ENERGY PERFORMANCE MODELING AND CONSUMPTION FORECASTING IN BUILT ENVIRONMENT

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By

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DECLARATION

I hereby declare that the work presented in the thesis “Energy Performance Modeling and Consumption Forecasting in Built Environment” is the result of research I conducted under the direction of Dr. R.L. Sharma, a Professor at the Lovely Professional University of Punjab, India, for the purpose of earning a doctorate in philosophy (Ph. D.). When the study presented here has relied on the findings of another investigator, appropriate acknowledgment has been made in accordance with standard reporting practices for scientific observations. This work has not been submitted, in whole or in part, to any other University or Institute for the purpose of conferring a degree.

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CERTIFICATE

It is certified that Ms. Laxmi Gupta, Reg. No. 41800062, conducted research for her doctoral thesis, titled "Energy Performance Modeling and Consumption Forecasting in Built Environment," and that the work is a true record of her original research completed under my supervision. Furthermore, it is confirmed that no portion of the thesis has been submitted for credit toward any other degree, diploma, or comparable course.

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ABSTRACT

The energy consumption in commercial buildings is a growing concern, necessitating further analysis to develop models that can accurately estimate energy usage. Several key factors contribute to energy consumption, including human behavior, appliance load, solar radiation, and temperature. In this study, a hotel building in Nagpur, Maharashtra (India), was selected and modeled using Revit software for energy analysis. The research provides a comprehensive review of methodologies and studies related to building energy performance.

Existing buildings are likely to consume more energy and emit more greenhouse gases than new buildings due to the inevitable decline in physical efficiency. Likewise, modernization to reduce energy consumption in the construction industry. However, there are limitations to accurately assessing the energy performance of existing buildings, as building materials physically deteriorate and actual conditions of use differ from construction documents. There are also differences in the level of data collection required to assess the energy efficiency of a building, depending on the conditions of the building. Building energy performance assessment is crucial to ascertain the efficiency of energy use in buildings and is the basis to make any decision for enhancing energy efficiency. The energy usage of the analysed buildings has to be measured before the energy performance of existing structures can be evaluated quantitatively.

The study begins by addressing the motivations and challenges associated with energy efficiency in hotel buildings, emphasizing the importance of reliable modeling and forecasting techniques. Accurate energy performance models and consumption forecasts offer various benefits, such as optimizing energy management strategies, aiding decision-making processes, and facilitating effective energy policy implementation. Currently, the biggest problem facing designers is the interoperability of building modeling and energy simulation tools.

To overcome this problem, the review emphasizes the significance of input variables and their impact on model performance.

These variables include building characteristics (such as geometry and envelope properties), occupancy patterns, weather conditions, and operational parameters. Various methods, such as engineering calculations, Revit software, and artificial neural networks, are employed for energy consumption forecasting. The strengths, limitations, and suitability of each method in different contexts and data availability are discussed.

The engineering method based on ASHRAE Fundamental Handbook is used to calculate cooling loads resulting from walls, windows, doors, and roofs. A comparison between the Revit estimate and the load predicted by the CLTD/CLF/SCL method reveals that, on average, the Revit estimate was 10.3% higher as compared to CLTD method. This finding underscores the importance of accurate models and forecasts in achieving energy efficiency goals.

The study concludes by identifying opportunities for future research and innovation in the field of energy modeling and forecasting. Advancing our understanding and capabilities in this area will pave the way for sustainable and energy-efficient built environments.

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Terminology Used

2D	Two-dimensional
3D	Three-dimensional
4D	Four-dimensional
5D	Five-dimensional
6D	Six-dimensional
7D	Seven-dimensional
ACH	Air Changes per Hour
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BASS	Bayesian Adaptive Spline Surface
BEEHive	Building Energy-Efficient Hive
BEPS	Building Energy Performance Simulation
BF	By-pass Factor
BIM	Building Information Modeling
BEM	Building Energy Modeling
BLAST	Building Loads Analysis and System Thermodynamics
CF	Coil Factor
CLF	Cooling Load Factor
CLTD	Cooling Load Temperature Difference
DB	Dry Bulb
DOE-2	Department of Energy-2
DT	Decision Tree
ESP	Environmental Systems Performance

GIS	Geographic Information System
GMM	Gaussian Mixture Model
GPR	Gaussian Process Regression
HBM	Heat Balance Method
HR	Humidity Ratio
HVAC	Heating, Ventilation and Air-Conditioning
IES	Integrated Environmental Solutions
IDM	Information Delivery Manual
IEA	International Energy Agency
IES VE	Integrated Environmental Solutions Virtual Environment
LRM	Linear Regression Model
LSTM	Long Short-Term Memory
ML	Machine Learning
MRT	Mean Radiant Temperature
MVD	Model View Definition
NZEB	Nearly Zero Energy Building
RDBMS	Relational Database Management System
ReLU	Rectified Linear Unit
RF	Random Forest
RH	Relative Humidity
RTSM	Radiant Time Series Method
SCL	Solar Cooling Load
SHGF	Solar Heat Gain Factor
SOM	Shared Object Model
SVM	Support Vector Machine

TA	Time Averaging
TEDA	Total Equivalent Temperature Difference
TFM	Transfer Function Method
TRNSYS	Transient Systems Simulation
WB	Wet Bulb
WWR	Windows-to-Wall Ratio

Chapter - 1

Introduction

Chapter – 1

Introduction

1.1 Introduction

Building sector that's growing very fast, accounts for 30% of total energy use and 28% of global energy-related Greenhouse Gas (GHG) emissions worldwide [1]. There is a rapid growth of building sector in several Asian and African countries. For example, the floor area in India is expected to double by 2035 [2]. Over the next 40 years, the world is likely to build 230 billion square meters of new constructions – adding an equivalent of Paris to the planet weekly. Strong economic progress, modernization, and growing population have resulted in higher energy demands globally. These factors led to ever serious concerns regarding about environmental deterioration and energy security. The concerns require continuous serious efforts towards energy consumption reduction and efficiency improvement in all sectors of the economy.

Energy consumption is a critical factor in assessing a society's economic development, technological advancement, and environmental impact. Monitoring and managing energy consumption are essential for promoting energy efficiency, reducing greenhouse gas emissions, and achieving sustainable energy practices. Governments, and organizations often strive to optimize energy consumption to ensure a balance between meeting needs and minimizing negative environmental consequences [3].

European Union's (EU) 2010 directive on the energy performance of buildings introduced the concept of "nearly zero-energy building". According to this directive, all new buildings were to be nearly zero-energy buildings by 31 December 2018 [4]. Nonetheless, current EU regulation indicates that many buildings-built decades ago are still inefficient in terms of energy use. Historically, indigenous materials were used to construct buildings in order to accommodate varying climates and maintain comfort. The building envelope, comprising - walls, roof, and floor of a building give security, comfort, and privacy in addition to shelter. Orientation and layouts were planned to maximize climatic advantages. Doors and windows were strategically placed for ventilation, light, and weather protection. This approach inspires sustainable practices, emphasizing energy efficiency.

The energy targets and energy savings potential in the building sector largely remains untapped due to lack of effective regulations, policies, end-user behaviour, and continued use of inefficient technologies. Innovative solutions and "outside the box" thinking are needed to address the critical issue of reducing energy usage and carbon footprint in the built environment. Energy performance modeling and consumption forecasting in the built environment can help improve energy efficiency.

Building performance modeling and quantifying energy consumption can lead to several efficiency improvement measures such as retrofits, technology adoption, or even demolition and re-construction of inefficient environment [5]. The process of quantifying energy demand in buildings through energy consumption modeling takes into account several input parameters such as building geometry, construction materials, weather, appliances used, operating schedule, inhabitants, and their behavior. Because of this complex nature of the building sector and a large number of factors affecting its performance, energy consumption is least understood as compared to other sectors of the economy. Typically, energy modeling is a computer-based simulation process to quantitatively predict the response of a building to key changes in structural, operational, behavioural or external elements.

Building energy modeling software plays a crucial role in this endeavour by simulating building performance and energy consumption. Prominent software includes EnergyPlus, ESP, IDA ICE, IES VE, and TRNSYS [6, 7]. These tools enable architects, engineers, and building owners to analyze various design alternatives, optimize energy usage, and mitigate the environmental impact of buildings. Utilisation of these software tools, has made it possible to assess and compare the energy performance of various building components, such as insulation, glazing and HVAC systems. However, it is often difficult to assess the numerous models and their features to decide the most suitable one for a particular purpose. “End user behaviour has a significant impact on the energy consumption and energy efficiency performance of the buildings. However, current practices do not display the necessary sophistication to reflect the interactions between indoor and outdoor weather conditions and the control actions at the level of end-users."

EnergyPlus is one of the prominent software used for building energy modeling and performance analysis [8]. It is an open-source tool known for its comprehensive whole-building energy simulation capabilities, including HVAC systems and lighting. Nowadays, artificial intelligence models such as neural network and support vector machines are used extensively because of their high performance and accurate nonlinear mappings. These methods are based on Machine Learning and their developments. However, all approaches are not suitable and applicable for all type of cases. It is crucial to analyze all approaches for building energy performance modeling to ensure their effectiveness and applicability [9].

1.2 The Role of Energy Consumption in the Building Sector

The importance of reducing energy consumption in buildings has increased worldwide. This is because the consumption of fossil fuels for the full-fledged operations of a building is as high as it is in other industries. Therefore, the adoption of energy efficient techniques during planning, construction and operation of buildings would play a crucial role in the creation of sustainable cities in the future. Among the key areas of focus for enhancing energy consumption is the heating and cooling system, especially during peak daytime demand. By optimizing the performance of these systems, energy consumption can be reduced, resulting in lower utility bills for both building owners and tenants [10]. Efficient heating or cooling not only helps maintain comfortable temperatures but also minimizes energy wastage. This is crucial during periods of peak load, as it alleviates strain on the power grid and reduces costs for utilities and consumers.

The number and size of buildings are expected to rise along with urbanization, especially in emerging nations, which would raise demand for electricity and other energy sources utilized in buildings. The benefits of improved energy efficiency extend beyond environmental and energy security aspects, positively impacting public health and safety. Through reduced energy consumption, buildings contribute to less greenhouse gas emissions, improved air quality, and a healthier environment. Moreover, energy-efficient buildings exhibit greater resilience to power outages and other disruptions, ensuring the safety and comfort of occupants in all circumstances [11]. The role of energy consumption in the building sector is multifaceted and crucial because of following reasons:

Reduced Energy Consumption: Energy-efficient buildings consume less energy for heating, cooling, lighting, and other operations. This helps to decrease the overall demand for energy, reducing strain on energy infrastructure and resources.

Environmental Impact: Buildings are responsible for a significant portion of global energy consumption and greenhouse gas emissions. Improving energy efficiency in buildings helps lower emissions by reducing the need for fossil fuels, thus contributing to climate change mitigation.

Improved Comfort: Energy-efficient design often involves better insulation, effective ventilation, and advanced heating and cooling systems. These factors contribute to improved indoor comfort and air quality for building occupants.

Educational and Behavioural Impact: Promoting energy efficiency in buildings can lead to increased awareness and understanding of energy consumption patterns, encouraging more responsible energy use by occupants.

Community Benefits: Energy-efficient buildings can positively impact local communities by reducing air pollution, enhancing energy security, and healthier environment.

1.3 Scope and Methodology

Energy consumption modeling and forecasting in the built environment encompasses a broad range of factors and considerations crucial for understanding and predicting energy usage within residential, commercial, and industrial structures. Various building elements such as building envelop, HVAC systems, lighting systems, appliances and equipment, occupant’s behaviour, renewable energy systems, etc. play significant roles due to their influence on energy usage patterns. By incorporating these building elements into energy consumption modeling and forecasting, stakeholders can gain insights into energy usage patterns, identify opportunities for efficiency improvements, and develop strategies to optimize energy performance in the built environment.

It involves the development and application of various modeling techniques, including white-box, black-box, and grey-box models, to analyze the complex interplay between building characteristics, occupant behavior, environmental conditions, and energy systems [12]. These models aim to provide insights into energy consumption patterns, identify opportunities for efficiency improvements, and support informed decision-making for energy management strategies.

Additionally, the scope of energy consumption modeling and forecasting extends to the integration of advanced technologies such as sensor networks, Internet of Things (IoT) devices, and machine learning algorithms to enhance the accuracy and timeliness of energy consumption forecasts [13]. Ultimately, energy consumption modeling and forecasting play a pivotal role in promoting sustainability, optimizing resource utilization, and mitigating environmental impacts in the built environment.

This study provides a comprehensive analysis and critical review of different models used for energy consumption modeling and forecasting within the built environment. It evaluates these models based on their structure, input-output relations, and limitations, while also considering various input parameters influencing energy consumption, such as building characteristics, weather data, occupancy patterns, and energy systems. Additionally, the study classifies these models according to their suitability and applications in the context of the built environment. Special attention is given to identifying research gaps and providing insights into future research directions to advance the field of energy consumption modeling and forecasting. Overall, the study of energy consumption modeling and forecasting in the built environment enables stakeholders to make informed decisions, optimize resources, and promote environmental sustainability. It helps mitigate risks, drive technology development, inform policy, and realize economic benefits.

1.4 Problem Statement and Objectives

The buildings are primarily constructed to provide shelter and comfortable living conditions. Yet not all buildings meet this challenge and have many performance issues. Buildings contribute to greenhouse gas emissions, surface water run-off, eutrophication, and damage local ecosystems, thus contributing to climate change, smog formation and acidification on a larger scale. The interrelation between buildings and the environment is an important challenge. Gradual climate change, extreme weather condition can impact both building processes and occupant's behaviour.

Hence, enhancing energy efficiency and mitigating energy consumption and gas emissions have become pivotal initiatives in numerous countries. While considerable focus has been placed on enhancing building energy efficiency, numerous research challenges remain unaddressed. The complexity and multitude of building parameters make establishing deterministic relationships between causative factors and energy performance impractical.

To develop a reliable predictive model, it is imperative to consider only significant independent variables. However, selecting these variables poses a pervasive challenge in building energy performance modeling, as the aim is to maintain simplicity in the model. While many energy models focus on quantitative analysis and optimization of energy infrastructures, understanding and managing the impact of building occupants remains a persistent challenge. Assessing consumer behavior and preferences is inadequately addressed in the literature. Further research is required to understand user attitudes, knowledge, and abilities, as well as the quality of indoor air and its impact on occupant health. Additionally, long-term load forecasting and the accuracy of forecasts, which depend on the time horizon, remain areas for improvement. Despite the benefits and increased adoption of energy performance modeling, challenges persist, including accuracy, data availability, and compliance with simulation standards. Exploring the application of machine learning and artificial intelligence techniques to refine forecasts and account for the effects of new technologies on energy consumption models is warranted.

Objectives

1. To identify the key variables that affect the building energy performance, their behavior, nature, and the relationship between the explanatory and dependent variables.
2. To develop models for energy performance and energy prediction in built environment using engineering and artificial intelligence (AI) techniques.
3. To make a comprehensive analysis and critical review of two different models based on their structure, input-output relations, applicability, and limitations.

Thesis Organization

Chapter 1 introduces the research, addressing the problem statement, significance, and objectives of the study to lay the groundwork and underscore the importance of finding a resolution.

Chapter 2 conducts a thorough literature review, providing an overview of existing research in the field and pinpointing gaps that the current study aims to fill.

Chapter 3 outlines the methodology utilized to measure heating and cooling loads, detailing the techniques employed, rationale behind their selection, and the process of data collection and analysis.

Chapter 4 describes details of data collection used in the energy consumption modeling for creating mathematical or computational representations of energy use in a building.

In Chapter 5, the research culminates in presenting its findings, delving into calculation results and their implications, alongside recommendations for future research and areas for enhancement.

Finally, Chapter 6 elaborates on suggested future endeavours, proposing steps to address literature gaps and extend the current research, emphasizing the potential benefits and relevance to the field.

Chapter – 2

Literature Review

Chapter – 2

Literature Review

Buildings exert a substantial influence on energy consumption across their entire lifespan, from inception to demolition. The recognition of energy-efficient building design's paramount importance has led to widespread adoption of whole building energy simulation programs during the design phase. This literature review delves into the myriad energy prediction methods and consumption forecasts, highlighting their inherent unpredictability. Extensive research has been conducted to optimize the energy performance of both new and existing buildings, with these programs aiding architects and engineers in identifying cost-effective, energy-efficient design strategies. Notably, studies underscore the pivotal role of a building's envelope in energy consumption, emphasizing the imperative of enhancing envelope energy efficiency to curtail overall usage and mitigate greenhouse gas emissions. Whole building energy simulations offer invaluable insights into various envelope design strategies, including insulation enhancements, high-performance glazing utilization, and optimal building orientation, enabling informed decision-making among designers.

Moreover, the operational and maintenance practices concerning the building envelope significantly impact energy consumption. Effective maintenance and operation practices can mitigate energy waste and bolster energy efficiency by ensuring airtightness, sealing doors and windows, and monitoring insulation and ventilation systems. By embracing best practices in envelope maintenance and operation, energy wastage is minimized, and efficiency maximized, yielding substantial long-term energy savings and environmental advantages. This comprehensive literature review serves as a foundational exploration, contextualizing existing research, pinpointing gaps for further investigation, identifying various building parameters that help in reducing energy consumption, selecting suitable methodologies, constructing theoretical frameworks, and buttressing arguments with evidence, thereby advancing knowledge in the domain of energy performance modeling and consumption prediction in the built environment.

2.1 Exploring and Analyzing Factors Influencing Energy Consumption in Buildings

In their study, Zaidi et al. [14] present a case study focusing on an 80,000 square foot university building situated in the United States, which underwent multiple renovations throughout its lifecycle to reduce energy consumption and improve efficiency. The primary objective of the investigation was to evaluate the building's energy efficiency utilizing a modeling system known as eQuest. The paper underscores the critical importance of various data types, encompassing architectural, mechanical, electrical, and operational data, in ensuring precise energy modeling. Architectural data, such as building orientation, floor area, height, envelope construction materials, and fenestration areas, emerge as pivotal factors influencing energy demand modeling. This dataset furnishes architects and designers with indispensable insights for making informed decisions regarding energy-efficient building attributes, considering both mechanical and electrical aspects.

In the realm of commercial buildings, where HVAC systems stand out as major energy consumers, meticulous data pertaining to HVAC size, zoning, distribution of conditioned floor area, zone activities, flow rates, equipment specifications, and control sequences assume paramount importance. Similarly, accurate electrical data, encompassing lighting types, interior and exterior loads and profiles, office equipment, refrigeration, and exterior lighting, prove indispensable for precise energy modeling. Furthermore, operational data encompassing occupancy patterns, lighting and equipment schedules, thermostat settings, fan schedules, and fan power, significantly influence energy consumption and necessitate precise information for thorough modeling and analysis.

Zhang et al. [10] direct their study towards the Qionghai region in southern China, known for its monsoon climate featuring consistently high sun elevation angles and significant solar radiation. The study aims to optimize building envelopes to mitigate cooling loads resulting from solar radiation and heat conduction. Various characteristics of the building envelope are examined to gauge their influence on cooling demands. Parameters and features assessed in the study include heat conduction, solar radiation, internal heat sources, and infiltration. Through numerical simulations, the study evaluates the energy-saving potential of different building shape factors and envelope materials.

The research indicates that roofs offer greater energy-saving potential compared to outside walls, sunshades, and exterior windows. Recommending an insulation thickness of 30–40 mm for walls and roofs significantly reduces cooling demands. Notably, windows facing west exhibit the highest potential for energy savings. For buildings oriented to the north and south, shading lengths of 500–600 mm notably alleviates cooling burdens. The study underscores the importance of optimizing building envelopes in low-latitude regions of China to enhance energy efficiency.

Osaji [15] underscores the importance of integrating environmental design concepts to achieve energy-efficient office buildings, exemplified by the BEEHive concept and a study on building energy and environmental evaluation. Despite notable progress, there exists a gap between anticipated and actual building energy consumption that requires attention. To address this disparity, the study proposes the development of BMS-Optimum, a building management system that integrates reliable building energy data, optimal environmental design principles, considerations of weather and microclimate, and efficient building energy and environmental assessment. This research highlights the significance of employing robust building energy and environmental assessment methods, alongside environmental design concepts, to create energy-efficient office buildings and bridge the gap between projected and observed energy usage.

Fawzy et al. [7] discuss the disruption of climate patterns primarily caused by human activities releasing greenhouse gases, resulting in a planned shift in climate. These actions have already led to a global temperature rise of approximately 1.0°C above pre-industrial levels. If current emission rates persist, projections indicate a temperature increase of 1.5°C between 2030 and 2052. Natural disasters, affecting 68.5 million people in 2018 and resulting in economic losses of $131.7 billion, vividly illustrate the impacts of climate change. Areas such as food, water, health, ecosystems, human habitats, and infrastructure are particularly vulnerable. The Paris Agreement, established in 2015, aims to limit the global temperature increase to 2°C by 2100, with an aspirational target of 1.5°C. This article explores three methods for mitigating climate change: traditional mitigation, emissions reduction, and geo-engineering utilizing radiative forcing. Conventional mitigation primarily targets emissions reduction from fossil fuels. To achieve the ambitious goals set by the Paris Agreement, additional technologies such as negative emissions and geo-engineering are essential. While some technologies are still in early development stages, biogenic-based carbon sequestration techniques have matured and are relatively straightforward to implement.

Kavgic et al. [16] highlight the challenges posed by the lack of comprehensive data, including detailed inputs, assumptions, and underlying algorithms, which hinder replicating the results of studies. Additionally, there is a dearth of information regarding the relative importance of variations in input parameters on projected demand outcomes. The socio-technical factors influencing energy consumption, particularly how individuals utilize energy and respond to changes in their homes due to energy conservation measures, remain largely unknown.

Cho et al. [3] advocate for retrofitting existing structures to reduce energy usage and greenhouse gas emissions. However, challenges such as material deterioration and discrepancies between documented and actual operational conditions may hinder accurate energy performance estimation. This research proposes three assessment techniques based on the quantity of data required. Type 1 assessment draws from existing literature, while Type 2 involves on-site audits for gathering more information. Type 3 assessment utilizes energy data to calculate building attributes. The paper presents case studies of three buildings in Seoul, South Korea, showcasing the efficacy of various assessment techniques. Older buildings often provide monthly total energy use statistics rather than detailed hourly sub-metering data. The ASHRAE Change Point Model is employed to disaggregate monthly measured energy data into heating, cooling, and base load components to assess building envelope performance. Actual weather data is adjusted to fit simulation files using the Metronome program, and energy efficiency is evaluated using simulation tools such as Design Builder and EnergyPlus.

2.2 Investigating Predictive Models to Analyse Energy Performance of Building

Utami et al. [17] delve into research conducted at Universitas Gadjah Mada, shedding light on the crucial role of reliable audit data in crafting a benchmark model to estimate energy consumption within a university campus. The study entailed the development of energy consumption models encompassing 20 faculties and over 200 buildings at UGM, employing the SCL/CLF/CLTD calculation method. The results underscore the indispensability of comprehensive and precise audit data, alongside electricity bills, in establishing a dependable reference building model.

To gather, organize, and model the requisite data for cooling load calculations and energy consumption modeling, the proposed methodology adopted a bottom-up approach, leveraging various software tools such as Microsoft Excel, Google SketchUp, ArcGIS, and Climate Consultant. The study juxtaposed the energy profiles derived from audit data against models computed using the CLTD/SCL/CLF method. Notably, the energy profile models generally exhibited higher energy consumption estimates compared to reported values from electricity bills. By honing in on modeling the energy usage of specific building types, identified at the onset of the modeling process, the bottom-up approach aimed at crafting a robust reference benchmark model for energy consumption at UGM.

Hou and colleagues [18] provide a detailed explanation of the methodology used to estimate cooling loads originating from various heat sources, as well as those associated with infiltration and ventilation. Their approach relies on the CLTD/SCL/CLF method, which is grounded in the transfer function principle. To validate their software, they utilized a model room with specific parameters, including a target temperature of 25°C and a relative humidity of 50%. The cooling load estimations generated by their software were then compared against those obtained from professional cooling load estimation and HVAC design software, resulting in closely aligned results. Additionally, their software's ability to generate cooling load curves for different seasons highlights the increased demand for cooling during warmer seasons compared to colder ones.

In their research, Mao et al. [19] delve into the methodologies for determining peak cooling loads in buildings, commonly achieved through the use of TFM, TETD/TA, and CLTD/SCL/CLF. Their investigation reveals discrepancies between the 1993 and 1997 ASHRAE Handbooks of Fundamentals, primarily attributed to inaccurate estimations of sol-air temperature. The comparison between TFM and TETD/TA approaches shows closely aligned dynamic cooling load profiles, albeit with a slight overestimation by TETD/TA. Conversely, the CLTD/SCL/CLF approach, placing the peak sensible cooling load between TFM and TETD/TA values, exhibits a somewhat distinct profile. Nonetheless, caution is advised in drawing definitive conclusions regarding the efficacy of these methodologies.

AlHarbi et al. [20] delve into the intricacies of crafting a comprehensive air conditioning system tailored for AlFahad Mosque in Unaizah, Saudi Arabia's Qassim Region. Their endeavour involves meticulous calculations of the cooling load, meticulously executed following ASHRAE standards and the E20 method.

The cooling load analysis is meticulously divided into external and internal components, accounting for heat gains from both external sources and internal heat sources within the conditioned space. To ascertain these loads, AlHarbi et al. employ the CLTD method alongside the TFM. Notably, the inclusion of a solar cooling load component within the CLTD approach reflects recent advancements, encapsulating the cumulative solar heat gain at a given hour and the fractional heat storage effect attributable to diverse room constructions and floor coverings. This holistic approach not only ensures precise load calculations but also underscores the evolving sophistication in addressing cooling demands, particularly in regions with distinct climatic considerations like Saudi Arabia.

Spitler et al. [21] advocate for a refined approach to calculating cooling demands, introducing the radiant time series method. This innovative technique utilizes a 24-term "radiant time series" to convert radiant heat gain into cooling loads, complemented by a 24-term "response factor series" for computing conductive heat gain. By segregating conductive heat gain into radiative and convective components, the method streamlines the heat balance procedure. It entails meticulous assessment of conductive heat gains per hour, segmentation into radiative and convective components, inclusion of solar heat gains, and summation of internal heat gains. Subsequently, radiative heat gains are translated into cooling loads using radiant time factors. This approach facilitates streamlined calculations for convective heat gain, accounting for radiant exchanges among surfaces and other zone elements, incorporating a time lag and dampening effect.

Strand et al. [22] elaborate on the efficacy of EnergyPlus, an advanced building energy simulation software renowned for its comprehensive approach. Unlike its predecessors such as DOE-2 and BLAST, EnergyPlus stands out for its utilization of a Building Systems Simulation Manager. This manager facilitates the simulation of HVAC and electrical systems, equipment, and components while dynamically updating zone-air conditions. This departure from sequential simulation methods enables

EnergyPlus to offer unparalleled flexibility and integration in modeling building energy dynamics.

