Building Energy Demand Uncertainty and Economic Assessment of Residential Energy Storage System

By

Ammar Ali

(Registration No: 00000401826)

Supervisor: Dr Shahbaz Abbas

Department of Engineering Management

Collage of Electrical and Mechanical Engineering (CEME)

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

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<u>**Annex A**</u>

<u>THESIS ACCEPTANCE CERTIFICATE</u>

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Signature: ______________________

Name of Supervisor: <u>Dr. Shahbaz Abbas</u>

Dated: <u>22 Jan 2025</u>

Signature: ______________________

Name of HOD: <u>Dr. Yasir Ahmad</u>

Dated: <u>22 Jan 2025</u>

Signature (Dean/Principal): ______________________

Dated: 22-1-2025

DEDICATION

This thesis is dedicated to my **parents** and **aunt**, whose steadfast love, support, and sacrifices have constituted the foundation of all my accomplishments. Specially to my mom, whose strength, kindness, and boundless encouragement have been my greatest source of inspiration—I am forever grateful for your belief in me and for always being my guiding light.

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ABSTRACT

Building energy management (BEM) with emphasis on Energy storage Systems for the household energy management is a conducive approach to navigate the challenges of energy demand uncertainty with limited grid energy supply. However, managing the efficiency and affordability of ESS for the residential consumers is quite dynamic and complex particularly for the third world countries which are struggling with accelerated population, declining economy and climate change vulnerabilities. Therefore, considering Pakistan as a case study, this study aims to predict demand uncertainty using BEM for the green buildings which are dependent upon efficient ESS and compares the levelized cost of storage (LCOS) between lithium-ion batteries (LiB) and lead acid batteries (LaB). BEM assists in analyzing the impact of weather on the energy load profile across various climatic zones in the major cities of Pakistan and aids in determining the size of photovoltaic (PV) systems and ESS). In addition, three green residential buildings are distributed as small, medium, and large houses, each with three occupancy profiles: low, medium, and high energy consumption across three distinct locales. The findings indicate that both ESS are the significant options to manage energy requirements of green buildings, irrespective of building size or occupancy profile. Moreover, the findings suggest that lithium-ion batteries are relatively better in terms of demand variability, as it exhibits greater resilience to fluctuations and continue to be appealing in such contexts. The uncertainty analysis reveals that the LCOS value is between 0.002¢/kWh and 169¢/kWh for all the selected ESS. More specifically, between 0.002¢/kWh and 61.9¢/kWh for LiB, and between 2.1¢/kWh and 169¢/kWh for LaB.

KEYWORDS:

Building Energy Modelling, Energy Storage System, Demand Uncertainty, Monte Carlo Simulation, LCOS

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CHAPTER 1: INTRODUCTION

1.1 Background of the research/Purpose of the study

Globally, residential buildings account for a significant 20.96% of total energy consumption, a figure that alarmingly climbs to 47% in Pakistan (National Electric Power Regulatory Authority. (2023)). This stark reality highlights a pressing need for change, particularly because over half (61%) of Pakistan's energy stems from thermal sources notorious for their CO2 emissions (Pakistan Economic Survey 2021-22). It's high time we pivot towards sustainable energy solutions to reduce our fossil fuel dependency and curtail CO2 emissions, safeguarding our environment for future generations.

Echoing this urgent call to action, António Guterres, the esteemed Secretary-General of the United Nations, has forcefully articulated the critical role urban planning plays in this global endeavor. In his captivating address, he underscored the decisive impact of how we design our power generation, transport, and buildings — indeed, the very layout of our cities — in meeting the objectives set forth in the Paris Agreement on climate change and the Sustainable Development Goals (SDGs). It's a powerful reminder that our choices in city and building design are not just about aesthetics or convenience; they are pivotal in steering us towards a greener, more sustainable future. Moreover, the comparison across diverse climates enables a better understanding of how environmental conditions impact the performance and reliability of these storage technologies. This aligns with SDG 7’s emphasis on reliable energy, as storage solutions adapted to specific climate challenges are essential for ensuring consistent access to power.

In this context, the concept of green buildings emerges not merely as an option but as a necessity. Aimed at harmonizing environmental friendliness and conservation, green buildings represent the epitome of how thoughtful design, construction, and usage can come together to create edifices that not only serve our immediate needs but also pay homage to the Earth (Hu et al., 2023) (Darko & Chan, 2018) By embracing green building practices, we take a significant step towards mitigating the adverse effects of climate change, advocating for a healthier planet, and ensuring that our developmental goals align with the safeguarding of our natural environment.

Addressing the world's escalating energy demands is crucial, and the most promising solution lies in tapping into sustainable and universally viable renewable energy sources, including wind, solar, geothermal, bioenergy, and hydropower. The challenge, however, stems from the inherent variability and unpredictability of renewable sources like wind and sunlight, which often prevents their standalone operation in power plants (Biswas et al., 2017). This obstacle might seem daunting, but it presents an exciting opportunity for innovation. Scientists have been diligently exploring possible solutions and have made a groundbreaking discovery: the integration of energy storage systems (ESSs) with renewable energy sources holds the key (Castillo & Gayme, 2014). By harnessing the power of ESSs, we can effectively mitigate the challenges posed by the intermittency of renewables, unlocking their full potential to sustainably meet our energy needs. Now is the moment to embrace this synergy of technology and nature, propelling us towards a greener and more resilient energy future.

To fully harness the potential of greener living within residential buildings, it's imperative to consider the integration of an Energy Storage System (ESS) as a cornerstone of sustainable development. However, this decision must not be made lightly. A comprehensive techno-economic analysis is indispensable to select the most fitting ESS model. The importance of this process cannot be overstated; an unsuitable choice might inadvertently inflate production costs(Ismail & Hashim, 2018)undermining the very essence of efficiency and sustainability we strive for. By embracing a meticulously strategic approach in our selection, we not only pave the way for enhanced operational efficiency but also ensure our investment is cost-effective in the long run. Let's make the choice that aligns with our commitment to sustainability, without compromising on performance or financial viability. This is our chance to lead by example, demonstrating that economic and environmental objectives can go hand in hand.

Understanding the load demand of residential buildings is essential for the accurate sizing of photovoltaic (PV) systems and Energy Storage Systems (ESS). Building Energy Models (BEM) are pivotal in this context, acting as a powerful instrument for precisely assessing energy consumption (Johari et al., 2020). The literature extensively recognizes demand uncertainty as a significant element that must be accounted for to minimize the total cost of the system while maximizing profitability and achieving other objectives (Kim et al., 2008). The predictions made by Building Energy Models regarding the electrical load demands have shown to be highly effective in analyzing and managing the uncertainties associated with these demands (Trairat & Banjerdpongchai, 2022). This capability underscores the importance of employing accurate and reliable simulations to ensure that both PV systems and ESS are correctly sized to meet the energy requirements of residential buildings efficiently.

The integration of solar systems within our energy frameworks has ushered in a new era of challenges, predominantly marked by the introduction of supply-side uncertainties. These uncertainties have necessitated the adoption of innovative and reliable analytical methods to ensure the feasibility and sustainability of such projects. Among the various techniques at our disposal, the Monte Carlo Simulation stands out as the most effective tool for this purpose. The choice of the Monte Carlo Simulation method is driven by a strategic focus not on the mere optimization of supply-side parameters, which, while important, do not encapsulate the full spectrum of variabilities we face. Instead, our goal is more nuanced and far-reaching. We aim to achieve a comprehensive and accurate assessment of variations in the Levelized Cost of Storage (LCOS). This approach acknowledges the complex nature of energy systems and the myriad factors that can influence their performance and cost-effectiveness over time. Furthermore, it is imperative to highlight the critical role of economic metrics in the evaluation of energy projects. Specifically, the levelized cost of energy (LCOE) and the levelized cost of storage (LCOS) emerge as pivotal benchmarks in this analysis. These metrics provide us with a clear, quantifiable measure of economic feasibility, guiding stakeholders in making informed decisions regarding the viability of solar energy projects. Thus, employing the Monte Carlo Simulation method is not just a technical choice; it is a strategic decision that reflects a deep understanding of the nuanced challenges inherent in integrating solar systems into our energy matrix. By focusing on accurately assessing fluctuations in LCOS, we can navigate the uncertainties of supply-side factors with greater confidence, ensuring that the adoption of solar energy is both economically feasible and aligned with long-term sustainability goals. This perspective is vital for all stakeholders involved in the development, funding, and implementation of solar energy projects. (Cremoncini et al., 2024; Xiang et al., 2024).

1.2 Research Rationale

The demand for reliable and affordable energy storage solutions is increasingly critical as global efforts intensify toward sustainable energy access, particularly in developing countries like Pakistan. Pakistan faces unique challenges in achieving Sustainable Development Goal 7 (SDG 7) due to its diverse climates, ranging from arid deserts to mountainous regions, which affect both energy demand patterns and the efficiency of energy storage technologies. Despite these climatic variations, research on how climate impacts the cost and performance of storage technologies—such as Lead Acid and Lithium-Ion Batteries—remains limited.

This thesis addresses this gap by examining the Levelized Cost of Storage (LCOS) for Lead Acid and Lithium-Ion Batteries across five Pakistani cities with distinct climatic profiles: Islamabad, Karachi, Quetta, Murree, and Sibi. To accurately assess energy demand in these regions, Building Energy Modeling (BEM) was utilized, enabling a detailed understanding of local demand patterns across different building types and climate conditions. This approach ensures that the LCOS calculations are grounded in realistic demand scenarios, enhancing the relevance of the findings for diverse energy requirements.

Understanding LCOS across these different environments is essential for developing energy storage systems that are both cost-effective and resilient to environmental stresses, which is critical for reducing dependency on the grid and promoting energy self-sufficiency. Furthermore, the findings of this research provide policymakers and stakeholders in the energy sector with data-driven insights on the most viable storage options for varying local conditions. Such insights are essential for making informed decisions about energy infrastructure investments and for formulating strategies to support affordable and reliable energy access. Ultimately, this research aims to contribute to the knowledge base necessary for advancing sustainable, climate-adapted energy solutions that align with Pakistan’s pathway to achieving SDG 7

1.3 Research Objective

- To understand what role does UBEM play in optimizing the integration of ESS in green residential buildings
- To determine the impact of demand uncertainty in determining the economic viability of energy storage systems in green residential buildings equipped with PV technology
- To find the cost effective ESS options for green residential buildings in the major cities of Pakistan

1.4 Problem Statement

Globally, residential buildings consume a substantial amount of energy, primarily derived from fossil fuels, which significantly harms the environment. While PV systems offer a promising solution to reduce fossil fuel reliance and mitigate environmental impacts, their economic viability is often hindered by the inadequate selection of ESS particularly in the developing countries. Demand uncertainty arises from factors such as occupant behavior, climate conditions and unpredictable load patterns, impacting the sizing and performance of PV and ESS systems while introducing financial risks that complicate investment decisions.

1.5 Thesis Structure

This thesis is structured to provide a comprehensive analysis of the Levelized Cost of Storage (LCOS) for energy storage technologies—specifically, Lead Acid Batteries and Lithium-Ion Batteries—across five Pakistan cities with differing climates: Islamabad, Karachi, Quetta, Murree and Sibi. Following this introductory chapter, Chapter 2 presents a thorough review of existing literature on energy storage technologies, Building Energy Modeling and the relevance of LCOS in sustainable development, highlighting key performance indicators like self-sufficiency and on-site energy ratios. Chapter 3 outlines the research methodology, detailing the comparative framework for LCOS calculations and the selection criteria for building types and occupancy profiles. In Chapter 4, the results are presented, analyzing the impact of demand patterns and financial uncertainties on LCOS across different locations and building types. Finally, Chapter 5 concludes the thesis with a summary of key insights, limitations, and recommendations for future research. This structured approach enables a clear and systematic exploration of the factors influencing LCOS in diverse contexts, contributing valuable insights to the field of sustainable energy systems.

CHAPTER 2: LITERATURE REVIEW

2.1 Evaluation of Existing body of Knowledge

This chapter delves into the intricate studies of Energy Storage Systems (ESS) for residential buildings, alongside Building Energy Modeling (BEM) and the concept of Green Buildings. The narrative commences with an analytical examination of ESS, highlighting its crucial role within the residential sector. It endeavors to provide a comparative study of the variety of ESS technologies currently employed in residential buildings, examining their efficiency, cost-effectiveness, and environmental impacts. This comparative analysis not only elucidates the strengths and weaknesses of each system but also explores their scalability and long-term sustainability in the face of evolving energy demands.

Subsequently, the focus shifts to Building Energy Modeling (BEM), a pivotal tool in the optimization of building energy consumption. This section outlines the fundamental principles of BEM, illustrating its significance in the design and operation of energy-efficient buildings. By integrating BEM with the principles of Green Buildings, the discourse emphasizes the synergy between architectural design, material selection, and energy management strategies. This holistic approach underscores the importance of BEM in achieving substantial energy savings while maximizing occupant comfort and minimizing environmental impact.

As the chapter progresses, it ventures into the complex dynamics of Demand Uncertainty and Supply-Side Uncertainty, offering a nuanced understanding of these phenomena. It critically examines the challenges associated with forecasting energy demand and supply, highlighting the implications for residential building energy management. Through a methodical analysis, it explores strategies to mitigate these uncertainties, focusing on the integration of renewable energy sources, demand response technologies, and advanced predictive models. The chapter concludes by reflecting on the critical role of innovation and adaptive strategies in navigating the uncertainties of energy demand and supply, advocating for a proactive and informed approach to residential building energy management.

This comprehensive exploration not only enhances the reader's understanding of contemporary issues in residential energy systems but also encourages a critical examination of the methodologies and technologies at the forefront of sustainable building practices

2.1.1 ESS

A battery plays a crucial role in bridging the gap between chemical and electrical energy within a PV system by storing surplus energy for periods of non-production. This technological approach underpins a more seamless infusion of renewable energy sources into the power grid. However, the variability in PV production, largely due to fluctuating weather conditions—a common challenge for many renewable sources—poses a significant reliability concern. This unpredictability exerts undue pressure on the grid infrastructure, highlighting a critical area of vulnerability in the broader adoption of renewable energy technologies.

Battery storage emerges as a strategic countermeasure, functioning as an intermediary buffer that mitigates the disparity between energy generation and consumption demand. It promises to alleviate grid stress through services such as peak shaving and load leveling, alongside contributing to the grid’s frequency and voltage regulation—critical for maintaining grid stability. Despite these advantages, the discussion on battery storage is incomplete without a thorough examination of battery characteristics, the technological differences that distinguish various batteries, and the performance metrics that quantify their effectiveness in a PV system.

While the deployment of battery storage presents an operative solution to the grid's adaptability challenges in accommodating renewable energy sources, it also warrants a critical analytical lens. This encompasses investigating the efficiency, cost-effectiveness, lifecycle, and environmental impact of different battery technologies. Such an analysis is paramount in deciphering the trade-offs involved and in guiding the strategic integration of battery storage within PV systems to bolster a resilient, sustainable, and economically viable energy grid.

Energy Storage Systems (ESS) are classified into five principal categories: chemical (such as hydrogen fuel cells), electrochemical (notably rechargeable batteries like lithium-ion), electrical (including supercapacitors), mechanical (such as compressed air energy storage), and thermal (e.g., molten salts). Each type of system demonstrates distinct characteristics in terms of power rating, lifetime, efficiency, and response time, necessitating a comparative analysis based on these parameters (Chadly et al., 2023). Within the scope of this research, a critical examination is focused on two specific types of electrochemical energy storage: Lithium-ion batteries (LIB) and Lead-acid batteries (LAB). This analysis aims to elucidate the relative advantages and limitations of these technologies, underpinned by an analytical exploration of their performance metrics (Storage, 2017). This comparison is essential for identifying the most effective energy storage solutions, considering the complex matrix of characteristics that define the suitability of different ESS technologies.

2.1.1.1 Lithium-ion batteries (LIBs)

Lithium-ion batteries (LIBs) have emerged as a pivotal technology in the realm of energy storage, particularly due to their high charge and discharge efficiency, rapid energy transfer capabilities, and significant energy density. The advancements in LIB technology have been driven by ongoing research into materials and battery management systems, which have collectively enhanced their performance and applicability in various sectors, including electric vehicles (EVs) and grid storage systems.

High Charge and Discharge Efficiency

The charge and discharge efficiency of LIBs is a critical parameter that influences their performance in practical applications. Recent studies indicate that LIBs can achieve efficiencies exceeding 90%, which is attributed to their electrochemical properties and the design of their electrode materials (Stroe et al., 2016). The efficiency is further enhanced by the implementation of advanced battery management systems (BMS) that monitor and optimize the charging cycles, thereby prolonging the battery's lifespan and maintaining its performance (Hemavathi, 2020a). The ability to rapidly charge and discharge makes LIBs particularly suitable for applications requiring quick energy delivery, such as in grid storage systems where energy must be stored and released in response to fluctuating demand (T. Chen et al., 2020)

Rapid Energy Transfer in Grid Storage Systems

The integration of LIBs into grid storage systems has been a focal point of research due to their ability to facilitate rapid energy transfer. The high power density of LIBs allows for quick response times, which is essential for balancing supply and demand in electrical (T. Chen et al., 2020). As renewable energy sources, such as solar and wind, become more prevalent, the need for efficient energy storage solutions that can handle intermittent generation is paramount. LIBs have shown promise in this regard, providing a reliable means to store excess energy generated during peak production times and release it during periods of high demand (Porzio et al., 2023). The economic feasibility of LIBs for grid applications is also improving, with projections indicating a significant reduction in costs, potentially making them a competitive option for large-scale energy storage (Projecting the Price of Lithium-Ion NMC Battery Packs Using a Multifactor Learning Curve Model, 2020).

High Specific Capacity and Long Service Life

One of the standout features of LIBs is their high specific capacity, which is a measure of the amount of charge a battery can store relative to its mass. Current generation LIBs exhibit specific capacities around 250 Wh/kg, with ongoing research aiming to push this figure closer to 400-500 Wh/kg through innovations in anode materials, such as lithium metal anodes (Bills et al., 2020; D. Lin et al., 2017). This increase in specific capacity is crucial for applications in electric vehicles, where weight and space are at a premium. Additionally, the long service life of LIBs, often exceeding 2000 cycles, is a significant advantage, reducing the frequency of replacements and associated costs (Hemavathi, 2020b). The longevity of LIBs is enhanced by advancements in materials science, particularly in the development of more stable and durable electrode materials that can withstand the rigors of repeated cycling (Molaiyan et al., 2023)

Energy Density and Its Implications

The energy density of LIBs is significantly higher than that of many alternative battery technologies, making them the preferred choice for a variety of applications. The theoretical energy density of LIBs is approximately 420 Wh/kg, which is nearing its practical limits (Y. Wang et al., 2018). This high energy density is essential for applications where space and weight are critical factors, such as in portable electronics and electric vehicles. Furthermore, the high energy density of LIBs contributes to their effectiveness in grid-scale applications, where large amounts of energy need to be stored without requiring excessive physical space (Fan et al., 2020). The ongoing research into solid-state batteries and novel materials aims to further enhance the energy density of LIBs, potentially unlocking new applications and improving their competitiveness against emerging technologies (R. Chen et al., 2019).

2.1.1.2 Lead Acid Batteries (LABs)

Lead-acid batteries (LABs) have been a cornerstone of energy storage technology for over a century, primarily due to their affordability, reliability, and established manufacturing processes. This literature review synthesizes recent findings on the economic aspects, recycling potential, and operational characteristics of lead-acid batteries, highlighting their continued relevance in various applications.

