JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

ENERGY PLANNING FOR MICROGRID BASED ON RENEWABLE ENERGY AVAILABILITY

Thesis submitted by

Kuheli Goswami

Doctor of Philosophy (Engineering)

Department of Electrical Engineering
Faculty Council of Engineering & Technology
Jadavpur University
Kolkata, India

2025

JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

INDEX NO. 159/19/E

1. **Title of the thesis:**

ENERGY PLANNING FOR MICROGRID BASED ON RENEWABLE ENERGY AVAILABILITY

2. **Name, Designation and Institution of the Supervisor/s:**

Dr. Arindam Kumar Sil
Associate Professor
Department of Electrical Engineering
Jadavpur University
Kolkata –700032, India

3. **List of Publications:**

Journals

i. **Kuheli Goswami, Arindam Kumar Sil, "Improvement of Energy Performance Index for Domestic Prosumers Based on Newly Proposed Dynamic Tariff and Rule-based Strategy,"** International Transactions on Electrical Energy Systems (ITEES), indexed by Scopus, SCIE, approved by UGC, Vol. 2022, Article ID: 5087908, August, 2022, https://doi.org/10.1155/2022/5087908.

ii. **Kuheli Goswami, Arindam Kumar Sil, "Renewable Energy based Dynamic Tariff system for Domestic load management"**, Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), indexed by Scopus, approved by UGC, Vol. 25, No. 2,pp 626-638, February, 2022, ISSN: 2502-4752, DOI: 10.11591/ijeecs.v25.i2.pp626-638.

4. **List of Patents:** Nil

5. List of Presentations in National and International Conferences

i. **Kuheli Goswami**, Dr. Arindam Kumar Sil, "**PREDICTIVE ENERGY MANAGEMENT IN MICROGRIDS: DAYLIGHT AND OCCUPANCY SENSORS WITH LIFE CYCLE COST ANALYSIS**", 32nd West Bengal State Science and Technology Congress, 2024-25 and 7TH Regional Science & Technology Congress, 2025, January, 2025

ii. **Kuheli Goswami**, Ayandeep Ganguly, Nayan Manna, Dr. Arindam Kumar Sil, "**Evaluating Classical and ANN-Based Load Forecasting Techniques Using Univariate and Multivariate Analysis,**" Innovations in Electrical and Electronic Engineering 2021, **Springer Conference**, January, 2021

iii. Ayandeep Ganguly, **Kuheli Goswami,** Dr. Arindam Kumar Sil, "**WANN and ANN based Urban Load Forecasting for Peak Load Management", IEEE Calcutta Conference,** 2020 (CALCON). Kolkata, February. 2020

iv. Ayandeep Ganguly, **Kuheli Goswami,** Dr. Arindam Kumar Sil, "**ANN technique based Mid Term Load Forecasting as a case study for Peak Load Reduction", IEEE Conference** on Applied Signal Processing (ASPCON 2018), Jadavpur University, Kolkata, December, 2018

v. **Kuheli Goswami**, Ayandeep Ganguly, Dr. Arindam Kumar Sil, "**Day Ahead Forecasting and Peak Load Management Using Multivariate Auto Regression Technique**," Applied Signal Processing Conference 2018, **IEEE Conference** (ASPCON), Kolkata, December, 2018

vi. **Kuheli Goswami**, Ayandeep Ganguly, Dr. Arindam Kumar Sil, "**Comparing Univariate and Multivariate method for Short Term Load Forecasting**", International Conference on Computing, Power and Communication Technologies, **IEEE Conference**, Noida, September, 2018

vii. Ayandeep Ganguly, **Kuheli Goswami,** Arpita Mukherjee, Dr. Arindam Kumar Sil, "**Short Term Load Forecasting using Artificial Neural Network for Peak Load Reduction**", International Conference on Emerging Trends in Engineering and Science, **Springer Conference**, March, 2018

JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

STATEMENT OF ORIGINALITY

I, **Ms. Kuheli Goswami** registered on **19^{th} June, 2019**, do hereby declare that this thesis entitled **"ENERGY PLANNING FOR MICROGRID BASED ON RENEWABLE ENERGY AVAILABILITY"** contains a literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis has been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the Policy on Anti Plagiarism, Jadavpur University, 2019 and the level of similarity as checked by iThenticate software is 4%.

Signature of the Candidate: Kuheli Goswami

Date: 02/06/2025

Certified by Supervisor:
(Signature with date, seal)

Arindam Kumar Sil 02/06/2025

(Dr. Arindam Kumar Sil)

Dr. Arindam Kumar Sil
Associate Professor
Electrical Engg Dept.
Jadavpur University
Kolkata - 700 032

JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled **"ENERGY PLANNING FOR MICROGRID BASED ON RENEWABLE ENERGY AVAILABILITY"** submitted by **Ms. Kuheli Goswami**, who got her name registered on 19th **June, 2019** for the award of **Ph.D. (Engineering)** degree of Jadavpur University is absolutely based upon her own work under the supervision of **Dr. Arindam Kumar Sil** and that neither her thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.

Arindam Kumar Sil 02/06/2025

(Dr. Arindam Kumar Sil)

Signature of the Supervisor
and date with Official seal

Dr. Arindam Kumar Sil
Associate Professor
Electrical Engg Dept.
Jadavpur University
Kolkata - 700 032

……

This research work is dedicated to my Mother

……

Acknowledgements

This work could not be properly accomplished without pertinent guidance, best wishes, continuous support and blessings from companions. I found myself fortunate enough to show my gratitude to all who have supported me wholeheartedly during my Ph.D. tenure. I am indebted for their aspiring guidance, friendly ad- vice and earnest care during this duration. I am earnestly thankful to them for their priceless supervision on different issues of the Ph.D. research.

First of all, I am gratified to my supervisor, Dr. Arindam Kumar Sil for his continuous support in my Ph.D. study and research. I consider myself extremely lucky to have such mentor who allowed me to explore on my own while offering support when I was in need. Throughout the entire process of conducting research and writing this dissertation, his advice has been praiseworthy. I am also grateful for his moral support to overcome the difficulties I experienced during this tenure.

I am thankful to the present and former Heads of the Department of Electrical Engineering, Jadavpur University for providing me with proper research facilities in the department. I would like to thank all the faculties and staff of the Department of Electrical Engineering, especially Prof. Goutam Sarkar and Prof. Sovan Dalai, for their advice and suggestions during this research work.

Finally, I am indebted to my mother Mrs. Rita Goswami, father Mr. Gour Goswami, my husband Mr. Amit Ghosh and my son Arik Ghosh for their continuous support and inspiration to reach this milestone. This success could not be achieved without having such pleasant accompanies which make my journey more comfortable.

Kuheli Goswami
02/06/2025

Kuheli Goswami
Electric Machine and Drives
Department of Electrical Engineering
Jadavpur University
Kolkata, India
January, 2025

Abstract

In today's world, one of the most important parameters deciding the global growth is determined by its per capita energy consumption. Energy in the form of electricity plays a vital role in day-to-day life. An unbalanced growth between the highly developed and economically backward countries makes the energy consumption scenario even worst. Rapid industrialization and urbanization lead to exponential growth in power consumption. Although power planning is drawing significant attention, the country is facing a persistent power crisis since last few years.

Meeting the ever-growing load demand and managing grid stress has become a significant challenge in today's world. The load demand fluctuates due to various factors, including human habits, economic growth, the acceptance of new technology advancements, geographical location and demographic cycles etc. Utility sectors have provided data indicating that in some countries, more than 25% of total energy is consumed by the domestic sector. Additionally, significant energy consumption in the commercial and agricultural sectors highlights the diverse energy needs across the economy, underscoring the need for improvements in the transmission system. The present energy transmission system often suffers from significant losses and the growing stress on the grid necessitates a shift towards more efficient energy management solutions. This is where microgrid becomes inevitable, as they can reduce transmission losses as well as grid stress through localized energy management. While traditional consumers rely mostly on grid energy and they never become part of the load management initiatives, in recent past consumers have been part of the generation by feeding their own generated electricity from roof top PV or wind to a storage system or directly to the grid. This has been a smart move towards load management initiatives. These consumers are called prosumers. Prosumers not only generate their own energy but also contribute demands to the system, creating a more dynamic energy ecosystem, by transitioning consumers, mostly domestic consumers into domestic prosumers where they play a pivotal role in addressing the current power scenario. This has helped in developing a dynamic, robust, yet flexible Energy Management System. Microgrid plays a significant role in providing capacity addition to generation in local grids by integrating Renewable Energy. Prosumers connected to microgrids contribute to a more stable and resilient energy system by providing additional generation capacity and demand response capabilities. The localized nature of microgrid ensures that the energy produced by prosumers is used efficiently within the community, reducing the need for long-distance transmission and optimizing local-level energy management. The growth of prosumers and microgrids encourages technological

innovation in energy storage, smart grid technologies and the energy management system. Both prosumers and microgrids empower communities to take control of their energy future, promoting sustainability and self-sufficiency. Factors that dictate energy management includes Load Forecasting, Load Profiling, Load Scheduling etc. Load forecasting plays vital role for the efficient and reliable operation of modern energy system. They enable effective integration of renewable energy sources, enhance grid stability, contribute to cost savings and sustainability goals. This is essential for meeting the growing demands and challenges for the energy sector.

To achieve an efficient energy management system, an accurate forecasting, load profiling and load scheduling based on tariff and Renewable Energy availability is utmost important. Various forecasting techniques have been studied and analyzed for load forecasting, including Time Series Analysis and Artificial Intelligence based methods. Auto Regressive Integrated Moving Average (ARIMA) and Auto Regressive Integrated Moving Average with exogenous variables (ARIMAX). ARIMA, ARIMAX are classical techniques, time series analysis whereas Artificial Neural Network (ANN), Wavelet and Artificial Neural Network (WANN) and others are AI based. Each technique has its own benefits. ARIMAX models are faster and requires less computational power compared to Long Short-Term Memory (LSTM) and ANN model, making them suitable for applications with limited resources.

Load scheduling, like load forecasting is an utmost important part of energy management system. Load scheduling involves strategically planning and controlling the distribution of electric loads to optimize energy usage and cost. Effective load scheduling aims to balance supply and demand, minimize energy cost, reduced peak load and enhance the reliability of the existing system. The present work proposes to develop a Load Management System which is meant for different kind of loads at present mainly with their prediction, Time of Use and followed by Renewable Energy availability and integration. A case study was needed to understand the nature of domestic load variation pertaining their time of use in a day, run time etc. We have explored various feature selection techniques to select appropriate parameters for scheduling household appliances and Energy Storage Systems (ESS) and found that Weighted K nearest neighbor method (WKNN) excels in selecting features compared to Complex Tree, Gaussian SVM (State Vector Machine) and Bagged Trees method, which in turn contributes towards an efficient Energy Management System (EMS). The reliability and sustainability of an EMS can be enhanced by incorporating ESS. ESS helps to balance supply and demand, maintaining grid stability by storing excess energy during low demand and releasing it during high demand leading to cost savings. On the other hand, ESS facilitates the innovation in energy storage, smart grid technologies and the energy management system. Both prosumers and microgrids empower communities to take control of their energy future, promoting sustainability and self-sufficiency. Factors that dictate energy management includes Load Forecasting, Load Profiling, Load Scheduling etc. Load forecasting plays vital role for the efficient and reliable operation of modern energy system. They enable effective integration of renewable energy sources, enhance grid stability, contribute to cost savings and sustainability goals. This is essential for meeting the growing demands and challenges for the energy sector.

To achieve an efficient energy management system, an accurate forecasting, load profiling and load scheduling based on tariff and Renewable Energy availability is utmost important. Various forecasting techniques have been studied and analyzed for load forecasting, including Time Series Analysis and Artificial Intelligence based methods. Auto Regressive Integrated Moving Average (ARIMA) and Auto Regressive Integrated Moving Average with exogenous variables (ARIMAX). ARIMA, ARIMAX are classical techniques, time series analysis whereas Artificial Neural Network (ANN), Wavelet and Artificial Neural Network (WANN) and others are AI based. Each technique has its own benefits. ARIMAX models are faster and requires less computational power compared to Long Short-Term Memory (LSTM) and ANN model, making them suitable for applications with limited resources.

Load scheduling, like load forecasting is an utmost important part of energy management system. Load scheduling involves strategically planning and controlling the distribution of electric loads to optimize energy usage and cost. Effective load scheduling aims to balance supply and demand, minimize energy cost, reduced peak load and enhance the reliability of the existing system. The present work proposes to develop a Load Management System which is meant for different kind of loads at present mainly with their prediction, Time of Use and followed by Renewable Energy availability and integration. A case study was needed to understand the nature of domestic load variation pertaining their time of use in a day, run time etc. We have explored various feature selection techniques to select appropriate parameters for scheduling household appliances and Energy Storage Systems (ESS) and found that Weighted K nearest neighbor method (WKNN) excels in selecting features compared to Complex Tree, Gaussian SVM (State Vector Machine) and Bagged Trees method, which in turn contributes towards an efficient Energy Management System (EMS). The reliability and sustainability of an EMS can be enhanced by incorporating ESS. ESS helps to balance supply and demand, maintaining grid stability by storing excess energy during low demand and releasing it during high demand leading to cost savings. On the other hand, ESS facilitates the integration of renewable energy sources, which are intermittent by nature. The integration of renewable energy sources into the existing grid presents both advantages and disadvantages. On the negative side, the most well-known disadvantage is the stability issue, due to the intermittent nature of renewable energy, which can affect grid reliability. However, on the positive side, renewable energy offers a crucial solution for reducing dependence on coal, lowering carbon emissions and promoting environmental sustainability. Proper utilization of renewable sources can also provide economic benefits, particularly through participation in the electricity trade market.

In this context, tariff structures play a crucial role by encouraging efficient energy usage and helping to balance the integration of renewable sources into the grid, ensuring both economic and operational sustainability. It plays a crucial role in shaping energy consumption patterns and cost management. Time Of Use (TOU), Demand Charges, Real Time Pricing (RTP) are the different tariff schemes which have been studied and implemented in the designed EMS.

Finally, a Tri-Optimized Tariff (TOT) has been proposed, an AI-based dynamic scheme that supports cost optimization, load balancing and promotes energy efficiency among prosumers.
The demand profiles of residential prosumers are influenced by geographic conditions and demographics, making the use of an appropriate optimization technique essential to the design and operation of the energy management system. It drives efficiency, cost effectiveness and sustainability ensuring that energy resources are utilized optimally while meeting the demands of reliability, environmental standards and economic feasibility. Implementation of robust optimization methods is essential for modern energy management in the face of increasing energy demand and the transition towards renewable energy sources. In this context, we have explored various optimization techniques, culminating in the development of a hybrid technique merging Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) etc and finally, we have proposed a novel hybrid synergic swarm approach that incorporates the strength of PSO and ACO with a specific focus on addressing Multiple Knapsack problems (MKP). The effectiveness of the proposed technique has been tested in IEEE 33 bus system which is commonly used for power flow analysis due to its moderate size and complexity, making it manageable for testing different algorithms and techniques. The outcome demonstrates the efficiency and real-world potential of our model. We have conducted a case study and developed an AI based Strategic Residential Load Management System (SRLMS) showing cost effectiveness and improved energy performance index (EPI) for prosumers. This work encourages the development of a harmonious relationship between utility sectors and prosumer

Contents

List of Figures

List of Tables

List of Abbreviations

A	
ACF	Auto Correlation Factor
ACO	Ant Colony Optimization
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
ARIMAX	Auto Regressive Integrated Moving Average with exogeneous variables
C	
CAPEX	Capital Expenditure
CEA	Central Electricity Authority
D	
DG	Distributed Generation
DGI	Demand Generation Index
DR	Demand Response
DSM	Demand Side Management
E	
EMS	Energy Management System
EPI	Energy Performance Index
ERLDC	Eastern Regional Load Dispatch Center
ESS	Energy Storage System

ESU	Energy Storage Unit
G	
GA	Genetic Algorithm
GHI	Global Horizontal Irradiation
GUI	Graphical User Interface
H	
HEMS	Home Energy Management System
HSSA	Hybrid Synergistic Swarm Approach
I	
IEA	International Energy Agency
L	
LSTM	Long Short-Term Memory Network
M	
MILP	Mixed Integer Linear Programming
MKP	Multiple Knapsack Problem
MTLF	Medium Term Load Forecasting
MATLAB	Matrix Laboratory
O	
OPEX	Operating Expense
P	
PACF	Partial Auto Correlation Factor

PAR	Peak to Average Ratio
PSO	Particle Swarm Optimization
PV	Photovoltaic
R	
RE	Renewable Energy
RES	Renewable Energy Source
RTP	Real Time Pricing
S	
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SOC	State of Charge
SRLMS	Strategic Residential Load Management
STLF	Short Term Load Forecasting
SVM	Support Vector Machines
T	
TFM	Transfer Function Model
TOT	Tri Optimized Tariff
TOU	Time Of Use
W	
WANN	Wavelet Artificial Neural Network
WCSS	Within Cluster Sum of Square
WKNN	Weighted K – nearest neighbor

List of Symbols

A list of all the symbols, their representative quantities and units has been provided below to familiarize the readers with the frequently used symbols within this thesis.