One notable advantage of EnergyPlus lies in its integrated simulation capabilities, which allow for realistic modeling of capacity limits and enhanced coupling between the air-side and water-side components of the system and plant. This holistic approach ensures that the simulated results accurately reflect real-world conditions, capturing the intricate interplay between various system elements. Moreover, EnergyPlus boasts the ability to specify various equipment types for a given zone, ranging from diffusers and reheat/recoil coils to high-and low-temperature radiant panels. This versatility enables users to tailor simulations to specific building configurations and HVAC systems, enhancing the accuracy and relevance of the results.

Additionally, EnergyPlus employs an iterative solution method for the air loop, a departure from the single-pass techniques utilized in earlier software. This iterative approach contributes to improved accuracy in simulation results by allowing for more comprehensive and refined calculations. Overall, EnergyPlus represents a significant advancement in building energy simulation software, offering a sophisticated yet user-friendly platform for modeling complex building systems and accurately predicting energy performance.

Dong et al. [23] present a comprehensive comparative analysis focusing on the data representations, structures, and applications of two key infrastructures: IFC and gbXML. Through selected examples highlighting their respective schemas, the study elucidates the intricate complexities involved in data representation. The findings underscore both the advantages and disadvantages of each strategy, shedding light on their hierarchical organization, official adoption, and practical usage.

Drawing from the study's insights, gbXML emerges as the preferred choice for extension to facilitate Radiance-based lighting simulation. This strategic extension is geared towards enhancing efficiency by streamlining the capture of project-related information while minimizing time and effort expenditure. By leveraging the common data schema, interoperability between the energy and lighting domains is achieved with minimal modifications. The extension of gbXML to support Radiance holds significant promise in facilitating the seamless integration of CAD models and lighting simulation software. This integration enables the sharing of crucial building geometry and material properties across concurrent engineering design frameworks. As a result, the arduous and error-prone task of acquiring and managing building data for different simulations in various domains is effectively mitigated.

Liu et al. [24] propose a novel framework aimed at automating the integration of crucial data required by performance analysis algorithms, thereby enhancing the energy efficiency of HVAC systems. Despite the potential benefits, the complexity of these algorithms has hindered their widespread adoption. To address this challenge, the framework systematically identifies and documents the information requirements gleaned from algorithm publications. Central to the framework's effectiveness is the extension of the IDM, originally grounded in the IFC schema. By mapping these requirements to diverse information sources featuring different formats and schemas, the framework streamlines the integration process. Notably, the extended IDM introduces a new stage tailored to the unique data needs of HVAC performance analysis methods, which may not be fully accommodated within the existing IFC model.

Crucially, functional parts serve as the cornerstone of this approach, representing fundamental units encompassing classes, properties, and relationships outlined in the schema. Through meticulous manual identification and categorization, including HVAC components, properties, and relationships, the framework ensures alignment with the exchange requirements derived from performance analysis algorithms. By effectively bridging the gap between algorithmic needs and available data, Liu et al. framework holds promise in facilitating the seamless integration of performance analysis methodologies into HVAC system design and optimization processes. Through this integration, stakeholders can harness actionable insights to enhance energy efficiency and drive sustainable practices in building management.

Khakre [25] delves into the context of Pusad, a city characterized by its surrounding hills and tropical climate, where the average annual rainfall ranges from 250 to 360 mm. Within this locale stands a three-level building measuring 10.59 by 6.12 meters, inclusive of the ground floor. The construction details reveal outer walls fortified with 102 mm and 203 mm face bricks, sandwiching 15 mm cement mortar sand and 6 mm plaster on both sides. The roof composition comprises 102 mm HW concrete, 6 mm plaster, and a 457 mm air gap beneath the slab, optimizing thermal insulation. Central to the discussion is the concept of cooling load, denoting the total heat removal required to achieve the desired indoor temperature and relative humidity. To ascertain this load and facilitate optimal HVAC system design, the study employs the HAP software, tailored for analyzing cooling and heating loads in commercial buildings within the Pusad region.

The functionality of the HAP software extends beyond mere load calculations. It encompasses a spectrum of tasks essential for HVAC system design and optimization. These include but are not limited to, computing cooling and heating loads for various spaces, zones, and coils within the system, determining airflow rates, and sizing cooling and heating components like coils and fans. To execute precise design calculations, the HAP software relies on specific information inputs. These encompass climatic data, construction material specifications, layout dimensions, internal load parameters, and HVAC equipment data. By leveraging this comprehensive dataset, the software facilitates accurate load estimations, simplifying the selection and specification of HVAC equipment tailored to the building's unique requirements.

Khakre's exploration underscores the critical role of advanced software tools like HAP in driving informed decision-making in HVAC system design, particularly in regions characterized by diverse climatic conditions like Pusad. Through precise load calculations and equipment sizing, such tools contribute to energy-efficient building design and enhanced occupant comfort.

Hyndman et al. [26] delineate the intricacies of air supply and exhaust management within hospital environments, which are governed by encryption and standards prescribing the requisite number of air changes per hour tailored to diverse room functions. This airflow, denoted by ACH, varies depending on factors such as the room's purpose, volume, and requisite pressure differentials with adjacent spaces. Crucially, the authors highlight the pivotal role of pressure differentials in ensuring infection control within healthcare settings. For instance, positive pressurization is employed in patient isolation rooms for transplant patients to prevent contamination. This strategy involves maintaining a higher air pressure within the room relative to its surroundings, achieved through a two-door isolation system that introduces more air than is exhausted. Conversely, negative pressure is utilized in spaces designated for infectious diseases, where air is continually exhausted at a higher rate than supplied to contain microorganisms effectively.

Moreover, the literature underscores the diverse requirements of different spaces within hospitals. While office spaces necessitate a neutral pressure relationship and low air exchange rates, operating rooms mandate high air exchange rates to minimize airborne contamination during surgeries. In terms of heating strategies, the study elucidates the prevalent practice of utilizing terminal reheat designs in hospital settings. This involves drawing air into an air handler and subsequently heating it through a heat exchange coil containing hot water from a specialized source. Control valves are employed to regulate water temperature, ensuring the desired air supply temperature is achieved. Various methods, such as steam heat exchangers, hot water boilers, and alternative heating techniques, are employed to produce hot water for this purpose. Furthermore, the literature review delves into cooling strategies within hospital environments. Cooling is achieved either directly through refrigerant coils or via chilled water systems for direct heat exchange, thereby maintaining optimal temperature levels conducive to patient comfort and healthcare operations.

In Li Kangji's article [27], the exploration of evolutionary and swarm intelligence algorithms application in optimizing energy analysis problems is presented. The paper conducts a review of various hybrid prediction techniques that integrate these algorithms. Accurate forecasting of energy consumption holds significant importance for fault detection, energy management, and conservation within buildings. The article meticulously analyzes data-driven methods, including regression models, artificial neural networks, support vector machines, fuzzy models, and grey models, for predicting building energy consumption. It thoroughly examines the advantages and challenges associated with current predictive models. The review primarily focuses on energy prediction methods utilized in buildings or larger scales, with a specific emphasis on six popular forecasting techniques. Time series forecasting commonly employs regression models such as ARIMA after data transformation to achieve stationarity. However, reliance solely on a single data-driven model may encounter convergence issues and reduced accuracy, particularly when handling large datasets. To mitigate these challenges, there is a growing adoption of AI-based hybrid models in building energy forecasting, leveraging multiple methodologies to enhance accuracy and robustness.

The article by Lung [28], BIM software is explored as a valuable tool in architectural design, offering several advantages. It enables 3D simulations of buildings and their components, facilitating collision prediction, visualization of environmental variables, and accurate calculations of material and time quantities. By allowing the creation of building elements once within a project, BIM improves efficiency by saving time and enabling designers to focus on other critical aspects. Compared to traditional design processes, BIM offers enhanced accuracy in estimating building quantities and ensuring superior quality.

Moreover, an energy simulation analysis is conducted on a case-study office building with consistent location and zones. This building, intended as a shared space for five companies, features a single-room cooling system for HVAC. The baseline construction includes concrete walls, double glazed windows on all four facades, concrete floors, and no ceiling treatment, resulting in the highest observed energy use intensity of 62 kBTu/sf/yr. To address this, the report recommends incorporating higher-performance materials to reduce energy consumption and minimize environmental impact.

Khaddaj et al. [29] examine the relationship between BIM and sustainability, particularly regarding energy saving in existing structures. Through a comprehensive literature review, the study analyzes over 200 publications focusing on terms related to information modeling and sustainable development. Themes like water, energy, waste reduction, materials, and indoor environmental quality are used to group these readings.

The article underscores the increasing importance of addressing energy consumption's negative environmental effects, particularly in terms of carbon emissions. Strategies to mitigate these effects include life cycle energy analysis and the concept of low energy buildings. However, applying BIM for retrofitting old buildings presents challenges due to multidisciplinary information exchange and technological diversity. To strengthen BIM's role in energy-efficient renovations, the paper proposes a research agenda to address these challenges and facilitate effective energy management in existing buildings.

Xian et al. [30] evaluate the utilization of BIM technology in building energy simulation and the effectiveness of BIM model’s communication with energy simulation tools. The study suggests a technical framework for exchanging building data between EnergyPlus, a widely used energy simulation tool, and Autodesk Revit, a popular BIM application. Additionally, the study addresses interoperability issues encountered during data transfer.

The energy usage of a single-family home is simulated to demonstrate how the suggested framework might be utilized. The comparison reveals deviations from monitored data of 8.0% and 7.1%, respectively. This study is significant as it illustrates how BIM can enhance building energy simulation and provides stakeholders with advice on minimizing data loss during BIM model translation. Furthermore, the study evaluates the accuracy of transferred building data and verifies energy simulation outcomes based on BIM using various sources. The suggested paradigm has practical implications for improving the effectiveness of BIM-based energy simulation, particularly given the widespread use of Revit and EnergyPlus in building design and energy simulation.

Giannakis et al. [31] propose a method for creating thermal simulation models using BIM in a semi-automatic fashion. While BIM provides information about building geometry and material attributes, it may lack second-level boundary information necessary for generating thermal simulation models. The suggested solution involves extracting geometry-related data from BIM and processing it using a second-level boundary detection algorithm. However, errors in the IFC file schema can impede the generation process, necessitating automatic error detection and correction mechanisms. Existing software packages like Solibri Model Checker TM can detect geometric inconsistencies and communicate them back to the AEC software for manual correction. Nevertheless, such mechanisms have limits, and manual correction is necessary for ambiguous conditions.

Bazjanac et al. [32] discuss the challenges of importing building geometry into energy performance simulations from the user's perspective. Software interoperability is crucial, and the BLIS group of software enables interactive importation of building geometry into EnergyPlus, reducing manual effort. Importing 3-D geometry directly without human intervention requires specialized interfaces, which are expensive and rare. Alternatively, simulation tools with GUI or pre-processors can accept 3-D definitions, but existing options may require manual editing and lead to increased errors.

The thermal simulation view differs from the architectural/engineering view, requiring specific details for accurate simulation. The paper also highlights progress in common data exchange using IFC and gbXML in the construction industry.

Sousa et al. [33] highlight the crucial role of energy simulation software tools in helping building designers reduce energy costs. Popular tools include EnergyPlus, ESP-r, IDA ICE, IES VE, and TRNSYS, each offering unique features and capabilities. For example, EnergyPlus combines BLAST's heat balance with a generic HVAC system, while ESP-r uses complex equations to simulate all aspects of a construction project. TRNSYS is a modular software tool for transient system simulation, capable of developing complex energy-related systems. IES VE provides a wide range of variables for building simulation analysis.

Wang et al. [34] employ a methodology to predict hourly electricity usage for heating in a classic single-family house using AI models and weather data. The study involves collecting energy consumption and climate data, preprocessing the data through various techniques, selecting parameters for prediction models, and training the models. Four AI-based models are utilized to forecast heating electricity usage, and their prediction accuracy for single-family homes is compared.

Truong et al. [35] discuss buildings and the IoT network, a database management system, and AI-based building energy analytics that constitute the architecture of AI applications for assessing energy performance in buildings. Various approaches such as predictions, classification, clustering, alerting, and monitoring are employed by these analytics to recommend cost- and energy-saving strategies. The article examines various AI models, including Support Vector Regression, Artificial

Neural Networks, and a new model called Activated Artificial Neural Networks, with a specific focus on the prediction task.

Seyedzadeh et al. [9] utilize artificial neural networks and clustering techniques in building energy performance research, which has been widely studied across various building types and locations. Studies have been conducted on educational buildings, residential buildings, office buildings, and marketable buildings, analyzing factors such as construction year, building geometry, internal environmental conditioning, site exposure, glazing ratios, roof shape, and degree days.

Clustering techniques have also been applied to school buildings, considering factors such as building age, insulation, number of students, and heating system capacity. Overall, these studies provide valuable insights into the factors influencing building energy performance and demonstrate the usefulness of machine learning in building energy research. This paper uses machine learning models, ANN, and SVM to predict HVAC loads in different building types and locations. These models are trained on various input parameters such as weather data, occupancy counts, building characteristics, and solar radiation. Some studies focus on specific building types, while others use data from multiple buildings or building types.

Elbeltagi et al. [36] propose a method developed to generate an energy consumption database by combining parametric modeling and simulation tools. The database is created based on the characteristics of 12,000 simulations conducted using Rhinoceros/Grasshopper. An energy efficiency prediction model is made using the EnergyPlus program and ANN. This approach is especially helpful for designers at the conceptual design stage, allowing assessment of various design possibilities and offering direction for the design team's deliberations. The study considers design factors including building size, orientation, window-to-wall ratio, building envelope, glazing type, lighting occupancy, plug loads, and temperature settings.

Ahmed et al. [37] found that air conditioning load estimation has traditionally relied on manual calculations or judgment-based estimations, which are time-consuming and prone to errors. To address this issue, computer automation offers a promising solution. In their study, they developed C#.NET software for air conditioning load estimation specifically targeting developing countries like Bangladesh. The software is designed to handle simple and typical load estimates and can be easily expanded to accommodate more complex and dynamic loads. While commercial packages are available for cooling load calculations and HVAC system design, they tend to be costly, particularly for developing countries.

The primary objective of this software is to provide a free and user-friendly tool for estimating cooling load in air conditioning systems. Developed in Microsoft Visual Studio, the software includes four tabs to input various parameters related to roof and wall constructions, indoor and outdoor conditions, air ventilation, equipment, and occupants.

Montiel-Santiago et al. [38] suggest that the building information modeling capabilities for deriving a building energy model using BIM 6D remain largely untapped. This computer model enables simulation of the building's energy efficiency, including upgrades to the lighting. For both new NZEB construction and restorations, particularly in healthcare facilities, BIM 6D enables informed decisions. It facilitates thorough energy impact analysis, improving energy and lighting efficiency, which is valued by patients and others. By utilizing BIM 6D, energy savings of up to 50% can be achieved, with lighting enhancements alone contributing up to 13% of the savings. BIM encompasses various dimensions, such as 2D, 3D, 4D, 5D, 6D, and 7D, each serving specific purposes in design, construction, and facility management.

Jeong et al. [39] introduce a framework aimed at bolstering decision-making throughout the construction process by integrating BIM with Object-Oriented Physical Modeling-Based BEM. Central to this framework is a system interface bridging

Modelica-based BEM and BIM, coupled with a visualization component embedded within the BIM environment. This visualization tool displays simulation outcomes, aiding designers in grasping the relationship between their design choices and the building's performance.

The framework utilizes the Modelica Buildings library from the Lawrence Berkeley National Laboratory as its thermal simulation engine. However, a significant hurdle arises as the current Modelica Buildings library necessitates programming expertise, which may be lacking among designers. To address this challenge, Jeong et al. propose the ModelicaBEM-based BIM, which streamlines the integration of BEM into the BIM workflow by automating the energy model creation process.

Key features of this framework include a system interface responsible for generating building topology and enhancing BIM models with thermal characteristics. Moreover, it enables seamless translation of BIM data into Modelica-based BEM, facilitating thermal simulations.

This designed BIM-based Modelica BEM solution eliminates the need for programming expertise from the Modelica Buildings library, thereby simplifying the process for designers to develop energy models and utilize simulation results within a BIM context. By fostering such integration throughout the design phase, this framework encourages informed decision-making, ultimately enhancing the overall efficiency and effectiveness of the construction process.

2.3 Comprehensive Analysis and Critical Assessment of various Energy Performance Models

Swan et al. [40] introduced Energy Performance Modeling, a computer-based process tailored for assessing the energy dynamics of built environments. This method integrates statistical analysis with engineering principles to predict a building's response to structural, operational, behavioural, and external factors. Their study contrasted top-down and bottom-up strategies in energy modeling. The top-down approach, while overlooking specific end-uses, identifies the residential sector as a major energy consumer. In contrast, the bottom-up approach estimates energy consumption based on individual household data and extends findings to larger populations. Both methods leverage statistical and engineering techniques, utilizing varying degrees of input data, calculations, and simulations to generate versatile outputs applicable across diverse scenarios.

Pedersen [41] delineates three primary methodologies for estimating thermal load and energy consumption in buildings: Regression analysis, energy simulation software, and advanced computer systems. Regression models leverage a significant volume of metered load data, long-term weather patterns, and some building-specific information. Energy simulation programs must encompass comprehensive building data, including sociological factors and realistic meteorological representations. Intelligent computer systems integrate metered load data, weather conditions, and building information. The essay evaluates the merits and limitations of each approach, providing recommendations for their optimal utilization. It delves into specific techniques within each methodology, such as conditional demand analysis, engineering methods, and neural networks, to illustrate their applicability. Ultimately, the paper scrutinizes diverse approaches for estimating thermal load and energy consumption in buildings, elucidating their respective advantages and disadvantages while highlighting practical applications through specific methodologies.

Neto et al. [42] conducted a comparative analysis of the anticipated energy demand in a university building in Sao Paulo, employing ANN models and EnergyPlus simulations. Their investigation focused on assessing the influence of single variable (temperature only) and multiple variables (temperature, relative humidity, solar radiation) inputs. The research findings underscored the significance of external temperature over other meteorological parameters in impacting energy demand.

Kumar Rajesh et al. [43] discuss the application of an ANN for forecasting the summer cooling requirements and carbon dioxide emissions of a six-story building. Their prediction model considers various parameters such as internal gain, solar heat gain, ventilation losses, and conduction losses, which collectively contribute to the complexity of estimating the building's energy usage accurately. Employing the conventional back-propagation learning approach, the ANN model yielded a calculated cooling demand of 0.87 million kW annually, achieving a high regression coefficient of 0.9955. Among the factors considered, conduction losses exhibited the most reliable validation performance.

Pinheiro et al. [44] suggested to use a standardized mechanism for information exchange between tools for BIM and BEPS. In order to speed up the procedure, this method applies the Model View Definition and Information Delivery Manual methodologies. The manual process now used to create BEPS models is time-consuming, unstandardized, and prone to mistakes.

The suggested method concentrates on the portion of the IFC data model that is pertinent to simulating building energy performance in order to fully realize the potential of BIM-based simulation. A bottom-up methodology is used to generate the MVD, using defined use cases to direct the export to IFC.

The foundation for identifying the pertinent data is IFC4 Addendum 2, the most recent iteration of the IFC schema. Although the schema contains most of the definitions needed for energy modeling, certain additional definitions, notably those pertaining to scheduling and internal loads, are generated to assure thorough coverage. This standardized approach improves the efficiency and accuracy of BIM-based energy simulation, encouraging regular and trustworthy data interchange between BIM and BEPS tools.

Wang et al. [45] evaluates to enhance energy efficiency in buildings, assessing their energy performance is crucial. This involves quantifying the energy use through different methods: calculation-based, measurement-based, and hybrid. The quantified energy use is then compared to predetermined criteria using quantitative energy performance assessment methodologies. Data from power bills, building audits, sub-metering systems, BMS monitoring, and computer simulations are used in energy quantification. Calculation-based methods employ complex building models, ranging from dynamic simulations to steady-state approaches. Both forward modeling and inverse modeling strategies can be used to build steady-state models. Measurement-based techniques collect data from a variety of sources, including sub metering systems, energy bills, and BMS monitoring. Methods that blend calculation and measurement-based components are called hybrid methods. Dynamic and steady-state methods that rely on calculations can be further separated. While steady-state approaches use correlation factors to simplify these dynamics, dynamic methods are used for full simulations that take into account system and building dynamics. The modeling process is established using two modeling techniques: forward modeling and inverse modeling. Inverse modeling trains and identifies model parameters or structures using accessible inputs and outputs, whereas forward modeling forecasts energy use based on building attributes and given conditions.

Hai-xiang Zhao [46] describes predicting building energy consumption is a challenging undertaking affected by a wide range of elements, including weather, building design, sub-level components, and occupancy patterns. This paper looks at many models that have been created to tackle this problem, including engineering, statistical, and artificial intelligence approaches. Each model has unique benefits and drawbacks, and the best model to choose depends on the application at hand. Future research in this field could focus on the development of new and improved prediction models, the refinement of system-level energy consumption analysis, the integration of energy prediction with BEMS, and the optimization of artificial intelligence models for enhanced accuracy. Accurately predicting building energy consumption necessitates a comprehensive analysis of various factors, making it a demanding task. The reviewed models in this study offer diverse approaches to tackle this issue, each with its own strengths and weaknesses. Further investigations are essential to advance the development of more effective models, enhance system-level energy consumption analysis, integrate energy prediction with BEMS, and optimize artificial intelligence models for accurate predictions.

Chou et al. [47] proposed big data analytics and cloud computing are powerful technologies for processing and analyzing large volumes of data. By utilizing advanced techniques like machine learning, organizations can uncover energy consumption patterns, predict future usage, and reduce costs. Cloud computing provides scalable and secure infrastructure, allowing organizations to focus on their core business while efficiently managing and analyzing data. Together, these technologies offer tremendous potential for improving energy efficiency and cost reduction in buildings.

Li Guangchen et al. [48] elucidate the application of multi-output energy models employing DNN and BASS algorithms for forecasting building energy consumption across various time scales. The study particularly focuses on daily, monthly, and annual time frames, where the BASS method, in conjunction with principal component analysis, effectively estimates energy usage. These multi-output models prove valuable for calibrating building energy models and conducting sensitivity and uncertainty analyses. The research emphasizes the significance of optimizing accuracy through appropriate hyper-parameter selection in machine learning models. Notably, the DNN models vary in terms of the number of neurons and hidden layers, with the multi-output DNN model featuring four layers for daily energy consumption prediction and three layers for monthly energy consumption prediction.

George [49] discusses the utilization of GIS technology in deriving descriptors for environmental analysis, encompassing factors such as flood-prone areas, environmental impairment, transportation stress, and resource utilization. Spatial data is stored in an external Relational Database Management System, while non-spatial data is directly inputted into the RDBMS. Two neural networks, NN-I and NN-II, are trained using the back-propagation algorithm, with input and target vectors derived from the processed data. The training patterns are presented in batches, and the learning rate is adjusted to expedite convergence. The integrated system is implemented on an HP 9000 series workstation using the C programming language. The training process is outlined, including the number of input vectors, minimization of mean-square error, and final network configurations. The study highlights the application of GIS technology and neural networks in environmental analysis and prediction.

Chapter - 3

Methodology

Chapter – 3

Methodology

3.1 Methods of Energy Consumption Modeling and Forecasting in Building Sector

Building energy consumption refers to the total amount of energy utilized by a building to maintain a comfortable indoor environment, encompassing heating, cooling, lighting, and ventilation systems. Research endeavours have been directed towards developing methodologies aimed at accurately predicting the hourly electricity consumption required for space heating and cooling within buildings. These predictive models are crucial for efficiently managing energy consumption and optimizing building operations. These methods are often categorized into three main types: white box models, black box models, and grey box models [49], as depicted in Figure 3.1.

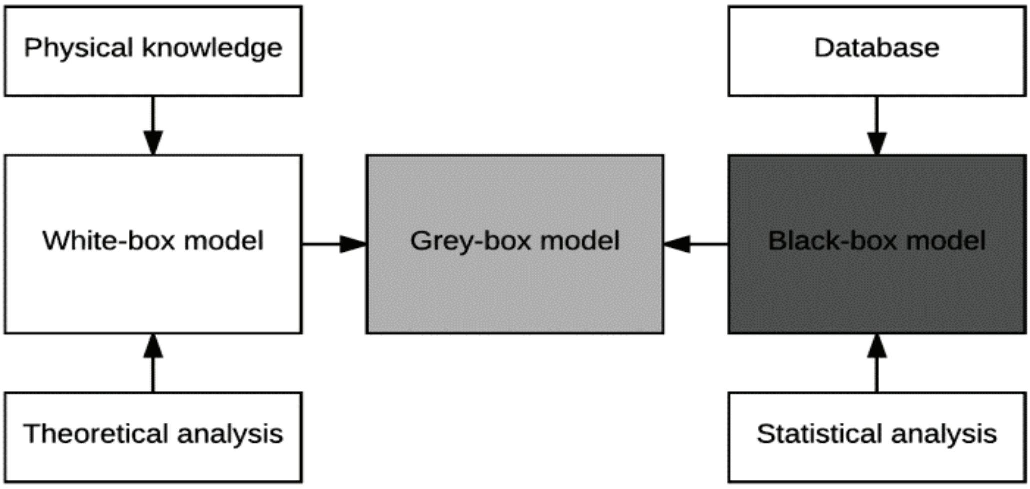


Figure 3.1: Methods of energy prediction and estimation in building sector

1. White Box Models

White box models, also known as physics-based models, are extensively employed in the building sector to predict energy consumption, particularly for cooling purposes. These models, often referred to as building physical energy models, rely on heat and mass balance equations to accurately represent the dynamic thermal behavior of buildings. By simulating the intricate interplay of heat transfer mechanisms within a building, white box models provide a detailed understanding of energy usage patterns, aiding in the optimization of cooling systems and overall energy efficiency.

In predicting the cooling load of buildings through white box models, a comprehensive analysis of the heat balance is conducted. These models consider three primary heat transfer mechanisms: conduction, convection, and radiation, occurring between the external walls of the building and its surrounding environment. This process involves solving systems of equations derived from the principles of heat transfer physics, which describe how heat moves within the building structure.

The deterministic nature of white box models stems from their foundation in physics. By precisely accounting for heat transfer processes and material properties, these models provide clear and interpretable results [34]. They allow for an in-depth understanding of the thermal behavior of buildings under varying conditions.

However, the usability of white box techniques is contingent upon the availability of detailed building information. Factors such as building materials, insulation levels, occupancy patterns, and climate conditions must be accurately represented in the model. Due to this requirement for comprehensive data, the practical application of white box models may be limited in cases where detailed information about the building is scarce or inaccessible. Some examples of white box models include:

Transfer Function Method (TFM): TFM is a technique used in building energy analysis and HVAC system design to model and calculate the dynamic response of a building's thermal and energy systems. Its detailed and comprehensive approach takes into account the time-dependent interactions between heat transfer mechanisms, including conduction, convection, and radiation, as well as the effects of building materials, components, and control systems [19].