Affordability and Manufacturing Costs

One of the most significant advantages of lead-acid batteries is their low manufacturing cost, which makes them an attractive option for a wide range of applications, from automotive to stationary energy storage systems. The cost-effectiveness of LABs is primarily attributed to the abundance of lead and sulfuric acid, which are relatively inexpensive compared to the materials used in other battery technologies, such as lithium-ion batteries (K. Liu et al., 2018). Recent studies indicate that LABs account for approximately 82% of global lead consumption, underscoring their widespread use and economic viability (K. Liu et al., 2018)(Tian et al., 2014). Furthermore, the manufacturing processes for lead-acid batteries are well-established and scalable, contributing to their affordability (Tian et al., 2014).

Reliability and Performance

Lead-acid batteries are known for their reliability and robustness, characteristics that have made them the preferred choice for numerous applications, including backup power supplies and automotive starting systems. Their ability to deliver high surge currents makes them particularly suitable for starting internal combustion engines (Okano et al., 2021) However, one of the challenges associated with lead-acid batteries is their sensitivity to over-discharge, which can significantly reduce their lifespan and performance Innovations in battery design, such as the use of graphite-based materials as cathode current collectors, have been explored to enhance the resistance of LABs to over-discharge conditions (Okano et al., 2021).

Recharge and Reuse

The rechargeability of lead-acid batteries is a critical aspect of their lifecycle. LABs typically require 8 to 10 hours for a full recharge after a significant discharge, which is essential for maintaining their operational efficiency (Sen et al., 2021)The ability to recharge and reuse lead-acid batteries is a significant factor in their economic appeal, as it allows for extended use and reduces the frequency of replacements. Moreover, the recycling of lead-acid batteries is highly efficient, with a recycling rate that can exceed 95% in some regions (Zan & Zhang, 2022). This high recycling rate not only mitigates environmental concerns associated with lead pollution but also contributes to the sustainability of lead-acid battery production by recovering valuable materials (Zan & Zhang, 2022).

Environmental Considerations

Despite their advantages, lead-acid batteries pose environmental challenges, particularly concerning lead pollution. Studies have shown that communities near lead-acid battery manufacturing facilities are at a higher risk of lead exposure, which can have detrimental health effects, especially in children (K. Chen et al., 2014). However, advancements in pollution control and recycling technologies are helping to mitigate these risks (K. Liu et al., 2018). The implementation of extended producer responsibility (EPR) systems has also been suggested as a means to improve recycling practices and reduce the environmental impact of lead-acid batteries (Zan & Zhang, 2022).

2.1.2 BUILDING ENERGY MODELLING

Building energy modeling (BEM) has emerged as a critical area of research and practice, driven by the need to enhance energy efficiency in the built environment. This literature review synthesizes various studies that explore methodologies, predictive models, and strategies for optimizing energy consumption in buildings. The integration of advanced computational techniques, such as artificial intelligence and machine learning, alongside traditional modeling approaches, has significantly advanced the field.

One of the foundational studies in this domain is by, which presents prediction equations for energy consumption in apartment buildings based on survey data. Their findings indicate that room heating constitutes the largest component of energy consumption, followed by electricity, hot water supply, and gas (Ju et al., 2014). This highlights the importance of understanding the specific energy demands of different building types, which is essential for developing targeted energy-saving strategies. Similarly, emphasize the role of regression analysis and artificial neural networks in modeling building energy consumption, showcasing how data classification can enhance the accuracy of energy predictions (Ridwana et al., 2020). This dual approach not only improves the reliability of energy consumption forecasts but also facilitates the identification of key factors influencing energy use.

Energy retrofitting is another critical aspect of building energy modeling. conducted a comprehensive study on energy consumption and indoor climate in residential buildings before and after retrofitting, demonstrating significant reductions in energy use post-retrofitting (Thomsen et al., 2016). This underscores the potential for existing buildings to achieve substantial energy savings through targeted interventions. Furthermore, propose a partition-based method for energy analysis that leverages Building Information Modeling (BIM) technology to optimize energy conservation measures (Z. Lin & Zhong, 2015). Their approach addresses common challenges in energy consumption analysis, such as low accuracy and poor sustainability, thereby enhancing the effectiveness of energy-saving designs.

The role of building envelopes in energy efficiency is also critical. explore the impact of green envelopes on energy consumption in library buildings, revealing that different envelope designs can lead to significant variations in energy use (Ariff et al., 2019). Their findings suggest that optimizing building orientation, wall insulation, and façade treatments can substantially reduce energy consumption. This is further supported by , who analyze energy consumption demand models for residential buildings, emphasizing the importance of considering energy structure adjustments and policy regulations in energy modeling (Yu et al., 2011). These studies collectively highlight the multifaceted nature of energy consumption in buildings and the need for comprehensive modeling approaches that account for various design and operational factors.

Energy audits play a pivotal role in identifying energy-saving potentials within buildings. 's work on energy audits at Xi'an Jiaotong-Liverpool University illustrates how systematic inspections can reveal energy consumption characteristics and inform strategies for reducing energy use (Jing & Nayel, 2013). This aligns with the findings of , who propose intelligent data analysis methods for modeling and predicting electricity consumption in buildings, enabling the identification of abnormal energy use patterns (Massaguer et al., 2014). Such methodologies are essential for developing effective energy management systems that can adapt to changing consumption patterns.

The integration of advanced computational techniques in energy modeling is further exemplified by the work of , who utilize kernel principal component analysis and support vector machines to analyze energy consumption in prefabricated buildings (Lv et al., 2022). Their approach highlights the potential of machine learning algorithms to enhance the predictive capabilities of energy models, particularly in complex building systems. Similarly, 's research on public buildings employs a particle swarm optimization-based radial basis function neural network to predict energy consumption, demonstrating the effectiveness of hybrid modeling techniques (Cao & Huang, 2017). These advancements in computational modeling are crucial for addressing the increasing complexity of energy systems in modern buildings.

Moreover, the impact of building design parameters on energy consumption has been extensively studied. investigate the quantitative relationships between design parameters and energy savings in cold regions, revealing how factors such as building dimensions and solar radiation influence energy use (J. Wang & Kang, 2017). This research underscores the importance of integrating design considerations into energy modeling to achieve optimal energy performance. Additionally, 's exploration of building physics forms further emphasizes the need for accurate simulations of energy consumption in representative buildings, utilizing software such as OpenStudio to model operational energy use (Y. Yang & Wang, 2022).

In the context of historical buildings, address the challenges of improving energy efficiency in protected structures, suggesting that careful measurements and assessments can reveal potential energy-saving measures without compromising architectural integrity (Blumberga et al., 2013). This highlights the need for adaptive strategies that respect cultural heritage while promoting energy efficiency. Furthermore, the concept of generalized building energy efficiency, as proposed by , advocates for a holistic approach to energy-saving design that encompasses all aspects of building performance, from construction to operation (L. Yang & Sun, 2019). This comprehensive perspective is essential for achieving sustainable energy outcomes in the built environment.

The literature also emphasizes the importance of government policies and regulations in shaping energy efficiency practices. discuss the role of comprehensive quality supervision in energy efficiency projects, advocating for rigorous oversight to ensure the successful implementation of energy-saving measures in civil buildings (H. Guo et al., 2013). This regulatory framework is vital for fostering a culture of energy efficiency and ensuring that building practices align with sustainability goals.

In conclusion, building energy modeling is a dynamic and multifaceted field that encompasses a wide range of methodologies, technologies, and strategies aimed at optimizing energy consumption in buildings. The integration of traditional modeling techniques with advanced computational methods, alongside a focus on design parameters and regulatory frameworks, is essential for achieving significant energy savings. As the building sector continues to evolve, ongoing research and innovation will be critical in addressing the challenges of energy efficiency and sustainability in the built environment.

2.1.3 GREEN BUILDING

The concept of green buildings has gained significant traction globally, particularly in relation to energy efficiency and the integration of renewable energy sources. Green buildings are defined as structures that are designed, constructed, and operated to minimize their environmental impact while maximizing resource efficiency, particularly concerning energy, water, and materials (Sutikno, 2022). This approach not only addresses the pressing issues of climate change and resource depletion but also aligns with the growing demand for sustainable living environments among users worldwide (Sutikno, 2022)

One of the primary advantages of green buildings is their potential for energy conservation. Research indicates that these structures can significantly reduce energy consumption through various design strategies, such as optimizing natural lighting, improving insulation, and utilizing energy-efficient appliances (Kurniawan et al., 2021) (Alshorman & Alshorman, 2017). For instance, the implementation of green roofs and walls has been shown to enhance thermal performance, thereby reducing the energy required for heating and cooling (Azis et al., 2019). Furthermore, the integration of smart technologies, such as IoT systems, allows for real-time monitoring and management of energy use, leading to further reductions in consumption (Abriaa & Vimbia, 2020).

In addition to energy efficiency, the incorporation of renewable energy sources is a critical component of green building practices. The use of solar panels, wind turbines, and geothermal systems can significantly decrease reliance on fossil fuels, thereby reducing greenhouse gas emissions (Harmathy, 2021)(Nur, 2023). For example, the Leadership in Energy and Environmental Design (LEED) certification emphasizes the importance of renewable energy in its evaluation criteria, encouraging buildings to utilize sustainable energy sources as part of their operational framework (Najed, 2023). This shift not only contributes to environmental sustainability but also offers economic benefits through lower operational costs and potential incentives for building owners (Plebankiewicz et al., 2019) (Basten et al., 2019)

Moreover, the global movement towards green buildings is supported by various regulatory frameworks and certification programs that promote energy efficiency and the use of renewable resources. Countries around the world have begun to adopt standards that require new constructions to meet specific energy performance criteria, thereby fostering a culture of sustainability within the building sector ((Sutikno, 2022); (A. Guo & Liu, 2020). For instance, the Green Mark Scheme in Singapore sets stringent requirements for energy efficiency and environmental protection, which have become benchmarks for green building practices internationally (Aryaningrum et al., 2018).

Despite the numerous benefits associated with green buildings, challenges remain, particularly in achieving consistent energy performance across different regions and building types. Studies have highlighted discrepancies between predicted and actual energy consumption in green buildings, often attributed to occupant behavior and operational practices (Ohueri et al., 2018). Addressing these gaps is essential for maximizing the energy-saving potential of green buildings and ensuring that they fulfill their intended environmental benefits (Ohueri et al., 2018); (Basten et al., 2019).

In conclusion, green buildings represent a vital strategy in the global effort to enhance energy efficiency and promote the use of renewable energy sources. By integrating sustainable design principles and technologies, these structures not only contribute to environmental conservation but also offer economic advantages and improved quality of life for occupants. As the demand for sustainable solutions continues to grow, the role of green buildings in shaping a more energy-efficient future will undoubtedly become increasingly significant.

The development of green residential buildings has emerged as a crucial strategy in addressing environmental concerns, particularly in relation to energy efficiency and sustainability. Green residential buildings are designed to minimize their ecological footprint while maximizing the use of renewable resources and energy-efficient technologies. This literature review synthesizes various studies that highlight the significance of green residential buildings in promoting energy conservation and sustainable living. One of the primary motivations for adopting green residential building practices is the urgent need to mitigate climate change. Residential buildings significantly contribute to global warming and environmental pollution, accounting for a substantial portion of energy consumption and carbon emissions (Elias & Lin, 2015)(Ramadhan et al., 2019). By implementing green building concepts, such as energy-efficient designs and renewable energy systems, the negative impacts of residential buildings on the environment can be significantly reduced (Ramadhan et al., 2019); (Gao, 2011). For instance, the integration of solar energy systems and water-saving fittings has been identified as a common practice in sustainable residential construction, which not only conserves resources but also enhances the quality of life for occupants (Mazli & Fauzi, 2022). The use of innovative building materials is another critical aspect of green residential buildings. Research indicates that selecting sustainable materials can lead to improved energy efficiency and reduced environmental impact (Y. Liu, 2013). For example, the application of new insulation materials and waterproofing technologies can enhance thermal performance, thereby reducing the energy required for heating and cooling (Y. Liu, 2013). Furthermore, the incorporation of green roofs and walls has been shown to provide additional insulation and reduce energy consumption, while also contributing to urban biodiversity (Azis et al., 2019);(Djordjevic et al., 2018). These features not only improve the energy performance of residential buildings but also offer aesthetic and ecological benefits. Community perspectives play a vital role in the successful implementation of green residential buildings. Engaging with potential homeowners and understanding their preferences can lead to more effective designs that meet user needs while promoting sustainability (Ramadhan et al., 2019); (K. S. Liu et al., 2017). Studies have shown that awareness of green building elements among potential homebuyers influences their purchasing decisions, highlighting the importance of education and outreach in fostering a culture of sustainability (Mazli & Fauzi, 2022) (Tan & Goh, 2018). Additionally, the psychological factors that drive consumer behavior towards green residential buildings, such as perceived value and environmental concern, are crucial for encouraging adoption (Tan & Goh, 2018). Despite the numerous benefits associated with green residential buildings, challenges remain in their widespread implementation. The initial costs associated with green building technologies can deter potential homeowners, as studies indicate that green building systems may increase construction costs by approximately 10% compared to traditional methods (C. Sun et al., 2019). However, the long-term savings on energy bills and the potential for government incentives often outweigh these initial investments (Said, 2019); (Badawy et al., 2021). Moreover, ongoing research into energy consumption patterns in residential buildings is essential for optimizing design strategies and ensuring that green buildings achieve their intended energy-saving goals (Zhang et al., 2021)In conclusion, green residential buildings represent a vital component of sustainable development, offering significant benefits in terms of energy efficiency and environmental conservation. By integrating renewable energy sources, utilizing innovative materials, and engaging with communities, the potential for reducing the ecological footprint of residential buildings can be greatly enhanced. As the demand for sustainable living continues to grow, the role of green residential buildings in shaping a more energy-efficient future will become increasingly important.

2.1.4 Demand Uncertainty

The literature surrounding electrical demand uncertainty is extensive, reflecting the complexities and challenges faced by utilities in forecasting load demand. This review synthesizes various methodologies and approaches that have been developed to address the inherent uncertainties in electrical demand forecasting. One of the primary challenges in forecasting electrical demand is its stochastic nature, which complicates the prediction of future load levels. Khuntia et al. highlight that traditional forecasting methods often struggle to accommodate the variability inherent in demand patterns, particularly over mid- and long-term horizons (Khuntia et al., 2016). This variability necessitates the development of more sophisticated forecasting techniques that can incorporate a range of influencing factors, including economic conditions, technological advancements, and changes in consumer behavior (Sowiński, 2019). For instance, Sowiński emphasizes the importance of end-use models in forecasting, which can provide insights into how structural changes in the electricity market affect demand uncertainty (Sowiński, 2019). To further enhance forecasting accuracy, various models have been proposed that integrate different data sources and methodologies. Nugraha et al. discuss the implementation of a forecasting module within Building Energy Management Systems (BEMS), which utilizes historical load data, weather forecasts, and occupant behavior to predict electricity demand (Nugraha et al., 2018). This approach underscores the necessity of incorporating diverse data inputs to mitigate forecasting uncertainty. Similarly, Zhou et al. present a fuzzy probability-based Markov chain model that accounts for uncertainties by allowing for fuzzy parameters in the forecasting process, thereby improving the robustness of long-term demand predictions (Zhou et al., 2013). In the context of long-term forecasting, Hyndman and Fan advocate for density forecasting, which provides a probabilistic view of potential peak demand levels rather than relying solely on point estimates. This method is crucial for utilities to evaluate and hedge against financial risks associated with demand variability (Hyndman & Fan, 2010). The integration of probabilistic approaches is echoed in the work of Jiang et al., who emphasize the importance of probabilistic load forecasting methods in reflecting uncertainties through prediction intervals, thus aiding decision-making in system operations (Jiang et al., 2021). Short-term load forecasting also presents unique challenges due to the rapid fluctuations in demand. Zou's research highlights the effectiveness of hybrid models that combine variational mode decomposition with advanced neural networks to address the non-linearity and uncertainty of load data (S. Li, 2023). This aligns with findings from Li, who notes that short-term forecasting models must adapt to the stochastic characteristics of electricity load data to enhance accuracy (S. Li, 2023). Additionally, the work of Stoutenburg et al. indicates that the variability of load forecasts can significantly impact operational strategies, particularly in systems with high penetration of renewable energy sources (Stoutenburg et al., 2013) Moreover, the integration of advanced machine learning techniques has gained traction in addressing demand uncertainty. For instance, the application of Bayesian deep learning, as discussed by Sun et al., allows for capturing uncertainty in residential net load forecasting, which is critical for smart grid management (M. Sun et al., 2020). This approach highlights the growing trend of utilizing artificial intelligence to improve forecasting accuracy and manage the complexities of modern electricity markets. In conclusion, the literature on electrical demand uncertainty reveals a multifaceted landscape of forecasting methodologies that are continuously evolving. The integration of probabilistic models, advanced data analytics, and machine learning techniques is essential for enhancing the accuracy of load forecasts and effectively managing the uncertainties inherent in electrical demand.

2.1.4 LCOS

The economic analysis of energy storage systems, particularly through the lens of Levelized Cost of Storage (LCOS), has gained significant attention in recent years. LCOS serves as a critical metric for evaluating the cost-effectiveness of various energy storage technologies, allowing for a comparative assessment against the Levelized Cost of Energy (LCOE) of generation technologies. Mostafa et al. emphasize that LCOS quantifies the discounted cost per unit of discharged electricity, incorporating all relevant technical and economic parameters, which makes it a vital tool for stakeholders in the energy sector (Mostafa et al., 2020) This metric is particularly useful in the context of renewable energy integration, where the intermittency of sources like solar and wind necessitates reliable storage solutions (Schmidt et al., 2019)). Recent studies have highlighted the diverse range of energy storage technologies available, including batteries, pumped hydro, and emerging options like hydrogen-bromine flow batteries. For instance, the hydrogen-bromine flow battery is noted for its high power density and potential for large-scale applications, which could significantly enhance the economic viability of renewable energy systems (Hugo et al., 2020) Furthermore, Zhang et al. present a novel gravity-enhanced compressed air energy storage system, which eliminates reliance on fossil fuels and offers a promising alternative for long-duration energy storage, thereby contributing to the economic analysis of energy storage systems (Zhang et al., 2022). The economic feasibility of energy storage systems is also influenced by external factors such as market dynamics and policy frameworks. For example, Zhao discusses the impact of subsidy policies on the economic analysis of photovoltaic energy storage integration in China, illustrating how financial incentives can alter the cost-benefit landscape for energy storage projects (Zhao et al., 2024)Similarly, the work of Li et al. highlights the importance of considering externalities in the economic evaluation of battery systems, suggesting that incorporating such factors can significantly enhance their perceived economic value (X. Li et al., 2018)

Similarly, study conducted by (Chadly et al., 2023) calculated LCOS for Green office building in USA leaving a gap for residential building

2.2 Research GAP

In a study conducted by (Chadly et al., 2023), the researchers used Monte Carlo simulation to conduct an uncertainty analysis on the Levelized Cost of Storage (LCOS) for various ESS in commercial building.

2.3 Research Question

- What role does (UBEM) play in optimizing the integration of ESS in green residential buildings?
- What is the impact of demand uncertainty in determining the economic viability of energy storage systems in green residential buildings equipped with photovoltaic (PV) technology?
- What is the cost-effective energy storage systems (ESS) for green residential buildings in the major cities of Pakistan?

