A Thesis

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Design of Energy Management System for Smart Home

by

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ॐ द्यौः शान्तिरन्तरिक्षँ शान्तिः,
पृथ्वी शान्तिरापः शान्तिरोषधयः शान्तिः ।
वनस्पतयः शान्तिर्विश्वे देवाः शान्तिर्ब्रह्म शान्तिः,
सर्वँ शान्तिः, शान्तिरेव शान्तिः, सा मा शान्तिरेधि ॥
ॐ शान्तिः शान्तिः शान्तिः ॥

शान्तिः कीजिये, प्रभु त्रिभुवन में, जल में, थल में और गगन में,
अन्तरिक्ष में, अग्नि पवन में, औषधि, वनस्पति, वन, उपवन में,
सकल विश्व में अवचेतन में!
शान्ति राष्ट्र-निर्माण सृजन, नगर, ग्राम और भवन में
जीवमात्र के तन, मन और जगत के हो कण कण में,
ॐ शान्तिः शान्तिः शान्तिः ॥

May peace radiate there in the whole sky as well as in the vast ethereal space everywhere.
May peace reign all over this earth, in water and in all herbs, trees and creepers.
May peace flow over the whole universe.
May peace be in the Supreme Being Brahman.
And may there always exist in all peace and peace alone.
Aum peace, peace and peace to us and all beings!

- Yajur Veda 36.17

Dedication

I Dedicate My Effort Towards the

Love of my Loving Parents Shri Ram

Kishor Verma and Smt. Daya Wati,

who saw their World in My Progress

CERTIFICATE

I hereby certify that the work which is being presented in the Thesis entitled, "***Design of Energy Management System for Smart Home***" in fulfillment of the requirement for the award of the Degree of ***Doctor of Philosophy*** submitted in the *Electrical & Instrumentation Engineering Department* of the **Thapar Institute of Engineering & Technology** is an authentic record of my own work carried out under the supervision of **Dr. Surya Prakash** and **Dr. Anuj Kumar** and refer other researcher's work, which are duly listed in the reference section.

The matter presented in this Thesis has not been submitted for the award of any other degree of this or any other University.

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This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

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Anurag Verma

ABSTRACT

In India, residential buildings account for nearly one-third of energy consumption related to Greenhouse Gas (GHG) emissions. The space heating, cooling, lighting, and Indoor Air Quality (IAQ) control systems significantly consume electricity in maintaining occupant's comfort. The residential sector's energy consumption has been increased steadily and occupied approximately 30-40% of overall energy consumption. At present, India's urban population is about 410 million, and by the year 2050, it is estimated to reach around 814 million. In the last few decades, India has improved its economy rapidly and is also cautious for high growth in the future. The research on energy consumption forecasting and management has highlighted the significance of residential building energy consumption forecast for enhanced decision-making regarding energy conservation plan. Nowadays, smart homes are introduced to save energy and provide comfort to the occupants. Smart homes are automated buildings that incorporate advanced automation systems to give the occupants advanced monitoring and control of their functions. The early design stage of a smart home requires an energy consumption prediction model to predict future energy consumption. On large-scale short-term, medium-term, and long-term energy consumption prediction models have been introduced so far, but one of the most significant drawbacks of the models that they have not include the daylight factor and relative humidity. Despite the importance of the efforts put forward, there is still some unexplored area in the residential level's long-term and precise energy consumption prediction model. Also, the energy consumption and comfort management are vital in designing the Energy Management System (EMS). Such type of researches would help to minimize energy consumption using the EMS.

This research aims to design a Smart Home Energy Management System (SHEMS) that manages the Heating, Ventilation, air conditioning (HVAC), and lighting system's energy consumption while meeting occupants' indoor comfort requirements. To achieve this goal, we need to analyze the future energy consumption in a smart home. Therefore, a long term precise, data-driven based energy consumption prediction model for a smart home is proposed. Firstly, a 2BHK single-story multi-zone residential building is modeled in TRNSYS16 building simulation software. Energy consumption for maintaining indoor comfort depends on environmental parameters such as temperature and relative humidity.

Hence, temperature and relative humidity are predicted by the year 2050 with the machine learning approach. The predicted temperature and relative humidity data have been fed as input to the TRNSYS16 for smart home energy consumption calculation. Considering the building structure's complicated design, user comfort parameters, including heating, cooling, ventilation, IAQ, and illumination level, the energy consumption prediction model has been developed up to the year 2050. The inclusion of the daylight factor predicts more accurately as compared to the conventional prediction model. Thus, the most accurate and precise model, with 95% coefficients bound, has been developed for energy consumption prediction. Further, this model can be integrated with various controlling techniques in energy conservation planning and management.

Secondly, the EMS design for a smart home also requires optimizing environmental parameters to provide comfort as per occupant's preferences. The energy consumption and occupant's comfort level often conflict with each other in indoor environmental conditions. To resolve the conflict, a multiobjective problem has been formulated, and solution methodology has been proposed. The proposed solution methodology considers occupants' adaptations while making decisions on fixed temperature, illumination level, and CO_2 value. The Crisscross Search Particle Swarm Optimization (CSPSO) with multiagent topology is incorporated to optimize the environmental parameters temperature, illumination level, CO_2 concentration with Fuzzy Logic Controllers (FLCs). The CSPSO is applied to the environmental parameters for an optimal solution corresponding to set temperature, illumination level, and CO_2 concentration.

Furthermore, Artificial Intelligence (AI) has been used to optimize environmental parameters like temperature, illumination, and CO_2 to maximize comfort and minimize energy consumption. To do so, a multivariable objective function has been formulated with set temperature, illumination and CO_2 constraints. A trust-region reflective algorithm based on AI has been used to solve it. Trust region reflective algorithm successfully optimized the environmental parameters within the set limits. The energy consumption is minimized while maintaining occupants indoor comfort.

Next, the performance evaluation has been done with the Genetic Algorithm (GA), Bat, NNA, PSO, and ABC optimization techniques are compared for thermal comfort. Bat optimization technique was superior to other utilized optimization techniques (GA, PSO, NNA, ABC). Optimization algorithms such as GA, Bat, Neural Network Algorithm (NNA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and machine

learning approach with FLCs are utilized to reduce the energy consumption and maximize the thermal comfort, visual comfort, and IAQ comfort.

Keywords: Energy and Buildings, Building Energy Efficiency, Occupants Comfort, Optimization, Smart Home, Building Management System.

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GLOSSARY OF ACRONYMS

Acronyms	Description
ABC	Artificial Bee Colony
ACH	Air Change per Hour
AI	Artificial Intelligence
ANFIS	Artificial Neural Fuzzy Inference Systems
ANN	Artificial Neural Network
AQI	Air Quality Index
AR	Auto Regressive
ASHRAE	American Society of Heating, Refrigerating and Air Conditioning Engineers
BEE	Bureau of Energy Efficiency
BEMS	Building Energy Management System
BHK	Bathroom Hall Kitchen
BMS	Building Management System
CNN	Convolution Neural Network
CO_2	Carbon dioxide
CSO	Crisscross Search Optimization
CSPSO	Crisscross Search Particle Swarm Optimization
DCPV	Demand Controlled Passive Ventilation
DF	Daylight Factor
DL	Deep Learning
DM	Data Mining
DNN	Deep Neural Network
EBO	Event Based Optimization
ECBC	Energy Conservation Building Code
EIA	Environmental Impact Assessment
EMS	Energy Management System
EPA	Energy Policy Act
FIS	Fuzzy Inference System

FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
GHG	Green House Gas
GNA	Gauss Newton Algorithm
GRIHA	Green Rating for Integrated Habitat Assessment
GUI	Graphical User Interface
HVAC	Heating Ventilation Air Conditioner
IAQ	Indoor Air Quality
ICT	Information and Communication Technologies
IEO	International Energy Outlook
IEQ	Indoor Environmental Quality
IFC	Industry Foundation Class
IoT	Internet of Things
IPSO	Improved Particle Swarm Optimization
ISO	International Organization for Standardization
IT	Information Technology
KKT	Karush Kuhn Tucker
kNN	k-Nearest Neighbour
kWhr	Kilowatt Hour
LED	Light Emitting Diode
LEED	Leadership in Energy and Environmental Design
LIG	Low Income Group
LMBP	Levenberg Marquardt Back Propagation
MATLAB	Matrix Laboratory
ML	Machine Learning
MLR	Multiple Linear Regression
NFC	Near Field Communication
NN	Neural Network
NNA	Neural Network Algorithm
OECD	Organization for Economic Cooperation and Development
OWA	Ordered Weighted Averaging
PC	Personal Computer

PID	Proportional Integrated Derivatives
PMV	Predicted Mean Vote
PSO	Particle Swarm Optimization
RFID	Radio Frequency Identification
RMSE	Root Mean Square Error
SHEMS	Smart Home Energy Management System
S-PSO	Sliced Particle Swarm Optimization
SVM	Support Vector Machine
TERI	The Energy Resources and Institute
TMY	Typical Meteorological Year
TRNSYS	Transient Systems Simulation
VOC	Volatile Organic Compound
W-PSO	Weighted Particle Swarm Optimization

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

As we know, throughout the world and even in countries like India, there is a lot of focus on building smart cities. Of course, the scope of smart cities in each of the different countries is different, and the scope again depends on the priority areas of each of these countries and their government. In India, since the last few years, a couple of cities have been identified, and phase-wise, these cities have been given funds to build or transform them into smart cities. When we talked about smart cities, what are they and the regular infrastructure in any city, such as the urban infrastructure consisting of residential buildings, office buildings, hospitals, schools, transportation, police, etc.

Let us think about such smart means; what smart means that it is in terms of the services given to these cities' respective stakeholders so citizens can do things in a better manner in an improved way than usual, and how is that made possible. It is possible with the help of Information and Communication Technologies (ICT), which also includes embedded electronics different other advanced technologies in electrical and electronics engineering and so on. So the computer and electronics put together can make these cities smart. Let us take an example at the outset to explain smart cities through Fig. 1.1. The smart city has some necessary components like smart home/residential building, smart hospital, smart waste management, smart traffic control, smart banking system, smart transport system, smart police control, smart schools, and smart railway system. We have to transform all these different components of any city to be smart, for which the technology we have to take help of following given below:

- Sensors
- Sensor Network
- Actuators
- Communication Technologies (RFID, NFC, Z-Wave, etc.

Therefore, all these technologies will have to be used to make this transformation. Thus, this work chooses a Smart Home Energy Management System (SHEMS) design concept to contribute to smart city transformation.

Fig. 1.1: Smart city essential components and research areas.

When we talk about humans; Humans have the skeleton, the skin, different types of organs, brain, nerves, sensory organs, cognition, and so on. Similarly, a smart city has also acted as a human system, explained through the analogy and given in Fig. 1.2. As depicted in Fig. 1.2, a human has a skeleton, skin, and various organs; likewise, smart cities or cities have buildings, industries, people, transportation, logistics, hospitals, police, banks, schools, etc. On top of that, if there is a human with a skeleton, skin, organs, and no cognition, there is no life in that human. The same analogy can be drawn, and analogously, we can say that in a smart city, the absence of embedded intelligence communication networks, sensors, tags, and software are embedded in these different components, and the infrastructure of the city will don't have any life. Therefore, ICT has to be embedded to provide life to existing cities with buildings, industries, transport, police, banks, etc. Embedded ICT includes ubiquitously embedded intelligence, digital communication networks, sensors, actuators, tags, different software smartly doing other things making these various devices act intelligently.

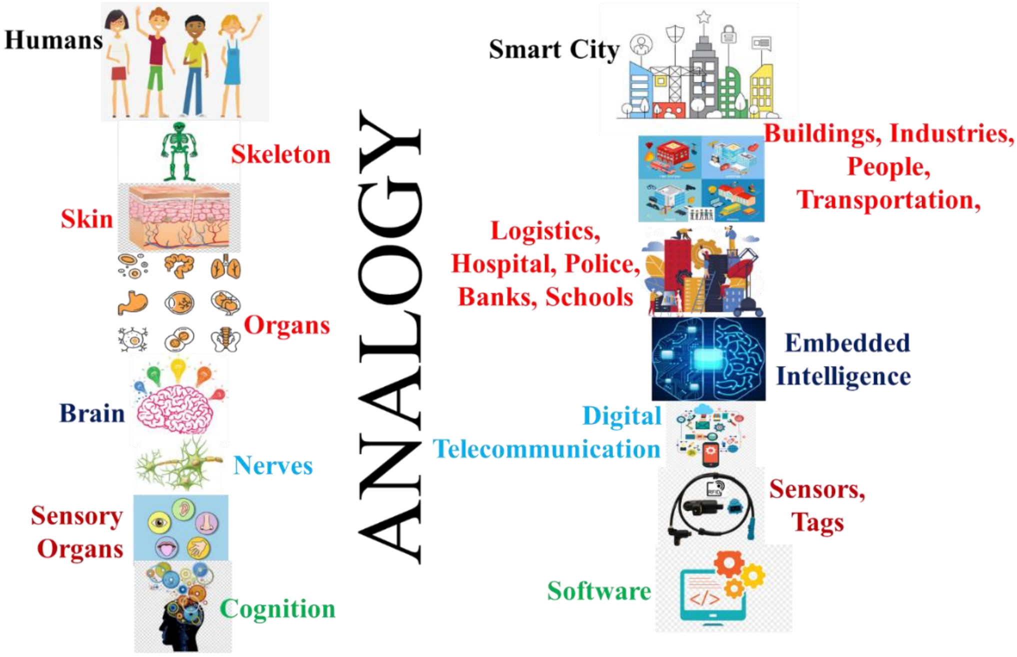

Fig. 1.2: Analogy between the humans and the smart city.

1.1.1 Application-Based Research Areas

Smart cities incorporate technological strategies to enhance public services and people's living experience. Municipal governments use the Internet of Things (IoT) sensors, communications technology to collect relevant data, such as traffic congestion, energy use, and environmental impact. These data could also be used by engineering solutions to enhance community services, including infrastructure, transport, and public services. So, these are some of the application focus areas given as **(Pellicer et al., 2013)**:

- Smart Economy- Competitiveness
- Smart Governance- Citizen participation
- Smart People- Social and human capital
- Smart Mobility- Transport and ICT
- Smart Environment- Natural Resources
- Smart Living- Quality of life

These are some of the application focus areas that we have to consider for a smart economy. So, because of the ever-increasing competitiveness, we need to improve our infrastructure, the economy to make it elegant. We also need to improve citizen participation in any good governance with ICT tools, social and human capital. We need to create social and human capital too smarter by giving them different technologies, agencies (ICT tools), and intelligent mobility to improve transportation.

1.1.2 Trending Focus Research Areas (Alhashmi et al., 2019)

- Smart homes (smart health monitoring, smart conservation of resources (electricity, fuel, water), smart security, and safety).
- Smart Parking Lots
- Smart energy (smart metering systems, smart energy allocation, and distributed system, incorporation of traditional and renewable energy sources in the same grid).
- Energy and buildings (highly developed sustainable buildings and smart grids, enhancing the energy efficiency of sustainable housing by optimization).

The above-mentioned trending research areas focused on smart homes management in terms of elderly people health monitoring, energy conservation of resources, and security features. Also, building smart parking lots will protect theft. The smart energy is achieved by developing the smart metering systems, smart energy allocation and distributed system, various incorporation of traditional and renewable energy sources in the grid.

1.1.3 Technological Research Areas

- Data collection (mobile devices, sensors, tags, architecture)
- Data transmission (radios, networking, topologies)
- Data storage (local storage, data warehouse)
- Data processing (data cleaning, analytics, prediction, or forecasting)

These are the technological research areas in data collection, data transmission to the server and end-user, data storage with local and warehouse and data processing techniques in data mining.

1.1.4 Mathematical Methods of Data Fusion

- Probability-Based (Bayesian analysis, statistics, recursive methods)
- Artificial Intelligence (AI) Based (Artificial Neural Network (ANN), machine learning algorithms, Convolution Neural Network (CNN), Deep Neural Network (DNN)).
- Theory of Evidence-Based (belief functions, transferable belief models)

These are the different mathematical methods that are to be used to come up with these bits of intelligence from the various data we know that are used secured from the IoT devices **(Battisti et al., 2020)**. IoT devices are usually restricted devices, creating correlations between hardware, software and protocols used **(Kruger et al., 2015)**.

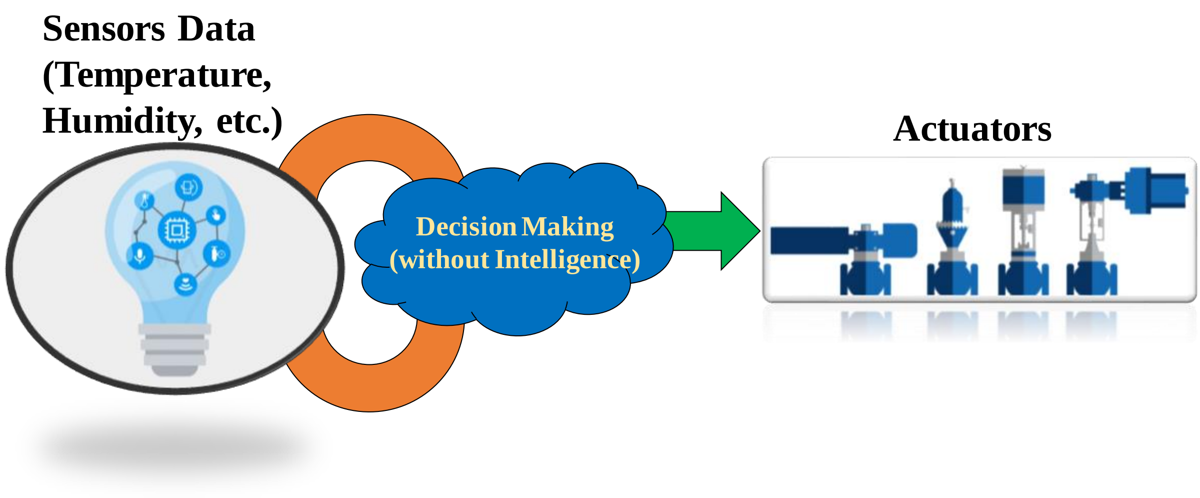

Fig. 1.3 (a): Decision-making gap without intelligence.

AI comes as a big helper in enabling the IoT devices by maintaining precise decision-making. Consider this particular Fig. 1.3 (a) **(Furqan et al., 2017)**; we have sensors and the sensor data which has to be transmitted over the communication medium. Based on that, some actuation is going to be made possible.

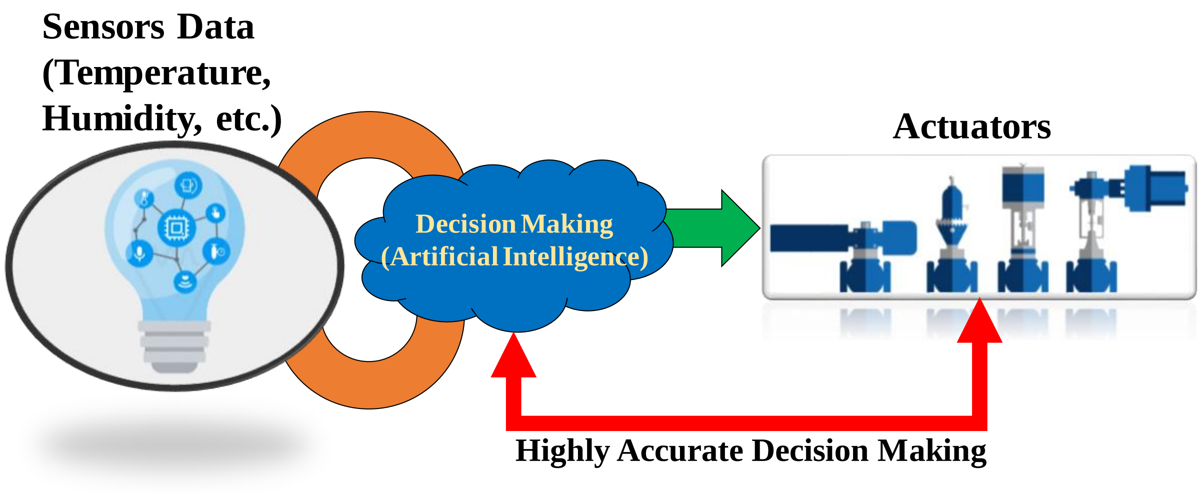

Fig. 1.3 (b): Highly accurate decision making with artificial intelligence.

But how that actuation is going to be made possible is it from one or two of these sensors based on these sensor values which will actuate. We can also do something better for positive decision-making by adding intelligence between these different sensors, and actuators can be seen in Fig. 1.3 (b) **(Furqan et al., 2017)**. It is all made possible with the help of AI tools, techniques, algorithms, etc. The same implementation has been also shown in Chapter 3 and Chapter 4.

1.2 HISTORICAL DEVELOPMENTS IN SMART HOME

The very first smart homes were theories, not real structures. Science fiction has been discussing the concept of home automation for decades. Prolific authors like Ray Bradbury dreamed of a world in which homes were highly interactive and automated. In Bradbury's strongly-worded science fiction, "*There Will Come Soft Rains*," he defines an autonomous home that continues to work even after humans have died. It's all well and scary before you realize the real advantages of a smart home, and then the idea will become more relaxing

Table 1.1: The history of smart homes development.

Timeline	Invention	Summary	Reference
1901-1920	Home Appliance Invention	These milestones began with the first vacuum cleaner operated by the engine in 1901. A more realistic vacuum powered by electricity was invented in 1907. For two decades, refrigerators, as well as clothes dryers, washing machines, irons, toasters, and more, might have been developed.	**Cowan, 1976**
1966-1967	Echo IV: The Kitchen Computer	ECHO IV was the first smart computer commercially marketed. This innovative system could compile shopping lists and monitor the home's temperature to put the devices on and off.	**Spicer, 1994**
1975	Communication Protocol	For electrical appliances, the first communication protocol X10 was developed in 1975 to control devices.	**Cook and Das, 2004**
1980	PC Interface	Since 1980, the awareness of home-operated appliances through various interfaces on a personal computer has been seen as the core of a smart home.	**Karmali et al., 2000**
1991-1998	Gerontechnology	Promoting human health and well-being using assistive technology.	**Sadasivan and Osman, 2006**
1998-2000	Smart Homes	Home automation started to increase in popularity in the early 2000s. Since these, various technologies have begun to evolve. Smart homes immediately became a more affordable alternative and thus a viable future technology. Home	**Hendricks, 2014**

		technologies, home networking, and other devices start to emerge on supermarket shelves.	
2000-Present	Wire/Wireless Communication Protocol, ICT Tools	Latest developments in smart home feature remote mobile control, automatic lighting, controlled heating system modification, scheduling devices, mobile/email/text alert, and wireless video surveillance. Several communication protocols (LoRa, IEEE 802.11, CEBus, wireless LAN, Bluetooth, RFID) were invented in the last ten years in the 20th century.	**Yamazaki, 2006; Hendricks, 2014**

than chilling, while the concept of home automation has been around for some time, real intelligent homes have only existed for a short time. This timeline focuses on hardware; that is, actual developments leading to smart homes that we know today and can expect from the near future. The history in developing a smart home is tabulated in Table 1.1.

1.3 SMART HOME AND RESEARCH AREAS

Smart homes are automated buildings with installed detection and control devices, such as air conditioning, heating, ventilation, lighting, hardware, and security systems. These are essential elements of the IoT. Smart homes deliver users adequately by communicating with various electronic gadgets based on IoT. In the ideal version of a wired future, all widgets in smart homes seamlessly communicate. IoT-based smart home technology has changed the human life and their efforts by providing connectivity to everyone regardless of time and place **(Xiao et al., 2020)**. Automated home systems have become increasingly sophisticated in recent years **(Madakam and Ramaswamy, 2015)**. These types of system provide infrastructure and methods to exchange all kinds of appliance information and services. Smart Home uses Information Technology (IT), management systems, display technology, and communications technology that will be linked together through a network of different areas to meet the whole system's automated needs and provide more efficient control and management **(Fang et al., 2011)**. A modified smart home with intelligent features is shown in Fig. 1.4.

Some key features of Smart Home are as follows **(Chan et al., 2009)**:

- Efficient utilization of electricity and promote the family's knowledge of energy-saving and environmental protection.

- A smart home can maximize the comfort, security, accessibility, and interactivity of home life and improve people's lifestyle.
- A smart home can support remote payments.
- A smart home understands real-time energy management and safety service with a water meter, an electrical energy meter, and a gas meter offering more comfortable conditions for a high-quality service.
- Smart homes support the business of "triple networks" and the perfect smart service.

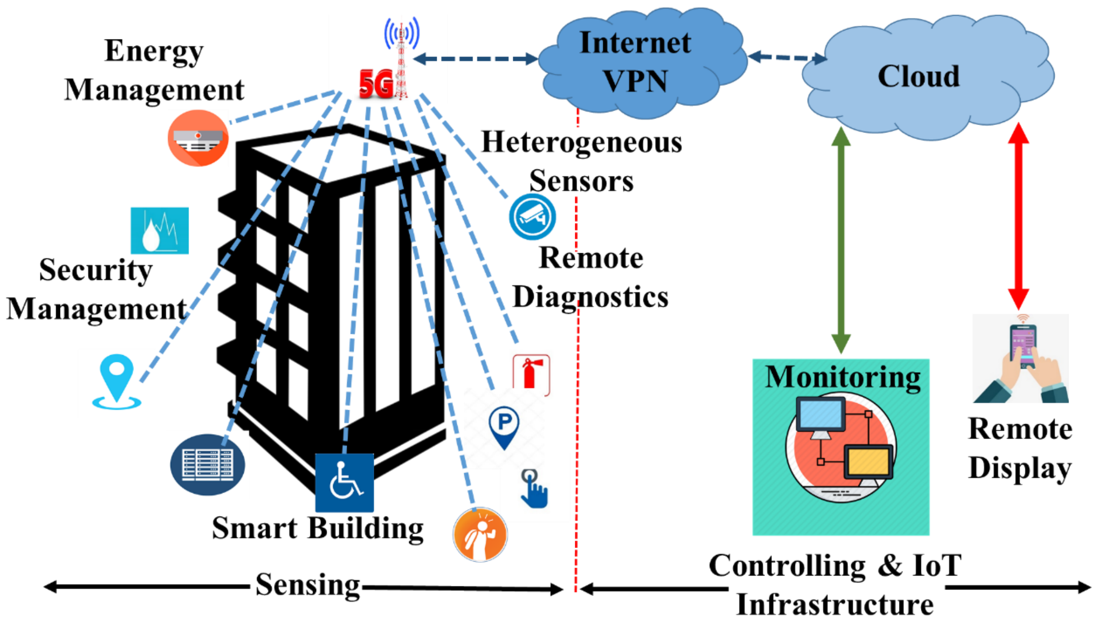

Fig. 1.4: Modified smart home with intelligent features.

Security and efficiency are the key factors behind the rise in the use of smart home technology. All the devices are connected to each other in the smart home, accessed and controlled by a single central agent or central point's such as smartphones, tablets, or laptops.

1.4 ENERGY CONSUMPTION AND COMFORT IN SMART HOMES

Although Building Management System (BMS) control technology has been nearly consistent and fundamental over the past few years, our knowledge of how people perceive environmental factors inside a building has overgrown. Following pioneer work by scientists such as Fanger **(Fanger, 1973)**, researchers understand how weather variables such as temperature, humidity, airflow, lighting conditions, and even colour can influence the comfort level and individual experience. Notably, our understanding of comfort is not fixed. For example, on a very hot day outside, people might find a temperature of 25 ^{0}C feels very comfortable, while on a cooler day, it would also be slightly warm for so many. With the latest research and "human comfort influences" models, it is now comparatively easy to predict how most people react to a specific building environment **(Platt et al., 2013)**. EIA's International Energy Outlook 2017 projects that India will see the highest increase in building energy demand by 2040 across world regions. In the reference scenario of IEO2017, the energy consumption delivered to residential and commercial buildings in India is projected to rise by an average of 2.7% each year between 2015 and 2040, more than double the worldwide mean rise **(IEO, 2017)**. This growth is attributed to the increasing use of electricity and the rising use of electrical appliances to maintain comfort in the living space. The annual average change in residential buildings' energy consumption is shown in Fig. 1.5 **(IEO, 2017)**.

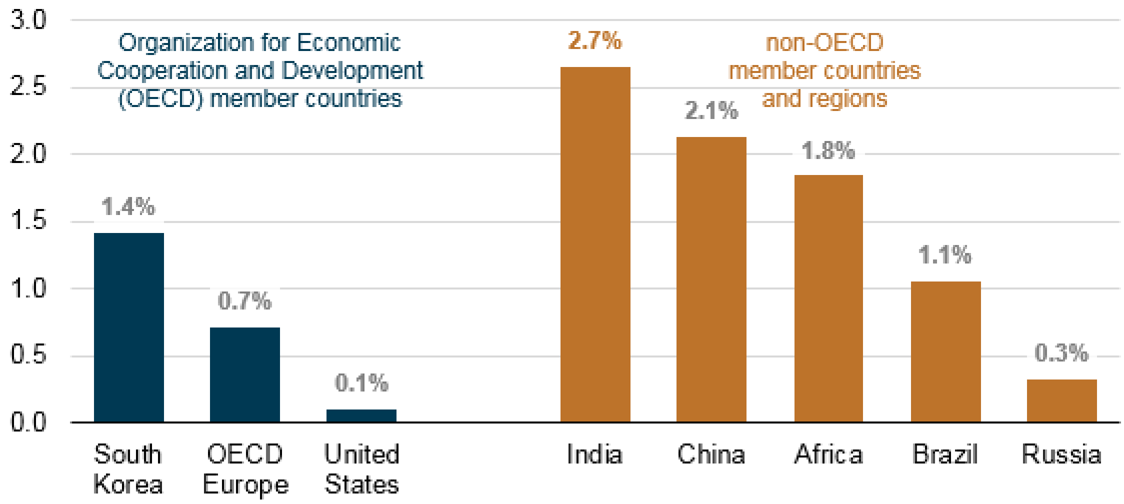

Fig. 1.5: Annual average change in energy consumption of buildings, 2015-2040.

1.5 BUILDING MANAGEMENT SYSTEM

BMS is one of the smart home's essential features, and intelligent building and IoT based BMS is the next step for improving energy efficiency. The BMS is the computer-based system that helps manage, monitor, and control energy consumption in a building. It can also gather information from the building to control the HVAC, artificial lighting, natural daylighting operation, and utilities connected with safety devices, fire detection, and protection. To make the building more efficient, BMS and IoT together play an important role in smart buildings. Researchers are taking advantage of the IoT and its bidirectional communication links to reduce energy consumption. On this concern, an author proposed a new BEMS capable of optimizing energy consumption **(Kane, 2018)**. In this BEMS, a novel control mechanism based on adaptive hybrid control techniques over the building's energy consumption is developed by keeping occupants comfortable and their actions in mind. Cyber-physical systems and real-time occupant behaviour are embedded as per the need of environmental anxieties. The IAQ and ventilation in the smart building is a prime component and affect human health. Therefore, IAQ's real-time monitoring is required in the BMS set, which examines significant gases like CO_2, SO_x, NO_x, (x=1, 2, 3, ….), Volatile Organic Compound (VOC), and formaldehyde. More recently, the research identified this problem and developed various radio frequency-based sensing systems for real-time monitoring of IAQ in BMS. Related to this, an author proposed a unique indoor environment monitoring system using smart sensors that communicate bi-directionally between the base station and smart sensor tag **(Yu et al., 2018)**. **Javed et al. (2018)** explained that energy-saving and making environment quality better as the primary goal of a BMS. That's why researchers in the smart building field were optimizing HVAC & lighting energy usage **(Agarwal et al., 2010; Tushar et al., 2018)**. An author proposed a real-time control algorithm of the heating and cooling system. The proposed model is based on the Lyapunov optimization technique and minimizes energy consumption in a multi-zone commercial building **(Depatla et al., 2015)**.

Occupancy estimation and space utilization are the basic requirements for optimizing HVAC and lighting systems in a smart building. Therefore, an author demonstrated a test system that extracts high-level building occupancy using a machine learning technique and low-cost IoT sensors **(Kadri et al., 2017)**. Another author designed and implemented the low-cost occupancy detection system using battery-operated wireless sensor nodes **(Howard et al., 2017)**. Using this low-cost occupancy system, HVAC energy consumption is reduced from 10% - 15%. Occupancy can also be estimated by Wi-fi power measurements **(Melfi et al., 2011; Yang et al., 2018)** that are continuously transmitted from Wi-Fi-enabled smart devices through ICT data streams **(Labeodan et al., 2015)** and the measurement of occupancy using existing network infrastructure **(Ding et al., 2016)**. In a real-time environment, an IoT-based occupancy sensing platform is developed and tested with 96.8% and 90.6% in occupancy detection and recognition **(Kim and Lee, 2015)**.

As we know, commercial office buildings require a large floor area and utilize large amounts of energy to satisfy occupant comfort needs. Therefore, few measurement techniques such as CO_2 based detection systems, PIR detection system, ultrasonic detection systems, image detection systems, sound detection systems, computer activity-based detection systems, and sensor fusion is explained in **(Möller, 2014)**. Experimental validation of the fine-grained occupancy information is validated for demand-driven control measures in buildings. It has a demerit that this system can't measure the standing position of occupants. A few recently established smart building research work in the area of BMS from different laboratories has been compared and presented in Table 1.2. These different research laboratories presented in Table 1.2 work in modeling, efficiency, energy management, comfort management, data interoperability, and construction activities.

Table 1.2: Laboratories involved in the area of smart building research.