The Transfer Function Method represents the thermal behaviour of a building as a network of interconnected nodes and branches, similar to an electrical circuit. Each node corresponds to a location within the building, such as a room or a surface, and each branch represents a thermal path of heat transfer. This method employs mathematical equations, typically in the frequency domain, to demonstrate the heat transfer and energy flow within a building.

The Transfer Function Method is particularly valuable when analyzing buildings with complex geometries, multiple thermal zones, and intricate building components. It provides insights into how different design choices, materials, and control strategies can affect a building's energy performance and indoor thermal comfort over time. While the method requires more detailed input data and computational resources compared to other simpler methods, it provides a high level of accuracy and precision in modeling dynamic thermal behaviour. This is the most complex of the methods proposed by ASHRAE and requires the use of a computer program or advanced spreadsheet.

ASHRAE Cooling Load Temperature Difference Method (CLTD): The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) provides guidelines for load calculations based on factors like climate, occupancy, equipment, and lighting [19]. These calculations help estimate cooling and heating loads. This method is derived from the TFM method and uses tabulated data to simplify the calculation process. On the other hand, the CLTD method assumes steady-state conditions and ignores any dynamic interactions between the building envelope, internal loads, and HVAC systems. It offers a simplified approach to estimate the cooling load requirements for a building and provides a quick and straightforward way to calculate the cooling load, only taking into account the solar, transmission and internal heat gain factors.

EnergyPlus: EnergyPlus is a whole-building energy simulation program developed by the U.S. Department of Energy. It uses a white box approach, integrating detailed physics-based algorithms to simulate the energy performance of buildings under various conditions [22].

DOE-2: Developed by the U.S. Department of Energy, DOE-2 is a widely used building energy analysis tool. It utilizes white box modeling principles to simulate the thermal behavior of buildings and predict energy consumption for heating, cooling, lighting, and other purposes.

eQUEST: It is another example of a white box model used for building energy analysis which relies on detailed physics-based algorithms to model building components and systems accurately. With eQUEST, users can simulate various aspects of a building's energy performance, including heating, cooling, ventilation, lighting, and more [14]. The software allows for the input of detailed building characteristics, such as geometry, construction materials, occupancy schedules, and HVAC systems. By utilizing white box modeling principles, eQUEST provides users with insights into how different design choices and operational strategies impact a building's energy consumption. This enables architects, engineers, and building designers to make informed decisions to optimize energy efficiency and sustainability.

Total Equivalent Temperature Differential/Time-Averaging (TETD/TA): This method is used in building energy analysis and thermal comfort studies. It involves calculating an average temperature difference over a specified period to represent the cumulative effect of temperature fluctuations on a building or a space. The basic idea behind TETD is to quantify the thermal stress experienced by a space due to temperature variations, especially in conditions where the temperature changes frequently or erratically. Rather than focusing on instantaneous temperature readings, TETD considers the cumulative impact of these variations. TETD is particularly relevant in situations where rapid temperature changes occur, such as in spaces with intermittent heating or cooling, or where occupants frequently move between indoor and outdoor environments. It provides a holistic view of thermal conditions by accounting for the dynamic nature of temperature fluctuations over time. The amount of computation needed is also large for such models.

2. Black Box Models

Black-box models use statistical techniques, as opposed to physics-based white-box models. These techniques infer links between provided inputs and outputs while requiring little or no prior knowledge of building features. The required inputs generally include information about the buildings themselves as well as past consumption and environmental data. As the name "black box" suggests, there is immense difficulty in the analysis and explanation of the outcomes of these models [40]. It is because the real impact of a given input value is often hard to pinpoint. This is especially the case with ANN. Although these models do not require such detailed information, they usually need heaps of it. Model selection and tuning are an emphasis when working with statistical models. Statistical methods involve the analysis and interpretation of data using statistical techniques. These methods are based on the idea of using data patterns and relationships to make predictions or decisions.

They are particularly useful when dealing with uncertainty, variability, and randomness in data. Statistical methods often involve estimating parameters from data and making inferences based on probability distributions. Some examples of white box models include:

Linear Regression: Linear regression aims to find if there is a linear relationship between an independent variable and a dependent variable (energy consumption). In the context of building energy consumption, independent variables include temperature, humidity, occupancy patterns, building size, etc. Linear regression estimates coefficients for each independent variable to determine its impact on energy consumption [11]. Linear regression is relatively easy to interpret. however, it assumes a linear relationship between variables, which may not hold for complex energy systems.

Multiple Linear Regression: Multiple linear regression extends the linear regression model to incorporate multiple independent variables. This allows for a more comprehensive analysis of how different factors collectively influence energy consumption. Building characteristics like insulation, window area, and heating/cooling systems can be included in the model. The equation for multiple linear regression is an extension of the simple linear regression equation, accommodating multiple independent variables. Multiple linear regression provides a more realistic representation of the relationships among variables, but it can be sensitive to multicollinearity (high correlation between independent variables) and overfitting.

Time-Series Regression: Time-series regression considers the temporal aspect of energy consumption, incorporating time-related variables such as time of day, day of the week, and season. Time-series regression models can capture daily and seasonal variations in energy consumption, making them particularly useful for understanding dynamic patterns. For instance, a time-series regression equation might be used to predict daily energy consumption.

Artificial Neural Network (ANN) Method: Artificial neural networks are computer-based models that mimic the way the human brain processes information, and are particularly well-suited to handling large and complex datasets. Support vector machines use mathematical algorithms to identify patterns and make predictions based on past data [27];[50]. ANN methods are a subset of machine learning techniques inspired by the structure and function of the human brain. They involve training artificial neural networks to recognize patterns and relationships in data. ANNs are capable of learning complex, nonlinear relationships from data, even when the underlying mechanisms are not fully understood. They excel at tasks like image and speech recognition, language translation, and pattern detection. ANNs are trained using large datasets and require iterative optimization processes to adjust the network's weights and biases. Once trained, ANNs can make predictions on new, unseen data. AI and ML techniques can be applied to large datasets to identify patterns and correlations that can help predict energy consumption more accurately. These methods include neural networks, decision trees, and clustering algorithms.

Black-box models use statistical techniques, as opposed to white-box models that are based on physics. These techniques infer links between provided inputs and outputs while requiring little to no prior knowledge of building features. These inputs generally include information about the buildings themselves as well as past consumption and environmental data. The name "black box" describes how difficult it is to analyse and explain the outcomes in these models [40].

3. Grey Box Model

Hybrid or grey box models integrate techniques from both groups. The hybrid approach can make it easier to meet the white box and black box methodologies criteria for data quantity and quality. For instance, estimating the physical parameters required by some physics-based models may be done using a statistical model [46].

3.2 Case Study of Commercial Building

To conduct an in-depth analysis of building energy performance, we chose a hotel situated in Nagpur, India, as our primary case study. Our investigation cantered on exploring the peak cooling load, peat total energy consumption, energy consumption patterns of this specific hotel, employing a diverse range of methodologies and techniques. This approach allowed us to meticulously evaluate the energy efficiency levels and usage trends within the selected building.

Nagpur, located in the Indian state of Maharashtra, is known for its varied climate and historical significance. The city experiences a tropical savanna climate, characterized by hot summers, a monsoon season, and mild winters. Summers typically last from March to June, with temperatures often soaring above 40°C (104°F). The city can experience scorching heat during this period, with occasional heatwaves.

The monsoon season in Nagpur usually begins in June and lasts until September, bringing moderate to heavy rainfall. The city receives a significant portion of its annual precipitation during this time, which helps maintain its greenery and supports agriculture in the surrounding region. Winters in Nagpur, lasting from November to February, are mild and pleasant. Temperatures typically range from around 10°C to 25°C (50°F to 77°F). This season is characterized by clear skies and cooler temperatures, making it an enjoyable time to explore the city's attractions.

Nagpur has witnessed both extreme high and low temperatures over the years. The highest temperature recorded in Nagpur can exceed 47°C (116.6°F) during the peak of summer, while winter nights can occasionally see temperatures dropping to around 5°C (41°F). Overall, Nagpur's climate offers a mix of hot summers, refreshing monsoon rains, and mild winters, contributing to its diverse and vibrant atmosphere throughout the year.

Figure 3.2: Building used in the case study (site photograph)

Figure 3.2 depicts a hotel building comprising six floors (G+6) situated in Nagpur. The building features brick walls with plaster, concrete floors, and double-glazed glass windows across all four facades. It is oriented along the North-South axis and operates continuously, 24 hours a day, 7 days a week. The vertical fenestration includes aluminium frames and double glazing.

3.3 Methods Used in the Case Study

In this study, the following methods were used to analyze the energy performance of the case building:

a) Cooling Load Temperature Difference (CLTD) Method
b) Revit Architecture
c) Artificial Neural Network (ANN)

(a) Energy Consumption Prediction Using CLTD Method

The CLTD method is indeed a widely used approach for determining the sensible cooling load in buildings, employed in building design and HVAC engineering to estimate cooling load requirements. It helps in determining the appropriate size and capacity of cooling systems to maintain indoor comfort levels. This method simplifies calculations by considering the difference between outdoor and indoor design temperatures along with heat gains from various building components.

The CLTD method incorporates heat conduction through walls, roofs, windows, and other surfaces, as well as internal heat gains from occupants, equipment, and lighting. Utilizing calculations based on the TFM, it can be implemented through software or manual calculations for quick estimation or verification purposes. As part of the TFM framework, the CLTD method primarily focuses on calculating sensible cooling loads for exterior walls, fenestrations, floors, and roofs.

To address solar heat gain and the heat storage effect of room constructions and floor coverings, the CLTD method incorporates factors known as the Solar Cooling Load Factor (SCL) and the Cooling Load Factor (CLF). The SCL factor accounts for the impact of solar heat gain during specific periods of the day and its subsequent storage within the building's structural elements. Essentially, it quantifies the additional cooling load imposed on the building due to solar radiation penetrating through windows and other openings, and the subsequent release of stored heat within the building.

On the other hand, the CLF factor accounts for internal sensible cooling loads within the building. These loads arise from various sources such as occupants, lighting, equipment, and other internal heat gains. By incorporating the CLF, the CLTD method accurately assesses the cooling requirements necessary to maintain comfortable indoor conditions while accounting for both external and internal heat sources.

The detailed procedure to determine the space cooling load of the case study building, which encompasses both sensible heat and latent heat gain using the CLTD method, is given below in Figure 3.3. It uses explicit equations to compute the heat gain or loss by the building components.

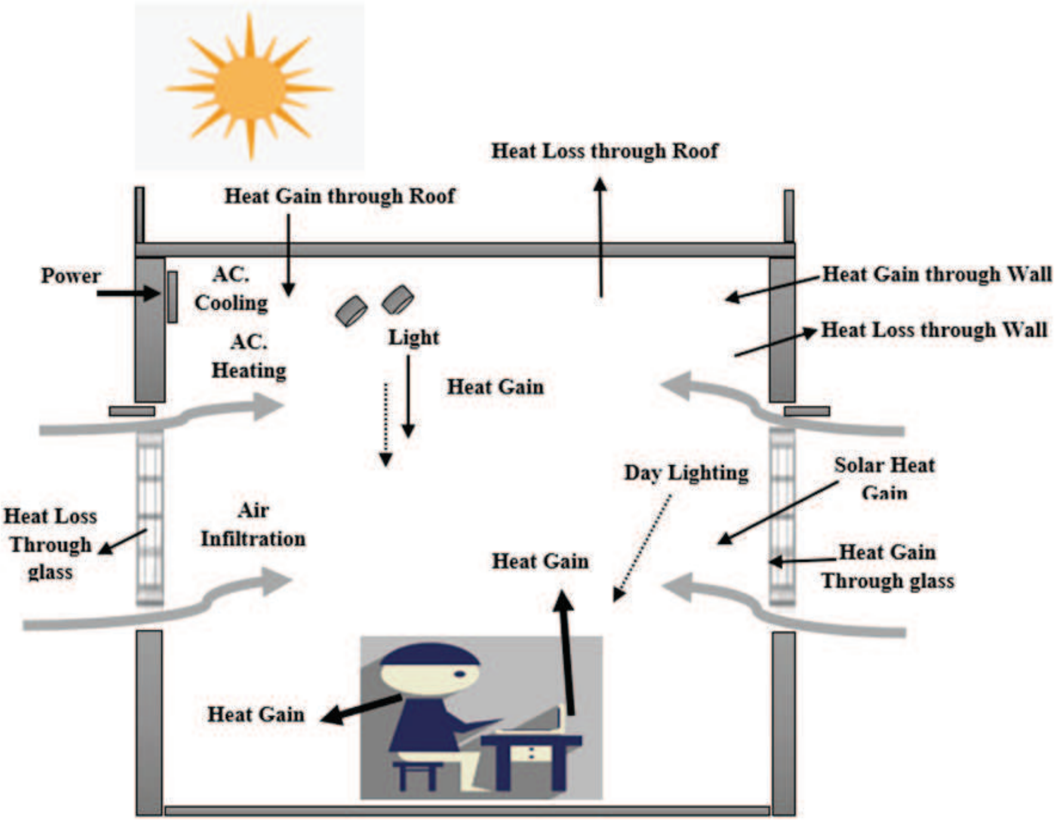


Figure 3.3: Modes of heat gain and loss through building

Sensible Heat Gain

Sensible heat gain in buildings is influenced by various factors that contribute to the overall thermal load within the conditioned space. These factors include heat gain through opaque surfaces such as exterior walls, roofs, and floors. Opaque surfaces absorb solar radiation, converting it into sensible heat that raises the temperature of the interior space.

Sensible heat gain through opaque surfaces

The sensible cooling load in buildings is primarily influenced by the heat conducted through opaque components such as walls, doors, floors, ceilings, and windows. To estimate this heat gain, a commonly used equation is applied, which takes into account the overall heat transfer coefficient (U), the surface area (A) of the opaque component facing the conditioned space, and CLTD across the surface.

The equation can be expressed as follows:

$$Q = U \times A \times CLTD \quad ...(1)$$

In this equation, U represents the overall heat transfer coefficient, which takes into consideration the thermal properties and construction of the opaque component. This refers to the surface area of the wall, roof, or glass that is exposed to the conditioned space. The CLTD represents across the surface, which is available in reference materials such as the 1977 ASHRAE Fundamentals book, specifically in Chapter 28. By utilizing this equation and obtaining accurate values for U, A, and CLTD, building professionals can estimate the sensible cooling load caused by the heat conducted through opaque components. This information is crucial for designing effective cooling systems and ensuring optimal thermal comfort within the conditioned space. The provided data comprises measurements taken from various sections within a building. The thermal conductivity of the west wall, labelled as the "P wall," is not considered.

The roof and floor sections do not contain temperature or thermal conductivity data. Lastly, the door's dimensions and temperature measurements are given. Overall, these measurements provide insights into the thermal properties of the building's walls and doors, offering a basis for further analysis and evaluation.

Heat gain through fenestration

The solar heat gained through windows and skylights consists of heat that is convicted over the window glass and then radiated through the window frame, referred to as convective and radiation loads, respectively. The convective load is determined using Eqn. 2. The solar heat gains due to solar radiation, represented as Q_f, are estimated by multiplying the area of the window or skylight by the Shading Coefficient and the CLF according to Eqn. 2.

$$Q_f = A \times SHGF \times SC \times CLF \quad ...(2)$$

In this equation, ‘A’ represents the unshaded area exposed to solar radiation, and SHGF denotes the maximum Solar Heat Gain Factor in W/m^2. The CLF values specific to different orientations and months for the 22° N latitude can be found in the 1977 ASHRAE Fundamentals book in Chapter 28 and 29.

The CLF takes into account that not all radiant energy entering the conditioned space contributes immediately to the cooling load. When solar radiation enters the conditioned space, only a negligible portion is absorbed by the air particles, resulting in a minimal temperature change. The remaining energy is absorbed by the thermal mass and released into the conditioned space at a later time.

The SC is typically provided by the glass manufacturer and can be obtained from the manufacturer's product data. Alternatively, some window/skylight manufacturers use the SHGC instead of SC. The provided data pertains to a specific item, namely the "Fenestration (All Glass)." The area of this fenestration is measured to be 3.66 square meters. The U-factor, which represents the rate of heat transfer, is given as 2.86. The subsequent columns display temperature differences and corresponding values for each month of the year.

This data provides insights into the thermal behavior of the fenestration, allowing for analysis and evaluation of its heat transfer characteristics throughout the year.

Heat gain due to ventilation and air infiltration

Ventilation air refers to fresh air needed to maintain indoor air quality and compensate for air leaving the space through exhaust systems. Additionally, air can enter a building through gaps and cracks in doors and windows, contributing both sensible and latent components. The cooling load, which represents the energy required to cool the infiltrated air to room temperature, is estimated using Eqn. 3.

$$Q_s = cp\ \rho\ q\ [T_o - T_i] \qquad ...(3)$$

In this equation, cp represents the specific heat (1.006 kJ/kg^{o}C), ρ represents the density (1.202 kg/m^3), and q represents the air volume flow rate in m^3/s. T_o and T_i denote the outside dry bulb temperature and the temperature of the conditioned space, respectively. By substituting the values of cp and ρ, Eqn. 4 can be simplified as:

$$Q_s = 1.21\ q\ [T_o - T_i] \qquad \text{...(4)}$$

The infiltration rate, q, is determined using the air change method and can be calculated with Eqn.5.

$$q = ACH \text{ x } V/3600 \qquad \text{...(5)}$$

Here, q represents the infiltration rate in m^3/s, V represents the volume of the conditioned space in m^3, and ACH represents the number of air changes per hour. The ACH value depends on the age and condition of the building, typically ranging between 0.5 and 2.0

Heat gain due to cooling coil positive by-pass factor

A portion of the ventilation air enters the conditioned space directly, bypassing the cooling coil, and contributes to the cooling load of the building. The sensible and latent heat components caused by the by-pass ventilation air can be determined using Eqn. 6, where q is the ventilation rate and BPF represents the by-pass factor of the cooling coil. To calculate the cooling load on the building, it is also necessary to consider air leakage in the supply ducts and the heat generated by the electric motor driving the fan.

The provided data includes information related to the by-pass factor and coil factor of a coil, as well as the volume of air required per person per square meter. The bypass factor of the coil is given as 0.12, representing the proportion of air that bypasses the coil without being affected by heat transfer. Conversely, the coil factor is calculated as 1 minus the bypass factor, resulting in a value of 0.88. The contact factor indicates the fraction of air that comes into contact with the coil and undergoes heat exchange. Additionally, the data specifies the volume of air required per person, which is 0.15

cubic meters per minute per person. This measurement indicates the amount of air needed to maintain adequate ventilation for each individual. Furthermore, the volume of air required per square meter is provided as 0.02 $m^3/s/m^2$. This value represents the necessary airflow per unit area to achieve proper air circulation. These data points contribute to understanding the parameters involved in designing and maintaining appropriate air conditioning and ventilation systems, ensuring efficient heat transfer and sufficient air supply in various environments.

Heat gain from occupants and appliances

The heat gains originating from occupants and appliances contribute substantially to the overall cooling load of a building. These heat gains are influenced by factors such as the number of individuals occupying the space, the heat gain factor, and the types and wattage of appliances present. To estimate the heat gain, the following generic equations are commonly used.

a. Occupants

The occupants contribute to both sensible and latent heat loads. The rate at which the sensible and latent heat transfer takes place depends mainly on the number of users, their level of activity, and CLF. It is estimated by the equation

$$Q_s = \text{No. of persons x Sensible heat gain per person x CLF} \qquad ...(6)$$

b. Lights

Lighting contributes to sensible heat gain only. The heat gain from the lighting system comprises of both radiation and convection components, hence, a CLF is used to account for the time lag.

The heat gain is given by

$$Q_S\text{, lighting} = \text{Installed wattage x Usage factor x Ballast factor x CLF} \qquad ...(7)$$

The usage factor takes into account lights installed but not switched on during the load calculations. The ballast factor is used to account for the load imposed by fluorescent lights and lamps. Its value may be taken as 1.25 for fluorescent lights, and

1.0 for incandescent lamps. The value of CLF is a function of the number of hours of operation. These values are available in the ASHRAE handbook.

c. Appliances

The equipment and appliances used in the conditioned space may contribute to both sensible as well as latent loads. The sensible load may be in the form of radiation and/or convection and is given by:

$$Q_s\text{, appliance} = \text{Installed wattage x Usage factor x CLF} \quad ...(8)$$

The installed wattage and usage factor depend on the type of the equipment. The CLF value is 1.0 for 24-hour operation buildings. In other devices such as computers, printers, etc., the load is in the form of acceptable heat gain and is estimated based on their estimated current consumption.

The provided data includes information related to the internal load, occupants, appliances, lights, additional heat gain, and the resulting sensible load. The sensible load, expressed in kilowatts, is calculated based on the number of occupants and their sensible heat gain per person. The data is provided for each month of the year. According to the data, 50 users are contributing to the sensible load, with a factor of 70. This results in a consistent sensible load of 3.5 kW throughout the year. When summing up the values, the total sensible load is calculated for each month. These calculations help in understanding and estimating the sensible load generated by occupants and appliances throughout the year, aiding in the design and management of cooling systems to ensure comfortable and efficient indoor environments.

Latent Heat Gain

The latent heat load in conditioned space is primarily associated with the moisture content of the air. Unlike sensible heat, which directly affects the temperature, latent heat focuses on the heat contained within water vapor. Moist air that enters the building through ventilation and air infiltration requires the input of latent heat to change its moisture content. The main sources contributing to the latent heat load are ventilation air, air infiltration through cracks in the building envelope, windows, and doors, as well as occupants themselves. When fresh air enters the building, it carries with it a certain level of humidity, requiring the transfer of latent heat to adjust the moisture content. Additionally, occupants contribute to the latent heat load through respiration, perspiration, and other activities that release moisture into the air. Lastly, lighting and plug loads also impact the latent heat load as electrical devices and lighting fixtures generate heat during operation, which can affect the moisture levels in the conditioned space.

In building environments, effective management of the latent heat load is of the utmost importance to maintaining optimal moisture levels in the air. Latent heat, which refers to the heat energy contained within water vapor, plays a vital role in adjusting the moisture content of incoming air. To ensure a comfortable and healthy indoor environment, it is essential to carefully manage the latent heat load. By considering the sources mentioned above and implementing effective strategies, such as proper ventilation, moisture control measures, and efficient cooling systems, building professionals can accurately calculate and address the latent heat load. One commonly used method for calculating cooling load is the CLTD method, which takes into account the temperature differentials associated with both sensible load and latent heat loads. By accurately assessing and managing latent heat load, building owners and occupants can enjoy an environment that promotes comfort, health, and optimal moisture levels.

Ventilation and Air Infiltration Heat Gain involves the transfer of heat through the introduction of outdoor air into a conditioned space. Ventilation is essential to maintain indoor air quality as fresh air enters, it brings with it heat energy from the outside environment.

Additionally, air can infiltrate the building through gaps in doors, windows, and other openings, leading to unwanted heat gain. The rate of infiltration depends on factors such as the building's air-tightness, the volume of conditioned space, and number of air changes per hour.

By properly accounting for latent heat gain, ventilation and air infiltration heat gain, and heat gain due to solar radiation, effective cooling strategies can be implemented to maintain a comfortable and energy-efficient indoor environment. The data provided includes information related to latent heat due to infiltration, specifically the latent heat gain. The calculation of latent heat gain is based on the room volume, air changes per hour, and the infiltration rate. The humidity ratio difference (w) is also considered in the calculation. The room volume is measured as 2737.40 m^3, and the ACH is given as 1. The infiltration rate (q) is measured in cubic meters per second and has a value of 0.76. The subsequent columns display the humidity ratio difference and the corresponding latent heat gain for each month of the year. This data provides insights into the latent heat gain resulting from infiltration, considering room volume, air changes per hour, and the infiltration rate.

It assists in understanding and managing the heat and moisture transfer within a space, aiding in the design and control of indoor environments for optimal comfort and energy efficiency.

Heat gains due to ventilation and air infiltration

Heat gain due to ventilation and air infiltration plays a significant role in the overall thermal load of a building. One aspect of this heat gain is the latent heat required to bring the moisture content to a comfortable level. The calculation for latent heat, denoted as Q_L, can be determined using Eqn. (9)

$$Q_L = \rho \, h_{we} \, q \, \Delta w \qquad \text{...(9)}$$

Where,
Q_L = latent heat in kW,
ρ = density of air,
q = air volume flow in m^3/s,
h_{we} = latent heat of vaporization of water (2454 kJ/kg - in air at atmospheric pressure and 20°C), and
Δw = humidity ratio difference in kg water/kg dry air.

In Eq.9, Q_L represents the latent heat in kW, ρ represents the density of air, q represents the air volume flow rate in cubic meters per second (m^3/s), h_{we} represents the latent heat of vaporization of water (2454 kJ/kg for air at atmospheric pressure and

20^{o}C) and Δw represents the difference in humidity ratio in kilograms of water per kilogram dry air. By accurately estimating the latent heat gain resulting from ventilation and air infiltration, building designers and engineers can effectively manage the cooling load and ensure a comfortable indoor environment. Understanding the impact of moisture content and its associated latent heat is crucial in maintaining optimal thermal conditions within the building.

Heat gains due to occupants

The heat gain due to occupants in a building is an important factor to consider when assessing overall thermal load. Occupants generate latent heat as they perform various activities, such as working, exercising, or simply being present in a space. The calculation for latent heat gain resulting from occupants given by Eq.10

$$Q_L = \text{Number of persons x Sensible heat gain per person} \quad ...(10)$$

In Eq.10, Q_L represents the latent heat gain in the form of energy (measured in units such as watts or kilowatts), and the sensible heat gain per person represents the amount of heat produced by each individual. It is influenced by several factors, including metabolic rate, clothing insulation, and activity level. Metabolic rate refers to the rate at which the human body consumes energy, and it varies based on factors such as age, gender, and physical activity. Activity level refers to the intensity and duration of physical activities performed by occupants within the space. By considering the number of occupants and their corresponding sensible heat gain, building designers and engineers can accurately assess the heat load associated with human occupancy.

This information is vital for implementing appropriate cooling strategies, such as proper ventilation and air conditioning, to maintain a comfortable indoor environment while optimizing energy efficiency. Understanding the latent heat gain from occupants helps ensure a conducive and thermally balanced space for building occupants.

Heat gains due to lighting and appliances

Heat gain resulting from lighting and appliances is a significant contributor to the overall thermal load in a building. Appliances, such as electronic devices and equipment, generate both sensible and latent heat during their operation. The calculation for latent heat gain due to appliances can be determined using the equation:

$$Q_L\text{, appliance} = \text{Installed wattage x Usage factor x Ballast factor} \quad ...(11)$$

In Eq.11, Q_L, the appliance represents the latent heat gain in the form of energy, measured in units such as watts or kilowatts. The installed wattage refers to the power consumption of the appliance or lighting fixture. The usage factor accounts for the percentage of time the appliance or lighting is in use within a given period. The ballast factor represents the efficiency of the ballast used in the lighting system. By considering these factors, building designers and engineers can accurately estimate the latent heat gain from lighting and appliances. This information is crucial for designing effective cooling systems and implementing energy-efficient strategies to manage the heat load. Proper consideration of latent heat gain allows for the selection of appropriate cooling equipment, adequate ventilation, and efficient thermal management to create a comfortable and sustainable indoor environment.