CHAPTER 3: METHODOOGY

The primary objective of this research is to examine how different energy storage systems (ESS) respond to diverse load profiles and supply side parameters. Figure 1 offers a detailed description of the methodology.

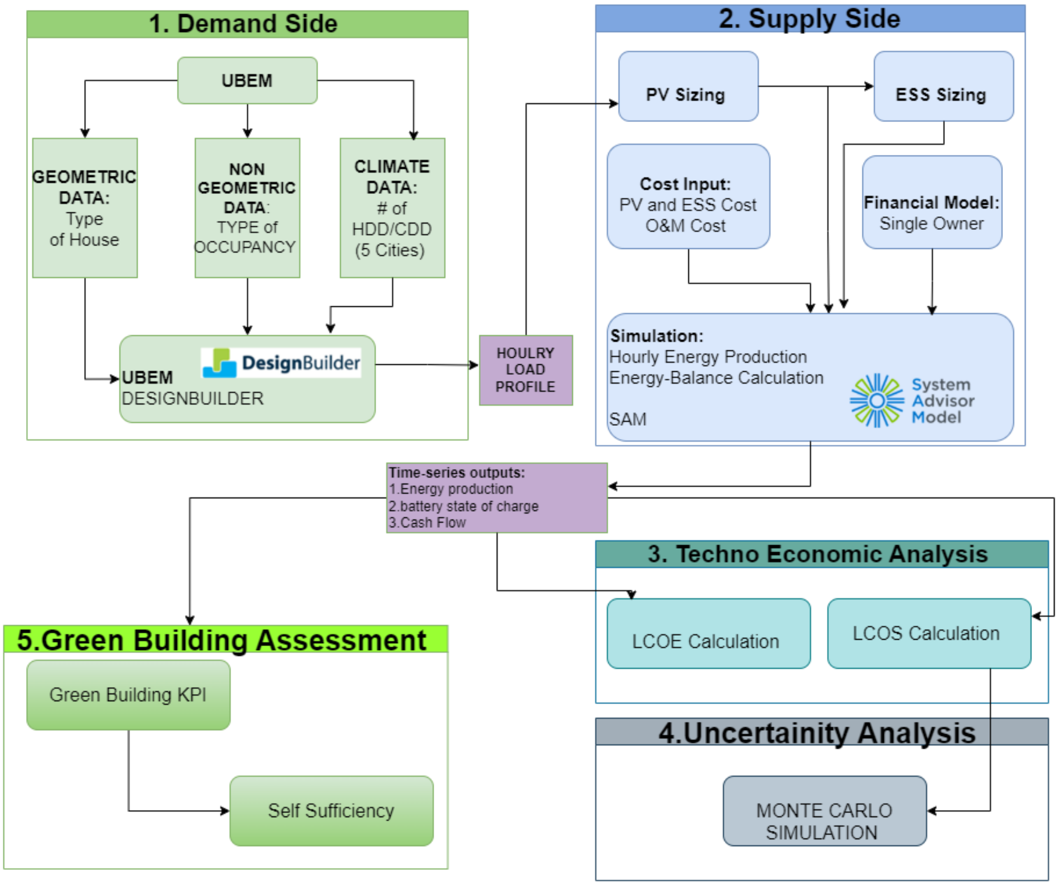

Figure 1.Methodology Framework

The research methodology employed in this study is meticulously organized and executed to ensure a comprehensive examination of energy systems within the realm of green residential buildings. This investigation deeply considers both the demand for energy within such structures and the diverse array of sources available to satisfy this need. The initial phase of the methodology involves an exhaustive evaluation of several critical factors, including the Urban Building Energy Model (UBEM), prevailing climate conditions, the architectural types of houses in question, and the levels of occupancy they experience. This phase is designed to cultivate a profound understanding of how energy demand is influenced and shaped within the context of green residential environments.

Following the detailed assessment of energy demand factors, the methodology advances to incorporate these variables into a dynamic building simulation process. This simulation is engineered to accurately replicate the patterns and behaviors of energy consumption within the buildings under study. It's a key analytical tool that allows researchers to visualize and quantify energy usage and demand with high precision.

On the supply side of the equation, the research delves into the precise sizing of photovoltaic (PV) systems and energy storage systems (ESS) that are optimal for meeting the calculated energy demands of the buildings. This involves a careful consideration of the capacity and efficiency of these systems to ensure that they can provide a reliable and sustainable energy supply.

To complement the technical analysis of energy demand and supply, the methodology incorporates a techno-economic analysis segment. This part of the research is crucial for calculating the Levelized Cost of Energy (LCOE) and the Levelized Cost of Storage (LCOS). These metrics are instrumental in assessing the economic feasibility and performance efficiency of the implemented energy systems. By evaluating the costs associated with energy production and storage over their operational lifetimes, the study aims to draw meaningful conclusions about their value proposition and sustainability.

Furthermore, to assess the Green Building status of the residential building, a key performance indicator (KPI) was developed, and all the buildings were evaluated based on it.

Finally, acknowledging the inherent uncertainties that can affect energy systems, the methodology includes an uncertainty analysis conducted through Monte Carlo simulations. This analysis is designed to test the reliability of the research results under a wide range of varying conditions. It's a pivotal aspect of the study, offering valuable insights into the resilience and viability of employing energy storage solutions in green residential buildings. Through this comprehensive research methodology, the study aspires to contribute significantly to the body of knowledge on sustainable energy solutions for residential living spaces, thereby promoting environmental stewardship and energy efficiency.

Throughout this research, a multitude of sophisticated software tools are leveraged to undertake various stages of the analysis. This meticulous approach ensures a comprehensive and in-depth evaluation of energy systems tailored to meet the specific requirements of green residential buildings. Figure 2 shows the details of the software being used.

Table 1. Methodology Tools

#	PROCESS	SOFTWARE
1	Floor Plan	REVIT
2	2d Model	
3	3d model	
4	Hourly Load profile	Design Builder
5	Load demand	
6	Solar system & ESS Simulation	SAM
8	Data for LCOE &LCOS	
9	Uncertainty Process	Microsoft Excel

<u>Revit:</u>

To develop the 2D and 3D models for our research, we relied on Revit, a Building Information Modeling (BIM) software. It allowed for the precise development of detailed architectural plans and comprehensive 3D models (Kumar et al., 2022) In order to communicate building information from design software to energy analysis tools, Energy analysis and simulation depend on the gbXML format .(Rostamiasl & Jrade, 2024)

<u>Design Builder</u>

In my Building Energy Modeling process, I rely on DesignBuilder software, an advanced tool that integrates with EnergyPlus, the industry standard for building energy simulation. DesignBuilder provides a comprehensive suite for modeling various aspects of building performance and has been widely used in academic research studies, including those by (Johari et al., 2020; Malhotra et al., 2022)

3.1 Demand side Setting

In our research efforts focusing on the demand-side setting, we employed the Urban Building Energy Model (UBEM) as a sophisticated tool to meticulously ascertain the hourly load profiles across a diverse array of residential architectures. This comprehensive analysis spanned across three distinct categories based on house sizes, thereby ensuring a broad spectrum of data representation. Furthermore, the study was geographically expansive, incorporating five different cities to account for variable climatic and socio-economic factors influencing energy consumption patterns. Additionally, variability in household occupancy was meticulously accounted for, with three different occupancy levels being investigated. This multi-dimensional approach facilitated a more nuanced understanding of energy demands, contributing significantly to the body of knowledge in energy management and sustainable urban planning.

3.1.1 Floor Plan and Covered Area

The foundational data for plot and building dimensions utilized in the research were derived from the "Islamabad Capital Residential Sector Zoning and Building Control Regulations," as issued by the Capital Development Authority in 1993. This critical documentation afforded a meticulous and precise framework of sizing pertinent to the construction of realistic urban area building models within the context of Pakistan. The dimensions extracted from these regulations were methodically incorporated into the architectural Revit software models, thereby assuring that the models accurately mirrored the architectural norms and specifications prevalent in Islamabad.

For the purpose of the research, three distinct models of houses were developed. The classification of these models is based on their covered area, represented in square feet (sq ft). The smallest model, designated as the "Small House," encompasses a total covered area of 2,090 sq ft. Progressing in size, the "Medium House" model exhibits a significantly larger footprint, with a covered area of 3,507 sq ft. The largest of the models, aptly referred to as the "Large House," spans an extensive area of 5,743 sq ft. This delineation of house models by size facilitates a structured approach to analyzing the varying impacts of architectural dimensions on the study's outcomes.

Upon the successful incorporation and validation of these dimensions, the model established for Islamabad served as a blueprint. This blueprint was subsequently adapted and applied with consistency across all the additional cities encompassed by the study. This methodical approach not only ensured a standardized protocol in the analytical phase but also facilitated a robust comparative analysis. Such an analysis was instrumental in assessing variations in energy performance, taking into consideration the diverse geographical and climatological conditions encountered across the different urban locales under investigation. This approach underscored the study's commitment to generating findings that are both comprehensive and universally applicable within the studied regions, thereby contributing valuable insights into the field of urban planning and sustainable building practices.

3.1.2 2d and 3d model:

To develop the 2D and 3D models for our research, we relied on Autodesk Revit's robust capabilities. This software proved to be invaluable for creating precise architectural models and detailed designs. Our process commenced by drawing inspiration from the floor plans of two previous studies (Malik & Hassan, 2019)(Anwar et al., 2021), which provided a solid foundation for constructing accurate models.

Once the 2D models had been established, our next crucial step involved transitioning these designs into 3D models. Leveraging Revit's advanced modeling features, we were able to create comprehensive 3D representations of the buildings. These 3D models were not only instrumental in visualizing the architectural design but also played a key role in conducting further simulations related to energy consumption and system integration within the building. The synergy between precise 2D and 3D models enabled us to conduct thorough analysis and make informed decisions throughout the research process.

Figure 2(Small House), figure 3(Medium House) and Figure 4(Large House) shows the floor plans each house. While figure 5, figure6 and figure 7 shows the 3d model of all 3 houses.

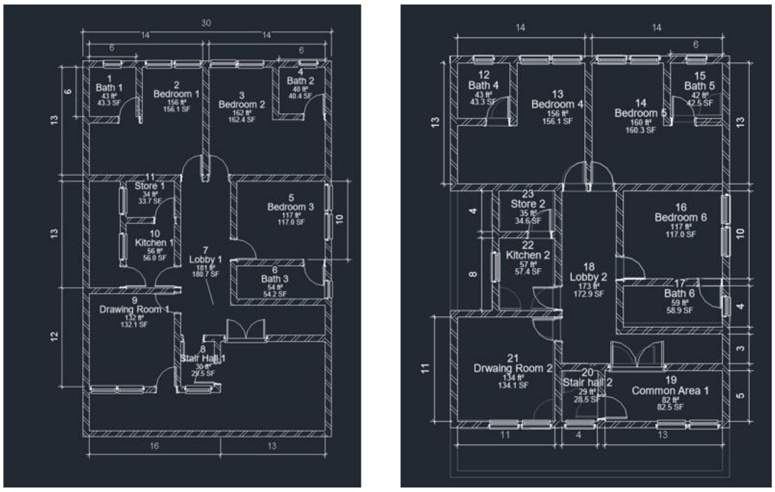

Figure 2.Small House Floor Plan

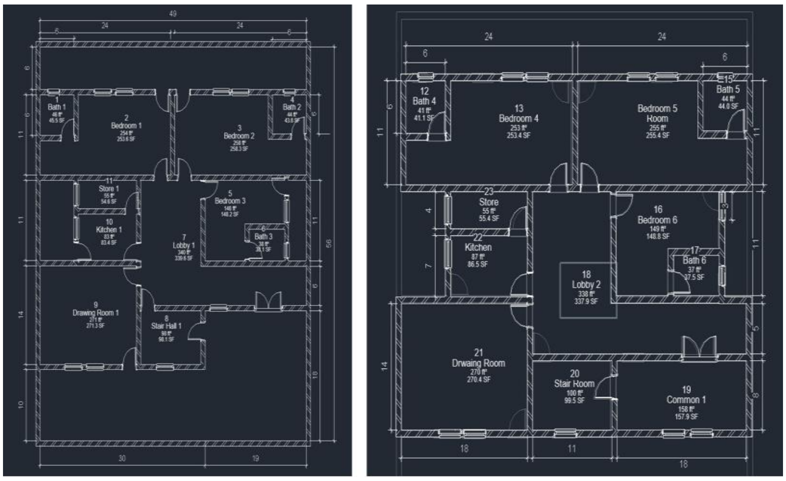

Figure 3.Medium House Floor Plan

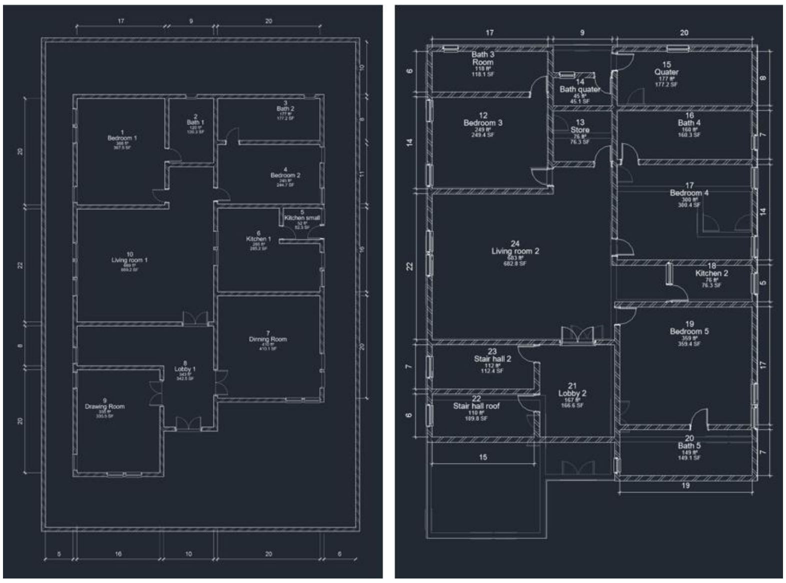

Figure 4.Large House Floor Plan

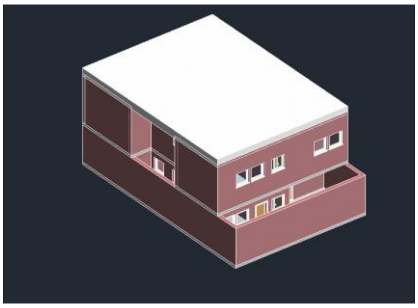

Figure 5.Small House 3d Model

Figure 6..Medium House 3d Model

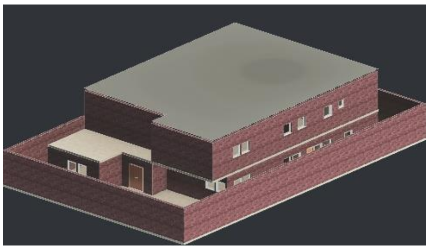

Figure 7.Large House 3d Model

3.1.3 Exporting GBXML file from Revit to BEM software

In the research process, after developing 2D and 3D models of residential buildings in Autodesk Revit, the next step was to export these models for use in Building Energy Modeling (BEM). Revit allows for the export of models in the Green Building XML (gbXML) format, which is widely accepted for transferring building information from design software to energy analysis tools. This export-import process is crucial as it ensures that the complex geometry and detailed information from the Revit model are accurately transferred to the BEM software. This integration is essential for performing reliable and detailed energy simulations, which are crucial for evaluating the energy efficiency of the building design and optimizing energy usage strategies.

3.1.4 Selecting cities based on HDD and CDD days

This study's formulation employed a meticulous method for selecting cities, predominantly based on Heating Degree Days (HDD) and Cooling Degree Days (CDD) metrics. These metrics are indispensable in comprehending a building's climatic-related energy requirements. They deftly quantify the extent of heating or cooling required to sustain optimal indoor temperature levels. The cities under consideration were systematically categorized into four discrete groups, contingent upon their HDD and CDD ranges as delineated in the study.(Amber et al., 2018)

Subsequently, from each of these quartiles, a quintet of cities was judiciously chosen to encapsulate the diverse climatic conditions prevalent across the nation. This curated selection aimed to enfold a broad spectrum of thermal requisites, ranging from zones necessitating heightened heating to locales demanding considerable cooling. The carefully chosen cities from the groups include **Islamabad, Quetta, Murree, and Sibi**. In addition to these selections, **Karachi** was included as an exceptional case owing to its distinctive geographical position near the coast. Coastal cities, by virtue of their location, often exhibit climatic characteristics distinct from those of inland areas, thereby justifying Karachi's inclusion for a nuanced assessment of how coastal proximity impacts energy consumption patterns and system performance within buildings.

This scrupulously strategic selection of cities furnishes a holistic foundation for the evaluation of the techno-economic performance of varied energy systems across distinct climatic zones. It guarantees that the outcomes of the study are not only extensively applicable but also accurately reflective of the wide-ranging conditions dispersed across the country, thereby enhancing the generalizability and reliability of the study's findings.

3.1.5 Selecting Weather Files

To accurately analyze the energy performance of buildings based on their Cooling Degree Days (CDD) and Heating Degree Days (HDD), the research began by selecting cities. The next crucial step was to obtain precise weather data for these locations. Weather files are essential for Building Energy Modeling (BEM) as they provide critical climatic conditions such as temperature, humidity, solar radiation, and wind speed.

To acquire these weather files, the Ladybug Tools online platform was used. Ladybug Tools is a suite of free and open-source applications that support environmental design and analysis, including the generation and processing of weather data for energy modeling.

Here are the steps followed for selecting weather files:

1. Accessing Ladybug Tools: The Ladybug Tools online platform was accessed to search for and download the appropriate weather files for each selected city. This tool is widely recognized for its extensive database of weather files derived from reliable sources such as EnergyPlus Weather (EPW) files.

2. City-Specific Weather Data: For each city selected based on CDD and HDD categorization, the corresponding EPW file was located using Ladybug Tools. These files contain detailed hourly weather data, crucial for accurate simulation in BEM. The weather data was chosen to match the location and climatic conditions of each city, ensuring that the energy modeling reflected real-world conditions.

3. Consistency and Accuracy: Ladybug Tools was chosen for its ability to provide consistent and accurate weather data, validated in previous studies. Studies (Kamel, 2021)and (H. Lin et al., 2023) also relied on Ladybug Tools for weather files, highlighting its reliability and widespread acceptance in the field of building energy simulation.

4. Integration with BEM Software: After downloading the necessary weather files, they were integrated into the BEM software used for this research, such as DesignBuilder or EnergyPlus. This integration allowed for accurate reflection of the climate-specific energy demands of each city, crucial for assessing the performance of energy systems under different environmental conditions.

Utilizing Ladybug Tools to select and download weather files ensured accurate and representative climatic inputs for the BEM. This step was fundamental to conducting precise energy simulations, providing valuable insights into how different energy-saving strategies would perform in various climatic zones.

3.1.6 Defining 3 Types of Occupancy

In the context of the present study, a comprehensive categorization of occupancy types has been developed to elucidate the variance in energy consumption behaviors observed within residential buildings. This typology serves as a foundational element in understanding the intricate ways through which diverse household habits exert influence on the global energy footprint. This is particularly pertinent within the scope of energy-efficient architectural design and the implementation of advanced building management systems.