Research Lab	Research work	Web link
SIEMENS, USA.	HVAC field devices and optimization systems are designed.	ww.usa.siemens.com
Lawrence Berkley National Laboratory, Berkley, US.	Research and development improve health, comfort, building occupant behaviour, and energy efficiency of residential buildings' indoor environment.	eta.lbl.gov
Center for the development & application of IoT technologies, Atlanta, GA.	Achieving data interoperability between building systems and the IoT.	cdait.gatech.edu
Centre for Intelligent and Network systems (CFINS), Beijing, China.	Modeling and Control in Energy-efficient Buildings	cfins.au.tsinghua.edu.cn
China Academy of Building Research (CABR), Beijing, China.	Building design and construction activities.	cabr.com.cn
Council of Scientific& Industrial Research-Central building research Institute (CSIR-CBRI), Roorkee-India	Research in improving the efficiency of buildings.	cbri.res.in
Smart buildings and IoT research lab, Lincoln, Nebraska	The focus of smart Buildings and IoT research lab is to explore emerging technologies, methods, and algorithms to improve people's comfort and optimize energy use in buildings.	engineering.unl.edu
Digital building lab, Atlanta, GA	Smart building, infrastructure, and environments.	dbl.gatech.edu
Smart building innovation laboratory, West Lafayette	Building information modeling, Internet of energy, development of algorithms, adaptable environments for occupant comfort.	polytechnic.purdue.edu

1.6 GAPS IN THE EARLIER RESEARCH

Numbers of researchers have carried out several theoretical and practical experiments on the energy management system in homes, buildings, and cities. In recent years' massive prediction models are developed reported by **(Zhao et al., 2012; Fumo, 2014; Amasyali and Gohary, 2018)**. Some authors have implemented the energy management system using network controlled approach & developed an intelligent controller **(Han et al., 2010; Singh et al., 2016; Pilloni et al., 2016; Yao et al., 2017)**. Few authors developed real-time energy management for micro-grid, smart grid **(Chen et al., 2012; Qian et al., 2013; Wang et al., 2013)** using artificial intelligence methodology. The current trends in literature review on EMS in smart homes and smart buildings lack in many aspects. Some of them are listed below:

- An accurate and long-term energy consumption prediction model is desired based on design information during residential buildings' design at an early stage. Still, several literature surveys lack a precise and long-term prediction model. Lighting load with natural daylighting has not yet been considered for the prediction model of energy consumption.
- As many researchers developed the energy management system for smart homes and smart buildings based on temperature data, illumination & air quality but relative humidity data and daylighting factor has not been included in HVAC operations in the prediction model.
- HVAC and lighting are ordinary household operations in homes and buildings but consume a large amount of energy. An optimized model needs to be developed in context with the user's comfort to minimize energy consumption and maximize comfort.
- Although many metaheuristics optimization algorithms and control approaches have been proposed to optimize environment parameters. However, machine learning-based optimization has not yet been explored in energy and comfort management.

Based on the above problem definitions, this research aims to develop a long-term energy consumption model based on an environmental parameter (temperature and relative humidity) and an automated energy management system for a smart home.

1.7 THESIS CONTRIBUTION AND OBJECTIVES

The research work presented in the thesis examines the energy consumption in residential building is directly linked to multiple variables, including the thermo-physical properties of building components, the technical details of their construction, the characteristics of the climate zone, the quality of the installed HVAC system, and the actions and activities of the occupants towards energy usage. Therefore, an accurate and long-term energy consumption prediction model is desired based on design information during residential buildings' design stage. A long-term and precise data-driven based energy consumption prediction model for a residential building up to 2050 is proposed. It helps in pre-planning as well as in energy management and CO_2 reduction. Energy consumption and human comfort always conflict with each other. Predictive energy consumption model can be built with the help of metaheuristic algorithms and machine learning-based optimization for minimum energy consumption and comfort management. A multiagent topology-based energy management system using optimization is presented to solve the conflict between energy consumption and comfort. This system maximizes occupant's comfort and minimizes energy consumption. Performance evaluation of various optimization models is also presented, which efficiently reduces energy with maximum comfort. Overall, this research aims to explore the design of an efficient EMS for indoor comfort while consuming minimum energy.

1.7.1 Thesis Objectives

1. To develop a prediction model for user comfort in energy management system.
2. To develop an optimized model for reducing the energy consumption for smart home.
3. To carry out the performance evaluation of developed optimization model for reducing the energy consumption.

1.8 STRUCTURE OF THE THESIS

The present thesis focuses on energy management design to improve user comfort at minimum energy consumption in light of the above introduction and energy and comfort management in the smart home. In the future, this work will attract researchers and engineers to make better energy management and conservation plan while meeting occupant's comfort conditions. The thesis has been organized into six chapters. The thesis discussed the prediction technique in the forecasting of residential energy consumption with prominent results. For minimum energy consumption, various optimization models are considered to solve the conflict between comfort and energy consumption. The literature survey related to the work has been included in each chapter. The main thesis contributions have been covered in the following presented chapters.

Chapter 1

In this chapter, the requirements of the smart home are discussed in detail. The research areas and the future of smart home with minimizing energy also discussed. Furthermore, it also discussed the trending methodologies of data fusion and smart city development with AI.

Chapter 2

In this chapter, an energy consumption data-driven prediction model is developed with 95% coefficient bounds using the ANN and TRNSYS16 software. This ANN model is trained with deep learning by using the Levenberg-Marquardt backpropagation algorithm. A 2BHK single-story multi-zone residential building having six zones (two bedrooms, one living room, one kitchen, and two toilets) has been modeled in TRNSYS to estimate the energy consumption based on predicted temperature and humidity. First, the data mining technique is used to discover and summarize the historical weather data for temperature and relative humidity prediction. Secondly, the cooling and heating energy consumption has been estimated based on predicted relative humidity and temperature in TRNSYS16. In contrast, the energy consumption of ventilation and lighting system is calculated mathematically based on SP-41 standard.

Chapter 3

In chapter 3, three parameters temperature, illumination level, CO_2 have been taken for users comfort with minimal energy consumption. Firstly, the CSPSO has been undertaken to search for the optimum value of environmental parameters respective to user-set preferences. In the heuristic approach, the improved particle swarm optimization approach updates an initial solution and then updates the best local solutions using horizontal and vertical crossover operators. The CSPSO technique search uses horizontal and vertical crossover operators to explore the search space in all dimensions and reduce the stagnation problem. CSPSO algorithm inputs are data from temperature, illumination, CO_2 sensors, and user-defined parameters, while optimization algorithm outputs are optimized parameters. Such optimized parameters will become the input to the fuzzy controllers that adjust various actuators' status according to the users' comfort. By utilizing the CSPSO technique, 22.74% energy of 625.372 kWhr energy saved during a day, and the comfort level has increased from 0.51692 to 0.75685.

Chapter 4

This chapter proposes AI-based building management and information system with multiagent topology for the energy-efficient building. The multiagent topology building management and information system are based on minimizing energy consumption and maximizing comfort by reducing the error between the environment's actual parameters and the desired environmental parameters. The constrained non-linear optimization algorithm is applied in the first optimization. Secondly, the optimization using artificial intelligence incorporating deep learning concept training and validation to obtain a set of optimized solutions. These solutions comprise values of temperature, illumination level, and concentration of CO_2 for maximum comfort level in terms of thermal, visual, and air quality and minimum energy consumption at the same time. The developed system is energy efficient and maintains a high comfort level for occupants.

Chapter 5

In chapter 5, the performance evaluation of the different model has been presented. In the performance evaluation, thermal comfort has been undertaken to evaluate the performance of the optimization models. The environmental temperature parameter is optimized using optimization techniques such as Genetic Algorithm (GA), Bat, Neural Network Algorithm (NNA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). The optimization's main objective was to reduce the gap/error between the temperature specified by the user and the environmental temperature. Afterwards, the discrepancy between optimized temperature and actual temperature is fed to the designed ML-based controller. The experimental results show that the designed system significantly improves energy efficiency and occupant comfort for energy-efficient buildings. The Bat model has demonstrated effectiveness in achieving a high comfort index with minimum power consumption compared to other considered models.

Chapter 6

In chapter 6, the major highlights of the contributions towards the design of the energy management system for a smart home are presented. Moreover, this chapter also highlights future research direction in present modern energy consumption and comfort scenario in residential buildings.

CHAPTER 2

BUILDING ENERGY CONSUMPTION PREDICTION MODEL

2.1 INTRODUCTION

In the last few decades, India has improved its economy rapidly and is also cautious for high growth in the future. Rapid economic development, urbanization, and increasing population have also increased the buildings' energy consumption rate **(IEO, 2019)**. At present, India's urban population is approximately 410 million, and by the year 2050, it is estimated to reach approximately 814 million **(GRIHA, 2018)**. Energy efficiency in buildings requires action beyond the scope of investment in new buildings, refurbishment, and equipment **(Lucon et al., 2014)**. Energy efficiency has become a prerequisite for building design due to increased energy consumption, resulting in Greenhouse Gas (GHG) emissions and energy costs **(Borah et al., 2015)**. The energy efficiency initiatives make it possible to reduce the building's energy demand **(Belussi et al., 2019)**. Reducing energy demand is a challenge that requires developing and developed countries to agree on more massive energy consumption and saving goals **(Maciel and Carvlaho, 2019)**.

In the coming decades, the urban sector will play an essential role in maintaining the Indian economy's structural change and higher economic development **(ECBC, 2017)**. If residential building increases, energy consumption will also increase. It is estimated that buildings account for about 40% of primary energy and 36% of GHG **(Agostino and Mazzarella, 2019; Hossain, 2019; Diaz-Acevedo et al., 2019)**. In the building's design process, the construction sector has several ways to make environmentally sustainable selections. For example, the construction sector can use recycled or renewable building materials that emit less carbon dioxide when they are constructed. Building designers must also consider the sustainability of a building or structure and the long-term waste generation and energy use requirements. Three primary sources of waste are from the municipal, industrial, and construction sectors. Wastes such as demolition waste, ash fly, agricultural waste can be easily used in the building industry. The overview presented here is just a few of the wastes that can be used for infrastructure in the building sector, thus saving considerable natural resources and protecting the atmosphere by mitigating GHG emissions. A substantial number of small GHG pollutant sources in the residential building sector was to follow energy-and climate-conscious activities, and overall emissions could be significantly reduced.

On the other hand, the construction sector can also deliver long term significant and cost-effective GHG emission reduction in existing building stock by retrofitting. Retrofits cover everything from prosaic to improved ventilation. Thus, more insulation to futuristic devices makes ice at night when energy is inexpensive and uses it to cool a building around the day. A few different strategic options that the construction sector can adopt to increase primary energy use efficiency and reduce existing buildings' GHG emissions. Increase in performance of thermal protection (insulation), an option of energy carrier or alter in heating and cooling system, implementation of a heat recovery ventilation system, making changes in the electrical system for more productive use of electricity (lighting, cooling, and home appliances), building and construction materials, installation of monitor and control of construction processes during the retrofit, installation of solar thermal and photovoltaic panels. Retrofitting provides a feasible alternative to minimize GHG emissions, delivering associated costs, comfort, and economic benefits. According to the US Department of Energy, the quality of societal energy is substantially higher than 20 years earlier **(IEO, 2019)**. Around the same time, though, these advances have been swamped by the impact of economic development, emerging technology, more energy needs, and more people, with increased energy consumption and carbon emissions gradually rising since the 1990s, even more effectively.

The Government of India is fully operational in energy conservation mode and can also make strict policies and regulations regarding energy conservation in the future. To achieve this goal, the change in building energy efficiency is ruthless to near-zero energy buildings **(ECBC, 2017)**. Sustainable energy is one of the most promising ways to solve energy demand problems in the residential sector for many users in India. Environmental and economic benefits from sustainable energy in residential buildings include generating energy that produces no GHG emissions (solar and wind installations in homes) and certain air pollution forms. The expansion of sustainable energy sources in the residential sector reduces dependence on imported fuel and generates economic growth and employment in the manufacturing and production sectors. A proper energy reduction plan can help efficiently use sustainable energy. About 12% of a typical residential utility bill accounts for maintaining visual comfort in residential buildings **(Department of Energy, 2015)**. The user should use natural daylighting to maintain visual comfort during the daytime, reducing the lighting load and saving energy. For night visual comfort, LEDs are to be used as suggested by the Energy Conservation Building Code (ECBC).

The lights should be turned off when they are not in use. If the residential building has single-pane windows, consider replacing them with more energy-efficient windows or adding solar shades or tinting film. The user dress for particular weather also matters in saving energy. Therefore, warm clothes in the winter should be wear and very light clothing in the summer to stay comfortable without using heating and cooling systems inside the building. The government of India should mandate the Green Building Ranking System (LEED). This rating focused on sustainability, water use, electricity, infrastructure, indoor environmental quality, and innovation. It will be the best systematic plan for all commercial, residential, industrial buildings to accept or adopt.

Considering the government's initial aspects, if we make a pre-plan of energy consumption in residential buildings, then the government will also get a lot of help in energy conservation towards sustainable development. For the pre-planning of energy accord, it is necessary to know the building's energy consumption profile, studied in this chapter. According to India's national building code, the building's energy consumption has been studied up to the year 2050; the average lifespan is 50 to 70 years. Therefore, the building built 5-10 years ago will remain until 2050, and its energy conservation planning can be done through this study. These are the main reasons for which a long-term energy consumption prediction model is significant.

The three techniques have been used to forecast building energy consumption, and these techniques are engineering, data-driven, and hybrid. The engineering method depends on the heat exchange through the wall, window glass, and ventilation to predict the energy consumption load **(Fumo, 2019)**. The data-driven method depends on the historical or collected weather data and the hybrid method for predicting energy **(Fumo, 2019)**. These methods have given much attention to the data-driven method/statistical methods in implementing ANN prediction models, which has become a significant class in non-linear experimental modeling **(Sharif and Hammad, 2019)**. The different building simulation software and building energy consumption prediction requirements are reported **(Zhao and Magoules, 2012)**. However, it may be possible that at the time of simulation, such detailed data may be unavailable to the user that results in the poor performance of the energy consumption prediction model.

2.1.1 Earlier Work

A massive number of predictive models for predicting the residential building's energy consumption load have been developed in the last few years, mostly based on a building's past usage information **(Daut et al., 2017)**. The prediction models are intended to construct a model based on specified inputs and outputs (historical information) that predicts results using an entirely new set of inputs **(Ashouri et al., 2017)**. According to authors, **(Zhao and Magoules, 2012),** Artificial Intelligence (AI) models are commonly used in ANNs as they have full access to the buildings' energy applications. Authors in (**Aydinalp-Koksal and Ugursal, 2008)** compared the three methods, *i.e.*, the ANN, the engineering, and the conditional demand analysis, used currently in calculating the residential building's energy consumption load. In 1993, the consumer-based domestic appliances, luminaries, cooling, and heating energy consumption load were modeled based on Canada's residential zone. The output variable is calculated and simulated using NN **(Ugursal et al., 2002; Aydinalp-Koksal et al., 2003; Aydinalp-Koksal et al., 2004)**. The ANN better suits the residential building energy consumption prediction compared to the other three models because other models perform better if they were compared with the traditional statistical methods, *i.e.*, linear regression analysis but not with the ANN as it can perform both the types of analysis, *i.e.*, linear as well as non-linear regression analysis (**Aydinalp-Koksal and Ugursal, 2008)**.

In the same way, the authors **(Kialashaki and Reisel, 2003)** compared the multiple linear regression (MLR) and NN models of the residential complex in the United States. Three different models were developed by Li et al. **(2005)** in which two models are developed based on traditional hybrid NN modeling, and one model is developed with a single variable in which the first-order differential equation is known. However, deep machine learning, which is supervised and unsupervised, has attracted a lot in model training due to its performance **(Chen et al., 2018)**. The authors are presented research data to utilize a machine learning algorithm's ratio for trained the model, such as 47% of the researches are used the ANN, and 25% are used the SVM, and 4% only is used the decision trees. 24% also uses the other statistical methods like ordinary least square regression, MLR, Autoregressive (AR), and AR integrated moving average **(Amasyali and El-Gohary, 2018)**. They also mentioned that 31% is focused on heating, and 20% are focused on cooling energy consumption prediction. And they focused on lighting load prediction is 2% only. But the lighting load with the integration of natural daylighting is a valuable parameter to the indoor visual comfort. And also, the ventilation and air quality are two essential parameters of IEQ. On the other side, data-driven accurate predictive modeling for building energy consumption does not involve such comprehensive data about simulated building or conduct such a complete analysis of energy. Instead, it learns from the previous data available for prediction. In the past, data-driven techniques for predicting energy consumption have been the critical component of residential building **(Esen et al., 2017)**. But the most focused research methodology for developing a prediction model is the machine learning used in historical research efforts.

A few methods are based on linear models such as AR, linear regression, and AR moving average **(Barak and Sadegh, 2016)**. But due to the non-linear behaviour of the humidity, air velocity, and temperature, several non-linear methods are proposed by the researchers, based on the wavelet-based methods, k-Nearest Neighbors (kNN), fuzzy models, ANN, random forests, and Adaptive Neural Fuzzy Interference Systems (ANFIS) **(Kiartzis et al., 1995; Tsekoural et al., 2003 and Antanasijević et al., 2015)**.

2.1.1.1 Main Contribution

The energy consumption of residential buildings is directly linked to multiple variables, including the thermo-physical properties of building components, the technical details of their construction, the characteristics of the climate zone, the quality of the installed HVAC system, and the actions and activities of the occupants towards energy usage **(Page et al., 2008; Chen et al., 2015)**. Therefore, an accurate and long-term energy consumption prediction model is desired based on design information during the residential buildings' design stage. Still, several literature surveys lack an accurate and long-term prediction model. Lighting load with natural daylighting has not yet been considered for the prediction model of energy consumption. Thus, to fill this research gap, we developed a data-driven prediction model for the long term and precise prediction of energy consumption at the residential building level in India.

2.2 METHODOLOGY

2.2.1 System Architecture

The general system architecture of the proposed study has been shown in Fig. 2.1. It depicts the study's workflow that the Delhi weather data (temperature and relative humidity) has been extracted and further processed using the MATLAB 2019a environment's data mining technique. A 2BHK single-story building multi-zone has been modeled with necessary user features in the TRNSYS16 building simulation environment and has been simulated. The complete methodology of the proposed prediction model has been also depicted in Fig. 2.2.

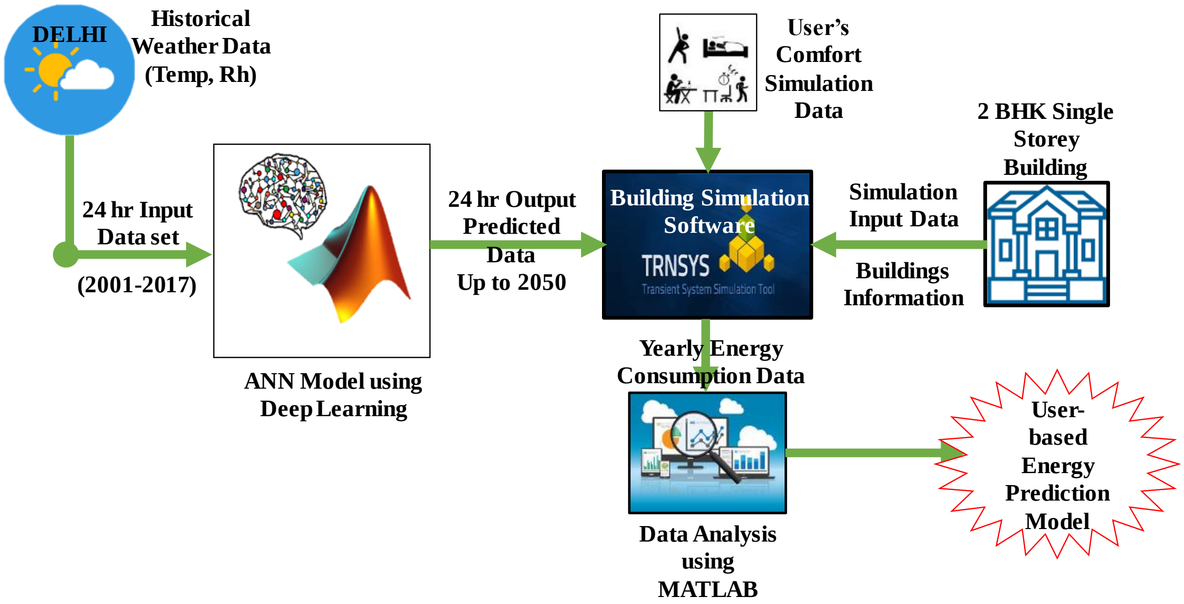

Fig. 2.1: The general architecture of the proposed prediction model.

2.2.2 Data Prediction with ANN

The Data Mining (DM) technique has been used to sort and classify the collected data. DM technique has been categorized into six categories: data classification (Support Vector Machine (SVM), ANN, decision tree method), clustering analysis, association rule mining, regression, summarization, and anomaly detection. These categories have been utilized by **Ashouri et al. (2019)** in developing a framework for energy performance evaluation of buildings, and results suggest that this framework is useful in revealing the occupants and energy-saving potential. Past weather data of Delhi has been taken from the Kaggle website **(Kukreja, 2016)**. The temperature and humidity data are extracted and sorted yearly from 2001 to 2017 using the DM technique. Interpolation using the 'spline' method is used to fill up the missing values. Thus, uniform hourly data of temperature and humidity for each year is obtained. Prediction of temperature and humidity is completed using the Deep Learning (DL) technique. The new machine learning study field launched to move it closer to its initial goals: AI. It is learning multiple layers of abstraction and representation that help make sense of data such as text, sound etc. **(Ahmad et al., 2019)**.

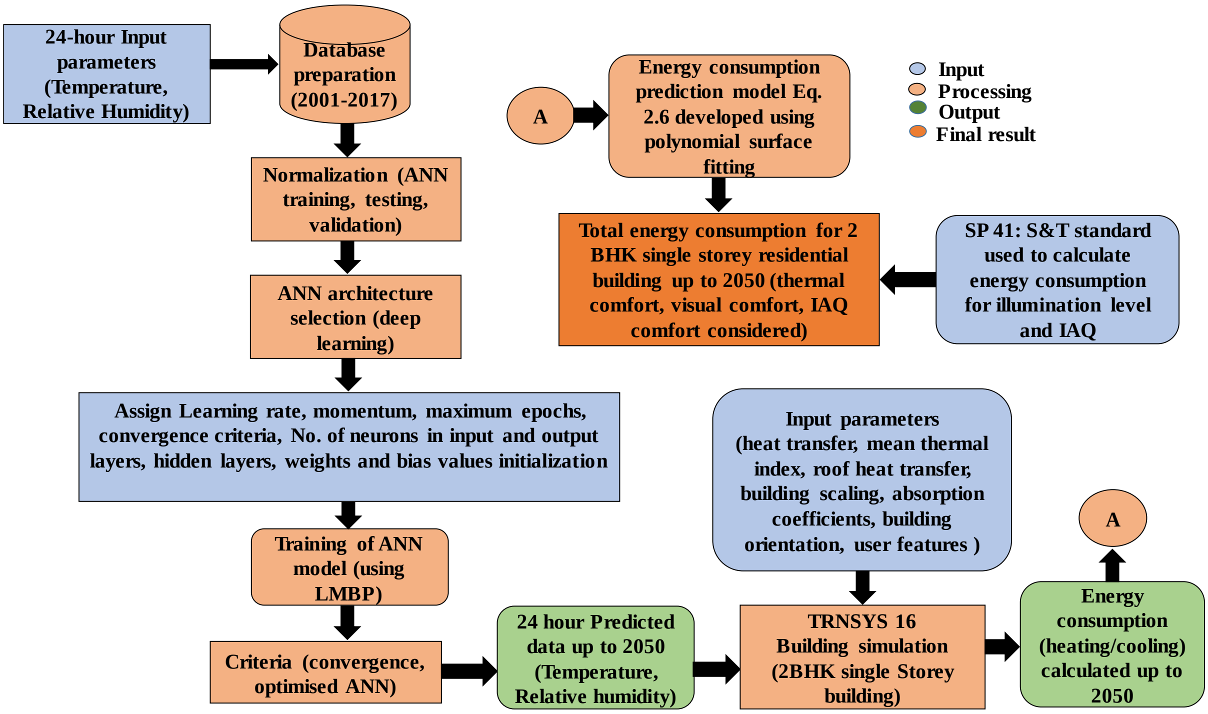

Fig. 2.2: Flowchart of the complete methodology of the proposed work.

The DL concept is historically originated from ANN research. An ANN can be defined as a computational intelligence modeling approach close to a biologically inspired neuron system. The artificial neurons are organized in a given architecture and are connected with weighted networks. An ANN starts with essential processing elements and then goes up in complexities by upgrading the relation weights so that the network can execute a task effectively **(Bhowmik et al., 2018)**. ANN-based models have demonstrated greater accuracy in identifying dynamic non-linear dynamics compared to conventional methods because they provide the opportunity for a standardized approach to non-linear modeling models **(Debnath et al., 2016)**. The use of hidden layers in DNN with many neurons considerably improves the DNN modeling power and generates various closely optimal configurations **(Ahmad et al., 2019; Fan et al., 2019)**. Even though the learning parameter is got trapped into a local optimum, the resultant DNN can still perform well as the possibility of having a poor local optimum is less when a small number of neurons are used in the network **(Song et al., 2019)**. The DL means making the computer to learn from their past experiences **(Fumo, 2019)**. An activation function for the hidden units has been required to introduce a non-linear network. Without nonlinearity, the hidden units cannot make the network more efficient than just straight perceptron's. Therefore, various activation functions are generally used as non-linear sigmoid function steps **(Şencan and**

Kalogirou, 2005; Ekicki and Aksoy, 2009). The output of the neuron 'net' computed using Eqs. (2.1) and (2.2) **(Şencan and Kalogirou, 2005)**.

$$y(t+1) = a\left[\sum_{j=1}^{m} W_{ij} X_j(t) - \theta_i\right] \tag{2.1}$$

$$f_i \underline{\Delta} \, net\, i = \sum_{j=1}^{m} W_{ij} X_j - \theta_i \tag{2.2}$$

where (X= $X_1, X_2, ...X_m$) is m inputs applied to the neuron, W_{ij} characterizes the weight for input is X_i , θ_i is bias value, and a is the activation function.

NN training means adjusting the weight and biases so that a specific input produces a specific output **(Karatasou et al., 2006)**. After training, a predictive system is obtained, capable of predicting the unknown outputs from known inputs. A two-layer feed-forward ANN with 1000 hidden neurons is trained in MATLAB 2019a **(Biswas et al., 2016)**. Feed-forward ANN is a class of extensible and commonly implemented models used to acquire the relationship between the input and output variables **(Lv et al., 2018)**. The input layer has eight neurons, while the output layer has one neuron. The problem can be provided as a function $f(F : \Re^d \rightarrow \Re)$ to achieve the expected values y from the input values x. The given function in Eq. (2.3) is induced in a typical multilayer perceptron to the neural network approach for prediction performance.

$$\hat{y}(k) = f(x, w) = \sum_{j=1}^{h} w_j \psi_j \left[\sum_{i=1}^{n} w_{ji} x_i + w_{j_0} \right] + w_0 \tag{2.3}$$

where the output of the network is expected values for a variable y, formulated with the function $f(x, w)$ of the input x and the free parameters to be fitted are the synaptic weights w_{ji} and w_j arranged into the weight vector- w.

2.2.3 Levenberg-Marquardt Backpropagation (LMBP) Algorithm

Kenneth Levenberg firstly introduced the LM Algorithm and Donald Marquardt independently to minimize non-linear function smoothly and efficiently, with a stable convergence. LMBP algorithm is used for training the network **(Ye and Kim, 2018)**.

According to the universal theoretical framework, a neural network with a single hidden layer consisting of a consequent network of neurons can map any input to any output to an acceptable degree of precision **(Bhowmik et al., 2016)**. As a result, a single hidden layer and an LMBP algorithm with 1000 epochs were chosen for training **(Debnath et al. 2016)**. This algorithm is known for its fast convergence while solving non-linear least-square problems **(Singh et al., 2007)**. The algorithm is appropriate in the ANN field for dealing with small and medium type problems. It is a blend of the steepest descent method and the Gauss-Newton Algorithm (GNA). It inherits the stability advantage of the steepest descent method and speed advantage of the GNA. For any non-linear equation, a Hessian matrix H is derived by the Newton method, a second-order derivative, and provides a proper evaluation of the gradient's change. The derivatives derived from the Hessian matrix can be very complicated. For that, Jacobian matrix J is introduced, and the relationship between the Hessian matrix and Jacobian matrix is given in Eq. (2.4) **(Wang et al., 2012)**.

$$H \approx J^T J \tag{2.4}$$

Now, talking about the Levenberg-Marquardt (LM) algorithm, a new approximate is introduced in the Hessian matrix given by Eq. (2.5) **(Ashouri et al., 2019)**.

$$H \approx J^T J + \mu I \tag{2.5}$$

where I is an identity matrix and μ is a combination coefficient/damping parameter is always positive and is an adaptive balance between two steps. The LM algorithm, by adding a short term μI to the Hessian matrix, boosts the learning. For the weight vector, the LM algorithm's updated rule is given in Eq. (2.6) **(Lv et al., 2018)**.

$$W_{k+1} = W_k - (J_k^T + \mu I)^{-1} J_k e_k \tag{2.6}$$

The network is trained using a set of input and target values such that the value of temperature or humidity for a year at any time instant depends upon the values of temperature or humidity of the previous eight years at the same time instant. For example, if the target value is the temperature on Jan. 01, 2000, at 12:00 hrs. Then its corresponding input values are the values of the previous eight years' temperature for the same month, day, and time, as shown in Fig. 2.3.

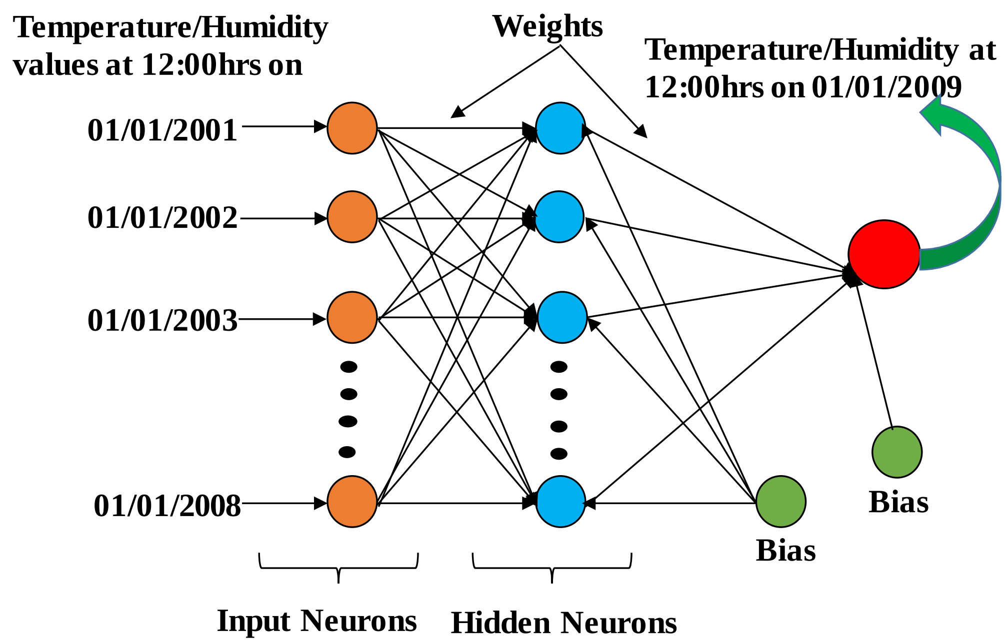

Fig. 2.3: A general architecture- Training of an ANN proposed model.

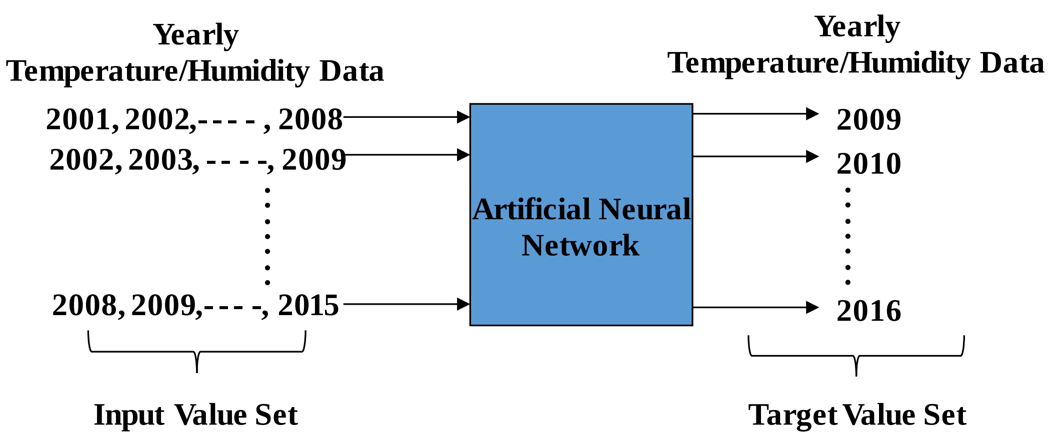

Fig. 2.4: Developed ANN model for predicting temperature and humidity profile.

Since leap years have one extra day, to make an endless number of days in a year, the additional day, *i.e.*, Feb. 29 in 2004, 2008, 2012, and 2016 are separated. This extra day has been predicted separately by using the same methodology as above. Ten hidden neurons where the target set is the hourly temperature/humidity data of Feb. 29, 2016, and the input set are the hourly temperature/humidity data of Feb. 29 of 2004, 2008, and 2012. Once the neural networks are trained, the temperature and humidity of 2017 have been predicted using temperature and humidity of the previous eight years, *i.e.*, from 2009 to 2016. The predicted temperature and humidity of the year 2017 are matched against the known temperature and humidity of the year 2017 up to Apr. 24. To verify the closeness between the expected and actual values of temperature and humidity, Root Mean Square Error (RMSE) has been used. The RMSE between the expected and actual temperature for 2017 is 3.44, whereas it is 20.40 between the expected and actual relative humidity.

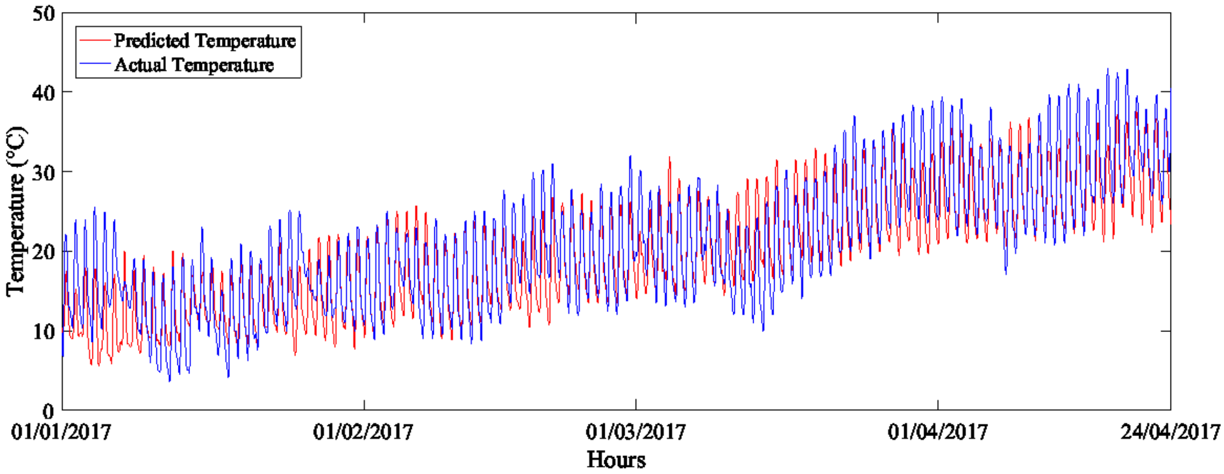

Fig. 2.5: Actual and predicted temperature profile of the year 2017.

