécurité énergétique, le changement climatique et le développement économique. Le secteur du bâtiment est sans doute le plus gros consommateur parmi l'ensemble des secteurs, ce qui est également perçu par les décideurs comme une première étape pour atteindre les objectifs d'efficacité énergétique locaux et mondiaux.

L'intensité énergétique du Qatar et de la région du Golfe (pays du CCG) est un problème complexe qui comprend de multiples facteurs difficiles à appréhender comme la croissance rapide, le climat désertique rigoureux, les politiques mises en œuvre et la sensibilisation du public. Chacune de ces questions est considérée comme un grand défi en soi qui nécessite des efforts sérieux pour être traitée de manière appropriée. Avec une part importante des réserves mondiales prouvées de pétrole et de gaz, les pays du CCG n'ont pas nécessairement des problèmes d’accès à l’énergie, mais de réels défis pour la gérer. Par conséquent, l'énergie renouvelable n'est peut-être pas la solution ultime à de tels défis énergétiques.

Le cadre actuel de conservation et d'efficacité énergétique étant sous-développé, il est impératif d'introduire de nouvelles technologies intelligentes et des approches d'ingénierie qui fournissent des solutions pratiques, intelligentes et rentables pour faire face à ces complexités. Les systèmes de gestion de la demande (DSM) grâce à la domotique et à la gestion de la charge sont des exemples de solutions appropriées où la demande de puissance peut être gérée automatiquement sans grande implication des consommateurs. De telles approches devraient éventuellement aider à compenser ou à combler le vide causé par le manque de politiques efficaces et de comportement des consommateurs. Au Qatar et dans la région du CCG, l'utilisation excessive d'énergie est principalement due au secteur domestique et plus particulièrement aux applications de refroidissement telles que la climatisation standard et les systèmes «HVAC» pour les bâtiments résidentiels. La grande consommation d'énergie pour les applications de refroidissement est inévitable en raison du besoin persistant de confort thermique intérieur et de qualité de l'air dans l'environnement désertique extrêmement chaud. Par conséquent, il est raisonnable de se concentrer sur un article aussi coûteux et de cibler l'utilisation finale du refroidissement avec des solutions de gestion de l'énergie appropriées pour cibler une intensité de puissance réduite tout en garantissant un confort intérieur et un niveau de qualité de l'air adéquats.

Le domaine du refroidissement, de la réfrigération et de la climatisation (« HVAC ») est vaste et comprend diverses technologies et applications. La climatisation en elle-même est un processus complexe qui puise dans de nombreuses branches de la science comme la thermodynamique, le transfert de chaleur et la mécanique des fluides.

Les systèmes de climatisation sont de différents types, tailles et formes en fonction de la technologie et de l'utilisation finale prévue. Ils commencent par la fenêtre à unité unique, la plus courante, ou par la climatisation fractionnée, jusqu'aux installations de refroidissement urbaines massives. La complexité des systèmes de climatisation provient généralement d'un grand nombre de variables entourant le processus de refroidissement qui peuvent influencer de manière dynamique les opérations, l'efficacité et les performances de ces systèmes. De plus, un système de climatisation standard souffre de plusieurs défauts inhérents qui les rendent loin d'être optimaux.

Le problème le plus évident avec les systèmes de climatisation réside dans le fait que les unités de climatisation les plus couramment utilisées sont conçues et fabriquées dans des ensembles de capacité standard (par exemple 1, 1,5, 2 tonnes ... etc.) qui ne correspondent généralement pas à la réalité - très aléatoire – des dimensions de la pièce ou du bâtiment. Ce fait conduit la plupart du temps à des conceptions d'espace refroidi soit surdimensionnés ou sous-dimensionnés à des degrés divers, ce qui signifie évidemment une inefficacité dans leur fonctionnement.

Les unités de climatisation standard fonctionnent à l'aveuglette dans des silos sans aucun moyen de communication ni d'interaction entre elles, ce qui (dans le cas d'un bâtiment à plusieurs unités de climatisation) entraîne des performances énergétiques chaotiques et déséquilibrées.