Category I: Low Consumption

The first category, referred to as Low Occupants, encapsulates individuals who exhibit a high degree of proactivity towards energy conservation. Characterized by their mindful approach to reducing energy intake, this demographic adopts a series of deliberate and uniform energy-saving measures. Notable practices include the integration of advanced, energy-efficient technologies—ranging from appliances to lighting solutions—and a rigorous commitment to minimizing wasteful habits. This includes actions such as consistently turning off non-essential devices and optimizing heating and cooling systems to achieve minimal energy expenditure without compromising on comfort.

Category II: Medium Consumption Occupants

Occupants falling within the medium category represent the quintessential household from an energy usage standpoint. Exhibiting a moderate engagement in energy conservation practices, these individuals navigate the delicate balance between achieving domestic comfort and maintaining an energy-efficient lifestyle. While certain energy-saving measures are employed, their application is often inconsistent, swayed by a preference for convenience or immediate comfort over long-term efficiency.

Category III: Wasteful Consumption Occupants

The third category, termed Wasteful Occupants, is characterized by a marked indifference towards energy conservation. Such occupants engage in energy consumption without restraint, showing little to no inclination towards adopting measures that could curtail energy use. Their lifestyle is marked by the indiscriminate use of high-energy appliances and technological solutions, with scant regard for energy efficiency ratings. This group's apparent disregard for energy conservation practices culminates in significantly elevated levels of energy consumption when compared to their more conservative counterparts.

The delineation of these categories affords the study a nuanced framework to model and scrutinize energy consumption patterns across varied household demographics. Insights derived from this analysis offer valuable perspectives on the potential impact of distinct behavioral patterns on the overarching energy demand and efficiency of residential buildings.

In order to better understand the differences between these types of occupants. The table provides a detailed explanation of specific behavior patterns and energy usage norms that set each type of occupant apart, offering a detailed comparison of their interactions with the residential building's energy systems. Such a detailed analysis is crucial for accurately modeling and predicting energy consumption trends. It allows for the simulation of various occupant behavior scenarios, which enhances the overall assessment of potential energy efficiency strategies.

3.1.7 Building Material

In order to accurately represent the thermal performance and energy efficiency of residential buildings in Pakistan in our Building Energy Modeling (BEM) research, it was crucial to carefully select building material properties. To achieve this, we utilized values from a study referred to as (Khan et al., 2022), which specifically examined houses in Pakistan. The study (Khan et al., 2022) provided a detailed analysis of the thermal and energy performance characteristics of common building materials used in Pakistani residential construction. It focused on materials such as bricks, concrete, insulation types, windows, and roofing materials, considering local construction practices and climatic conditions in the region.

3.1.8 Urban Building Energy Modeling (UBEM)

Urban Building Energy Modeling (UBEM) represents a critical analytical method for designing and implementing policy measures aimed at optimizing energy consumption within building stocks. This rigorous simulation technique elucidates the physical interactions and processes at the granular level of buildings or energy end-uses, engaging in what is known as the Q4 (Bottom-up/Whitebox) approach. This methodology embarks with the assimilation of model inputs, encompassing climate data, geometric information (for instance, GIS City Models), alongside non-geometric data (such as building archetypes and characteristics). These inputs are then processed through a simulation engine, deploying physics-based algorithms to project building energy utilization. To ensure reliability and real-world applicability, the simulated results are corroborated with empirical data. Upon validation, these model outcomes are visualized and scrutinized to assess energy performance across an urban canvas, thereby facilitating informed energy planning and enhancement initiatives.

In a particular strand of research, the commencement phase entailed the selection of cities and the procurement of essential weather files, followed by the initiation of the UBEM procedure via DesignBuilder—a comprehensive BEM software. This process entailed the modelling of diverse scenarios to simulate and analyze the energy performance of residential buildings under varying climatic conditions, dwelling sizes, and occupancy typologies.

The configuration of the UBEM in DesignBuilder was delineated through several steps:

Input Parameters:

Selection of five cities was based on their Cooling Degree Days (CDD) and Heating Degree Days (HDD), aiming for a broad representation of climatic zones.

Definition of three house sizes to mirror the spectrum of residential building types (small, medium, and large homes).

Establishment of three unique occupancy types (Low, Medium, and Wasteful), each characterized by distinct energy consumption patterns.

Modeling 45 Scenarios:

A synthesis of the five cities, three house sizes, and three occupancy types culminated in the modeling of 45 unique scenarios within DesignBuilder. This facilitated a comprehensive exploration of how varying conditions impact energy consumption.

Data Collection:

The temporal scope of data collection extended over four years, from 2019 to 2023, capturing fluctuations in weather patterns and other external variables influencing energy use.

To mitigate the influence of anomalies—arising from atypical weather events or irregularities—energy consumption data across these years were averaged, providing a solid analytical foundation.

Key Data Points:

The analysis encapsulated critical metrics of energy consumption within the buildings, notably peak and average values for Receptacle Loads, Lighting, and Cooling.

Analysis:

A thorough examination of data from the 45 scenarios unveiled trends and patterns in energy consumption, yielding insights into the dynamics of energy systems, the efficacy of conservation strategies, and furnishing recommendations for the optimization of energy usage in residential buildings.

In essence, the application of UBEM via DesignBuilder afforded an intricate examination of residential energy consumption across multifarious scenarios, empowering a holistic assessment of the diverse factors that modulate energy use.

3.1.9 Urban Building Energy Modeling (UBEM) Result Verification

Upon completion of the Urban Building Energy Modeling (UBEM) process, the subsequent essential step involved validating the accuracy of the simulation results. The city of Islamabad was chosen as the reference location for this validation. This process entailed comparing the modeled energy consumption data with actual electricity consumption data obtained from households in Islamabad.

Verification Process:

1. Household Selection:

For each of the three house types—small, medium, and large—20 households were meticulously selected, resulting in a comprehensive dataset of 60 data points. The selection process aimed to capture the typical energy consumption patterns across various house sizes in Islamabad.

2. Electricity Consumption Data:

The authentic electricity consumption data for these households was obtained from IESCO (Islamabad Electric Supply Company) bills, covering monthly usage. This data served as a dependable reference for comparison with the UBEM simulation results.

The dataset encompassed diverse months and seasons to account for varying weather conditions and their influence on energy consumption.

3. Comparative Analysis and Verification:

The electricity consumption data from IESCO bills was thoroughly juxtaposed with the corresponding modeled data generated from the UBEM simulations for small, medium, and large house types. This comparison was pivotal in evaluating the UBEM model's accuracy in forecasting real-world energy utilization. The scrutiny aimed to pinpoint any disparities between the modeled and actual data, indicating areas warranting potential model adjustments or refinements.

The process of result verification, utilizing actual electricity consumption data from IESCO bills, played a pivotal role in validating the UBEM model. By scrutinizing the modeled data against real-world consumption across 60 households in Islamabad, the study reaffirmed the reliability and accuracy of the simulation results. This validation process not only bolstered the credibility of the research findings but also instilled confidence in the model's relevance to other cities and scenarios examined in the study.

3.2 Supply side Setting

The supply-side settings in this research play a crucial role in determining the overall energy performance and economic viability of green residential buildings. The focus on solar photovoltaic (PV) system sizing and energy storage system (ESS) sizing is essential for understanding how these technologies can be optimized to meet the energy demands of different household scenarios modeled in the UBEM process.

3.2.1 PV System Sizing

The research emphasized the importance of properly sizing PV systems to meet the energy needs of residential buildings and to charge Energy Storage Systems (ESS) for nighttime use. The sizing was informed by insights from Study A and Study B, focusing on optimal PV system design for residential buildings.

PV System Sizing Methodology:

1. Selection of PV System Sizes:

Three types of PV system sizes were chosen to match the energy demands of small, medium, and large houses:

Small House PV System: Designed for small households, this system meets daily energy needs, charges the ESS for nighttime use, and powers daytime consumption.

Medium House PV System: Sized for medium-sized houses with moderate energy demands, this system balances energy generation and storage to power the household day and night.

Large House PV System: Selected for houses with higher energy consumption, this system generates ample power for daytime usage and fully charges a larger ESS for nighttime independence.

Meeting Daily and Nighttime Demand:

The primary criterion was for each PV system to cover the total daily demand, including daytime and nighttime usage, by calculating average and peak energy consumption for each house size, and determining the appropriate PV system capacity. Moreover, excess energy generated during the day is stored in the ESS for nighttime use, reducing or eliminating the need for grid power after sunset.

Integration with ESS:

The integration of the PV system with the ESS was crucial, ensuring that the PV systems met immediate and charging needs of the household. By fully charging the ESS by the end of the day, a consistent and reliable energy supply was maintained throughout the day and night. Details are given in the table

Table 2. Design parameters of PV System

Design Parameters For Solar System				
Parameter	Value		Unit	Note/reference
Nominal System Size	Small	9.995	KW	
	Medium	22.212		
	Large	33.318		
PV module Type	Mono -c- Si	555.3	W	
PV Module efficiency	22.30%			
Inverter DC/AC	Size	550	V	
Inverter Efficiency	97.44%			
PV Cost	47rs/wdc			Current Market (Assumed)
Inverter Cost	29.5rs/wdc			Current Market (Assumed)
O&M of PV system	2rs/w			Ahmad et al., 2023

ESS Type:

In this thesis, two widely used types of batteries are analyzed for Energy Storage Systems (ESS): Lithium-ion (Li-ion) batteries and Lead-acid flooded batteries. These two battery technologies are commonly chosen for residential energy storage systems due to their distinct advantages and suitability for different residential applications.

Lithium-Ion (Li-ion) Batteries

Lithium-ion batteries are the leading choice for residential energy storage due to their high energy density, long cycle life, and efficiency. They are well-suited for applications where space is limited and high performance is required.

Key Features:

Li-ion batteries have higher energy density and cycle life compared to lead-acid batteries, making them ideal for residential use. They also offer higher efficiency and are low-maintenance, making them user-friendly for residential applications.

Residential Applications:

Li-ion batteries are commonly used in residential settings for maximizing energy independence and efficiency, particularly in pairing with solar PV systems. Their compact size and higher energy density make them ideal for modern, space-conscious residential designs, especially in urban settings.

Lead-Acid Flooded Batteries

Overview:

Lead-acid flooded batteries are one of the oldest and most widely used types of rechargeable batteries known for their reliability, durability, and relatively low cost, making them a staple in residential energy storage.

Key Features:

Lead-acid batteries offer a cost-effective and proven technology for homeowners on a budget, with a long track record of reliable energy storage. However, they have a lower energy density than Li-ion batteries, meaning they need more space to store the same amount of energy. Additionally, they have a shorter cycle life and lower efficiency, requiring regular maintenance such as topping up with distilled water, which could be cumbersome for those looking for low-maintenance solutions.

Residential Applications:

Lead-acid flooded batteries are often used in off-grid or backup power applications in residential buildings, particularly in rural or less space-constrained environments where the cost advantage outweighs space considerations.

3.2.2 ESS System Sizing

This research endeavors to delineate the procedural methodology for sizing Energy Storage Systems (ESS) within residential buildings, ensuring a continuous and dependable energy provision during periods of diminished solar generation and grid disruptions. The sizing methodology employed herein is predicated upon the principles outlined in (Masters, 2013), which furnishes a comprehensive guideline for determining the requisite capacity of ESS for residential environments. This methodology is specifically tailored to fulfill not only the conventional nocturnal energy requirements but also to supply auxiliary power during prolonged instances of reduced solar output, such as during inclement weather or grid malfunctions.

ESS System Sizing Methodology

1. Guidance from (Masters, 2013)**:**

Study K proposes an exhaustive framework for the sizing of ESS systems, taking into account the energy consumption patterns of residential edifices. This study accentuates the significance of configuring ESS systems capable of accommodating both routine daily cycles and exigent scenarios, such as extended periods of cloudy weather or grid failures.

2. ESS Sizing for Diverse Residential Typologies:

Small House ESS: Dimensioned to reliably cater to nocturnal energy demands and provisioned with sufficient reserve capacity to sustain household operations for up to three days during grid outages or continuous cloudy conditions, thereby ensuring operational continuity absent grid reliance.

Medium House ESS: Configured with an augmented capacity commensurate with the elevated energy consumption of a medium-sized household, this system similarly assures three days of standby power, thereby guaranteeing uninterrupted energy usage amidst adverse meteorological conditions or grid failures.

Large House ESS: For residences with substantial energy requisites, the ESS is dimensioned to provision a significant energy cache, designed not just to fulfill regular night-time energy needs but also to support household operations for up to three days during scenarios of inadequate solar generation or grid disruptions.

Considerations for Nighttime and Emergency Power:

The quintessential role of the ESS entails the storage of surplus energy harnessed by the photovoltaic (PV) system during daylight hours, subsequently availed during nocturnal periods when solar power is unattainable. This cyclical charging and discharging process is pivotal in minimizing grid dependency and optimizing the utilization of renewable energy resources. Additionally, the ESS was designed with enough capacity to handle emergency situations. By ensuring that the ESS could power the household for up to three days without any input from the solar PV system, the research aimed to create a robust energy solution that could withstand unpredictable weather patterns and potential grid failures.

Design specification for ESS system is given in the table

Table 3. Design parameters for Energy

Design Parameters For Battery System					
Parameter	LI Ion		Lead Acid Flooded		Note
Nominal System Size KWH	Small	38	Small	38	KWH
	Medium	91	Medium	91	
	Large	151	Large	151	
Amount	69,791rs /Kwh		25,925rs/kwh		Current Market (Assumed)
Battery O&M Cost			2,502 PKR/kwh/year		Kebede et al., 2021

3.3 Economic Analysis

In this research, the economic analysis played a crucial role in evaluating the financial feasibility of the proposed energy systems for residential buildings. The analysis focused on calculating two important metrics: the Levelized Cost of Energy (LCOE) and the Levelized Cost of Storage (LCOS). These metrics provide a comprehensive understanding of the long-term cost-effectiveness of the solar photovoltaic (PV) systems and the Energy Storage Systems (ESS), respectively. The calculations were based on data from the System Advisor Model (SAM), a sophisticated tool widely used for analyzing renewable energy projects.

Economic Analysis Overview:

System Advisor Model (SAM) as the Analytical Tool:

SAM was used for the economic analysis due to its robust capabilities in modeling the financial performance of renewable energy systems. SAM allows for the detailed simulation of both the technical performance and the economic implications of energy projects, making it an ideal tool for this research.

The input data for SAM included the specifications of the PV systems and ESS that were sized for small, medium, and large houses, as well as financial parameters such as capital costs, operation and maintenance costs, discount rates, and project lifetimes.

Calculation of Levelized Cost of Energy (LCOE):

Definition: LCOE represents the average cost per unit of electricity generated by the PV system over its lifetime. It is a critical metric for comparing the cost-effectiveness of different energy generation options.

Data Inputs: The LCOE calculation in SAM used inputs such as the total installed cost of the PV system, annual energy production, operation and maintenance costs, and the expected system lifetime. SAM also factored in the degradation of the PV system's efficiency over time.

Calculation Process: Using the data, SAM calculated the LCOE by dividing the total lifecycle costs of the PV system by the total energy generated over its lifetime. This provided a single value that represents the cost of generating each kilowatt-hour (kWh) of electricity, making it easier to compare with other energy sources or scenarios.

Analysis**:** The LCOE results were analyzed to assess the cost-effectiveness of the PV systems across the different house sizes. This analysis helped determine whether the investment in solar energy would be economically viable under various scenarios, including different geographic locations and energy consumption patterns.

Calculation of Levelized Cost of Storage (LCOS):

Definition: LCOS measures the cost per unit of electricity that is stored and later discharged by the ESS over its operational lifetime. It is crucial for evaluating the financial feasibility of energy storage solutions.

Data Inputs: The LCOS calculation incorporated data such as the initial cost of the ESS, battery replacement costs (if applicable), operation and maintenance expenses, and the total energy throughput (the total amount of energy stored and later used) over the system's lifetime.

Calculation Process: SAM calculated the LCOS by dividing the total lifecycle costs associated with the ESS by the total energy discharged by the system over its lifetime. This provided a clear indication of the cost-effectiveness of storing energy for later use, which is particularly important in scenarios where energy storage is critical for ensuring a reliable power supply.

Analysis: The LCOS was analyzed to understand the financial implications of using ESS in conjunction with PV systems. The results were compared across the different house sizes and scenarios to identify the most cost-effective storage solutions.

Conclusion:

The economic analysis conducted using SAM provided critical insights into the financial viability of integrating solar PV and ESS systems in residential buildings. By calculating the LCOE and LCOS, the research was able to quantify the long-term cost-effectiveness of these energy systems, taking into account both the generation and storage of electricity. The analysis not only demonstrated the potential economic benefits of renewable energy adoption but also highlighted the importance of optimizing system design to achieve cost-effective solutions. The findings from this analysis are essential for guiding policy decisions, investment strategies, and future research in the field of residential energy systems.

3.4 Uncertainty Analysis

In this research, we used a Monte Carlo simulation to conduct a detailed uncertainty analysis, specifically focusing on how variations in supply-side parameters could influence the Levelized Cost of Storage (LCOS). Why Monte Carlo Simulation?

High Accuracy through Large-Scale Simulations

Monte Carlo simulation is known for its ability to perform large-scale simulations that incorporate thousands or even millions of iterations. This capability allows for a comprehensive exploration of how different variables and their uncertainties can impact the final outcomes. In this research, the simulation was used to model the potential fluctuations in key supply-side parameters and assess their combined effects on LCOS.

Real-World Application and Acceptance

Monte Carlo simulation is widely accepted and used in various fields, including energy economics, finance, and risk management, due to its robustness and versatility. Its real-world applicability makes it an ideal choice for analyzing the economic performance of energy storage systems in residential buildings, where multiple uncertainties can significantly influence costs.

Parameters Considered in the Simulation

The Monte Carlo simulation focused on several key supply-side parameters critical to the calculation of LCOS. These parameters were chosen because of their potential variability and significant impact on the overall cost-effectiveness of the ESS:

1. Battery Cost:

The simulation modeled variations in the cost of batteries, including potential increases or decreases in the rate at which battery prices change over time. This factor is crucial as battery costs are a major component of the total cost of energy storage systems.

2. Operation and Maintenance (O&M) Costs:

The simulation accounted for potential fluctuations in O&M costs, which can vary due to factors such as inflation, technological advancements, or unexpected maintenance needs. Changes in these costs directly affect the long-term financial sustainability of the ESS.

3. Grid Electricity Purchase Cost:

The simulation also considered the cost of purchasing electricity from the grid, including both increases and decreases in unit rates. Since the ESS may be used to store grid electricity during off-peak times, changes in grid electricity prices can significantly impact the economic performance of the ESS.

4. End-of-Life/Battery Replacement Costs:

The simulation also considered the costs associated with battery replacement at the end of their operational life. This factor is critical for long-term economic analysis, as replacement costs can vary based on market conditions and advancements in battery technology.

Table 4. Parameter Details

Parameters Uncertainty			
#	Parameter	Low	High
1	Battery Cost increase AND dec	-30%	30%
2	OM cost	-30%	30%
3	Grid Electricity purchase increase and decrease on unit rate	-30%	30%
4	END of life/ Battery Replacement cost	-30%	30%

Approach to Monte Carlo Simulation

The Monte Carlo simulation used a normal distribution to model the variations in each of the above parameters. This approach provided a statistical framework to understand how fluctuations in these parameters could influence the LCOS.