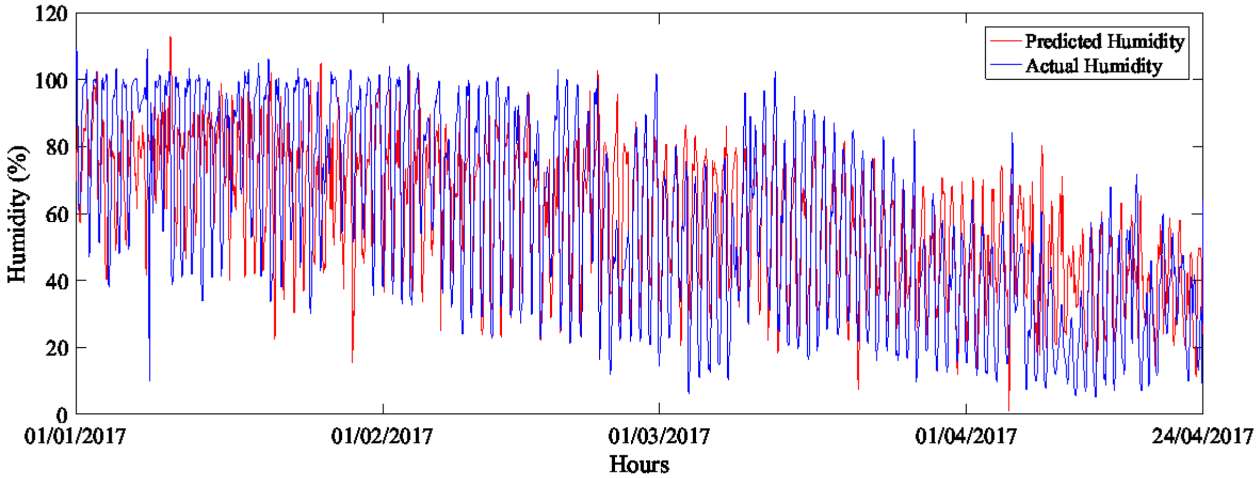

Fig. 2.6: Actual and predicted humidity profile of the year 2017.

Figs. 2.5 and 2.6 show the actual and predicted temperature and humidity, respectively, for 2017 up to Apr 24. As seen from the above plots, the red line indicates the predicted temperature and relative humidity, and the actual data points are represented in blue colour. The temperature and relative humidity profile of the year 2017 from Jan to April, 24th 2017 are plotted.

2.3 ENERGY CONSUMPTION CALCULATION OF A RESIDENTIAL BUILDING

The energy consumption and the thermal comfort in a residential building have inconsistent relation with nature. Energy conservation in the commercial and the residential buildings becomes a necessity rather than an option without compromising the humans' thermal comfort **(Wang et al., 2012)**. Whereas another work by **Shaikh et al., (2018)** used a Fuzzy Inference System (FIS) to derive empirical relationships for power consumed by thermal, humidity, illumination, and air quality actuators. FIS takes error between real value and set value as input and gives the necessary energy to maintain high comfort as output. Moreover, membership functions have been used to accredit the FIS. **Kumar et al., (2019)** proposed an adaptive thermal comfort model and found a temperature range of 23^0 C – 32^0 C as a comfort zone at an indoor condition based on direct thermal acceptance. Another study proposed an adaptive thermal comfort equation at different educational stages to estimate indoor comfort temperature in classrooms **(Kumar et al., 2019)**. The ANN method has emerged as an impressive solution to address nonlinearity for predicting residential building energy consumption **(Ye et al., 2018)**.

2.3.1 Building Simulation Using TRNSYS16

TRNSYS16 software has been used for building simulation to estimate the energy consumption load based on predicted temperature and humidity. A 2BHK single-storey residential building with six zones (two bedrooms, one living room, one kitchen, and two toilets) is modeled in TRNSYS16 software. The residential building that has taken into account the energy consumption prediction model is LIG 2BHK single storey. Hence the maximum number of occupants can be 5 to make proper use of energy efficiently. The building's considered direction is North, South, East, West, Horizontal, Northeast, Northwest, Southeast, and Southwest. Then the number of exterior walls is taken as five. The building is naturally ventilated, with infiltration and ventilation rate being 1 Air Change per Hour (ACH) and 5ACH, respectively **(Kumar et al., 2010)**. Table 2.1 presents the thermo-physical properties of building materials and different types of walls/windows. According to the properties of building materials given in the SP:41 (S&T) standard, these values are standard **(SP-41, 1995)**. Based on the above building materials, the U-values of different walls are determined. Different type of walls, their thickness, and U-values are tabulated in Table 2.2. The mean heat transfer coefficient of building walls, mean inert thermal index of building walls, roof heat transfer coefficient, building scale factor, solar absorption coefficient of exterior walls also given in Table 2.2. All the required building parameters are taken as per Delhi's composite climate (Hot and Arid Zone) and SP:41 (S&T) standard **(SP-41, 1995)**.

Table 2.1: Thermo-physical properties and Different wall /window types properties.

Building material	**Thermal conductivity (kJ/h-m-K)**	**Specific heat (kJ/kg-K)**	**Density (kg/m³)**
Burnt brick	3	0.88	1820
Plaster	2.6	0.84	1762
Stone	5	1	2000
Concrete	6.26	0.88	2410
Plywood	0.63	1.76	640
Wall type/window	**Thickness (cm)**	**U-value (W/m²-K)**	
External wall	36.4	1.635	
Internal wall	25.1	2.101	
Roof	13.9	2.927	

Table 2.2: Input parameters are taken into account to calculate the energy consumption.

Wall type/window	**Thickness (*m*)**	**Surface Coefficient U-value (*W/m²K*)**	**Mean heat transfer coefficient (*kJ/h²m²K*)**	**Mean inert thermal index**	**Solar absorption coefficient**
External wall	0.364	1.635	11(front) 64 (back)	125	0.75 (front) 0.3 (back)
Internal wall	0.251	2.101	11 (front) 11 (back)	-	0.6 (front) 0.6 (back)
Roof	0.139	2.927	11 (front) 64 (back)	100	0.35 (front) 0.75 (back)
Ground	0.425	0.310	11 (front) 999 (back)	-	0.8 (front) 0.4 (back)
Building scale factor	1:1				
Floor area ratio	1.23				

TMY2 weather data is used for simulation of the whole year. The external temperature and humidity are given to the house model using type62. Tyep62 has been used to export the data to an excel file. This residential building model is then used to evaluate the temperature and relative humidity within each area about ambient relative humidity and temperature.

Figs. 2.7 and 2.8 show the temperature and relative humidity profile of the kitchen, and similarly, for the living room, bedroom1 and bedroom2 are also plotted, respectively. Temperature and relative humidity data of the year 2001 has been used in the simulation of a residential building.

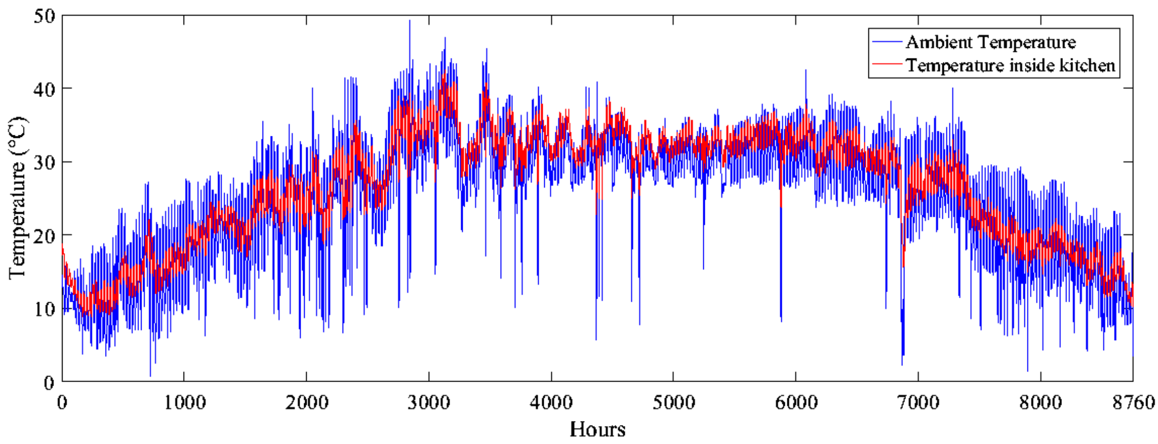

Fig. 2.7: Temperature profile of the year 2001 in the kitchen.

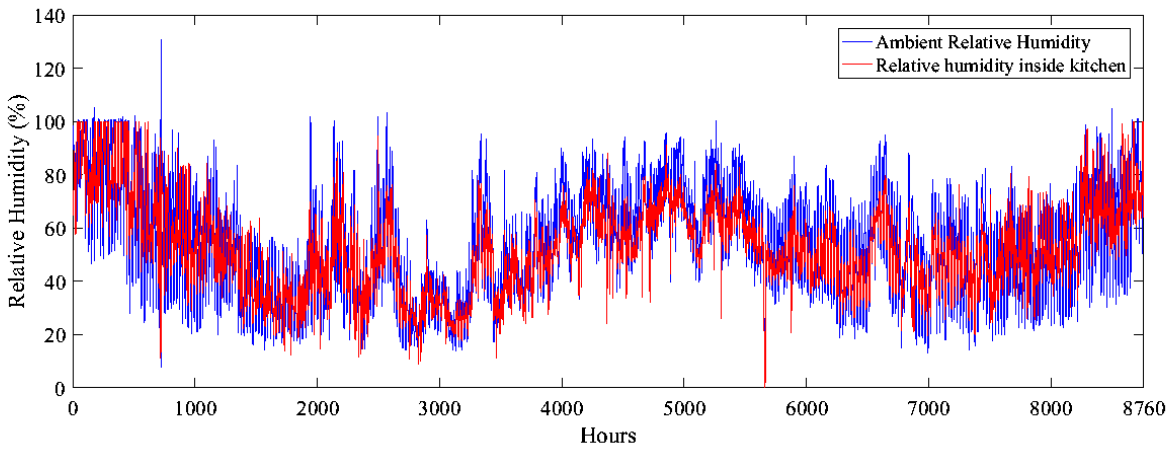

Fig. 2.8: Relative humidity profile of the year 2001 in the kitchen.

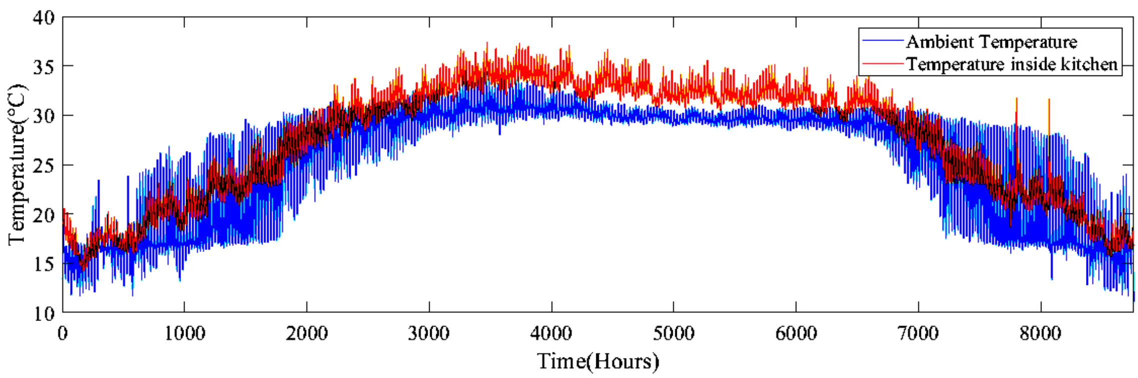

Fig. 2.9: Temperature profile of the year 2050 in the kitchen.

Fig. 2.9 shows the temperature profile in the kitchen of the year 2050. Similarly, for living room, bedroom1, and bedroom2 has been generated respectively but not shown here due to same procedure whereas, Fig. 2.10 depicts the relative humidity profile in kitchen, of the year 2050, and similarly, for all other zones living room, bedroom1, and bedroom2 are plotted respectively for the year 2050. The predicted temperature and relative humidity data up to the year 2050 have been used in the simulation.

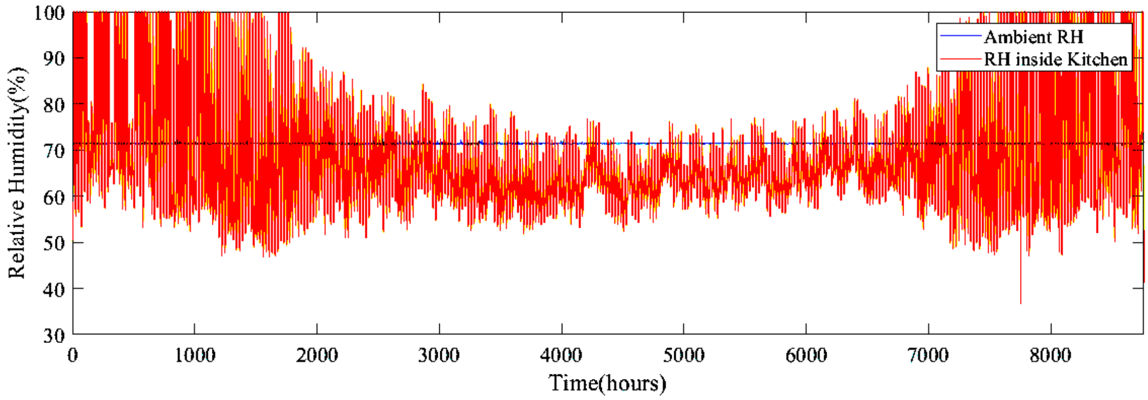

Fig. 2.10: Relative humidity profile of the year 2050 in the kitchen.

To make the residential building environment conducive for the residents, cooling and heating systems are used in the kitchen, living room, bedroom1, and bedroom2. Threshold temperatures for cooling and heating systems are selected to save the right amount of energy. According to the Bureau of Energy Efficiency, India (BEE), 24^0 C can be chosen as threshold temperature for cooling and heating systems, respectively, in the composite climate of Delhi, India. According to SP:41 (S&T) standard by the Bureau of Indian Standards, the relative humidity is kept between 40% and 70% for a comfortable indoor atmosphere.

Similarly, each zone's temperature and relative humidity are calculated for given or predicted temperature and relative humidity.

2.4 BUILDING SIMULATION RESULTS AND DISCUSSION

The proposed data-driven energy consumption model shows accepted results with 95% coefficients bounds. According to their respective threshold temperatures, the heating system for winter and cooling system for summer are defined in TRNSYS16. In this manner, the yearly energy consumption for each zone's heating and cooling system is estimated. Fig. 2.11 clearly shows the annual energy consumption of cooling and heating system for all zones bedroom2, bedroom1, living room, and kitchen. The Y-Y left axis represents the cooling load (kWhr), whereas the Y-Y right axis represents the heating load (kWhr). Fig. 2.11 shows that temperature increase in the future requires more cooling load than the heating load. The heating load trend from 2001 to 2050 is continuously decreasing as global warming is increasing.

Therefore, the energy consumed through the cooling and heating system depends on the indoor temperature and relative humidity. A mathematical relation can be established between energy consumption and indoor temperature and relative humidity. The polynomial surface fitting has been used to establish a mathematical relationship between energy consumption and temperature and relative humidity. For T temperature and Rh relative humidity, the energy consumption, E (T, Rh), a mathematical relation is developed with 95% coefficients bounds, Eq. (2.7).

$$
\begin{aligned}
E(T,Rh) &= p_{00} + p_{10} \times T + p_{01} \times Rh + p_{20} \times T^2 + p_{11} \times T \times Rh + p_{02} \times Rh^2 \\
&+ p_{21} \times T^2 \times Rh + p_{12} \times T \times Rh^2 + p_{03} \times Rh^3
\end{aligned}
\tag{2.7}
$$

T has been normalized by mean 26.54 and a standard deviation of 7.619, and Rh has been normalized by mean 52.77 and standard deviation of 17.03126. The coefficients with 95% confidence bounds have the following values, tabulated in Table 2.3.

Table 2.3: Different coefficients of modeled energy equation.

Coefficient	Numerical value	Range
p_{00}	-40.03	(-51.87,28.19)
p_{10}	219.9	(218.9,220.9)
p_{01}	4.816	(4.045,5.586)
p_{20}	0.9196	(0.7907,1.049)
p_{11}	0.1149	(0.03945,0.1903)
p_{02}	0.002677	(-0.01991,0.02526)
p_{21}	-0.03596	(-0.04324,-0.02868)
p_{12}	-0.02309	(-0.02664,-0.01954)
p_{03}	-0.004244	(-0.00511,-0.003378)

2.4.1 Thermal Comfort

American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) 55-2013 **(Singh et al., 2018)** states that thermal comfort is the status of mind that expresses satisfaction with the thermal environment **(Ličina et al., 2018; ASHRAE, 2013)**. This definition indicates that thermal comfort is a contextual response and cannot assign a value

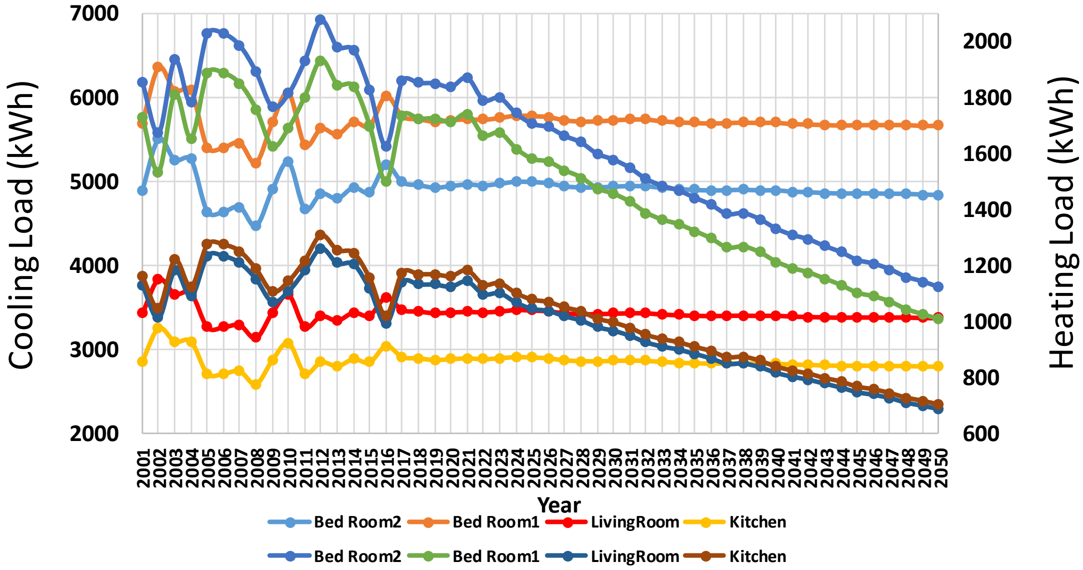

Fig. 2.11: Yearly energy consumption of the heating system (Y-Y right axis) & cooling system (Y-Y left axis) in each zone

specifically. It mostly depends on the metabolic rate, clothing insulation, relative humidity, air temperature, relative air velocity, and external work. Predictive Mean Vote (PMV) defined in both ASHRAE 55-2013, and ISO 7730 is an index to measure the thermal comfort based on the above six factors. Based on these standards ASHRAE55-2013/2017, we have calculated the parameters for thermal sensation, and value ranges +3 to -3 where +3 hot, +2 warm, +1 slightly warm, 0 neutral, -1 slightly cool, -2 cool, and -3 cold. Clothing level and relative air velocity change with seasons while metabolic rate and external work are assumed constant with value 1.2 met and 0, respectively, for residential building **(Kumar et al. 2014)**. A year is divided into three seasons; winter (Jan., Feb., Nov., and Dec.); summer (Apr., May., Jun., and July); moderate (Mar., Aug., Sept., and Oct.). The values of clothing level and relative air velocity for different seasons is given as Summer- 0.35 and 0.6 m/sec, Winter- 1.0 and 0.3 m/sec, Moderate- 0.6 and 0.5 m/sec.

Based on the temperature and relative humidity inside the living room and employing the cooling/heating system, PMV values of the living room for 2001 and 2050 using Fanger thermal comfort equations **(Fanger, 1970)** are calculated and given -1.6211, 0.3733, and -0.5834. Energy consumed by the living room's cooling and heating systems to maintain these PMV values is **4431.62kWhr** and **548.7kWhr,** respectively, for the year 2001, whereas for the year 2050, these values are **16677.26 kWhr** and **3520.24 kWhr,** respectively.

2.4.2 Visual Comfort and Indoor Air Quality

Visual comfort can affect the residents' health and efficiency in a straight line, as the work's efficacy relies on vision and not instantly because the lighting and air quality can be immediately attentive or impact motivation **(Asadi et al., 2017)**. Visual comfort relies mainly on the level of luminance, *i.e.*, the occupants' excellent quality and light balance to perform their work. Similarly, IAQ is also the most crucial factor in occupants' comfort requirements in residential buildings. Some studies are regarded as a crucial factor that can influence the occupant's health and productivity **(Lachhab et al., 2017)**. Therefore, it is essential to assess the IAQ and determine whether the clean and fresh air is efficiently distributed following the total concentration of indoor pollutants CO_2 and CO **(Kumar et al., 2010)**.

2.4.3 Illumination with Natural Daylighting

Structural lighting considers aesthetic aspects and practical aspects of the amount of light needed, structure occupants, energy efficiency, and cost. Artificial lighting considers the quantity of daylight obtained in a room using calculations of the daylight factor. Lighting requirements of the kitchen, living room, and bedrooms are calculated according to SP:41 (S&T) standards. The recommended illumination values (lux or lumens per m^2) are 200 lux for kitchen and 50 lux for living room, and 150 lux for bedrooms. Due to windows, Daylight Factor (DF) for kitchen, living room, and bedrooms can be calculated to calculate the number of LED bulbs required. It is performed to decrease the energy consumption of the lighting device if adequate daylight is already accessible. The formula for calculating average DF is given in Eq. (2.8) **(Du and Sharples, 2011)**.

$$\textbf{Average DF} = \frac{WMT\theta}{A(1-R^2)} \tag{2.8}$$

where, W- an area of the window in m^2; M- window maintenance factor (≈ 0.7); A- total internal surfaces area (m^2); T is the glass transmittance corrected for dirt (≈ 0.8); θ - Sky visible angle (°) from the middle of the window (≈ 85 for no obstruction) and R- reflection factor (≈ 0.6). According to the Bureau of Indian Standards SP:41 (S&T), the average outdoor horizontal illumination due to the whole sky is 8000 lux for the composite climate of Delhi, and DF 1% implies 80 lux and design sky illumination 8000 lux. Based on this data, the daylight factor for the kitchen, living room, and bedrooms are calculated and given in Table 2.4.

Table 2.4: Daylight factor and number of LED bulbs required.

Zone	Window Area (W) (m^2)	Internal Total Surface Area (m^2)	Average DF (%)	Incoming Lumens from Window (lux)	Recommended Illumination Level (lux)	Number × Wattage of LED Bulbs (watt)
Kitchen	1.08	46.26	1.74	150.336	200	1×7 watt,1×5watt, 1×3watt
Living Room	1.8	57.6	2.30	331.20	50	2 × 3watt
Bed Room1	1.08	61.2	1.30	112.32	150	1 × 15watt
Bed Room2	1.08	54	1.50	129.60	150	1 × 14watt

When sufficient daylight is available, 7watt and 5watt LED bulbs are used in the kitchen, whereas one 3 watts LED bulb is used in the living room. Due to the low daylight factor of bedrooms, single LED bulbs fulfill the recommended illumination level. Based on the above data and assuming that lights operate for 3 hrs in the morning and 7 hrs in the evening. The approximate energy consumption of the lighting system E_L = **0.482 kWhr/day**. Therefore, the one-year energy consumption of the electrical lighting system is recorded as **175.93 kWhr**.

2.4.4 Indoor Air Quality and Ventilation

Ventilation allocates the fresh air inside a building or space and distributes air within the building or room. The ventilation in residential buildings aims to provide better breathing air by diluting and removing pollutants **(Etheridge and Sandberg, 1996; Singh et al., 2017)**. IAQ can be tracked and evaluated using sensors, graphical user interface apps, and communication technologies **(Phala et al. 2016)**. For the ventilation system, SP:41 (S&T) standard recommends an exhaust fan of 90 watts for buildings like homes and small offices to maintain good air quality. Assuming that an exhaust fan operates for about 2 hrs in the kitchen, living room bedrooms, and toilets, the exhaust fan E_X = **1.08 kWhr/day**. Therefore, the one-year energy consumption for the ventilation system will be **394.2 kWhr.**

2.5 CONCLUSIONS

A long term prediction model has been presented in work based on ANNs, developed as per the electrical energy consumption required for a residential 2BHK single-story building (multizone). We realized that temperature and relative humidity are the two most important factors that have been most influential in predicting the residential building energy consumption during this study. The information received from the user comforts is also very important, especially the thermal comfort. Two different methodologies are proposed from which one methodology is deep learning ANN model that considers the historical weather data (temperature and relative humidity) and predicts same, up to the year of 2050. Secondly, the predicted temperature and humidity data is used as input for TRNSYS16 software. Considering the complicated design of the building structure, which involves the various aspects such as heating, cooling, ventilation, air quality index, and illumination level, the energy forecast is given up to 2050. Thus, it is considered the most accurate and precise model with 95% coefficients bound that predicts the residential building's electrical energy consumption, which could further be integrated with various controlling techniques. The total required energy (heating, cooling, lighting, and ventilation) in 2BHK L.I.G residential building for the year 2050 is around **20767.63 kWhr**.

CHAPTER 3

OPTIMAL ENERGY CONSUMPTION AND COMFORT MANAGEMENT BASED ON MULTIAGENT TOPOLOGY

3.1 INTRODUCTION

According to the EPA 2005 SEC. 914, the concept of high-performance building includes a building that incorporates and optimizes all significant high-performance building characteristics, including energy consumption, efficiency, life-cycle sustainability, and occupant productivity **(Srinivas et al., 2015)**. In residential buildings/smart homes, a considerable portion of energy consumption is individually consumed in maintaining indoor comfort. In the future, it is believed that energy consumption in residential buildings can increase up to 8 times **(EPA, 2005)**. Therefore, it is a challenging task for a developing country in India that consumption can be managed by keeping in mind the occupant's comfort. Even the government of India has also taken many necessary steps in which our Ministry of Power, Ministry of Housing and Urban Poverty Alleviation, BEE, Ministry of Environment, Forest and Climate Change Ministry of Urban Development, Department of Science & Technology and Department State Levels are also involved to conserve the energy without affecting indoor comfort **(IEO, 2019)**.

No matter whatever the type of building is, the most critical issue is to reduce energy consumption and provide high comfort to the occupants. The most vital thing with all types of buildings is to reduce electrical energy usage and provide residents with high comfort. When time continues, there is sufficient demand for electrical energy owing to the exponential rise in electricity-using equipment. The growth in electricity consumption is getting costlier to sustain the convenience of large consumers. The truth is, however, that reducing energy consumption has to do with optimizing occupant comfort. Fig. 3.1 shows the high-performance building energy and comfort management model for the proposed novel design solution. High-performance building model comprises of various incorporated sensors (temperature, illumination and CO_2 sensors), optimization techniques to optimize environmental parameters and fuzzy logic controllers with several actuators to operate accordingly. The high-performance building model has been designed to minimize energy consumption and maximize occupants comfort.

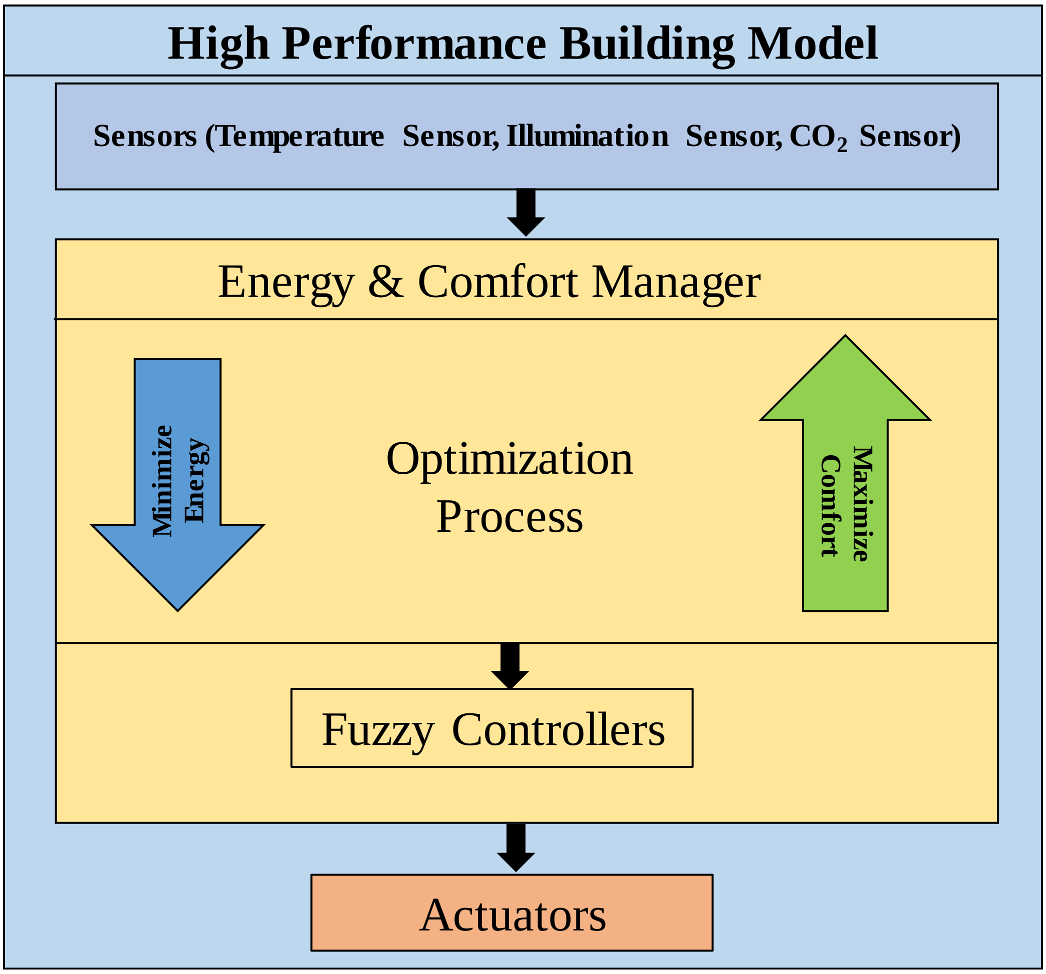

Fig. 3.1: A framework of the proposed solution for building energy management.

Hence trade-off management between energy use and user comfort is needed. In all buildings, the control system is essential to maintain minimum energy usage and maximum user convenience. Monitoring user comfort requires three basic comfort metrics, such as visual comfort, thermal comfort, and IAQ **(Kumar et al., 2017)**.

The ambient temperature of the buildings reflects the thermal comfort. A cooling or heating auxiliary unit is necessary to retain the temperature of the comfortable area of the building. An illumination system is used to involve visual comfort in a building, whereas the air quality is maintained by using the CO_2 concentration according to user satisfaction. The user's overall comfort index is maintained according to user demand by considering all the three comforts **(Waibel et al., 2019; Kumar and Hancke, 2014)**. According to the literature reports, all three parameters are considered for monitoring the comfort inside residential buildings according to user requirements. We also considered these parameters to satisfy occupant comfort requirements in the proposed work.

3.1.1 Earlier Work

The literature is abundant with various energy efficiency strategies introduced to conserve energy usage within residential buildings and reduce it. Many of those solutions are based on the conventional control method **(Levenmore, 1992; Benard et al., 1992; Curtiss et al., 1996)**. Such controllers include optimal controllers, PID (Proportional Integrated Derivatives), and adaptive controllers. But such traditional controllers have some drawbacks associated with them. For instance, they are significantly unable to manage and monitor, and less user-friendly, considering to inability to manage comfort parameters. In such a case, the implementation of specialized fuzzy controls to retain environmental criteria for residential buildings was suggested **(Kolokotsa et al., 2002)**.

The few other predictive control based methods using internal-cooling, heating, and ventilation system used weather prediction **(Kusiak et al., 2010; ÅirokÃ et al., 2011)**. **Wang et al. (2010)** have proposed a control system using the intelligent optimization technique PSO. This control system consisted of two-level agents, one higher-level central agent, and several lower-level local agents. This framework was designed to control energy and comfort. Similarly, the author's **Wang et al. (2012)** developed a multi-agent-based control method in which information integration was used. The authors have used ordered averaging weighted aggregation to monitor the indoor energy management. This system was based on the idea that the behavior of the occupant directly affects system performance. A multi-objective PSO technique was applied in the central agent to find the optimal trade-off solution for informed decision making. **Ullah et al. (2017)** have proposed a model to improve optimization function to achieve maximum users' maximum comfort in the living environment of building with less energy consumption. They performed a comparative study of the PSO and GA optimization algorithm with a baseline scheme. Several factors, such as personal factors, social factors, and internal building factors, have a substantial impact on user satisfaction within a residential building. The authors' work in contrast to the factors **(Bluyssen et al., 2011)** presented a model for understanding the interaction between the dynamic variables.

In contrast, **Marino et al. (2012)**, proposed a framework for evaluating environmental conditions, both outdoor and indoor, for user comfort and energy management. Various forms of forecasting, classification, and optimization approaches for energy control and management systems have also been developed for various objectives. Similarly, the authors **Solla et al. (2016)** discussed the necessity of integrating IT with green building. The authors addressed a detailed study of the energy management model using the smart city concept **(Ejaz et al., 2017)**. The authors have concluded various issues, challenges, and opportunities in smart cities for effective energy management. They categorized smart cities' energy management systems into two groups, including energy-efficient approaches and energy conservation. Each of these types was further discussed, demonstrating the technology systems, policies, and designs. The artificial bee colony was rarely used in energy management and control based applications relative to other optimization techniques. **Govardhan et al. (2012)** implemented an ABC optimization algorithm for efficient microgrid control. The aim was to provide scheduling of short-term load forecasting using the micro grid's reduced operational costs. Multi-objective ABC was implemented by **(Tiwari et al., 2012)** to optimise energy-efficient data center operation placement schemes. The article aimed to minimize the energy cost for effective and efficient data center control and management, as the energy cost in data centers is higher than in office buildings.

In **(Bamane et al., 2014)**, the authors introduced an artificial bee colony for maximal power flow dependent on temperature. The aim was to minimize fuel cost, loss of power, and improve the voltage profile. In conjunction with the Markov chain, the artificial bee colony has been implemented by **(Marzband et al., 2017)** for the energy management system. **Zhang et al. (2018)** proposed the visual comfort model in which light sensors measure the incident light. The cloud-based software analyses this data using the developed framework and PSO and then sends the corresponding command to drive automatic curtains. In terms of convergence time, the proposed CSPSO algorithm is found to be superior. It is also considered more robust concerning four recent multi-objective particle swarm optimization algorithms and four differential evolution variants in a comprehensive comparative study **(Trivedi et al., 2020)**.