Y_t	tth time series of load demand
Y_{t-1}	(t-1)th time series of load demand
B	mathematical tool known as the backward shift operator
V	mathematical tool known as the backward difference operator
s	time span
D	order of seasonal difference in ARIMA
d	order of continuous difference in ARIMA
$\emptyset_P(B)$	operator used in auto regression
V^d	difference operator of the order d
$\theta_q(B)$	operator used in moving average
p	order of AR process
q	order of MA process
a_t	white noise series
Y_t	response series
X_t	predictor data series
C	constant term
N_t	stochastic disturbance
$v(B)X_t$	transfer function
h	number of terms plus one of the independent variables.
r	number of terms plus one of the dependent variables

b	dead time
a_t	zero mean and normally distributed white noise
C'	intercept in regression model
B'	coefficients of regression
U_t	series of disturbance
Ai	Actual value
F_i	Forecasted value
ε_t	innovation series
A	Set of appliances
T	Time period of 24 hours
$\phi_{a1}(t)$	State of operation vector for appliance a1
S_{a1}	Start time of a1
F_{a1}	Stop time of a1
σ_{a1}	total energy consumed by a1 appliance
T_{ON}	Operation time of a1
α_{a1}	Rating of a1
E_{GRID_used}	Conventional Energy used from Grid
E_{RE}	Available Renewable Energy
E_{RE_used}	energy consumed by RES
$\gamma_{t.GRID}$	forecasted price of energy from main grid at time t
$\gamma_{t.PV}$	forecasted price of solar energy at time t
$\gamma_{Total(h)}$	cost calculation for each hour
γ_{Day}	cost calculation for each day
τ_{ra1}	request time of the appliance a1

$\tau_{w.avg}$	Average waiting time
τ_{wa1}	waiting time of the appliance a1
τ_w	Total waiting time
ϑ_{ai}	Flexibility Index
PI	Priority Index
α_{ai}	rating of appliance
ρ_{a1}^{t}	operating time of a1 over 24 hours
fa1	frequency of operation of a1 or No. of switch ON
U_{ai}	Utilization factor
ϑ_{ai}	Priority Ranking
η_B	Round efficiency
θ_x	Solar Zenith Angle
α	the latitude in the radian
δ	solar declination
d	day of the year (from 1 to 365)
H	hour angle in degree
I_t	Solar Irradiance on Earth’s Surface
I_o	solar constant
η	efficiency of the PV system
$P_{PV}(\tau)$	PV Output
$E_{PV.load}$	Energy used for home appliances
$E_{PV.storage}$	Energy used for storage system
$\eta_{discharging}$	Discharging efficiency
$\eta_{charging}$	Charging efficiency

η_B	Round efficiency,
PP	Energy Price in Peak hours
OPP	Energy Price in Off-peak hours
IP	Energy Price in Intermediate hours
E_P	Energy consumption in Peak hours
E_{OP}	Energy consumption in Off-Peak hours
E_I	Energy consumption in Intermediate hours
x_i	Binary variable representing the state (ON/OFF) of the household appliance i at a specific time t
$P_i(t)$	Power consumption of appliance i at time t.
$W_i(t)$	Waiting time before appliance i can be operated at time t.
R(t)	RE available at time t.
$x_i(t)$	binary variable (1 if appliance i is on at time t, 0 otherwise).
$P_i(t)$	power consumption of appliance i at time t.
Δt	duration of the time interval (in hours).
W_{max}, i	maximum allowable waiting time for appliance i.
$x_{n,d}^{I}$	Position of nth particle in d dimension at I iteration
$v_{n,d}^{I}$	Velocity of nth particle in d dimension at I iteration
ω	Inertia
μ	acceleration constant for cognitive component
ϑ	acceleration constant for social component
R1, R2	stochastic component of algorithm a random value between 0 to 1.
$Pbest_{n,d}^{I}$	local best for nth particle in dimension d.
$Gbest_{n,d}^{I}$	Global best for all particle in dimension d
$\rho_{n,d}$	Pheromone

γ	evaporation rate of pheromone
Dn	distance of the path traversed by nth swarm particle
$\lambda_{m,d}$	traversed distance by swarm particle m in d dimension towards particle j if τ is minimum
$\epsilon_{mj,d}$	distance between mth and jth particle in d dimension
$\varepsilon_{n,d}$	heuristic information
P_{mj}	probability of selecting a path towards j
$V_{j(i)}$	Voltage level of bus j
$V_{k(i)}$	Voltage level of bus k
Pi , Q_i	Sending end active and reactive power flow through ith branch
$\mathrm{P_i^Y}$	Real power flow before Y
$\mathrm{Q_i^Y}$	Reactive power flow before Y
I''	Current flowing through the series parameter of ith branch
R_i	ith branch resistance
X_i	ith branch reactance
B_i	ith branch susceptance
G_i	ith branch conductance
$\mathrm{P_{k(i)}^{Load}}$	Real load power at bus k
$\mathrm{Q_{k(i)}^{Load}}$	Reactive load power at bus k
$\mathrm{P}_{\mathrm{k(i)}}^{I}$	Real injected power at bus k
$\mathrm{Q}_{\mathrm{k(i)}}^{I}$	ctive injected power at bus k
N_{PV}	Number of PV unit
N_{ESU}	Number of Energy storage unit
$PV\_DG_{capacity}$	capacity of PV based DG
$PV\_DG_{capacity}^{min}$	Minimum capacity of PV based DG

$PV\_DG_{capacity}^{max}$	Maximum capacity of PV based DG
$ESS_{capacity}$	Capacity of ESS
$ESS_{capacity}^{min}$	Minimum Capacity of ESS
$ESS_{capacity}^{max}$	Maximum Capacity of ESS
V_{min}	Minimum allowable voltage in pu
V_{Y}^{E}	Expected voltage magnitude
V_{max}	Maximum allowable voltage in pu
P_{level_max}	Maximum penetration level
UB_{RE}	Renewable energy utilization benefit
C_{IH}^{RE}	Renewable energy consumption in intermediate hours
CET_{IH}	Conventional energy tariff in intermediate hours
C_{PH}^{RE}	Renewable energy consumption in peak hours
CET_{PH}	Conventional energy tariff in peak hours
RET	Renewable energy tariff
UB_{ESS}	Energy Storage System Utilization Benefit
C_{OPH}^{RE}	Renewable energy consumption in off-peak hours
C_{OPH}^{CE}	Conventional energy consumption in off-peak hours
CET_{OPH}	Conventional energy tariff in off-peak hours
$C"_{IH}^{RE}$	Renewable energy consumption in intermediate hours using ESS
RET_{ESS}	renewable energy tariff using ESS
$C"_{OPH}^{CE}$	Renewable energy consumption in off-peak hours using ESS
$C"_{PH}^{CE}$	Conventional energy consumption in peak hours using ESS

CET_{PH}	Conventional energy tariff in peak hours
$C"^{CE}_{IH}$	Conventional energy consumption in intermediate hours using ESS
CET_{IH}	Conventional energy tariff in intermediate hours
UB_{LS}	Load Scheduling Benefit / Incentives

CHAPTER 1

Introduction

India's power sector is changing significantly as the country moves towards cleaner energy sources for several reasons. First, there's growing concern about air pollution and climate change caused by burning fossil fuels like coal. Shifting to renewable energy sources, such as solar and wind, helps reduce harmful emissions and improve air quality. India's commitment to international climate agreements also drives this change, as the country aims to meet its climate goals. Advances in technology have made renewable energy more affordable and efficient, making it a better option compared to traditional fuels. With rising energy demand due to a growing population and urbanization, cleaner energy sources offer a sustainable solution. This transition not only tackles environmental and health issues but also provides economic benefits. Despite this shift, coal continues to be the main source of electricity, accounting for over 70% of the country's total generation, as reported by the Central Electricity Authority (CEA). Coal's abundant availability and low cost make it a vital part of India's energy infrastructure. This is especially important as the nation faces growing energy demands due to rapid population growth, increased industrial activity and expanding urban areas. Although renewable energy technologies like solar and wind are advancing and becoming more prevalent, coal remains crucial because it provides the stable and reliable power needed to meet the country's base-load requirements. Base-load power refers to the constant minimum level of demand that must be always met, which coal reliably supports. Government reports continue to show that coal contributes more than 70% of India's electricity, reflecting its ongoing significance. This reflects the challenge of balancing the transition to cleaner energy while still relying on coal to ensure a stable and consistent power supply.

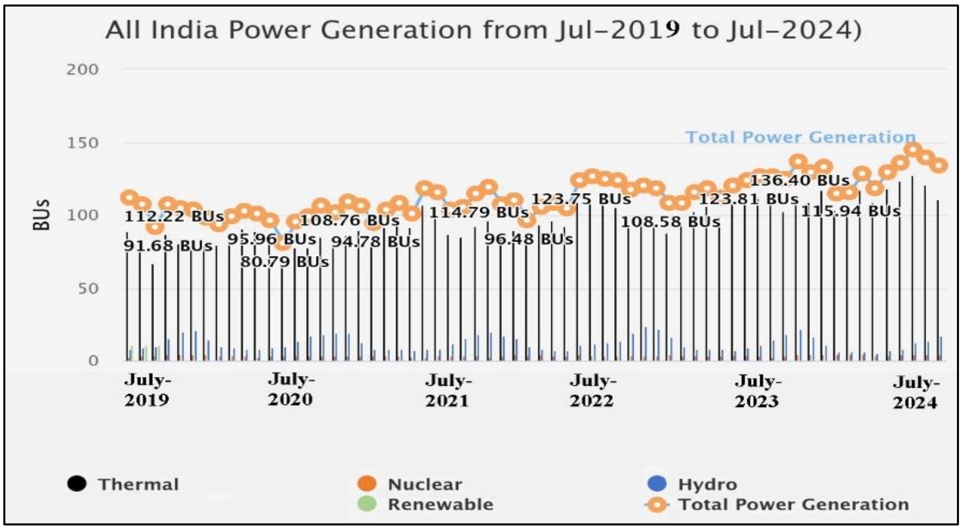


Fig 1.1 Power Generation Report [Central Electricity Authority]

The government is actively working to reduce dependence on coal over time, but it will remain essential during India's transition to a more sustainable energy mix as power consumption is increasing daily in both rural and urban areas. A report by CEA reveals the plan wise growth of electricity sector in India in terms of installed generation capacity and electrification from the year of 1947.

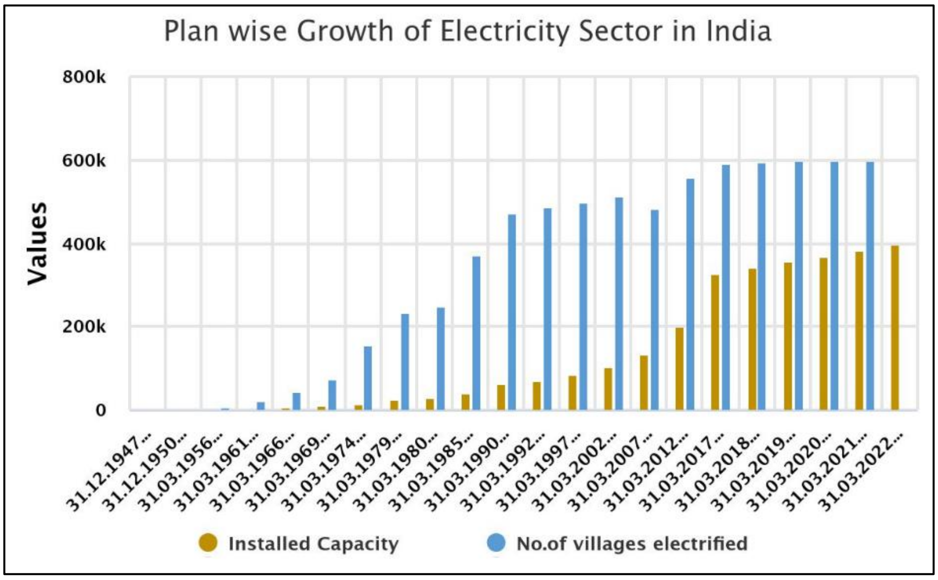


Fig 1.2 Growth of Electricity Sector Report [Central Electricity Authority]

In rural areas, the government has connected over 28 million households to the power grid, leading to higher usage of basic appliances. In cities, the situation is different. Here, power consumption is growing because people are using more high-capacity and energy-intensive appliances. These include air conditioners, refrigerators, washing machines and even electric vehicles. As more urban residents buy and use these appliances, the demand for electricity continues to rise. This growing demand adds pressure to the power grid, highlighting the need for a balance between using coal and expanding cleaner energy sources, there by using India's per capita energy consumption. Per capita energy consumption refers to the average amount of energy consumed per person in each period, usually measured annually. It is a key indicator of a country's energy use and overall economic development. According to the CEA, India's per capita electricity consumption was 1,255 kWh in 2022 and it is anticipated to grow further as more people gain access to electricity and purchase appliances.

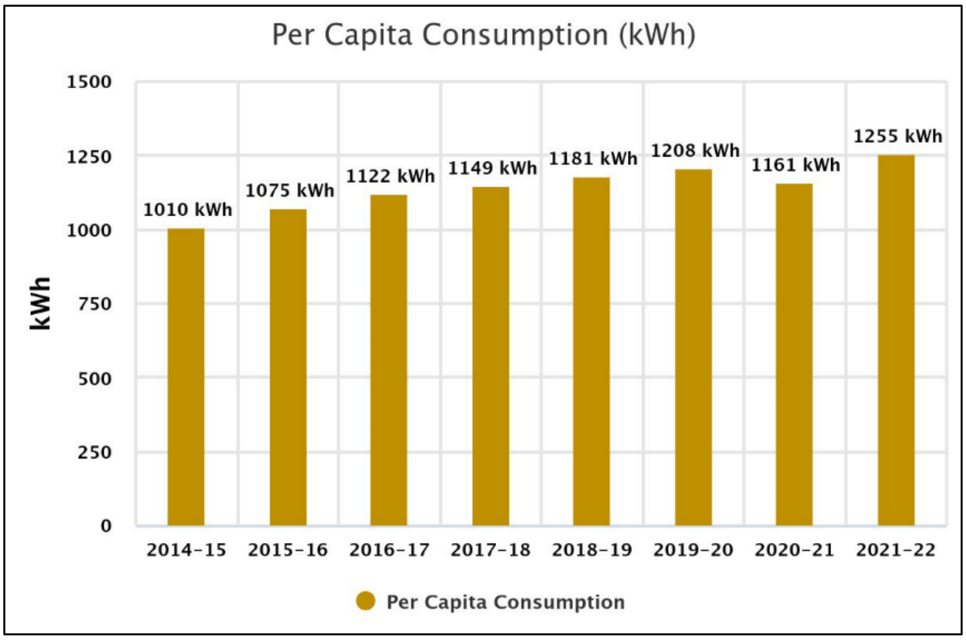


Fig 1.3 Per Capita Consumption Report [Central Electricity Authority]

This figure reflects the average amount of electricity used by each person in India over the year, which has a rising trend from last 10 years. As India continues to develop and more households gain access to electricity, this number is expected to increase. The rise in per capita consumption is influenced by factors such as economic growth, increased appliance ownership and higher living standards. Tracking per capita energy consumption helps in understanding the energy needs of a population and planning for future energy infrastructure and resource management. On the other hand, this increase in consumption is raising the overall demand for electricity nationwide, particularly during peak hours when many people use energy simultaneously, which has been reflected in a report by CEA in terms of Peak Demand in last 5 years. Peak consumption, which often occurs during evenings with high usage of household appliances, puts additional strain on the power grid and presents challenges in supply management.

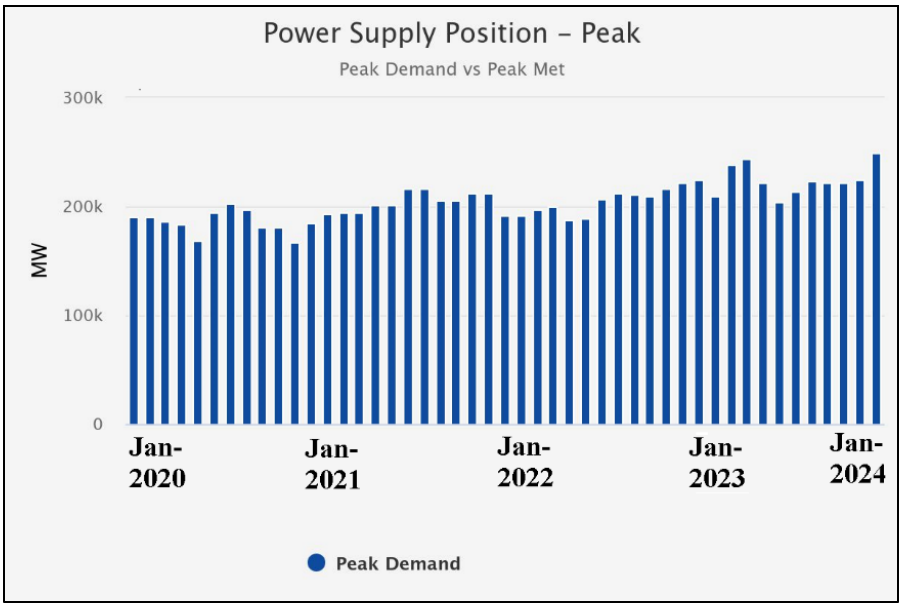


Fig 1.4 Power Supply – Peak Demand Report [Central Electricity Authority]

To address this rising demand, renewable energy is becoming a reliable solution due to its sustainability, decreasing costs and expanding capacity. Solar and wind energy have experienced rapid growth, with these sources providing clean and abundant power, helping to reduce reliance on coal and cut carbon emissions. The government is focusing on increasing power capacity and boosting the share of renewable energy, which reached about 40% of installed capacity by 2023. The CEA reported that India's total installed power capacity was approximately 412 GW in 2023, with renewables making up around 120 GW. The government aims to achieve 500 GW of renewable energy by 2030, with significant emphasis on solar and wind energy.