In addition to the normal distribution, other types of Monte Carlo simulations were considered, including: **Beta Distribution:** Useful for modeling variables that have a natural minimum and maximum, such as efficiency rates or cost percentages. **Triangular Distribution:** Often used when only limited data is available, representing the minimum, most likely, and maximum values. **Lognormal Distribution:** Applied to variables that are positively skewed, such as financial costs, which cannot fall below zero but can rise significantly. These alternative distributions provided additional insights into how different forms of uncertainty might affect the economic analysis.

Other Uncertainty Techniques

In addition to Monte Carlo simulation, other uncertainty approaches were explored to provide a comprehensive analysis:

1. Aleatory (Stochastic) Uncertainty Approaches:

These approaches focus on inherent randomness in the system, modeling uncertainties that arise from natural variability, such as weather conditions affecting solar generation.

2. Epistemic (Systematic) Uncertainty Approaches:

Epistemic uncertainty deals with uncertainties due to a lack of knowledge or data. This approach was considered to address uncertainties related to technological advancements or future market conditions that are not yet well understood.

3. Scenario-Based Approaches:

This approach involves creating different scenarios based on varying assumptions about future conditions (e.g., best-case, worst-case, and most likely scenarios). Scenario-based analysis provided additional context for the Monte Carlo results by exploring how different future states could impact the LCOS.

The Monte Carlo simulation provided a thorough analysis of how uncertainties in supply-side parameters affect the LCOS in residential energy storage systems. By factoring in variations in key cost parameters using different types of distributions, the study accurately modeled the potential range of outcomes. The findings from this analysis are important for understanding the economic risks and opportunities linked to the deployment of energy storage systems. Ultimately, this contributes to more informed decision-making in the design and implementation of residential energy solutions.

3.5 Green Building Assessment

By emphasizing how much of a building's energy demand is met by on-site renewable sources, SS reflects a building’s ability to operate with minimal reliance on external power sources. This is crucial for sustainable development, as it aligns with reducing environmental impact, enhancing energy security, and achieving cost savings over time.

Detailed Aspects of Self-Sufficiency in Green Buildings

Understanding the SS Metric:

Definition: Self-Sufficiency (SS) is the ratio of energy demand met by on-site renewable sources, such as PV panels and battery storage, in relation to the total electricity demand of the building.

Calculation Formula:

Equation 1 shows the equation used to calculate the Self Sufficiency of the system.

Equation 1.Self Sufficiency

$$\boldsymbol{Self\ Sufficency} = (\text{Total Conspumtion} - \text{Import})/\text{Total Conspumtion}$$

(Kumar et al., 2022)

Interpretation: A higher SS percentage indicates greater independence from the grid. For instance, an SS of 80% means that 80% of the building's total energy demand is supplied through on-site renewable energy, while only 20% is imported from external sources.

Components Influencing Self-Sufficiency:

Photovoltaic (PV) Generation: The primary source of renewable energy in many green buildings, PV panels convert solar energy into electricity. The size, efficiency, and orientation of PV installations significantly impact the SS rate.

Battery Storage: Energy storage is crucial to ensure self-sufficiency, especially in areas where solar energy may not be consistently available throughout the day. Batteries store surplus energy produced during peak solar hours, enabling the building to use this stored power when demand is high or solar generation is low.

Demand Management: Efficient energy use through demand-side management strategies, such as load shifting and peak shaving, can help increase SS by aligning energy use with the availability of renewable energy. This is especially relevant in buildings with fluctuating energy needs.

CHAPTER 4: RESULTS AND ANALYSIS

This section of the findings explores the demand for green buildings, the supply of green buildings, and the verification processes associated with green buildings. I examine the technological and economic feasibility of green buildings, along with the uncertainties that this study presents. This section initiates with an overview of the Demand Side Analysis, subsequently leading to the introduction of composite data that integrates key performance metrics to emphasize demand trends. The hourly results reveal load swings and patterns that are crucial for accurately characterizing demand. Findings derived from the Building Energy Model (BEM) Verification is a key factor that enhances the trustworthiness of conclusions, ensuring that the model accurately represents real-world scenarios. The Supply Side Analysis provides a concise overview of the inputs and outputs related to energy sources and efficiency. This is achieved by employing composite data. The Levelized Cost of Energy (LCOE) is a calculation conducted through Techno-Economic Evaluation to determine the cost-effectiveness of energy generation. Furthermore, the Levelized Cost of Storage (LCOS) is calculated to determine the financial implications that energy storage has on supply and demand during the evaluation process using this approach. Additionally, the Uncertainty Analysis serves to reduce the effects of substantial parameter fluctuations, thereby enhancing the results of the study. In summary, this represents an important advancement. This structured approach aims to deliver a comprehensive insight into energy dynamics and the feasibility of systems. The approach focuses specifically on sustainable energy solutions that align with Sustainable Development Goal 7. The utilization of the SS KPI has been demonstrated as a means to validate green building practices.

4.1 Demand Side

A simulation-based assessment of the residential space energy consumption in five different cities in Pakistan, namely Islamabad, Karachi, Quetta, Murree, and Sibi, was conducted over the course of one year. The results gained from this assessment were presented. There are nine different scenarios that are used to measure the energy usage. These scenarios combine three different sizes of houses with three different forms of occupancy. A summary of the annual energy usage in five different cities is presented in Figure.8. In this case, each column shows the combined amount of energy that the medium archetype house consumes (with blue representing HVAC load, yellow representing lighting load, and red representing equipment load). The dot in green symbolizes the amount of energy that is consumed by the large archetype, while the dot in black shows the amount of energy that is consumed by the small archetype.

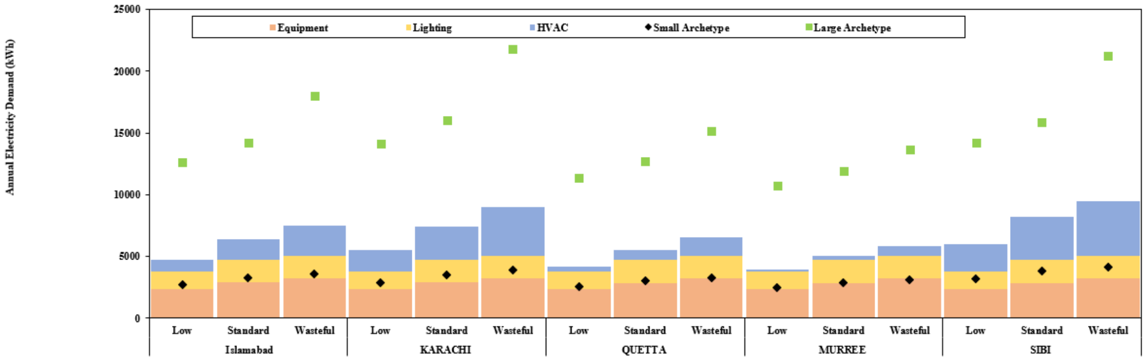

Figure 8. Annual Electricity Demand

Table 5. Annual Energy Consumption by each Archetype

Demand Breakdown		Equipment	Lighting	HVAC
Islamabad	Low	2345.5	1461.5	954.6
	Standard	2874.6	1859.6	1632.8
	Wasteful	3195.7	1859.6	2475.4
KARACHI	Low	2345.5	1461.5	1683.1
	Standard	2874.6	1858.7	2722.1
	Wasteful	3195.7	1858.7	3950.9
QUETTA	Low	2345.5	1452.3	351.3
	Standard	2869.6	1852.3	809.2
	Wasteful	3190.2	1852.3	1484.6
MURREE	Low	2345.5	1461.0	96.1
	Standard	2869.6	1852.0	306.3
	Wasteful	3190.2	1852.0	826.0
SIBI	Low	2345.5	1454.5	2163.1
	Standard	2873.1	1851.4	3473.0
	Wasteful	3194.0	1851.4	4452.8

HVAC Systems:

The energy consumption patterns in Karachi, Quetta, Murree, Sibi, and Islamabad exhibit unique characteristics shaped by the specific climatic conditions and lifestyle choices prevalent in each location. A significant share of energy consumption across various urban areas can be linked to HVAC systems, particularly in cities with warmer climates. The data indicates that Karachi and Sibi experience elevated temperatures compared to other cities, leading to a significantly higher energy consumption by the HVAC systems in residences, as illustrated in figure 8.

An analysis of the LARGE archetype and wasteful occupancy across all five cities reveals that Karachi and Sibi exhibit the highest energy consumption, primarily attributed to the energy utilized by HVAC systems. In contrast, the city of Islamabad experiences a moderate temperature, which contributes to its moderate energy consumption. Upon further examination of Table 5 and Figure 1, it is evident that the cities of Quetta and Murree experience lower temperatures, resulting in significantly reduced energy consumption in these areas.

Lighting and Equipment: While essential, these two categories (represented in gray and blue) are relatively stable across the cities and categories, showing less variability compared to HVAC.

4.1.1 City Wise Breakdown of Energy Consumption

For more clearly understand how each city is different in term of energy consumption we will disc each city.

Islamabad Figure 9 and Table 6

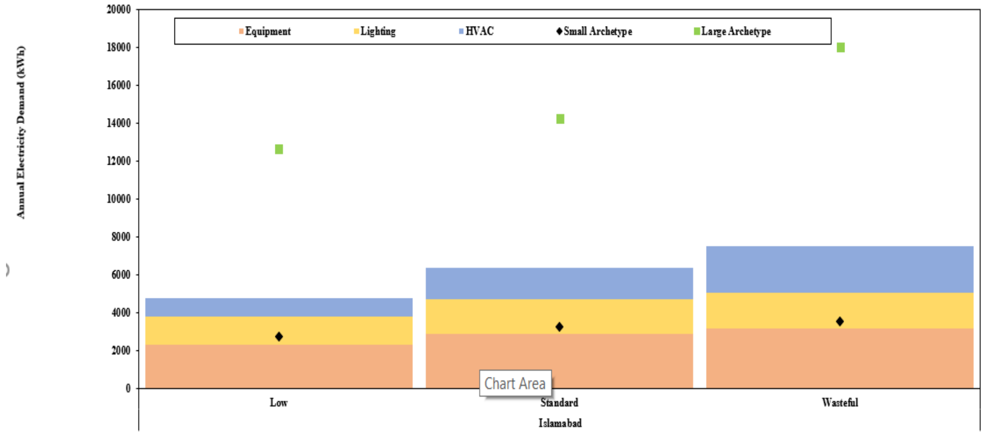

Figure 9. Annual Electric Demand in city of Islamabad

Table 6. Annual Electric Demand in city of Islamabad

Medium (Yearly)	Islamabad		
	Low	Standard	Wasteful
TOTAL ELECTRICITY (kWh)	4761.5536	6367.0609	7530.7483
Equipment	2345.4917	2874.6177	3195.7342
Lighting	1461.49379	1859.6438	1859.6438
HVAC	954.567971	1632.79912	2475.37035
Small Archetype	2741.3886	3253.5112	3572.2159
Large Archetype	12648.4049	14249.3931	18046.2944

Figure 9 shows details about the energy demand for the city of Islamabad and table 4 shows the energy consumption breakdown of each type of load for the Medium Archetype.

HVAC demand increases steadily from Low to Wasteful, though not as extreme as in other cities. Equipment and lighting usage remain stable but increase slightly in the Wasteful category. Improving HVAC and equipment efficiency, especially in Wasteful archetypes, could lead to significant energy savings.

Karachi

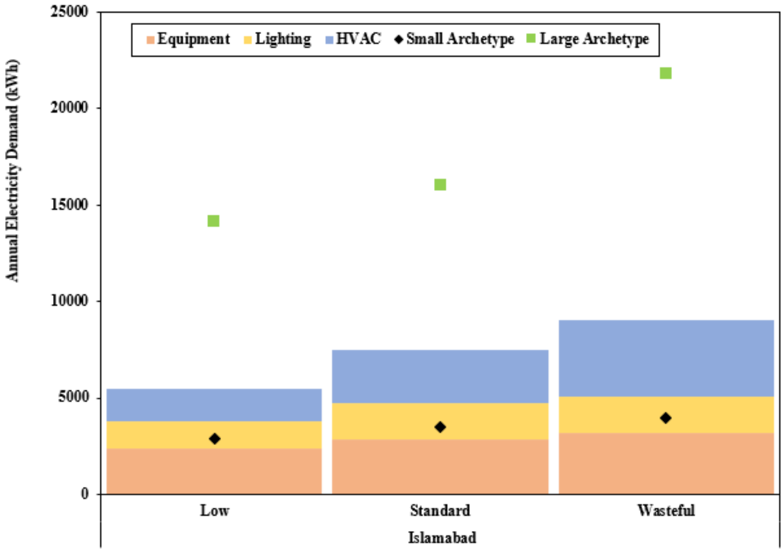

Figure 10 Annual Electric Demand in city of Karachi

Table 7. Annual Electric Demand in city of Karachi

Medium (Yearly)	KARACHI		
	Low	Standard	Wasteful
TOTAL ELECTRICITY (kWh)	5756.6178	7455.402	9005.3586
Equipment	2345.4917	2874.6177	3195.7342
Lighting	1461.53786	1858.6838	1858.6838
HVAC	1683.114005	2722.10019	3950.94083
Small Archetype	2876.7835	3509.5648	3930.2441
Large Archetype	14154.4116	16025.9528	21837.3658

Figure 10 shows details about the energy demand for the city of Karachi and table 7 shows the energy consumption breakdown of each type of load for the Medium Archetype.

Karachi's warm climate drives significant cooling demand, especially in inefficient buildings. HVAC accounts for a substantial portion of energy consumption, with a sharp rise from Low to Wasteful categories. Reducing HVAC energy use through more efficient cooling systems would have a major impact. Equipment and lighting also increase but are secondary to HVAC concerns.

Quetta

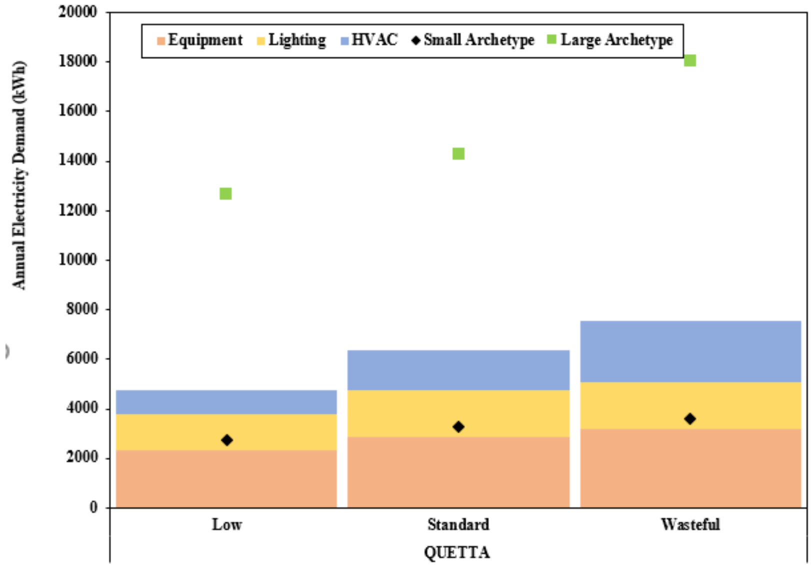

Figure 11.Annual Electric Demand in city of Quetta

Table 8Annual Electric Demand in city of Quetta

Medium (Yearly)	QUETTA		
	Low	Standard	Wasteful
TOTAL ELECTRICITY (kWh)	4761.5536	6367.0609	7530.7483
Equipment	2345.4917	2874.6177	3195.7342
Lighting	1461.49379	1859.6438	1859.6438
HVAC	954.567971	1632.79912	2475.37035
Small Archetype	2741.3886	3253.5112	3572.2159
Large Archetype	12648.4049	14249.3931	18046.2944

Figure 11 shows details about the energy demand for the city of Quetta and table 8 shows the energy consumption breakdown of each type of load for the Medium Archetype.

HVAC demand is steady across all categories and HVAC demand is less extreme compared to Karachi or Sibi. Equipment and lighting demand remain relatively low but rise incrementally as building size increase and occupancy level changes from low to wasteful.

Murree

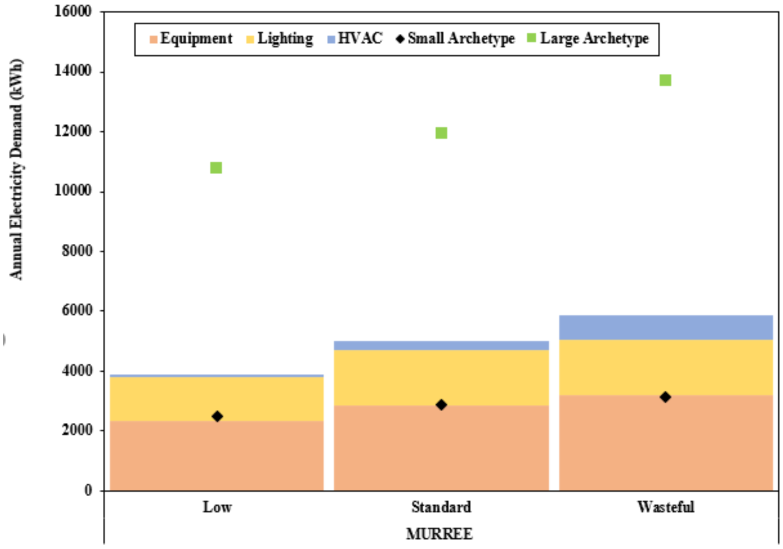

Figure 12.Annual Electric Demand in city of Murree

Table 9.Annual Electric Demand in city of Murree

Medium (Yearly)	MURREE		
	Low	Standard	Wasteful
TOTAL ELECTRICITY (kWh)	3902.5089	5027.92473	5868.22778
Equipment	2345.4917	2869.64127	3190.16815
Lighting	1460.96299	1852.01335	1852.01335
HVAC	96.053863	306.269732	826.046196
Small Archetype	2485.9289	2897.4767	3135.4827
Large Archetype	10778.4662	11929.2565	13705.1908

Figure 12 shows details about the energy demand for the city of Murree and table 9 shows the energy consumption breakdown of each type of load for the Medium Archetype.

Due to its cooler climate, HVAC demand in Murree is lower compared to warmer cities. However, Wasteful buildings still show an increase in energy consumption, largely due to inefficient heating systems. Equipment and lighting consumption are stable and less impactful. Targeted improvements in HVAC efficiency could yield benefits.