Keeping in mind the strengths of PSO, a noble solution CSPSO optimization approach has been implemented to maximize the comfort index value of user comfort within the residential building and the efficient use of energy consumption. The primary goal is to improve user comfort in high-performance buildings, thus reducing energy consumption.

3.2 SYSTEM DESCRIPTION AND MODELING

Smart home energy and comfort management model based on multiagent topology is shown in Fig. 3.2.

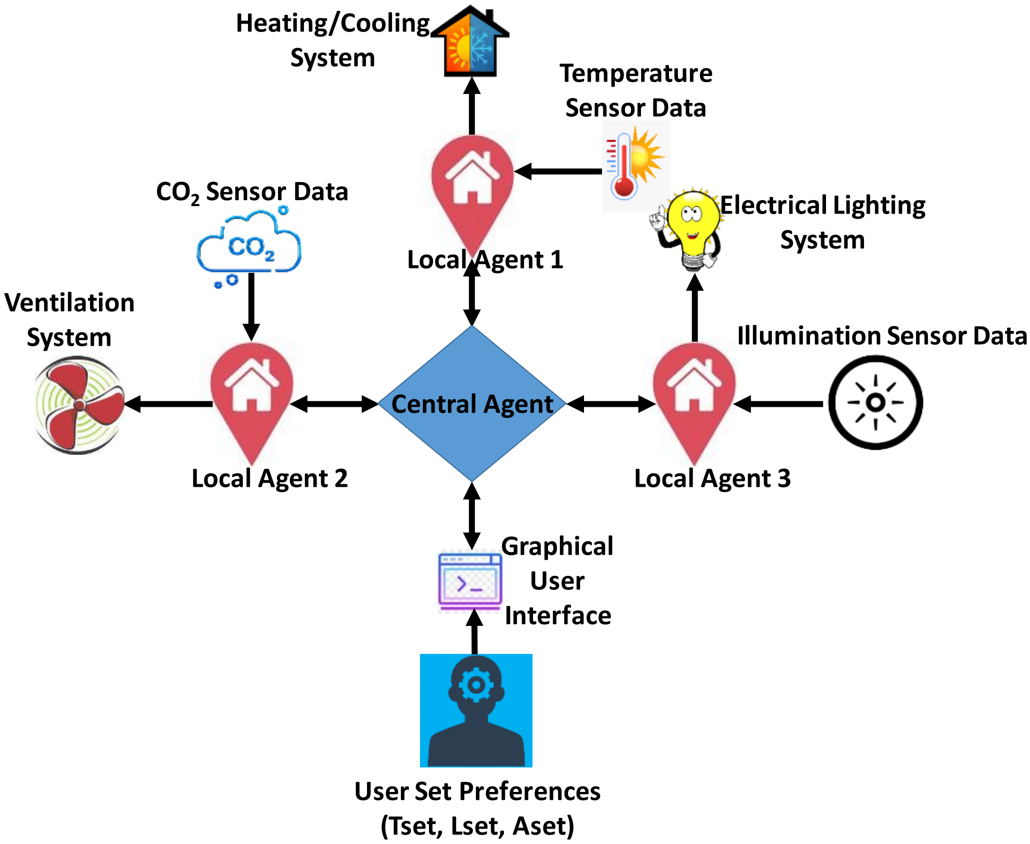

Fig. 3.2: Multiagent based building energy and comfort management system.

The multiagent topology comprises local agents (local agent-1, local agent-2, local agent-3), a central agent, and a graphical user interface. The three sensors (temperature, illumination, and CO_2) attached to local agents, will collect the data of temperature (^{0}C), illumination level (lux), and CO_2 (ppm) from the indoor environment and fed to their respective local agents. The central agent will activate the actuator by coordinating with all local agents according to the user set preferences (T_{set}, L_{set}, A_{set}).

3.2.1 Comfort Index Model

Comfort index has been calculated using Eq. (3.1) **(Verma et al., 2020),** which has been presented mathematically:

$$\text{Comfort Index} = W_1\left[1-\left(\frac{E_T}{T_{set}}\right)^2\right]+W_2\left[1-\left(\frac{E_L}{L_{set}}\right)^2\right]+W_3\left[1-\left(\frac{E_A}{A_{set}}\right)^2\right] \qquad (3.1)$$

where W_1, W_2, and W_3 are user-set preferences concerning temperature, illumination level, IAQ, respectively, and $W_1+W_2+W_3 = 1$. The errors are E_T, E_L, and E_A, the difference between the CSPSO optimized value and the environmental value.

3.3 PROPOSED SOLUTION METHODOLOGY

The solution method is based on the CSPSO optimization technique. The input parameters for the CSPSO are temperature, lighting, IAQ, and external environmental temperature, lighting, and air quality. CSPSO optimizer optimizes the environmental parameters according to the requirements set by the users to achieve the optimal comfort index value as per their needs. In the proposed work, two conditions have been considered to achieve the optimal comfort level with minimum energy consumption. The fuzzy temperature controller, the fuzzy lighting controller, and the fuzzy IAQ controller have been used to control the cooling/ heating, illumination, and ventilation system within the building. The feedback of the fuzzy controllers is the error discrepancy between the environmental parameters and the CSPSO optimal value.

3.3.1 Optimization Using CSPSO Algorithm

The PSO technique has been traditionally applied extensively by researchers. However, some of the limitations of the PSO technique have been identified, such as premature convergence, incomplete optimism, and challenges about population diversity **(Patwal and Narang, 2018 and Peng et al., 2015)**. Through the swarm search method, the size of the population and stagnancy prevention plays a vital role in getting the best feasible solution. CSPSO is one of the potential optimization techniques among swarm-based techniques. In the CSPSO approach, through the application of horizontal and vertical crossover operators, CSO further improves the best local solutions obtained from PSO. In this proposed solution, the improved version of PSO (IPSO) has been implemented to optimize the different process parameters for continuous decision variables, instead of classical PSO reported in **(Patwal and Narang, 2018)**.

3.3.1.1 Improved PSO

The individual solutions are replaced by local best solution, and velocity is updated using the mean value of best local particles (avg^N_{best}) and best global particles (BP^N) in the IPSO technique. The direction of the search is defined and is performed as per the Eq. (3.2).

$$V_i^N = W * V_i^N + C_1 * rand_1^N * (avg^N_{best} - LBP_i^N) + C_2 * rand_2^N * (BP^N - LBP_i^N)$$
$$(i \in n, N \in D), \tag{3.2}$$

where, W is the inertia weight which is updated with iteration as:

$$W = (W_{max} - W_{min}) * e^{-b * iteration} + W_{min} \tag{3.3}$$

And the C_1 and C_2 are updated as **(Ratnaweera et al., 2004)**:

$$C_1 = (CF_1 - CI_1) * \left(\frac{iteration}{iteration_{max}} \right) + CI_1 \tag{3.4}$$

$$C_2 = (CF_2 - CI_2) * \left(\frac{iteration}{iteration_{max}} \right) + CI_2 \tag{3.5}$$

The updated position (LBP_i^N) in the IPSO technique doesn't move directly into the next iteration. If the objective function value of the updated position is better than that of the parent particle, only the updated particle replaces the parent particle position; otherwise, it will be eliminated as noted in Eq. (3.6) also.

$$LBP_i^N = \left\{ \begin{matrix} LBP_i^N + V_i^N ; \mu_N (LBP_i^N + V_i^N) > \mu_N (LBP_i^N) \\ LBP_i^N ; else \end{matrix} \right\} (i \in n, N \in D) \tag{3.6}$$

In case of binary decision variables, the particle velocity is updated using Eq. (3.2) and parameters of the optimization algorithm are updated by using Eqs. (3.3) - (3.5). The sigmoid function is then used to scale the position from 0 to 1 and is indicated as:

$$\text{Sigmoid } (V_i^N) = \frac{1}{1 + e^{-V_i^N}} \qquad (i \in n, N \in D_{binary}) \tag{3.7}$$

The updated best local position of the binary decision variable is given as:

$$U_i^N = \begin{cases} 1, \text{if rand} > \text{sigmoid}(V_i^N) \\ 0, \quad \text{else} \end{cases} \qquad (i \in n, N \in D_{binary}) \tag{3.8}$$

In this way, the local best position is updated continuously by the IPSO search as well as by the binary decision variable.

3.3.1.2 Crisscross search optimization

The CSO serves as a robust agent capable of searching for the global best solution with faster convergence features without altering swarms' diversity. The CSO is composed of two crossover operators, including horizontal and vertical crossover operators. The reasonable solutions obtained through the crossover are from the parent population replicated offsprings **(Meng et al., 2014)**. The blend of horizontal and vertical crossover serves as a favour for crisscross Searching and improving convergence speed and accuracy performance. In the following sections, the horizontal and vertical crossover process has been explained:

3.3.1.3 Horizontal crossover

The arithmetic crossover operation is carried out horizontally crossover search to produce a reasonable solution of all dimensions between two separate individuals in the population. Considering that the parent particle (i^{th}) is LBP_i and the parent particle (h^{th}) is LBP_h selected. Mathematical expressions of a reasonable solution by both individuals are given in Eqs. (3.9) and (3.10).

$$MHS_i^N = \text{rand}_i^N * LBP_i^N + (1 - \text{rand}_1^N) * LBP_h^N + EC_1^N * (LBP_i^N - LBP_h^N) \quad (i \in n, h \in n, N \in D) \tag{3.9}$$

$$MHS_h^N = \text{rand}_2^N * LBP_h^N + (1 - \text{rand}_2^N) * LBP_i^N + EC_2^N * (LBP_h^N - LBP_i^N) \quad (i \in n, h \in n, N \in D) \tag{3.10}$$

3.3.1.4 Vertical crossover

The vertical crossover process provides stagnation mitigation for multimodal challenges. It is facilitated by the performance of an arithmetic operation of a crossover of two different dimensions. To carry out the vertical crossover, N_1^{th} and N_2^{th} dimensions are used which are obtained from the individual's horizontal crossover. The updated individual offspring for the N_1^{th} dimension is as follows (Eq. 3.11):

$$MVS_i^{N_1} = rand_3^{N_1} * LBP_i^{N_1} + (1 - rand_4^{N_2}) * LBP_i^{N_2}$$
$$(i \in n, N_1 \in D, N_2 \in D) \tag{3.11}$$

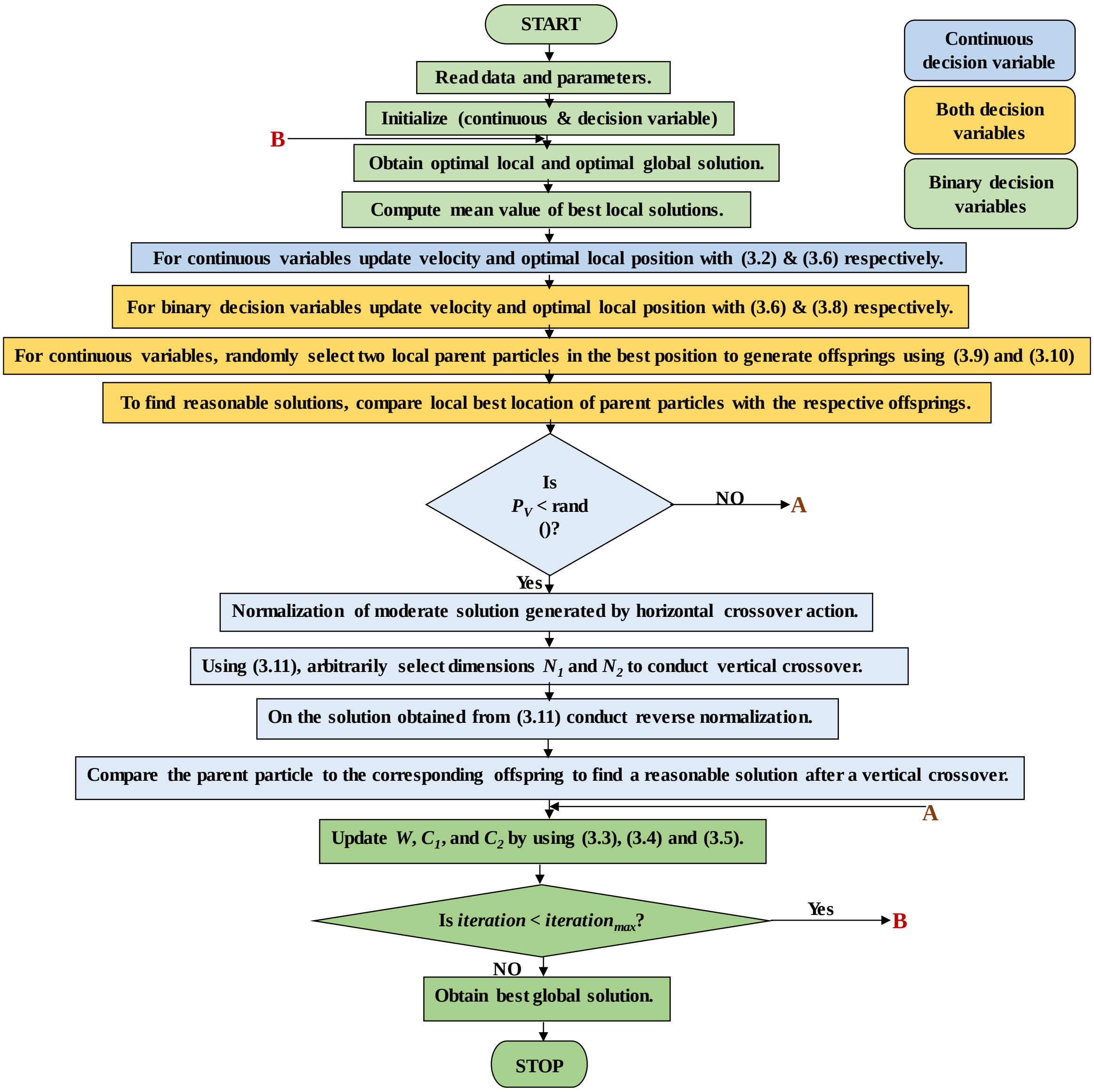

Fig. 3.3: Flowchart of the CSPSO technique.

To ensure the replicated offspring is situated inside the limited region, vertical crossover shall be performed to normalize parents' process and reverse uniformity after completion. To ensure the limited population participation in the vertical crossover process and crossover probability (P_v) is used. As in the horizontal crossover, they are only better performing newly generated reasonable solutions allows them to enter the next generation. The flowchart for the CSPSO technique has been depicted in Fig. 3.3.

3.3.2 Fuzzy Logic Controllers

The idea behind the concept of fuzzy was given by Professor L. A. Zadeh **(Bellman and Zadeh et al., 1970)**. In the proposed work, the actuator's required energy to maintain the comfort index value has been computed using three FLCs. These three controllers are fuzzy temperature controller, fuzzy illumination controller, and fuzzy IAQ controller. The controller's main components are fuzzifier, fuzzy knowledge base, fuzzy rule base, inference engine, and the defuzzifier **(Bellman and Zadeh et al., 1970)** shown in Fig. 3.4.

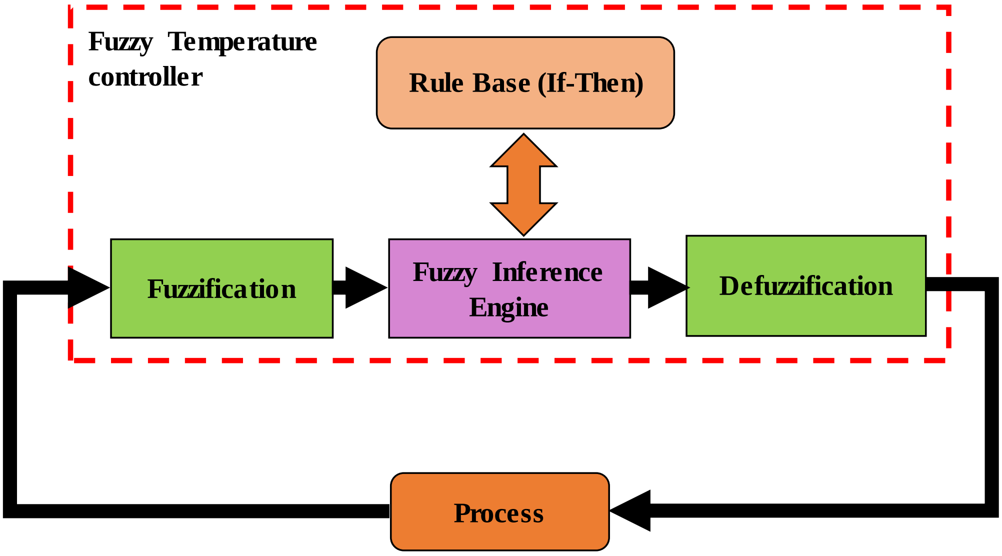

Fig. 3.4: General block diagram of an FLC.

The input to the controllers is the error between the optimized environmental parameter and real environmental parameters. The output of the controllers will be energy required for controlling the state of the respective actuator installed. The fuzzy logic rules of the three controllers are given in Table 3.1. In the given rules E_T, E_L, and E_A are the error difference between the environmental values and CSPSO optimized values corresponding to temperature, Illumination, and IAQ. Based on these error differences, the FLCs will compute energy and provide to actuators. The seven membership functions (NB, NS, NM, NS, ZE, PS, PM, PB) are defined for the fuzzy temperature controller. The triangular membership function has been employed in FLC to compute energy consumption. Where input variable error is E_T and E_1 is required energy for the temperature controller. For the fuzzy illumination controller, six membership functions (HS, MS, BS, OK, SH, H) are defined where E_L is input variable error, and E_2 is required energy for the illumination controller.

Similarly, for IAQ, the five membership functions (LOW, OK, SH, LH, HIGH) are defined in which E_A is input variable error, and E_3 is the required energy for IAQ fuzzy controller. The total required energy (E_{TOTAL}) is expressed by Eq. (3.12).

$$E_{TOTAL} = E_1 + E_2 + E_3 \tag{3.12}$$

The total required energy is fed to the coordinator to control heating/cooling, lighting, and ventilation system. The energy is supplied through the available energy sources available in the building.

Table 3.1: Fuzzy logic controller's rules.

Temperature rule base	Illumination rule base	IAQ rule base
If (E_T = = NB) then (E_1 = NB)	If (E_L = = HS) then (E_2 = HS)	If (E_A = = LOW) then (E_3 = LOW)
If (E_T = = NM) then (E_1 = NM)	If (E_L = = MS) then (E_2 = MS)	If (E_A = = OK) then (E_3 = OK)
If (E_T = = NS) then (E_1 = NS)	If (E_L = = BS) then (E_2 = BS)	If (E_A = = SH) then (E_3 = SH)
If (E_T = = ZE) then (E_1 = ZE)	If (E_L = = OK) then (E_2 = OK)	If (E_A = = LH) then (E_3 = LH)
If (E_T = = PS) then (E_1 = PS)	If (E_L = = SH) then (E_2 = SH)	If (E_A = = HIGH) then (E_3 = HIGH)
If (E_T = = PM) then (E_1 = PM)	If (E_L = = H) then (E_2 = H)	
If (E_T = = PB) then (E_1 = PB)		

3.4 SIMULATION RESULTS AND DISCUSSION

The experimental setup was carried out on Intel(R) Core (TM) i7-8550 CPU with 1.80 GHz 1.99GHz processing speed. FORTRAN90 compiler and MATLAB 2019a have been used to implement the proposed solution for high performance building energy and comfort management.

3.4.1 CSPSO Technique Parameter Setting

To set the best value of different parameters in CSPSO technique, 30 independent trials were conducted. The acceleration constants C_1 and C_2 are varied from 0.5 to 0.30, taking a step size of 0.05. The weight of inertia (W) is also varied with respect to each iteration from W_{max} to W_{min} linearly. W_{max} is varied between 1.5 and 1.0, and W_{min} is varied between 1.0 and 0.5 in a standard manner. P_v is varied between 0.2 and 0.8, and the best value is set after several executions. A simulation study has been performed to determine the optimum population size, and it has been found that the swarm size of 100 is adequate to achieve the best global solution. Due to the higher time of simulation, the larger size of the population is not preferred. The best parameter is set after the number of trails with the various value of parameters. The values for these parameters are given in Table 3.2.

Table 3.2: CSPSO technique parameter setting numerical values.

N	W_{max} and W_{min}	CF_1 and CF_2	CI_1 and CI_2	b	P_v
100	0.9 and 0.4	1.5 and 2.5	1.5 and 2.5	0.001	0.8

3.4.2 Environmental Parameters Optimization

The maximum and minimum limits are pre-defined in the optimization algorithm to get optimal environmental parameter value for the user. These values are adjusted between the user maximum and minimum limit, as given in Table 3.3. The primary aim of the CSPSO is to reduce the computed separation value between the user setpoint and the environmental parameters.

Table 3.3: Parameters taken into account in experiments with their limits.

Environmental parameter	Unit	User minimum limit	User maximum limit	User set point	Environment minimum limit	Environment maximum limit
Temperature	^0C	22	26	24	25	35
Illumination	lux	400	600	500	50	559
IAQ (CO_2)	ppm	300	500	400	480	947

3.4.3 Temperature Control System

The temperature has been controlled by utilizing the fuzzy temperature controller, which computed the required energy according to the difference in the CSPSO optimized temperature value and actual environmental temperature. Comparing the optimized temperature value and the actual temperature for 24 hrs is shown in Fig. 3.5.

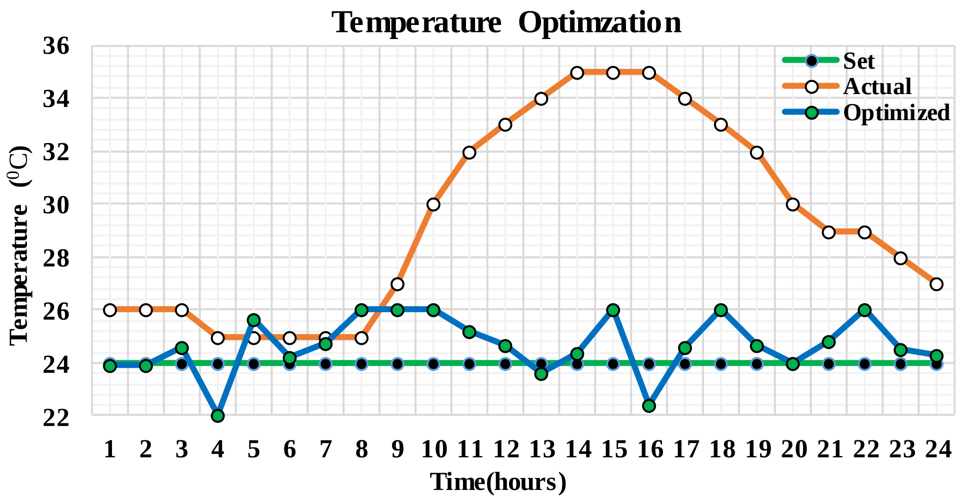

Fig. 3.5: Optimization of environmental temperature.

From Fig. 3.5, it has been clear that the optimized temperature is much closer to the user set preferences. The CSPSO successfully optimized the environmental temperature as per the user set limit. Accordingly, the computed energy from fuzzy temperature controller through optimized temperature and actual environmental value for 24 hrs has been shown in Fig. 3.6. The energy will maintain thermal comfort by operating the heating and cooling system. The utilization of CSPSO optimization technique successfully minimized the energy consumption corresponding to optimized temperature.

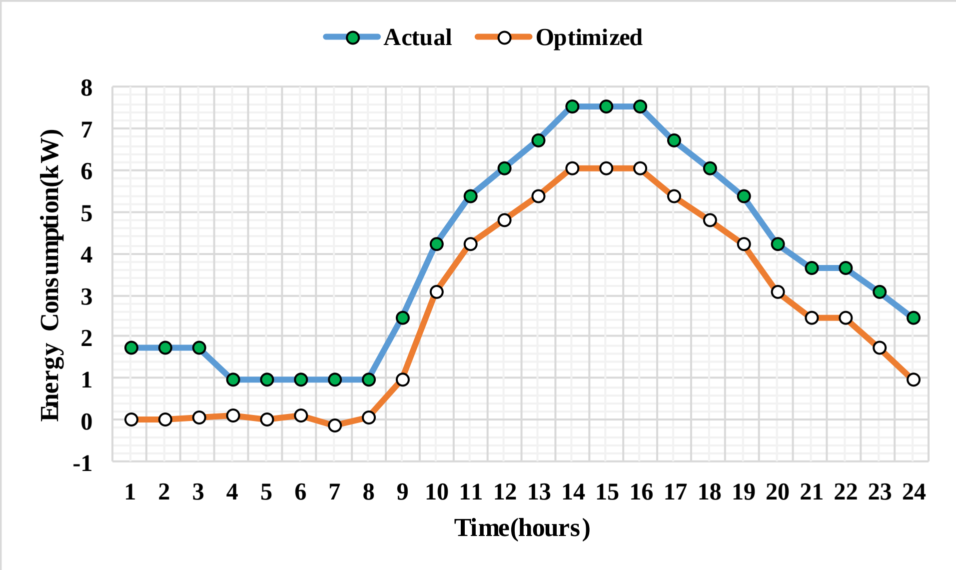

Fig. 3.6: Optimization of energy consumption corresponding thermal comfort.

The 24 hrs energy consumed in maintaining thermal comfort without and with optimization is 92.18 kWhr and 62.18 kWhr.

3.4.4 Illumination Control System

The lighting control system is an advanced network-based electric lighting solution that integrates communication between different system inputs and outputs related to lighting control by using one or more central computers. Lighting control systems are commonly used for indoor and outdoor lighting in commercial, industrial and residential areas. Lighting control systems are used to provide the amount of light wherever and when it is needed. The illumination control system also does the same work as the temperature control system. In the illumination control system illumination fuzzy controller computed the required energy for visual comfort. The data has been considered for 24 hrs. Several fluctuations can be observed from Fig. 3.7, but the overall CSPSO successfully optimized the environmental illumination data. The optimized values are very much closer to the user set preferences.

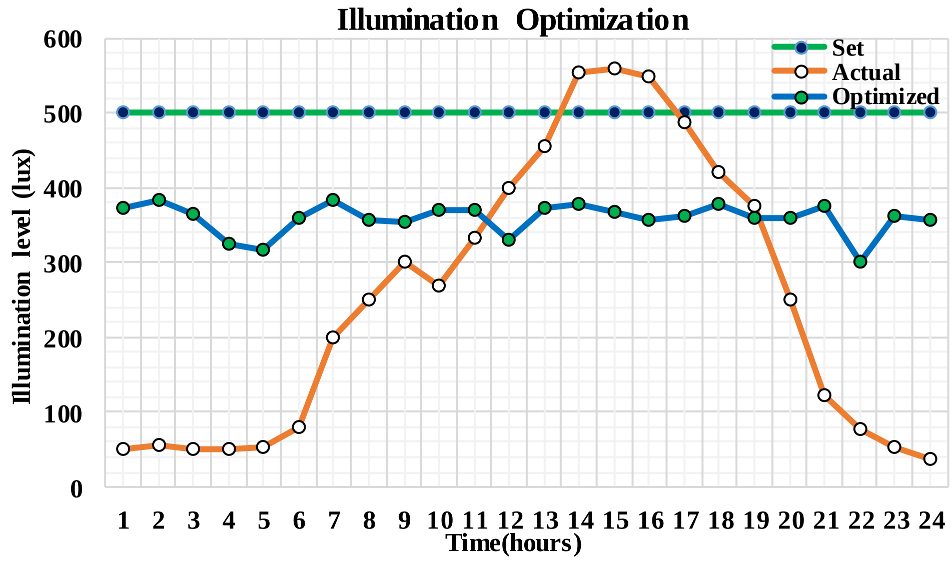

Fig. 3.7: Optimization of environmental illumination level.

The energy corresponding to the optimized and actual environmental illumination data has been plotted in Fig. 3.8. In the lighting system, the 24 hrs energy consumption without and with optimization is 142.807 kWhr and 104.863 kWhr.

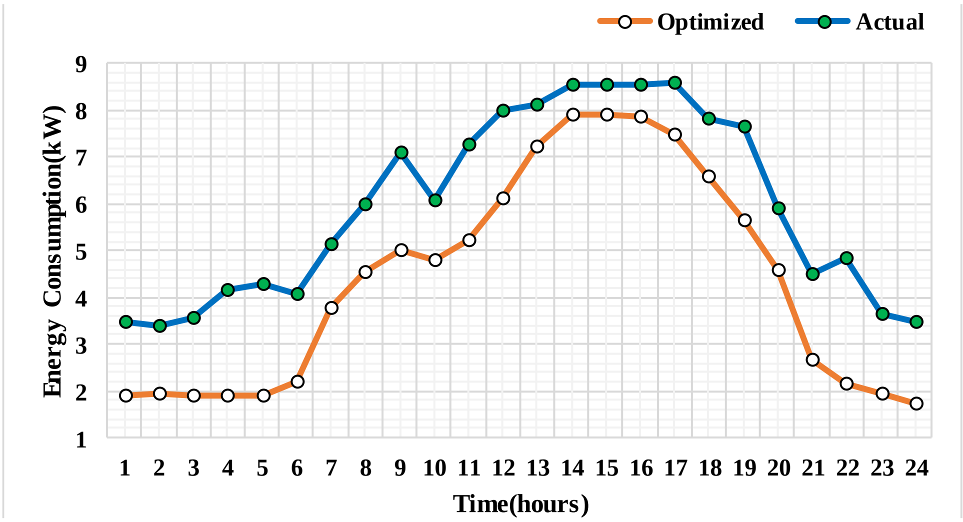

Fig. 3.8: Optimization of energy consumption corresponding visual comfort.

It has been clear from Fig. 3.8 that the implemented technique successfully optimized computed energy from the controller for visual comfort. The blue line with green dot shows the actual values which have been optimized with proposed CSPSO technique. The orange line with white dots shows the optimized values. The CSPSO optimization technique successfully optimizes the energy consumption corresponding to the visual comfort. The electrical lighting system consumes the energy to maintain visual comfort.

3.4.5 IAQ Control System

The IAQ control system is also similar to the temperature and illumination control system. In this control system, environmental CO_2 (ppm) is taken as input to the CSPSO optimization technique and optimized results shown in Fig. 3.9. On the other hand, the optimized CO_2 concentration fed to the fuzzy IAQ controller, which computed the required energy to maintain IAQ comfort. The 24 hrs actual and optimized energy has been shown in Fig. 3.10. The comfort corresponding to the IAQ is successfully improved by optimizing the indoor CO_2 concentration.

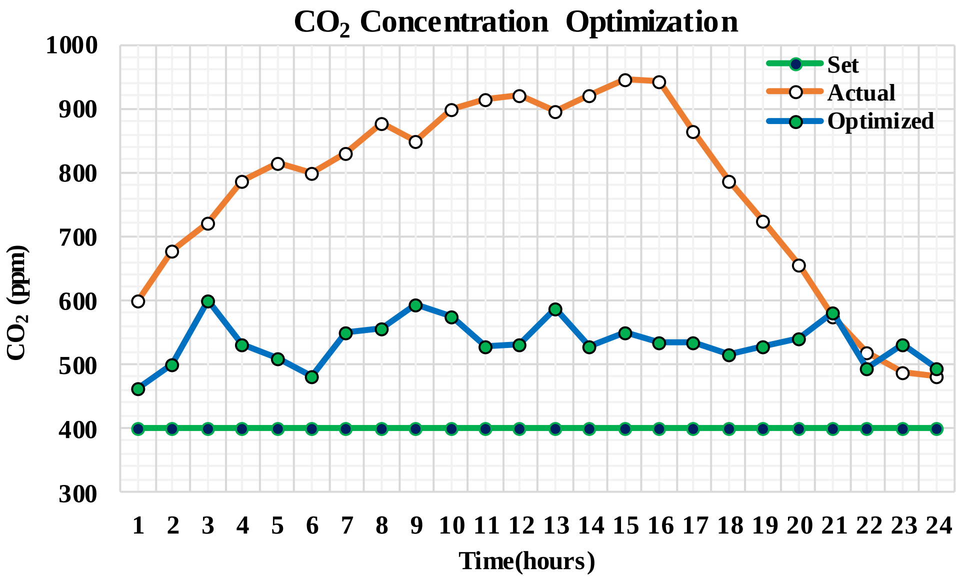

Fig. 3.9: Optimization of environmental CO_2 concentration.

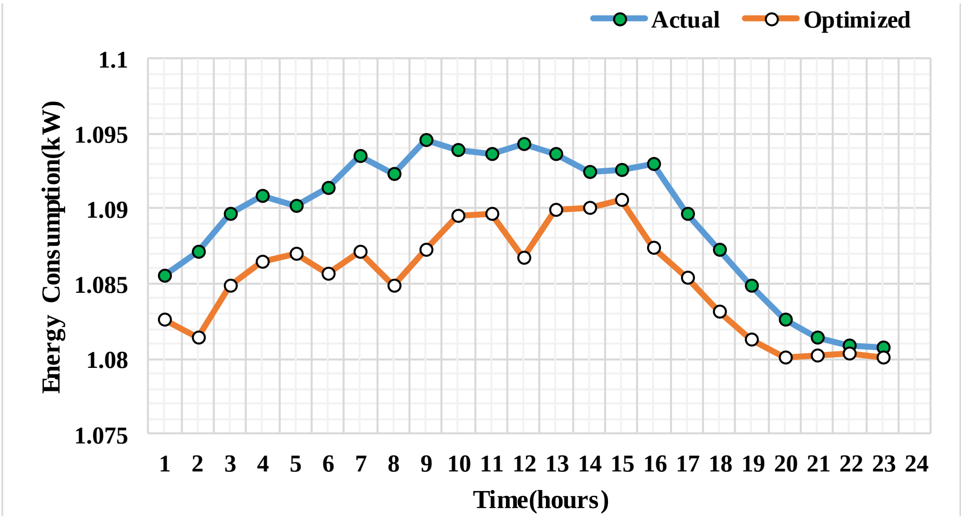

Fig. 3.10: Optimization of energy consumption corresponding IAQ comfort.

To maintain the IAQ comfort for 24 hrs, the required energy computed without and with optimization is found to be 26.13 kWhr and 23.04 kWhr.