Heat gains due to solar radiation

When sunlight strikes a glass surface, a portion of the solar radiation passes through the glass, resulting in heat gain inside a building. This heat gain due to solar radiation can be calculated using a simple equation:

$$Q = A \times SHGF_{max} \times SC \times CLF \quad ...(12)$$

In Eq.12, Q represents the heat gain in watts (W), a represents the area of the glass exposed to sunlight, $SHGF_{max}$ denotes the maximum solar heat gain factor in (W/m^2), SC represents shading coefficient specific to the glass, and CLF represents the cooling load factor. The $SHGF_{max}$ value indicates the maximum heat gain potential of the glass from solar radiation. The shading coefficient accounts for the glass ability to block or transmit solar heat, and the CLF considers the delayed release of absorbed heat into the conditioned space. By using Eq.12, architects and engineers can estimate the amount of heat gained due to solar radiation through glass surfaces. This information is crucial for designing effective cooling systems, selecting appropriate glazing materials, and implementing energy-efficient strategies to manage solar heat gain in buildings.

(b) Energy Consumption Prediction Using Revit Architecture

An existing service building in Nagpur was modelled using Revit architecture to create a digital representation of the building as shown in Figure 3.4. Revit Architecture is a powerful architectural design and documentation software for architectural design and construction professionals created by Autodesk. The Energy Analytical Model of Revit software provides tools to quickly and flexibly create energy simulation models. The work environment of Revit allows users to work with entire buildings or assemblies (in the design environment) or individual 3D forms (in the family editor environment). The model can be created directly from architectural building elements and room/space elements or manually using the conceptual stack. Modeling tools can be used with ready-made solids or imported geometric models.

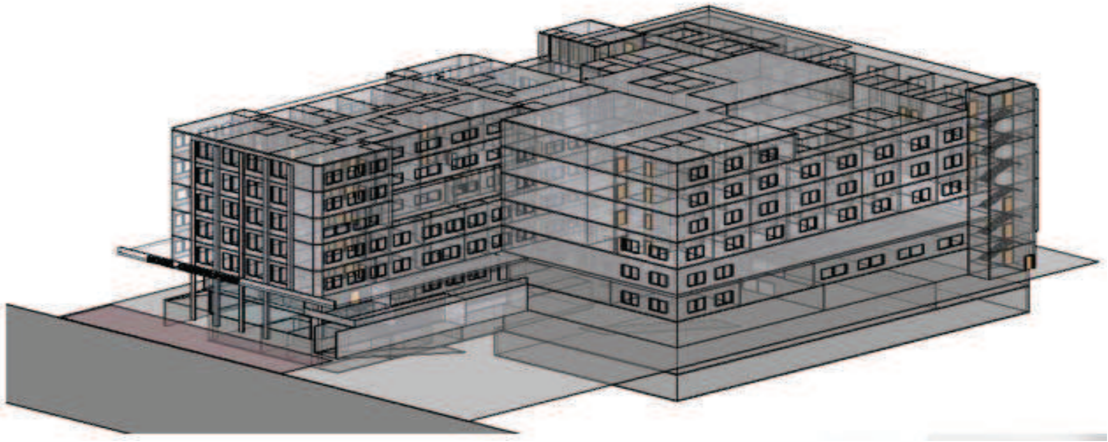


Figure 3.4: Modeling an existing building in Revit Architecture

The building used in the research has an area of 2973.63 m^2. The total built-up area is distributed evenly across all floors The components of a building that impact more in the energy analysis are recognized and investigated such as Building Orientation, Daylighting & Occupancy controls, HVAC, Fenestration, Wall and Roof to determine the cooling requirement inside the building.

Energy performance analysis using Revit falls under the category of "Physics-Based Simulation". Revit is an open-source simulation software that enables energy simulation and performance analysis of buildings. EnergyPlus has been in development since 1997 and was first released in 2001. It is an open-source program (U.S. Department of Energy, 2021) and is considered a popular and powerful energy simulation tool in buildings. This is a simulation tool used in Revit to calculate and analyze the energy consumption of various buildings and energy systems, especially on large time scales such as annual and monthly simulations.

BIM-BEM Simulation Process

BIM-BEM simulation is a three-step process Figure 3.5 that involves: (i) the creation of a detailed 3D digital model of the building by transferring the entire building information into BIM software, such as ArchiCAD or Autodesk Revit; (ii) transformation of BIM data to an energy simulation engine DOE-2 or EnergyPlus using relevant data exchange systems such as IFC or gbXML; and (iii) prediction of energy consumption and efficiency of the building. The BIM model contains structured building data and always remains consistent and coordinated throughout the entire process. At any stage, if any element is changed, BIM software updates the model immediately to reflect the change. The whole process of creating the digital BIM model and exporting the information to energy analysis tools relies on the enriched building information and data exchange ecosystems, categorized as Application Programming Interfaces, Green Building (gbXML) schema, and Industry Foundation Classes [23]. Each approach has useful features, but IFC is an open, ISO standard for information sharing between various software programs over the whole building life-cycle. Unfortunately, studies show that some data is constantly lost and the conversion of IFC-based models into other proprietary BIM systems is not entirely correct. For better reliability, third-party products like EnergyPlus require BIM technologies like Revit or ArchiCAD. Autodesk Insight is the finest example of this approach that directly obtains BIM design information in the form of a gbXML file and carries out building energy simulation. The biggest disadvantage, however, is that BIM design data can only be communicated through a connected BIM authoring tool's API, which limits its flexibility and extensibility.

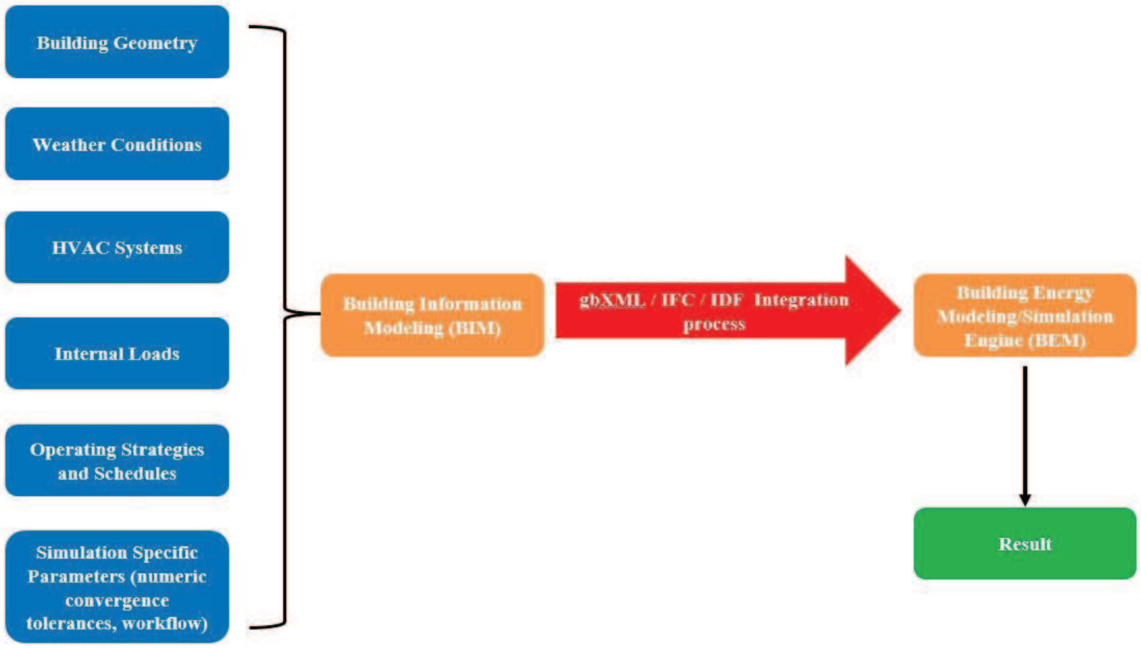


Figure 3.5: BIM-BEM simulation flow

The Green Building XML schema (gbXML), is a spin-off from Green Building Studio that facilitates the interoperability of building data between BIM and BEM. Extensible Markup Language (XML), a text-friendly computer language that enables software programs to transmit information with little to no human interaction, serves as the foundation for this system. The schema is integrated into several CAD software and engineering tools and is supported by many leading vendors which have made it a standalone the facto industry standard. Since the gbXML format uses centreline representation for geometry, variances in estimated surface areas and space volumes have been noticed, which sometimes exceed the tolerance limits for larger complex building geometries. The absence of geometric representation of HVAC systems and equipment, which accounts for more than 15% of the total energy consumption in buildings, is yet another significant flaw in the gbXML format.

The BIM input file containing the building information including spaces and zones of the building and the weather data was imported to EnergyPlus to run an energy performance analysis. There are many formats available for data exchange between BIM and BEM applications. However, IFC and gbXML are the two well-known and commonly used schemas in the industry.

The gbXML, which is a simple and forthright format, is used to integrate data between the BIM and EnergyPlus. The simulated output includes peak heating, cooling load, the energy needed for lighting and operation of equipment and appliances, and annual energy consumption for the same.

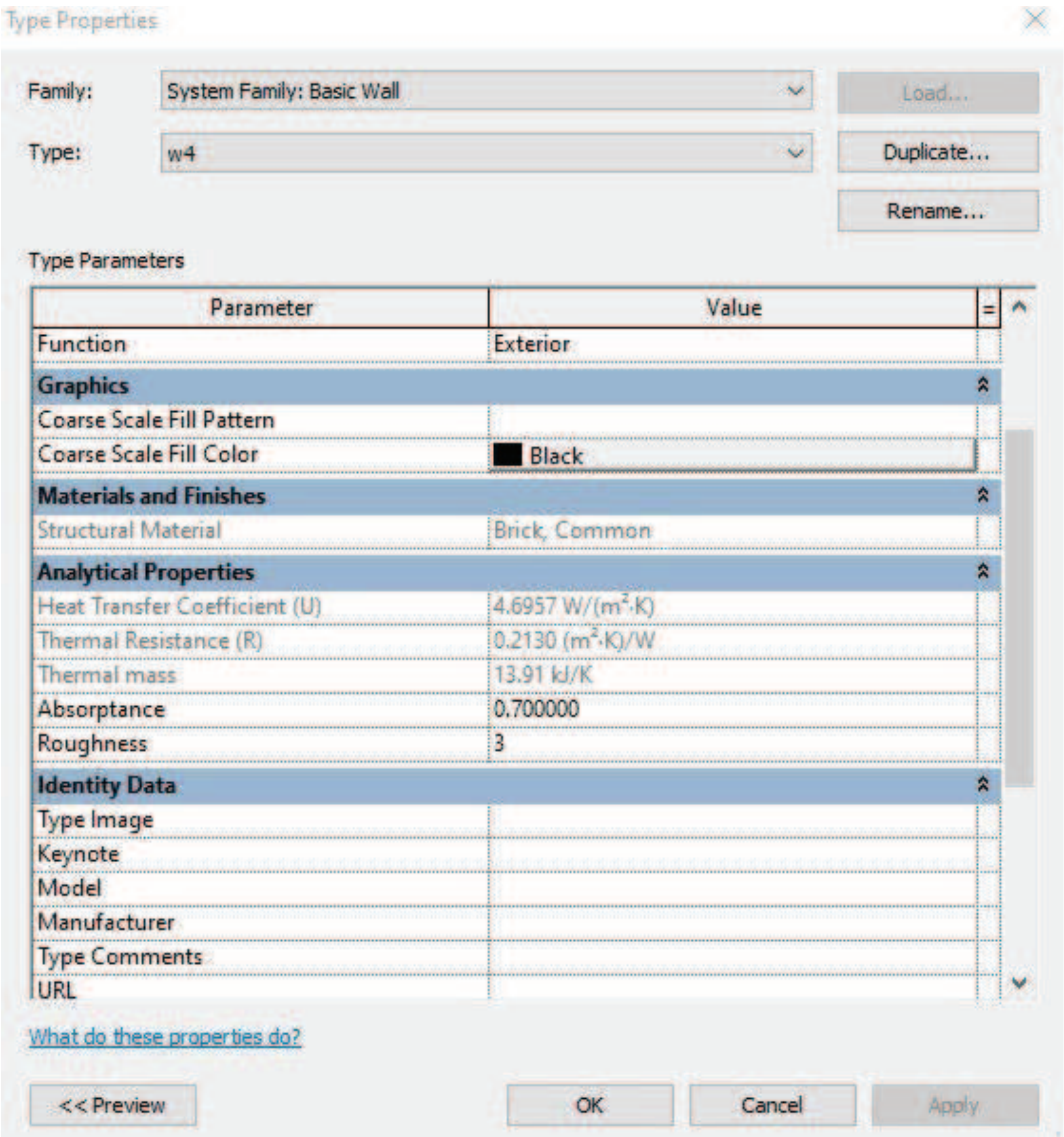
Peak Load Calculation by Revit Software

The building level is divided into 7 zones, with each consisting of spaces corresponding to the number of rooms on each floor. The building model contains parameter data and descriptions of the building elements. However, some modifications are necessary to enhance the accuracy of the Energy model's expected results since the original model was designed specifically for energy simulation. These modifications were made using Autodesk Revit 2021.

In the Revit file, all the buildings are clustered together. For analysis purposes, the buildings to be analyzed need to be isolated. Revit first creates analytical surfaces based on the elements in the model and their stage of development. Second, the default parameters for energy modeling rely on the size they vary for various building types. There are several alternatives for building an energy simulation model in Revit. Utilizing conceptual masses is one choice that enables analysis at the project's conceptual stage. Since a building model was already available in the present instance, the building elements were used to include the thermal characteristics of the building elements in the energy simulation. As a result, these thermal characteristics must be included as part of the parameters for the design's elements.

The thermal characteristics may be used for the building elements before the energy simulation using Revit's properties palette. Spaces or rooms are employed to provide additional energy data for the simulation, such as lighting, equipment, and occupancy. If spaces are set as the export category, these data can be specified, whereas default values are used when the room is selected as the export category. For this simulation, the space category is utilized. If the bounding elements do not touch, spaces will not be generated. Accurate area and volume calculations are essential for the analysis model and can significantly impact the results.

The floors of the building are defined as zones, with spaces corresponding to each room created within the respective room zones using the software. Figure 3.6 shows a table containing information about a specific wall element in Revit. In the first column, we have various parameters related to the wall type, while the second column displays their corresponding values.



Family: System Family: Basic Wall

Type: w4

Type Parameters

Parameter	Value
Function	Exterior
Graphics	
Coarse Scale Fill Pattern	
Coarse Scale Fill Color	■ Black
Materials and Finishes	
Structural Material	Brick, Common
Analytical Properties	
Heat Transfer Coefficient (U)	4.6957 W/(m²·K)
Thermal Resistance (R)	0.2130 (m²·K)/W
Thermal mass	13.91 kJ/K
Absorptance	0.700000
Roughness	3
Identity Data	
Type Image	
Keynote	
Model	
Manufacturer	
Type Comments	
URL	

Figure 3.6: Properties of palette

The "Family" column indicates that the wall belongs to the "System Family" category, specifically the "Basic Wall" system family. This classification helps to organize and categorize different elements within the software. Moving to the "Type Parameters", we find specific details about the selected wall type.

The parameters listed include the structural material, heat transfer coefficient (U), thermal resistance (R), thermal mass, absorptance, and roughness. For this particular wall category, the structural material is identified as brick. The heat transfer coefficient (U) is given as 4.6957 W/m^{2}K, representing the rate of heat transfer through the wall. The thermal resistance (R) is specified as 0.213 m^{2}K/W, indicating how well the wall resists heat flow. The thermal mass is measured at 13.91 kJ/K, which reflects the wall's ability to store and release heat.

The absorptance value is stated as 0.7, representing the wall's capacity to absorb solar radiation. Finally, the roughness is noted as 3, indicating the surface texture of the wall. This information provides crucial data for understanding the thermal characteristics and behaviour of the wall type in the Revit software.

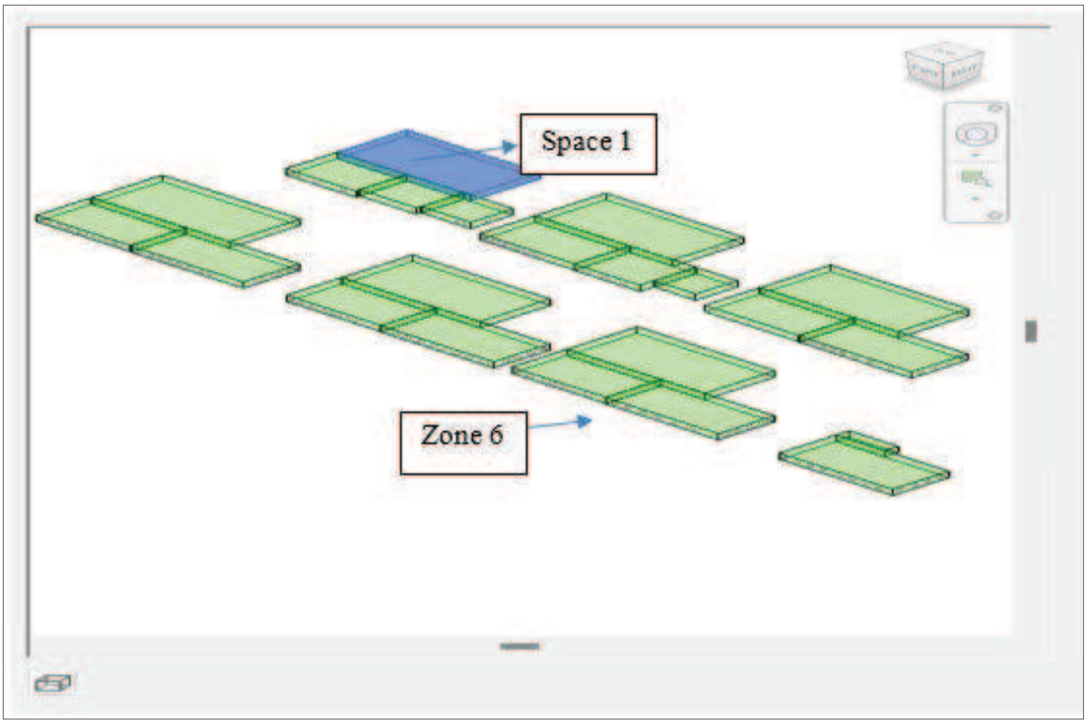
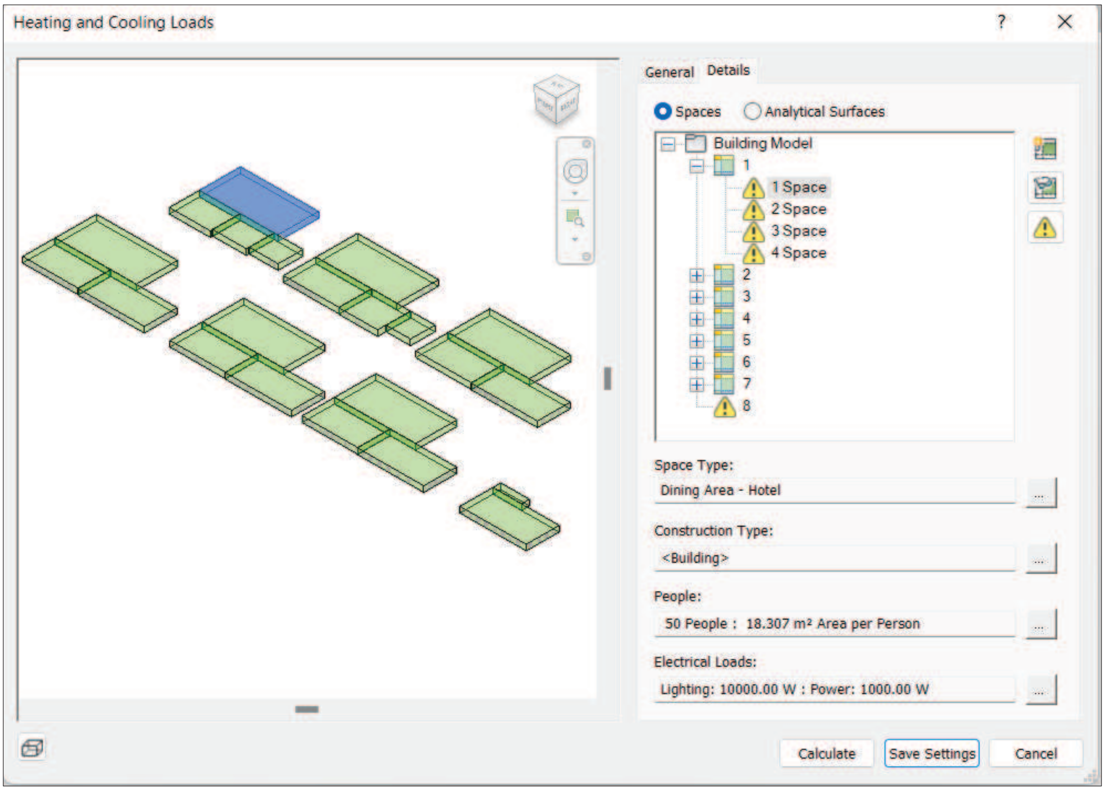


Figure 3.7: Spaces for each room



● Spaces ○ Analytical Surfaces

Building Model
- 1
  - 1 Space
  - 2 Space
  - 3 Space
  - 4 Space
- 2
- 3
- 4
- 5
- 6
- 7
- 8

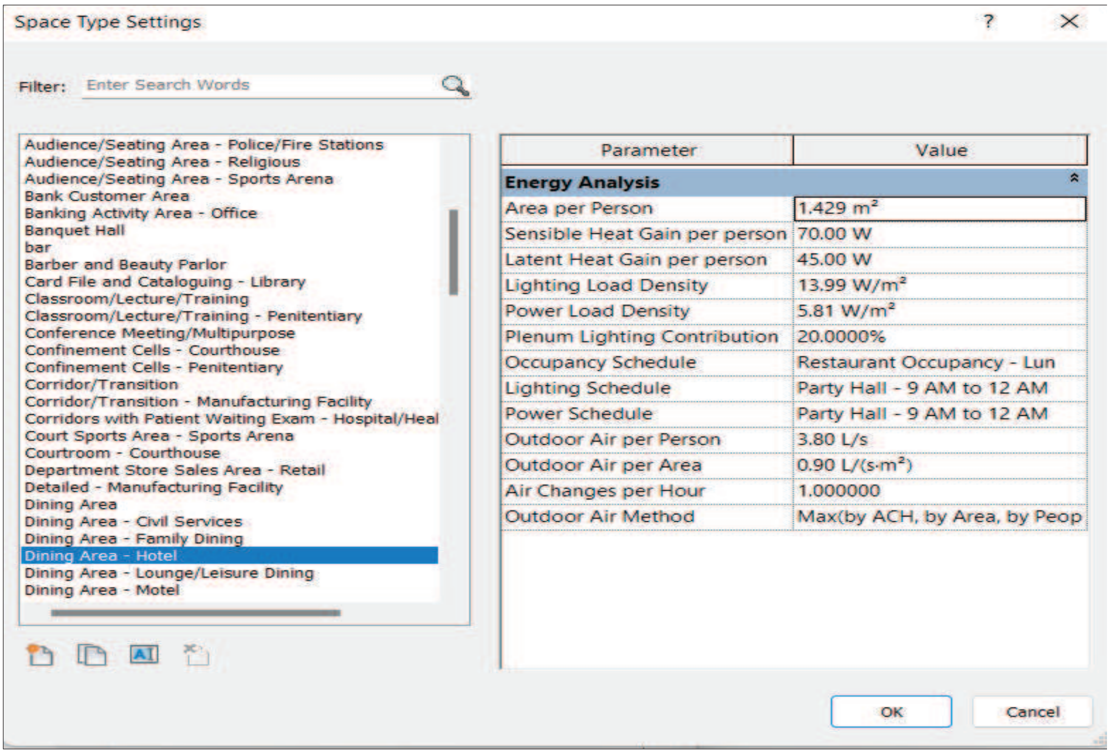
Space Type: Dining Area - Hotel

Construction Type: <Building>

People: 50 People : 18.307 m² Area per Person

Electrical Loads: Lighting: 10000.00 W : Power: 1000.00 W

Figure 3.8: Input the space property

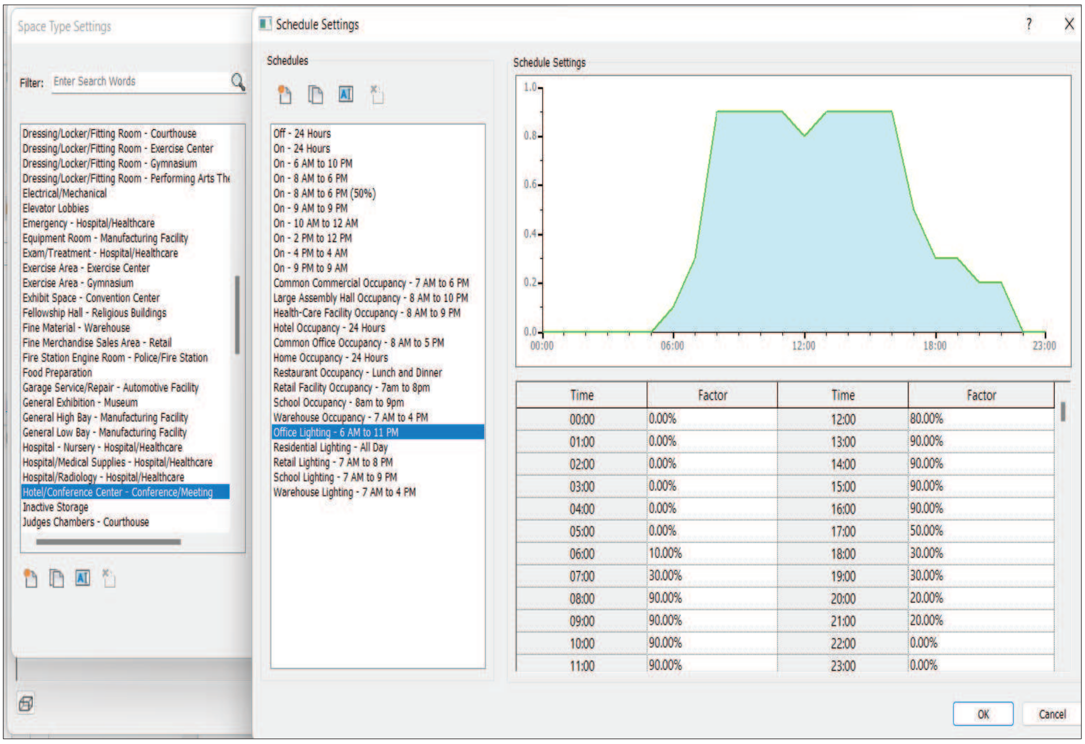


Filter: Enter Search Words

Audience/Seating Area - Police/Fire Stations
Audience/Seating Area - Religious
Audience/Seating Area - Sports Arena
Bank Customer Area
Banking Activity Area - Office
Banquet Hall
bar
Barber and Beauty Parlor
Card File and Cataloguing - Library
Classroom/Lecture/Training
Classroom/Lecture/Training - Penitentiary
Conference Meeting/Multipurpose
Confinement Cells - Courthouse
Confinement Cells - Penitentiary
Corridor/Transition
Corridor/Transition - Manufacturing Facility
Corridors with Patient Waiting Exam - Hospital/Heal
Court Sports Area - Sports Arena
Courtroom - Courthouse
Department Store Sales Area - Retail
Detailed - Manufacturing Facility
Dining Area
Dining Area - Civil Services
Dining Area - Family Dining
Dining Area - Hotel
Dining Area - Lounge/Leisure Dining
Dining Area - Motel