SIBI

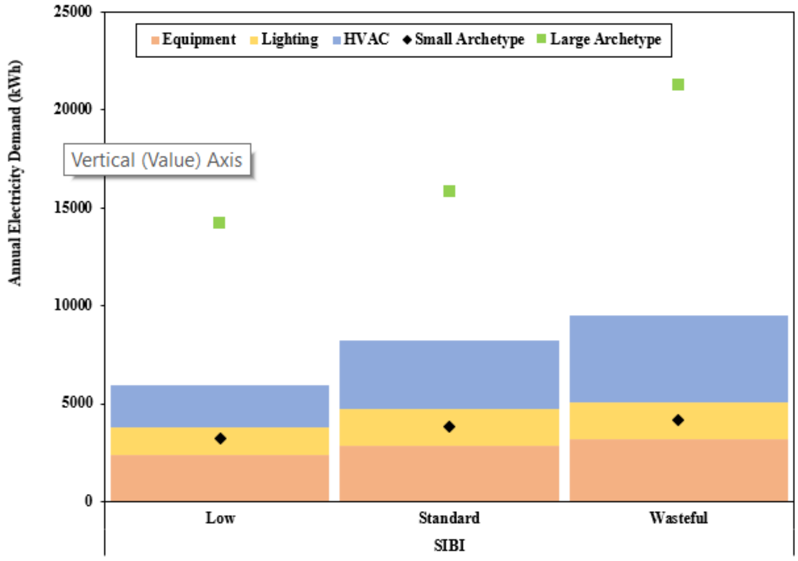

Figure 13. Annual Electric Demand in city of Sibi

Table 10.Annual Electric Demand in city of Sibi

Medium (Yearly)	SIBI		
	Low	Standard	Wasteful
TOTAL ELECTRICITY (kWh)	5963.1486	8197.4922	9498.16716
Equipment	2345.4917	2873.11908	3193.99524
Lighting	1454.51283	1851.3828	1851.3828
HVAC	2163.143738	3472.99012	4452.78894
Small Archetype	3214.8723	3820.2824	4139.5544
Large Archetype	14237.1536	15845.4174	21290.6984

Figure 13 shows details about the energy demand for the city of Sibi and table 10 shows the energy consumption breakdown of each type of load for the Medium Archetype.

Sibi's hot and dry climate leads to very high cooling demand, especially in the Wasteful category. HVAC is the dominant energy consumer, and large-scale inefficiency in cooling systems represents a major opportunity for energy savings. Equipment and lighting consumption also increase from Low to Wasteful, but HVAC remains the key area of concern.

4.1.2 Hourly Load Profiles

An hourly load graph for electrical data represents the demand for electricity or power usage at each hour over a day. This graph is useful for analyzing consumption patterns, identifying peak demand hours, and understanding load fluctuations, which is essential in planning for energy supply and optimizing energy use. For better comparison and understanding we will review the hourly load demand of each archetype of home separately.

Small Archetype Load Profile

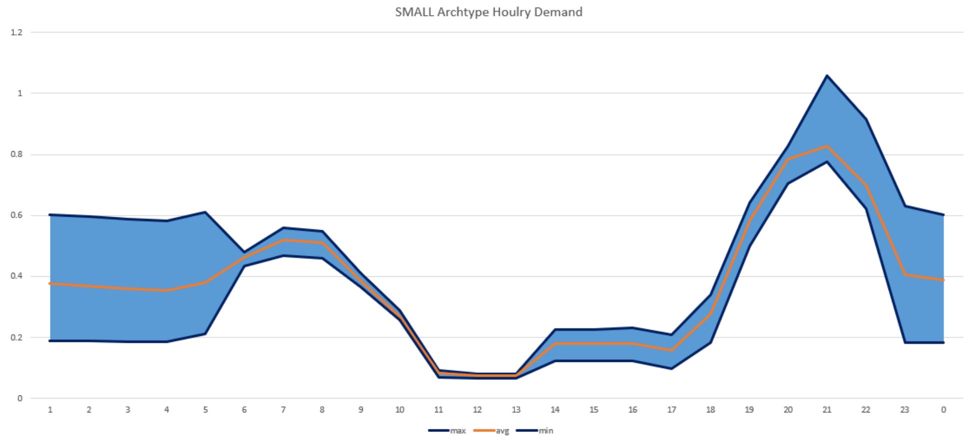

Figure 14. Small Archetype Hourly Load Profile

Figure 14 shows the hourly load profile for small archetype of house.

Low Occupancy:

The load profile in the Low occupancy category shows a **steady, low baseline demand** throughout the day for most cities, with a notable **increase in demand during the evening hours (18:00 to 21:00)**. This is likely due to lighting and appliance use as residents return home, followed by a reduction in demand post-evening. **Sibi** exhibits the highest peaks, especially in the late evening, reflecting higher cooling needs due to the warmer climate. Murree, with a cooler climate, has consistently lower demands. Islamabad, Karachi, and Quetta have similar profiles with moderate peaks, indicative of typical residential usage in regions with mixed climate demands.

Standard Occupancy:

For the Standard occupancy, the daily profile resembles the Low occupancy pattern but with **higher energy consumption across all cities**, reflecting increased activity within the household. There is a slight increase in daytime demand, possibly due to additional appliances and moderate occupancy throughout the day. **Evening peaks** remain prominent across all cities, with Karachi and Sibi showing the highest consumption levels. The elevated evening demand suggests a higher reliance on cooling systems and domestic appliances during peak hours. The differences between cities are more evident in this category, with Sibi consistently leading in demand due to climate-induced cooling loads, while Murree maintains a relatively flat and lower profile, consistent with reduced heating or cooling requirements.

Wasteful Occupancy:

The Wasteful occupancy profile displays **substantially higher overall consumption**, especially during evening hours. This suggests less efficient usage patterns, with more energy-intensive appliances or behaviors contributing to an increased load. Sibi and Karachi show significantly higher peaks in the evening, driven by elevated cooling needs, while Murree remains comparatively low. This contrast reflects the impact of climate, where warmer cities require more energy for cooling, particularly in households with less controlled or efficient energy usage. Interestingly, Quetta and Islamabad follow a similar trend but with slightly lower peaks compared to Sibi and Karachi, suggesting that even within wasteful households, the impact of climate variations is pronounced.

Medium Archetype Load Profile

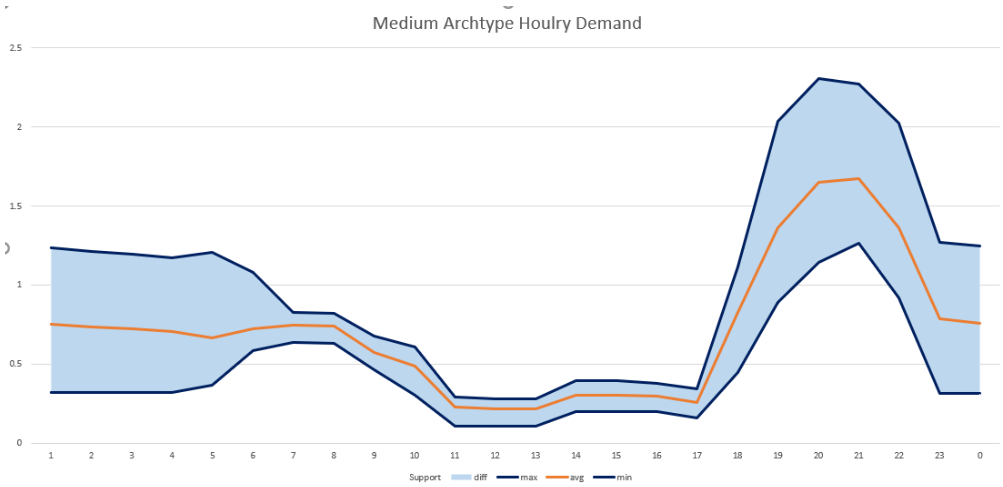

Figure 15.Medium Archetype Hourly Load Profile

Figure 15 shows the hourly load profile for medium archetype of house. **Low Occupancy:**

Daytime Stability, Evening Peak: Across all cities, the load profile in the Low occupancy category maintains a steady demand during the day, followed by a **pronounced peak in the evening (18:00 to 21:00)**. This trend is typical for homes with minimal daytime activities, where energy demand surges when occupants return in the evening. **Sibi's Higher Demand:** Similar to the small archetype, **Sibi shows the highest evening peak** due to its warmer climate, driving greater cooling requirements. The other cities have lower evening peaks, with **Murree** exhibiting the least demand, reflecting reduced cooling and heating needs. **Midday :** A noticeable dip in demand occurs around midday, particularly in Karachi and Quetta, indicating minimal daytime energy usage, likely due to unoccupied homes during work hours.

Standard Occupancy:

Increased Baseline Demand with Evening Peak: Compared to Low occupancy, the Standard occupancy profile shows a **higher baseline consumption** throughout the day, reflecting moderate daytime activities in medium-sized homes. The evening peak remains prominent, though it's more spread out, suggesting a mix of evening appliance use. **Regional Climate Impact: Sibi** and **Karachi** continue to show the highest peaks, reinforcing the impact of climate-induced energy needs. These cities have higher cooling requirements in the evening, pushing up demand. **Less Pronounced Midday Drop:** Unlike the Low occupancy profile, there is less of a midday dip in the Standard category, particularly in **Islamabad** and **Murree**, indicating a more consistent use of energy throughout the day in these areas.

Wasteful Occupancy:

Higher Overall Consumption and Steeper Peaks: The Wasteful category exhibits the highest demand across all hours, with a **sharp evening peak**. This category likely represents inefficient energy use, with more appliances running in the evening. **Significant Variation Among Cities: Sibi** shows the steepest peak, followed by **Karachi** and **Quetta**, illustrating a heavy dependency on cooling systems and higher usage of energy-intensive devices. **Murree**, as expected, shows the lowest overall demand, consistent with its cooler climate. **Flatter Midday Demand:** The midday demand remains relatively consistent across all cities in this category, suggesting ongoing energy usage throughout the day, regardless of occupancy.

Large Archetype Load Profile

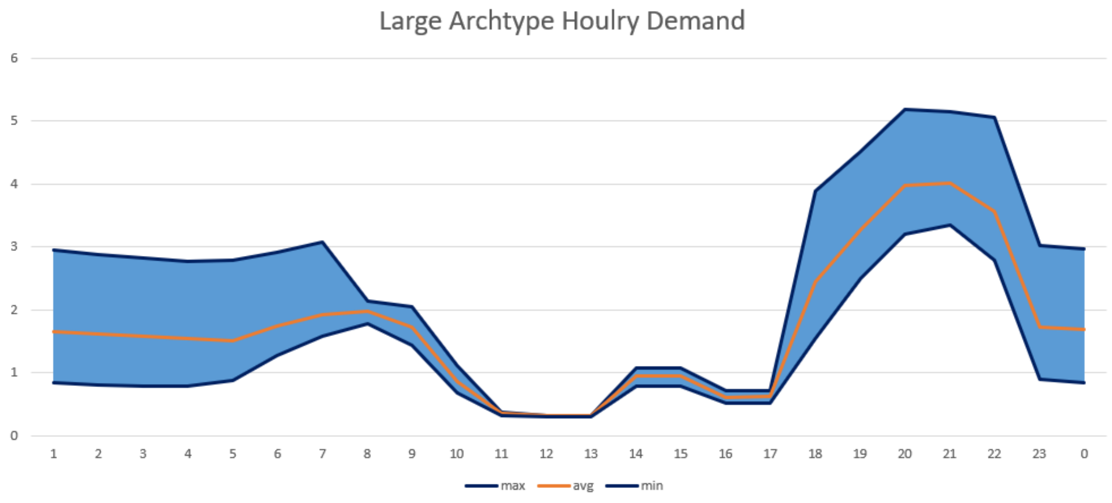

Figure 16.Large Archetype Hourly Load Profile

Figure 16 shows the hourly load profile for large archetype of house.

1. Low Occupancy:

Steady Daytime Demand, Strong Evening Peak: Across all cities, the Low occupancy category shows steady, relatively low demand during the day, with a **notable evening peak from 18:00 to 21:00**. This is likely due to increased household activity in the evening, particularly in large homes where even minimal occupancy can lead to higher base demand.

Pronounced Climate Influence - Sibi and Karachi: As expected, **Sibi and Karachi exhibit the highest peaks**, driven by cooling needs in the evening. The higher baseline throughout the day in these cities reflects ongoing demand for temperature control.

Minimal Midday Demand Fluctuation: There is a slight dip in demand around midday, especially in **Islamabad and Murree**, indicating reduced energy usage when occupants may be away from home or when cooling is less needed.

Standard Occupancy:

Higher Baseline and Expanded Evening Peak: The Standard occupancy profile shows **increased energy consumption throughout the day** compared to Low occupancy, reflecting moderate usage patterns that are more consistent. The evening peak is higher and extends into late evening hours.

City-Specific Peaks - Sibi and Karachi Leading in Demand: As with the Low occupancy category, **Sibi and Karachi show the highest evening peaks**, underscoring the role of climate. Higher cooling demands in large homes drive up evening consumption significantly.

Reduced Midday Consumption Dip: The midday drop in demand is less pronounced in the Standard category, indicating more continuous use of household appliances or temperature control, especially in cities like Quetta and Islamabad.

Wasteful Occupancy:

Elevated Consumption Across All Hours: The Wasteful occupancy category displays **high demand throughout the day** with significant evening peaks. This pattern suggests inefficient energy usage, with more appliances and systems running continuously in large homes.

Steep Evening Peaks in Warmer Cities: Sibi, Karachi, and Quetta demonstrate sharp evening peaks, with Sibi reaching the highest levels. This is consistent with excessive cooling loads and inefficient energy behaviors in wasteful households.

Consistent Midday Demand Across Cities: Unlike the Low and Standard categories, the Wasteful occupancy maintains consistent energy demand throughout the day, with only a minor midday dip, indicating continuous energy use irrespective of time or external conditions.

4.2 BEM RESULTS VERIFICATION

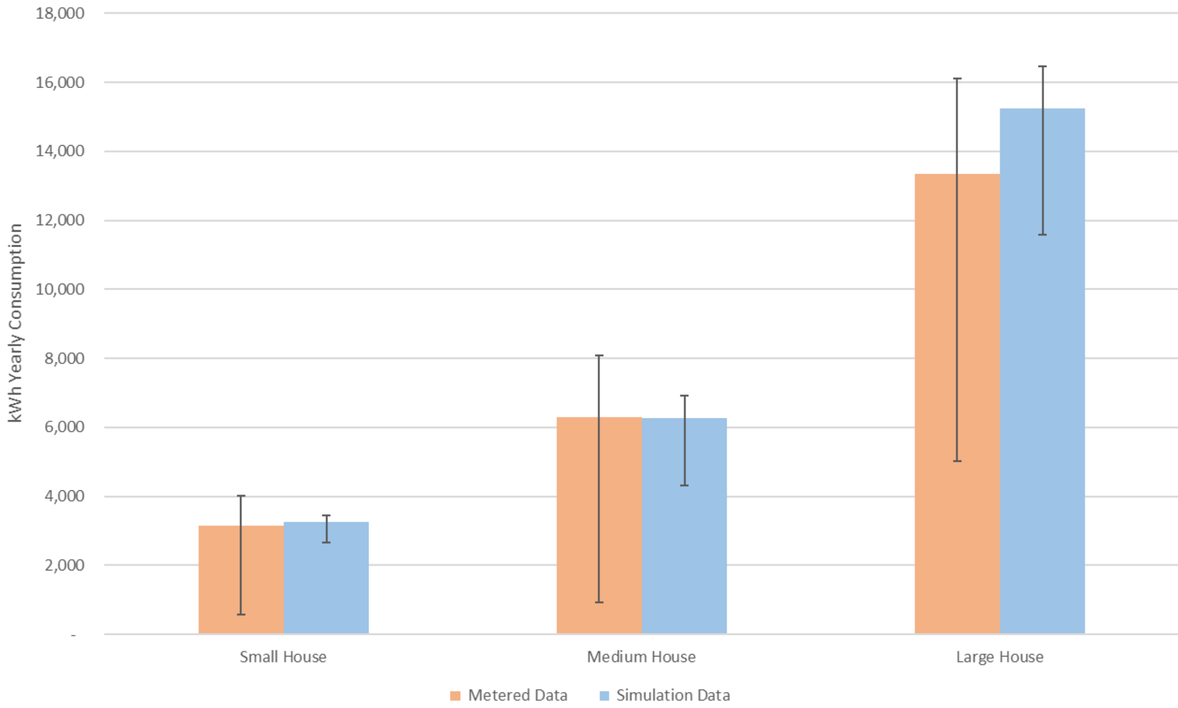

Figure 17. Meterd data vs Simulated Data

This graph presents the verification of Building Energy Model (BEM) simulation results by comparing metered data (actual measured values) against simulation data for different house sizes: Small, Medium, and Large. Each bar represents the average yearly energy consumption in kilowatt-hours (kWh) for each house size, with metered data in orange and simulation data in blue.

The error bars show the range between maximum and minimum values recorded in each category, capturing the variability in energy consumption. This range can be due to factors such as seasonal fluctuations, occupant behavior, and environmental conditions.

Analysis by House Size:

Small House:

The average energy consumption for both metered and simulation data is close, with only a slight difference, suggesting that the BEM simulation accurately models the energy use of small homes.

The error bars for metered data are relatively larger, indicating greater variability in actual measured values.

Medium House:

For medium-sized homes, the average values for metered and simulation data remain similar, with a small discrepancy. This suggests a strong correlation between the model and real-world data for medium homes as well.

The error bars for metered data are wider than those for the simulation data, reflecting larger deviations in measured energy use. This could be due to more varied occupancy patterns or differences in appliance use intensity in medium homes.

Large House:

In large homes, the average energy consumption from simulation data is slightly higher than the metered data. The model tends to overestimate consumption for larger homes, which might suggest that the BEM could be refined to more accurately represent large spaces in future studies.

The error range is the widest for large houses, especially in the metered data, indicating significant variability in actual energy use. This variability may stem from diverse occupancy levels, different appliance usage patterns, or variations in HVAC needs in large spaces.

From BEM results and verification, we can conclude the following:

Impact of House Size on Energy Consumption: There is a clear trend across all cities: **energy consumption increases with house size**. For instance, in **Islamabad**, small houses under the Low category consume **2,741 kWh/year**, while large houses in the same category consume **12,648 kWh/year**. This trend suggests that larger houses have more significant energy demands, likely due to increased space and the need for more extensive HVAC systems, lighting, and appliances. In accordance with the findings in (Bawaneh et al., 2024)(Milner et al., 2023), the simulation results show that the impact of larger homes consuming more electricity.

Influence of Consumption Category (Low, Standard, Wasteful): Across all cities and archetypes, moving from **Low to Standard to Wasteful** categories results in a marked increase in energy consumption. For example, in **Karachi**, the energy consumption for small houses rises from **2,876 kWh** in the Low category to **3,930 kWh** in the Wasteful category. This indicates that consumption efficiency plays a crucial role in energy demand. Homes classified as "Wasteful" are likely less efficient, with more energy-intensive behaviors or systems, contributing significantly to higher energy use. The results of this model were validated using a similar analysis presented by (Boukarta & Berezowska-Azzag, 2018)

City-Specific Variations: Karachi and Sibi exhibits the highest energy consumption across all archetypes and categories, especially in the Wasteful category for large homes, which reaches **21,000 kWh/year**. This high energy demand is likely due to extreme warm climate, which requires more energy for cooling. The validation of the BEM results can be achieved through the findings of (Daioglou et al., 2022) and (Bezerra et al., 2021), which indicate that warmer temperature zones exhibit higher energy consumption. **Murree** consistently shows the lowest energy consumption among the cities, even in larger archetypes. For example, large wasteful homes in Murree consume **13,705 kWh/year**, significantly lower than in other cities. This lower demand can be attributed to Murree's cooler climate, reducing the need for extensive HVAC use. **Islamabad and Quetta** exhibit moderate energy demands, with Islamabad showing slightly higher values, likely due to its warmer climate and increased cooling requirements.

4.3 Supply Side :

The three figures fig18,fig19,fig20 depict the yearly load distribution and self-sufficiency (SS) for large, medium, and small residential Each graph illustrates the contributions from various sources: Battery (Yellow), Grid (Orange) and PV System (Green).