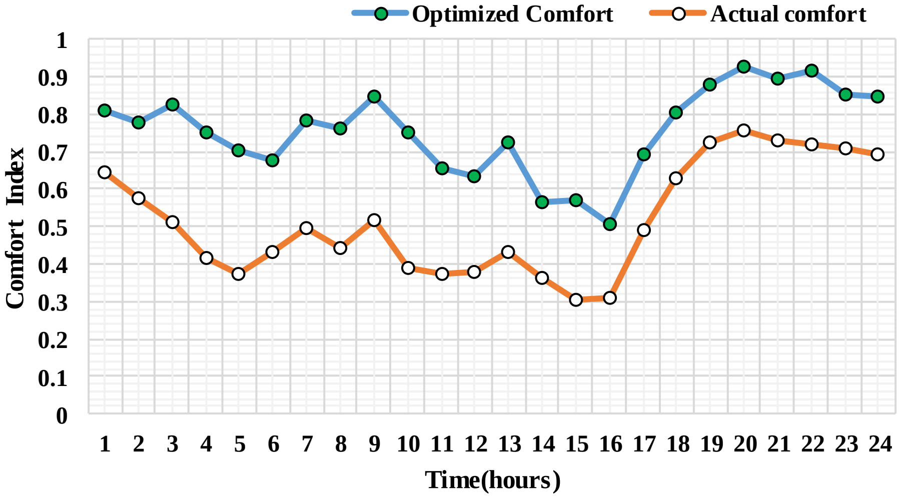

Fig. 3.11: Overall comfort index with and without optimization.

The proposed solution CSPSO optimization technique successfully maximized the overall comfort, as shown in Fig. 3.11. For the 24 hrs, the overall comfort without optimization was 0.5169 (average value). It has maximized using CSPSO optimized environmental parameters and found to be 0.7568 (average value), *i.e.* closer to 1.

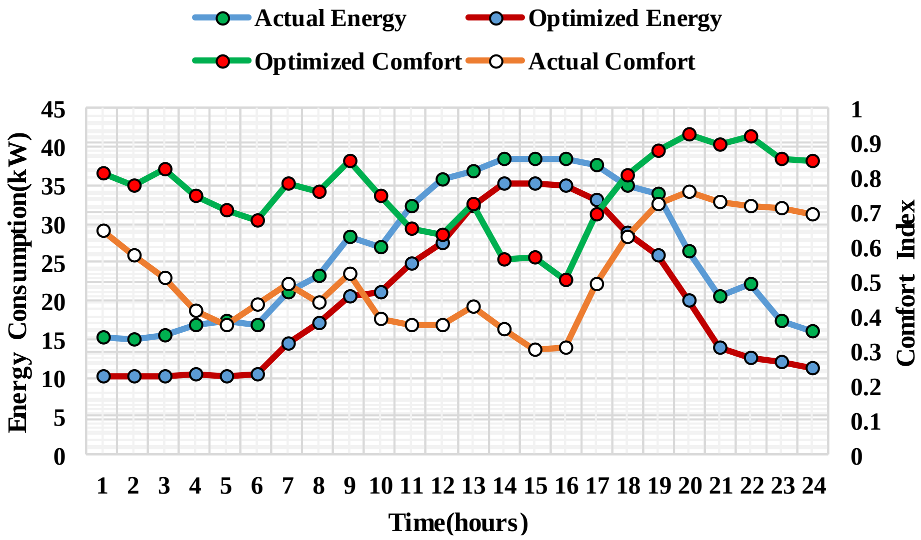

Fig. 3.12: Optimization of energy consumption corresponding overall comfort index.

The overall energy consumption in maintaining all three comfort (thermal, visual, IAQ) has been shown in Fig. 3.12. The red line indicates the optimized energy consumption after applying CSPSO technique. Similarly, the green line indicates the optimized comfort index. The overall comfort index with CSPSO optimization is 0.75685. The orange color line shows the actual comfort before applying the optimization process.

3.6 STATISTICAL ANALYSIS

Table 3.4 presents the statistical analysis of the proposed solution methodology for minimizing energy consumption and maximizing the comfort index value. Figs. 3.5, 3.6, 3.7, 3.8, 3.9, 3.10, 3.11 and 3.12 clearly shows the experimental data that have been used for statistical analysis.

Table 3.4: Statistical analysis of proposed solution methodology.

Temperature Controller				**Illumination Controller**				**IAQ Controller**			
Energy (kWhr)		**Thermal comfort**		**Energy (kWhr)**		**Visual Comfort**		**Energy (kWhr)**		**IAQ Comfort**	
Actual	**CSPSO**	Actual	**CSPSO**	Actual	**CSPSO**	Actual	**CSPSO**	Actual	**CSPSO**	**Actual**	**CSPSO**
1.7564	**1.33E-15**	0.9930	**0.992683**	3.4850	**1.889817**	0.1900	**0.583008**	1.083226	**1.081739**	0.75	**0.348451**
1.7564	**1.33E-15**	0.9930	**0.992228**	3.4048	**1.946812**	0.2079	**0.56646**	1.085558	**1.082666**	0.520444	**0.322594**
1.7564	**0.036507**	0.9930	**0.996631**	3.5687	**1.889817**	0.1900	**0.600096**	1.087132	**1.081421**	0.351975	**0.375149**
0.9561	**0.098540**	0.9982	**0.984375**	4.1518	**1.889817**	0.1900	**0.698428**	1.089689	**1.084891**	0.0591	**0.528794**
0.9561	**-0.0100**	0.9982	**0.999301**	4.2953	**1.912341**	0.1971	**0.717994**	1.090809	**1.086516**	0.07641	**0.559366**
0.9561	**0.117401**	0.9982	**0.998974**	4.0820	**2.202673**	0.2944	**0.689342**	1.090185	**1.087038**	0	**0.514598**
0.9561	**-0.11090**	0.9982	**0.99991**	5.1234	**3.774444**	0.6400	**0.86638**	1.091452	**1.085679**	0.15563	**0.791219**
0.9561	**0.058230**	0.9982	**0.998264**	5.9711	**4.551707**	0.7500	**0.955003**	1.093544	**1.087116**	0.42206	**0.929693**
2.4534	**0.956139**	0.9843	**0.998264**	7.0930	**5.013313**	0.8400	**0.98811**	1.092324	**1.084901**	0.26563	**0.981422**
4.2419	**3.083141**	0.9375	**0.972222**	6.0865	**4.779641**	0.7884	**0.95953**	1.094548	**1.087239**	0.55626	**0.936766**
5.4019	**4.241946**	0.8888	**0.91885**	7.2754	**5.226527**	0.8884	**0.994155**	1.093952	**1.089566**	0.65123	**0.990867**
6.0333	**4.812105**	0.8593	**0.879227**	8.004	**6.09868**	0.9600	**0.980267**	1.093684	**1.089679**	0.69	**0.969166**
6.7330	**5.401991**	0.8263	**0.813484**	8.1119	**7.220662**	0.9926	**0.972077**	1.094362	**1.086665**	0.53141	**0.95637**
7.5375	**6.033337**	0.7899	**0.804629**	8.5651	**7.898475**	0.9879	**0.87516**	1.093637	**1.08988**	0.69651	**0.804937**
7.5375	**6.033337**	0.7899	**0.859375**	8.5645	**7.924371**	0.9860	**0.854645**	1.092456	**1.090019**	0.87006	**0.772883**
7.5375	**6.033337**	0.7899	**0.723438**	8.5644	**7.854766**	0.9907	**0.852677**	1.092589	**1.09059**	0.8496	**0.769808**
6.7330	**5.401991**	0.8263	**0.846899**	8.5666	**7.494393**	0.9994	**0.935914**	1.092992	**1.08741**	0.35141	**0.899865**
6.0333	**4.812105**	0.8593	**0.914931**	7.8202	**6.577026**	0.9756	**0.99283**	1.089689	**1.085452**	0.0591	**0.988798**
5.4019	**4.241980**	0.8888	**0.906798**	7.6698	**5.654355**	0.9394	**0.998938**	1.087243	**1.083152**	0.339844	**0.998341**
4.2419	**3.083141**	0.9375	**0.937578**	5.9114	**4.565912**	0.7519	**0.952598**	1.084912	**1.081311**	0.587194	**0.925934**
3.6720	**2.453494**	0.9565	**0.96962**	4.4987	**2.680489**	0.4284	**0.742471**	1.08257	**1.080033**	0.810775	**0.59761**
3.6720	**2.453494**	0.9565	**0.984375**	4.8431	**2.172624**	0.2842	**0.801084**	1.081379	**1.08016**	0.91	**0.689194**
3.0831	**1.756481**	0.9722	**0.979165**	3.6589	**1.935109**	0.2043	**0.618077**	1.080846	**1.080279**	0.9516	**0.403246**
2.4534	**0.956139**	0.9843	**0.987001**	3.4910	**1.709323**	0.1388	**0.584222**	1.080714	**1.080077**	0.96	**0.350347**
Total Energy Consumption				625.372 kWhr (Actual)			**483.110 kWhr (CSPSO)**				
Overall Average Comfort Index Value				0.51692 (Actual)			**0.75685 (CSPSO)**				
Energy Savings in 24 hrs (1 DAY)				**142.262 kWhr (22.74%)**							

Table 3.4 verifies that the CSPSO optimization technique successfully maximized the comfort index value with minimum energy consumption. The analysis is based on the actual and CSPSO optimized data. It can be seen from the analysis that the proposed solution methodology minimum energy consumption and maximum comfort index value achieved by using CSPSO optimization technique. The total energy consumption (483.110 kWhr) with maximum comfort index (0.75685) is achieved.

3.7 CONCLUSIONS

The work addressed in this chapter provide the solution to solve the conflict between user comfort and energy consumption. The conflict of the high level of comfort in minimum energy consumption for high-performance buildings is successfully solved using CSPSO optimization technique and the fuzzy-based controller. The comfort is calculated using the mathematical comfort index formula through environmental parameters. The required energy to maintain comfort is calculated using three FLCs that provide energy to the actuator for operation. The total energy consumption without optimization technique found 625.372 kWhr and with CSPSO optimization technique 483.110 kWhr. Therefore, with CSPSO optimization technique, the energy savings of 22.74% with maximum comfort index value 0.75685 is achieved. Thus, the presented solution methodology is used to investigate and inspire more electricity conscious user activities and come up with evidence for projected energy savings in the present energy scenario.

CHAPTER 4

AI BASED BUILDING MANAGEMENT AND INFORMATION SYSTEM ON MULTI-AGENT TOPOLOGY

4.1 INTRODUCTION

Buildings generally consume about 32% of total electrical energy and are accountable for around 30% of the global CO_2 emissions **(Pinzon et al., 2019)**. This fact has contributed to building energy management and information systems to minimize energy consumption and maximize comfort. Energy consumption and the indoor environment are two fundamental yet conflicting building design goals. Because of the number of parameters and strategies concern, finding a design that takes exclusive benefit of a scenario while meeting both of these goals is a challenge even for researchers. The projected inflation of electricity prices over the next few years is expected to be one of the significant challenges facing energy regulators and residents worldwide **(Tushar et al., 2019)**. The residential sector accounted for about one-third of the total electrical energy consumption and expected to rise further. All this is attributed to the occupants who spend most of their time in the buildings. They require an improved environment for their comfort.

Consequently, maintaining a high level of indoor comfort requires a large amount of energy. Three parameters determine this indoor comfort: thermal comfort, visual comfort, and IAQ. The thermal comfort represented by temperature and relative humidity, the level of illumination indicates visual comfort, and IAQ comfort exhibited in terms of CO, CO_2, VOC, formaldehyde, Ozone (O_3) levels **(Verma et al., 2019)**. But, only the effect of CO_2 can be taken into consideration in modeling, as CO_2 is the primary pollutant source that affects IAQ in residential buildings. On the other hand, the thermal comfort calculation depends on the PMV. The PMV calculation depends on the ISO 7730 and ASHRAE 55-2013 standards. The question array-based calculation depends on human thinking and indoor temperature, relative humidity, clothing condition, metabolic rate, *etc*. **(Luo et al., 2019)**. The business as usual scenario reported that energy consumption in India is estimated to increase by two times by 2028 and six times by 2047, of which more than 65% will be consumed by cooling systems alone **(TERI, 2019)**. This increase in power demand requires more fossil fuel, which will increase the CO_2 emission. This situation can be mitigated by using energy-efficient devices in residential buildings.

According to Lawrence Berkeley National Laboratory, the USA, a 30% increase in the efficiency of air conditioners in India will reduce the country's carbon emission by 180 million metric tons per year by 2030. These are mostly used in offices, shopping complexes, and hotels. So, these sectors demand special attention to their improvements. A slight change in the operating temperature of the cooling system can save a lot of energy. However, these actions should be under user preference, as there is a massive change in user predilections. According to the Union Ministry of Power, if all consumers set their air conditioner at 24 ^{0}C than conventional temperature 20 ^{0}C – 21 ^{0}C, around 20 billion units of electricity will be saved yearly **(Bhalla, 2018)**. Moreover, about 338 megatonnes of oil equivalent of energy savings can be made in the upcoming decades and the decrease in emission intensity, as claimed by the Energy Resources and Institute **(TERI, 2019)**.

4.1.1 Earlier Work

Smart building management and information systems include a processor-based control system that can supervise the building's environment. The intelligent control system keeps the comfort parameters within the user-defined range. Its intelligence depends upon how it maintains maximum comfort with the least amount of energy consumption. Since user comfort and energy consumption are conflicting in nature, some optimization techniques must be employed to meet all the requirements. The conclusions drawn from the related literature are presented in this section. **Dounis and Caraiscos (2009)** discussed several classical, predictive, adaptive, and intelligent control strategies for managing comfort and energy consumption. They also proposed a smart coordinator based on the master-slave coordination mechanism. The master agent produces optimal points by evaluating energy efficiency and users' comfort, whereas the slave agent, activated by the master agent, avoids conflicts between the sub-systems. **Sun et al. (2013)** advocated integrated control of the HVAC, lights, and shading blinds to cut energy consumption cost using stochastic dynamic programming, Lagrangian relaxation, and rollout technique for the summer season only. They only considered uniform temperature throughout the building without occupancy detection sensors and humidity constraints. Energy consumption and comfort optimization have been done in several studies until now. These studies have used the ordered weight averaging method with heuristic optimization of setpoints using (PSO), Sliced- PSO, and Weighted-PSO **(Wang et al., 2010; Wang et al., 2011; Wang et al., 2012)**.

Similarly, in another work, **Yang and Wang (2013)** have proposed two optimization techniques based on multi-objective methodology, including multi-objective particle swarm optimization and weighted aggregation for Pareto fronts' production up of Pareto-optimal solutions. Such tradeoff approaches are useful for informed decision-making in dynamic construction settings for power and comfort management. Although they built a significant multi-agent energy building and comfort management system in another study, two case studies were presented.

The first case study reveals how individual agents understand the occupants' desires for thermal comfort and how the central HVAC agent used to make tradeoffs between different users' preferences. Whereas the second case study presented the relationships between several local agents and the central agent and shows how they operate together with enormous energy supply to achieve the occupant's satisfaction **(Yang and Wang, 2012; Yang and Wang, 2013)**. The author **Gupta and Kar (2015)** proposed a distributed consensus algorithm for minimizing energy consumption and discomfort in a building with several occupants with different preferences. They obtained the feedback from occupants through mobile-based applications. **Yu et al. (2018)** minimized the total cost by considering uncertainties in tariff plans, optimum comfortable temperature, and temperature difference using a cost-aware distributed real-time algorithm based on the Lyapunov optimization technique protects users' privacy as well. Moreover, they only considered the thermal comfort and electricity cost due to heating and cooling devices. **Joo et al. (2012)** proposed a method of minimizing energy consumption and maintaining a healthy and comfortable by optimizing the ratio of makeup air to recirculation air. Their research was subjected to CO_2 concentration inside and outside the building and desired summer and winter temperatures in Seoul, Korea.

With the advent of renewable energy sources like solar and wind, the power supply side also includes intermittent renewable energy sources. **Wu et al. (2016)** proposed an Event-Based Optimization (EBO) technique for energy saving using a local-event-based methodology. Unlike other methods, the EBO method responds to some selected events rather than all the events. Insulating the outer walls is an economical way to increase building efficiency by reducing heating or cooling systems' energy consumption. **Simona et al. (2017)** proposed insulating buildings in cold regions and trapping the rooms' heat, thereby dispensing with a heating system. However, the proposed approach is permanent and prevents outside heat from coming inside the rooms during sunshine. **Jacobsz and Gryzagoridis (2017)** used the circulated water as a coolant through the hydronic pipe circuit embedded in the rooms' ceilings. This system is known as a thermally activated building system, reduces temperature fluctuations, and is implemented using a finite difference method. Nonetheless, the availability of water and leakage detection and correction are some of the developed system's shortcomings.

Hu et al. (2014) introduced energy monitoring sensor data in a personal office to build management systems through a pre-installed IT network to improve building efficiency and thermal comfort. However, they considered only thermal comfort and personal computer-printers as power-consuming devices. **Zhu et al. (2015)** proposed a computer-aided system for measuring thermal comfort amidst uncertainty with a PMV using advanced sensors and virtual instrumentation technology. The experimentally obtained PMV values were compared with the ISO:7730 and found that the computer program is correct for the calculation of PMV. **Ku et al. (2015)** proposed an inverted PMV method for determining the desired temperature. ANFIS and PSO algorithms are used to solve this proposed model. The designed system automatically drives the air conditioner at the desired temperature without interfering with its internal devices. Moreover, the results proved that the PSO algorithm is far better than ANFIS. The metabolic rate and clothing level are assumed constant. **Higuera et al. (2014)** proposed a method to manage artificial lighting for visual comfort and the HVAC sub-system for thermal comfort based on wireless sensor and actuator network using the ANN and fuzzy logic algorithm. **Fazelpour and Asnaashari (2015)** improved air conditioner efficiency by using an earth-air heat exchanger as a natural pre-heating-cooling coil for maintaining an appropriate temperature inside the room. Insufficient fresh air supply and poor IAQ are some of the flaws of the developed system. **Beazley et al. (2017)** used building information modeling software for architectural modeling and thermal analysis of buildings that led to better building design and improved energy efficiency. However, BIM software is neither compatible with energy simulation tools nor with Industry Foundation Class (IFC) files. **Jiang et al. (2017)** proposed a decentralized and flat-structured building automation method in which each zone- controlled independently. They used parallel computing of nodes, which is time-consuming. The simulation results of Demand-Controlled Passive Ventilation (DCPV) and passive stack ventilation system through EnergyPlus building simulation software. It was proved that DCPV is a better option for maintaining IAQ and reducing energy consumption without using separate air handling units **(Southall, 2018)**. **Priyadarshana et al. (2017)** integrated various systems such as air conditioning, lighting, ventilation, and security system through a multi-agent system built on the IoT platform using Node-MCU and ESP-8266 modules. A ZigBee could be employed to reduce the project cost. The optimization of comfort has not been done. **Han and Lim (2010)** proposed an intelligent building network using ZigBee to control and manage devices and energy, respectively. They used CC2430, a system-on-chip solution, to cut down the cost of building smart nodes with light, temperature, and humidity sensors. **Ali et al. (2017)** devised a system for energy management of homes using IoT and big data approach. They used IoT based on message queuing telemetry transport for data acquisition and big data for collecting information from all areas. The business intelligence technique is used for data analysis, and a user-friendly interface is developed on mobile for monitoring and controlling. **Altayeva et al. (2017)** proposed a system with the utility grid, microgrid, and multi-agents. They used three types of data for comfort and energy management, namely sensor data, user preferences, and energy data, whereas policies used for decision making. A multi-objective genetic algorithm used for optimization. **Zhao et al. (2013)** proposed a cyber-enabled energy management system for minimizing the energy consumption of buildings. They used the EnergyPlus simulation software for carrying out simulations. However, the proposed system neither includes a hardware portion nor controller design. **Wang et al. (2011)** proposed a multi-agent framework for energy and comfort optimization in which the information fusion process used by the aggregation operator Ordered Weighted Averaging (OWA). They used S-PSO and W-PSO, respectively, to change the setpoints and OWA weights. Similarly, in another work, they developed a hierarchical multi-agent system with PSO as an optimization strategy for a microgrid with distributed renewable energy resources. Moreover, customer's preferences are input through a Graphical User Interface System (GUI) **(Wang et al., 2012)**. **Shaikh et al. (2018)** used a Fuzzy Inference System (FIS) to derive empirical relationships for power consumed by thermal, humidity, illumination, and air quality actuators. FIS takes error between real value and set value as input and gives the necessary power to maintain high comfort as output. Moreover, membership functions have been used to accredit the FIS. **Fayaz and Kim (2018)** used a bat algorithm to maximize the comfort level and minimize energy consumption. They also showed that the Bat algorithm is superior to a genetic algorithm and particle swarm optimization. Fuzzy based controllers were used for controlling the actuators. **Coleman and Li (1996)** proposed a methodology based on trust-region to optimize nonlinear function with constraint and boundary conditions. Their proposed method requires solving a quadratic sub-problem with ellipsoidal constraints rather than an inequality constraint. It forms the basis of many modern-day optimization techniques. **Gordon and Tibshirani (2012)** applied Karush-Kuhn-Tucker (KKT) equations for optimizing nonlinear function subjected to both equality and inequality constraints. The KKT equations provide necessary conditions for determining whether a solution obtained is optimal or not.

4.1.2 Main Contribution

It has been discovered from the literature study that optimizing comfort parameters not only breaks the monotony in the environment but also can save a significant amount of energy. Besides this, it will also be conducive to the environment. This study focuses on resolving the conflict between comfort level and energy consumption. A building management and information system based on a multi-agent topology control design is proposed to fulfil the objective. The agents have been classified hierarchically according to their utilities. The primary contribution was to apply two optimization methods. To our best knowledge, the used optimization methods have not yet been considered in the presented models in the proposed study. In the first case of optimization, a constrained nonlinear optimization algorithm is applied to optimize the environment parameters (T_s, L_s, and A_s). In the second optimization, ANN is used to obtain a set of optimized solutions. These solutions comprise temperature, illumination level, and CO_2 concentration for maximum thermal, visual, and air quality comfort, respectively, and minimize energy consumption. A thorough literature survey of recently used optimization techniques for managing energy consumption and comfort with comfort type in the type of buildings is presented in Table 4.1.

4.2 PROBLEM FORMULATION

The mathematical formulation of the proposed multi-agent system has been achieved by developing a nonlinear, multi-variable function of the sum of weighted squared errors as Eq. (4.1) and subject to a constraint Eq. (4.2).

Objective function

$$\delta_1(T_s - T)^2 + \delta_2(L_s - L)^2 + \delta_3(A_s - A)^2 \tag{4.1}$$

Subject to Constraints

$$\left(T_S - T\right)^2 + \left(L_S - L\right)^2 + \left(A_S - A\right)^2 \le \left(T_S - T_{Set}\right)^2 + \left(L_S - L_{Set}\right)^2 + \left(A_S - A_{Set}\right)^2 \tag{4.2}$$

where δ_1, δ_2 and δ_3 are weights in the range (0, 1). The T_s, L_s, and A_s are the environment temperature, illumination, and CO_2 concentration, respectively, as measured by the respective local agents' sensors. T, L, and A are the variables representing temperature, illumination level, and CO_2 concentration, respectively, for which Eq. (4.1) attains the minimum value. These are thus optimum set values for which comfort level is maximized, and the energy consumption is minimized. The objective function in Eq. (4.1) will be minimized using a constrained nonlinear optimization algorithm based on the trust-region approach and KKT conditions. The KKT equations provide necessary conditions for finding an optimal solution of a constrained nonlinear function. Therefore, optimal values or tuned values of temperature, illumination level, and concentration of CO_2 are obtained. The difference between the actual environment values (T_s, L_s, A_s) and set values (T_{set}, L_{set}, A_{set}) is used to calculate the actuator's power to maintain the set values. The power consumption is correlated with this difference.

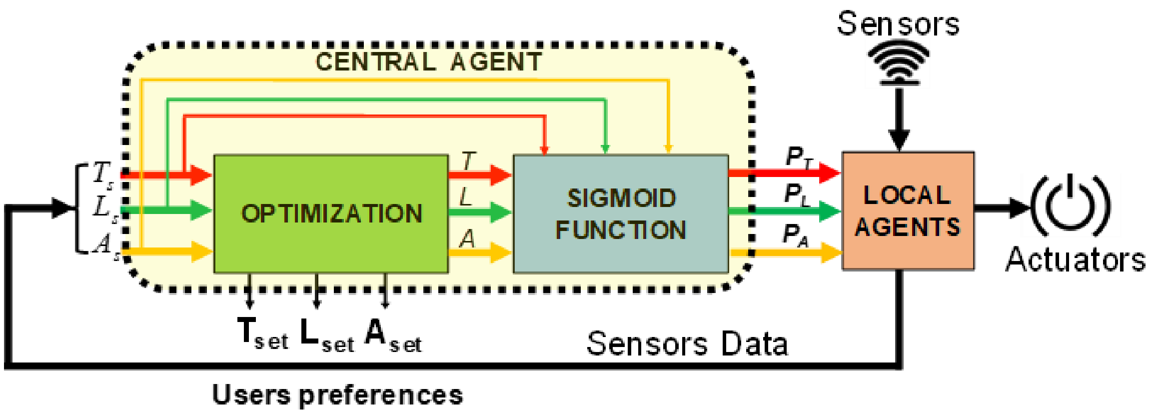

Fig. 4.1: Central agent configuration.

The more the difference value, the more will be the power consumption **(Fayaz and Kim, 2018)**. Therefore, the sigmoid function is used to establish a relation between the difference and power consumption. The difference is pre-processed before sending it to the sigmoid function. Here, the pre-processed means that before sending the data to the sigmoid function, the values have been optimized, or we can say that the error has been minimized with the help of optimization. The outputs are the required powers (P_T, P_L, P_A) in the normalized form, which the local agents interpret to operate the actuators accordingly. The power allocated by the local agents to their respective actuator is directly proportional to these values. A detailed configuration of the central agent with local agents has been shown in Fig. 4.1.

Measuring comfort is another essential aspect of the proposed system. The mathematical function of overall comfort generally depends on three environmental parameters: temperature, illumination level, and concentration of CO_2. The difference between the actual environment values obtained from sensors and set values used to measure the overall comfort level in terms of numerical values **(Zhao et al., 2013)** if this difference increases, comfort level decreases, and vice versa. In general, while dealing with each comfort parameter in a single function, the weighting factor needs to be added and mathematically written as Eq. (4.3) **(Shaikh et al., 2018)**.

Overall Comfort

$$\sum_{j=1}^{3} W_j * \text{Comfort} \tag{4.3}$$

An expanded mathematical form for an overall comfort expressed as Eq. (4.4):

$$W_1 e^{\left[-\left\{\frac{T_s - T_{set}}{T_{set}}\right\}^2\right]} + W_2 e^{\left[-\left\{\frac{L_s - L_{set}}{L_{set}}\right\}^2\right]} + W_3 e^{\left[-\left\{\frac{A_s - A_{set}}{A_{set}}\right\}^2\right]} \tag{4.4}$$

where, W_1, W_2, and W_3 weights corresponding to each comfort parameter. These weighting coefficients and the user's environmental set parameters are defined based on the occupant's preferences. These are selected such that they will lie in the range (0, 1) with $W_1+W_2+W_3 = 1$ so that Eq. (4.3) obtains a normalized value in the range (0, 1).

4.3 PROPOSED METHODOLOGY

4.3.1 System Architecture

The building management and information system based on multi-agent topology have been proposed, comprising local agents, a central agent, and a GUI. In Fig. 4.2, the proposed architecture of AI-based building management and information system has been demonstrated. The system architecture of AI-based building management and information system has been demonstrated. Three main factors affect the user comfort **(Wang et al., 2010)**, which are temperature (°C) representing the thermal comfort; illumination level (lux), meaning the visual comfort and CO_2 concentration (ppm) representing the air quality **(Sun et al., 2013)**.

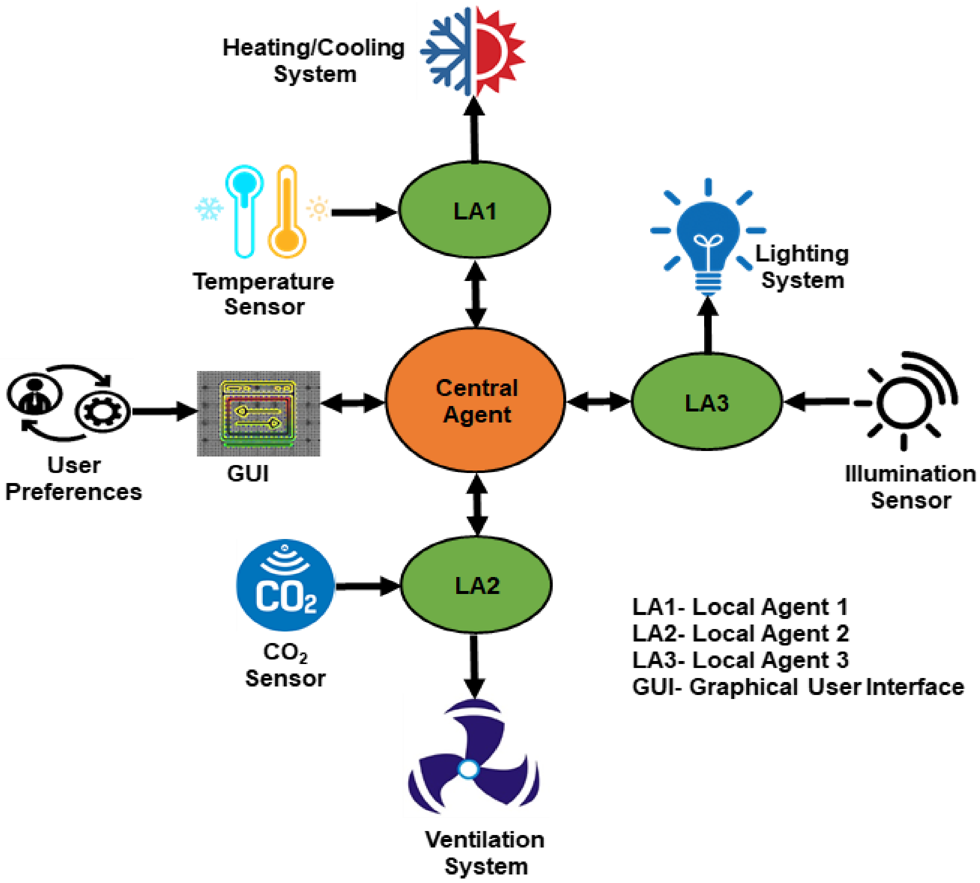

Fig. 4.2: The architecture of the proposed multi-agent system topology.

The dedicated local agents have been used to maintain each comfort parameter. They collect outside environment data via sensors, and the respective actuators have attached to them. The temperature sensor can be used to sense the outside and inside temperature. To maintain the desired temperature, an auxiliary heating and cooling system can be utilized. Similarly, the illumination sensor and CO_2 sensor can measure the outside and inside illumination levels and CO_2 concentrations. The lighting system is used to maintain the desired illumination level, and the ventilation is used to keep the IAQ. The central agent coordinates all the local agents and assimilates the user's preferences. It collects sensor data from the local agents and user's preferences through the GUI for optimizing the set points for maximum comfort and minimum energy consumption. Improving the building's energy efficiency begins with information and insight into the involved processes **(Palensky and Dietrich, 2011)**.

Table 4.1: Classification of an earlier work in optimization techniques, kind of management, and comfort parameters for building management and information system.

Ref.	Optimization Techniques	Management Type	Comfort Type	Building Type
Wang, et al., 2010	PSO	Energy management, Comfort management	Thermal, Visual, IAQ	Residential building
Wang et al., 2011	OWA method with heuristic optimization using PSO	Energy management, Comfort management	Thermal, Visual, IAQ	Residential building (a home)
Wang et al., 2012	Information fusion based OWA method-PSO	Energy management, Comfort management	Thermal, Visual, IAQ	Residential building
Wang et al., 2012	PSO	Energy management, Comfort management	Thermal, visual, IAQ	Residential building
Yang et al., 2012	WA and MOPSO	Energy management, Comfort management	Thermal, Visual, IAQ	Residential building
Sun et al., 2013	Combining Lagrangian relaxation, stochastic dynamic programming, and rollout technique within the surrogate optimization framework	Energy management, Comfort management	Thermal, Visual, IAQ	Six-floor building with 144 rooms
Yang et al., 2013	MOPSO	Energy management, Comfort management	Thermal, Visual, IAQ	Residential building
Gupta et al., 2015	Consensus algorithm with the use of alternating direction method of multipliers	Energy management, Comfort management	Thermal	Residential building
Ku et al., 2015	ANFIS and PSO	Energy management, Comfort management	Thermal	Commercial Building
Wu et al., 2016	Event-based optimization, a gradient-based algorithm	Energy management	-	Residential building (2 room)
Al-Ali et al., 2017	Business Intelligence and Big Data analytics software packages	Energy management, Comfort management	Thermal	Small residential area

Yu et al., 2018	Lyapunov optimization technique and cost-ware distributed real-time algorithm	Energy management, Comfort management	Thermal	Commercial building
Fayaz et al., 2018	Bat algorithm	Energy management, Comfort management	Thermal, visual, IAQ	Residential building
Jin et al., 2019	Integration by parts formula generates energy consumption optimization model	Energy Management, Comfort Management	Thermal	Residential building (a house)

4.3.1.1 Local agent

In the multi-agent system, local agents play an essential role. They function in this multi-agent system as a mediator, data supplier, decision-maker, and executor of control. There are three local agents: local temperature agents, local lighting agents, and local air quality agents corresponding to the thermal, visual, and air quality comforts **(Wang et al., 2011 and Wang et al., 2012)**. The local agents have appropriate sensors attached to them so that the environmental parameters can be measured and transferred to the central agent for further processing. All the local agents also have suitable actuators connected to them to maintain the desired comfort parameter. They receive control signals from the central agent to support a particular set of comfort parameters. Local temperature agent incorporates a temperature sensor for measuring ambient temperature and an auxiliary heating-cooling system for maintaining a specific temperature indoors. It sends the measured ambient temperature to the central agent and receives a control signal from the central agent to set a particular temperature **(Fazelpour and Asnaashari, 2015)**. The local lighting agent measures the indoor illumination level through an illumination sensor and has an electrical lighting system connected to it for maintaining the desired illumination level. It transfers the measured illumination to the central agent and receives a control signal from the central agent to set a specific illumination level **(Higuera et al., 2014)**. Air quality comfort depends upon the concentration of CO_2 **(Joo et al., 2012)**. The local air quality agent measures CO_2 concentration indoors and has a ventilation system to maintain the desired IAQ. It transfers the measured value of CO_2 concentration to the central agent and receives the central agent's control signal to set a specific CO_2 concentration.

4.2.1.2 Central agent

The central agent is situated at the top of the hierarchical pyramid in multi-agent topology-based building management and information system. All types of processing have been reported in **(Wang et al., 2011; Wang et al., 2012)**. It receives data from various sensors through local agents and user's preferences through GUI. The user's preferences are in the form of a set of desired temperature (T_{set}), illumination level (L_{set}), and CO_2 concentration (A_{set}), which gives maximum comfort to the user. It also includes the user's preferred ranges of each comfort parameter, i.e., T_{min}, L_{min}, A_{min} and T_{max}, L_{max}, A_{max} serve as lower and upper bounds, respectively. Its responsibility is to maximize comfort and minimize energy consumption. It does so by minimizing the errors between the sensor values and set values of comfort parameters.