Parameter	Value
Energy Analysis	
Area per Person	1.429 m²
Sensible Heat Gain per person	70.00 W
Latent Heat Gain per person	45.00 W
Lighting Load Density	13.99 W/m²
Power Load Density	5.81 W/m²
Plenum Lighting Contribution	20.0000%
Occupancy Schedule	Restaurant Occupancy - Lun
Lighting Schedule	Party Hall - 9 AM to 12 AM
Power Schedule	Party Hall - 9 AM to 12 AM
Outdoor Air per Person	3.80 L/s
Outdoor Air per Area	0.90 L/(s·m²)
Air Changes per Hour	1.000000
Outdoor Air Method	Max(by ACH, by Area, by Peop

Figure 3.9: Input the space values

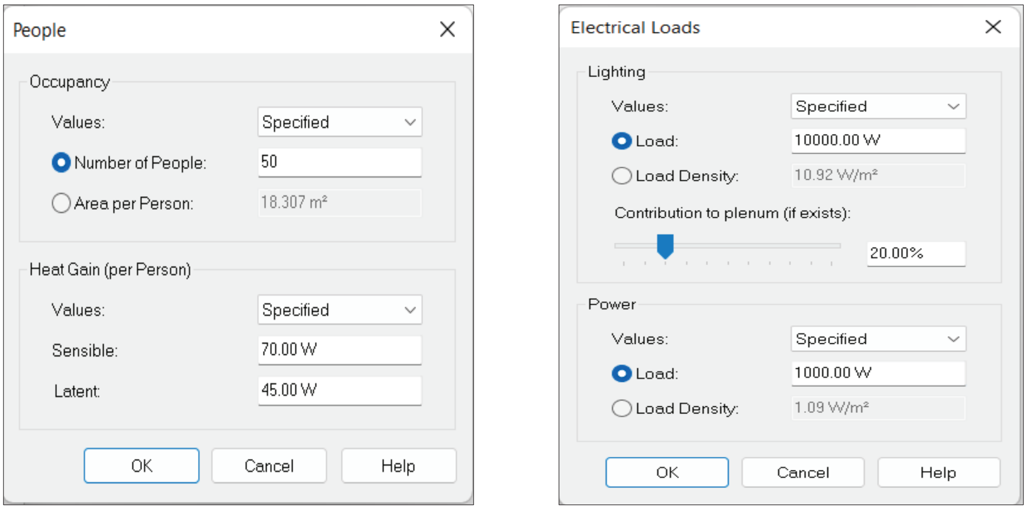


Time	Factor	Time	Factor
00:00	0.00%	12:00	80.00%
01:00	0.00%	13:00	90.00%
02:00	0.00%	14:00	90.00%
03:00	0.00%	15:00	90.00%
04:00	0.00%	16:00	90.00%
05:00	0.00%	17:00	50.00%
06:00	10.00%	18:00	30.00%
07:00	30.00%	19:00	30.00%
08:00	90.00%	20:00	20.00%
09:00	90.00%	21:00	20.00%
10:00	90.00%	22:00	0.00%
11:00	90.00%	23:00	0.00%

Figure 3.10: Input the schedule settings

Figure 3.7 shows the space management feature in Revit software. It allows users to define and allocate individual spaces for each room within a building model. By assigning spaces, it becomes easier to analyze and simulate various parameters related to energy performance and occupant comfort. The image displays a visual representation of rooms with designated spaces, facilitating a more organized and comprehensive approach to building design and analysis. In Figure 3.8, the user is presented with an interface to input the space properties within Revit. These properties include information such as the space name, area, volume, occupancy load, and any specific characteristics relevant to the room.

By accurately inputting the space properties, Revit can provide accurate data for energy simulations, code compliance, and other analytical purposes. Figure 3.9 shows the inputting of space values in Revit software. It allows users to assign specific values to different parameters associated with the spaces. These values may include lighting power density, equipment heat gain, occupancy levels, and other factors that influence the energy consumption and performance of the space. By inputting the space values, users can generate more precise energy analyses and make informed decisions during the design process. Figure 3.10 shows the schedule settings feature in Revit, which enables users to define and customize schedules for various space-related parameters. The schedule settings allow users to create and manage schedules for room areas, volumes, occupancy, lighting, and other relevant data. This feature is particularly useful for tracking and evaluating spatial characteristics throughout the project and can assist in maintaining consistency and accuracy in the building model.



People

Occupancy

Values: Specified

● Number of People: 50

○ Area per Person: 18.307 m²

Heat Gain (per Person)

Values: Specified

Sensible: 70.00 W

Latent: 45.00 W

Electrical Loads

Lighting

Values: Specified

● Load: 10000.00 W

○ Load Density: 10.92 W/m²

Contribution to plenum (if exists): 20.00%

Power

Values: Specified

● Load: 1000.00 W

○ Load Density: 1.09 W/m²

Figure 3.11: Input of people and electric loads

In the process of designing a building using Revit software, it is essential to input accurate data regarding people and electric loads for effective energy analysis. This involves specifying the occupancy details and electrical requirements for each space within the building model. Revit provides a user-friendly interface to input the people load, where designers can define the number of occupants in each room or space. This information is typically based on occupancy standards or project-specific guidelines. By accurately inputting the people's load, Revit can calculate the corresponding heat gains from human presence, which is crucial for evaluating thermal comfort and designing an efficient HVAC system. Similarly, inputting the electric loads in Revit involves specifying the electrical equipment, lighting fixtures, and other devices present in each space. Designers can input the power consumption, operating schedules, and other relevant parameters to accurately model the electrical loads. This information is vital for evaluating energy consumption, sizing electrical systems, and analyzing the overall impact on a building performance.

Figure 3.11 shows that Revit's advanced data management capabilities enable users to input and manage people and electric loads systematically. This ensures that the data is organized and easily accessible throughout the design process. By having this information readily available, designers can conduct comprehensive energy analyses, make informed decisions about space planning, and equipment selection, and optimize the building's energy efficiency. The software's powerful analytical tools allow for detailed energy simulations and help designers make informed design choices to meet the required energy performance.

Overall, putting people and electric loads in Revit is a critical step in the design process, enabling designers to create energy-efficient buildings that meet the needs of their occupants. Therefore, using Revit the complete cooling load calculation is done for the whole Building.

(c) Energy Consumption Prediction Using Artificial Neural Network (ANN)

Energy consumption prediction is a crucial aspect of building energy analysis, especially for existing buildings seeking energy efficiency improvements. One effective approach to tackle this challenge is by employing ANN. Artificial Neural Networks is a machine learning technique inspired by the human brain's neural network structure, capable of learning complex patterns and making accurate predictions. ANN was proposed by Cheng and Titterington (1994) and Warner and Misra (1996) [42]. In the context of existing buildings, ANN can be trained using historical data on various parameters such as outdoor weather conditions, building characteristics, and cooling loads. By analyzing these inputs, the neural network learns the relationships and patterns between them, enabling it to predict the cooling load for a given set of input parameters. ANN falls under the category of statistical approaches, as its learning process involves statistical techniques like optimization algorithms to adjust the network’s parameters and minimize errors during training. Using an ANN for cooling load prediction offers several advantages. It can capture the nonlinear relationships between the input variables and the cooling load, making it suitable for complex building systems. Additionally, ANN models can adapt and improve their predictions over time as they learn from more data, enhancing their accuracy and reliability.

The utilization of ANN in predicting cooling loads for existing buildings has gained significant attention due to its effectiveness and accuracy. Unlike traditional methods that rely on simplified assumptions and models, ANN takes advantage of its ability to learn from complex datasets and capture complex relationships between input variables and cooling loads. To apply ANN for cooling load prediction in existing buildings, a dataset comprising historical cooling load data, weather conditions, building characteristics, and operational parameters is required [36]. This dataset is then used to train the neural network, where it learns the patterns and correlations between the input variables and the corresponding cooling loads. Once trained, the ANN model can accurately predict cooling loads based on new sets of input data. This prediction capability enables building owners and energy professionals to make informed decisions regarding energy management strategies, such as optimizing HVAC systems, implementing load-shifting techniques, or evaluating the impact of energy-saving measures.

ANN offers a powerful and flexible approach to predicting cooling loads in existing buildings. By leveraging the capabilities of ANN, it becomes possible to capture the complex interactions between various factors influencing cooling loads, leading to more accurate and reliable predictions. When applying ANN to existing buildings, a diverse range of input variables can be considered, including outdoor temperature, humidity, solar radiation, building envelope characteristics, occupancy patterns, and internal heat gains. These variables collectively contribute to the cooling load experienced by the building [51]. By feeding the historical data containing these input variables and corresponding cooling load values into the ANN model, it can be trained to recognize the underlying patterns and relationships. The trained ANN model can then be used to predict cooling loads for new or future scenarios, allowing building owners and operators to optimize energy consumption, plan HVAC system operations, and assess the effectiveness of energy efficiency measures. Overall, the integration of ANN in cooling load prediction for existing buildings empowers stakeholders with valuable insights to enhance energy efficiency and make informed decisions for sustainable building operations.

Building energy consumption prediction plays a unique role in energy planning, conservation and in developing a model’s predictive controller for consumers and optimizing energy distribution plans for utilities. Physical-models, data-driven models, and hybrid models are common ways of predicting energy [27]. The capacity of data-driven techniques to identify statistical trends without the need for specialized knowledge has made them one of them in recent years.

Constantly improving the performance of prediction models is the key to ensuring the efficient operation of energy systems. The forecast of building energy use is crucial for energy management, planning, and conservation. The secret to maintaining the effective operation of energy systems is to continuously improve the effectiveness of prediction models. Additionally, model success is no longer just determined by accuracy; instead, it is crucial to assess the model from a variety of angles, including into account an existing building.

Dataset Description

The objectives of this study are to propose an ANN model that can used to predict the energy use of a hotel building in Nagpur, Maharashtra. The dataset used for this study pertains to the energy modeling information of the hotel building. It includes various parameters such as room volume, light load, number of users, area of doors and windows, appliances, etc. Several inspections were made to evaluate the different types of internal loads (lighting, appliances and occupancy) and their schedules. It should be pointed out that there are no historical records of occupancy profiles in this building. Therefore, some assumptions related to this profile were made in this case study.

The steps to develop an ANN model are presented below in Figure 3.12.

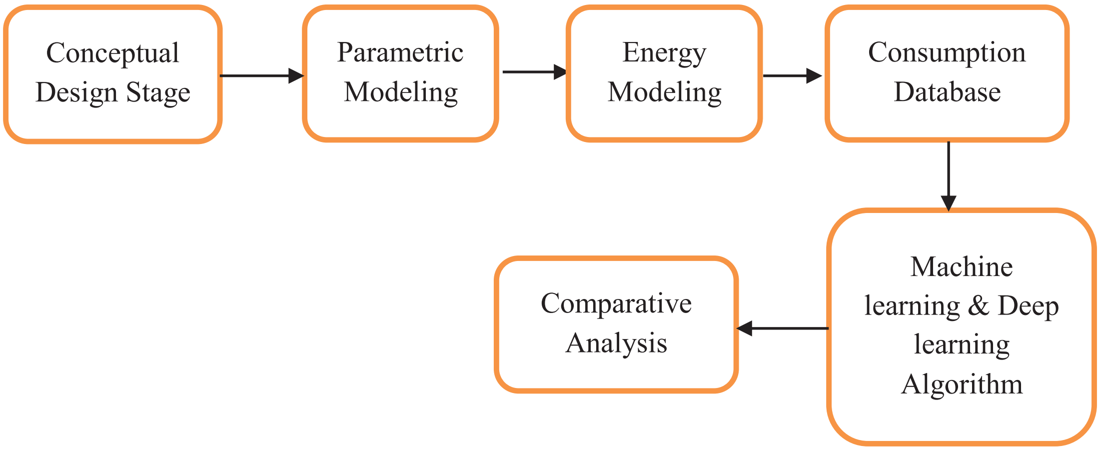


Figure 3.12: Diagrammatic representation of energy prediction

Algorithms Used

Machine learning and deep learning algorithms are used to predict the ANN model. Machine learning is a subset of Artificial Intelligence that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed. In machine learning, algorithms are designed to improve their performance over time as they are exposed to more data. It includes algorithms such as linear regression, logistic regression, decision trees and random forest.

Linear Regression: It is used for predicting a continuous target variable based on one or more input features. It assumes a linear relationship between the input features and the target variable.

Logistic Regression: Logistic regression is used for binary classification problems, where the goal is to predict one of two possible outcomes. It estimates the probability that a given input belongs to a particular class.

Decision Trees: A decision tree breaks down a dataset into smaller subsets based on different criteria. It makes decisions by asking a series of questions, each leading to a binary choice. The goal is to split the data in a way that each resulting subset is as homogeneous as possible with respect to the target variable.

Random Forest: An ensemble learning method that constructs multiple decision trees during training and combines their predictions to improve accuracy and control overfitting. It's often used for classification and regression tasks.

Deep learning is a subfield of machine learning that specifically focuses on training deep neural networks with multiple layers (hence the term "deep"). Deep learning has gained significant attention and success in recent years due to its ability to automatically learn and extract hierarchical features from data, leading to state-of-the-art performance on various tasks, such as image recognition, natural language processing, and more. ANN and LSTM are the two algorithms used for the energy prediction models.

Artificial Neural Network (ANN): A versatile machine learning model inspired by the structure of biological neural networks. It consists of layers of interconnected nodes (neurons) that process and transform data. ANNs are used for various tasks, including image recognition, natural language processing, and more.

Long Short-Term Memory (LSTM): A type of recurrent neural network architecture often used for sequence data like time series, natural language, and speech. LSTMs are well-suited for capturing long-range dependencies in sequences.

Developing ANN Architecture:

- Input and Output Layers determine the number of neurons in the input layer based on the features of the input data and the number of neurons in the output layer based on the desired output.
- Depending on the complexity of the problem, decide on the number of hidden layers and the number of neurons in each hidden layer. This can involve experimentation and tuning based on the problem domain.
- Select appropriate activation functions for each layer, considering factors such as non-linearity and the range of outputs.
- Connect layers establish connections between neurons in adjacent layers, ensuring that each neuron in a given layer is connected to every neuron in the subsequent layer in a fully connected architecture.

Plotting Membership Functions:

- Identify variables and their ranges to determine the input variables for your fuzzy logic system and their corresponding ranges. For example, in a temperature control system, variables might include temperature, humidity, etc.
- For each input variable, define linguistic variables (e.g., "low," "medium," "high") and their associated membership functions.
- Use appropriate software or libraries to plot the membership functions for each linguistic variable. These plots illustrate the degree of membership for different values within the variable's range.
- Tune membership functions refine the shapes and parameters of the membership functions based on domain knowledge, data analysis, or experimentation to accurately capture the relationships between input variables and fuzzy sets.

There are 4 input parameters of Machine learning models and Deep learning models, which are month, cooling load, electric load, and total energy consumption. The cooling load and electric load data are calculated for the database. There is 1 output for this study, which is the predicted energy consumption that is calculated by the ML and DL models shown in Table 3.1. The cooling load, which is extracted from the database with the input data, is taken as the basic values to be compared with the predicted value.

Table 3.1: ANN model input and output parameters.

Components	Parameters
Input layer	Month
	Cooling load
	Electric load
	Total Energy Consumption
Output layer	Prediction model

An initial ANN model is constructed with four input layers representing four parameters as described before, the three hidden layers and the output layer for one.

The three transfer functions used in hidden layers are reflux, SoftMax and dense. Before training, all inputs and output data are scaled within the range of [low to high]. The initial ANN model components and values are summarized in Table 3.2.

Epochs in machine learning refer to the number of times a model iteratively learns from the entire training dataset. Each epoch involves passing the entire dataset through the model, calculating errors, and adjusting the model's internal parameters to reduce those errors. More epochs allow the model to refine its understanding of the data, but too many epochs may lead to overfitting, where the model performs well on training data but poorly on new data. The optimal number of epochs is often determined through experimentation to find the right balance between learning and generalization.

Table 3.2: Initial ANN model components and values

Parameter		**Component and values**
ANN structure	-	4 input layer and 1 output layer
Transfer function	Hidden layer	Reflux
		Softmax
		Dense
Training method	Goal	Accuracy (%)
	Epoch	50 times
	Algorithm	ANN

Figure 3.13 shows the data visualization of a dataset for the prediction of energy consumption. The prediction model assumes low, medium and high values in the data set. The energy consumption in (kWh) is plotted on the Y-axis with respect to the year shown on the X-axis. The yellow line shows visualization for low values, the green line visualizes the trend for high values, and at last blue line visualizes the medium values for energy consumption prediction.

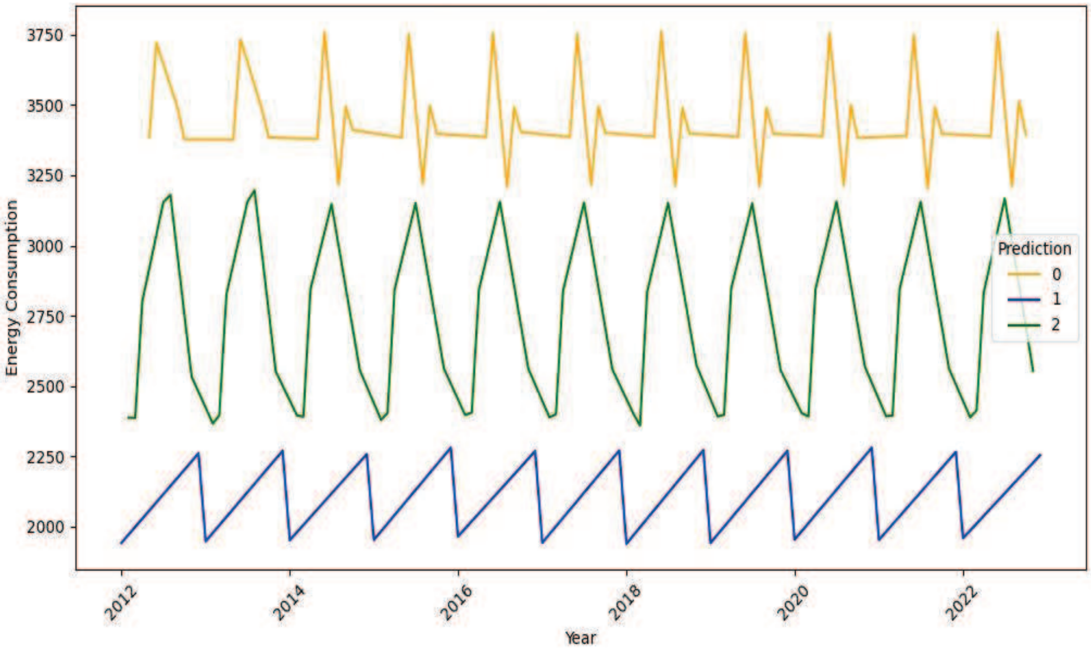


Figure 3.13: Data visualization of a dataset for the prediction

Chapter - 4

Energy Consumption Modeling

Chapter - 4

Energy Consumption Modeling

Energy consumption modeling refers to the process of creating mathematical or computational representations of energy use in a specific system, such as a building, a city, an industrial process, or an entire country. These models help researchers, engineers, and other stakeholders to understand, analyze and forecast energy consumption patterns under different scenarios and conditions. Energy consumption models can vary in complexity and scope from simple spreadsheet-based calculations to highly sophisticated simulation tools. Energy consumption refers to the amount of energy needed or required to perform a certain task, operate a device or provide services. It is a measure of the total energy used over a period of time and is usually expressed in kilowatt-hours (kWh) or British thermal units. Energy consumption is a critical factor in understanding the environmental and economic impacts of various operations and systems. Energy consumption modeling plays a crucial role in developing strategies to reduce energy consumption, promote sustainable development and mitigate climate change.

The significance of energy efficiency in buildings cannot be overstated, given the significant role that buildings play in energy consumption worldwide. According to the International Energy Agency, buildings are responsible for about 40% of the world’s carbon dioxide emissions and almost 36% of final energy usage [28]. Increasing energy efficiency in buildings can help to reduce energy consumption and associated emissions, while also providing cost savings for building owners and occupants. Building energy consumption relates to how much energy is needed to heat, cool, and ventilate a building, provide services and to operate the equipment and appliances. To address the challenge of improving energy efficiency in buildings, a series of approaches and technologies have been developed, including building energy modeling, building automation systems, and use of energy-efficient building materials and appliances. Effective implementation of these approaches requires accurate collection of building data, as well as effective analysis and modeling.

This study focuses on modeling energy consumption in a hotel building, using a combination of engineering and machine learning approaches, specifically examining peak, monthly, and annual energy consumption. The building is a commercial establishment located in the downtown area of Nagpur city in Maharashtra, India. By employing both quantitative and qualitative methods, a comprehensive understanding of the factors influencing energy consumption in the building was obtained. The findings of this study can serve as a basis for developing strategies and technologies to optimize operational efficiency, reduce costs, and enhance sustainability by identifying areas for improvement and guiding strategic decision-making. The following steps were taken to model the energy consumption of the building:

4.1 Data Collection for the Building

Gathering information about the building, including floor plans, envelop characteristics, construction materials, window types, insulation levels, occupancy schedules, and HVAC system details is important for modeling of energy consumption. This information serves as the foundation for creating an accurate 3D model of the building using software tools like Revit, ensuring that the model reflects the building's geometry, layout, and thermal characteristics. Some of the required information is easy to obtain, while others are more difficult to obtain with reasonable accuracy [14]. In existing hotel commercial buildings, it can be especially challenging to gather all the necessary data with adequate accuracy due to potential changes resulting from renovations or upgrades. For energy modeling and consumption forecasting of the hotel building, the following information was collected.

Building Location and Floor Plans: The case study hotel building comprising six floors (G+6) with latitude 21.13° N and longitude 79.07° E situated in Nagpur, in the state of Maharashtra, India at an elevation of about 310.5 m above sea level. Nagpur city is known for its composite climate. Detailed floor plans shown in Figure 4.1 and 4.2, shows layout of the hotel includes guest rooms, common areas, restaurants, kitchens, laundry facilities, corridors, and mechanical rooms.

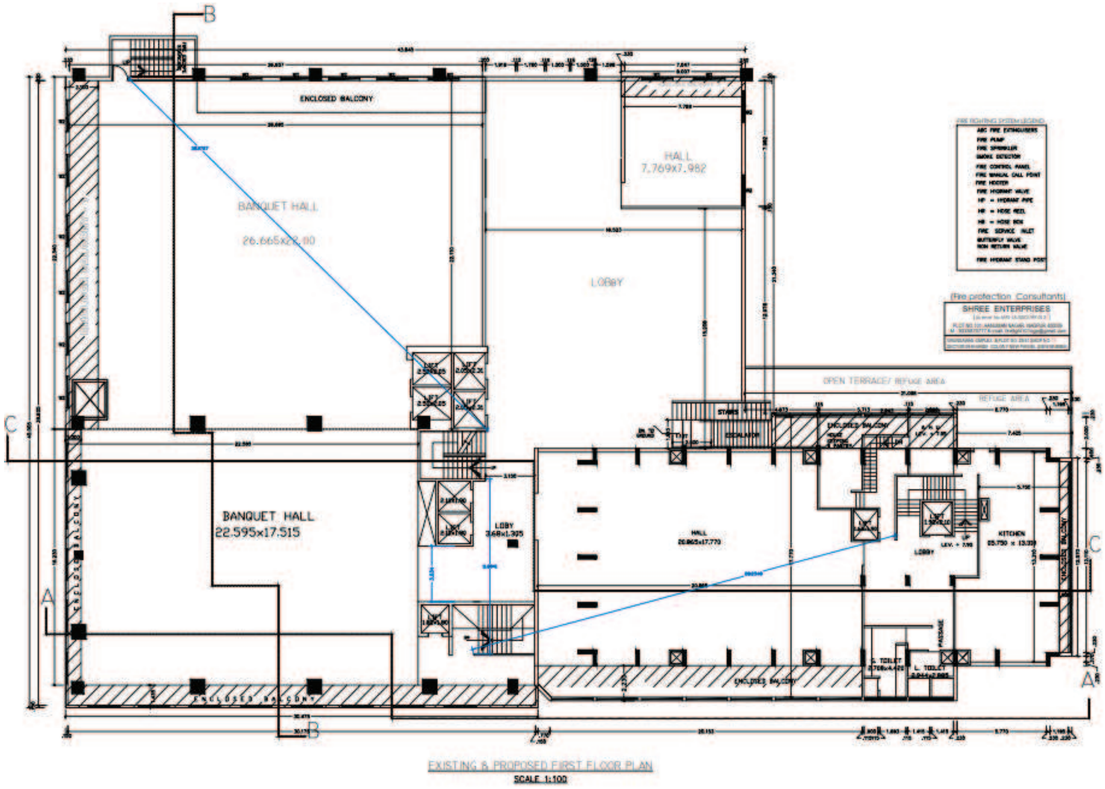


Figure 4.1: First-floor plan of the case building

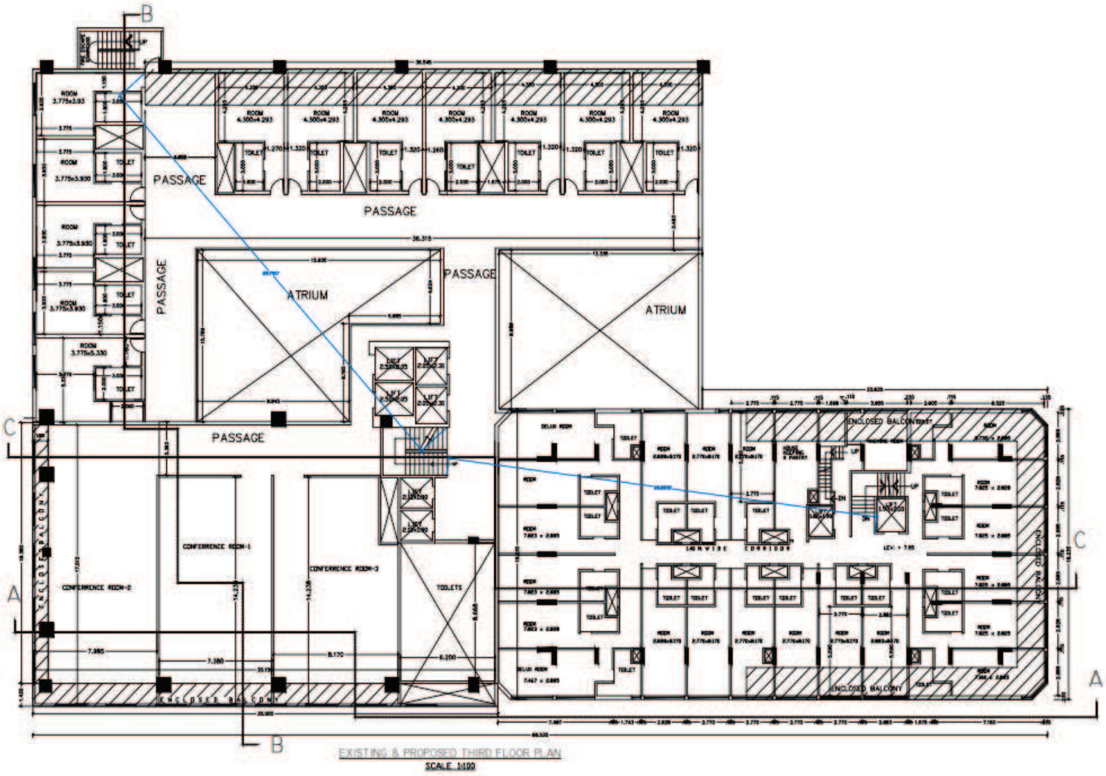


Figure 4.2: Second-floor plan of the case building

Building Envelope Characteristics: Building energy modeling tools simulate the interactions between the envelope characteristics (Insulation, air tightness, windows and glazing, solar heat gain, thermal mass, type of roof, etc.) and the building's heating, cooling, lighting, and ventilation systems to predict energy consumption. By accurately representing the building envelope in these models, designers and engineers can evaluate different design options, identify energy-saving strategies, and optimize building performance to meet energy efficiency goals. Information collected on building materials, insulation levels, window types, and glazing properties to assess thermal performance and potential heat gain/loss is described in Table 4.1.