Small Archetype shown in figure 18.

- **Battery as Primary Supply Source:** Across all cities and occupancy levels, the battery plays a significant role in meeting annual energy needs. Its dominance indicates a strong capacity to store and discharge energy effectively, covering much of the load, especially during periods without direct solar input.
- **PV System Contribution:** The PV system also provides a substantial portion, but it largely functions in tandem with the battery. The battery’s role as a buffer allows for more consistent energy availability even when solar production varies.

- **Minimal Grid Dependence:** Grid reliance is minimal across all occupancy levels, suggesting that the combination of battery and PV systems sufficiently meets the demand for small buildings.

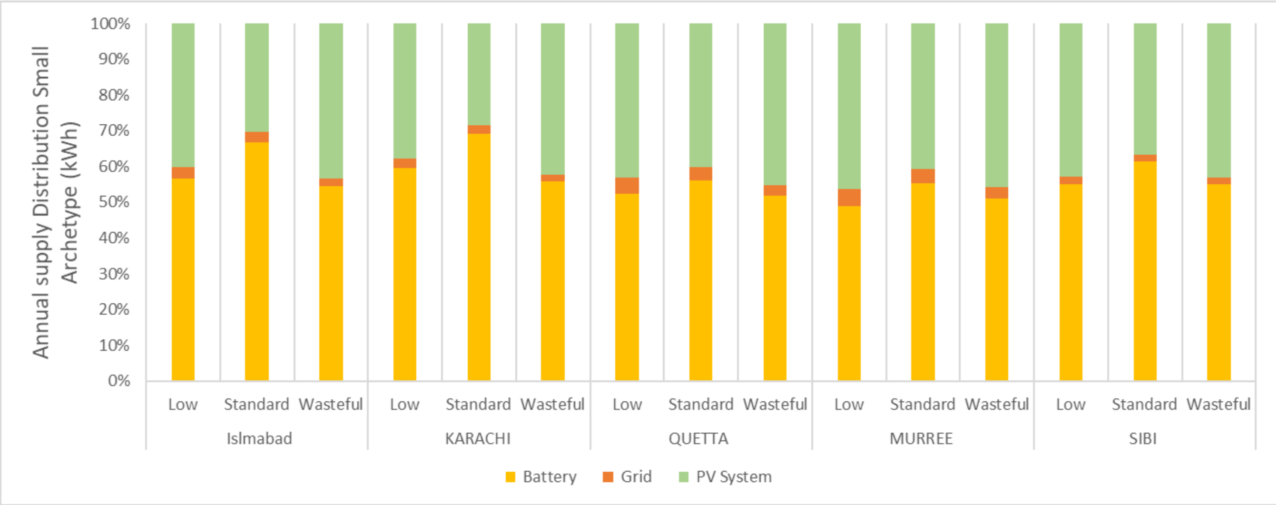

Figure 18. Annual Supply compostion for Small Archetypes

Medium Archetype shown in figure 19

- **Dominant Role of Battery:** In medium buildings, the battery remains the primary supply source across occupancy levels. Its consistent contribution highlights its importance in supporting the load effectively as energy demand grows.
- **Supporting Role of PV System:** While the PV system contributes significantly, it largely serves to recharge the battery rather than directly meeting the load. This reinforces the battery's position as the main energy source in this setup.
- **Slight Increase in Grid Usage in Wasteful Occupancy:** Although grid dependence is still low, it does increase slightly in the Wasteful occupancy level, indicating that higher demand in medium buildings may exceed what the PV and battery system can consistently cover.

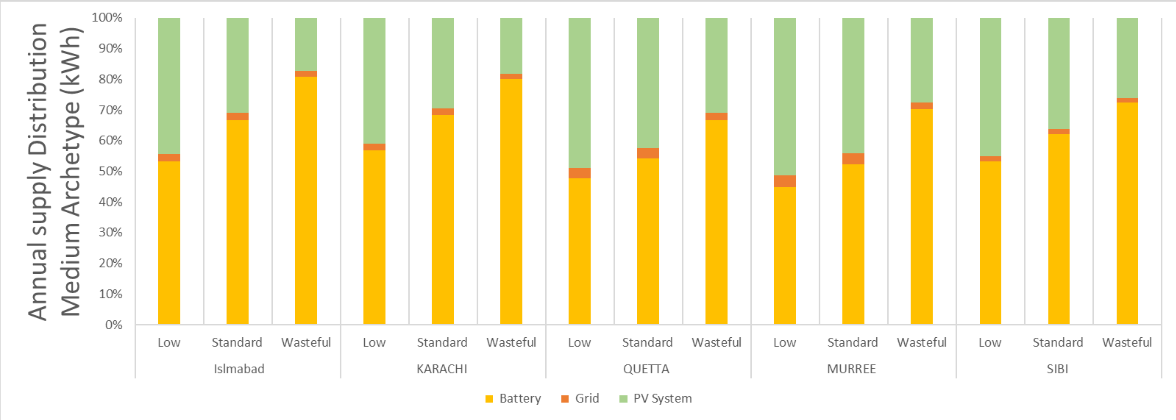

Figure 19.Annual Supply compostion for Medium Archetypes

Large Archetype shown in figure 20

Battery as the Primary Source, Even in Large Buildings: For large buildings, the battery continues to be the main contributor to energy supply, even as occupancy levels and demand increase. This highlights the battery's capacity and storage adequacy in managing larger loads.

PV System as a Secondary Contributor: The PV system maintains a strong presence but primarily supports the battery by charging it, rather than directly addressing the load.

Increased Grid Dependency in Higher Demands: In Wasteful occupancy levels, grid reliance is more visible, suggesting that as energy demands rise, the combined PV and battery systems approach their limits, necessitating supplementary support from the grid.

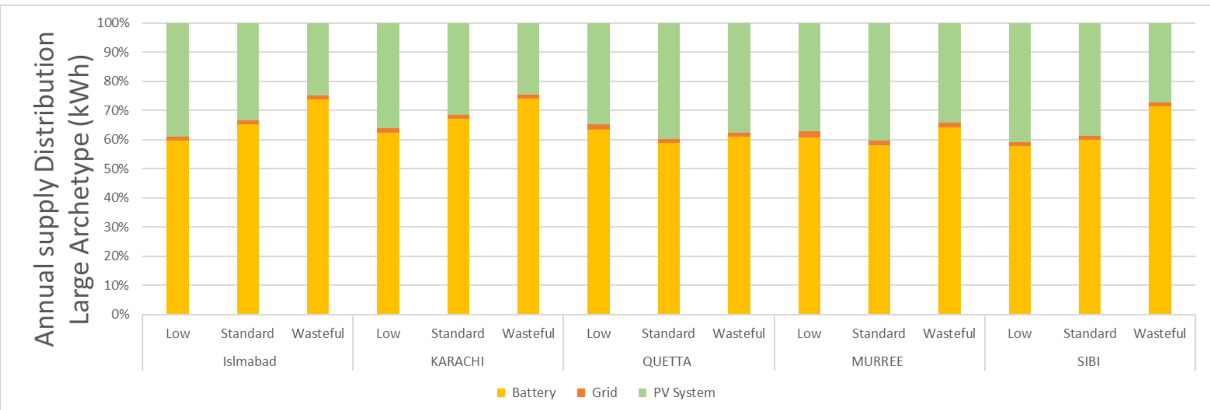

Figure 20.Annual Supply compostion for Large Archetypes

4.4 TECHNOECONOMICAL

4.4.1 LCOE

After running the model is SAM, we collected the Levelized Cost of Energy (LOCE). As per results the LCOE are 0.054$/kWh in Quetta, 0.060 $/kWh in Sibi, 0.061$/kWh in Karachi and 0.065$/kWh for Islamabad and Karachi.

The difference in the locations and the weather zones is highly noticeable in the LCOE. Therefore, we can say that regions with higher GHI, like Quetta, can get more irradiance, thus lowering the cost of the generated electricity.

The high value in Quetta indicates a high competitiveness of PV in that geographical location. On the other hand, Islamabad and Murree have low-capacity factors, and that indicates that power generation from the solar PVs is less efficient for the area. Figure 21 shows in details the link between LCOE and the GHI of the city. Same trend is followed by study done by. (Chadly et al., 2023)

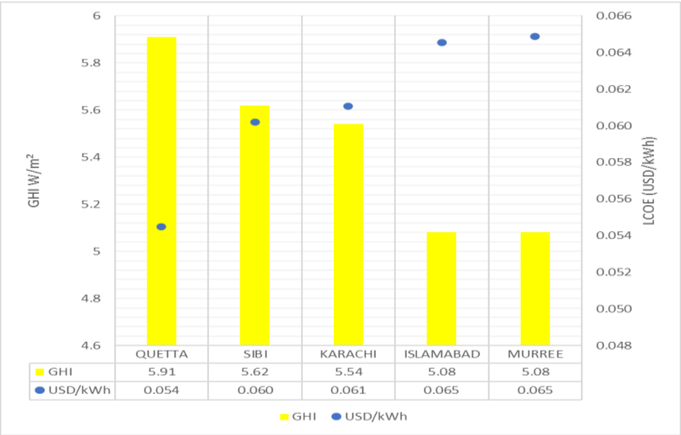

Figure 21. LCOE vs GHI

The observed Levelized Cost of Energy (LCOE) values in our study range from **0.054 to 0.065 PKR/kWh.** To ensure the accuracy and reliability of these findings, we can compare our results with those reported in the literature. For instance research conducted by (Aziz et al., 2024) determined the LCOE value of **0.057 PKR/kWh** and research conducted by (Xu et al., 2019) shows that the value of LCOE is **0.073 PKR/kWh.** Both of these studies were specifically focused on the **energy market in Pakistan**

4.4.2 LCOS

The yearly energy generation of the photovoltaic system in a small house is 14,214 kWh for Islamabad, 15,072 kWh for Karachi, 16,894 kWh for Quetta, 14,137 kWh for Murree, and 15,093 kWh for Sibi, according to SAM calculation. For a medium-sized house, photovoltaic (PV) systems generate 32,087 kWh in Islamabad, 33,828 kWh in Karachi, 37,950 kWh in Quetta, 31,922 kWh in Murree, and 34,529 kWh in Sibi. The photovoltaic system placed in a large house generates 48,096 kWh in Islamabad, 50,717 kWh in Karachi, 56,894 kWh in Quetta, 47,853 kWh in Murree, and 51,740 kWh in Sibi.

The provided graphs fig22,23,24 show the Levelized Cost of Storage (LCOS) in dollars per kWh for Lithium-ion (Li-ion) and Lead-acid batteries across various archetypes (small, medium, and large) in five cities: Islamabad, Karachi, Quetta, Murree, and Sibi. The LCOS indicates the total cost of using energy storage systems over their lifetime, including capital, operational, and replacement costs. It helps in comparing the economic feasibility of different storage technologies across different consumption categories (Low, Standard, and Wasteful).

Small Archetype LCOS Observation is shown in figure 22.

LIB shows lower LCOS compared to LAB in all cities and categories, suggesting that it is more cost effective for smaller homes. LIB LOCS for Small archetype ranges from 17.46 ¢/kWh to 28.73 ¢/kWh and LAB LCOS ranges from 59.79 ¢/kWh to 82.43 ¢/kWh. For all cities LCOS value is higher for LOW occupancy type and the value of LCOS is lower for wasteful occupancy type. Islamabad and Karachi has moderate LCOS for both type of batteries where LIB ranges between 20.84 ¢/kWh and 28.73 ¢/kWh while for LAB LCOS ranges between 59.79 ¢/kWh and 72.26 ¢/kWh. Overall city of Islamabad has higher LCOS when compared to Karachi. Cities of Murree and Quetta shows highest LCOS values for both type of batteries. Where city of Murree has highest LCOS for both LIB 29.64 ¢/kWh and for LAB 82.43. City of Sibi shows the minimum values of LCOS value 17.46 ¢/kWh for LIB and 68.43 ¢/kWh for LAB.

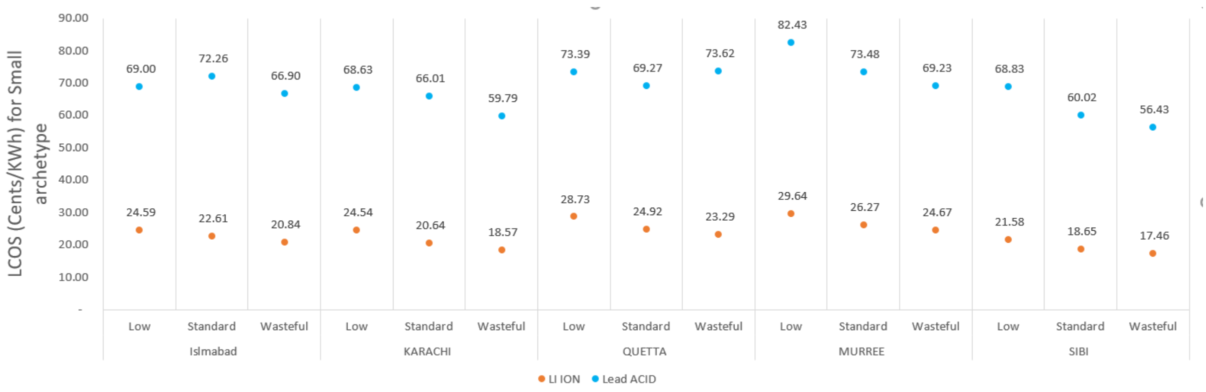

Figure 22. LCOS for Small Archetype

Medium Archetype LCOS Observation is shown in figure 23.

Similar to smaller archetype LCOS value for LIB is lower for all cities and occupancy level for medium archetypes. Where the value of LOCS for LIB range between 19.5¢/kWh and 42.10 ¢/kWh and for LAB the LCOS value ranges between 63.79 ¢/kWh and 109.03¢/kWh. Similarly, if occupancy is compared it can be observed that the wasteful occupancy has lower LCOS value. It can be observed from the figure that the city of Murree and Quetta has highest LCOS values for both type of batteries. Whereas city of Islamabad, Karachi and Sibi shows lower LCOS values for both types of batteries.

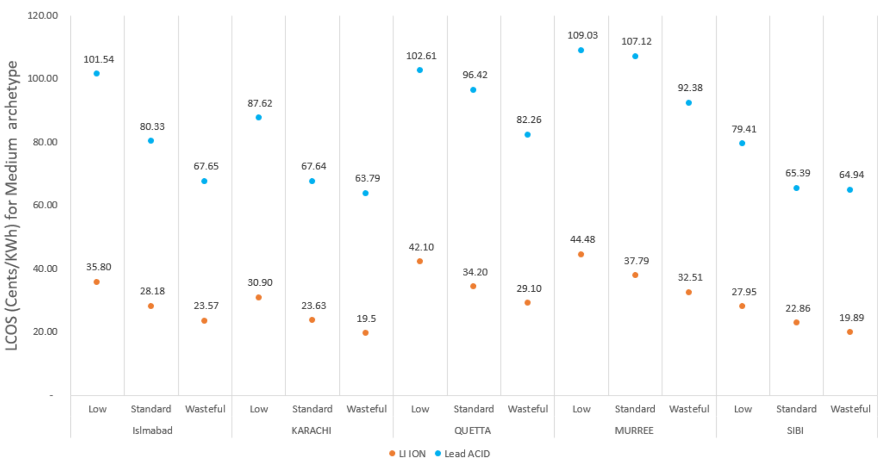

Figure 23.LCOS for Medium Archetype

Large Archetype LCOS Observation is shown in figure 24.

For large archetype similar trend is followed where LIB has lower values of LCOS when compared to LAB. The value of LIB ranges from 13.41¢/kWh to 26.42¢/kWh and for LAB the LCOS value is between 51.51¢/kWh and 78.58¢/kWh.

As it was observed in previous archetype same trend is observed in the large archetype. Where it shows that the city of Murree has the highest LCOS values for LIB and for LaB . It is also observed that the city of Sibi has the lowest LCOS values for both type of batteries.

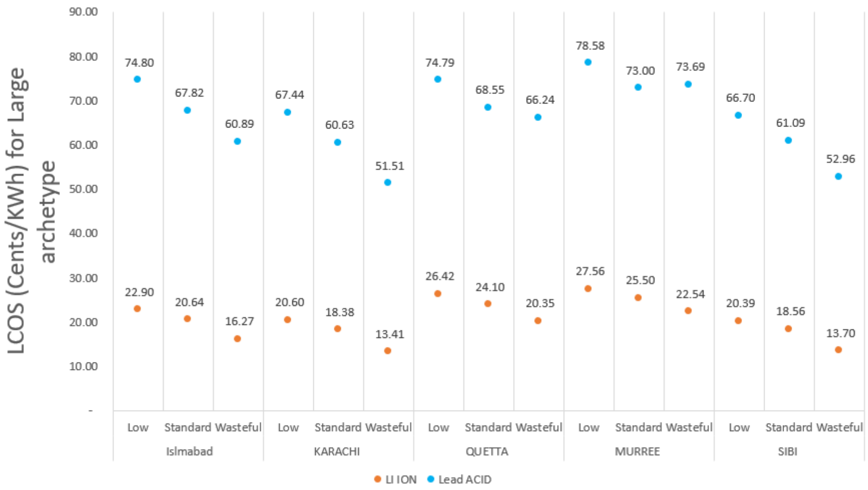

Figure 24. LCOS for Large Archetype

Following conclusion could be drawn from the figures

1-LIB exhibits lower LCOS values, reflecting its higher efficiency, longer lifespan, and better performance under various temperature conditions. Whereas LAB is marked in blue and shows higher LCOS values in most cases, which can be attributed to its shorter lifespan

2-Across all cities, LCOS values generally decrease as consumption profiles move from Low to Wasteful. This trend may indicate economies of scale, where higher energy demands make storage solutions more cost-effective. As though low energy consumption is meant for energy savings, it eventually results in higher LCOS values for all building sizes and all ESSs.

4.5 Uncertainty Results Analysis

The results of the Monte Carlo simulation demonstrate the variations in the LCOS while accounting for uncertain demand. To enhance comprehension of the potential range of LCOS under uncertain conditions, box and whisker plots were created. Figures 18, 17, and 19, as well as Tables 7, 8, and 9, illustrate the minimum and maximum values, along with quartiles, for each building type, occupancy profile, and energy storage system in Islamabad, Karachi, Quetta, Murree, and Sibi.

Small Archetypes:

With the help of figure 25 and table11, we are able to do an analysis of the LCOS value for the small archetype. In general, the LCOS values fall somewhere in the range of 0.03¢/kWh to 120¢/kWh , with the Lead Acid batteries more frequently indicating higher pricing in comparison to the Li-ion batteries. The "low" archetypes have a tendency to exhibit the highest LCOS values across the board in every city. This behavior is consistent across the board. It is more noticeable that the LCOS fluctuates in places like Quetta and Murree, which are located in areas that experience more severe weather conditions. It is possible to notice this by observing the longer range of error bars, which may suggest that there is a greater degree of uncertainty in energy requirements as a result of the effects of climate change. On the basis of this information, it would appear that Li-ion batteries have the potential to offer a solution that is more economically viable for small-scale installations, particularly for "Low" and "Standard" usage profiles.