Un autre problème inhérent, communément partagé avec les unités de climatisation conventionnelles, est le mode de fonctionnement marche-arrêt typique. Malgré sa simplicité, les systèmes de climatisation marche-arrêt provoquent des fluctuations de charge défavorables et n'offrent pas un grand avantage en termes d'efficacité énergétique ou de contrôle précis de la température. Les systèmes de climatisation conventionnels sont progressivement remplacés par une technologie d'inverseur «DC» nouvellement introduite (efficace) qui offre un mode de fonctionnement continu surmontant les limites de la climatisation conventionnelle. Malgré ce fait, les climatiseurs conventionnels dominent toujours le marché et les maisons des consommateurs et il est peu probable qu'il soit bientôt remplacé par la nouvelle technologie. Il est donc sage de gérer correctement cet héritage considérable avec des mesures de mise en valeur et de conservation pendant la transition vers la nouvelle technologie.

La complexité de ces systèmes de climatisation nécessite des stratégies de contrôle complexes et intelligentes, en particulier du côté de la demande, capables de réguler et d'optimiser le fonctionnement de ces appareils sophistiqués individuellement et en groupe dans une approche systémique.

Répondre à la demande d’énergie pour la régulation des applications de climatisation est une étape clé dans le contrôle et l’amélioration de l’efficacité globale du système. Cependant, d'autres facteurs externes affectant les performances des systèmes «HVAC» doivent également être pris en compte pour garantir une efficacité et une fiabilité maximales. Un excellent exemple de ces facteurs externes est l'effet de la poussière en suspension dans l'air. Dans le contexte des environnements désertiques, la poussière est un facteur difficile à résoudre ayant un impact indirect sur l'efficacité et les performances du courant alternatif. L'accumulation de particules de poussière sur les pièces internes du courant alternatif, les conduits et les filtres à air peut compromettre la fiabilité et l'efficacité énergétique. Cet effet néfaste va au-delà du fait d'affecter l'équipement pour avoir un impact même sur les êtres humains, car l'échec d'un climatiseur à fournir un air suffisamment pur à l'intérieur peut finalement causer de graves problèmes de santé pour les occupants.

Les filtres à air sont la première et principale ligne de défense contre les particules de poussière indésirables. En raison de leur rôle crucial et de leur impact significatif sur les performances de la climatisation, la conception et la sélection appropriées de ces dispositifs de filtration sont d'une importance primordiale pour compléter les efforts d'optimisation et de réglage fin des performances des systèmes de climatisation.

Par conséquent, relever les défis énergétiques liés aux applications de refroidissement dans les régions désertiques chaudes nécessite une approche systémique holistique qui évalue et affine tous les composants individuels dans le but de maximiser l'efficacité globale du système grâce à une bonne adéquation entre l'offre et la demande d'énergie sans compromettre la qualité et de manière optimale.

Les travaux menés et résultats

Cette étude vise à étudier, explorer et éventuellement aborder les problèmes de l'utilisation à haute intensité des systèmes de climatisation dans les climats désertiques et ses implications sur l'environnement, la santé et l'économie. En raison de leur consommation d'énergie extrêmement élevée, l'efficacité énergétique et les performances des systèmes communs de climatisation et des «HVAC» ont été le thème principal de cette étude en mettant l'accent sur les pays arides où la demande de refroidissement est très élevée.

Le premier chapitre de ce travail prépare le terrain en mettant en lumière les enjeux et les défis liés à l'énergie, en particulier dans les régions désertiques et productrices de pétrole comme le Qatar et les pays du CCG où l'abondance d'énergie émettrice de carbone et élevée (principalement liée au refroidissement) la demande d'énergie contribue à former un tel profil de consommation agressif. Figure 1 illustre les émissions de CO2 liées à la production d'électricité au Qatar.