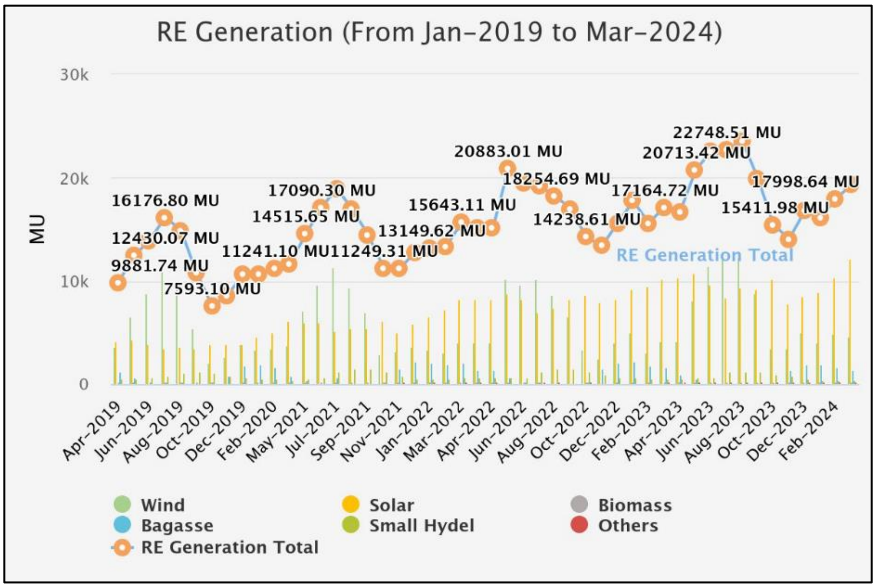


Fig 1.5 RE Generation Report [Central Electricity Authority]

As the population grows and appliance ownership rises in both cities and villages, the challenge is to manage the increasing demand for electricity. The government is also working on improving the energy efficiency of appliances and upgrading grid infrastructure to ensure a reliable supply of power. These measures are crucial to meeting the rising energy needs and ensuring a stable and sustainable electricity supply for the future, which in turn inspires the proposal of an effective energy management system. A robust yet flexible energy management is crucial for sustainability, cost-efficiency and environmental stewardship.

An Energy Management System (EMS) serves as a comprehensive framework that enables organizations to monitor, control and optimize their energy consumption. By integrating advanced technologies and data analytics, an EMS not only reduces energy costs but also enhances operational efficiency and supports compliance with regulatory standards. As businesses and institutions strive to minimize their carbon footprint, implementing a robust EMS becomes essential in driving both economic and environmental benefits. Within this framework, two key types of energy management play distinct but complementary roles: grid management and load management.

Grid management involves managing the entire electrical grid to ensure a stable and reliable supply of electricity from power plants to consumers. This type of energy management focuses on real-time monitoring and control, utilizing advanced technologies like PMU, SCADA to continuously monitor the grid's performance and make real-time adjustments to maintain stability and prevent outages. It also includes the integration of renewable energy by managing the variability of sources such as wind and solar through forecasting and using energy storage systems to balance supply and demand. Furthermore, grid management employs demand response programs to encourage consumers to reduce or shift their electricity usage during peak times, preventing grid overload and maintaining efficiency. Regular maintenance and upgrades of grid infrastructure ensure it can handle present and future energy demands, incorporating microgrids for better performance, resilience, immediate and local solutions.

Microgrids as dynamic decentralized energy systems offer a good way to make energy distribution optimized in local areas. They can easily include renewable energy sources, storage systems and smart controls. This not only makes energy supply more dependable but also supports the idea of being eco-friendly. The integration of microgrid solutions with residential load management strategies is particularly captivating, as it holds the potential to foster a harmonious relationship, optimizing energy consumption patterns at both macro and micro levels.

Load management, on the other hand, focuses on optimizing the energy consumption patterns of end-users to improve efficiency and reduce costs, thereby complementing the stability provided by grid management. Key aspects of load management include energy efficiency programs that encourage the use of energy-efficient appliances and lighting to reduce overall energy consumption. Time-of-use pricing strategies incentivize consumers to use electricity during off-peak hours when demand is lower and electricity is cheaper. Automated systems, such as smart thermostats and programmable lighting, adjust energy usage based on real-time data. Peak load shaving reduces energy consumption during peak demand periods by shifting non-essential usage to off-peak times, helping prevent grid stress and lowering energy costs for consumers. User education and engagement are also critical, providing consumers with the information and tools to better understand and manage their energy usage, promoting sustainable habits and practices.

An effective Energy Management System incorporates both grid management and load management strategies to create a balanced and efficient energy ecosystem. By ensuring the reliable operation of the electrical grid and optimizing energy usage at the consumer level, an EMS plays a critical role in achieving sustainability goals, reducing operational costs and enhancing the overall resilience of the power infrastructure. This interconnected Renewable energy-based approach, supported by judicious tariff structures ensures that energy is managed efficiently, addressing both the supply side and demand side to create a sustainable and efficient energy future.

Integral to this approach are various forecasting techniques and optimization techniques that enable organizations to anticipate future trends, behaviours, and outcomes, thereby facilitating strategic planning and informed decision-making. Leveraging historical data and advanced analytical methods, these techniques, provide valuable insights across various domains, enhancing the EMS's ability to navigate uncertainties, optimize operations and gain a competitive edge in an ever-evolving scenario.

Amongst the two, grid management plays a significant role. Because this side as known as DSM, allows us to develop better understanding of different types of loads, their daily, weekly, monthly, yearly and seasonal profiles, we are more focused in load management, which indirectly co-relates or reflects Grid management.

Effective load management and grid management are integral components of a comprehensive energy management system, as they work together to optimize energy usage, stabilize the grid and ensure efficient and reliable energy delivery. Several key factors define a robust and flexible energy management system, including load forecasting, load scheduling, decision-making and the incorporation of the intermittent behaviour of renewable energy sources into the existing system.

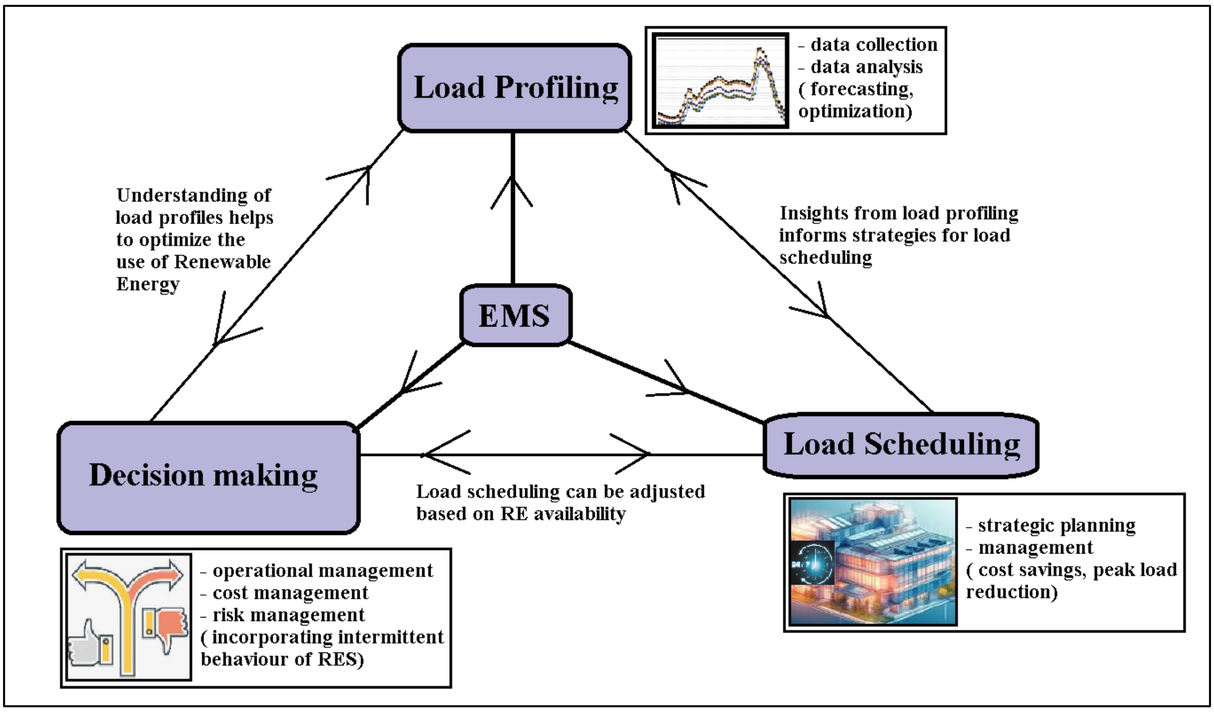


Fig 1.6 Conceptual Framework of EMS

The image presents a conceptual framework illustrating the interaction between Load Profiling, Load Scheduling and Decision Making within an Energy Management System (EMS). At the core is the EMS, which integrates data from both Load Profiling and Load Scheduling to optimize energy use. **Load Profiling** involves data collection and analysis, such as forecasting and optimization, which provides an understanding of energy consumption patterns. This helps in identifying the most efficient ways to utilize renewable energy sources. The insights gathered from load profiling directly inform **Load Scheduling** strategies, where energy use is planned and managed for optimal cost savings and peak load reduction. Load scheduling can be dynamically adjusted based on the availability of renewable energy, which aids in strategic planning and enhances overall energy management efficiency.

Finally, **Decision Making** is influenced by both load profiling and load scheduling. The EMS helps decision-makers with operational, cost and risk management, especially when incorporating the intermittent behaviour of renewable energy sources (RES). By understanding load profiles and adjusting schedules based on renewable energy availability, decisions can be made to optimize the use of energy resources. This holistic approach allows for better integration of renewable energy, efficient use of resources and overall improved energy management outcomes.

Renewable energy integration is another crucial aspect of decision-making in an energy management system. It involves determining how to incorporate renewable energy sources effectively based on their availability and the needs of the system. Integrating renewable energy into the grid presents both opportunities and challenges. While it offers the potential for sustainable energy solutions, it also introduces uncertainties and intermittent behaviours that must be managed carefully when designing an energy management system. As renewable energy sources are inherently variable, with generation fluctuating throughout the day. this variability can create mismatches between supply and demand, making energy planning more complex. Accurate forecasting of renewable energy generation is challenging and can disrupt grid operations if not managed properly. To address these issues, effective storage solutions are required to manage intermittency and reduce stress on the grid. However, these storage solutions can be costly and demand significant maintenance, adding another layer of complexity to the integration process.

In this context, microgrids offer a valuable solution by providing localized control, flexibility and resilience. They effectively address the uncertainties and variabilities associated with renewable energy, ensuring a more stable, reliable and efficient energy system which is robust yet flexible.

This research work looks closely at different ways of working together to make energy use better. It pays special attention to making energy use more efficient. Similarly, it covers a wide range of area, from energy planning for microgrids to the complicated details of managing energy use in residential sectors. It includes a variety of connected parts, all aiming towards the big goal of using energy in a way that is good for the environment and keeps going for a long time.

The thesis focuses on the critical component of residential load management, an area of study that gains increasing significance as households evolve technologically. The dynamics of energy consumption within these spaces have become notably complex, necessitating the implementation of sophisticated load management techniques. Demand response programs and the infusion of smart home technologies emerge as potent tools in shaping and regulating energy demand patterns, aligning them with broader energy efficiency goals.

This explores microgrid technologies and residential load management strategies. Its aim is to cultivate an understanding of their interplay within the larger context of enhancing overall energy efficiency. The thesis successfully demonstrated the feasibility and advantages of planning a microgrid based on renewable energy availability. Key contributions include:

1. **Advanced Forecasting Techniques:** Development and application of advanced forecasting methods to predict renewable energy availability accurately, enhancing the reliability and efficiency of the microgrid.
2. **AI-based Load Management:** Design and implementation of an AI-driven load management system that optimizes energy use, reduces wastage and balances demand with supply in real-time.
3. **Practical Implementation:** A detailed case study showing the practical aspects of microgrid deployment, including infrastructure requirements, system integration and operational performance, providing valuable insights for future projects.

Therefore, the objective of this thesis is to pioneer integrated approaches that enhance energy efficiency, extending from microgrid dynamics to the intricacies of residential load management. Building upon the identified shortcomings in previous research, our focal point is the proposition of a Strategic Residential Load Management System (SRLMS) for large residential complexes / area in tropical countries.

1.1 Outline of the dissertation

The dissertation report outline has been represented in the following section. Based on the previously discussed three major components of EMS we have structured our research work into three main sections: A) Residential Load Profiling and Scheduling, B) AI-based System design for Residential Load Management and C) Microgrid Integration in a Residential Complex: A Case Study. A brief discussion of each chapter has also been presented here. This thesis report is divided into six chapters, including the introduction and the conclusion. The pictorial view of the entire research work has been represented in the following Figure 1.7.

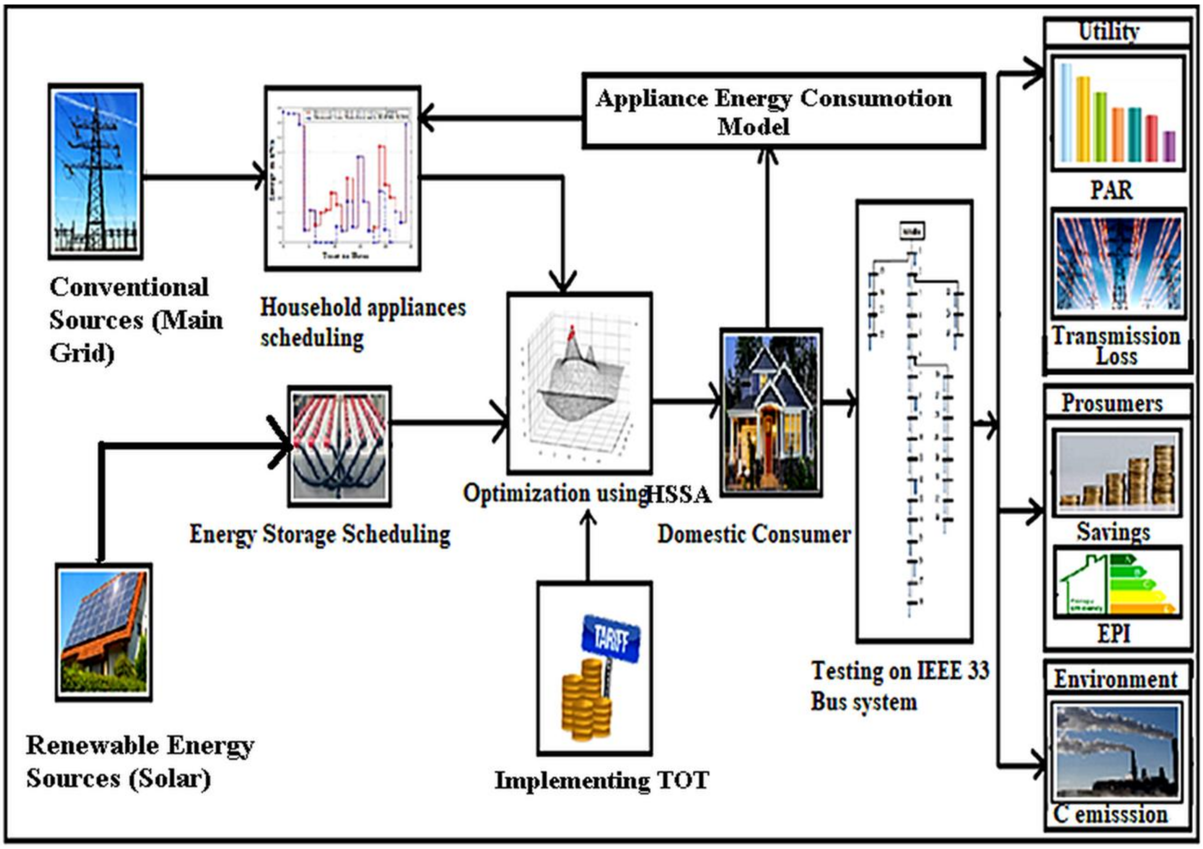


Fig 1.7 Graphical Abstract

The flow of the streamline is as follows.