Table 4.1: Building envelope characteristics

Parameter	Value	Description
Building materials	-	RCC building
Orientation	South	South
Net conditioned building area	12498.67 m^2	Total built-up area of the building
Floor-to-floor height	3 m	All floor
Window types	-	The windows consist of double-glazed insulated glass, consists of two panes of glass separated by a space filled with air or an insulating gas.
Gross wall area	4037.54 m^2	The external and internal walls of building consist of 230mm common bricks with both side cement plaster.
Roof	-	Roofs consist of RCC slab of thickness 125mm.
Footprints	-	Hospitality
HVAC System	-	Central VAV
Building operation schedule	-	Default

HVAC System: The HVAC data collected typically includes:

- HVAC system type: Variable air volume (VAV) systems enable energy-efficient HVAC system distribution by optimizing the amount and temperature of distributed air.
- Equipment specifications: Lubby model of compressor capacity 135 kW (4 Nos.).
- Operating schedules for heating, cooling, and ventilation systems: Depends on the functional operations in the building.
- Auxiliary equipment such as pumps: Primary and secondary pumps of 20 and 40 Ampere used along condenser pump of 40 Ampere.

Electrical Appliances and Equipment: Electric appliances play a vital role in building energy consumption modeling and forecasting. Accurate representation of these appliances in energy models enables designers and building managers to optimize energy efficiency, plan for future energy needs, and implement cost-effective energy-saving measures. The data collected for energy modeling and consumption forecasting includes:

- Lighting system specifications including types of fixtures, bulbs, and wattages.
- Electrical equipment specifications including make, model, and power ratings of appliances, kitchen equipment, and entertainment systems.
- Operating schedules for lighting and electrical equipment.
- Energy usage data from meters or submeters for different areas or systems within the building.
- Historical utility bills to track energy consumption and costs and compare with the predicted results.

Details of lighting fixtures, electrical equipment, and appliances including wattages, and operating schedules, is also given in Table 4.2

Occupancy Schedule and Operational Data: Data on hotel occupancy rates, guest room occupancy, and usage patterns for common areas, restaurants, and meeting spaces to predict energy demand. The complete building details have been collected from the site. Accurate knowledge of operation plans is crucial because they have a significant impact on energy usage. To obtain the schedule of occupants, lighting, equipment, appliances, and processes that contribute to the internal loads and determine whether air conditioning equipment needs to be operated continuously or intermittently (such as, shut down during off periods, and night set-back). The following information includes:

- Information about the occupancy patterns in different areas of the hotel throughout the day and week, including guest rooms, common areas, meeting rooms, restaurants were collected. This includes data on hotel occupancy rates, guest room occupancy, and usage patterns for common areas, restaurants, and meeting spaces are also included in Table 4.2.
- People and Equipment: Human occupancy and use of equipment generate internal heat gain, increasing the cooling load during the summer. However, during winter, internal heat gain can reduce heating loads. Table 4.2 shows the number of people in the different components of the building. The details of the data collected are given in Appendix I.

Table 4.2: Floor area and Energy appliances data

Location		Nagpur (India); Climate - Composite									
Sr. No.	**Component**	**Floor**	**L (m)**	**W (m)**	**H (m)**	**Area (m^2)**	**Volume (m^3)**	**No of Users**	**ACH**	**Light load (kW)**	**Equipment load (kW)**
1	Party Hall	Ground Floor	42.38	21.87	3.05	926.85	2826.89	50	1	10	1
2	Kitchen		22.27	16.25	3.05	361.81	1103.51	8	1	0.9	33.31
3	Bar & Restaurant		18.04	14.77	3.05	266.42	812.58	20	1	2.5	2.00
4	Reception		15.37	13.31	3.05	204.55	623.87	15	1	3	-
5	Banquet hall 1	1st Floor	43.38	22.11	3.05	959.13	2925.35	40	1	15	29.31
6	Banquet hall 2		30.15	17.52	3.05	528.08	1610.64	20	1	15	2.00
7	Hall		20.87	17.77	3.05	370.77	1130.85	20	1	5	-
8	Lobby + Kitchen		13.19	13.31	3.05	175.60	535.58	15	1	2	1.00
9	Service Floor	2nd Floor	43.38	22.11	3.05	959.13	2925.35	8	1	20	-
10	Cafeteria		30.15	17.52	3.05	528.08	1610.64	6	1	2	12.00
11	Rooms		35.77	17.77	3.05	635.63	1938.68	32	1	10.5	-
12	Food Store	3rd Floor	43.38	22.11	3.05	959.13	2925.35	25	1	10.5	-
13	Conference hall		30.15	17.52	3.05	528.08	1610.64	50	1	10.5	-
14	Rooms		35.77	17.77	3.05	635.63	1938.68	32	1	10.5	-

Location		Nagpur (India); Climate - Composite									
Sr. No.	**Component**	**Floor**	**L (m)**	**W (m)**	**H (m)**	**Area (m^2)**	**Volume (m^3)**	**No of Users**	**ACH**	**Light load (kW)**	**Equipment load (kW)**
15	Grand Hall	4th Floor	43.38	22.11	3.05	959.13	2925.35	25	1	18	10.00
16	Conference hall		30.15	17.52	3.05	528.08	1610.64	50	1	10	-
17	Rooms		35.77	17.77	3.05	635.63	1938.68	32	1	10.5	-
18	Silver Chamber	5th Floor	43.38	22.11	3.05	959.13	2925.35	25	1	10	10.00
19	Conference hall		30.15	17.52	3.05	528.08	1610.64	50	1	14	-
20	Rooms		35.77	17.77	3.05	635.63	1938.68	32	1	8	-
21	Office	6th Floor	15.68	4.29	3.05	67.29	205.24	5	1	1.5	-
22	Rooms		35.77	17.77	3.05	635.63	1938.68	32	1	10.5	-

4.2 Setting Up Spaces and Zones in the Building and Assigning Thermal Properties

The entire building comprising of G+6 floors was divided into convenient individual spaces and zones based on their usage, orientation, and occupancy patterns. Appropriate thermal properties were assigned to each zone and components.

Thermal Transmittance of Building Components

Table 4.3 shows the thermal transmittance, commonly known as U-factor, which measures the amount of heat transfer through a material or combination of materials. It is expressed in W/m^2□C. U-value formula is based on ECBC code. A lower U-factor indicates better insulation, while a higher U-factor indicates poor insulation. U-factor is crucial in determining the energy efficiency of buildings and is commonly used in building design and construction. The overall heat transfer coefficient of a building material and component is amount of its ability to conduct heat. It is a combination of the thermal conductivities of the individual materials, as well as the thicknesses and geometries of the different layers.

Table 4.3: Thermal properties of building components

Item	U- factor (W/m^{2}C)
Exposed walls with 230 thick brick and 12.5 mm cement plaster on either side)	0.487
Partition walls	1.86
Ceiling/Roof (150 mm thick RCC slab with cement mortar on either side)	2.82
Roof	0.256
Floor	4.5
Vertical Fenestration (Overall Assembly including the Sash and Frame) - double glazing	2.86
Fenestration (non-opaque metallic) double glass	2.86
Doors	1.8
Equipment	21.6

4.3 Assigning Input Design Conditions

Defining the design conditions for the building includes indoor and outdoor air temperature, humidity levels, solar radiation, and internal heat gains from occupants, lighting, and equipment, etc. The design conditions used in the energy modeling and forecasting are given below:

Weather Data (Building Outdoor and Indoor Conditions)

Collecting information about weather design parameters, such as dry bulb temperature, relative humidity, wet bulb temperature, and humidity ratio, is crucial for energy modeling and consumption forecasting in hotel buildings for several reasons which include thermal comfort within the building, HVAC system sizing, operational schedule optimization, energy demand analysis, and renewable energy integration, etc.

The building envelope plays a critical role in creating a barrier between the outside environment and the indoor conditions. It is responsible for regulating the heat flow, air movement, and solar heat. Not only does it protect the building occupants from external elements, but it also ensures that the indoor environment is conducive to their comfort, health, and safety. To achieve this, building systems must maintain the desired room temperature, relative humidity, air quality, and lighting levels within acceptable limits.

Average weather design parameters considered for energy consumption modeling during different seasons are given in Table 4.4.

Table 4.4: Average weather design parameters

Parameter		**Ambient (Outside)**	**Indoor**
Summer (May)	Dry bulb temperature (°C)	42.6	23
	Relative humidity (%)	28.85	50
	Wet bulb (°C)	26.6	15.43
	Humidity ratio (%)	0.0154	0.0082

Parameter		**Ambient (Outside)**	**Indoor**
Winter (Jan)	Dry bulb temperature (°C)	27.5	23
	Relative humidity (%)	57.5	60
	Wet bulb (°C)	21.23	16.87
	Humidity ratio (%)	0.0132	0.0099
Monsoon (July)	Dry bulb temperature (°C)	32	23
	Relative humidity (%)	82.40	50
	Wet bulb (°C)	29.3	15.36
	Humidity ratio (%)	0.019	0.009

The cooling load is determined by the desired indoor and outdoor conditions on a given day. The indoor conditions are typically based on human comfort, while outdoor design conditions vary by location. The outdoor conditions can be obtained from published data, weather bureau or airport records, or from the ASHRAE handbook, which provides climatic data for over 1,400 locations worldwide. The data collected includes dry-bulb, wet-bulb, and dew-point temperature values, wind speed and direction. The data are outlined in Table 4.4.

The cooling and humidity conditions of dry bulb temperatures correspond to the 1% annual cumulative frequency of occurrence. The wet bulb temperatures correspond to the 1% annual cumulative frequency of occurrence and the mean coincident dry-bulb temperature.

The design parameters in Table 4.4 indicate that during summer (May), the dry bulb temperature is 42.6°C, the relative humidity is 28.85%, the wet bulb temperature is 26.6°C, and the humidity ratio is 0.0154 kg of humidity per 1 kg of dry air. Similarly, the table shows the dry bulb temperature, relative humidity, wet bulb temperature, and humidity ratio for winter and monsoon seasons. These design conditions serve as a basis for determining HVAC system requirements to ensure indoor thermal comfort for building occupant.

Table 4.5: Four-year monthly temperature analysis

Month	**2016**	**2017**	**2018**	**2019**	**Avg. temp.**
Jan	29.20	31.10	29.50	27.40	29.30
Feb	29.00	33.00	33.90	29.10	31.25
Mar	33.30	33.30	36.20	31.00	33.45
Apr	44.00	44.00	41.60	43.20	43.20
May	47.30	47.30	45.60	46.30	46.63
Jun	45.50	45.50	43.20	46.50	45.18
Jul	35.60	35.60	33.50	33.80	34.63
Aug	27.40	27.40	32.00	25.00	27.95
Sep	33.70	33.70	28.10	33.50	32.25
Oct	32.00	32.00	34.60	30.00	32.15
Nov	31.80	31.80	32.00	29.40	31.25
Dec	32.60	32.60	30.40	25.00	30.15
Average temperature					34.78

Based on the data collected as given in Table 4.5, it is observed that:

a. The average temperature for the entire period (2016-2019) is 32.01□C.

b. On average, the hottest month is May with a temperature of 46.63□C.

c. On average, the coldest month is August with a temperature of 27.95□C.

d. There is a significant difference in temperature between the warmest and coldest months, with a difference of almost 19□C.

e. The temperature data shows some variability year-to-year, with some years having higher or lower temperatures in certain months compared to others.

f. In 2017 and 2018, there were some particularly hot months, with February 2017 and March 2018 having the highest temperatures recorded during the four-year period. Instead of other months, August 2019 was particularly cold.

Figure 4.3 displays the variation of month-wise average temperature and relative humidity in Nagpur over a period of four years. The temperature ranges from a low of 29.1°C in January to a high of 43.8°C in May. The relative humidity ranges from a low of 31.4% in August to a high of 81.7% in July. The data suggests that the location experiences a composite climate with high temperatures and low relative humidity in the summer months and more moderate temperatures with higher relative humidity in the winter months. This information is useful for understanding the climate conditions of the location and for designing energy-efficient buildings.

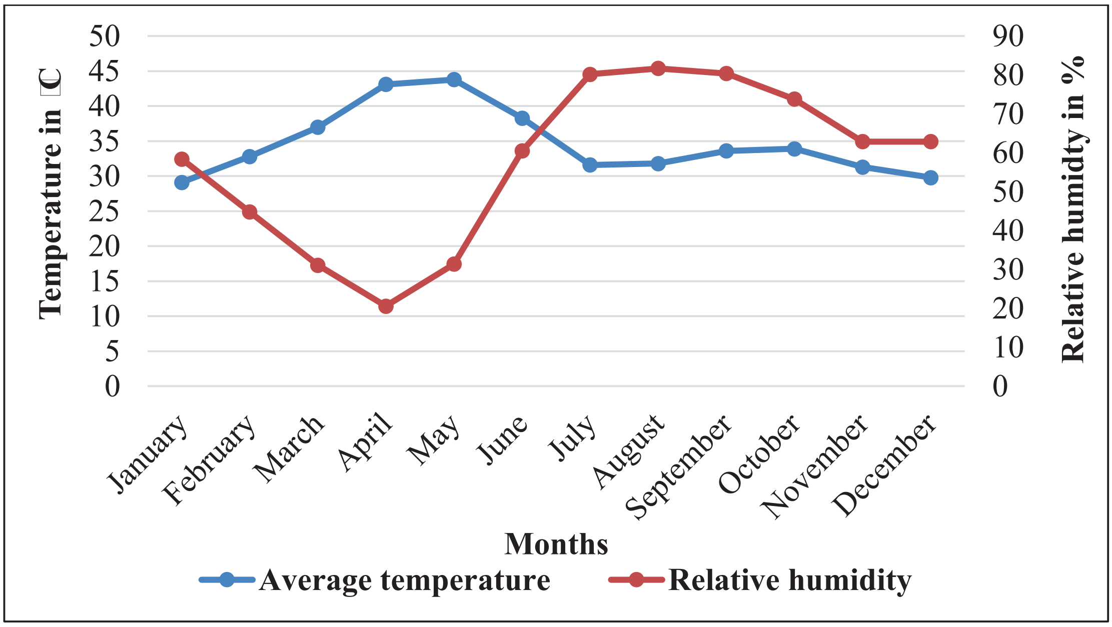


Figure 4.3: Variation of average temperature and relative humidity

Solar Heat Gain Factors (SHGF)

Solar heat gain is the increase in thermal energy of a space or structure when it absorbs incoming solar radiation. SHGF values represent the amount of solar radiation that can pass through the glazing and enter the building as heat gain and is a fraction of solar radiation coming through a window, door, or skylight. In general, the SHGF values are higher for glazing facing the south, east and west directions, where the sun's rays are direct, and lower for glazing facing the north directions, where the sun's rays are indirect. The lower the SHGF, the less solar heat it transmits and the better its shading ability. The maximum SHGF for 22° N as per ASHARE code depends on various factors, including the wall orientation, glazing type, and shading devices. This value varies depending on specific aspects such as the building orientation and local climate conditions [51].

It is important to note that high SHGF values can lead to excessive solar heat gain, which can increase the building's cooling load and energy consumption. Therefore, proper glazing selection and shading design are important to optimize energy performance and occupant comfort in buildings. Table 4.6 shows the maximum SHGF values in W/m² for a building located at latitude 22° N, in different orientations, throughout the months January to December.

Table 4.6: Maximum SHGF (W/m^2) for 22^o N Latitude

Direction	**North**	**South**	**East**	**West**
Month				
Jan	82	640	568	568
Feb	88	533	647	647
Mar	98	366	685	685
April	110	192	662	662
May	129	129	631	631
June	167	123	612	612
July	136	129	618	618
Aug	114	205	640	640
Sep	104	360	650	650
Oct	91	517	621	621
Nov	82	631	558	558
Dec	79	672	533	533

4.4 Energy Performance Modeling and Consumption Forecasting

Using the data collected, the energy performance modeling and consumption forecasting is carried out using the following methods as explained in Chapter 3.

a) Cooling Load Temperature Difference (CLTD) Method,
b) Revit Architecture, and
c) Artificial Neural Network (ANN).

The energy consumption comprising of peak cooling and heating load to maintain the desired temperature in the building, energy consumption by electric appliances and equipment, has been carried out for the case study building.

Chapter - 5

Results and Discussion

Chapter - 5

Results and Discussion

5.1 Estimation of Energy Consumption by CLTD/CFL/SCL Method

The case study hotel building, located in Nagpur, India, primarily requires energy for cooling, lighting, and operating various facilities and equipment throughout most of the year. The peak energy consumption load has been assessed using two different methods: CLTD/CFL/SCL and the BIM-based Revit 2021 methods.

5.2 Estimation of Peak Cooling Load by CLTD/CFL/SCL Method

Figure 5.1 illustrates the peak cooling load computed using the CLTD method for individual floors of the hotel building.

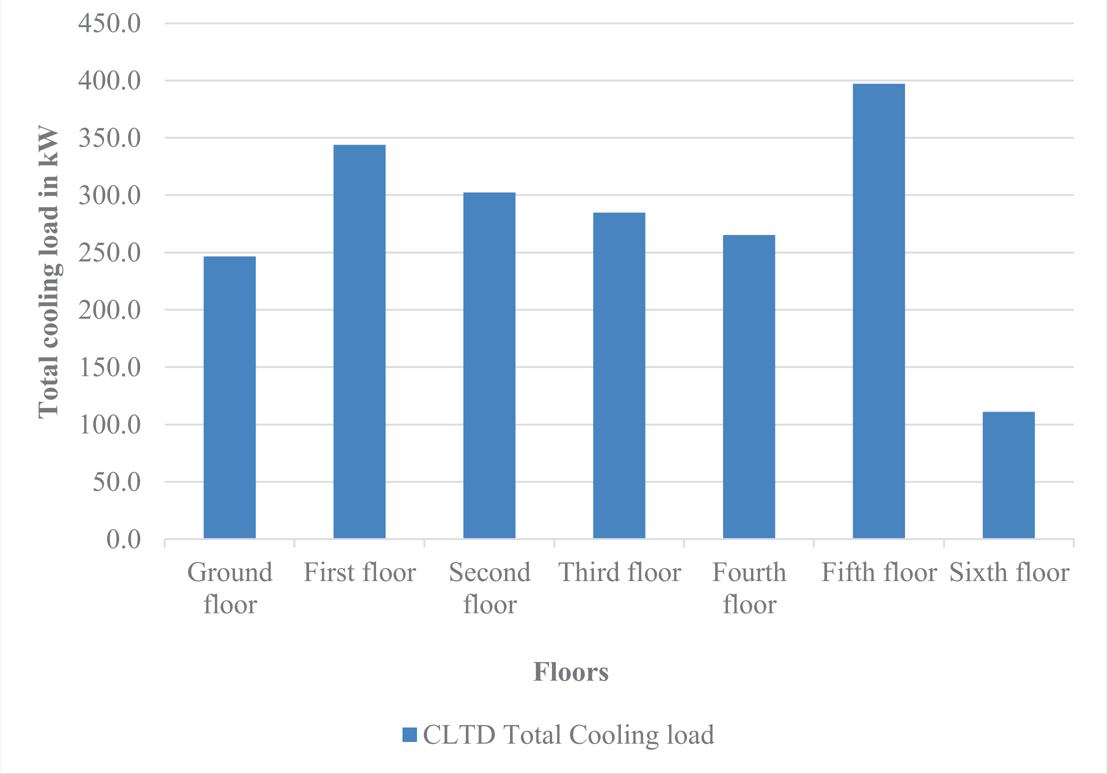


Figure 5.1: Peak cooling load calculated using CLTD method

The figure in question, 5.1, illustrates the variation in peak cooling load across different floors within the building, attributable to varying user requirements and the installation of different equipment for distinct purposes. Beginning with the ground floor, a total peak load of 246.7 kW is observed, indicative of the cooling necessary to maintain a comfortable indoor temperature. Transitioning to the first floor, this load escalates to 343.9 kW, signalling a heightened demand for cooling.

Moving upward to the second floor, a closely comparable total peak load of 302.5 kW is recorded. Upon reaching the third floor, a slight decrease is noted, with the load measuring 284.9 kW due to a relatively reduced cooling requirement. Progressing further to the fourth floor, a further reduction in load is evident, measuring 265.2 kW.

Unexpectedly, the fifth floor presents a notable spike in total peak load, reaching 397.2 kW, suggesting a significant demand for cooling at this level. Finally, the sixth floor exhibits the lowest load among all floors, registering at only 111.0 kW, attributed to a smaller floor area and consequently reduced energy needs.

Understanding the variation in total peak cooling load across different floors helps in optimizing the HVAC system design and effectively managing energy consumption to maintain a comfortable indoor environment.

5.3 Estimation of Peak Cooling Load by Revit Method

In Figure 5.2, the total peak cooling load for each floor of the building is depicted, as determined using Revit software. Analysis of these values underscores the variance in peak cooling load requirement among the different floors as also indicated by the CLTD method. The ground floor manifests a total peak load of 212.03 kW, while the first floor demonstrates a slightly elevated peak load of 310.3 kW. Progressing to the second floor, the cooling load measures 277.1 kW, followed by 267.5 kW for the third floor. The fourth-floor peak load of 260.9 kW, with the fifth floor displaying a higher value of 354.7 kW. Lastly, the sixth floor exhibits the lowest peak load of 92.3 kW. These disparities in energy consumption load across the floors underscore the significance of floor-specific factors.

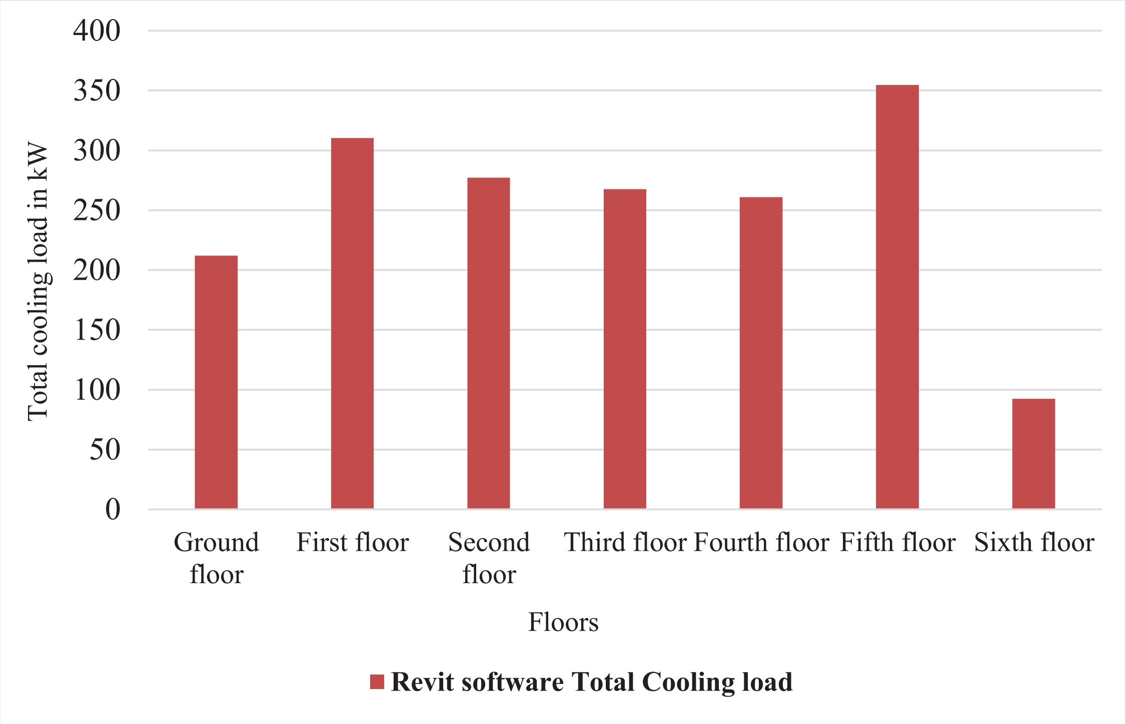


Figure 5.2: Total peak cooling load calculated using Revit software

This data provides valuable insights into the distribution of the peak cooling load throughout the building, floor by floor. It indicates that the peak load tends to vary depending on the specific floor location. Factors such as floor area, orientation, occupancy, and insulation levels can influence the peak load requirements for each floor. By understanding the peak load distribution, building designers and engineers can make informed decisions regarding the sizing and capacity of cooling systems, the placement of air conditioning units, and the optimization of energy efficiency measures. Efficient cooling system design can help maintain comfortable indoor temperatures while minimizing energy consumption and associated costs.

Additionally, this data represents more precise control of cooling systems throughout the building.

5.4 Comparison of Peak Cooling Load by CLTD and Revit Methods

A comparison has been made between the loads calculated by two methods to determine the difference and accuracy of each method. The total peak cooling load computed by both methods is listed in Table 5.1 month-wise for the year 2021.