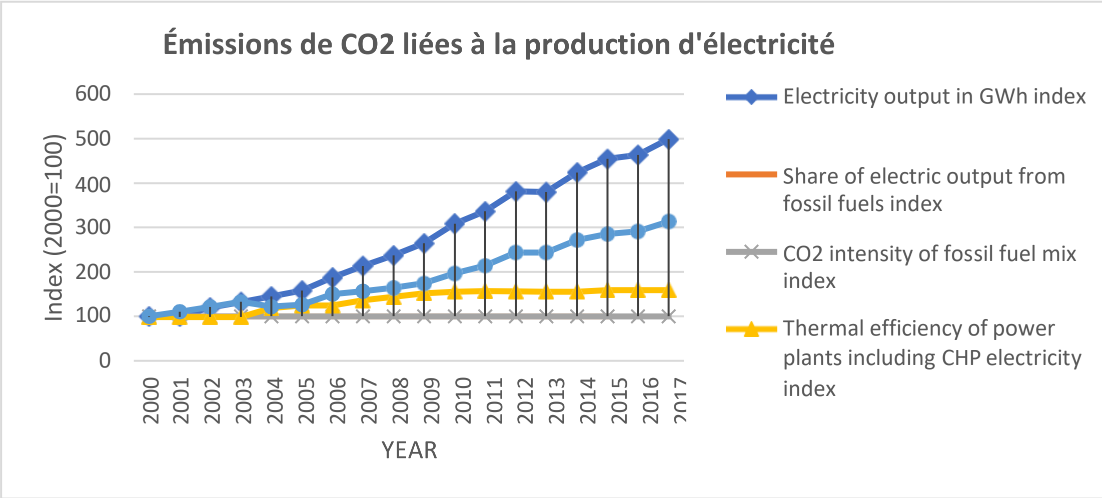


Fig. 1 Émissions de CO2 liées à la production d'électricité au Qatar [7]

Le deuxième chapitre étudie la possibilité de réduire la consommation électrique des ménages en ciblant principalement la réduction de la demande de pointe grâce à une approche pragmatique de l'ingénierie de la gestion de la charge. L'approche de gestion de la charge de climatisation proposée a montré une capacité considérablement significative à réduire les intensités de puissance dans les bâtiments. Comme exemple, Figure 2 montre une comparaison de la puissance totale de quatre climatiseurs avec et sans le contrôle de charge de groupe proposé. Plus d'informations et de détails peuvent être trouvés dans notre travail en référence [4].

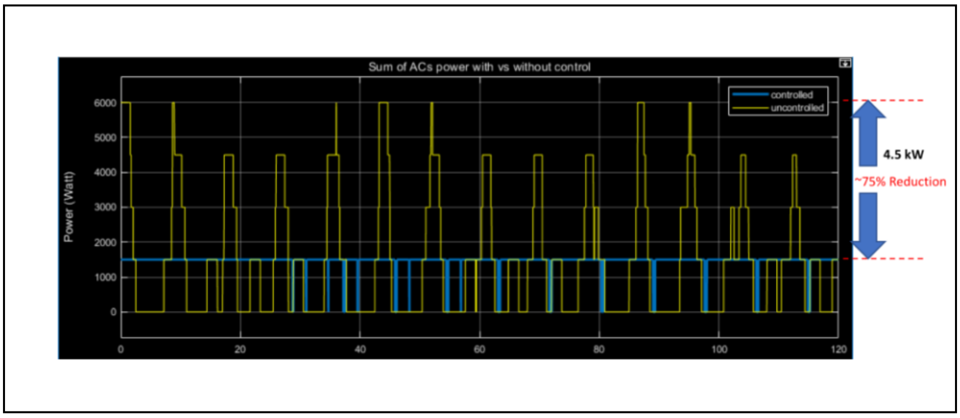


Fig. 2 Comparaison de la puissance totale de quatre climatiseurs avec et sans le contrôle de charge de groupe proposé

Au chapitre trois, un schéma de commande marche-arrêt optimal du climatiseur est proposé pour améliorer les performances et la fiabilité du système dans des conditions météorologiques très exigeantes et difficiles (voir Figure 3). La stratégie de commande marche-arrêt optimale proposée est capable d'améliorer et d'optimiser le fonctionnement, la fiabilité et la longévité du courant alternatif en réduisant ses fluctuations inhérentes tout en fournissant la charge de refroidissement requise avec moins de charge de calcul. Ceci est réalisé grâce à l'intégration transparente entre l'optimisation hors ligne et le contrôle adaptatif en ligne ainsi que l'outil de prévision de température basé sur un réseau neuronal. Plus d'informations peuvent être trouvées dans notre publication [1].