4.4 OPTIMIZATION

4.4.1 Optimization-I

A constrained nonlinear optimization algorithm available as fmincon used to minimize the function given in Eq. (4.1) subjected to nonlinear constraints Eq. (4.2). The constrained nonlinear optimization algorithm is flexible, fast, and easy in implementation compared to other optimization techniques incorporated in literature. The constraint helps in achieving global minima. The desired environment parameters are T_{set} = 24°C, L_{set} = 500 lux, A_{set} = 400 ppm. Whereas the preferred ranges for each parameter, *i.e*., [T_{min}, L_{min}, A_{min}] and [T_{max}, L_{max}, A_{max}] are [22, 400, 300] and [26, 600, 500] respectively. These ranges provide the necessary boundary conditions. The system is designed not to optimize the set values when the actual environment values are equal to desired values.

Moreover, if the indoor illumination level is greater than the desired illumination level, optimization will not occur because of boundary conditions. The subjected constraints help in achieving global minima. All this ensures further energy savings by reducing the error or difference between the actual and environmental parameters. Finally, optimized set values of temperature, illumination level, and concentration of CO_2 are obtained for respective actual environmental conditions. After minimizing the difference between sensor values and set values and obtaining optimized set values, the power consumption is calculated to check the efficiency of the system. The power consumption is directly affected by the actual environment values and set values. The power consumption is determined by using the sigmoid function. The difference between the actual environment parameters and set values is pre-processed. It serves as an input to the sigmoid function, and output is the actuators' power to maintain that set values. Optimization does; reduce the gap between the actual environment parameters and set values, thus reducing power consumption.

4.4.2 Optimization-II

Incorporating AI through deep learning is also an essential aspect of the proposed system. Deep learning is a machine learning branch based on a collection of algorithms that build computational models to represent abstractions of high-level information. Deep learning is a process inspired by the learning procedures of humans and animals **(Praveena et al., 2020)**. Like humans and animals learn from their experiences; similarly, deep learning means making the computer learn from their past experiences. It uses neural networks to make a predictive system based on data given during the neural network training. Using this technology is to do away with the calculations required for optimizing the set values every time external parameter changes. Thus, incorporating artificial intelligence makes the system expeditious.

The ANN usually consists of an input layer, a hidden layer, an output layer, and nodes or neurons. The input data processed through the input layer, and the output data transmitted through the output layer. The number of neurons in the input and output layers is determined by the number of input and output forms. When the NN is used as a classifier, the input and output nodes match the input and output classes. However, when the NN is used as a function approximation, it usually has an input and an output node. However, the number of hidden nodes designed is greater than that of the input nodes **(Issac et al., 2018)**. During training, both the input values and target values are provided to the neural network to enable the network's learning. The network adjusts its weights according to the target value to produce an accurate result even in the absence of target values. ANNs are used most frequently as controllers for many tasks. The key advantages of ANN controllers are rapid signal processing, learning and robustness, generalisation and insensitivity to parameter changes, and improved performance compared to traditional controllers **(Jaladi and Sandhu, 2019)**.

4.4.2.1 Training, testing, and validation

The dataset has been constructed by taking ranges of temperature, illumination level, and the concentration of CO_2 with appropriate step size to train the network. The temperature has been taken in the range of 15 ^{0}C to 50 ^{0}C with unit step size, and illumination level has been made in the range of 50 to 1000 lux with a step size of 50, CO_2 concentration is taken in the range of 300 to 1000 ppm with a step size of 50. Finally, a dataset with all the possible combinations of temperature, illumination level, and CO_2 concentration is constructed dataset thus obtained has been a matrix of size 10500×3. For the predefined set values corresponding optimized set, values are calculated in the same manner as explained earlier. Now both input values and target values are available to train the NN model. The number of neurons in the hidden layer is 500, whereas the Bayesian regularization algorithm trains the neural network. The Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that the resulting network has better generalization qualities at the end of the training. Out of the total samples (10500), 80% used for training, 10% used for validation, and 10% for testing. The visualization or partition of sample data has been depicted in Fig. 4.3.

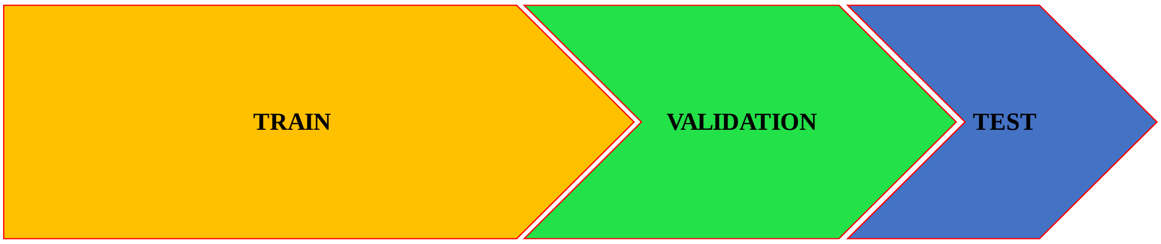

Fig. 4.3: A Visualization of the splits for training, testing and validation

In training the actual dataset, we train the model (weights and biases in the case of a NN). The model sees and learns from the data. In the case of testing, the test dataset sets the global standard used to validate the model. It is only used once the model has been fully trained. The test set is commonly used to compare competing models. The validation set is often used as a test set, but this is not a good practice. In general, the test collection is well selected. It contains carefully sampled data spanning the different groups that the model will face when used in the real world. The validation set is used to validate the model, but it is used for periodic evaluation. As machine learning engineers, we use this data to fine-tune the model hyperparameters. As a result, the model sometimes sees this data, but never "Learn" from it. We use the results of the validation collection and update the higher level hyperparameters. Thus, the validation collection affects the model, but only indirectly. The validation set is also referred to as the “Dev” set or the Production set. This makes sense, as this dataset helps during the "development" process of the model.

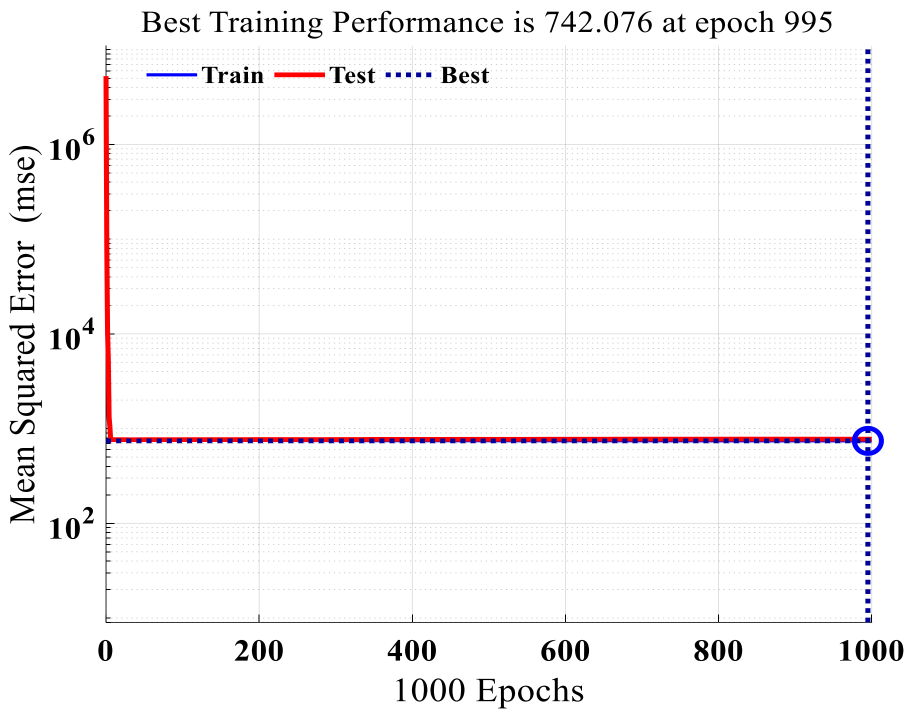

Fig. 4.4: Plot depicting the training performance of the neural network.

To test the developed neural network's performance in predicting the optimized set values, a performance plot has been shown in Fig. 4.4. Best training performance is achieved at the 995th epoch when the value of mean squared error is 742.076.

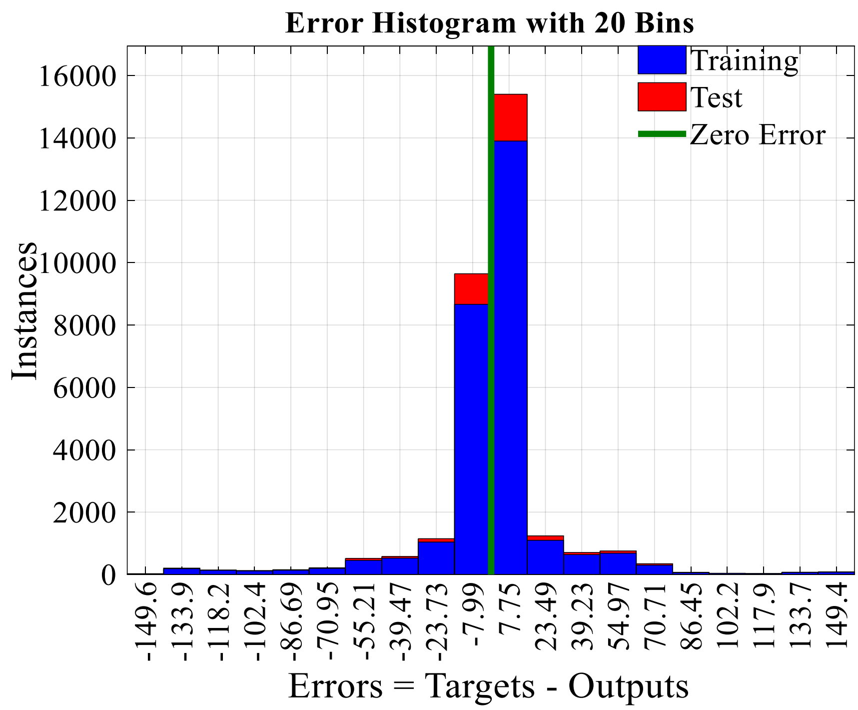

Fig. 4.5: Plot depicting error histogram of the neural network

Due to the converging nature of the curves, it has concurred that the developed network is stable. For further monitoring, the developed neural network's performance, error histogram for training, and testing data plot can be seen in Fig. 4.5. The regression plot is another vital plot to depict how accurate the correlation is between the outputs and targets. The closer the value of regression to 1, the better is the relationship, as shown in Fig. 4.6. From the regression plot, R's obtained value is very close to 1. Thus, it can be concluded that a perfect fit has been obtained. After obtaining the neural network function, it tested to determine the optimized set values corresponding to actual environment values and desired set values.

4.5 RESULTS AND DISCUSSION

The proposed building management and information system based on multi-agent topology are simulated in a MATLAB 2019a environment. Optimized set values, original values, and actual sensor values corresponding to the temperature, illumination level, and concentration of CO_2 for 24 hrs have been given in Figs. 4.7, 4.8, and 4.9, respectively.

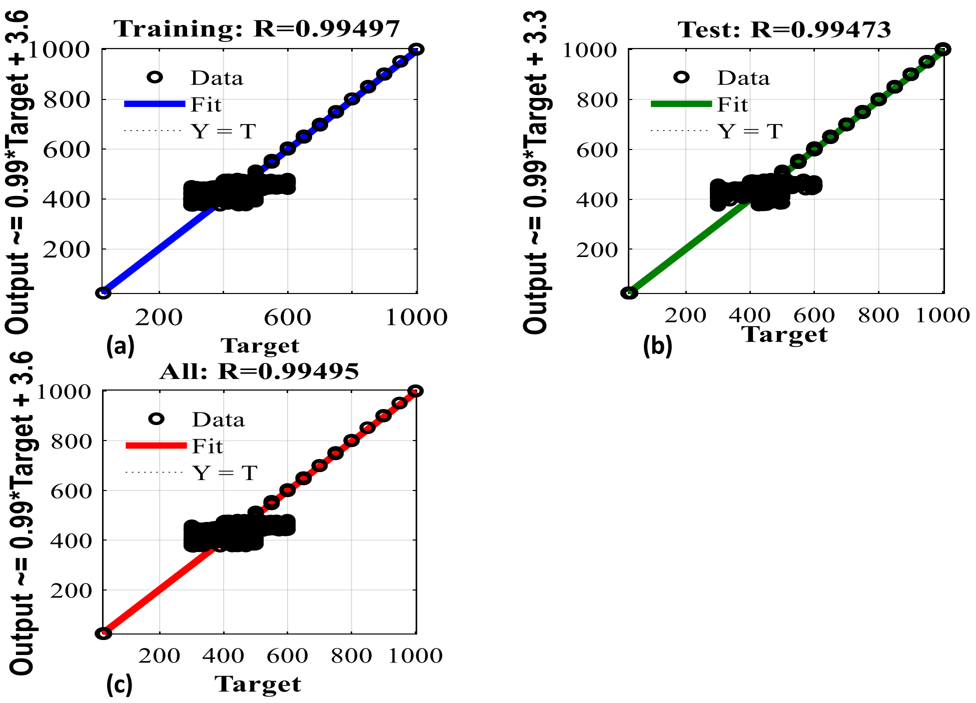

Fig. 4.6: Regression plot between targets and outputs of the neural network.
(a) Training plot between target and output (R=0.99497), (b) Testing plot between target and output (R=0.99473), (c) Training plot between target and output (R=0.99495).

In Fig. 4.7, the red line with sky blue dot and black line with yellow dot shows the actual values for the temperature control system, which are not optimized. Whereas, the red dotted with sky blue and black dotted with yellow shows the optimized values.

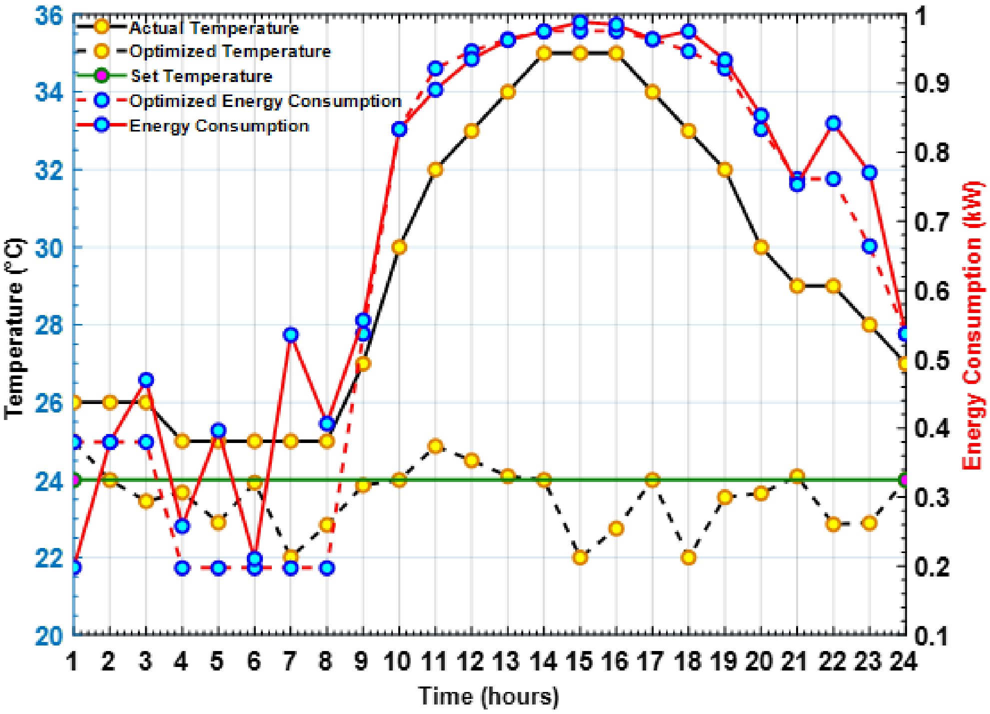

Fig. 4.7: Optimization of actual temperature and energy consumed by the heating-cooling system.

In Fig. 4.8, the red line with sky blue dot and black line with yellow dot shows the illumination system's actual values, which are not optimized. Whereas, the red dotted with sky blue and black dotted with yellow shows the optimized values.

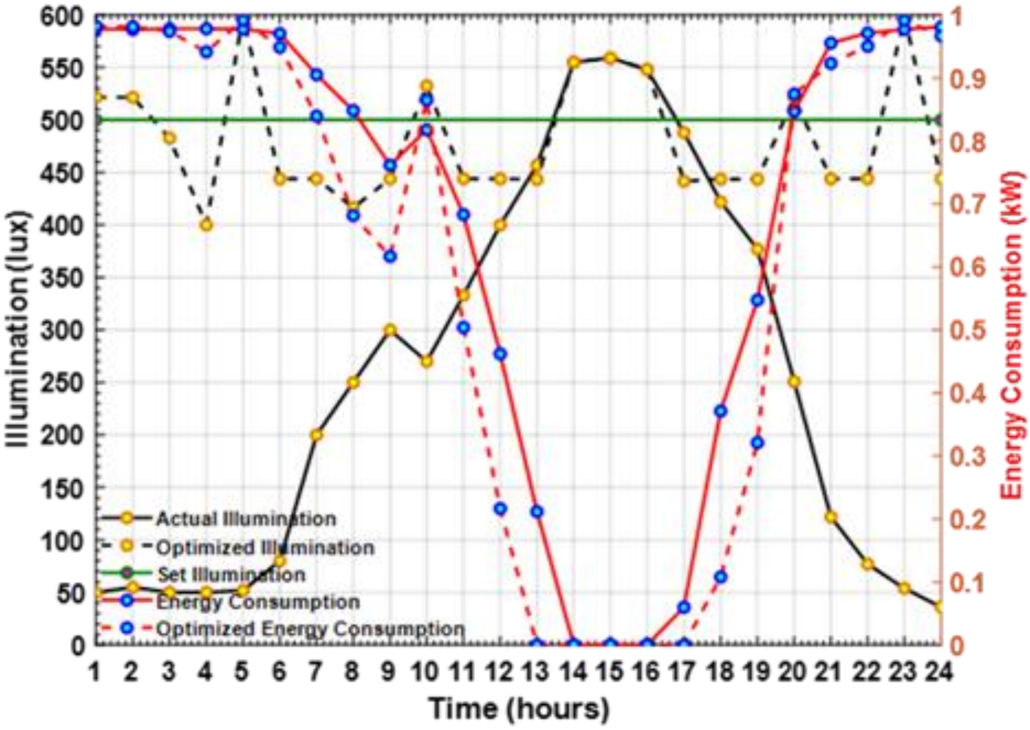

Fig. 4.8 Optimization of actual illumination and energy consumed by the electric lighting system.

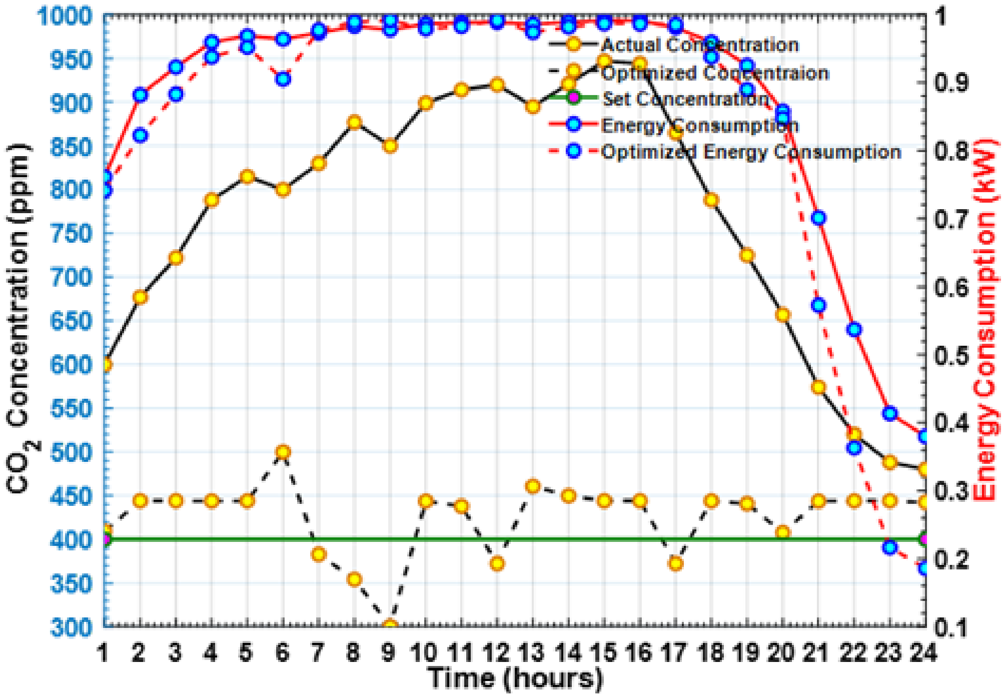

Fig. 4.9: Optimization of actual CO_2 concentration and energy consumed by the ventilation system.

From Fig. 4.10, it is clear that optimizing the set values results in an improved comfort level. Therefore, the comfort level for 24 hrs has been improved by the first optimization.

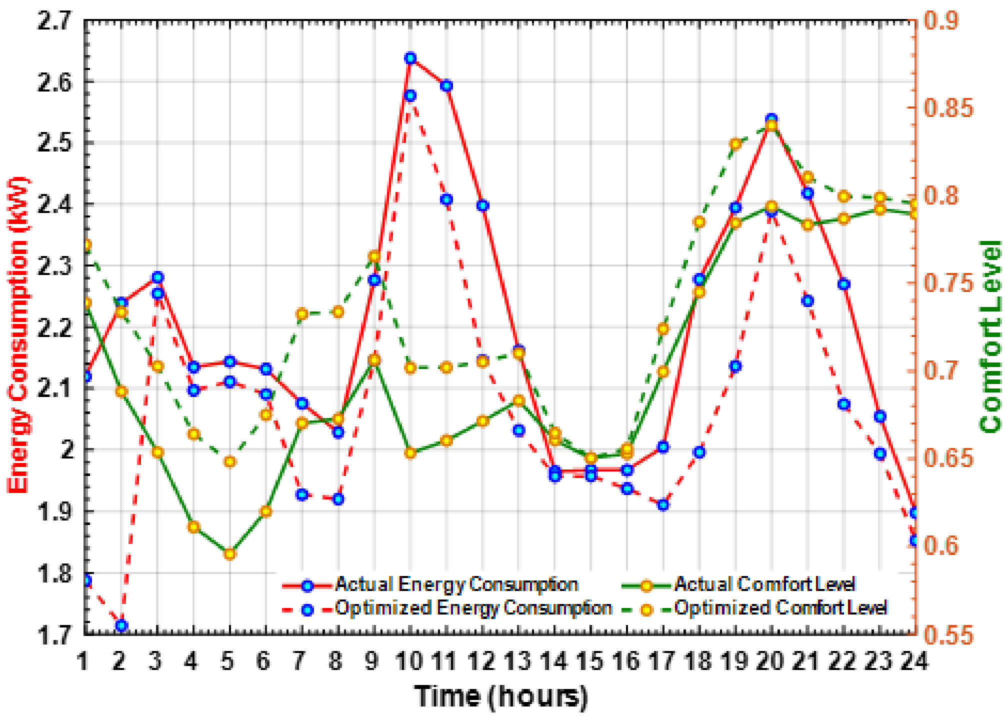

Fig. 4.10: Optimization of energy consumed by all the actuators and comfort level.

According to actual environment values, optimising the sensor values will reduce energy consumption and increase the overall comfort level. Figs. 4.7, 4.8, and 4.9 also show energy consumed (with and without optimization) by each actuator, and Fig. 4.10 shows the comfort level and its corresponding energy consumption of all the actuators.

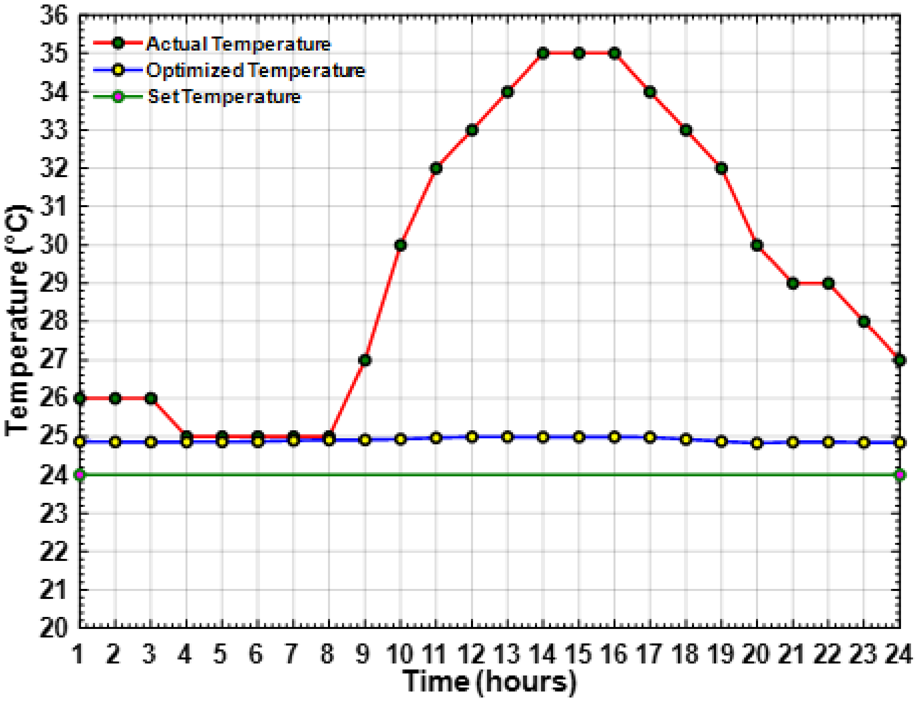

Fig. 4.11: Optimization of the actual temperature

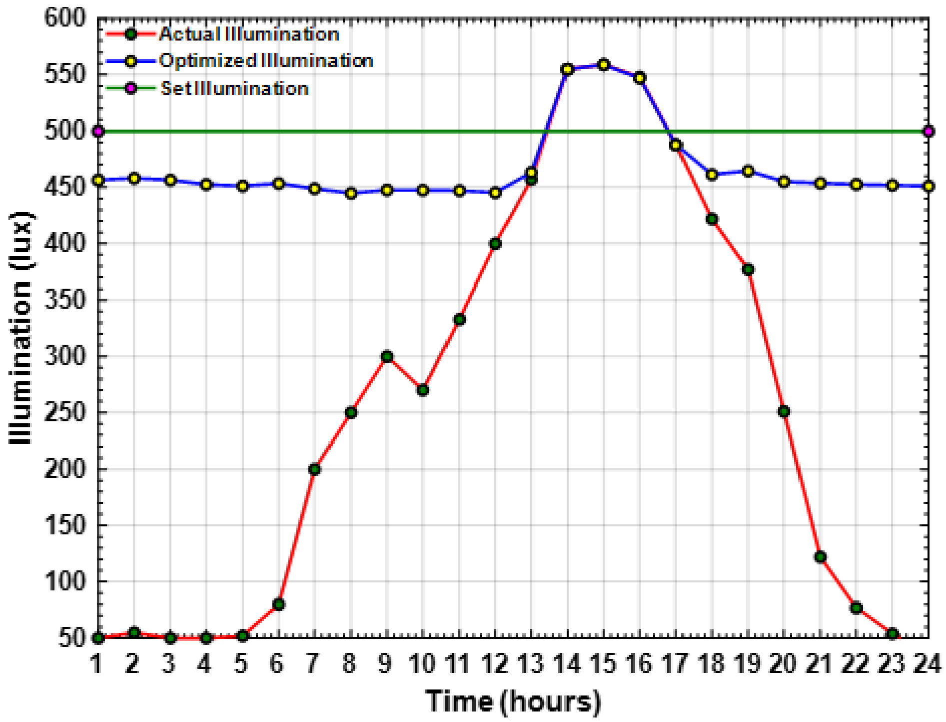

Fig. 4.12: Optimization of the actual illumination level

It is evident from the results obtained that the proposed optimization strategy has reduced power consumption significantly. Maximization of comfort is another objective of the proposed multi-agent system. Optimized set values of temperature, illumination, and CO_2 using the developed neural network are shown in Figs. 4.11, 4.12, and 4.13.

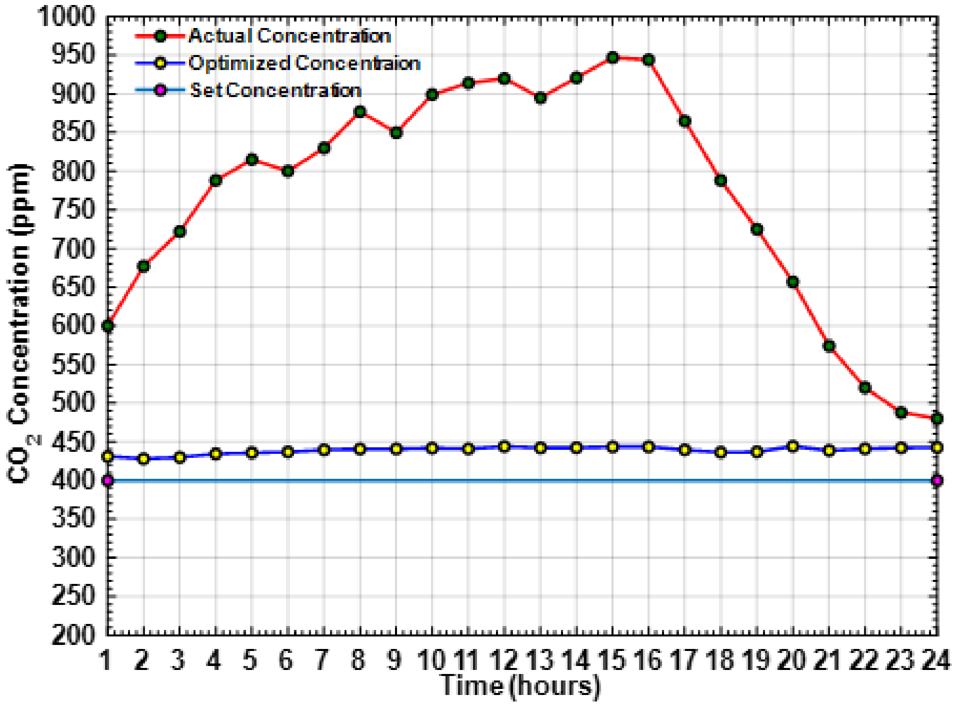

Fig. 4.13: Optimization of the actual CO_2 concentration level

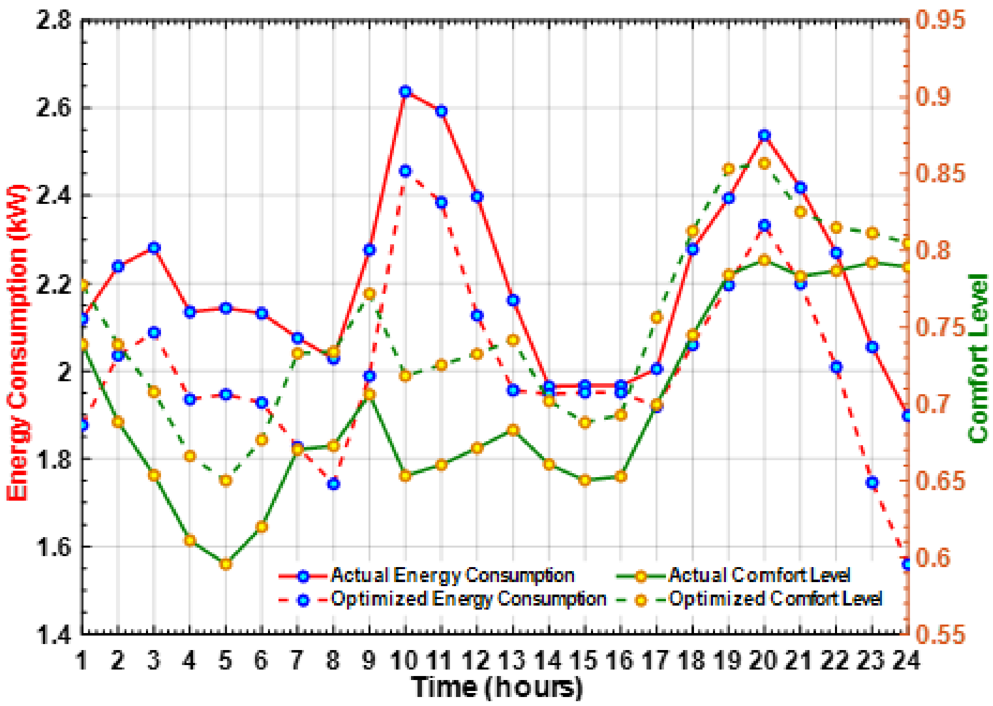

Fig. 4.14: Optimization of energy consumed by all the actuators and overall comfort level.

Energy consumption and comfort level with and without using Artificial Intelligence calculated for fixed and optimized set values have been shown in Fig. 4.14, respectively. It has concurred that the trained neural network has successfully optimized the set values for a better comfort level with minimum energy consumption.

4.6 CONCLUSIONS

Building automation for energy conservation and comfort management is the main problem in balancing the conflict between user comfort level and energy consumption. These two conflict with each other and difficult to balance. Therefore, this chapter presented the design of multi-agent topology-based building management and Information system. The objective was to minimize the difference between the actual environment values and the user's set values that determine the overall comfort level. A mathematical multivariable objective function is formulated to represent the difference between the actual environment parameters and set values. The nonlinear multivariable constrained optimization algorithm, fmincon, is applied to optimize the set values for 24 hours continuously. After that, power consumption and comfort level are calculated to determine the efficiency of the proposed system. The results show that the proposed system was successfully simulated in the MATLAB 2019a environment, which reduced energy consumption and increased the occupants' comfort level.

CHAPTER 5

PERFORMANCE EVALUATION OF DEVELOPED OPTIMIZATION MODELS

5.1 INTRODUCTION

Energy-efficient buildings are described as buildings designed to efficiently reduce the energy requirements in heating and cooling, regardless of the energy and equipment were chosen to heat or cool the building **(Srinivas et al., 2015)**. In the world's current scenario, a massive part of the energy generated is consumed in buildings to maintain a user-comfort. In context with the annual energy outlook 2019 reference case, energy consumption delivered for buildings increased by 0.2% per year from 2018 to 2050. Growth later in the projected duration vastly exceeds energy efficiency improvements **(EIA, 2019)**. The rapid growth in global energy use raised concerns about supply problems, energy resource depletion, and a substantial impact on the environment *viz*. GHG **(Thambi et al., 2018)**.

We have two ways to tackle this problem either we generate more electrical power; we will need more resources and human efforts, or use existing resources adequately and conserve energy. Efficiently utilizing our existing resources is more convenient and also cost-free with an energy-efficient energy management system. An energy-efficient system in residential buildings can manage and control energy consumption and user-comfort level.