1.1.1 Chapter 2: Literature Review

The increasing demand for efficient energy utilization has driven significant advancements in Energy Management Systems (EMS). The formal research and development of EMS began in earnest during the 1970s, spurred by the oil crises that highlighted the necessity of energy conservation and efficiency. Early systems focused on basic monitoring and control of energy use in industrial settings. Recent literature underscores the pivotal role of EMS in optimizing energy consumption, reducing operational costs and minimizing environmental impact. For instance, some researchers highlighted that modern EMS integrates renewable energy sources, smart grids and advanced analytics to enhance energy efficiency and resilience. Moreover, advancements in Internet of Things (IoT) technologies have facilitated real-time monitoring and control, enabling more responsive and adaptive energy management strategies. Additionally, researchers are emphasizing the importance of machine learning algorithms in predicting energy usage patterns and improving the accuracy of energy forecasts. Despite these advancements, challenges such as cybersecurity risks and the need for more robust data integration frameworks remain. Overall, the literature indicates a trend towards increasingly intelligent and integrated EMS solutions, capable of meeting the dynamic demands of modern energy systems.

1.1.2 Chapter 3: Problem Identification and Research Contribution

Based on the literature survey, this chapter has focused on identifying the area of research in Energy Management Systems which involves focusing on key aspects such as integration of renewable energy sources, development of microgrid technologies and enhancement of data analytics for energy optimization. Implementation of these research areas can be seen in pilot projects and real-world applications, where advanced EMS technologies are deployed to improve energy efficiency, reduce costs and support sustainable energy practices.

1.1.3 Chapter 4: Residential Load Profiling and Scheduling

As mentioned earlier, forecasting and scheduling are critical components of modern energy management systems. Accurate forecasting models utilize historical data and machine learning algorithms to predict future energy demand and supply patterns. Developing power profiles involves creating detailed consumption and generation schedules to optimize energy use and integrate renewable sources effectively. These techniques help in reducing energy costs, enhancing grid stability and supporting sustainable energy management practices.

1.1.4 Chapter 5: AI-based system design for Residential Load Management

This chapter deals with another important aspect of AI-based system design for residential load management which leverages artificial intelligence to optimize energy consumption within homes. By analysing real-time data and predicting usage patterns, these systems can automate the scheduling of appliances, enhance energy efficiency and reduce electricity costs. Key benefits include improved load balancing, integration of renewable energy sources and personalized energy-saving recommendations, making residential energy management more intelligent and sustainable.

1.1.5 Chapter 6: Microgrid Integration in a Residential Complex: A Case Study

Energy planning for microgrids involves strategic design and management to ensure reliable, efficient and sustainable energy supply. This includes integrating renewable energy sources, optimizing load distribution and incorporating storage solutions. A case study on a community microgrid demonstrates the practical application of these strategies, showcasing improved energy resilience, reduced costs and enhanced environmental benefits. Such case studies highlight the potential of microgrids in achieving localized energy independence and sustainability.

1.1.6 Chapter 7: Conclusion and Future Scope

This chapter concludes all the research works presented in this dissertation. The analysis of outcomes revealed significant improvements in energy efficiency, cost savings and sustainability. The implementation of advanced energy management strategies and technologies demonstrated their effectiveness in real-world scenarios. In conclusion, the study confirms that targeted energy planning and innovative solutions, such as AI-based systems and microgrid configurations, are vital for achieving optimal energy performance and resilience. Future research should focus on addressing remaining challenges and scaling these solutions for broader application. To proceed with the proposed research work, conducting a thorough literature survey is essential. The next chapter provides a detailed discussion of the literature reviewed to support and guide this research.

CHAPTER 2

Literature Review

2.1 Introduction

Energy is crucial for the long-term survival of communities and economic growth and the demand for electricity is continuously increasing. To address this challenge, our main concern is meeting the load demand without putting additional stress on the grid. This demand fluctuation is influenced by various factors such as human habits, economic growth, technological advancements, geographical location and demographic cycles. These elements shape the energy scenario of a country, which is characterized by the gap between available energy and energy demand, also known as per capita energy consumption. This gap highlights the importance of managing energy resources carefully to meet growing demands. In this context, achieving a balance between energy supply and energy consumption is crucial for sustainability. Efficient energy consumption is dependent on several factors and electric load forecasting plays a vital role in planning for this efficiency. By accurately predicting energy usage patterns, decision-makers can ensure that energy resources are distributed more effectively.

2.2 Evolution of Load Forecasting Techniques

Over the years, numerous models and methods have been developed to improve the accuracy of load forecasting across different time horizons—short-term, medium-term and long-term.

Initially, statistical methods were predominantly used for load forecasting. Autoregressive Integrated Moving Average (ARIMA) models were widely used due to their simplicity and effectiveness in capturing time series data patterns. Inspired by the work of their predecessors, some researchers began exploring the Semi-Parametric Additive approach, a classical method that also found application in forecasting. For instance, Fan et al. utilized this model for Short-Term Load Forecasting (STLF), demonstrating its potential in capturing complex load patterns [1]. As computational capabilities advanced, researchers increasingly turned to machine learning and evolutionary algorithms, which began dominating the field of load forecasting. For example, Neural networks, known for their ability to model nonlinear relationships in load data, were extensively explored. Hinojosa et al. proposed a hybrid model that combined fuzzy inductive reasoning with evolutionary algorithms for STLF, showcasing how integrating expert knowledge with optimization techniques could improve performance [2]. Building on this, Lee, Ko et al. introduced a novel approach by combining ARIMA models with wavelet transforms for STLF, enabling better handling of time-series data [3]. Around the same time, Al-Hamadi applied fuzzy linear regression techniques for long-term electric power load forecasting, which allowed the incorporation of historical data fuzziness into the modeling process [4]. Further advancements led Feilat and Bouzguenda et al. to demonstrate the flexibility and effectiveness of neural networks in medium-term load forecasting, highlighting their adaptability to different forecasting horizons [5]. In parallel, researchers explored other mechanisms to enhance forecasting accuracy, with Support Vector Regression (SVR) emerging as a prominent method. When combined with optimization algorithms, SVR offered robust solutions for load prediction challenges. Eventually, researchers shifted their focus to hybrid models, which effectively combined the strengths of various techniques. The results were remarkable, as these models significantly improved forecast accuracy and reliability.

2.3 Advances in Load Forecasting Applications

Accurate load forecasting plays a crucial role in the planning and operation of modern power systems, enabling better resource allocation, demand-side management, and grid stability. In recent years, the integration of artificial intelligence (AI) and optimization algorithms has significantly enhanced forecasting accuracy and reliability. For instance, Hong et al. introduced a seasonal recurrent SVR model integrated with a chaotic artificial bee colony algorithm for electric load prediction, which outperformed traditional models [6]. Similarly, Hong et al. and Wang et al. respectively used hybrid chaotic genetic algorithms with SVR for tourism demand forecasting and annual load forecasting, respectively, illustrating SVR's adaptability to various prediction tasks [7,8].

Building on the success of hybrid models, researchers continued to innovate with new methods and techniques. Chen et al. enhanced forecast accuracy in high-frequency short-term load forecasting by leveraging ARIMA, a model well-suited for handling time-series data with strong temporal dependencies [9]. In the same year, Taylor et al. introduced exponentially weighted methods, which adeptly adapted to recent changes in load patterns, making them a staple in forecasting due to their responsiveness [10]. Another significant contribution came from Montgomery, who adopted a statistical approach that further enriched the forecasting methodologies [11]. Similarly, Guan et al. proposed a very short-term load forecasting model based on wavelet neural networks with data pre-filtering, highlighting the critical role of data preprocessing in improving the performance of neural network-based forecasts [12]. Expanding on the application of optimization techniques, Li et al. combined least squares support vector machines with fruit fly optimization algorithms for annual load forecasting, showcasing the versatility of optimization-based hybrid models in addressing diverse forecasting horizons [13]. Neural network approaches also continued to gain prominence, as evidenced by their widespread use by numerous researchers to achieve accurate predictions across various load forecasting scenarios [14]. Following the advancements in hybrid forecasting models, Wu, Wang et al. applied regression with seasonal exponential adjustment for Short-Term Load Forecasting (STLF), highlighting the potential of seasonally adjusted models for capturing load variations effectively [15]. Around this time, after a long period dominated by classical and statistical approaches, researchers began exploring AI-based forecasting tools. Among these, Artificial Neural Networks (ANN) and Wavelet Neural Networks (WANN) emerged as prominent methods. Sahay and Tripathi compared ANN with multiple linear regression techniques, showing that regression-based approaches could still offer competitive performance in specific scenarios [16].

Building on optimization-based advancements, fruit fly optimization proved effective in diverse forecasting tasks. Hong-ze Li et al. integrated a generalized regression neural network with the fruit fly optimization algorithm for hybrid annual power load forecasting, demonstrating how optimization algorithms significantly enhance model performance in forecasting tasks characterized by high variability [17].

In parallel, Zhao et al. proposed an optimal power scheduling method in a Home Energy Management System (HEMS) based on demand response, illustrating how consumer participation in energy optimization could lead to more efficient power usage [18]. Around the same time, Goude et al. applied their models to Medium-Term Load Forecasting (MTLF), showcasing the growing interest in intermediate forecasting horizons [19-22]. Classical approaches like time series analysis continued to find application as Sarhadi et al. demonstrated, while hybrid approaches evolved further with Lee et al. applying a fuzzy-based hybrid model for MTLF, enhancing forecast flexibility and precision [23,24]. Meanwhile, Khwaja et al. introduced boosted neural networks as an ensemble method, improving STLF accuracy by leveraging the combined strengths of multiple models [25].

Artificial Intelligence (AI) and machine learning techniques gained further focus during this period. Lahouar and Slama et al. developed a random forest model for one-day-ahead load forecasting, outperforming traditional statistical methods with its superior accuracy and adaptability [26]. Gutierrez et al. explored wavelet neural networks in energy management, highlighting their potential for denoising and analyzing complex energy consumption patterns [27]. Similarly, Zhuang et al. compared various neural network-based models for STLF, concluding that neural networks consistently deliver better accuracy for fluctuating load predictions [28]. Researchers also tailored forecasting techniques to specific consumer sectors. For instance, Hsiao et al. proposed a methodology for forecasting household electricity demand based on context information and user schedules. This approach improved prediction accuracy by incorporating detailed usage patterns, emphasizing the importance of customized models for different user groups [29].

2.4 Forecasting in Smart Grids and Microgrids

As smart grids and microgrids evolve with advanced control and communication technologies, accurate forecasting becomes essential for efficient energy management and reliability. Hernandez et al. provided a comprehensive survey on electric power demand forecasting in the context of smart grids, microgrids and smart buildings. This work underscored the critical role of predictive models in effectively managing residential energy use, especially within advanced grid infrastructures [30]. In the same vein, Olivares et al. introduced a centralized energy management system for isolated microgrids. This system proved essential for maintaining stability in remote areas, where energy resources are limited and require careful coordination to ensure reliability [31].

Building on these advancements, evolutionary algorithms found new applications in energy management. Nguyen et al. and others proposed a distributed demand-side management model that utilized energy storage to optimize energy consumption across multiple households. This approach highlighted the significance of coordination among various energy sources to achieve sustainable consumption in residential settings [32,33]. Recognizing the growing complexity of modern energy systems, Basit et al. discussed efficient and autonomous energy management techniques for future smart homes. Their work focused on integrating advanced technologies, such as IoT and machine learning, to enable optimal energy usage and pave the way for more sustainable residential energy systems [34]. Advancements in forecasting techniques continued to shape energy management practices. For an example, Dudek et al. and others introduced pattern-based regression for Short-Term Load Forecasting (STLF), offering a more advanced method for identifying recurring load patterns [35,36]. Further exploring neural network applications, Rajankar and Talbar et al. and Gutierrez et al. demonstrated the potential of wavelet neural networks in energy management, particularly in denoising and analyzing energy consumption data, thereby improving forecasting precision [37]. Similarly, Cheepati and Prasad et al. conducted a comparative analysis of various STLF techniques, shedding light on the strengths and limitations of different models and their suitability for specific applications [38].

These forecasting techniques have proven equally valuable for predicting electricity generation, particularly from renewable energy (RE) sources. As RE generation becomes a cornerstone of modern Energy Management Systems (EMS), accurate forecasting is essential for balancing supply and demand. Vagropoulos et al. (2016) evaluated several models for short-term photovoltaic (PV) generation forecasting, including SARIMA (seasonal ARIMA) and ANN-based models, demonstrating their effectiveness in different scenarios. Such models are critical for efficiently integrating solar power into the grid and ensuring system stability [39].

In parallel, demand response (DR) emerged as a key component of Demand-Side Management (DSM), enabling consumers to adjust their energy usage in response to real-time price signals or grid conditions. Esther and Kumar et al. provided a comprehensive survey of residential DSM architectures, optimization models and methods, highlighting various strategies for improving household energy efficiency and their respective effectiveness [40]. Complementing this, Rasheed et al. explored real-time information-based energy management systems that leverage customer preferences and dynamic pricing, emphasizing the benefits of adaptive DSM [41]. Further expanding on DSM strategies, Samadi et al. investigated load scheduling and power trading in systems with high renewable energy penetration. Their framework optimized power usage while considering market dynamics, paving the way for more effective integration of renewables into energy markets [42]. Before this, Ma et al. and few researchers proposed a residential power scheduling model that combined demand response with renewable energy integration, offering a holistic approach to optimizing household energy usage [43-46].

2.5 Indian Scenario and Smart Energy Systems

India's growing energy demand, along with its commitment to sustainability, has accelerated the adoption of smart energy systems and demand-side management (DSM) strategies. Research in this domain highlights both global insights and region-specific approaches to energy efficiency and optimization. In India, creating a flexible, robust and efficient energy system remains a significant challenge. Grid management and Demand-Side Management (DSM) play pivotal roles in achieving this goal by integrating renewable energy sources (RES) and balancing supply and demand through load shifting or reduction during peak periods. Gellings et al. traced the evolution of DSM practices, highlighting their crucial role in reducing energy consumption and facilitating the integration of renewable energy into the grid [47].

Building on this, Yousafzai et al. and Ahmad et al. respectively explored optimized Home Energy Management Systems (HEMS) that incorporate renewable energy and storage resources. Their work demonstrated how integrating solar power and batteries could significantly enhance energy efficiency in residential settings [48,49]. Similarly, Celik et al. and Wu et al. proposed a decentralized neighbourhood energy management system, which enabled smart homes to share energy resources. This approach not only improved grid stability but also reduced energy costs, offering a collaborative solution to energy challenges [50,51].

Researchers have increasingly focused on improving the power scenario of countries where domestic energy consumption constitutes a substantial portion of total energy use. By advancing forecasting techniques and integrating modern technologies like IoT, AI and renewable energy systems, they aim to optimize energy use and management. Such efforts address the critical impact of residential consumption on the overall energy system and contribute to sustainable energy practices.

Energy scheduling in HEMS presents a particularly challenging task, especially as the penetration of renewable energy sources grows. Wu et al.

addressed this challenge by examining optimal battery sizing for smart homes. Using convex programming techniques, they demonstrated how to balance energy consumption and storage effectively, thereby maximizing the benefits of renewable energy integration [52]. Celik et al. expanded on decentralized neighbourhood energy management by examining coordinated energy sharing among smart homes. This approach not only optimized individual household energy consumption but also enhanced overall grid stability by leveraging shared resources [53]. Similarly, Sanjari et al. introduced an analytical rule-based approach for online optimal control of smart residential energy systems, which successfully minimized energy costs while maintaining system stability [54]. Building on this, Jeddi et al. employed dynamic programming techniques in Home Energy Management Systems (HEMS) to optimize energy usage, factoring in the availability of photovoltaic (PV) systems and battery storage [55].

2.6 Optimization and Storage in Microgrids

With the increasing deployment of microgrids, efficient optimization and energy storage management have become critical for enhancing reliability, reducing costs, and integrating renewables. Advanced algorithms and forecasting methods are being employed to improve decision-making and operational performance. In the context of microgrid energy management, Fathy et al. utilized the Sparrow Search Algorithm, demonstrating its effectiveness in achieving optimal energy distribution within microgrids [56]. Meanwhile, Matsila et al. focused on forecasting for medium voltage distribution networks, emphasizing the importance of predictive models in distribution system planning [57]. Tian et al. applied a fuzzy-based wavelet neural network (WNN) for traffic flow forecasting, showcasing the versatility of such methods in handling complex datasets [58].

Microgrids, recognized as one of the most reliable solutions for local energy demand, have been extensively explored by researchers. Ahmad et al. others emphasized efficient energy management within microgrids, highlighting the role of real-time data and adaptive strategies in optimizing energy distribution and accommodating variable renewable energy sources [59,60]. In the same year, Bao and Bin et al. presented a hybrid model for real-time tide prediction that incorporated wind data to enhance accuracy, a methodology pertinent to renewable energy forecasting for effective microgrid management [61].