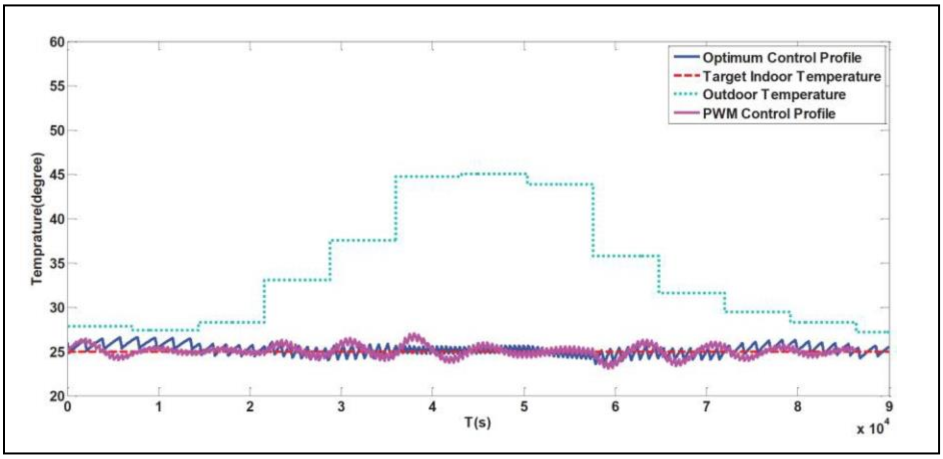


Fig. 3 Profil de contrôle de la température dans une journée typique avec de grandes variations de température

Le quatrième chapitre explore la possibilité de gérer de manière optimale la puissance d'un groupe d'unités de climatisation dans un bâtiment d'une manière qui facilite la manipulation d'une charge de correspondance efficace de l'offre et de la demande grâce à la réduction des charges de pointe et à l'intégration de la puissance photovoltaique (PV) dans un environnement de micro-réseau. Une méthode d'optimisation a été fondée sur la technique «MIQP» qui a été proposée pour gérer le contrôle quotidien de la charge de climatisation de manière optimale. Grâce à l'utilisation de puissants solveurs d'optimisation, l'algorithme d'optimisation s'est avéré efficace pour contrôler de manière coordonnée le cluster de climatisation afin de générer le profil de consommation d'énergie régulier et stable souhaité tout en maintenant les variations de température intérieure dans des limites acceptables. La Figure 4 montre les résultats obtenus pour la réduction de la charge de pointe du côté PV par la commande de groupe de climatiseurs avec mode ternaire. Plus d'informations peuvent être trouvées dans notre publication [2].

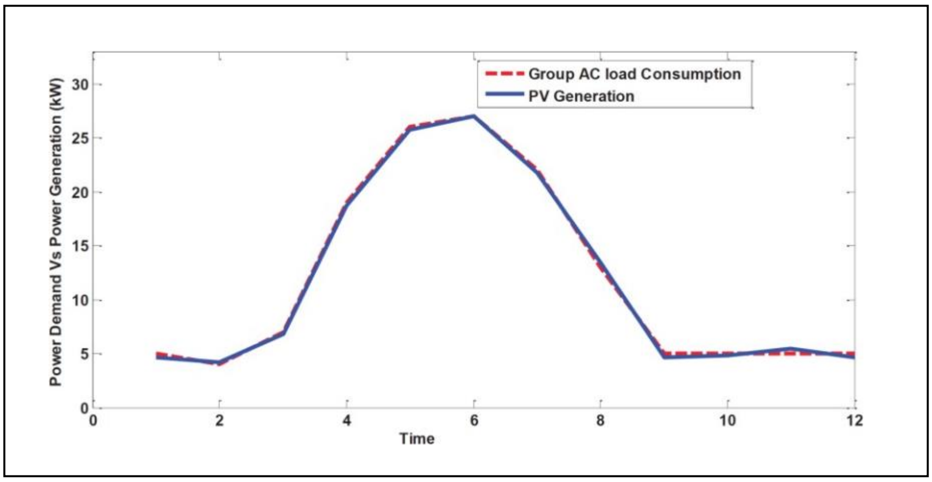
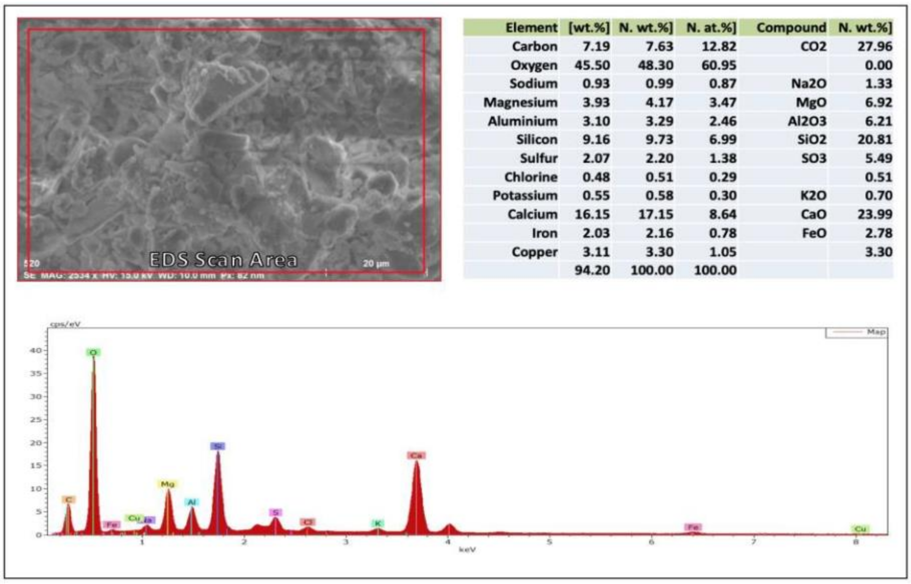