Table 5.1: Peak energy requirement computed by CLTD and Rivet 2021 software

Month	BIM Revit 2021 (kW)	CLTD/CLF/SCL (kW)
January	799.8	743.1
February	1020.3	951.5
March	1211.8	949.5
April	1571.0	1156.3
May	1531.3	1412.2
June	1658.8	1626.8
July	1371.6	1307.0
August	1356.7	1345.6
September	1709.9	1479.3
October	1630.3	1429.4
November	1282.3	1022.9
December	905.8	895.0

The comparison demonstrates that peak load demands can be accurately predicted using both the Revit 2021 and CLTD/SCL/CFL modeling techniques. The graphical representation of the peak cooling load for the building, as listed in Table 5.1, is depicted in Figure 5.3. The figure illustrates that the peak load predicted by the two methods follows a comparable and similar trend, with lower demand during the winter months from January through December. Specifically, Revit measured a peak load of 1709.9 kW, whereas the CLTD/CLF/SCL method yielded 1626.8 kW. The comparison indicates that, on average, the peak cooling load estimated using Revit is 10.30% higher than the load predicted using the CLTD/CFL/SCL approach.

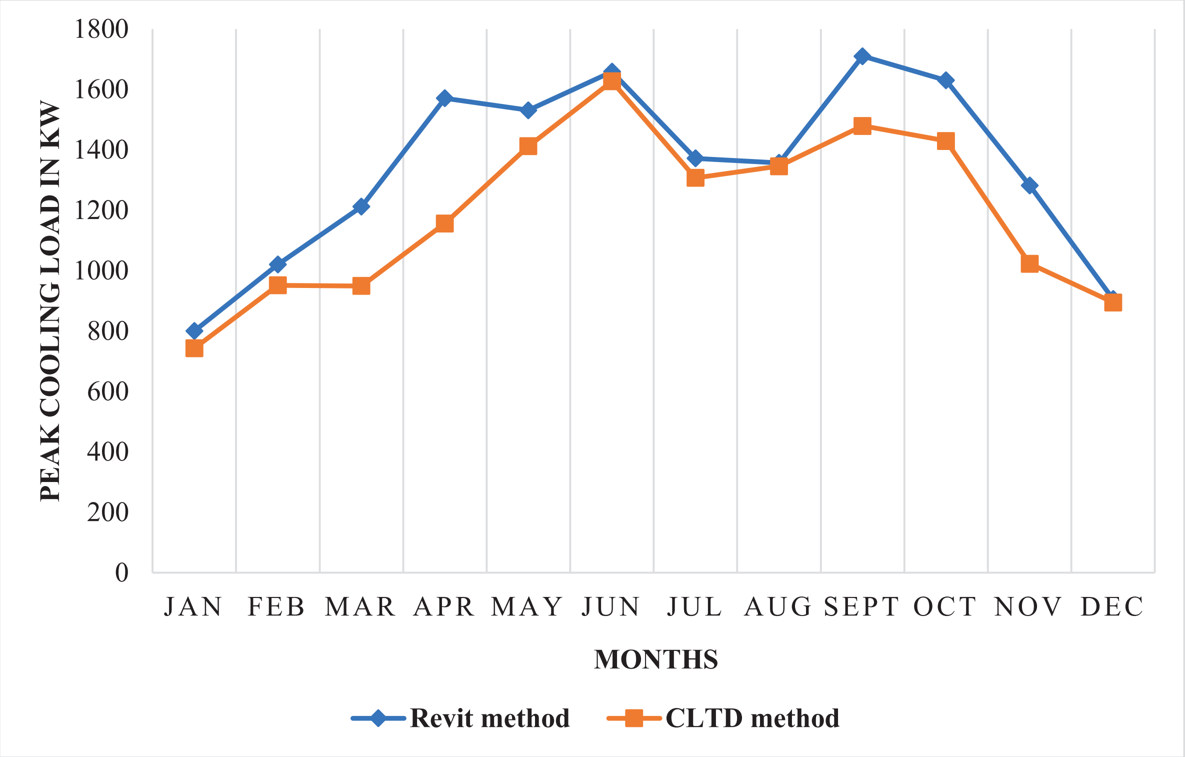


Figure 5.3: Comparison of peak cooling load (kW) predicted by Revit and CLTD methods

5.5 Computation of Total Energy Consumption for the Building

To compute the peak total energy consumption for a building, it must be fully occupied and operating at peak capacity. This typically occurs with service buildings like hotels located in tourist destinations or larger cities. However, this isn't always the case for buildings in less prominent locations or during off-peak times, when occupancy fluctuates based on client availability. This fluctuation occurs periodically and seasonally. In such instances, accurately predicting true peak heating or cooling loads necessitates strict adherence to the actual operational schedule, which may not always be feasible, especially with multi-storey complex buildings.

The total energy consumption for the building has been computed using both the CLTD and Revit methods, and a comparison of the results has been conducted to illustrate the variation. CLTD method allows for precise customization based on regional climate data, making it well-suited for comparisons under similar climatic conditions at a regional or local level. Engineers can adjust calculations to reflect the specific weather patterns, solar exposure, and temperature ranges characteristic of the area, enabling more accurate estimations of cooling loads. While the Revit method may not explicitly incorporate regional climate data, it can still be tailored to reflect similar conditions by adjusting input parameters to match the characteristics of the region or climate zone. This allows for comparisons at a national or global level, where buildings may vary in design, materials, and occupancy patterns but operate under similar climatic conditions. The CLTD and Revit methods can facilitate comparisons under similar conditions at regional, national, and global levels, with the former providing more explicit customization based on regional climate data and latter allowing for adjustments to input parameters to reflect regional characteristics.

Figure 5.4 displays the comparison between the total energy consumption variations estimated by the CLTD and Revit methods. While the CLTD method offers a relatively quick estimation of the cooling load, it may lack accuracy compared to more detailed approaches. On the other hand, the Revit method yields more precise results than the CLTD method because it considers the building's characteristics and components. The CLTD method relies on simplified cooling load estimates based on temperature differentials and predefined CLTD values, whereas the Revit method leverages advanced modeling and simulation capabilities to provide tailored and detailed cooling load calculations that account for specific building attributes.

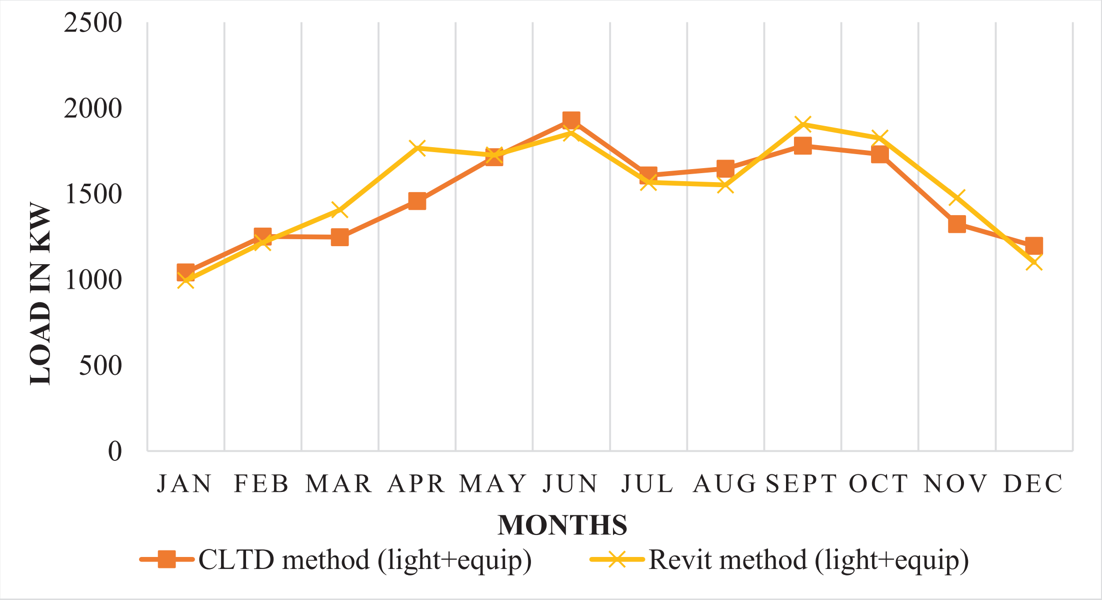


Figure 5.4: Comparison of total peak energy consumption by CLTD and Revit Methods

Figures 5.5 and 5.6 depict pie charts illustrating the breakdown of end-use energy consumption for the case building, providing a comprehensive overview of the total load distribution between the CLTD and Revit methods. The comparison reveals that, for the case building, the majority of the energy is required for cooling purposes throughout the year. Energy consumption for lighting accounts for approximately 14%, while that for appliances is around 7% of the total energy requirement. Peak energy consumption requirements are minimal, constituting just 5% of the total.

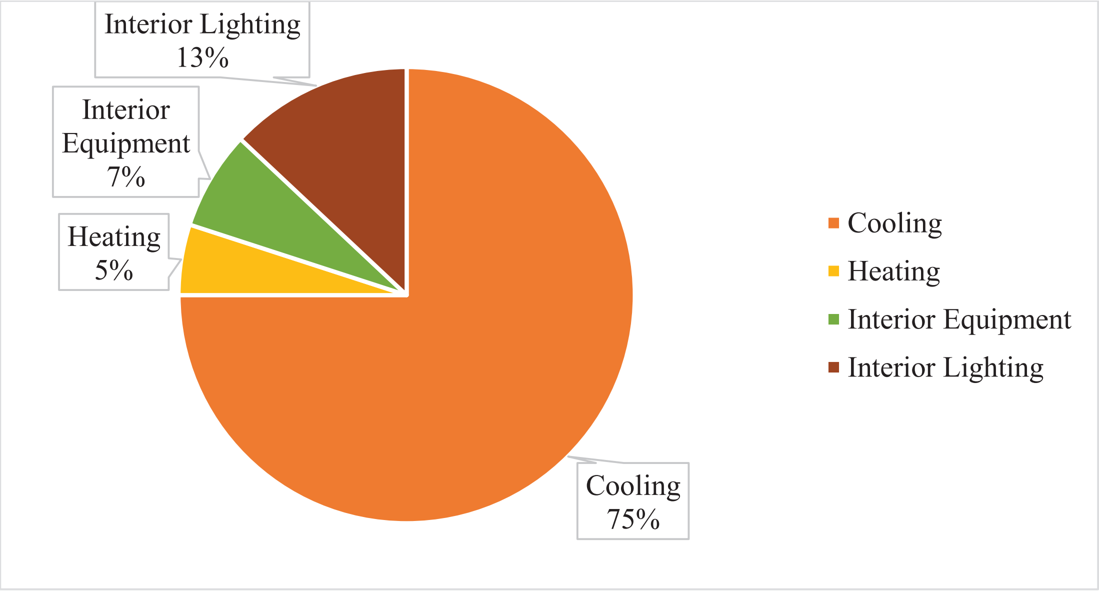


Figure 5.5: End use energy consumption by CLTD method

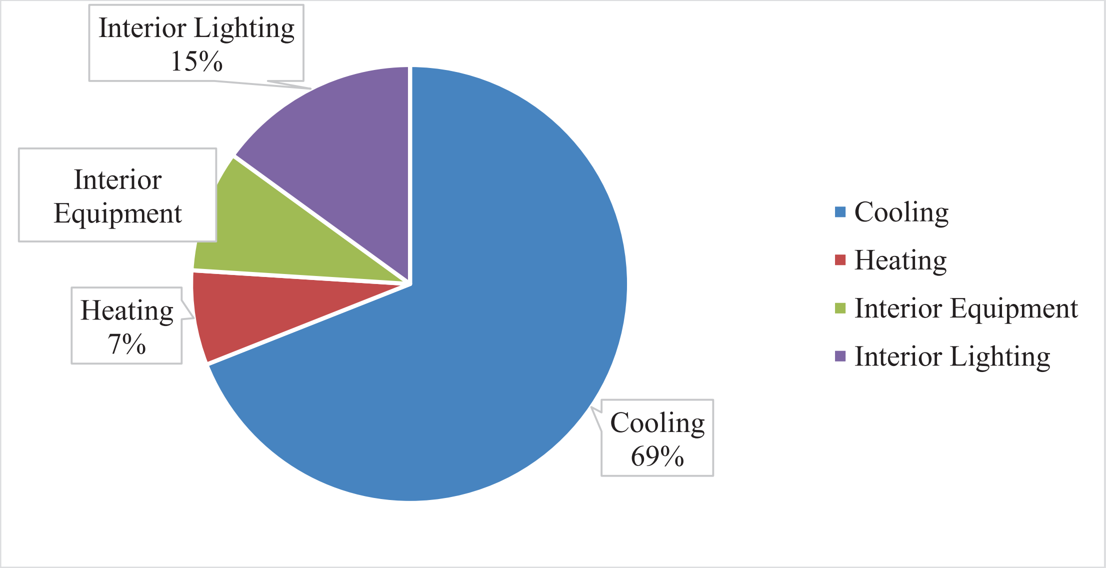


Figure 5.6: End use energy consumption by Revit Method

This visual representation empowers stakeholders to pinpoint areas of heightened energy consumption, facilitating the strategic prioritization of energy-saving initiatives. By focusing on optimizing cooling loads and integrating energy-efficient solutions like advanced HVAC systems and smart building technologies, significant reductions in energy consumption can be achieved. This aligns with findings from studies such as those conducted by the IEA, which emphasize the crucial role of energy-efficient measures in enhancing the sustainability and resilience of buildings while simultaneously reducing greenhouse gas emissions and operating costs.

Understanding the distribution of these loads is crucial for optimizing energy efficiency and making informed decisions regarding system design and operation. By visualizing the proportion of each load component through the pie chart, it becomes apparent that a significant portion of the total load is dedicated to cooling.

This emphasizes the importance of implementing energy-efficient cooling systems and strategies to reduce energy consumption and associated costs. Additionally, the electric load serves as a significant contributor to the overall energy consumption within the building, highlighting the need for energy-efficient electrical appliances and lighting.

5.6 Energy Performance Modeling and Consumption Forecasting Evaluation by ANN

The proposed energy performance modeling and consumption forecasting of the case building using the CLTD and Revit methods were evaluated through the implementation of ANN. The utilization of ANN offers a sophisticated approach to assess the efficacy and reliability of energy performance modeling and consumption forecasting techniques. Through ANN, the computational model can learn and adapt to complex patterns and relationships within the data, providing valuable insights into the convergence and accuracy of the CLTD and Revit methods. This approach enables researchers and stakeholders to make informed decisions regarding energy efficiency measures and building design strategies, ultimately contributing to more sustainable and resilient built environments. The analysis revealed that the results exhibited convergence.

Prediction of results using ANN

The graph shown in Figure 5.7 consists of total number of epochs on the X-axis and Y-axis is the accuracy labels for training and validation accuracy. It shows the training accuracy and validation accuracy are increasing with each epoch until the last epoch which is 50. Accuracy is a metric that measures how well a model correctly predicts the target values (labels) for a given set of input data. It is expressed as a percentage and represents the ratio of correctly predicted instances to the total number of instances in the dataset.

Mathematically, accuracy is calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

In Figure 5.8, training Loss and validation loss are decreasing with each epoch until the last epoch which is 50. Losses measure how well the model is performing in terms of its ability to minimize the error between its predictions and the true outcomes. The aim of training an ANN is to minimize this loss, which leads to the model making better predictions over time. The blue line represents the training accuracy, which shows how accurate the model is on the training data as the number of epochs increases.

Accuracy is inversely proportional to the loss. Hence, it can be said that in ANN model with 50 epochs, the Accuracy curve is increasing and the loss curve is decreasing. Similarly, in Figure 5.9 and 5.10 the same trend is observed for LSTM model, after 30 epoch accuracy increases, and as the loss decreases, the model becomes more accurate in its predictions.

Hence, for LSTM model, measured accuracy obtained is 85% and ANN model accuracy obtained is 99%, we can conclude that ANN Model is giving us better accuracy as compared with LSTM model.

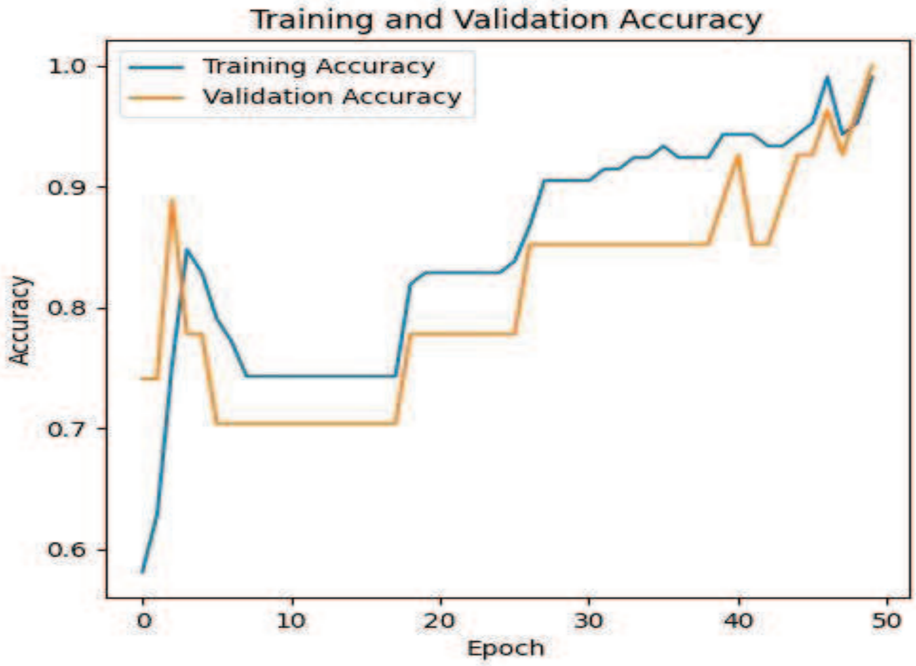


Figure 5.7: Measured training and validation accuracy for ANN model

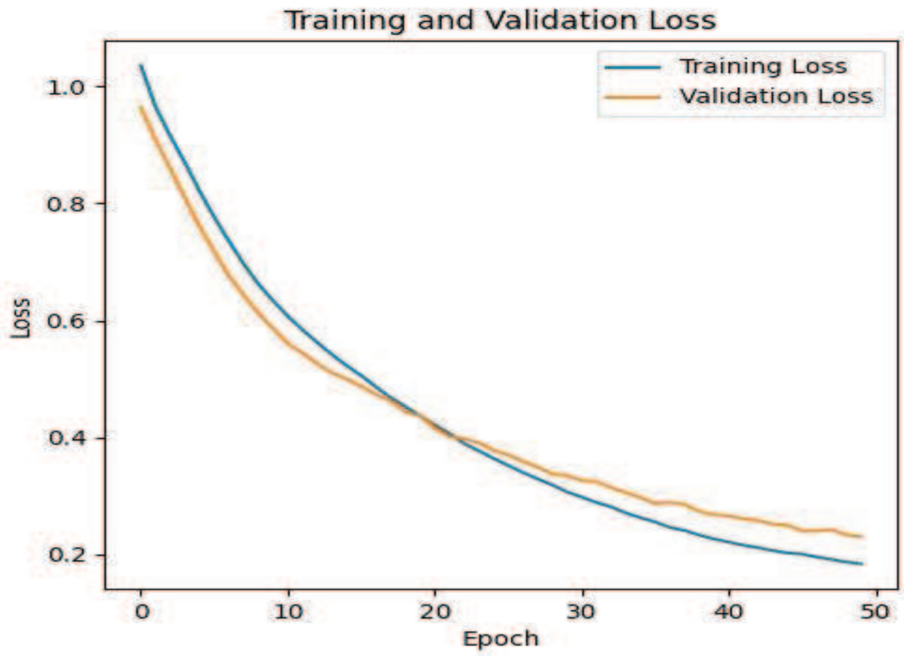


Figure 5.8: Measured training and validation loss for ANN model

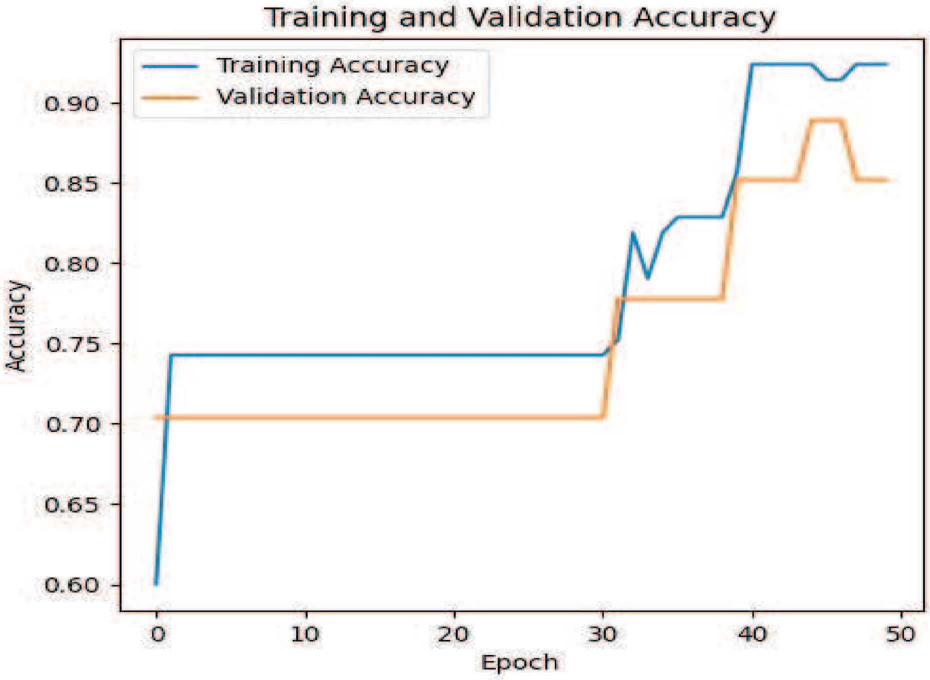


Figure 5.9: Measured training and validation accuracy for LSTM model

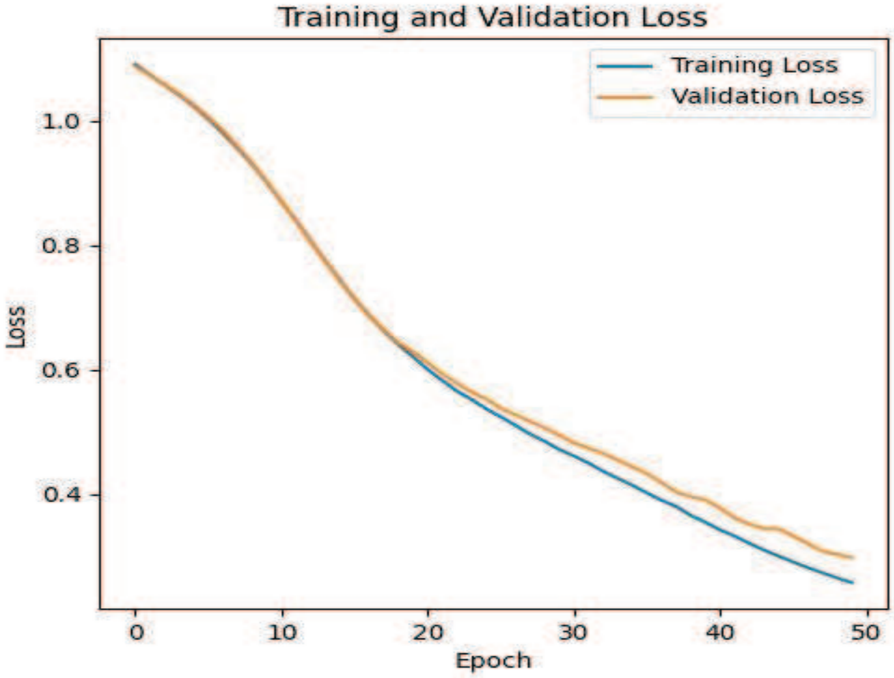


Figure 5.10: Measured training and validation loss for LSTM model

5.7 Comparative Analysis of Energy Models Accuracy by different Algorithms

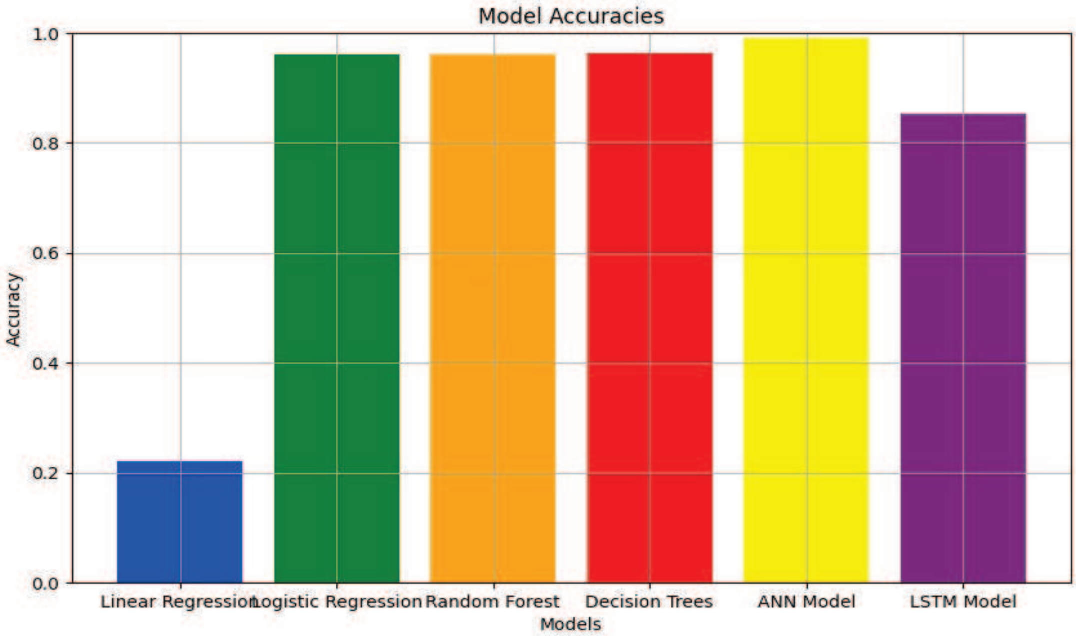


Figure 5.11: Comparative analysis of energy model accuracy with different algorithms

Figure 5.11 shows a bar chart of different algorithm models trained with respect to the dataset, like linear regression, logistic regression, random forest, decision trees, ANN model and LSTM model, measured to obtained the maximum accuracy with good prediction.

The linear regression model achieved an accuracy of 22%. This low accuracy indicates that the linear relationship assumed by the model is not well-suited for capturing the complexities present in the data. Linear regression assumes a linear relationship between the input features and the target variable, which might not be the case for energy consumption prediction.

It is worth noting that logistic regression is often used for binary classification tasks, so achieving 96% accuracy indicates that the problem is formulated as a binary classification, which may not fully capture the nuances of energy consumption prediction. If energy consumption is a continuous variable, using logistic regression may not be ideal for this purpose.

The random forest model achieved an accuracy of 96%. Random forests are ensemble methods that combine multiple decision trees to make predictions. The high accuracy suggests that the random forest model is capable of capturing the non-linear relationships and interactions in the data, making it a strong entrant for energy consumption prediction.