As HEMS continue to evolve, Killian et al. proposed a comprehensive framework using mixed-integer quadratic programming to optimize household energy consumption, providing robust solutions for modern energy challenges [62]. Complementing this, Issi, Kaplan et al. analyzed appliance-level load profiles, offering valuable insights into the development of more effective energy management strategies [63]. Ahmad et al. further addressed adaptive and responsive energy management in microgrids, emphasizing the integration of renewable energy sources for greater efficiency [64]. Microgrids, designed to meet local energy demands efficiently, have proven instrumental in incorporating renewable energy sources without causing grid instability. Ahmad et al. explored low-complexity residential energy management strategies, underscoring the importance of renewable resource integration in residential settings [65]. The following year, Wang et al. investigated peak shaving and valley filling potential in high-rise residential buildings, demonstrating the role of HEMS in reducing peak loads and overall energy costs [66].

Although understanding future energy demands through forecasting is critical, it must be complemented with optimization techniques to enhance energy systems. Optimization methods enable resource allocation to be fine-tuned, reducing waste and ensuring supply meets demand efficiently and sustainably. Various algorithms have been proposed for optimizing energy distribution, load scheduling and storage management in smart grids [67]. Dong et al. highlighted the importance of data-driven approaches by utilizing a Bayesian optimal algorithm for home microgrid energy management, emphasizing the role of data in improving efficiency [68].

Additionally, extensive research has been conducted on storage system management, addressing key aspects such as sizing, placement and capacity. These efforts are crucial in ensuring that storage solutions align with energy systems' dynamic requirements, ultimately supporting the transition to smarter and more sustainable energy management practices [69]. Lu et al. introduced an optimal appliance scheduling model tailored for smart households equipped with photovoltaic energy storage systems. This model emphasized maximizing the use of renewable energy while minimizing dependency on grid power [70]. Building on this, Zupančič et al. employed genetic programming-based multi-objective optimization to develop innovative strategies for Home Energy Management Systems (HEMS), addressing both energy efficiency and cost minimization [71].

To further enhance domestic energy planning, Xu et al., and Dinh et al. and some other researchers proposed advanced HEMS that integrate renewable energy sources and storage systems. These systems aim to reduce reliance on the main grid by leveraging local renewable generation and efficient storage utilization [72-76]. However, the inherent variability of renewable energy sources such as solar and wind continues to challenge effective forecasting and scheduling. Addressing this, Alilou et al. developed stochastic models that consider the intermittent nature of solar energy and electric vehicle (EV) usage in residential microgrids, improving the reliability of energy management strategies [77]. Continuing this trend, Kumaravel et al. introduced a hybrid optimization technique for power flow management in smart grids. Their approach integrates various optimization methods to effectively handle the challenges posed by renewable energy sources, ensuring balanced and efficient power distribution [78]. Fuzzy logic-based approaches have gained significant attention in forecasting, particularly for their ability to address uncertainty and imprecision in data. These methods have been effectively integrated into load forecasting, enabling researchers to handle the variability and ambiguity inherent in energy consumption patterns [79]. Building on this foundation, Mansouri et al. proposed a multi-objective optimization framework to manage energy in microgrids with interconnected smart homes. Their approach highlighted the potential of combining fuzzy logic with optimization techniques to balance energy efficiency, cost savings and user comfort [80].

2.7 Intelligent Optimization in Modern EMS

Modern Energy Management Systems (EMS) increasingly rely on intelligent optimization techniques to handle complex, dynamic energy environments involving renewables, storage, and variable tariffs. These techniques aim to enhance operational efficiency, cost-effectiveness, and grid resilience. Advancements in nature-inspired algorithms have further revolutionized energy management systems (EMS). Fathy et al., for example, demonstrated the efficacy of the Sparrow Search Algorithm in optimizing microgrid energy management. This innovative approach underscored the utility of bio-inspired methods in tackling the complexity of modern EMS [81].

Despite these strides, numerous challenges remain in EMS research. The integration of diverse energy sources, achieving real-time optimization and maintaining user comfort continue to pose significant hurdles. Addressing these concerns, Tostado-Véliz et al. introduced a Mixed Integer Linear Programming (MILP) framework for electricity tariff selection in smart homes. On the same year, some of the researchers worked on the tariff and proposed beneficial solutions. Their study incorporated ‘happy hours’ tariffs, providing a user-centric solution that aligns economic benefits with energy efficiency goals [82-89].

Building on prior research, Erenoğlu et al. proposed an enhanced Home Energy Management System (HEMS) that integrates energy storage, demand response mechanisms and renewable energy sources. Their work introduced an optimal energy management framework tailored for microgrids, emphasizing efficiency and sustainability [90].

Recent advancements in hybrid techniques and intelligent systems are significantly influencing the evolution of energy management strategies. For instance, Jabeur et al. utilized multi-agent systems for microgrid energy management, showcasing the potential of decentralized decision-making in dynamic and uncertain environments [91]. Similarly, Yang et al. focused on coordinated energy management for islanded microgrids, incorporating multi-energy and multi-storage units to enhance grid resilience and operational flexibility [92].

Further progress in optimization approaches is evident in the work of Cortés-Caicedo et al., who employed multi-objective Particle Swarm Optimization (PSO) for DC microgrids. Their study highlighted efficient battery management strategies and cost minimization, essential for sustainable microgrid operations [93]. In parallel, Brillianto et al. examined the optimal sizing and placement of battery storage systems, emphasizing demand response flexibility and increased renewable energy penetration. This research underlined the critical role of storage systems in accommodating variable renewable energy sources [94].

More recently, some of the researchers, for example El-Afifi et al. and other researchers presented a multi-objective hybrid optimization approach for demand-side management in smart buildings as well as microgrids. Their study tackled the complexities of balancing energy cost reduction, user comfort and grid stability, providing valuable insights into the challenges and potential solutions in modern Energy Management Systems (EMS) [95-101].

Based on the literature survey, several key trends and advancements have been identified in the field of energy management systems (EMS) and specifically, home energy management systems (HEMS).

2.8 Chapter Summary

The literature survey underscores the critical need for advanced and integrated approaches to energy management. Initially, researchers focused on the load profiles and power consumption of individual home appliances to develop efficient scheduling strategies. However, this approach faced limitations due to practical constraints such as human interaction, unreliable power supply and consumer preferences. To overcome these challenges, various methodologies were proposed to optimize energy consumption with minimal consumer interaction, marking a significant shift towards automation and intelligent system design.

Recent studies have expanded the scope of EMS by incorporating factors such as consumer satisfaction and energy costs, recognizing that an efficient EMS must balance technical efficiency with user experience and financial viability. The integration of renewable energy sources (RES) has been particularly beneficial, contributing to more sustainable and resilient energy systems. However, it is evident that RES integration alone is insufficient. Effective communication and optimization schemes are essential to fully leverage the potential of RES and ensure system reliability.

The research by Malik et al. and Nguyen et al. emphasizes the importance of comprehensive strategies that combine RES integration, load scheduling and robust communication and optimization frameworks. These integrated approaches are crucial for developing next-generation HEMS and EMS that can adapt to varying conditions and user needs while maintaining high efficiency and reliability.

Therefore, the literature survey highlights the significant advancements and ongoing challenges in the field of energy management. The future of HEMS and EMS lies in the development of holistic systems that seamlessly integrate renewable energy, optimize load scheduling and incorporate intelligent communication and control mechanisms. This has been used to identify the problem and define the research contribution area. Outlining the planned course of action.

CHAPTER 3

Problem Identification and Research Contribution

Based on a comprehensive literature survey, the area of research identified focuses on enhancing energy efficiency in the domestic sector through advanced Energy Management Systems (EMS). Existing research has highlighted the effectiveness of energy conservation codes and star-leveling programs across various countries.

While energy management systems (EMS) have evolved significantly, there are still some critical gaps that need to be addressed for enhanced performance and sustainability. For example, existing EMS often have a limited focus on dynamic and real-time energy optimization. Many systems rely on static or pre-defined strategies, which are not sufficient to handle the variability of renewable energy sources or sudden changes in demand. On the other hand. there is inadequate integration of renewable energy with load forecasting. Accurate load forecasting is essential for maximizing the use of renewable energy while ensuring grid stability, but many systems fail to effectively link these components. For domestic consumers, several key challenges persist that limit their ability to manage energy effectively and reduce costs. First, high electricity bills are a common concern, primarily caused by inefficient load management. Many households struggle to optimize their energy consumption due to the lack of tools or awareness, leading to increased energy wastage and costs. Secondly, there is inconsistent utilization of renewable energy sources, such as solar and wind. While many consumers have access to renewable energy systems, their integration with household energy management remains suboptimal, resulting in underutilization of these resources.

Addressing these challenges is crucial for enhancing energy efficiency at the domestic level and fostering greater adoption of renewable energy. Hence based on above discussion, it is evident that development of EMS based on available RE sources and further implementation in microgrid is essential at the present scenario. It is also evident that loads like agriculture, commercial, domestic and public lighting can be explored more with proper AI based system or model design to extract better output from the existing network or grid.

The following areas or points have been identified as shortfalls in the present context of research and our area of contribution: a) Efficient Usage of RE sources, b) User-Centric design and Engagement strategies, c) Real-time Adaptive Control Strategies and d) Large-scale, Real-world Implementations and Validation.

3.1 Literature Void

Despite advancements in domestic load management systems, several research gaps persist.

First, **efficient usage of renewable energy sources and energy storage solutions** in residential settings is under-researched, particularly regarding their impact on grid stability and energy efficiency. Renewable energy integration in residential settings has grown with advancements in solar panels, wind turbines and energy storage systems like lithium-ion batteries. While renewable sources are intermittent, their integration into homes introduces challenges in maintaining grid stability, especially during peak and off-peak hours. For example, sudden dips in solar generation on cloudy days could destabilize local grids without effective storage or backup systems. The effectiveness of renewable energy depends on optimal utilization, which involves aligning generation with household demand.

Second, user behaviour and acceptance of automated load management systems remain underexplored, highlighting the need for studies that incorporate **user-centric design and engagement strategies**. The success of load management systems hinges on user acceptance, which is influenced by trust, perceived benefits and ease of use. Most research focuses on technological advancements rather than human factors like adoption barriers or behavioural inertia. Automated systems often lack intuitive interfaces or fail to provide actionable feedback to users, leading to disengagement. Studies rarely explore strategies to enhance user participation, such as gamification, incentives, or education on energy-saving benefits. For instance, users might resist automation if they feel it undermines their control over appliances.

Third, there is limited exploration of **real-time adaptive control strategies** that respond dynamically to changing household energy demand patterns. Dynamic control systems capable of responding to real-time demand fluctuations are essential for efficient energy use. Existing systems use predefined schedules or static optimization techniques that fail to adapt to unexpected demand changes and most adaptive control models are tested on small-scale setups, making it unclear how they perform in larger, more complex residential environments. On the other hand, real-time control requires seamless integration with IoT devices and smart meters, which is still underdeveloped in many regions. Finally, while many studies focus on theoretical models, there is a scarcity of **large-scale, real-world implementations and validation** of these systems. Proposed models are often tested in controlled laboratory conditions or simulated environments, ignoring real-world variables like weather fluctuations, diverse household types, or unpredictable user behaviour. However, high costs, lack of infrastructure and regulatory challenges prevent the widespread adoption of load management systems. Therefore, very few studies track the long-term performance of implemented systems, such as energy savings, maintenance requirements, or user satisfaction.

3.2 Area of Contribution

This section highlights the specific domain within which this research seeks to make an impact. The selected area is crucial in addressing prevailing challenges, advancing knowledge and bridging the identified gaps in the field. The area of contribution of this research work are mentioned below.

- Dealing with a forecasting technique which can respond to dynamic nature of. RES as well as demand profile.
- The scheduling process for managing loads and ESS needs to be carried out more judiciously by utilizing feature selection techniques to identify the most critical and relevant features, which in turn leads to efficient use of RES.
- Analysis of model performance under the influence of a newly proposed tariff structure which aims to provide significant benefits to prosumers while maintaining sustainable and adequate revenue generation for utility companies, ensuring. A balanced and mutually advantageous system.
- Performance evaluation of the developed model with a newly proposed optimization technique, which is best suited for multi-dimensional, multiple knapsack problems.

- Development of a user centric smart application, which empower prosumers to control, monitor and manage their usage a day ahead.
- Testing the model in a large-scale, real-world environment for energy planning of a microgrid, aiming to improve the EPI.

By targeting these aspects the research aims to contribute meaningfully to both theoretical advancement and practical applications, thereby enhancing the understanding and implementation of solutions.

3.3 Implementing Solutions

Acknowledging these shortcomings, a Smart Strategic Residential Load Management System (SRLMS) has been meticulously developed.

3.3.1 Efficient Use of Renewable Energy Sources

The primary challenge lies in integrating renewable energy sources and energy storage solutions. To address this challenge, we need to develop a strategy, centred around the utilization of renewable energy sources based on their availability, demand profile and efficiency of the storage unit. Forecasting the availability of renewable energy sources is a key step in our approach. Utilizing K-means clustering, we need to identify optimal locations for deploying solar energy, where the demand and renewable energy availability, both are abundant. Subsequently, leveraging the availability of solar power, we must implement an energy storage system to ensure optimal electricity usage with judicious load and ESS scheduling. This approach not only promotes cost savings but also enhances energy efficiency for consumers.

3.3.2 User-Centric design and Engagement strategies

To encourage user participation in electricity trading, we hcan developed a user-friendly application. Through this platform, users can select suitable tariff schemes based on various factors for the following day. To facilitate informed decision-making, users are required to provide appliance ratings and plan their energy consumption for the next day. To incentivize reduced energy consumption during peak hours, users are motivated by a newly proposed tariff scheme where penalties are imposed for high consumption during peak periods, while rebates are offered for reduced consumption or shifting high-capacity energy intensive appliances from peak to off-peak hours. Additionally, the integration of renewable energy sources, such as solar power, further reduces users' monthly electricity bills, providing additional benefits to consumers, without compromising the revenue generation.

3.3.3 Real-time Adaptive Control Strategies

A good optimization technique empowers an energy management system to achieve real-time adaptive controllability by enabling rapid decision-making, dynamic adjustment, adaptive learning, predictive capabilities and multi-objective optimization. These features ensure that the system can effectively respond to dynamic energy conditions and user requirements, maximizing efficiency, reliability and sustainability.

To address the challenge of real-time adaptive control and strategies, it is important to develop a powerful optimization technique, allowing the system to dynamically respond to changing conditions. By utilizing this technique to tackle multiple knapsack problems, the system can adjust its operations in real-time based on fluctuations in energy demand and supply. This enhancement significantly improves the system's real-time adaptability and control capabilities, enabling it to optimize performance efficiently. This can be further enhanced with a smart user-friendly application through which prosumers can communicate with the utilities to plan their next day uage.

3.3.4 Large-scale, Real-world Implementations and Validation

The final challenge lies in the large-scale, real-world application and validation of the proposed optimization technique. This involves testing the optimization technique in practical settings to validate its effectiveness. We selected the IEEE 33 Bus System as the testing platform due to its moderate size and widespread use as a testing benchmark for researchers. The proposed algorithm and system were rigorously tested on the IEEE 33 Bus System using MATLAB SIMULINK and their efficiency has been successfully validated.

This thesis aims to contribute to the advancement of sustainable energy management practices in residential settings, offering insights and solutions to address the challenges faced in modern energy ecosystems.

3.4 Chapter Summary

In conclusion, this research makes significant contributions to the advancement of domestic energy management systems by addressing existing gaps and presenting practical, scalable solutions. In the following chapters, we provide an in-depth discussion on all the objectives and the methodologies employed to achieve them.

CHAPTER 4

Residential Load Profiling and Scheduling

4.1 Introduction

Depleting fossil fuels are one of the most significant reasons why countries need an effective energy management system. In India's current power scenario, developing a judicious, robust and flexible energy management system is essential to bridge the gap between energy demand and generation. With the rapid increase in electricity consumption, designing a proper EMS becomes crucial for the country. This system will not only help manage demand but also improve the response time of service providers.

As discussed in previous sections, load profiling is a key factor in an EMS. Load profiling involves different tasks, such as forecasting and data analysis. Load forecasting plays a vital role in enhancing the efficiency of EMS. It involves predicting future electricity demand or load on the power grid, which is essential for utility companies and grid operators to ensure a reliable and uninterrupted power supply. Accurate load forecasting optimizes the operation and planning of electricity generation, transmission and distribution systems.

In India, load demand has surged due to urbanization, industrialization and increased household consumption. According to government data, more than 25% of the total demand has been placed by the country’s domestic sector in 2022-23, which in turn contributed in the increment of the total demand by 6.8%. This growing demand also emphasizes the need for residential load profiling and load scheduling, which can significantly contribute to ensuring reliability and efficiency in power systems. The research work has been modelled for demand pattern across all kind of loads. However, a detailed approach for more effective load management has been tested and tried for domestic load.

Within domestic load, household appliance scheduling has been focused with different criteria to understand the system eventualities and render a better solution.

4.2 Residential Load Profiling

Historical data analysis is essential for load profiling and developing demand profiles, involving the collection and cleaning of past power consumption data and examining patterns, trends and correlations with factors like weather. Following this, forecasting methods for future demands are evolving with advancements in data analytics, machine learning and computational power, offering increasingly accurate insights for decision-makers. Time series analysis, anomaly detection and clustering techniques help in identifying consumption patterns across different consumer segments. Statistical and machine learning models are then trained on this data to predict future demand. Models are validated and back-tested to ensure accuracy. Continuous integration of new data refines these models, leading to more reliable and optimized power management.