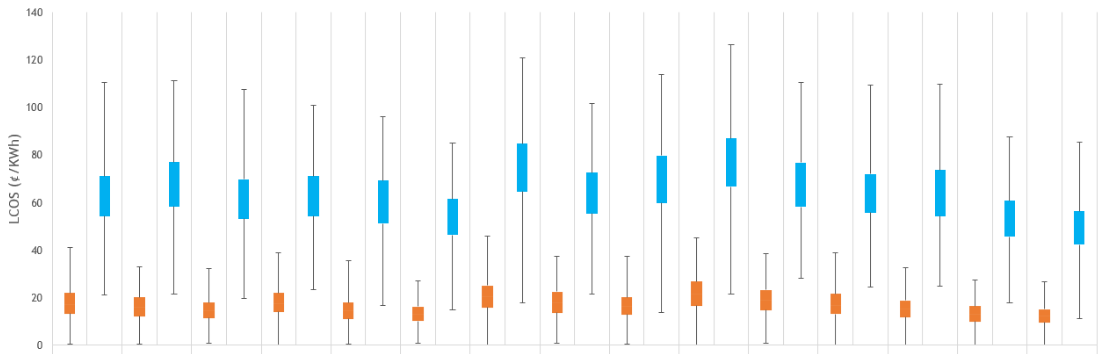

Figure 25.Distribution of Simulation Outcome from Monte Carlo Simulation for Small Archetype

ISLAMABAD KARACHI QUETTA MURREE SIBI

Table 11.Distribution of Simulation Outcome from MOntecarlo Simulation for Small Archetype

cents/kWh		Min	Max	Median	Min	Max	Median
ISLAMABAD	Low	0.55423739	41.01686	17.224156	21.0051811	110.614922	62.1639269
	Standard	0.59192726	32.9927378	16.0442668	21.5858025	111.192209	67.6778694
	Wasteful	0.72719033	32.2823368	14.6613847	19.6453739	107.671633	61.6339184
KARACHI	Low	0.22663985	38.8861235	17.631649	23.1518779	100.976636	62.7519209
	Standard	0.50152533	35.4312476	14.4737899	16.5523091	96.1563669	60.0698333
	Wasteful	0.63815747	26.8503351	13.0067458	14.7859028	84.8651193	53.5059631
QUETTA	Low	0.03275861	45.8449187	20.6003068	17.6549954	120.897274	74.1669319
	Standard	0.92320912	37.173067	17.9342203	21.5415436	101.466063	63.9549478
	Wasteful	0.28270863	37.279933	16.6566159	13.9100673	113.750212	69.9333458
MURREE	Low	0.03275861	45.8449187	0.03983603	17.6549954	120.897274	21.5942686
	Standard	0.92320912	37.173067	0.69665841	21.5415436	101.466063	28.213838
	Wasteful	0.28270863	37.279933	0.14442629	13.9100673	113.750212	24.5391397
SIBI	Low	0.1675526	32.3716429	15.3672481	24.9655161	109.810355	64.0147447
	Standard	0.10552372	27.5198358	13.2349205	17.7272534	87.5376066	53.6085322
	Wasteful	0.07691681	26.5321423	12.3201013	11.1985655	85.3190979	49.4479821

Medium Archetypes:

An analysis of the box plot and the value for LCOS can be conducted by referencing figure 19 and table 12. In specific cases, the LCOS range for medium archetypes can extend notably higher, approaching 169¢/kWh. This observation holds especially true in Murree. Li-ion batteries consistently exhibit lower LCOS values compared to lead acid batteries, aligning with the established model that indicates these trends are coherent. The archetype referred to as "Standard" typically exhibits a moderate range of LCOS, achieving a balance between affordability and reasonable energy requirements. The LCOS is markedly reduced in locations like Islamabad and Karachi, likely due to the more stable meteorological conditions present there. Conversely, the levels of uncertainty and expenses tend to increase in colder or more extreme environments, like Quetta and Murree.

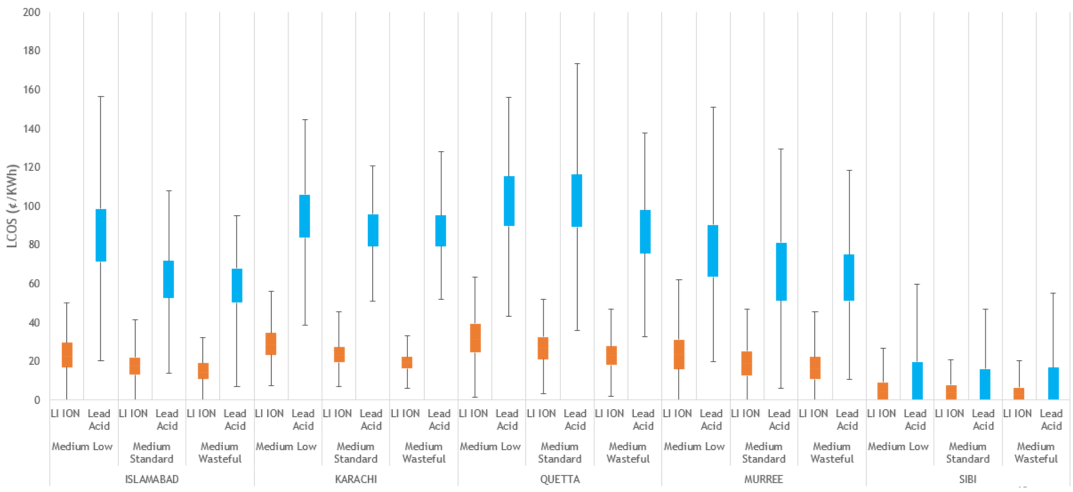

Figure 26.Distribution of Simulation Outcome from Montecarlo Simulation for Medium Archetype

Table 12.Distribution of Simulation Outcome from Montecarlo Simulation for Medium Archetype

Medium Archetype $/kWh		LI ION			Lead Acid		
		Min	Max	Median	Min	Max	Median
ISLAMABAD	Low	0.02957126	52.5075832	25.2832124	33.0279834	169.367702	98.5411994
	Standard	0.29048228	44.4561564	20.6691864	26.9782333	121.214523	75.2822308
	Wasteful	0.5327832	34.2755567	16.507981	9.30465737	97.0176653	60.3822348
KARACHI	Low	1.04242352	49.6631894	22.3476624	25.8902652	132.047988	82.3137591
	Standard	0.56451572	39.2118913	16.6003369	24.0252551	93.9934064	60.6785687
	Wasteful	0.60524528	27.5670328	13.8049065	22.54228	98.9788616	58.1185203
QUETTA	Low	0.05078285	61.961199	30.2337474	37.4876236	150.071249	97.8988877
	Standard	1.49980145	50.0225731	24.902745	25.6653078	163.641868	93.3566954
	Wasteful	0.09997452	45.1738917	21.1898006	36.2895894	141.373991	90.4278602
MURREE	Low	0.05078285	61.961199	0.17958378	37.4876236	150.071249	45.5759518
	Standard	1.49980145	50.0225731	0.08361932	25.6653078	163.641868	43.5753849
	Wasteful	0.09997452	45.1738917	0.72040435	36.2895894	141.373991	34.9300507
SIBI	Low	1.25327574	42.3604755	20.2292755	14.0467312	122.790139	73.0265246
	Standard	0.53908799	32.8179929	16.1903503	22.6399119	98.1149057	58.9860446
	Wasteful	0.00997273	30.6364707	13.7106789	24.0416075	106.071334	59.9565285

Large Archetypes:

A Monte Carlo simulation was conducted on the large archetype, with the findings illustrated in Figure 27 and Table 13. At its peak, the LCOS attains its highest values, which can exceed 169¢/kWh in specific cases, especially in Quetta and Murree. It is evident that larger installations exhibit a broader spectrum of potential outcomes, likely due to heightened energy unpredictability and greater capacity demands, resulting in a noticeable increase in the variability of the LCOS distribution. This represents a notable escalation. Lead acid batteries persist in demonstrating elevated LCOS values, especially within "Wasteful" archetypes. This underscores the importance of choosing the right battery technology for large-scale installations, which is particularly crucial. This graph highlights the potential advantages of Li-ion batteries in lowering costs, particularly in challenging environments. This also underscores the financial limitations linked to sustaining minimal storage expenses for extensive, high-demand systems.

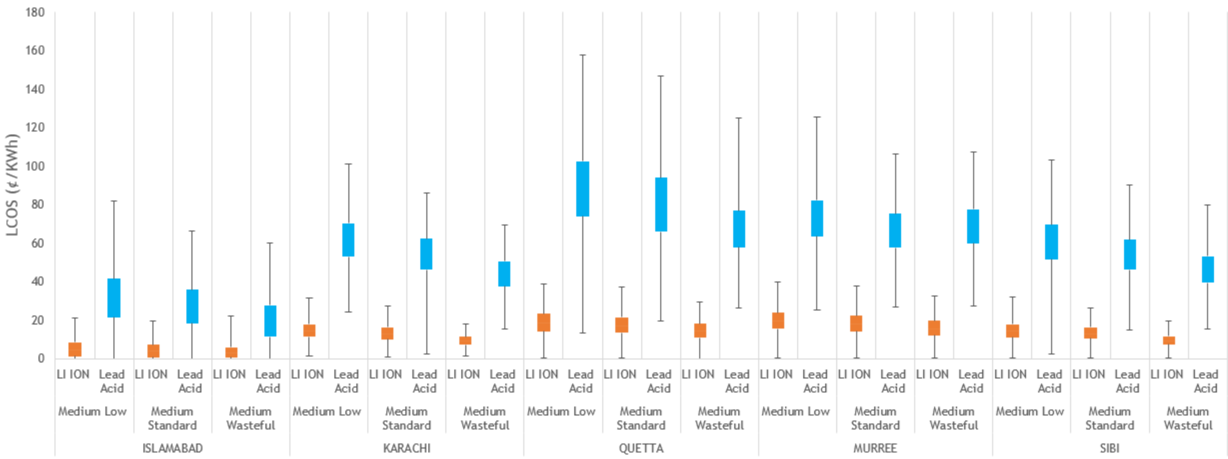

Figure 27.Distribution of Simulation Outcome from Montecarlo Simulation for Large Archetype

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Table 13.Distribution of Simulation Outcome from Montecarlo Simulation for Large Archetype

Large Archetype $/kWh		LI ION			Lead Acid		
		Min	Max	Median	Min	Max	Median
ISLAMABAD	Low	1.217	31.84	15.76	21.39	120	69.48
	Standard	0.533	30.04	14.48	18.4	100.7	61.8
	Wasteful	0.749	30.23	11.37	11.4	93.74	53.43
KARACHI	Low	1.087	31.19	14.5	24.27	100.9	61.36
	Standard	0.584	27.27	12.76	2.522	86.06	54.53
	Wasteful	1.158	17.94	9.346	15.21	69.45	43.7
QUETTA	Low	0.467	38.5	18.75	13.28	157.7	87.64
	Standard	0.036	36.89	17.38	19.71	146.7	79.98
	Wasteful	0.003	29.55	14.5	26.49	125	67.5
MURREE	Low	0.467	38.5	0.216	13.28	157.7	25.09
	Standard	0.036	36.89	0.322	19.71	146.7	26.52
	Wasteful	0.003	29.55	0.012	26.49	125	27.17
SIBI	Low	0.276	31.83	14.47	2.13	103.3	60.99
	Standard	0.346	26.45	13.19	14.92	90.17	54.58
	Wasteful	0.025	19.29	9.439	15.09	79.58	46.26

Summary Insights: These graphs collectively suggest that battery choice and energy usage archetype significantly impact storage costs across different city climates. Li-ion batteries consistently perform better in terms of cost-effectiveness across all archetypes and cities. However, the cost implications increase with scale and usage, especially in cities with more variable or extreme climates like Murree and Quetta. These findings support the strategic selection of battery types based on the specific archetype and geographic location to optimize LCOS.

4.6 Green Building

The chart you provided illustrates the Self-Sufficiency (SS) metric across five distinct cities: Islamabad, Karachi, Quetta, Murree, and Sibi. The classification of these cities falls into three distinct categories: Low, Standard, and Wasteful. The values of the SS are analyzed across three distinct archetypes: small, medium, and large. These archetypes could indicate distinct building sizes or differing degrees of energy efficiency compared to each other.

City Comparison: Climate and the energy demand profiles of buildings are likely the factors contributing to the slightly varying SS levels observed in each city across the three archetypes and categories. For example, cities like Quetta and Murree exhibit significantly low SS scores specially for low and standard, with many low as 95%, especially in the Standard and Wasteful categories.

Category Analysis:

Low: Across all cities, the Low category generally shows slightly lower SS values compared to the Standard and Wasteful categories. **Standard and Wasteful**: These categories typically have higher SS values, with some reaching or nearing 99%. This suggests that buildings in these categories have configurations or energy use patterns that promote a higher self-sufficiency rate.

Archetype Analysis:

Small Archetype: The SS values for small buildings tend to vary more and are slightly lower than those for medium and large buildings, particularly in Quetta and Murree. This may be due to differences in energy demand and PV generation capabilities for smaller structures. **Medium and Large Archetypes**: These often show closer values, with large buildings frequently reaching the highest SS rates. This may indicate that larger buildings have a configuration or capacity that optimally utilizes PV and storage to meet demand.

Implications for Green Building Verification:

High SS rates across cities and archetypes suggest these buildings are meeting a significant portion of their energy demand through renewable sources, aligning well with green building principles. Consistently high SS values, especially for Standard and Wasteful categories, indicate that even in potentially higher consumption scenarios (Wasteful), the buildings can achieve self-sufficiency, underscoring the potential robustness of green design strategies.

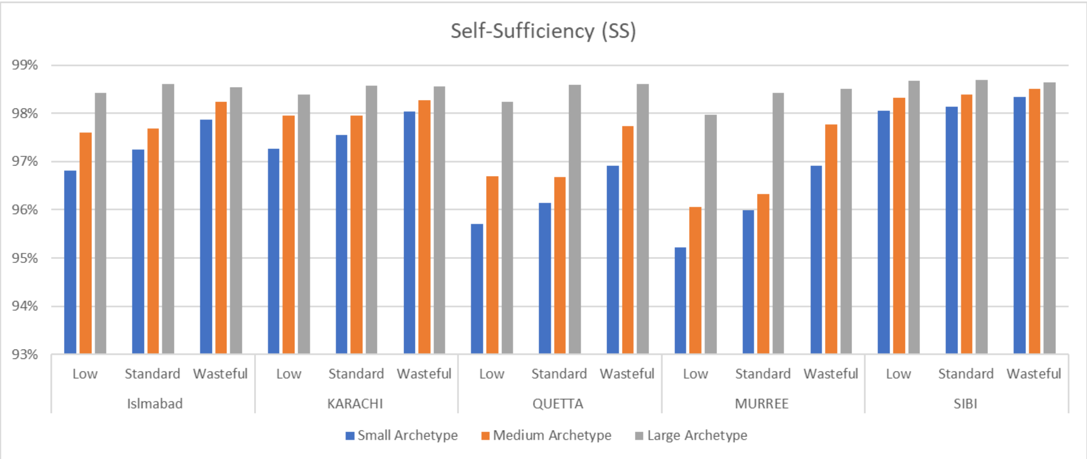

Figure 28.Self Sufficincy

CHAPTER 5: CONCLUSION & FUTURE RESEARCH

This study demonstrates that high levels of self-sufficiency and sustainability in residential buildings can be attained through a combination of BEM, and calculation of feasible ESS system. Moreover, it has illustrated the significance of undertaking such actions. Utilizing Building Energy Modeling, we obtained insights into the distinct energy demands that fluctuate across various climates and occupancy categories. These insights were subsequently employed to inform our research of the Levelized Cost of Energy (LCOE) and Levelized Cost of Storage (LCOS) for various storage solutions. The impact of demand and the volatility of financial conditions highlighted the necessity for adaptable and scalable systems capable of withstanding variations in energy demand and economic conditions.

The research conducted with Building Energy Modeling (BEM) was significant in identifying energy demand trends for residential buildings of diverse sizes and occupant numbers across various climates and occupancy levels. In each analyzed city, the BEM results revealed significant disparities in energy usage, determined by climatic and architectural factors. The need for cooling was markedly elevated in hotter locales like Karachi and Sibi, resulting in a rise in the total energy consumption across the region. Conversely, the cooling and equipment load were more significant factors in temperate regions such as Murree. Among these towns is Murree. In contrast to Murree, which has a lower average temperature, the energy demand for a large residence in Sibi and Karachi might attain up to 21,000 kWh annually. In Murree, the load required for the same sort of property might attain 13,900 kWh. The importance of localized energy modeling is emphasized due to these variances. Buildings in varying climates encounter distinct issues regarding energy efficiency and sustainability development. The BEM results identified opportunities for energy conservation by examining low, standard, and high occupancy levels across various occupancy patterns. Low-archetype occupancy frequently signifies reduced energy use universally across all locales. For instance, we can conserve around 5,000 kWh per year for a comparable house in the same city by utilizing a residence with a reduced occupancy rate and diminished energy consumption.

By employing BEM, we established a framework to assess the performance of various energy storage and generation systems. The demand profile of each kind directly influences the necessary energy mix to meet these requirements. The justification for employing energy-efficient architectural and engineering methods was reinforced by the findings of the Building Energy Model (BEM), which underscored the significant impact of design improvements on energy consumption.

Utilizing the responses derived from the BEM technique, we ascertained the optimal dimensions of photovoltaic (PV) systems for each city. The BEM results provide precise sizing of the energy storage system, which possesses a backup capacity of three days should the photovoltaic system in our sustainable residential building fail to generate electricity.

The data obtained from the SAM were evaluated and employed to facilitate the calculation of LCOS and LCOE for each battery. The data indicate that lithium-ion batteries are superior options due to their consistently reduced LCOS values across all scenarios. Lithium-Ion (Li-Ion) batteries surpass Lead Acid batteries in all categories, as indicated by the Levelized Cost of Storage (LCOS) analysis. Li-Ion batteries have superior efficiency, elevated energy density, and extended longevity compared to Lead Acid batteries. Karachi and Sibi possess a more favorable climate, leading to reduced localized cost of living (LCOS) levels. Conversely, areas like Murree incur higher costs due to environmental constraints.

The Monte Carlo simulation reveals that the Levelized Cost of Storage (LCOS) for both lead-acid and lithium-ion batteries can vary significantly across numerous small archetypes and weather conditions. The uncertainty analysis corroborates the prior findings, indicating that the LIB is more advantageous than the LAB, irrespective of tenant behavior, house size, or city. The distribution ranges indicate that Li-Ion batteries constantly exhibit lower median costs with reduced fluctuation, demonstrating their reliability amid uncertain demand and financial circumstances. Lead acid batteries, conversely, demonstrate a broader pricing spectrum, signifying their greater vulnerability to elevated levels of uncertainty. The findings of this study underscore the resilience of Li-Ion technology across diverse environments, further affirming its appropriateness for energy storage systems that are both efficient and environmentally sustainable.

Future Research:

This thesis aims to establish a basis for future research examining the integration of emerging storage technologies, including flow batteries and solid-state batteries, into energy systems to assess their levelized cost of storage (LCOS) across diverse climatic conditions and occupancy patterns. The integration of real-time data and machine learning models to optimize battery performance and cost forecasts could enhance the precision of analyses. The examination of hybrid storage systems, integrating technologies such as lithium-ion with hydrogen-based solutions, may yield insights into achieving enhanced sustainability and self-sufficiency for green buildings. To get comprehensive energy planning, it is essential to perform longitudinal research on the impacts of policies and the dynamics of grids.

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