Fig. 4 Réduction de la charge de pointe du côté PV par la commande de groupe de climatiseurs avec mode ternaire

Le cinquième et dernier chapitre de cette thèse explore le phénomène de la poussière en tant que caractéristique intrinsèque des environnements désertiques et comment il affecte les performances et l'efficacité énergétique des systèmes de climatisation et des systèmes HVAC courants. La taille, la composition et l'impact des particules de poussière sur la santé humaine et l'équipement sont abordés avec un bref aperçu des politiques, réglementations et meilleures pratiques en matière de qualité de l'air mondialement connues.

L'analyse chimique globale de la poussière de filtre a conduit à la détection d'une liste d'éléments indiqués dans le tableau de la figure 5 ci-dessous. Les résultats indiquent un large éventail d'éléments suggérant des composés / espèces complexes qui ont également été étudiés plus en détail par cartographie élémentaire, diffraction des rayons X (XRD) et analyse thermique (TGA / MS).



Element	[wt.%]	N. wt.%]	N. at.%]	Compound	N. wt.%]
Carbon	7.19	7.63	12.82	CO2	27.96
Oxygen	45.50	48.30	60.95		0.00
Sodium	0.93	0.99	0.87	Na2O	1.33
Magnesium	3.93	4.17	3.47	MgO	6.92
Aluminium	3.10	3.29	2.46	Al2O3	6.21
Silicon	9.16	9.73	6.99	SiO2	20.81
Sulfur	2.07	2.20	1.38	SO3	5.49
Chlorine	0.48	0.51	0.29		0.51
Potassium	0.55	0.58	0.30	K2O	0.70
Calcium	16.15	17.15	8.64	CaO	23.99
Iron	2.03	2.16	0.78	FeO	2.78
Copper	3.11	3.30	1.05		3.30
	94.20	100.00	100.00		

Fig. 5 Exemple d'analyse EDS réalisée d'un échantillon de poussière

Des technologies d'épuration et de filtration de l'air ont également été étudiées, ce qui permet de lutter contre les problèmes de poussière et de qualité de l'air intérieur (QAI). La modélisation du filtre à air particulaire à haute efficacité était en cours de conception dans une étape visant à comprendre le processus et la dynamique de filtration. En raison de la complexité de la conception et de la sélection des filtres à air, ainsi que du rôle crucial qu'ils jouent sur la santé humaine, les performances des équipements et l'intégrité, un algorithme d'aide à la décision fondé sur l'optimisation a été proposé pour guider le processus de conception et de sélection des filtres. En utilisant la technique "PSO" d'optimisation de l'essaim de particules, un algorithme d'optimisation de filtre contraint et variable multiple a été conçu de manière à balayer de manière itérative l'espace de recherche et à renvoyer des combinaisons optimales de paramètres de filtre en fonction des critères de recherche. La technique proposée a montré une grande capacité à générer des résultats intéressants pour une conception et des performances optimales du système. Plus d'informations peuvent être trouvées dans le chapitre 5 de la thèse.