4.2.1 Load Forecasting

Load forecasting methods can be classified into univariate and multivariate approaches. The univariate ARIMA model forecasts load based on a single time series, while the multivariate ARIMAX model includes additional variables for more accurate predictions. Both models have their strengths and can be compared with AI-based techniques to evaluate their effectiveness. By leveraging these methods, India can improve the efficiency of its power management system, reduce energy waste and support its transition towards cleaner energy sources. Therefore, load forecasting is an essential tool for ensuring the reliability, efficiency and sustainability of power systems. With advancements in data analytics, machine learning and computational power, load forecasting techniques continue to evolve, offering more accurate and actionable insights. As the energy scenario becomes more dynamic with the integration of renewable sources and smart grid technologies, the importance of precise load forecasting will only grow.

The Univariate time series methods are good enough for the short-term forecasting as the weather variable does not change rapidly. ARIMA is a univariate method, which have been applied to a wide variety of time series forecasting applications. In the following section, procedure to build ARIMA model for load forecasting has been described.

Model of Auto Regressive Integrated Moving Average (ARIMA): Statistical Approach

The load data, that we have considered as the historical data for load forecasting is not stationary. Therefore, differencing is first performed to make the time series data stationary. This step may be repeated as per requirement. The difference process of first order can be expressed as in Eq. (4.1),

$$VY_t = Y_t - Y_{t-1} = (1 - B)Y_t \tag{4.1}$$

For load data with periodicity, it can be expressed as Eq. (4.2),

$$V_S Y_t = Y_t - Y_{t-S} \tag{4.2}$$

Both continuous and seasonal difference may be applied together. This can be written as Eq. (4.3).

$$V_S^d V^D Y_t = (1 - B^S)^D (1 - B)^d Y_t \tag{4.3}$$

Finally, ARIMA with order (p, d, q) is obtained.

$$\emptyset_P(B) V^d Y_t = \theta_q(B) a_t \tag{4.4}$$

The input time series consists of the load demand previous of three to four similar days. To make the time series stationary differencing process is performed. Then the input series is tested for statistical stationarity. Auto Correlation Factor (ACF) and Partial Auto Correlation Factor (PACF) have been evaluated, based on which the value of p and q is selected. The diagnostics checks are performed through residual analysis and finally forecasting is done. A complete ARIMA model can be expressed as Eq. (4.5) using the seasonal operator.

$$\emptyset_P(B^S) \emptyset_P(B) V_S^D V^d Y_t = \Theta_Q(B^S) \theta_q(B) a_t \tag{4.5}$$

Then residual check and fitting check are applied. Finally, the model is selected to perform the prediction. The overall process to build ARIMA model for load forecasting has been briefly explained.

Mathematical Model of Auto Regressive Integrated Moving Average with Exogenous Variables (ARIMAX): Time Series Analysis

In this section, two different approaches of ARIMAX modelling have been discussed. The two different approaches are Transfer Function Model approach and Conversion of a Regression model with ARIMA error to an ARIMAX model.

ARIMAX using Transfer Function Model

To build ARIMAX model for forecasting Y_t and X_t have been assumed two stationary time series. The TFM can be written as,

$$Y_t = C + v(B)X_t + N_t \tag{4.6}$$

$$v(B)X_t = (v_0 + v_1 B + v_2 B + \cdots)X_t \tag{4.7}$$

In ARIMAX, we work with two different time series X_t and Y_t. Therefore, it differs from ARIMA or any other univariate method.

The Transfer Function $v(B)X_t$ can be written as,

$$v(B)X_t = [w_b(B)B^b/\delta_r(B)]X_t \tag{4.8}$$

Theoretically, $v(B)X_t$ has infinite number of coefficients.
here,

$$w_b(B) = w_0 + w_1 B + \cdots + w_h B^h \tag{4.9}$$

$$\delta_r(B) = 1 - \delta_1(B) - \cdots - \delta_r B^r \tag{4.10}$$

N_t can be written as

$$N_t = [\theta(B)/\emptyset(B)(1-B)^d].a_t \tag{4.11}$$

Therefore, TFM can be finally expressed as,

$$Y_t = C + v_0 X_t + v_0 X_{t-1} + \cdots + v_K X_{t-K} + [\theta(B)/\emptyset(B)(1-B)^d].a_t \tag{4.12}$$

First, we must choose K and then N_t must be specified to find out (b, r, h). To represent TFM (b, r, h) can also be identified by visually comparing the estimated in pulse response function with some common theoretical functions. Several diagnostic checks are involved to conclude whether the model is adequate based on residuals.

Conversion of a Regression model with ARIMA error to an ARIMAX model

The Regression model with ARIMA errors can be written as,

$$Y_t = C' + B'X_t + U_t \tag{4.13}$$

$$a(L)A(L)(1-L)^D(1-L^S)u_t = b(L)B'(L)\varepsilon_t \tag{4.14}$$

$$L^j Y_t = Y_{t-i} \tag{4.15}$$

$$a(L) = 1 - a_1 L - \cdots - a_P L^P \tag{4.16}$$

$$A(L) = 1 - A_1 L - \cdots - A_{PS} L\,{}^{P}_{S} \tag{4.17}$$

$(1-L)^D$ is non-seasonal integration polynomial of degree D

$(1-L^S)$ is seasonal integration polynomial of degree s

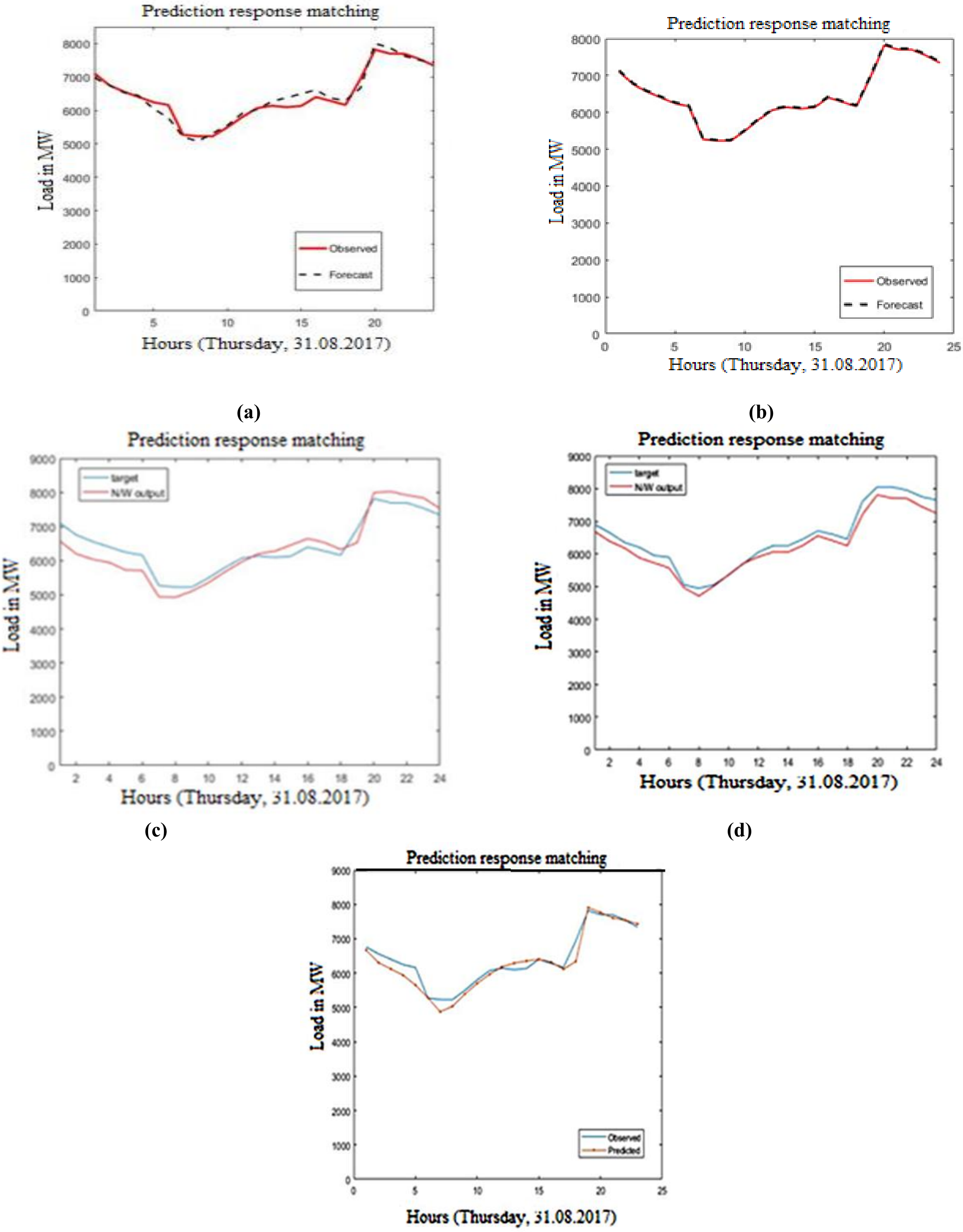
$b(L) = 1+b_1L+\ldots +b_qL_q$, nonseasonal moving average polynomial of degree q

$B(L) = 1+B_1L+\ldots+B_{qs}L_q$, seasonal moving average polynomial of degree qs

Based on these, ARIMAX model can be built to have an efficient enough load forecast tool for Demand Side Management.

4.2.2 Performance analysis of different Forecasting Methods (ARIMA, ARIMAX, ANN & LSTM)

Here the load demand of West Bengal's electricity network in Eastern Regional Load Dispatch Centre (ERLDC) has been considered for implementation of the proposed approach. This study includes hourly load and peak load from January, 2017 to December, 2017. Here, we have performed week ahead forecasting and day ahead forecasting for different season of West Bengal. One of them has been presented in this section. The week ahead forecasting has been performed for 31st August, 2017, Thursday. To have as much as accurate forecast, here the load demand data of previous Thursday i.e. 3rd, 10th, 17th and 24th August, 2017 has been used as historical data. On the other hand, here the load demand data of previous days i.e.18th,19th, 20th, 21st September and 13th, 14th November, 2017 respectively has been used as historical data.



(a) (b)

(c) (d)

(e)

Figure 4.1: Prediction accuracy using (a) ARIMA, (b) ARIMAX, (c) Univariate ANN, (d) Multivariate ANN and (e) LSTM

From the MATLAB output in Figure 4.1, it can be concluded that ARIMAX is performing better than other forecasting techniques.

4.2.3 Calculation of Prediction Error

Finally, the prediction accuracy has been compared based on MAPE (Mean Average Percentage Error) amongst the mentioned techniques and it has been found that for this case ARIMAX is outperforming. The comparative study has been illustrated below in Table 4.1.

Here,

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i-F_i}{A_i}\right| \times 100 \tag{4.18}$$

Table 4.1: Comparative study based on Prediction accuracy

Day type	Day of the Year	Type	Univariate method (without considering the effect of temperature)		Multivariate method (considering the effect of temperature)		Long-Short-Term Memory (LSTM) Network Prediction Error
			Prediction Error using ANN	Prediction Error using ARIMA	Prediction Error using ANN	Prediction Error using ARIMAX	
Thursday 31.08.2017	Week days	Week ahead	4.6934	2.1778	3.3299	0.4008	2.6342
Friday 22.09.2017	Week days	Day ahead	3.3461	2.9668	3.3253	1.8973	1.8274

From this discussion, it can be concluded that ARIMAX is outperforming. This error can be further minimized by introducing different parameters like humidity, wind speed, economic parameter, occasional spikes etc., which will increase the complexity of the model. By this method, minutes ahead forecasting is also possible which may help in Real Time Load Forecasting. The more accurate prediction leads to more accurate decision making for designing Energy Management System.

4.3 Residential Load Scheduling

Insights from residential load profiling are crucial for developing effective load scheduling strategies. Residential load profiling, specifically load forecasting helps to identify patterns in household energy consumption, which in turn informs how energy should be distributed and scheduled.

Load scheduling is the process of adjusting energy consumption based on the availability of power sources. These sources can include both conventional energy (like coal and gas) and renewable energy (like solar and wind). By understanding how households consume energy, we can better allocate resources, especially during peak and off-peak hours.

There are two key aspects shape the strategy for load scheduling. The first one is Understanding the Load. In residential contexts, the load primarily consists of household appliances, such as air conditioners, refrigerators, washing machines, etc. These appliances have different energy needs at different times of the day. Understanding this demand allows for better planning and optimization of energy use. And the second one is Scheduling the Load. Load scheduling involves distributing energy consumption across various time periods in a day. For example, heavy-use appliances like washing machines can be scheduled during off-peak hours when energy demand is lower. This process can be adjusted based on the availability of energy sources. For instance, during the daytime, when solar power is abundant, more consumption can be scheduled.

According to the Central Electricity Authority of India, with the increased consumption by residential sector, RE demand is also increasing and with this rising adoption of renewable energy, strategies like load scheduling are becoming increasingly important to balance demand and supply efficiently. By scheduling loads during periods when renewable energy is available, such as during sunny or windy conditions, households can reduce their reliance on fossil fuel-based electricity. This process not only helps in optimizing energy use but also reduces costs for consumers and decreases stress on the power grid. Smart grid technologies and smart meters play a critical role in facilitating real-time load scheduling, allowing for better integration of renewable energy and more efficient consumption patterns.

Incorporating insights from residential load profiling into these strategies is essential for a more sustainable and efficient energy management system. With India's growing energy needs and its commitment to renewable energy (targeting 50% non-fossil fuel capacity by 2030), load scheduling informed by accurate data is becoming increasingly important. Here, the entire process of Load Scheduling has been divided into two steps: Designing Energy Consumption Model and Categorization of Load

4.3.1 Appliance Energy Consumption Profiling

Here, we have considered five different consumers and each home with set of appliances A and N is the total number of appliances. a1, a2, …. aN are N number of domestic appliances used in a home. They are operated over a time period t ϵ T, where Suppose, Sa1 is the starting time instants of appliance a1 and

Fa1 is the finishing time instants of appliance a1. Therefore, operation time interval for scheduled appliances a1 is [S_{a1}, F_{a1}].

$$A \triangleq \{a1, a2, a3, \ldots\ldots\ldots\ldots, aN\} \tag{4.19}$$

$$T \triangleq \{1, 2, 3, \ldots\ldots\ldots\ldots\ldots\ldots, 24\} \tag{4.20}$$

Here, in this model we have considered CES (Conventiaonal Energy sources) and RES to satisfy the demand. We have assumed, $\in_{t.PV}$ as generated or available solar energy at time t, which should be known or forecasted. However, the price of the renewable energy is variable.
Therefore, for a1 appliances state of operation of an appliance a1 at time t,

$$\phi_{a1}(t) = \begin{cases} 0 \ when \ \mathrm{a1} \ appliance \ is \ not \ operating \\ 1 \ when \ \mathrm{a1} \ appliance \ is \ operating \end{cases} \tag{4.21}$$

Consumer will place a day ahead request for a1 appliance in time interval [S_{a1}, F_{a1}], where [S_{a1}, F_{a1}] ϵ T. Consumer needs to specify α_a and F_a for availing the best suited tariff scheme. Total energy demand of a1 can be satisfied by CES and RES. Hence the total energy consumed by a1 appliance can be determined as,

$$\sigma_{a1} = \sum_{t=1}^{T} \sum_{a_1 \epsilon \mathrm{A}} \ \alpha_{a1} . T_{ON} \tag{4.22}$$

Prioritizing RES first,if E_{RE} is insufficient, main grid supplies remaining energy.

$$E_{GRID\_used} \ = \ \max(0, \ \sigma_a - E_{RE})$$

Similarly, energy consumed by RES is the minimum of E_{RE} and σ_{a1}

$$E_{RE\_used} = \min(\ \sigma_a, E_{RE}) \tag{4.23}$$

After allocating energy from PV and main grid, the cost calculation for each hour

$$\gamma_{\mathrm{Total(h)}} = (\gamma_{t.PV} . E_{t.RE\_used} + \gamma_{t.GRID} . E_{t.GRID\_used}) \tag{4.24}$$