The decision tree model also achieved 96% accuracy, which is consistent with the performance of the random forest model. Decision trees are the building blocks of random forests and can work well for certain tasks, especially when there are clear decision boundaries in the data. The LSTM model achieved 85% accuracy in predicting energy consumption. LSTMs are a type of RNN designed to process sequential data. An accuracy of 85% indicates that the LSTM model is able to capture temporal dependencies and patterns in energy consumption data.

The ANN model achieved the highest accuracy of 99% in predicting energy consumption. This remarkable performance shows that ANN has successfully learned complex relationships and patterns in the data. ANNs are highly flexible and can model complex relationships, which may explain their excellent performance in this analysis.

Based on the obtained results, it is clear that the ANN model outperformed other models in terms of the accuracy of energy consumption prediction. ANNs are known for their ability to capture complex patterns and relationships in data, making them well suited for tasks with complex dependencies.

In addition, the choice of evaluation metrics should be aligned with the specific goals and requirements of the energy consumption prediction task.

The critical review of two different models based on their structure, input-output relations, applicability, and limitations is also made and is discuss in Table 5.2 below:

Table 5.2: Critical review of two different models based on their structure, input-output relations, applicability, and limitations.

	Revit model	**ANN model**
Structure	➢ Revit models are BIM tools used in architectural and engineering design, construction, and maintenance. ➢ They represent the physical and functional characteristics of a building or structure, including elements such as walls, floors, doors, windows and systems such as HVAC and electrical equipment.	➢ ANN models consist of interconnected layers of artificial neurons that process data. ➢ The structure of ANN is more flexible and can capture complex relationships, but lacks a direct interpretation of physics-based equations.
Input-Output Relations	➢ Revit models rely on user input to define building geometry, materials, and systems. ➢ Revit model output includes detailed drawings, schedules, and specifications that provide a comprehensive view of the physical structure.	➢ ANN models learn input-output relationships from data without the need for clear knowledge of the underlying physics. ➢ Although ANN can approximate complex functions, the relationships they learn can be less interpretable than those derived from physics-based equations.

	Revit model	**ANN model**
Applicability	➢ Revit models are advisable for the architecture, engineering and construction industry, enabling collaboration and coordination between different disciplines. ➢ They facilitate design visualization, crash detection, cost estimates and maintenance planning.	➢ ANNs are suitable for tasks where the underlying physics is complex or unknown and a significant amount of data is available for training. ➢ They can be used for energy consumption forecasting, demand forecasting and other data tasks.
Limitations	➢ Revit models are primarily used to design and represent the physical aspects of buildings and structures. ➢ They do not include complex relationships in non-physical domains (eg. energy consumption forecast). ➢ Creating and maintaining accurate Revit models can be time-consuming, especially for complex projects.	➢ ANNs require a significant amount of training data to generalize well. Not having enough information can cause overfitting or poor performance. ➢ ANN models can be difficult to interpret and often act as black boxes without explanation. ➢ ANN require significant computational resources for training and can be difficult to refine efficiently.

Chapter - 6

Conclusions and Summary

Chapter - 6

Conclusions and Summary

6.1 Conclusions

Energy consumption modeling and simulation play a crucial role in optimizing energy efficiency and sustainability in service buildings, particularly hotels. The high energy demand resulting from various appliances, space heating and cooling, ventilation, lighting, food and beverage service, utilities used to provide comfort and perform daily tasks poses challenges in terms of economic viability and environmental impact. To address these concerns, tools such as BIM and BEM and machine learning, etc. have emerged in recent years to simulate, analyze energy demand, and reduce energy consumption in buildings.

The integration of BIM and BEM methodologies and machine learning tools enables the early incorporation of energy performance analysis in building projects, facilitating calculations of EUI, allocation of energy budgets, prediction of annual energy consumption, comparison of HVAC systems and appliances, establishment of utility schedules, and definition of energy and comfort standards. These modeling and simulation techniques provide valuable insights to support decision-making processes and assist in selecting competent and sustainable models for energy-efficient hotel buildings. By harnessing the power of energy consumption modeling and simulation, hotels can strive towards enhanced energy performance and reduced environmental impact.

Higher energy use in hotel buildings results in increased emissions, leading to environmental degradation. To mitigate this, hotels can update energy systems and monitor energy use to contain or reduce consumption. Implementing sustainable practices helps identify excessive consumption and reduce energy waste. Sustainable practices offer cost savings, enhance brand reputation, and ensure compliance with regulations, benefiting both the environment and the hotel industry. This study aimed to analyze energy modeling and simulation tools, as well as the factors related to energy consumption in hotel buildings by considering a case study. The main objective is to assist in decision-making processes and the selection of competent and sustainable models for constructing energy-efficient hotel buildings. After conducting a modeling study and thorough performance investigation of this standard hotel building, the conclusions are summarized in Table 6.1.

Table 6.1: Objectives and corresponding conclusions derived from the current research

Objective No.	Objective	Conclusions
1.	To identify the key variables that affect the building energy performance, their behavior, nature, and the relationship between the explanatory and dependent variables.	➢ The energy consumption in hotel buildings is influenced by several key parameters. These factors include the building's orientation, location, shape, level of thermal insulation, window to wall ratio, user behavior, HVAC systems, weather conditions, and operational schedules necessary to sustain various services within the building. ➢ Among all the variables, HVAC systems are the primary contributors to energy consumption in hotel buildings. These systems are required for maintaining comfortable indoor environments, and energy demand is significantly impacted by their overall energy performance and efficiency. The energy demand and running costs can be significantly reduced through the selection of the right HVAC systems involves a combination of strategic planning, technology selection, and operational practices. ➢ Lighting represents another significant parameter contributing to higher energy consumption. Efficient lighting strategies, such as the use of LED bulbs, smart lighting controls, and natural light utilization, are crucial in reducing energy usage and optimizing energy efficiency within hotels.

Objective No.	Objective	Conclusions
2.	To develop models for energy performance and energy prediction in built environment using engineering and artificial intelligence (AI) techniques.	➢ Autodesk's Revit, a comprehensive building energy simulation program, combines BIM authoring tools and BEM to enable users to analyze the thermal performance of their designs. The simulation capabilities in Revit offer valuable insights into peak heating or cooling demand, peak electricity demand for lighting, and the operation of appliances. The program's add-on feature efficiently automates the creation of energy models and conducts energy simulations across various time scales, resulting in time savings. ➢ ANN provides a comprehensive environment for developing and implementing ANN models, making it easy to customize and optimize the model architecture and parameters. The ideology of model integration developed a novel improved integration model for forecasting building energy consumption in existing buildings.
3.	To make a comprehensive analysis and critical review of two different models based on their structure, input-output relations, applicability, and limitations.	➢ The comparison of peak cooling load highlights the reliable predictive capabilities of both Revit 2021 and the CLTD/SCL/CFL modeling techniques in accurately estimating peak cooling demands. Furthermore, a consistent trend is observed in the peak cooling load and overall energy consumption predictions by these two methods. ➢ However, significant disparities are observed between the measured and predicted annual energy consumptions, highlighting the considerable uncertainties and factors involved in the monthly and annual prediction processes in service buildings. ➢ ➢ These differences stem from various factors, including individual choices, perceptions, habits,

Objective No.	Objective	Conclusions
		and physiological conditions that influence energy consumption and appliance usage. ➢ The intricate interplay of these factors underscores the need for comprehensive strategies and approaches that consider human behavior and diverse variables to improve the accuracy of energy consumption predictions in service buildings. ➢ In conclusion, it is acknowledged that both Revit 2021 and the CLTD/SCL/CFL modeling techniques are suitable tools for accurately estimating peak cooling load and overall energy demands in hotel buildings, enabling the design and sizing of efficient HVAC systems. However, it is important to note that this may not hold true for monthly and annual predictions of heating or cooling loads. These predictions necessitate strict adherence to the actual operation schedule, which may pose several challenges, particularly in multi-storey complex hotel buildings.

6.2 Research Findings

- The CLTD/CLF/SCL method yields reasonably accurate results on various time scales since suitable coefficients specific to the region can be readily selected from the SCL tables found in the ASHRAE Handbook. Using this method, the predicted peak cooling loads for the hotel building amount to 1626.8 kW. The study also reveals that lighting accounts for the second-highest energy consumption in commercial settings.

- The Revit analysis yielded a peak cooling load of 1709.9 kW, while the CLTD/CLF/SCL method resulted in a load of 1626.8 kW. Comparing the two approaches, it is evident that, on average, the Revit estimate was 10.30% higher than the load predicted by the CLTD/CLF/SCL method.

- The total yearly energy usage stands at a significant 5,423,595 kWh, with the cooling load dominating and accounting for approximately 81% of the total annual energy consumption. Following closely behind, lighting and appliances contribute 724,275 kWh and 242,069 kWh, respectively. The electric load is approximately 13% of the total annual energy consumption by the utility building. The yearly energy use intensity is recorded at a remarkably high 433.9 kWh/m^2. These findings shed light on the substantial energy demands within the setting, emphasizing the need for proactive measures to enhance energy efficiency and reduce overall consumption.

- The data was aggregated from the experimented dataset. It was subjected to ANN techniques, where the parameters were optimized with the aid of machine learning and deep learning algorithms. At last, the experimental analysis has shown that the given energy performance modeling and consumption forecasting in the built environment provide better prediction. The values for linear regression, logistic regression model, random forest, decision tree, long-short term model, and ANN were 22%, 96%, 96%, 96%, 85%, and 99%. Based on the obtained results, it was clear that the ANN model outperformed other models in terms of the accuracy of energy consumption prediction.

6.3 Recommendations

In the hotel industry, the focus on the building's envelope is often limited to its exterior aesthetics, with significant attention placed on interior products and systems. However, it is crucial to also prioritize the energy efficiency of the building envelope.

1. The orientation and arrangement of the building should be determined only after conducting energy modeling and life-cycle analysis. This approach ensures the optimization of all components of the building envelope to enhance overall performance.

2. In order to optimize the energy performance of the building envelope, several considerations should be taken into account. Incorporating optimal insulation in the opaque elements of the envelope is essential to cater to both heating and cooling seasons. Additionally, the use of shading devices, such as vertical fins

and daylighting controls, should be carefully balanced to avoid excessive costs without significant energy reduction.

3. Local climatic conditions should be considered to select suitable construction materials for the envelope and determine the appropriate performance characteristics of glazing based on orientation and overall energy performance.
4. Furthermore, it is imperative to calculate the Net Global Warming Potential for each building and include this information on building plans during the approval process. In addition, the Department of energy should play a crucial role in the approval process, ensuring the establishment of a maximum limit for Net Global Warming Potential.
5. Similarly, other buildings such as residential buildings, institutional buildings, etc. should also be studied for energy consumption modeling. The aim of the measure is to promote ecological practices and sustainability in construction projects.

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Appendices

APPENDICES - I

Table 1: Ground floor Wall and Area Specification

Sr. No.	Component		L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Party Hall		41.92	21.41	3.05	897.51	2737.40	50	1
2	Kitchen		21.81	15.79	3.05	344.30	1050.12	8	1
3	Bar & Restaurant		17.58	14.31	3.05	251.54	767.20	20	1
4	Reception		14.91	12.85	3.05	191.57	584.28	15	1
Sr. No.	**Component**	**Wall Type**	**L**	**H**	**Area**	**Area of Doors**	**Area of Windows**	**Net Area**	**Shading Factor**
1	Party Hall	North (Outside wall)	21.41	3.05	65.3	-	-	65.3	1
		South (Outside wall)	21.41	3.05	65.3	-	-	65.3	1
		East (Outside wall)	41.92	3.05	127.86	6.3	3.66	117.9	1
		West (P wall)	41.92	3.05	127.86	-	-	127.86	1
2	Kitchen	North (Outside wall)	15.79	3.05	48.16	-	11.88	36.28	1
		South (P wall))	15.79	3.05	48.16	-	-	48.16	1
		East (P wall)	21.81	3.05	66.51	-	-	66.51	1
		West (Outside wall)	21.81	3.05	66.51	-	11.88	54.63	1
3	Bar & Restaurant	North (P wall)	14.31	3.05	43.65	-	-	43.65	1
		South (P wall)	14.31	3.05	43.65	-	-	43.65	1
		East (P wall)	17.58	3.05	53.61	-	-	53.61	1
		West (Outside wall)	17.58	3.05	53.61	-	-	53.61	1
4	Reception	North (P wall)	12.85	3.05	39.19	-	-	39.19	1
		South (Glass wall)	12.85	3.05	39.19	7.32	31.87	119.54	1
		East (Outside wall)	14.91	3.05	45.47	-	-	45.47	1
		West (outside wall)	14.91	3.05	45.47	-	-	45.47	1

Table 2: First floor Wall and Area Specification

Sr. No.	Component	L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Banquet hall 1	43.38	22.11	3.05	959.13	2925.35	40	1
2	Banquet hall 2	30.15	17.52	3.05	528.08	1610.64	20	1
3	Hall	20.87	17.77	3.05	370.77	1130.85	20	1
4	Lobby + Kitchen	13.19	13.31	3.05	175.60	535.58	15	1

Sr. No.	Component	Wall Type	L	H	Area	Area of Doors	Area of Windows	Net Area	Shading Factor
1	Banquet hall 1	North (Outside wall)	22.11	3.05	67.44	-	19.52	47.92	1
		South (Outside wall))	22.11	3.05	67.44	-	7.92	59.52	1
		East (Outside wall)	43.38	3.05	132.31	3.15	22.77	106.39	1
		West (P wall)	43.38	3.05	132.31	-	-	132.31	1
2	Banquet hall 2	North (Outside wall)	17.52	3.05	53.42	-	16.26	37.16	1
		South (P wall))	17.52	3.05	53.42	-	-	53.42	1
		East (P wall)	30.15	3.05	91.96	-	-	91.96	1
		West (Outside wall)	30.15	3.05	91.96	-	26.02	65.94	1
3	Hall	North (P wall)	17.77	3.05	54.20	-	-	54.20	1
		South (P wall))	17.77	3.05	54.20	-	-	54.20	1
		East (Outside wall)	20.87	3.05	63.64	-	-	63.64	1
		West (Outside wall)	20.87	3.05	63.64	-	13.40	50.24	1
4	Lobby + Kitchen	North (P wall)	13.31	3.05	40.60	-	-	40.60	1
		South (Outside wall)	13.31	3.05	40.60	-	-	40.60	1
		East (Outside wall)	13.19	3.05	40.24	3.15	-	37.09	1
		West (Outside wall)	13.19	3.05	40.24	-	-	40.24	1

Table 3: Second floor Wall and Area Specification

Sr. No.	Component	L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Service Floor	43.38	22.11	3.05	959.13	2925.35	8	1
2	Cafeteria	30.15	17.52	3.05	528.08	1610.64	6	1
3	Rooms	35.77	17.77	3.05	635.63	1938.68	32	1

Sr. No.	Component	Wall Type	L	H	Area	Area of Doors	Area of Windows	Net Area	Shading Factor
1	Service Floor	North (Outside wall)	22.11	3.05	67.44	-	-	67.44	1
		South (Outside wall))	22.11	3.05	67.44	-	-	67.44	1
		East (Outside wall)	43.38	3.05	132.31	3.15	13.37	115.79	1
		West (P wall)	43.38	3.05	132.31	-	-	132.31	1
2	Cafeteria	North (Outside wall)	17.52	3.05	53.42	-	-	53.42	1
		South (P wall))	17.52	3.05	53.42	-	-	53.42	1
		East (P wall)	30.15	3.05	91.96	-	-	91.96	1
		West (Outside wall)	30.15	3.05	91.96	-	-	91.96	1
3	Rooms	North (P wall)	17.77	3.05	54.20	-	11.91	42.29	1
		South (Outside wall))	17.77	3.05	54.20	-	11.91	42.29	1
		East (Ourtside wall)	35.77	3.05	109.10	-	20.06	89.04	1
		West (Outside wall)	35.77	3.05	109.10	-	23.81	85.28	1

Table 4: Third floor Wall and Area Specification

Sr. No.	Component	L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Food Store	43.38	22.11	3.05	959.13	2925.35	25	1
2	Conference hall	30.15	17.52	3.05	528.08	1610.64	50	1
3	Rooms	35.77	17.77	3.05	635.63	1938.68	32	1
					2122.84	6474.67		

Sr. No.	Component	Wall Type	L	H	Area	Area of Doors	Area of Windows	Net Area	Shading Factor
1	Food Store	North (Outside wall)	22.11	3.05	67.44	-	29.77	37.67	1
		South (Outside wall))	22.11	3.05	67.44	-	-	67.44	1
		East (Outside wall)	43.38	3.05	132.31	3.15	47.63	81.53	1
		West (P wall)	43.38	3.05	132.31	-	-	132.31	1
2	Conference hall	North (Outside wall)	17.52	3.05	53.42	-	29.77	23.65	1
		South (P wall))	17.52	3.05	53.42	-	-	53.42	1
		East (P wall)	30.15	3.05	91.96	-	-	91.96	1
		West (Outside wall)	30.15	3.05	91.96	-	47.63	44.33	1
3	Rooms	North (P wall)	17.77	3.05	54.20	-	-	54.20	1
		South (Outside wall))	17.77	3.05	54.20	-	11.91	42.29	1
		East (Outside wall)	35.77	3.05	109.10	-	17.86	91.24	1
		West (Outside wall)	35.77	3.05	109.10	-	23.81	85.28	1

Table 5: Fourth floor Wall and Area Specification

Sr. No.	Component	L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Grand Hall	43.38	22.11	3.05	959.13	2925.35	25	1
2	Conference hall	30.15	17.52	3.05	528.08	1610.64	50	1
3	Rooms	35.77	17.77	3.05	635.63	1938.68	32	1
					2122.84			

Sr. No.	Components	Wall Type	L	H	Area	Area of Doors	Area of Windows	Net Area	Shading Factor
1	Grand Hall	North (Outside wall)	22.11	3.05	67.44	-	29.77	37.67	1
		South (Outside wall))	22.11	3.05	67.44	-	-	67.44	1
		East (Outside wall)	43.38	3.05	132.31	3.15	47.63	81.53	1
		West (P wall)	43.38	3.05	132.31	-	-	132.31	1
2	Conference hall	North (Outside wall)	17.52	3.05	53.42	-	23.81	29.61	1
		South (P wall))	17.52	3.05	53.42	-	-	53.42	1
		East (P wall)	30.15	3.05	91.96	-	-	91.96	1
		West (Outside wall)	30.15	3.05	91.96	-	17.86	74.10	1
3	Rooms	North (P wall)	17.77	3.05	54.20	-	-	54.20	1
		South (Outside wall))	17.77	3.05	54.20	-	11.91	42.29	1
		East (Outside wall)	35.77	3.05	109.10	-	17.86	91.24	1
		West (Outside wall)	35.77	3.05	109.10	-	23.81	85.28	1

Table 6: Fifth floor Wall and Area Specification

Sr. No.	Component	L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Silver Chamber	43.38	22.11	3.05	959.13	2925.35	25	1
2	Conference hall	30.15	17.52	3.05	528.08	1610.64	50	1
3	Rooms	35.77	17.77	3.05	635.63	1938.68	32	1

Sr. No.	Components	Wall Type	L	H	Area	Area of Doors	Area of Windows	Net Area	Shading Factor
1	Silver Chamber	North (Outside wall)	22.11	3.05	67.44	-	14.88	52.55	1
		South (Outside wall))	22.11	3.05	67.44	-	-	67.44	1
		East (Outside wall)	43.38	3.05	132.31	3.15	53.58	75.58	1
		West (P wall)	43.38	3.05	132.31	-	-	132.31	1
2	Conference hall	North (Outside wall)	17.52	3.05	53.42	-	23.81	29.61	1
		South (P wall))	17.52	3.05	53.42	-	-	53.42	1
		East (P wall)	30.15	3.05	91.96	-	-	91.96	1
		West (Outside wall)	30.15	3.05	91.96	-	35.72	56.24	1
3	Rooms	North (P wall)	17.77	3.05	54.20	-	-	54.20	1
		South (Outside wall))	17.77	3.05	54.20	-	28.06	26.14	1
		East (Outside wall)	35.77	3.05	109.10	-	8.34	100.75	1
		West (Outside wall)	35.77	3.05	109.10	-	17.86	91.24	1

Table 7: Sixth floor Wall and Area Specification

Sr. No.	Component	L (m)	W (m)	H (m)	Area	Volume	No of Users	ACH
1	Office	15.215	3.833	3.05	58.3191	177.873	5	1
3	Rooms	35.31	17.31	3.05	611.216	1864.21	32	1

Sr. No.	Components	Wall Type	L	H	Area	Area of Doors	Area of Windows	Net Area	Shading Factor
1	Office	North (Outside wall)	3.833	3.05	11.69065	-	-	11.6907	1
		South (Outside wall))	3.833	3.05	11.69065	-	-	11.6907	1
		East (Outside wall)	15.215	3.05	46.40575	-	17.8608	28.545	1
		West (P wall)	15.215	3.05	46.40575	6.3	-	40.1058	1
2	Rooms	North (P wall)	17.31	3.05	52.7955	-	-	52.7955	1
		South (Outside wall))	17.31	3.05	52.7955	-	11.9072	40.8883	1
		East (Ourtside wall)	35.31	3.05	107.6955	-	17.8608	89.8347	1
		West (Outside wall)	35.31	3.05	107.6955	-	23.8144	83.8811	1

APPENDICES – II

List of Publications

Sr. No	Name of Journal	Name of the Paper Published
1	Journal of Data Acquisition and Processing	BIM-based Energy Performance Modeling and Simulation of Hotel Building
2	Asian Journal of Civil Engineering	ODDTCN Energy Modeling: A Meta Heuristic-aided Energy Performance Designing and Consumption Forecasting in Existing Building Environment

Sr. No	Name of Conference	Name of the Paper Presented
1	4th International Conference on Multidisciplinary and Current Educational Research (ICMCER-2023)	Energy Modeling of a Hospitality Building - A Case Study
2	International Conference on Climate and Weather-Related Extremes	The Role of Building Energy and its Environmental Assessment
3	International Conference on Recent Advances in Engineering and Computer Applications-2023	ODDTCN Energy Modeling: A Meta Heuristic-aided Energy Performance Modeling and Consumption Forecasting in Existing Building Environment
4	Proceedings on Engineering Sciences ISSN: 2620-2832	Building Energy Performance Modeling and Simulation of Hotel Building

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BIM-BASED ENERGY PERFORMANCE MODELING AND SIMULATION OF HOTEL BUILDING

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Abstract

Building energy simulation using building information modeling (BIM) is proving to be an efficient technique in recent years for overcoming the challenging energy modeling process, reducing time, and advancing building energy modeling (BEM) and simulation into the digital design process. It facilitates the simulation of the energy performance of both new and existing buildings on a single platform. However, there is still a sizable discrepancy between the actual energy usage and the outcomes anticipated on longer time scales (monthly or annual basis) for a variety of reasons. We simulated the energy performance of a multi-story hotel to investigate the applicability and efficacy of this approach. Using the same building data, ASHRAE's CLTD/SCL/CLF method and Autodesk's Revit 2021 were used to anticipate the cooling load of the building. Revit 2021 was also used to model the building's actual annual energy use, which was then contrasted with the measured data. As far as the peak cooling load is concerned, the results demonstrate good agreement. However, compared to measured data, annual energy consumption prediction greatly deviates.

Keywords: Building information modeling (BIM), building energy modeling (BEM), Autodesk Revit, EnergyPlus,

1. Introduction

According to the International Energy Agency (IEA), the operation lifecycle phase of buildings accounts for one-third of global energy use [1]. It is anticipated to grow at an average annual rate of 1.0% until 2035 [2]. If the energy consumed in the building's construction phase is also included, this number grows to more than 50%. Over the years, large-scale exploitation of mechanical systems for active cooling of buildings and other anthropogenic activities has significantly impacted our fragile ecosystem, leading to serious environmental problems. The extreme heat that engulfed significant portions of India and Pakistan in April/May 2022 had numerous, cascading effects on human health and ecosystems, agriculture, water and energy supplies, and many other key sectors of the economy. It will take months to assess the health and economic ramifications and cascading impacts of the present heat wave, including the number of extra deaths, hospitalizations, lost wages, and reduced working hours [3]. Such catastrophic realities coupled with ever-increasing energy prices are leading to the creation of many regulatory mechanisms to reduce energy consumption and promote energy-efficient solutions for buildings.

These climatic occurrences show that the traditional mitigation measures - such as adopting low-carbon technologies, implementing regulatory policies, and limiting energy consumption - are not sufficient to meet the targets outlined in the Kyoto Protocol and Paris Agreement.

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RESEARCH

ODDTCN energy modeling: a meta-heuristic-aided energy performance designing and consumption forecasting in existing building environment

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Abstract

Nowadays the prediction of average energy consumption in the building has acquired a major role in energy conservation, management as well as planning. It is also significant in the case of optimizing the energy distribution plan and designing the model predictive controller for consumers. In general, hybrid and data-driven models are considered the most common techniques for energy prediction. But, in recent times, data-driven techniques have become the most crucial topic because it has the potential to discover statistical patterns without the knowledge of experts. By constantly enhancing the working performance of the prediction model, it is regarded as the key factor that assures the efficient operation of the energy model. But the accuracy is no longer for validating the overall performance of the model. Moreover, it is very essential to validate the model through multiple perspectives concerning the engineering applications. Based on the idea of model integration, this paper proposes a novel improved integration model (stacking model) that can be used to forecast building energy consumption in the existing building. In the initial stage, the data are aggregated from the experimented dataset. Then, the data undergoes data-cleaning techniques to attain the pre-processed data. Further, it is fed into the weighted feature extraction phase, where weights are optimized with the help of fitness-based spider monkey optimization (F-SMO). Then, the weighted features are subjected to the optimized dilated deep temporal convolution network (ODDTCN) techniques, in which the parameters are optimized with the aid of the same F-SMO algorithm. The implementation results are compared with the classical forecasting model to validate the effectiveness of the developed system.

Keywords Energy consumption forecasting · Energy performance modeling · Building environment · Fitness-based spider monkey optimization · Optimized dilated deep temporal convolution network · Weighted features

Introduction

In accordance with the building, it has been utilized to effectively depict the crucial net amount of total energy consumption all over the world (Nabavi et al., 2021). On considering the "World Energy Balance", nearly forty percent of the energy has been contributed to the global carbon dioxide emission as well as more than thirty percent of the energy has been utilized by the building sector globally (Valencia et al., 2016). In addition to that, carbon emissions and energy consumption have been regarded as attaining gradual growth in the forthcoming years (Azmat et al., 2016). For both optimization and validation of the building operation and design, the building energy performance model has been depicted as the most significant technique. The performance model has the potential to maintain the energy system of the building effectively (Buddhahai et al., 2020). Moreover, in the initial stage, the construction has acquired the energy per total energy consumption globally (Buddhahai et al., 2020). Additionally, the growth rate of building energy consumption has been considered as 3.7%. To design economic savings and immense energy, there is a requirement to maximize the building energy efficiency (Mohy-ud-din et al., 2021). Further, reliable cooling load determination outcomes have been regarded as the basis for optimized building designs as well as significant techniques for enhancing the efficiency

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