5.1.1 Earlier Work

Building management is a type of control system designed to reduce energy consumption without affecting or maximizing the user-comfort **(Wang et al., 2012)**. The IEQ describes the indoor environment's quality and occupant's health in the indoor environment **(Chen et al., 2015)**. The IEQ depends on the three primary parameters, air quality, thermal comfort, and illumination. The 60% power is consumed in the heating, cooling, ventilation, and lighting inside the buildings **(Zhang et al., 2019)**. Other electrical home appliances utilize the rest of the energy. The heating, cooling, illumination, and ventilation are also variables with environment temperature and natural delighting in nature. It depends on the maximum and minimum temperature range set by the user and environmental temperature. Therefore, we need a convenient and economical EMS and control methodology for HVAC operation and lighting systems. To manage energy consumption in building effectively, we need to focus on maximizing the user's comfort with less energy consumption. The user's comfort is defined by three major factors: temperature, relative humidity, IAQ, and illumination level. We considered the temperature for thermal comfort, CO_2, NO*x* (*x*=1, 2, 3 . . .) concentration for IAQ, and illumination level for visual comfort **(Dounis and Caraiscos, 2009)**. In general, user-comfort and energy management are both conflicting in nature. This conflict between the comfort index and energy consumption can be overcome with the utilization of optimization techniques. Researchers have developed several traditional methodologies to resolve energy consumption conflict with user-comfort in residential buildings published in **(Waibel et al., 2019)**. In the last few decades, there is an advancement in optimization techniques adopted to solve linear and non-linear problems.

The degree of comfort calculated depends on three factors that are thermal comfort, visual comfort, and indoor AQI **(Kumar and Hancke, 2014)**. Expressing satisfaction with the thermal environment and evaluating it subjectively is called thermal comfort, also known as the state of mind **(Waibel et al., 2019)**. For temperature control, a heating or cooling system is required. Similarly, for visual comfort, the illumination is considered, and electrical lighting is used for its measurement. The IAQ is indicated by the concentration of CO_2 present inside the room, maintained by the ventilation system. Collectively, these three together are termed as HVAC. In the past, many valuable energy management systems based on conventional controllers have been proposed. Researchers proposed PID controllers, adaptive controllers, and optimal controllers. These controllers have drawbacks like difficult operation and examination, less user-friendly, and energy loss, causing failure in controlling the comfort parameters.

The main objective of this performance evaluation to improve the accuracy and perform a comparative analysis without optimization and using optimization techniques like the Genetic Algorithm (GA), Bat, Neural Network Algorithm (NNA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC).

The optimization of the building's control parameter has currently become a popular research area in the literature. A series of control methodologies have been devised to minimize energy consumption in residential and commercial buildings without affecting user-comfort. Several energy management techniques have been proposed for energy consumption and comfort management. The methods introduced in the literature were based on conventional control techniques. **Wang et al. (2010)** proposed a control system using the intelligent optimization technique PSO. It consists of two-level agents, one higher-level central agent, and several lower-level local agents. This framework has been designed to control energy and comfort.

Similarly, they proposed and developed another multiagent control system based on information fusion, utilizing ordered weighted average aggregation using a heuristic intelligent optimization technique **(Wang et al., 2012)**. In another work, **Wang et al. (2012)** developed a multiagent control system to manage the energy consumption of building and user-comfort based on the occupants' behavior. This system was based on the idea that the action of the occupant directly affects system performance. A multiobjective PSO technique was applied in the central agent to find the optimal trade-off solution for informed decision making. **Sheikh et al. (2018)** developed a multiobjective system. They added another comfort parameter, relative humidity, and employed an evolutionary multiobjective GA for attaining a trade-off between comfort and energy consumption.

Similarly, **Kim et al. (2018)** came up with a novel control strategy, which uses the FLC and a Bat algorithm as an optimization technique. On the other side, **Ullah et al. (2017)** have proposed a model to improve optimization function to achieve maximum user's maximum comfort in the living environment of building with less energy consumption. They performed a comparative study of the PSO and GA optimization algorithm with a baseline scheme. **Kolokotsa et al. (2003)** proposed an environmental management system capable of satisfying the occupant's preferences using the FLC and programmable logic controllers. The GA optimization technique was used in providing the required energy to meet the user preference in less energy usage. Using the GA technique helped minimize an objective function for the control strategy **(Poursamad and Ghalichi, 2006)**. A model was proposed by **Bluyssen et al. (2011),** which shows a relationship between social, personal, and building parameters that affect the user's comfort. They have discussed the influence of personal, social, and building parameters on the user's comfort and the other parameters discussed above. An optimization-based simulation model has been proposed for HVAC systems that have complex interconnections are reported in **(Mossolly et al., 2009)**. Much work has been done in the research field of building energy consumption and comfort value optimization. Many well-known AI-based optimization techniques have also been used to apply energy management in intelligent buildings **(Wahid et al., 2019)**. The authors in their work **(Ali and Kim, 2016)** have proposed an energy consumption and comfort management system based on a residential building prediction approach. They were processed the data using a data smoothing approach before and after optimization to improve the comfort index and minimize energy consumption. The authors of **(Wahid et al., 2019)** applied the

ABC optimization technique with a knowledge base to manage the power consumption regarding occupant's comfort. The proposed model was efficient in achieving a high comfort index with minimum energy consumption. **Fazli et al. (2019)** proposed an efficient AI hybrid approach for reducing energy consumption and maximized comfort index. The authors have utilized a hybrid of firefly algorithms and GA for optimization. A control system design that minimizes energy consumption without affecting or maximizing the comfort index is still challenging. The conventional control strategies' inherent drawbacks are accurate, require specific building models and parameter monitoring difficulty caused by non-linear features. To overcome these drawbacks, intelligent control strategies have been proposed and implemented.

5.2 SOLUTION METHODOLOGY

The room's environment temperature and the user setpoint temperature have been taken into account, and the optimization technique is applied. The difference between optimized temperature and environment temperature has been calculated and fed to a temperature FLC whose output has been collected. A dataset is prepared for the Machine Learning (ML) based controller training, and thus, the results have been plotted and presented in the result section. The proposed methodology of the study has been shown in Fig. 5.1.

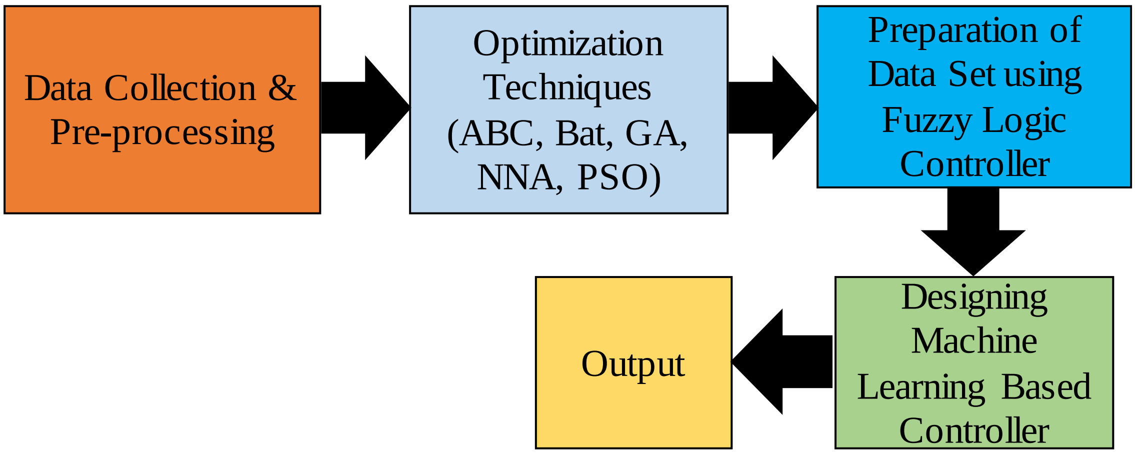

Fig. 5.1: Workflow block diagram of the comparative study.

The hourly temperature dataset, 2017 of Delhi, India, has been taken from the kaggle website **(Kukreja, 2016)**. The dataset was contained many columns, out of which some were not useful in experimental work. Therefore, the pre-processing of data was required. Since hourly data were available, so the average temperature of each day has been calculated. Some of the data points were not available in the dataset, so they were replaced with zero, and then the average temperature was calculated. Those days have been dropped from the dataset for which the average temperature was zero. This comparative study has been concentrated on maximizing thermal comfort and reducing the energy consumption for energy-efficient buildings. The mathematical comfort index value has been considered an objective function Eq. (5.1) **(Wahid et al., 2019)**.

Objective function

$$CI = \sum_{i=1}^{N} \alpha_i \times \left(1 - \left(\frac{E_r}{T_S} \right)^2 \right) \tag{5.1}$$

Subject to

$$E_t(n+1) = E_t(n) + L \tag{5.2}$$

$$E_{i/p}(n) \le E_{max}(n) \tag{5.3}$$

where $\sum_{i=1}^{N} \alpha_i = 1$ and, α_i is a user-defined factor. T_S is the user set temperature and E_i the difference of actual temperature and the optimized value of the comfort parameter. The required energy to operate the temperature controller is E_t. The supply source's total energy is the maximum energy that can supply source provide is E_{max}, and L is a small value for compensation of energy loss in distribution and n is the time instants.

5.3 OPTIMIZATION TECHNIQUES

In the optimization process, we begin with some initial parameters for the experiment's parameters. Since these values may not have been the best options to use, we must improve them until we get the best ones. A noisy data, weak learning algorithm, or lousy selection of parameters maybe results in bad classification accuracy. Therefore, it is essential to do optimization to reduce the error. Researchers and scientists developed and suggested various optimization techniques to perform optimization tasks. To solve problems of optimization nature, various swarm intelligence techniques have been developed, e.g., cuckoo search, Bat algorithm, glow-worm optimization, krill herd bio-inspired optimization algorithm, PSO, ABC optimization, ant colony optimization, firefly algorithm, grey wolf optimizer, whale optimization algorithm, ant lion optimizer, and many more hybrid algorithms **(Wahid et al., 2019)**. These techniques have been categorized into four main categories viz. combinatorial optimization, multimodal optimization, multiobjective optimization, constrained optimization **(Mezura-Montes et al., 2008)**.

The optimization has been done in the proposed solution to reduce the error between environment temperature and user set point. Several optimization techniques have been used in the past. In this chapter, GA, Bat, NNA, PSO, and ABC have been utilized in the optimization, and obtained results are compared for analysis.

5.3.1 GA Based Optimization

The GA is a metaheuristic classical evolutionary algorithm based on a random basis **(Srinivas and Patnaik, 1994)**. This algorithm represents the natural selection process that selects the most appropriate individuals for reproduction to produce the next generation's offspring. GA based optimization performs in five phases viz. Initial population, fitness function, roulette selection, crossover, mutation **(Awasthi et al., 2017)**. The data flow diagram of the GA approach has been depicted in Fig. 5.2. With successive iterations, GA ceases either to a maximum number of iterations or no successive changes observed in fitness values. The size of the population was 100. After running GA many times, a single point crossover, a probability of 0.9, and the mutation rate set to 0.1. Fig. 5.3 shows the pseudocode for the GA optimization method.

Steps of GA based optimization are summarized as follows **(Hermawanto, 2013)**:

Step 1. Initialization of random population.

Step 2. The comfort index using Eq. 5.1 will be computed.

Step 3. Best population for crossover and mutation selected using rank-based selection.

Step 4. For the selected best population, a one-point crossover was performed.

Step 5. After crossover, offspring is obtained.

Step 6. Comfort index calculated for the offsprings obtained from ***Step 5***.

Step 7. Combine populations obtained from ***Step 3*** and ***Step 5***.

Step 8. Mutation criterion is met; the mutation will be performed.

Step 9. Repeat until the number of iterations required is achieved.

Step 10. The best-fit chromosome is selected when the termination criteria are met.

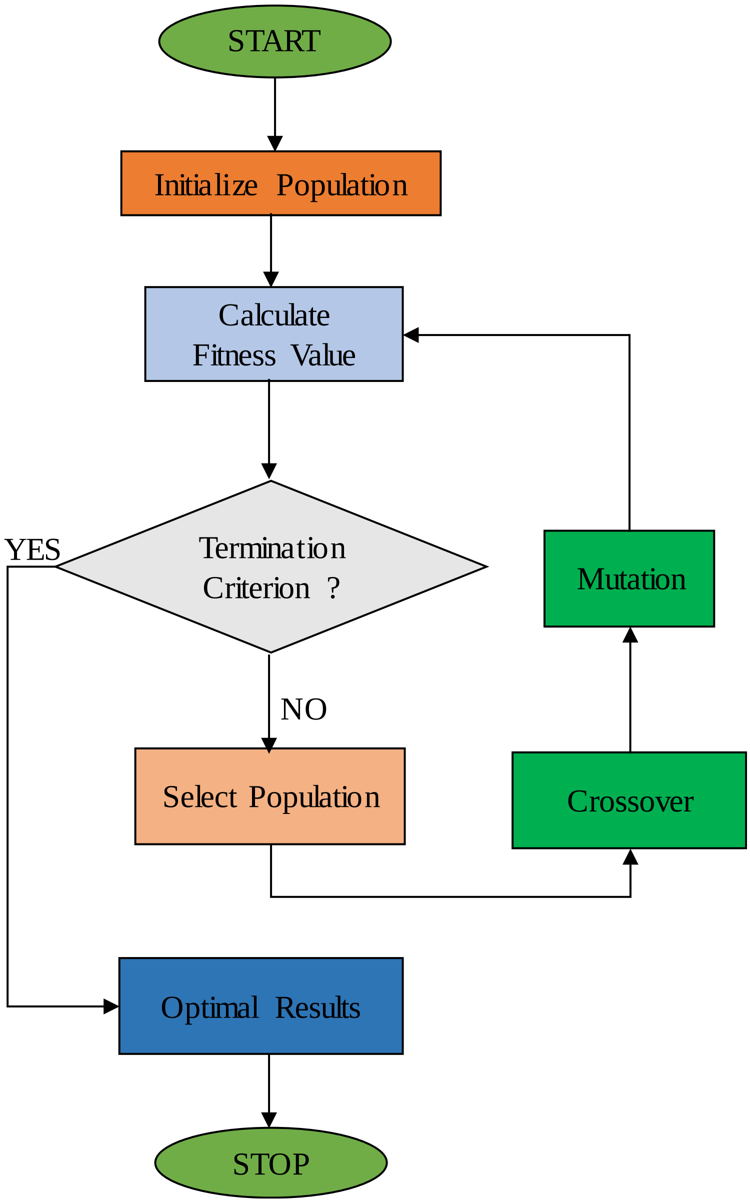

Fig. 5.2: Flowchart of the GA based optimization approach.

5.3.2 Bat Based Optimization

A metaheuristic optimization algorithm based on the echolocation property is termed the Bat algorithm **(Yang, 2010)**. The property echolocation assists Bat in flying and in hunting. It is a frequency tuning strategy to maximize the variety of population-based solutions while at the same time using automated zooming to attempt to balance exploration and manipulation during the selection process of imitating differences in pulse emission levels and Bats' loudness while looking for prey **(Yang, 2010)**. These are the three generalized rules used in implementing the Bat algorithm **(Talbi, 2019)**. Randomly flying Bat's, having a velocity (V_i) at position (X_i) at set loudness (A_0), frequency (f) and, varying wavelength

(λ), looking for their prey. The pulse emission (*r*) lies in the range of 0 and 1 depending upon the target proximity. Loudness can be varied in various ways. But here, we have considered loudness ranges vary in the range A_0 (high value) to A_{min} (low value).

```
/////////////// Pseudocode of Genetic Algorithm ////////////////
Begin
        Set of Parameters: blocks (S- Set of blocks)
        Superstring of set S
        Initialize t=0
        Population Pt to random individuals from S*
Evaluation
        fitness-GA (S, Pt)
while termination criteria not met
do
        Individual selection from Pt (fitness proportionate),
        recombination, mutation.
Evaluation
        fitness-GA (S, modified individuals)
        newly created individuals= Pt+1
        t=t+1
return (superstring derived from best individual in Pt)
        procedure Evaluate-fitness-GA (S, P)
        P=Population of individuals; i ∈ P
do
        Generate derived string S(i)
        From S all blocks that are not covered by S(i)=m
        Concatenation of S(i) and m= S`(i)
        1/|S(i)|^2 = fitness(i)
```

Fig. 5.3: Pseudocode of the GA based optimization approach.

Steps of Bat based optimization are summarized as follows **(Talbi, 2019)**:

Step 1. Initialization of algorithm parameters and the problem-specific parameters.

Step 2. The objective function is defined.

Step 3. Bat Population X_i and V_i initialized.

Step 4. Define the frequency of Q_i at E (Q_{min}, Q_{max}).

Step 5. Initialize r_i and A_i.

Step 6. While ($t < T_{max}$) / total iterations.

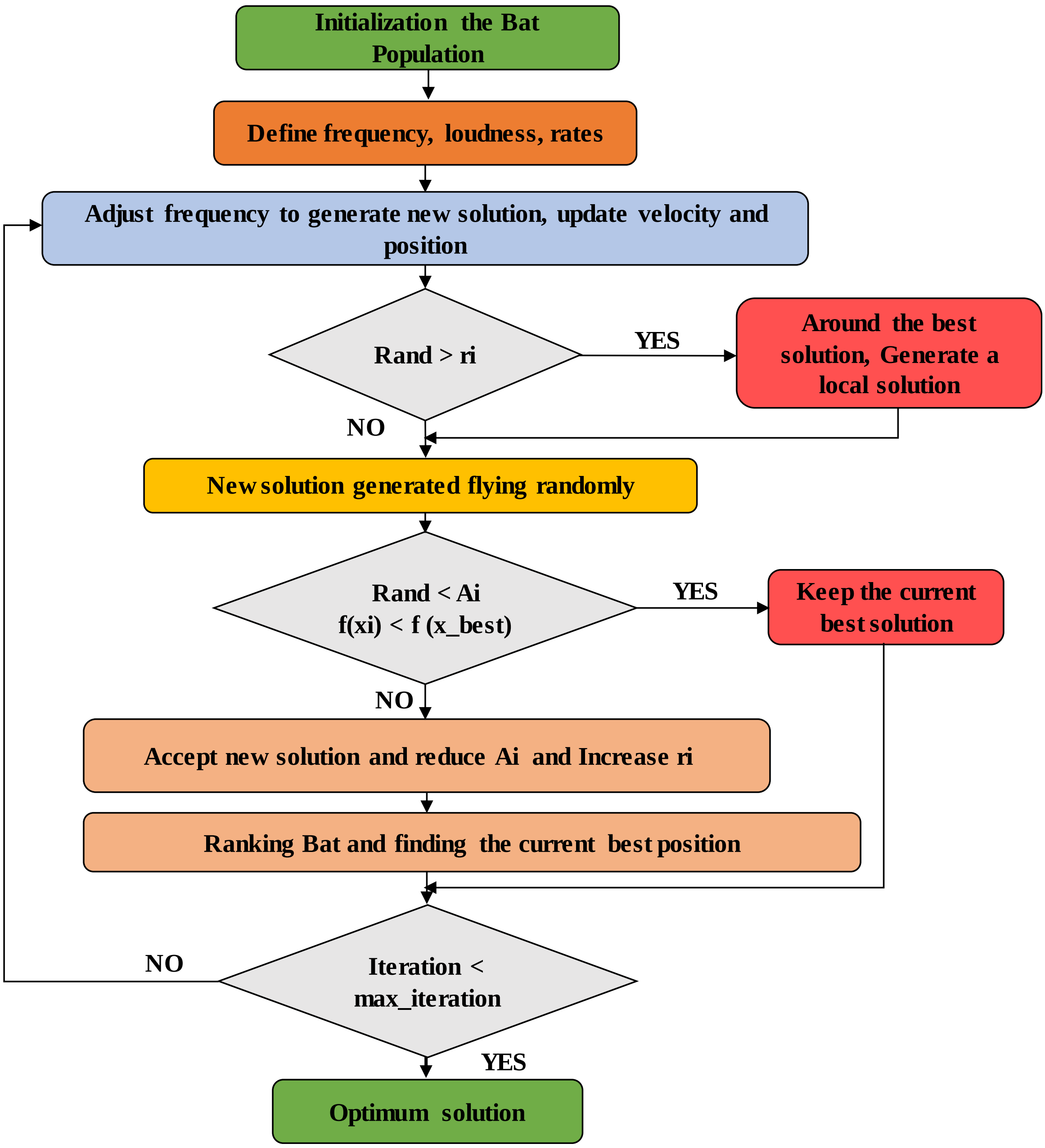

Fig. 5.4: Flowchart of the Bat based optimization approach.

Step 7. Produce new results by altering the frequency and updating the location and velocities.

Step 8. Generate a new solution by adjusting the frequency.

Step 9. If randomness greater than r_i.

Step 10. The solution is nominated as one of the best solutions.

Step 11. A local solution is generated nearby the best solution.

Step 12. End of if statement.

Step13. If randomness less than A_i and f(x) < f(x).

Step 14. A new solution will be accepted.

Step 15. Decrease r_i and A_i.

Step 16. In the end, if the Bat's are ranked, and the present best is found.

These steps are also visualized in the flowchart in Fig. 5.4. The pseudocode of the Bat approach has been shown in Fig. 5.5 **(Pourhadi and Mahdavi-Nasab, 2020)**.

5.3.3 ABC Based Optimization

An ABC algorithm is influenced by the bee colonies' action, which the Karaboga team introduced in 2005 to improve algebra **(Karaboga and Akay, 2019)**. The ABC technique's

```
//////////////// Pseudocode of Bat algorithm ////////////////
Objective function f(x), [x1, x2. . . xd]
Begin
        Initialize the population of BAT.
        xi (i=1,2 ,…., n) & velocity (Vi)
        Set pulse frequency fi at xi
        Initialize the pulse rates ri and the loudness Ai
While
        (t < maximum no. of iterations)
        Adjust frequency, velocities and generate new
        solutions/locations.
if (rand > r)
        Select a solution among the best solutions
        Generate a local solution around the selected
best solution
end if
        Generate new solution by flying randomly
if (rand<Ai & f(xi)<f(x_best))
        Accept the new solutions
Increase ri and reduce Ai
```

Fig. 5.5: Pseudocode of the Bat approach.

main objective is to find the optimal global solution, a flower patch with maximum nectar size. For this reason, ABC categorizes bee swarms into three categories: employed bees, scout bees, and onlooker bees. ABC often use the memory principle to store the best fitness location. The bee visits to the new location compared to the best location that was visited earlier. After comparison, the new position is memorized if the new location is better and the old location is forgotten. Initially, sending bees to random places starts with ABC. After returning to the beehive, the bees work on sharing the information with them who pick the flower to be used depending on the selection Eq. (5.4) **(Karaboga and Basturk, 2007)**.

$$p_i = \frac{fcn_i}{\sum_{n=1}^{FS} fcn_n} \tag{5.4}$$

where fcn is the objective function (maximum nectar size) of the solution 'i'. Here, the objective function is the function outlined in Eq. (5.1). The total number of food sources is 'FS.' The roulette wheel's selection process is based on the probability values used. The more the nectar size that an employed bee shares, the greater is onlooker bees' possibilities of selection from Eq. (5.4).

$$new_i = r_i + rand_i (r_i - r_j) \tag{5.5}$$

With the help of Eq. (5.5), the onlooker bee moves to a new position, led by a selected employed bee. Where 'r_i' is a present memory location, 'r_j' is selected employed bee on a probability basis, and '$rand_i$' is randomness, added to find nectar around the position 'r_j.' It is substituted by scout bees p_{new} after many iterations bees any of the three bees that have been not able to find a better food source. The scout bee used to search the area by invoking the failed bee roams around any unexpected or unexplored region using Eq. (5.6) **(Karaboga and Basturk, 2007)**.

$$p_{new} = lv_i + rand_i (uv_i - lv_i) \tag{5.6}$$

Where lv_i uv_i and $rand_i$ are lower value, upper value, and randomness (0, 1). The next cycle begins again with employed bees entering the neighbourhoods in memory-present location.

ABC based optimization steps are summarized and given as follows:

Step1. Randomly distributed populations of solutions (r_i) generated in search space, $r \in \{1, 2, ...FS\}$

Step 2. Evaluate the objective function value of solutions in ***Step 1***.

Step 3. Cycle =1, Repeat.

Step 4. Produce new solutions (new_i) for employed bees using Eq. (5.5) and evaluate their present maximum value.

Step 5. The greedy selection scheme on employing bees applied between (new_i and r_i).

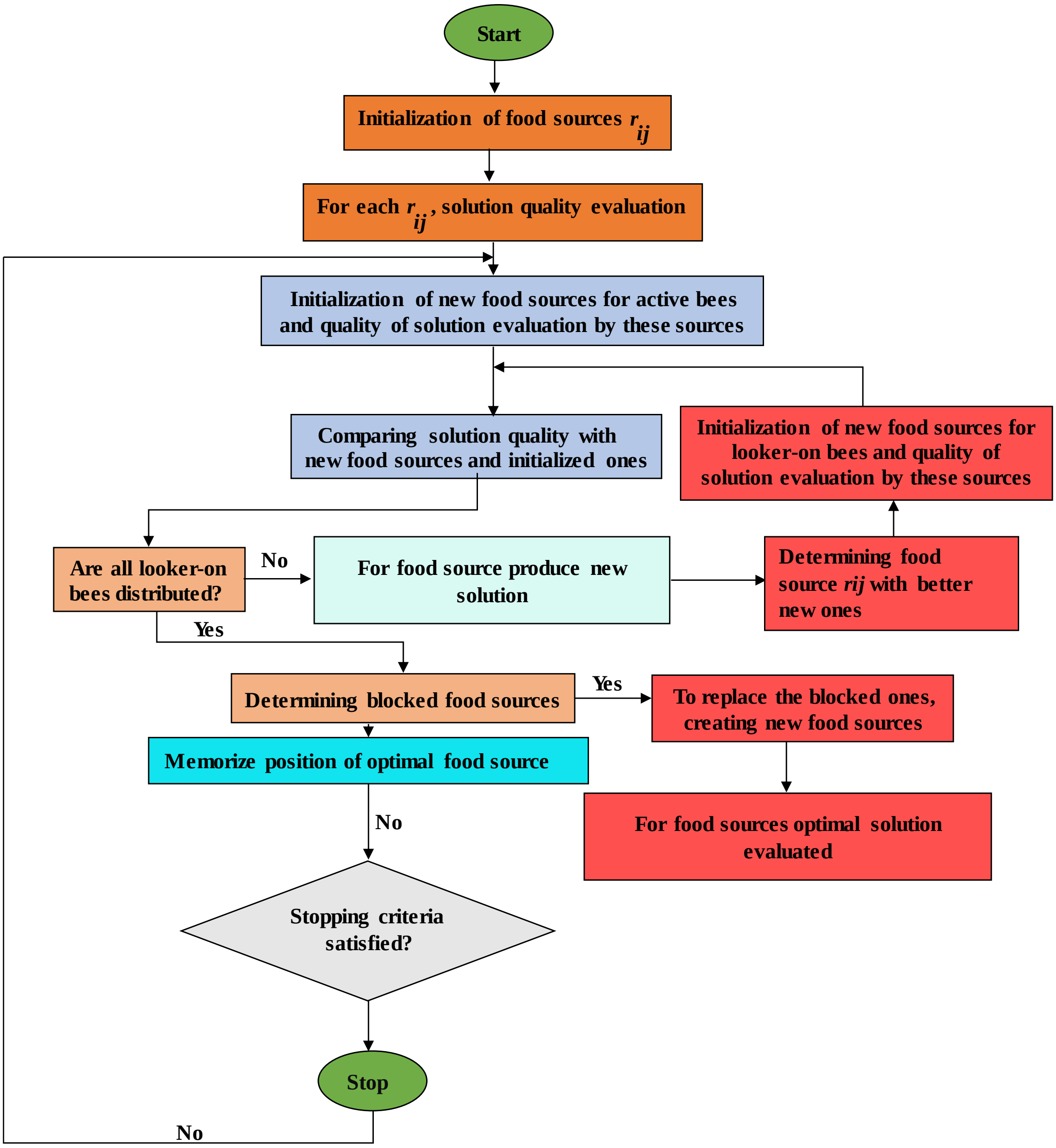

Fig. 5.6: Flowchart of the ABC based optimization approach.

Step 6. Calculate the possible value 'p_i' for the solution 'r_i'.

Step 7. Assign looker-on bees to the solutions with probabilistic selection.

Step 8. Using Eq. (5.5), Generate new solutions (new_i) for looker-on bees and evaluate their present maximum values.

Step 9. On onlooker bees, the greedy selection process is applied.

Step 10. For scout bee, determine the rejected solution, if there, and replaced it with a randomly-generated solution (r_i) using Eq. (5.5).

Step 11. Generate new solutions (r_i) for scout bees if no solution was rejected.

Step 12. Store the best solution, found till now.

Step 13. Cycle = Increase one more cycle

Step 14. Until cycle equals a maximum number of cycles.

These steps could be visualized in Fig. 5.6, and the pseudocode for the ABC approach shown in Fig. 5.7 **(Memon et al., 2018)**.

//////////////////////////////// **Pseudocode of ABC Algorithm** ////////////////////////////////
Objective function *f(x)*
Begin
Initialize parameter number of food sources (*FS*) and Population Size(N_{pop})
Generate initial population of food sources
Evaluate fitness of each food source
while (t< maximum generation) or (! stop criteria)
%for employed bees phase%
for i=1: N_{pop}
Generate new solution $new_{i,j}$ in the neighbourhood of $X_{i,j}$
if $f(new_{i,j}) < f(X_{i,j})$
then replace $X_{i,j}$ with the new food source $new_{i,j}$
end if
end for i
Select best food sources using the roulette wheel selection
%for onlooker bees phase%
for i=1: N_{pop}
Generate new solution new_i in the neighbourhood of X_i
if $f(new_i) < f(X_i)$
then replace X_i with the new food source new_i,
end if
end for i
%for scout bees phase%
If any food source does not improve for a *FS, then* change it with new *FS*
Save the best food source
end while

Fig. 5.7: Pseudocode of the ABC based optimization approach.

5.3.4 PSO Technique

PSO technique is a computing method that optimizes the problem by iteratively attempting to improve the candidate solution for a given quantity measure **(Cai and Yang, 2013)**. The PSO initially produces several solutions spontaneously, called population solutions. It then finds an optimal solution by iteratively updating the generations. PSO's potential solution is considered a particle that approaches the current best local solution to pass through the whole solution set to find the best global solution **(Gupta and Mohanty, 2015)**. The position vector, 'X', and velocity vector, 'V' are two vectors that reflect a possible PSO solution. The pace tends to move to its most robust particle and tries to memorize its own best location in each turn.

Velocity:

$$V_{i+1} = WV_i + C_1R_1(P_i - X_i) + C_2R_2(P_g - X_i) \tag{5.7}$$

Position:

$$X_{i+1} = X_i + V_i + 1 \tag{5.8}$$

Eqs. (5.7) and (5.8) **(Benard et al., 1992)** are for velocity and position update in which 'W,' C_1, and C_2 are randomly generated weights, and acceleration constants are R_1, R_2. The best previous position is P_i of the ith particle, and P_g is the best previous position of all the particles in the swarm. Here, M_1 and M_2 are two positive constants, and R_1, R_2 are two randomly generated values between 0 and 1.

Steps for PSO based optimization are summarized as follows:

Step 1. Initialization population with random position and velocity in dimensional space.

Step 2. Velocity and position at each iteration update using Eqs. (5.7) and (5.8).

Step 3. Update memory, global best position (P_g), and particle best position (P_i).

Step 4. Repeat ***Step 2*** and ***Step 4***, the best fit, or the maximum number of iterations is reached.

Step 5. If the condition is satisfied, the termination criterion will be examined.

These steps are visualized in Fig. 5.8 and the pseudocode presented in Fig. 5.9 **(Digehsara et al., 2020)**.

5.3.5 NNA Based Optimization

NNA is a computational approach used in optimization to find an optimal solution to a given problem. ANN is, therefore, a knowledge or signal processing network composed of a vast number of basic computing units, called artificial neurons or superficial nodes, which are interconnected by direct connections, called links, and which function together to perform continuous distributed processing to solve a particular computational issue

(Sadollah et al., 2018). Similar to other metaheuristic optimization algorithms, the NNA also initializes with a pattern solution based population.

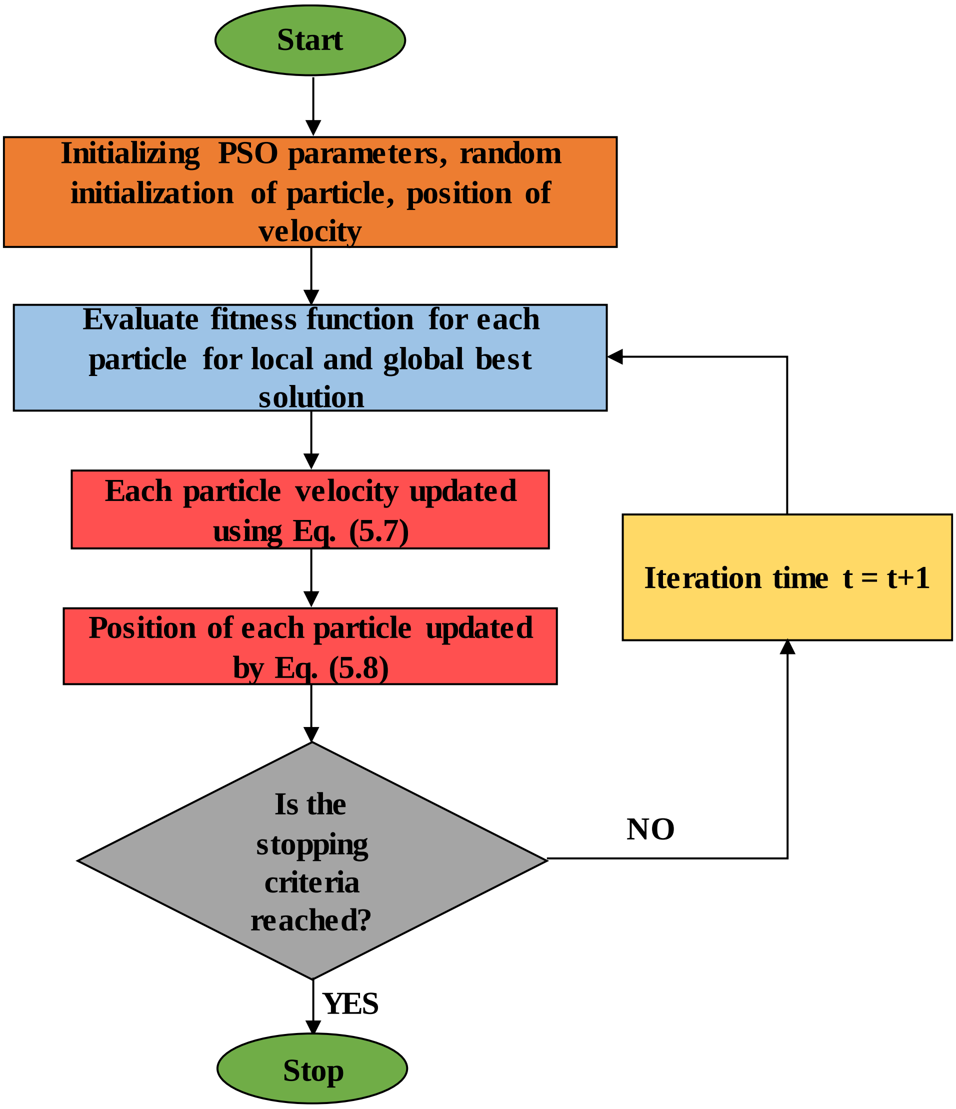

Fig. 5.8: Flowchart of the PSO approach.