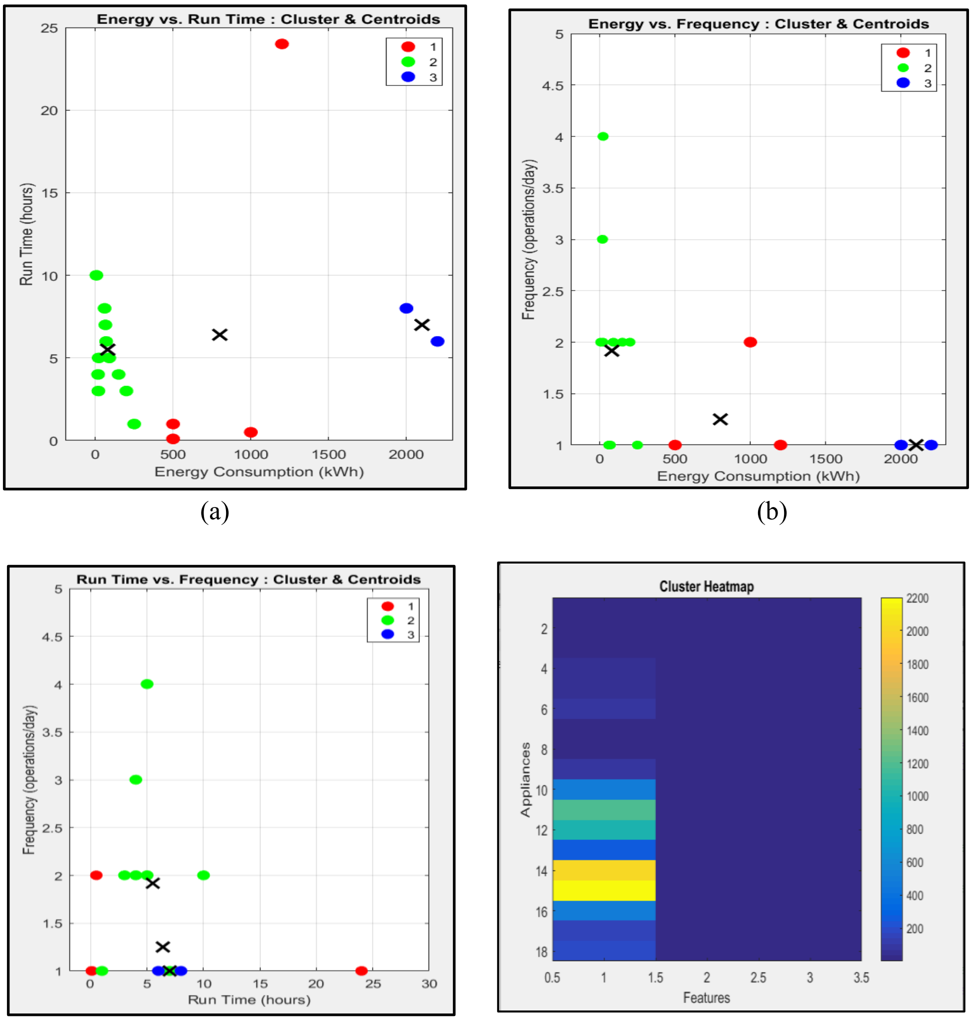
The total cost over 24 hours can be calculated as,

$$\gamma_{\mathrm{Day}} \ = \sum_{t=1}^{T} (\gamma_{t.PV} . E_{t.RE\_used} + \gamma_{t.GRID} . E_{t.GRID\_used}) \tag{4.25}$$

The Energy Consumption Model within the Energy Management System plays a critical role in optimizing energy usage, reducing operational costs and promoting sustainability. By leveraging real-time data analytics and advanced forecasting techniques, the model provides actionable insights that enable efficient energy allocation and minimize waste. The integration of such a model not only enhances the overall performance of energy systems but also supports compliance with environmental regulations and contributes to a greener future. Continuous refinement and adaptation of the model will be essential to meet the evolving energy demands and technological advancements, ensuring the EMS remains a pivotal tool in energy conservation and management.

4.3.2 Categorization of Load

In this section, Domestic consumers have been considered as Prosumers. The home appliances are classified as i) Interruptible Loads, ii) Non-interruptible loads and iii) Interruptible loads with minimum delay.



(a) (b)

(c) (d)

Figure 4.2 (a), (b),(c) Categorization of domestic Loads using K-means clustering and (d) Heatmap representing Appliance Index

Here power consumption of different domestic loads such as refrigerator, washing machine, Induction oven, Iron, Fan, Light, Computer, Television etc has been discussed and analysed in detail for different operating modes.

Here, the K-means clustering technique has been used to categorize the loads in 3 different clusters with 3 different priorities. Figure. 4.2 is showing the clusters based on which the loads are marked with their priority ranking for different domestic consumers respectively and the heatmap is representing 3 different groups of appliances like non-interruptible, interruptible with minimum delay and interruptible appliances from top to bottom.

Cluster analysis, an essential technique in data mining and machine learning, involves grouping similar objects into clusters. Among the various clustering methods, K-means clustering stands out as a widely employed approach. Its primary objective is to partition a given set of objects into K clusters, striving to minimize the collective squared distances between each object and its designated cluster mean. The steps to perform K-means Clustering has been illustrated below.

Step 1. Choosing the number of clusters.

The Elbow method, one of the effective ways to find out the number of clusters, which uses WCSS (Within Clusters Sum of Squares) value concept.

$$WCSS = \sum_{i=0}^{n} DP_{i\ in\ cluster\ 1}\ distance(DP_i . C_1)^2 + \sum_{i=0}^{n} DP_{i\ in\ cluster\ 2}\ distance(DP_i . C_2)^2 \tag{4.26}$$

Here, $\sum_{i=0}^{n} DP_{i\ in\ cluster\ 1}\ distance(DP_i . C_1)^2$ is the sum of the square of the distances between each data point and its centroid within a cluster and the same for the other term (for all 2 clusters).

Step 2. Selecting Centroids.

K random points from the data set can be selected as centroids.

Step 3. Assignment.

After initialization of centroids, each data point is assigned to the nearest centroid based on a distance metric, typically Euclidean distance, which in turn forms clusters.

Step 4. Recomputing the Centroids.

After all data points have been assigned to clusters, the centroids are updated by calculating the mean of all data points assigned to each cluster. This moves the centroids to the centre of their respective clusters.

Step 5. Convergence.
Last two steps are repeated iteratively until the converging conditions are met.

Converging Conditions:

i) Centroids no longer change significantly.
ii) Maximum number of iterations is reached.
iii) Data points remain in the same clusters.
iv)

The result that has been obtained using K-means clustering can be further verified with a mathematical model. This mathematical modeling needs to use feature selection technique for selecting the important features based on which the model will be designed.

Feature Selection

The domestic loads can be prioritized based on some characteristics or features of the loads. The features are selected using different feature selection techniques. We have considered seven features here and used four different methods, which are Complex Tree, Gaussian SVM, Weighted KNN and Bagged Trees. The performance of these four methods has been compared in Table 4.2 based on model accuracy and prediction speed. Finally, we have concluded that Weighted KNN is performing better than other methods with highest accuracy and prediction speed. The pseudocode for the proposed WKNN algorithm is provided in Appendix A section A3 for detailed reference.

Table 4.2: Feature selection for home appliances Scheduling

Method Used		**Predictors**						
		Power Rating of appliances	**No. of appliances**	**Energy Consumption**	**Total runtime**	**No. of switch ON**	**Frequency of operation**	**Operation in Peak hours**
Complex Tree	Model accuracy	36.10%	13.90%	36.10%	38.90%	22.20%	44.40%	19.40%
	Prediction speed	2900 obs/sec	15000 obs/sec	13000 obs/sec	17000 obs/sec	11000 obs/sec	5600 obs/sec	8000 obs/sec
Gaussian SVM	Model accuracy	52.80%	13.90%	80.60%	88.90%	25%	88.90%	19.40%
	Prediction speed	160 obs/sec	93 obs/sec	82 obs/sec	160 obs/sec	99 obs/sec	160 obs/sec	96 obs/sec
Weighted KNN	Model accuracy	52.80%	13.90%	**94.40%**	**88.90%**	25%	**88.90%**	19.40%
	Prediction speed	11000 obs/sec	5300 obs/sec	**4400 obs/sec**	**12000 obs/sec**	9500 obs/sec	**7800 obs/sec**	12000 obs/sec
Bagged Trees	Model accuracy	52.80%	13.90%	94.40%	86.10%	25%	88.90%	19.40%

	Prediction speed	1400 obs/sec	790 obs/sec	1200 obs/sec	1600 obs/sec	1600 obs/sec	1400 obs/sec	1600 obs/sec

Modeling

Based on the abovementioned results, we have chosen energy consumption, Total run-time and Frequency of operation as the three most important features to design the following model and the clustering result has been re-verified again using a mathematical model.

Suppose, request time of the appliance a1 is $\tau_{ra1}$and waiting time of the appliance a1 is τ_{wa1}.

Therefore, $$\tau_{wa1} = S_{a1} - \tau_{ra1} \tag{4.27}$$

Total waiting time, $$\tau_{w} = \sum_{i=1}^{N} \tau_{wai} \tag{4.28}$$

Average waiting time, $$\tau_{w.avg} = \tau_{w} / N \tag{4.29}$$

Here, we have considered α_{ai} as the rating of appliance ai where i = {1,2,3, ….. , N},

$$\rho^*_{a1} = \frac{\text{time of run}}{\text{No.of switch ON}} \tag{4.30}$$

$$\rho^*_{a1} = \rho^t_{a1}/f_{a1} \tag{4.31}$$

$$\rho^*_{ai} = \sum_{t=1}^{24}\sum_{a_1 \in A}\delta^t_{ai}/f_{ai} \qquad \forall \text{ ai } \epsilon \text{ A} \tag{4.32}$$

Utilization factor, $$U_{ai} = \frac{1}{24}[\alpha_{ai} * \rho^t_{ai} * f_{ai}/\alpha_{ai}] \tag{4.33}$$

Flexibility Index, ϑ_{ai}= 0 (high ρ^*_{a1} and low f_{ai} : Non-Interruptible),
1 (Interruptible with delay) and
2 (low ρ^*_{a1} and high f_{ai} : Interruptible)

Priority Index, $$PI = [U_{ai}]/[\vartheta_{ai}+1] \quad \forall \text{ ai } \epsilon \text{ A} \tag{4.34}$$

Based on this ranking finally the load has been categorized as non-interruptible load, interruptible load with minimum delay time and interruptible load.

This Load scheduling can become even more effective if intermittent nature of renewable energy sources can be accounted for the like solar and wind. Since renewable energy is not available continuously—solar power depends on sunlight and wind energy varies with wind speed—integrating these sources into the grid requires smart planning. By incorporating this variability into load scheduling, we can optimize energy consumption based on the availability of renewable energy. For example, energy-intensive tasks like running washing machines or charging electric vehicles could be scheduled when solar power is abundant during the day. This reduces the reliance on conventional power sources like coal or gas, which are more polluting and put stress on the grid.

The integration of renewable energy is crucial for reducing the overall stress on the power grid. As renewable energy sources become more widespread, proper load scheduling can balance the supply-demand equation more effectively. In India, renewable energy capacity reached 125 GW in 2022, accounting for 39% of the country's installed power capacity, shown in Figure 4.3. This growing share of renewable energy makes it essential to incorporate its variability into energy management strategies.

According to the International Energy Agency (IEA), smart load scheduling, combined with renewable energy, can lead to a 15-20% reduction in peak load demand. This not only helps in managing grid stability but also supports India's target of achieving 50% energy from non-fossil sources by 2030.

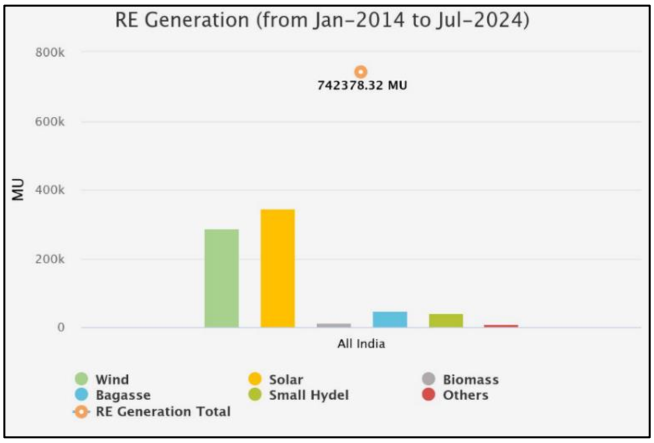


Figure 4.3 RE Generation Report [IEA]

Therefore, integrating the intermittent behaviour of renewable energy into load scheduling is one of the most effective ways to reduce grid stress, reducing cost while promoting cleaner energy consumption.

4.3.3 Renewable Energy Integration

To integrate renewable energy sources into the design of a proposed energy management system, it is crucial to understand the renewable energy availability in a particular area. Accurate forecasting can help predict renewable energy availability in future days. However, it is essential to first select an appropriate area for planning the energy management system for the residential load sector using a microgrid.

This planning can only be executed effectively if we have a proper understanding of the renewable energy availability in a specific area based on its latitude-longitude and the demand profile of that particular area . In this context, clustering techniques can help us to categorize different areas as having light, moderate, or heavy solar power availability.

Using the latitude and longitude of a specific area along with its domestic demand profile, the K-means clustering technique can be applied to identify areas with high demand and significant renewable energy availability. Based on this analysis, the optimal location for renewable energy-based distributed generation (RE-based DG) can be selected. Additionally, locations with similar demand profiles and RE availability can be grouped into clusters to facilitate efficient energy sharing. This approach ensures that the energy management system is designed and implemented in the most efficient and effective manner. The process has been discussed in detail in the following section.

The solar irradiance (the power per unit area received from the sun in the form of electromagnetic radiation) at a given location on earth's surface depends on several factors. The relationship is affected by the earth's tilt, solar declination, hour angle including its latitude and longitude. A simplified mathematical equation to estimate solar irradiance on a clear day can be derived from the solar zenith angle, which depends on latitude, longitude, and time of day.

Solar Zenith Angle (θ_x):

$$\cos(\theta_x) = \sin(\alpha).\sin(\delta) + \cos(\alpha).\cos(\delta).\cos(H) \tag{4.35}$$

α is the latitude in the radian

δ is the solar declination

$$\delta = 23.45° \sin\left(\left(\frac{360°}{365} + (284 + \mathrm{d})\right)\right) \tag{4.36}$$

d is the day of the year (from 1 to 365)

H is the hour angle in degree, representing the earth's rotation relative to solar noon.

$$H = 15° * (t-12) \tag{4.37}$$

t is the local solar time in hours.

Solar noon at t=12

Solar Irradiance on Earth's Surface (I_t):

$$I_t = I_o.\cos(\theta_x) \tag{4.38}$$

I_o is the solar constant which is the solar irradiance received at the top of the earth's atmosphere.

Atmospheric Effect:

This effect includes the scattering and absorption by the atmosphere.

$$I_t = I_o.\cos(\theta_x).T_a \tag{4.39}$$

T_a depends on atmospheric conditions (air mass, cloud cover, pollution etc.).

$$P_{PV}(\tau) = GHI(t).A.\eta \qquad \forall t \;\; 0 \le \tau \le 24 \tag{4.40}$$

Where global horizontal irradiation (GHI) is in kW/m^2. A is the area of solar panel and η is the efficiency of the PV system.
The electrical energy generated (E_{PV}) by the PV system in time duration Δt,

$$E_{PV}(t) = P_{PV}(\tau).\Delta t \tag{4.41}$$

where τ is the real time.
This energy will be used for home appliances ($E_{PV.load}$) and energy storage ($E_{PV.storage}$).

$$E_{PV}(t) = E_{PV.load}(t) + E_{PV.storage}(t) \tag{4.42}$$

Constraints:

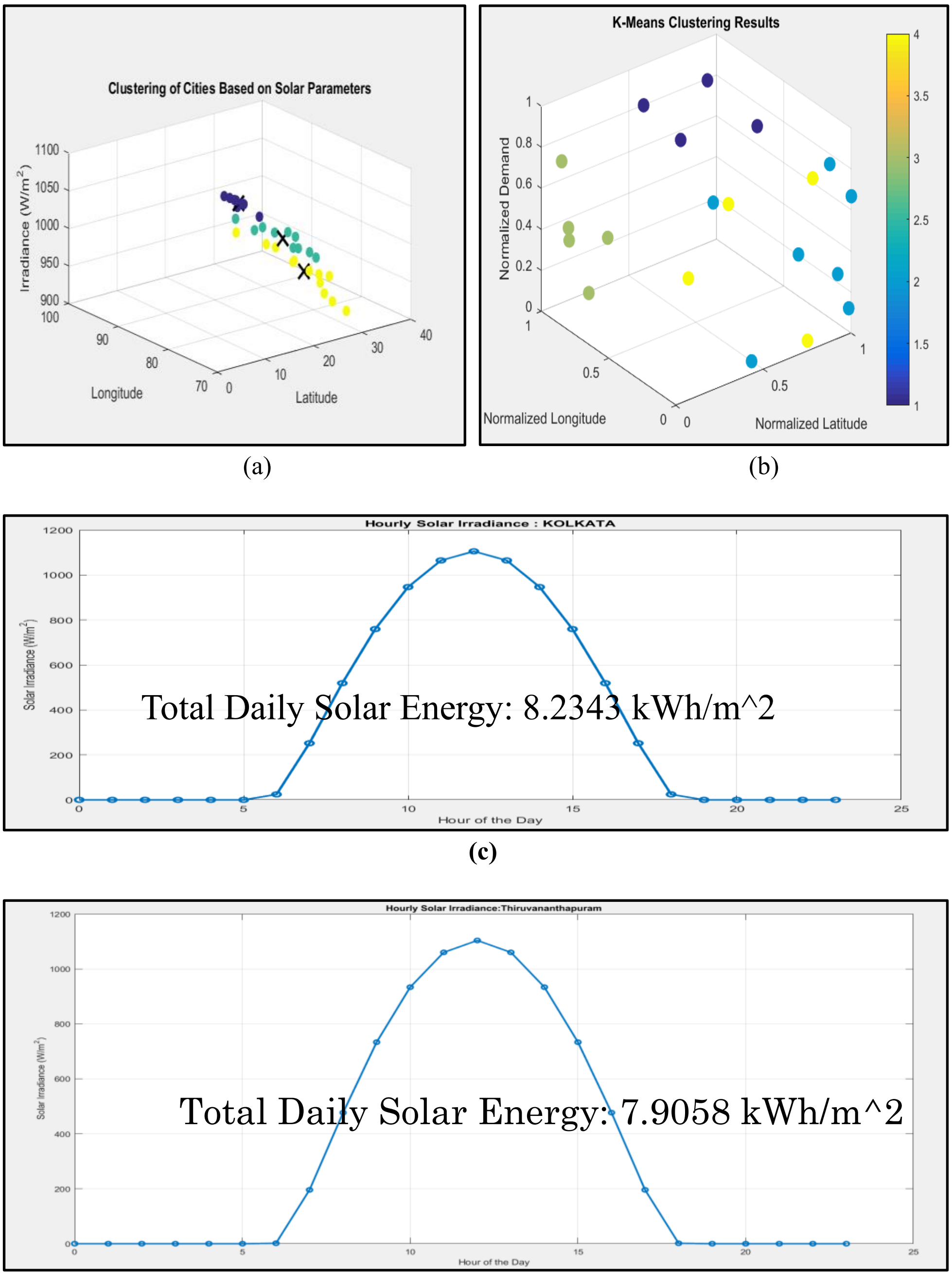
$$0 < E_{PV.load}(t) \le GHI(t).A.\eta.\Delta t \tag{4.43}$$

$$0 < E_{PV.storage}(t) \le GHI(t).A.\eta.\Delta t \tag{4.44}$$

Therefore, clustering based on latitude and longitude to identify heavy, medium and light penetration of photovoltaic (PV) can be a valuable approach for understanding the distribution of solar energy infrastructure. Based on the demand profile and RE availability DGI can be calculated.