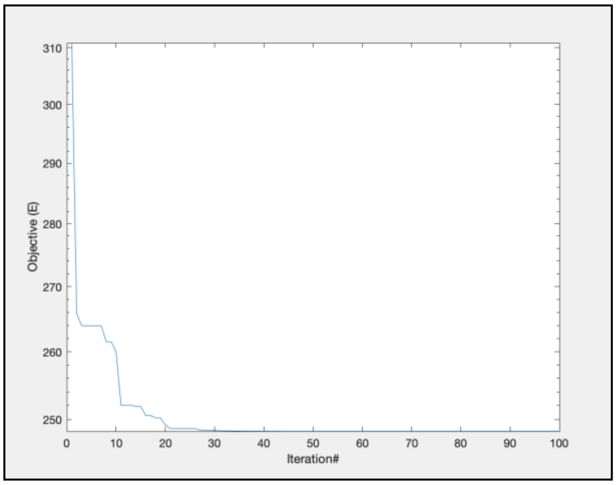


Fig. 6 Convergence vers le résultat de la solution en utilisant l'algorithme PSO pour des paramètres de filtre optimaux

Comme on peut le voir sur la figure 6 ci-dessus, l'algorithme PSO a réussi à converger vers la solution optimale après l'itération numéro 30. Voici les 5 dernières itérations montrant les valeurs optimales des paramètres de filtre par rapport aux contraintes et hypothèses considérées :

```
Iteration 96; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 97; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 98; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 99; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
Iteration 100; Best fitness = 248.3004; Optimal solution (v, A, dp) = 0.1349988      1.093507      153.6073
```

L'algorithme PSO est une technique simple mais puissante pour explorer les systèmes de «black-box» et renvoyer les solutions optimales d'une manière relativement rapide. Les performances de l'algorithme PSO proposé sont assez satisfaisantes pour suggérer des solutions optimales en termes de meilleures combinaisons de paramètres de filtre pour un coût réduit.

Conclusions

En conclusion, cette étude a démontré l'importance, la signification et les implications (environnementales et économiques) de l'utilisation de systèmes de climatisation dans les régions désertiques. Des solutions d'ingénierie pragmatiques sont proposées pour résoudre les problèmes de gestion de l'énergie électrique. L'étude examine également les problèmes de fiabilité des climatiseurs afin de minimiser les coûts de maintenance et d'augmenter la durée de vie de l'équipement.

Enfin, l'effet de la poussière - qui est une caractéristique clé de l'environnement désertique - sur les performances, l'efficacité et la santé humaine est examiné. Les processus de filtration de l'air sont explorés et une technique d'optimisation est proposée pour une performance optimale du système pour une qualité maximale de l'air intérieur et un coût d'exploitation minimum.

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[2] Al-Azba, M., Cen, Z., Remond, Y., & Ahzi, S. (2017). Air-Conditioner Group Power Control Optimization for PV integrated Micro-grid Peak-shaving. Journal of Industrial & Management Optimization, 13(5), 0–0. https://doi.org/10.3934/jimo.2020112

Articles de conférence

[3] M. Al-Azba, Z. Cen and S. Ahzi, "Air-Conditioner On-Off optimization Control under Variant Ambient Condition," 2018 6th International Renewable and Sustainable Energy Conference (IRSEC), Rabat, Morocco, 2018, IEEE Xplore pp. 1-5, doi: 10.1109/IRSEC.2018.8703001.

[4] M. Al-Azba, Z. Cen, S. Ahzi and Y. Remond, "Complex On-Off Air-Conditioning Control Strategy for Peak Demand Reduction in Desert Climate Conditions," 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), Agadir, Morocco, 2019, pp. 1-4, doi: 10.1109/IRSEC48032.2019.9078186.

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[6] Development of a holistic engineering approach for improved energy efficiency in buildings under harsh desert climate conditions, JOURNÉE POSTERS, L'École Doctorale (Mathématiques, Sciences de l’information et de l'Ingénieur), le lundi 8 octobre 2018 à Télécom Physique Strasbourg - Pôle API – Illkirch

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