In ANNs, initialized weights are the random numbers, and with an increase in the iteration, they will be updated. Initial weights are defined as W(t), where W is a weight matrix having dimension $N_{pop} \times N_{pop}$, and t is the iteration index.

$$\sum_{k=1}^{N_{pop}} W_{ik}(t) = 1, \quad k = 1, 2, 3, \ldots\ldots, N_{pop} \tag{5.9}$$

$$W_{ik} \in U(0, 1) \qquad i, k = 1, 2, 3, \ldots\ldots, N_{pop} \tag{5.10}$$

//////////////////// **Pseudocode of PSO Algorithm** /////////////////////

```
Objective function f(x)
Begin
    Initialize parameters C1, C2, Wmax, Wmin, Population Size (Npop)
    Generate population of particles
    Evaluate fitness of each particle; Set all initial position to Pi
While
    t< Maximum generation or! Stop criteria
    Select Pg (global best) in the swarm having minimum fitness value
for i=1: Npop
    Calculate velocity of particle Xi
    Update position of particle Xi
end for i
for i= 1: Npop
    Evaluate fitness of updated particle Xi
    If f(Xi)< f(Pi)
    Set current position to Pi
end if
end for i
    find the best particle
end while
```

Fig. 5.9: Pseudocode of the PSO approach.

Weight values belong to random numbers uniformly distributed between 0 and 1 Eq. (5.10) **(Hermawanto, 2013)**. After weight matrix formation, evaluation of new pattern solutions performed using Eq. (5.11).

$$\overline{Y}_k^{New}(t+1) = \sum_{k=1}^{N_{pop}} W_{ik}(t) \times \overline{Y}_i(t) \qquad k = 1,\ 2,\ 3, \ldots\ldots, N_{pop} \tag{5.11}$$

$$\overline{Y}_i(t+1) = \overline{Y}_i(t) + \overline{Y}_i^{New}(t+1), \qquad i = 1, 2, \ldots\ldots, N_{pop} \tag{5.12}$$

$$W_i^{Updated}(t+1) = \overline{W}(t) + 2\,\mathrm{rand}(\overline{W}^{Target}(t) - \overline{W}_i(t)), \qquad i = 1, 2, 3, \ldots\ldots\ldots\ldots, N_{pop} \tag{5.13}$$

$$\beta(t+1) = \beta(t) \times 0.99 \qquad t = 1,\ 2,\ 3 \ldots\ldots, \mathrm{Iteration}_{max} \tag{5.14}$$

Here, β in Eq. (5.14), acts as a bias operator, which modifies a certain percentage of pattern solutions in the new pattern solutions population $(\overline{Y}_k^{New}(t+1))$ and weight matrix is updated $\overline{W}_i^{Updated}(t+1)$ also acts as a noise **(Wang et al., 2004)**.

$$\overline{X}_i^{*}(t+1)=TF(\overline{X}_i(t+1))=(\overline{X}_i(t+1)+2rand((\overline{X}^{Target}(t)-(\overline{X}_i(t+1)),\quad i=1,2,3,............,N_{pop} \tag{5.15}$$

The general type of NNA behaviour is defined in Eq. (5.15) **(Srinivas and Patnaik, 1994)**.

$$\overline{Y}_i(t+\Delta t)=f(\overline{Y}_i(t),\ P(t)),\quad i=1,2,3,.....,N_{pop} \tag{5.16}$$

where, $\overline{Y}_i(t+\Delta t)$ and $\overline{Y}_i(t)$ are next and present locations of i^{th} pattern solutions respectively. *P(t)*, the pattern solutions population with updated weights in Eq. (5.16) **(Wang et al., 2004)**.

Besides, the steps of NNA based optimization are summarized as follows **(Sadollah et al., 2018)**:

Step 1. Initialize population size and maximum iterations.

Step 2. Generate randomly initial pattern solution population between LB and UB.

Step 3. Evaluate initial pattern solutions cost.

Step 4. Generate a weight matrix randomly between 0 and 1 considering the constraints.

Step 5. Set target solution (Y^{Target}) and its corresponding weight target (W^{Target}).

Step 6. Generate Y^{New} and using Eqs. (5.11) and (5.12) update the pattern solutions.

Step 7. Using Eq. (5.13), update weight matrix (W) with given constraints in Eqs. (5.9) and (5.10).

Step 8. Bias condition check. If $rand \le \beta$ performs a bias operator for the latest pattern solutions as well as weight matrix updates.

Step 9. Else ($rand \le \beta$), Transfer Function (TF) applied for updating of a new position of pattern solutions $(\overline{Y}_i^{*})$ by using Eq. (5.15).

Step 10. For all the latest pattern solutions, the objective function value has been calculated.

Step 11. Update Y^{Target} and its corresponding W^{Target}.

Step 12. Update β value using Eq. (5.14).

Step 13. Stopping condition if met, the NNA will stop, else it returns to ***Step 6***.

The pseudocode for the NNA approach has been shown in Fig. 5.10 **(Zhang and Chen, 2019)**.

```
//////////////////// Pseudocode of NNA ////////////////////////
Objective function f(x)
Begin
        Initialize population size (N_pop), Weight matrix (W) with
number of solutions (N)
        Evaluate fitness value of each solution and set optimal
        solution & optimal weight
Repeat
        Generate new solution Y^new using Eqs. (5.11) & (5.12) and
        update new weight matrix W_i^Updated using Eq. (5.13)
for each individual i ∈ N_pop
do
if rand ≤ β(t)
        Execute bias operator for updating solution Y_k^new(t+1) and the
weight matrix W_i^Updated (t+1)
else
        Execute the transfer function for updating the solution
        Y_k^new(t+1)
end if
end for
        Generate the new modification factor β^(t+1) using Eq. (5.14)
        Evaluate the fitness value of each solution and search
        optimal solution (Y^Target) and optimal weight (W^Target)
Until (stop condition = = false)
        Post process output and visualization
end
```

Fig. 5.10: Pseudocode of the NNA based optimization approach.

5.4 IMPLEMENTATION AND PREPARATION OF DATASETS

5.4.1 Temperature Fuzzy Logic Controller

In this stage of implementation, using an FLC, the optimized temperature and user set temperature difference have been utilized to calculate required energy consumption. An appropriate fuzzy temperature controller has been designed for this purpose. Fuzzy logic is used to deal with the notion of incomplete truth, where the true value lies between totally true and utterly false 0 or 1 **(Mamdani and Assilian, 1988)**. It has also been discussed earlier about FLC in chapter 3. In chapter 3, Fig. 3.4 shows the general block diagram of

FLC. The major components of the controller are fuzzifier, fuzzy knowledge base, fuzzy rule base, inference engine, and defuzzifier **(Zadeh, 1988)**. The crisp input values to fuzzy output values are converted with the help of a fuzzifier. Fuzzy knowledge base stores the knowledge of all the input-output fuzzy relationships. The fuzzy rule base keeps the information about the operation of the process of the domain. The assessment of all rules in the rule base shall be carried out, and the aggregate of each membership function value has been calculated using the maximum operation. The defuzzification method has been carried out by converting fuzzy values to non-fuzzy values using the centroid method. The triangular membership function has been employed in the temperature FLC. The input and output of the fuzzy temperature controller are tabulated in Table 5.1.

Table 5.1: Temperature fuzzy controller rules.

If (E_r = = NB)	then	(Output P = NB)
If (E_r = = NM)	then	(Output P = NM)
If (E_r = = NS)	then	(Output P = NS)
If (E_r = = ZE)	then	(Output P = ZE)
If (E_r = = PS)	then	(Output P = PS)
If (E_r = = PM)	then	(Output P = PM)
If (E_r = = PB)	then	(Output P = PB)

Since the system taken into consideration in this study is linear. So, we can easily extend the operating range of temperature FLC. The input to the temperature FLC is the difference between environmental temperature and the optimized temperature. The output of temperature FLC is the required power for heating and cooling. The detailed rules for the temperature FLC have been tabulated in Table 5.2. In the fuzzy rule base, E_r denotes the difference in actual/environmental temperature and optimized temperature. The seven membership function has been defined in the condition of E_T, the input variable, and the output variable, and Output P represents the output power computed by temperature FLC for heating and cooling operation to maintain the thermal comfort. These seven-membership function associated with input variable 'E_r' and output variable 'Output P' is NB, NM, NS, ZE, PS, PM, PB which are abbreviated for negative big, negative medium, negative small, zero error, positive small, positive medium and positive big respectively. In the temperature, the fuzzy controller E_r represents the error difference between the environmental temperature and the optimized temperature. The input of the fuzzy temperature controller is a resultant error. Depending on the error discrepancy, the fuzzy temperature controller must determine the required power (Output P) to supply the heating/cooling actuators. The range of input values corresponding to the temperature fuzzy controller's output values is tabulated in Table 5.3.

Table 5.2: Fuzzy temperature controllers' rules in detail.

Energy required by a temperature controller (E_T)		**Error (E_r)**						
		NB	NM	NS	ZE	PS	PM	PB
Change in error (CE_r)	NB	NB	NS	PS	PB	PB	PB	PB
	NM	NB	NM	ZE	PM	PM	PB	PB
	NS	NB	NM	NS	PS	PM	PB	PB
	ZE	NB	NM	NS	ZE	PS	PM	PB
	PS	NB	NB	NM	NS	PS	PM	PB
	PM	NB	NB	NM	NM	ZE	PM	PB
	PB	NB	NB	NB	NB	NS	PS	PB

Table 5.3: Input and output range of the fuzzy temperature controller.

Type	**Input Error**			**Output P**		
NB (Negative Big)	-48	36	-24	-34	-25.5	-17
NM (Negative Medium)	-36	-24	-12	-25.5	-17	-8.5
NS (Negative Small)	-24	-12	0	-17	-8.5	0
ZE (Zero Error)	-12	0	12	-8.5	0	8.5
PS (Positive Small)	0	12	24	0	8.5	17
PM (Positive Medium)	12	24	36	8.5	17	25.5
PB (Positive Big)	24	36	48	17	25.5	34

5.4.2 Design of Machine Learning-based Controller

The dataset obtained from the previous step is used for the training linear regression model. Linear regression has been implemented in Jupyter Notebook. This linear regression model represents the ML-based controller. 80% of data have been used to train the model, and the remaining 20% have been used for testing the model. The R^2 value has been calculated, and the plot for actual values of power consumption and predicted values of energy consumption has been shown in Fig. 5.11. The linear regression is useful when we have two continuous variables. One is called an independent vector or predictor, and the other one is called the dependent vector or response. The core idea of this technique is to find the best fit for the data. The linear regression searches for statistical relationships, i.e., it does not find the exact relationship, preferably an approximate one between the variables. The Mean Squared Error (MSE=0.05), variance score (σ^2=1.00), and coefficient of determination (R^2=0.9974) have been selected as the metric for the regression model being trained. These values show an accurate best fit.

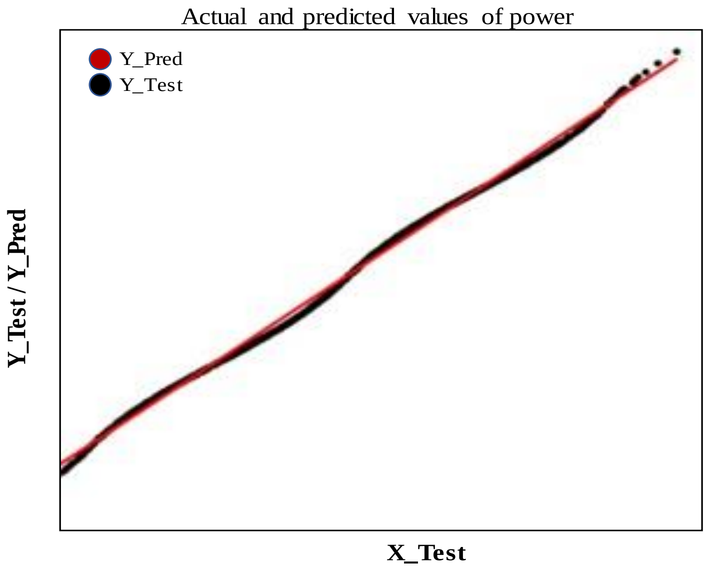

Fig. 5.11: Plot of actual and predicted values of energy consumption.

5.5 RESULTS AND DISCUSSION

All the implementation and experimental studies were carried out on Intel(R) Core(TM) i7-8550U CPU @1.80GHz 1.99GHz with MATLAB 2019a installed. In this section, extensive simulation results obtained from a comparative study of various optimization techniques (GA, Bat, NNA, PSO, and ABC) have been discussed. In the comparative analysis, the input to the temperature FLC was the error difference between the optimized temperature data from the optimizer and the environmental temperature data. It is implemented using a fuzzy logic toolbox available in MATLAB 2019a.

5.5.1 Parameter Settings

Successful implementation of various algorithms for the comparative studies requires selecting optimal GA, Bat, NNA, PSO, and ABC parameters. The parameters of algorithms are selected after many trails performed on the thermal comfort model outlined in Eq. (5.1). These selected parameters of algorithms for optimal solution are tabulated in Table 5.4.

Table 5.4: Optimization parameter setting values of algorithms.

GA Parameter	Value	Bat Algorithm Parameter	Value
Selection Method	1	Number of Generation	5
Cross Method	1	Population Size	20
Population Size	20	Maximum Iterations	200
Maximum Iterations	200	Loudness	0.5
Cross Percent	0.7	Pulse Rate	0.5
Mutate Percent	0.05	Minimum Frequency	0

		Maximum Frequency	1
		Pulse Emission Rate	0.001
ABC Algorithm Parameter	**Value**	**PSO Algorithm Parameter**	**Value**
Population Size (Colony Size)	50	Population Size (Swarm Size)	50
Maximum Iterations	200	Maximum Iterations	200
Number of Onlooker Bees	50	Inertia Coefficient	0.9
Acceleration Coefficient	1	Damping Ratio of Inertia Coefficient	0.4
NNA Parameter	**Value**	Personal Acceleration Coefficient	0.5
Population Size	100	Social Acceleration Coefficient	0.7
Maximum Iterations	200		
Te	30		

5.5.2 Temperature Parameter Optimization

The minimum and maximum temperature of the occupant are set for optimization techniques. The optimization approaches' primary responsibility is to maintain the temperature parameter inside the occupant's preferred range. The primary goal of all the optimization approaches is to minimize the error/difference. Considering an example, the environment temperature is 43.25 ^{0}C, then the difference between the occupant's set point and this environment value is 19.25 ^{0}C. In this case, the most optimum value is 22 ^{0}C (the occupant's minimum temperature), which makes the only difference of 2.75 ^{0}C.

Table 5.5: Temperature parameter description with ranges.

Occupant's minimum temperature	**Occupant's maximum temperature**	**Occupant's Setpoint**	**Environment minimum temperature**	**Environment maximum temperature**
22 ^{0}C	26 ^{0}C	24 ^{0}C	4.96 ^{0}C	43.25 ^{0}C

Optimization methods would aim to get this value as close as possible to 22 ^{0}C to reduce the error difference. This error discrepancy is used in the estimation of the power consumption for the temperature parameter. The minimum the error difference, minimum will be the energy consumption and vice-versa. Table 5.5 presented as a description of the temperature parameter along with their ranges.

5.5.3 Comparative Analysis of Energy Consumption

The user setpoint temperature is fixed to 24 ^{0}C as recommended by the BEE **(TERI, 2019)**, and T_{max} = 26 ^{0}C, and T_{min} = 22 ^{0}C is selected as a maximum, minimum range in the optimization process. After the successful simulation, the obtained energy consumption profile using the optimization techniques (GA, Bat, NNA, PSO, and ABC) of a non-leap year is shown in Fig. 5.12. It is evident that the obtained energy consumption profile through various optimization techniques. The proposed study has successfully reduced energy consumption for a year. The energy consumption is per hour, so according to non-leap year time instants are 8760 hr has been shown in Fig. 5.12. In Fig. 5.13, the comparison of optimization techniques for few time instants between 1000 and 1200 hrs of a year is shown for a visualization. These time instants show that the energy is consumed only by the heating load. In obtained plots given in Figs. 5.12 and 5.13, negative values on the Y-axis show energy consumed through the heating load, and positive values show energy consumed through the cooling load. Some iterations identical convergence rates overlap between few iterations but have successfully optimized both energy consumption and comfort index for a year.

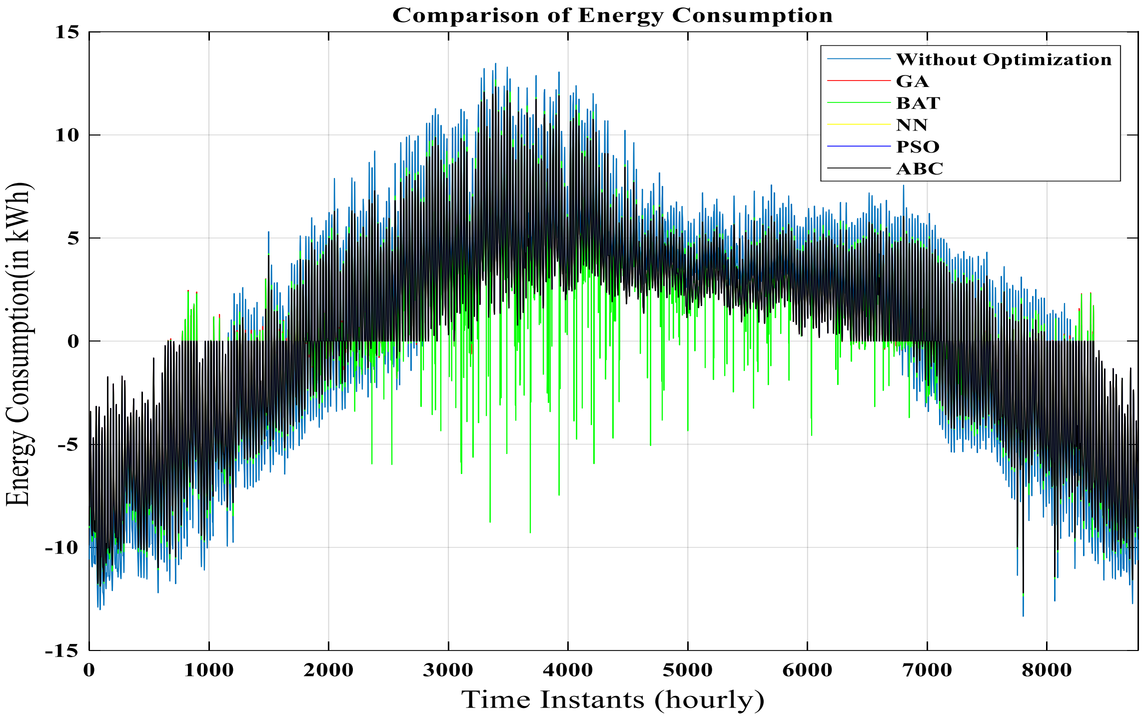

Fig. 5.12: Energy consumption profile for a year with and without using optimization techniques

The energy consumption without optimization was 6805.7 kWhr (heating and cooling) of a year. Later, this energy consumption was minimized using various optimization techniques (GA, Bat, NNA, PSO, and ABC) and found to be 4566.1 kWhr, 3430.1 kWhr, 4527.8 kWhr, 4527.9 kWhr, and 4527.6 kWhr, respectively. It is very clear from the obtained results that the techniques have successfully minimized the energy consumption and found that Bat based optimization is superior over all other utilized techniques in this comparative study. Bat technique reduced the energy consumption by 3430.1 kWhr as compared to others and without optimization.

5.5.4 Comparative Analysis of Comfort Index

The comfort index profile of a year obtained after the successful optimization is shown in Fig. 5.14. The comfort index value obtained without optimization is 0.883, and the values obtained with optimization techniques are (GA, Bat, NNA, PSO, and ABC) are 0.927, 0.930, 0.926, 0.830, and 0.831 respectively. From the plot (please see Fig. 5.14) of the comfort index for a year, it is seen clearly that all optimization techniques successfully maximized the comfort index values viz. close to 1. As the comfort index values are much closer to 1, more will be the occupant's thermal comfort. The comfort index values in Fig. 5.15 is shown for few time instants between 5800 and 6000 hrs for clear visualization of optimized and non-optimized comfort index values. Improving comfort index with minimizing energy consumption has been successfully achieved in Bat based optimization. However, other techniques (GA, PSO, ABC, NNA) have also improved comfort with minimal energy consumption when compared to optimization.

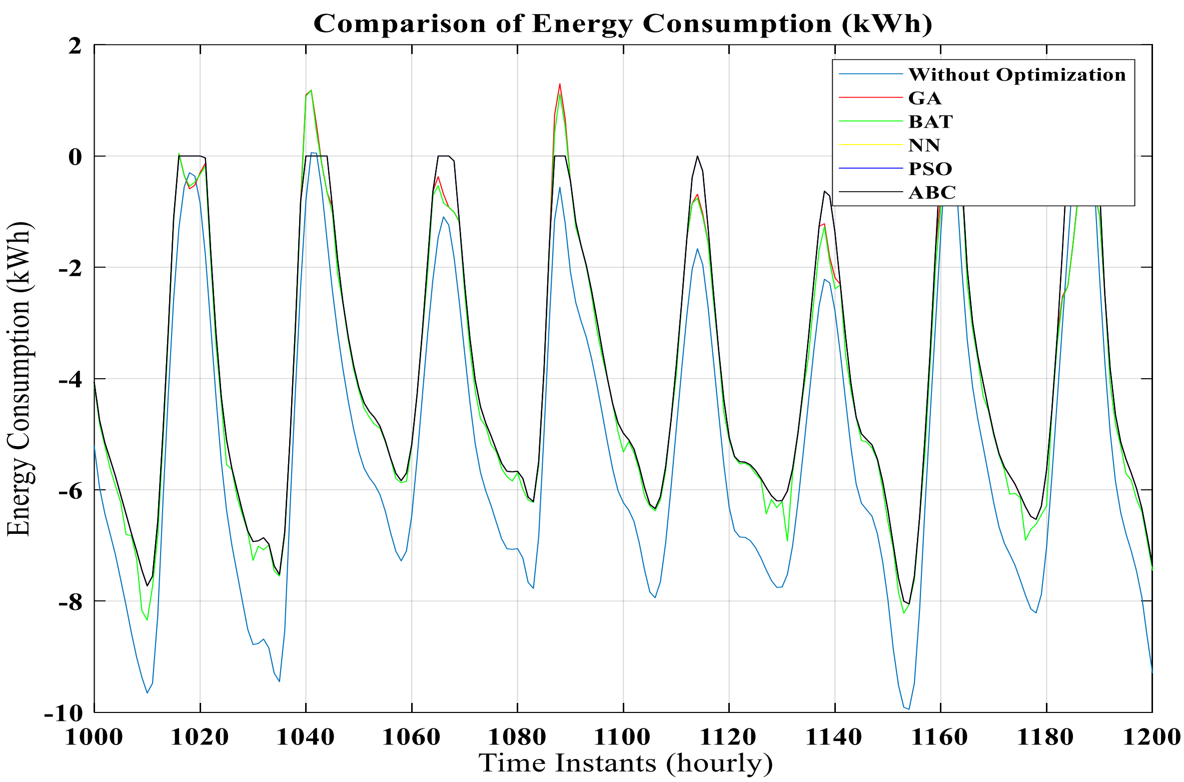

Fig. 5.13: Energy consumption comparison at few time instants

It is evident from the Figs. 5.14 and 5.15 that the optimization techniques have maximized the comfort index value. Bat is still superior to other optimization techniques (GA, NNA, PSO, and ABC). The comfort index value obtained from Bat based optimization is 0.930, which is higher than all other techniques.

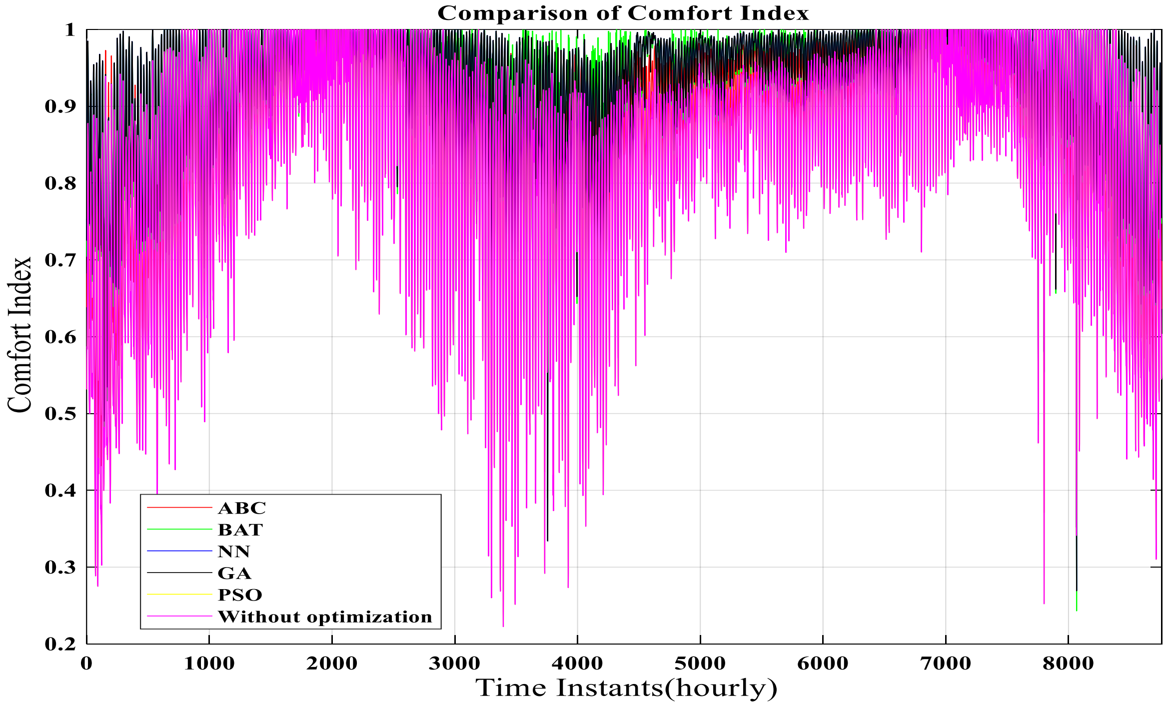

Fig. 5.14: Comfort index comparison of a year with and without optimization.

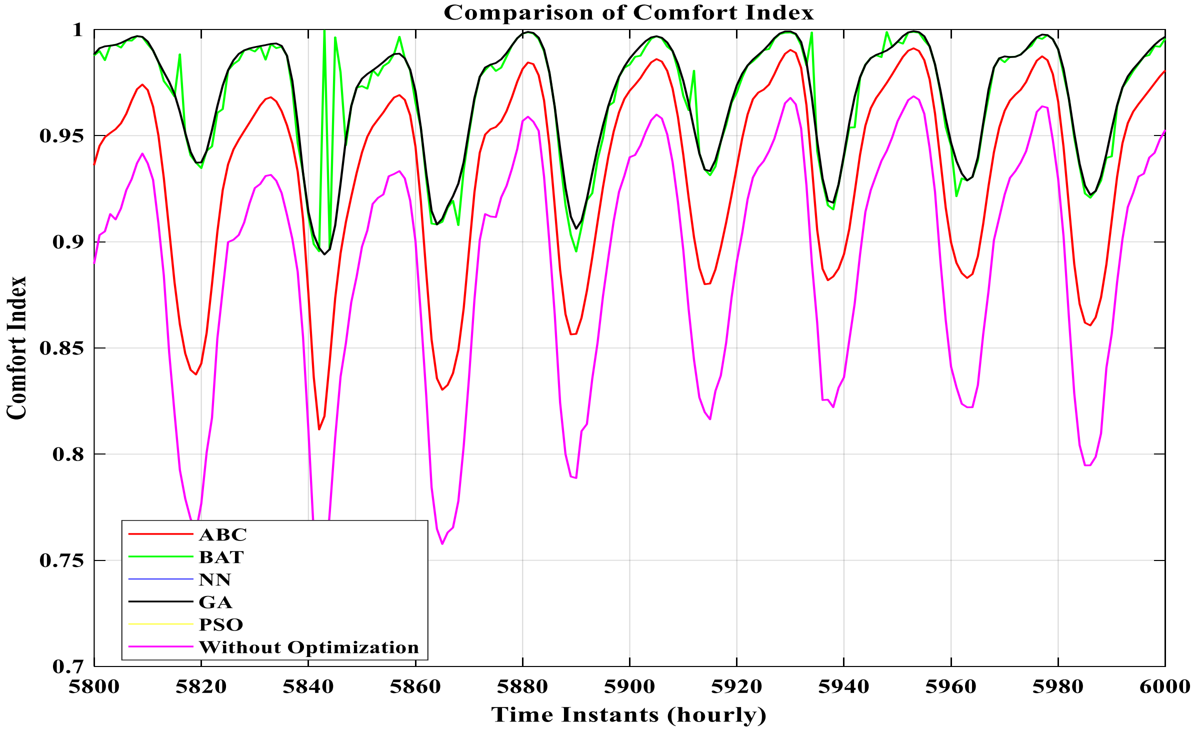

Fig. 5.15: Comfort index comparison at few time instants.

Table 5.6: Comparative statistical analysis of GA, Bat, NNA, PSO and ABC based optimization.

Optimization Technique	**Energy Consumption (Mean Value)** kWhr	**Comfort Index (Mean Value)**
Without	6805.7	0.883
GA	4566.1	0.927
Bat	**3430.1**	**0.930**
NNA	4527.8	0.926
PSO	4527.9	0.830
ABC	4527.6	0.831

Table 5.6 shows the performance evaluation of GA, Bat, NNA, PSO, and ABC optimization model. Actual energy consumption is 6805.7 kWhr while with optimization techniques is has been reduced. Bold values in Table 5.6 indicate better Bat-based optimization results than the other optimization approaches mentioned in the earlier work.

5.6 CONCLUSIONS

Extensive simulation results show that the comparative study successfully minimises energy consumption while maintaining accuracy and user comfort. This work addressed minimizing energy consumption and maximum user-comfort in energy-efficient buildings using GA, Bat, ABC, PSO, and NNA optimization techniques and designed a machine, learning-based controller. In this chapter, the parameter environment temperature was considered for thermal comfort improvement while minimizing energy consumption. Optimization techniques such as GA, Bat, ABC, PSO, and NNA have been applied to optimize the environmental temperature. The applied optimization techniques minimize the environmental temperature difference and the set point (24 ^{0}C). The obtained simulation results from optimization are compared and analysed. In performance evaluation, Bat based optimization model shows better performance with other applied evolutionary optimization algorithms such as GA, PSO, ABC, and NNA.

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE

6.1 INTRODUCTION

Essential and substantial contributions to the thesis have been addressed in this chapter. Few brief contributions for future research have also been reported.

6.2 CONCLUSIONS

Based on the thesis work, important conclusions have been drawn and outlined in this section which is following as:

1. Although predicting energy consumption is becoming more important in building energy management systems, it remains a challenge to continuously improve the performance of predictive models in combination with engineering disciplines. This research work has introduced an efficient and novel energy consumption prediction model for the future based on model integration. The model was used to investigate and inspire more electricity-conscious occupant activities and provide evidence for projected energy savings in the modern world.
2. A novel design approach is developed to solve the conflict between energy consumption while maintaining occupant's comfort. The CSPSO optimization technique and artificial intelligence-based trust-region reflective algorithm optimize the environmental parameter to reduce energy consumption while providing maximum comfort. The goal was to find a global optimum solution between two divergent objectives: indoor comfort and energy consumption. The multi-agent topology-based building management and information system thus formed take care of user's preferences and energy consumption. It effectively controls the actuators for maintaining the desired environment parameters.
3. In the performance evaluation, it is found that the results obtained from the Bat optimization technique are superior to all other applied GA, ABC, PSO, and NNA optimization techniques. The proposed architecture was consisting of an optimizer, an ML-based controller, and a coordinating agent. The input to the optimizer was the environmental temperature parameter, and the user set temperature. The output

of the optimizer, along with the environment temperature, was fed to the controller. The actuators' status was changed as per the coordinating agents' direction, whose input is decided through controller output. From the output plots shown in the results section, it is concluded that energy consumption is reduced by utilizing optimization techniques, and the user's comfort is improved.

4. To check the robustness of the model in performance evaluation ML-based controller is developed in Jupyter notebook. The developed controller's output is further provided to coordinator agents, giving the actuators the power accordingly. The linearity of the developed model improves the performance of the ML algorithm. Dataset obtained from the fuzzy temperature controller was used to design an ML-based controller. The use of an ML-based controller eliminates the need for knowledge of system dynamics. In comparison, only a limited amount of data is needed for the controller design.

6.3 FUTURE SCOPE OF RESEARCH

The future research involves analysing the disaggregation of energy systems into different subsystems that can make it easier to recognize the building's energy consumption dynamics, especially for the HVAC installation, which is difficult to predict. The proposed system can enrich empirical model databases for building energy demand forecasting and boost the overall performance of energy consumption forecasting through actual case verification. The developed ANN can be used to establish the framework of controllers' on-line multi-objective optimization process.

Furthermore, other optimization techniques will be applied with several more comfort parameters in future work to improve the system's efficiency. Several objectives given below can also be carried out in future to explore the presented research work.

1. To improve the accuracy in prediction model and use a technique in big data analytics that can measure and predict the energy change's economic outcomes.
2. Impact of real-time context-aware feedback on heating and cooling behaviour for adaptation of occupants.
3. To study the influence of temperature and relative humidity on adaptive thermal comfort, visual comfort, and IAQ comfort in real-time environments.

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4. A. Verma, S. Prakash and A. Kumar, “A Comparative Analysis of Data-Driven Based Optimization Models for Energy-Efficient Buildings,” in *IETE Journal of Research*, Nov. 05, 2020. doi: 10.1080/03772063.2020.1838347.
5. A. Verma, S. Prakash and A. Kumar, “A novel design approach for indoor environmental quality based on a multiagent system for intelligent Buildings: Towards occupant's comfort,” (**Under Review**).