Demand Generation Index = Mean Demand / Mean Generation (closer to 1indicates most beneficial cluster to integrate RE).

Here, we have successfully utilized latitude-longitude data and domestic demand profiles to identify high-demand areas with substantial renewable energy potential using K-means clustering. Optimally selected locations for renewable energy-based distributed generation (RE-based DG) and efficiently grouped locations with similar characteristics to enhance energy sharing and system efficiency based on DGI value, shown in Figure 4.4. A detailed pseudocode implementation of this method is included in Appendix A section A2.



(a) (b)

(c)

(d)

Figure 4.4 (a),(b) Clusters based on Solar irradiance level and (c),(d) available solar energy in 24 hours in Kolkata and Thiruvananthapuram respectively

While the integration of renewable energy sources can help reduce grid stress, it is only effective for limited periods, especially during the day. The real challenge arises during peak consumption hours, typically between 5:00 p.m. and 9:00 p.m. This is when energy demand spikes, especially in the evening when people return home, turn on lights, appliances and other electrical devices. During this peak time, relying solely on renewable energy sources like solar power is not enough, as solar energy is not available after the sun sets. In tropical regions like India, solar energy production typically stops around 3:00 to 4:00 p.m., well before the peak demand period. To address this, integrating energy storage systems (ESS) becomes essential. Energy storage systems can store excess energy generated by solar power during the day and release it during the evening peak hours. This helps reduce stress on the grid when demand is highest.

Thus, while load scheduling is crucial for managing energy consumption, it is not sufficient on its own. Scheduling the use of energy storage systems (ESS) also plays a vital role in balancing supply and demand. By combining load scheduling with ESS, we can ensure that renewable energy is available when it is most needed, even after solar power generation has ceased for the day.

According to a report by the Central Electricity Authority (CEA), energy storage systems, when paired with renewable energy, could reduce peak load demand by up to 20-25%. This combined approach improves the efficiency of the overall energy system, ensuring reliable power supply during peak hours without relying solely on conventional energy sources.

4.3.4 Scheduling of Energy Storage

The ESS need to be optimally scheduled to achieve cost effective energy consumption. This section will be dealing with the scheduling of ESS and its modelling.

Feature Selection

We have considered nine features here and used four different methods, which are Complex Tree, Gaussian SVM, Weighted KNN and Bagged Trees. Performance of these four methods has been compared in Table 4.3 based on model accuracy and prediction speed.

Table 4.3. Feature Selection for ESS scheduling

		Predictors								
Method used		ESS cycle	Daily Energy Consumption	RES Availability	Charging rate	Round Efficiency	Discharging Rate	Population	Weekend	Electricity Bill
Complex Tree	Model Accuracy	40%	66.70%	33%	66.70%	66.70%	66.70%	46.70%	40.00%	66.70%
	Prediction speed	590 obs/sec	5100 obs/sec	7100 obs/sec	6400 obs/sec	5600 obs/sec	6200 obs/sec	7000 obs/sec	3500 obs/sec	7100 obs/sec
Gaussian SVM	Model Accuracy	40%	100%	33.33%	93.30%	93.30%	86.70%	60%	40%	100%

	Prediction speed	540 obs/sec	520 obs/sec	1100 obs/sec	1100 obs/sec	870 obs/sec	1100 obs/sec	1100 obs/sec	990 obs/sec	1000 obs/sec
Weighted KNN	Model Accuracy	40%	**100%**	26.70%	**93.30%**	**93.30%**	**86.70%**	60%	40%	**100%**
	Prediction speed	2700 obs/sec	**4300 obs/sec**	5400 obs/sec	**3600 obs/sec**	**3600 obs/sec**	**5400 obs/sec**	4300 obs/sec	5400 obs/sec	**5400 obs/sec**
Bagged Trees	Model Accuracy	40%	100%	33.33%	93.30%	93.30%	80%	60%	40%	100%
	Prediction speed	640 obs/sec	720 obs/sec	770 obs/sec	750 obs/sec	770 obs/sec	780 obs/sec	750 obs/sec	770 obs/sec	800 obs/sec

Finally, we have concluded that Weighted KNN is performing better than other methods. On the basis of the above-mentioned result, we have chosen Daily energy consumption, Charging rate, Round efficiency, Discharging rate and Electricity bill as five most important features to design the following model.

Modelling

In this section, we have defined the charging and discharging of a battery based on its round efficiency, SOC (state of charge) and charging-discharging rate.

Here, in this section, we have considered a battery with a capacity of 10 kW.

Round efficiency,
$$\eta_B = \eta_{\text{charging}} * \eta_{\text{discharging}} \tag{4.45}$$

$\eta_{\text{charging}} = 0.98$ and $\eta_{\text{discharging}} = 0.95$

Here, SOC_{min} and SOC_{max} have been considered as 15% and 90% respectively.

Therefore, SOC can increase by 0.18 kW by every hour.

As per the assumed charging-discharging rate, it will take 5 hours to get fully charged.

During charging,
$$Energy\ used = Change\ in\ SOC * \frac{Battery\ capacity}{\eta_{\text{charging}}} \tag{4.46}$$

During discharging,

$$Energy\ discharged = Change\ in\ SOC * \text{Battery capacity} * \eta_{\text{discharging}} \tag{4.47}$$

Rule-based strategy

Here, in this section, a rule-based strategy has been proposed for efficient scheduling of ESS. We have assumed EP, EOP and EI as energy consumed in peak hours (5:00 pm – 11:00 pm), off-peak hours (11:00 pm – 6:00 am) and intermediate hours (6:00 am – 5:00 pm) respectively. Similarly, PP, OPP, IP have considered as unit energy price in peak, off-peak and intermediate hours respectively.

The scheduling of battery leads to three conditions for each of two different cases.

CASE 1: When $E_P < E_{OP}$ and $E_P < E_I$,

Condition 1, $$\frac{PP}{OPP} * \frac{E_P}{E_{OP}} > \eta_B * \frac{OPP}{IP} * \frac{E_{OP}}{E_I}$$

Condition 2, $$\frac{OPP}{IP} * \frac{E_{OP}}{E_I} > \eta_B * \frac{IP}{PP} * \frac{E_I}{E_P}$$

Condition 3, $$\frac{IP}{PP} * \frac{E_I}{E_P} > \eta_B * \frac{PP}{OPP} * \frac{E_P}{E_{OP}}$$

CASE 2: When $E_P > E_{OP}$ and $E_P > E_I$,

Condition 1, $$\frac{PP}{OPP} * \frac{E_P}{E_{OP}} < \eta_B * \frac{OPP}{IP} * \frac{E_{OP}}{E_I}$$

Condition 2, $$\frac{OPP}{IP} * \frac{E_{OP}}{E_I} < \eta_B * \frac{IP}{PP} * \frac{E_I}{E_P}$$

Condition 3, $$\frac{IP}{PP} * \frac{E_I}{E_P} < \eta_B * \frac{PP}{OPP} * \frac{E_P}{E_{OP}}$$

Therefore, the charging and discharging of ESS must follow certain rules, which are mentioned in Table 4.4.

Table 4.4. Strategy for ESS scheduling

Clear sky (when sufficient solar energy is available)			
Condition (CASE 1&2)	Off-peak	Intermediate	Peak
1	N/A	Charge	Discharge
2	Discharge	Charge	Discharge
3	N/A	Charge / Discharge	Discharge
Cloudy sky (when sufficient solar energy is not available)			
Condition (CASE 1&2)	Off-peak	Peak	Intermediate
1	Charge	N/A	Discharge
2	Charge	Discharge	Discharge
3	Charge	Charge / Discharge	Discharge

In the above listed cases, if condition 1 is satisfied, then ESS will be charging in Intermediate hours, discharging in Peak hours, for condition 2, ESS will be charging in Intermediate hours, discharging in Off-peak and Peak hours and so on. These are listed in Table 4.4.

4.4 Chapter Summary

This chapter examines load forecasting and power profile development for the state of West Bengal and its electricity network at Eastern Regional Load Dispatch Centre (ERLDC). Using hourly and peak load data from 2017, it employs week-ahead and day-ahead forecasting, finding the ARIMAX model to be the most effective, with potential improvements by adding more variables.

The chapter also focuses on developing a power profile within modern energy management systems (EMS), including energy consumption modeling, load scheduling and energy storage system (ESS) management to enhance efficiency and grid reliability. It highlights renewable energy integration through accurate forecasting and area-specific planning using K-means clustering.

Furthermore, the chapter details the energy consumption model within EMS, utilizing real-time data and advanced forecasting to optimize energy use and comply with environmental regulations. Finally, it discusses load scheduling for domestic consumers, classifying appliances into different categories for effective power consumption analysis and ESS management.

Significant Findings from this chapter are:

- Achieved less than 1% prediction error using ARIMAX forecasting technique.
- Selected 3 important features like energy consumption, total run time and frequency of operation for load scheduling using WKNN as a feature selection technique.
- Selected 3 important features like daily energy consumption, round efficiency of ESS and energy tariff using WKNN as a feature selection technique.
- Proposed a Rule-based-Strategy for ESS scheduling.

However, in the next chapter, the same residential loads have been analyzed using a newly proposed AI based tariff structure and optimized for better performance using a proposed advanced optimization technique, specifically tailored for multidimensional and Multiple Knapsack Problems for effective residential load management.

Related Publication:

The research work presented in this chapter has contributed to the following publications.

- Kuheli Goswami, Ayandeep Ganguly, Dr. Arindam Kumar Sil, "Comparing Univariate and Multivariate method for Short Term Load Forecasting”, International Conference on Computing, Power and Communication Technologies, IEEE Conference, Noida, September, 2018

- Kuheli Goswami, Ayandeep Ganguly, Dr. Arindam Kumar Sil, “Day Ahead Forecasting and Peak Load Management Using Multivariate Auto Regression Technique,” Applied Signal Processing Conference 2018, IEEE Conference (ASPCON), Kolkata, December, 2018

- Ayandeep Ganguly, Kuheli Goswami, Arpita Mukherjee, Dr. Arindam Kumar Sil, “Short Term Load Forecasting using Artificial Neural Network for Peak Load Reduction”, International Conference on Emerging Trends in Engineering and Science, Springer Conference, March, 2018.

These publications focus on prediction efficiency of demand profile using ANN, ARIMA and ARIMAX discussed in section 4.2

- Kuheli Goswami, Arindam Kumar Sil, “Renewable Energy based Dynamic Tariff system for Domestic load management”, Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), indexed by Scopus, approved by UGC, Vol. 25, No. 2,pp 626-638, February, 2022, ISSN: 2502-4752, DOI: 10.11591/ijeecs.v25.i2.pp626-638.

This publication focuses on Appliance energy consumption profiling and RE integration discussed in section 4.3.1, section 4.3.2 and section 4.3.3.

- Kuheli Goswami, Arindam Kumar Sil, “Improvement of Energy Performance Index for Domestic Prosumers Based on Newly Proposed Dynamic Tariff and Rule-based Strategy,” International Transactions on Electrical Energy Systems (ITEES), indexed by Scopus, SCIE, approved by UGC, Vol. 2022, Article ID: 5087908, August, 2022, https://doi.org/10.1155/2022/5087908.

This publication focuses on Feature selection and ESS scheduling discussed in section 4.3.3 and section 4.3.4.

CHAPTER 5

AI-based system design for Residential Load Management

5.1 Introduction

Due to rapid industrialization, urbanization and population growth, power consumption in India is increasing day by day. As demand rises, the gap between electricity generation and consumption is widening. Over the last five to ten years, electrification efforts have expanded, with more villages being connected to the grid. This has contributed to a notable increase in power consumption, especially in rural areas where appliances like lights, fans and televisions are becoming more common. In urban areas, domestic consumption has also risen significantly.

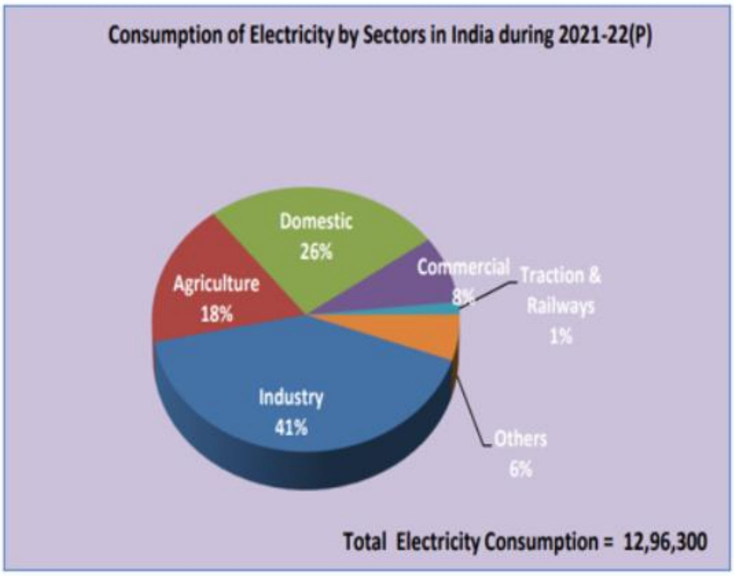


Figure 5.1 Consumption by sector in India during (a) 2021-22

According to reports, domestic electricity usage now accounts for over 25% of total power consumption, which is shown in Figure 5.1. The growing ownership of household appliances, particularly energy-intensive devices like air conditioners and refrigerators, has driven this increase. In tropical regions, changes in weather patterns have further boosted the use of these appliances, contributing to higher power demands.

In this scenario, simply relying on load scheduling or shifting consumption from peak to off-peak hours is not sufficient to manage the increasing demand. While these methods can help balance energy usage, additional strategies are required. One key approach is to encourage domestic consumers to become "prosumers", where they both consume and produce electricity, often by using rooftop solar panels. This not only reduces reliance on the grid but also enables them to participate in the electricity trade market, where they can sell excess energy back to the grid. Offering special incentives in terms of tariffs can motivate consumers to engage in such practices. These tariffs can vary based on factors such as time of day, season and level of consumption. Common types include flat-rate tariffs, time-of-use (TOU) tariffs, tiered tariffs and demand charges. These pricing models are designed to influence consumer behaviour, encouraging energy usage during off-peak hours and helping to manage demand more effectively.

However, traditional tariff-based approaches alone may not be enough to handle the complexities of modern energy consumption. The rapid advancement of technology, combined with the increasing complexity of household energy use, has created a need for more innovative solutions. This is where Artificial Intelligence (AI) plays a transformative role. AI-driven load management systems can automate and optimize energy usage by analysing real-time data and forecasting future consumption patterns. These systems can dynamically adjust the operation of household appliances to align with tariff schedules and the availability of renewable energy.

5.2 Proposing a new Tri-Optimized-Tariff

The effectiveness of tariffs in influencing consumer behaviour can be significantly enhanced when integrated with AI-based domestic load management systems. These systems use real-time data and predictive analytics to automate energy consumption adjustments, ensuring that households can maximize the benefits of complex tariff structures without manual intervention. Firstly, AI can schedule the operation of appliances to take advantage of lower tariffs automatically. Secondly, AI algorithms can predict household energy needs and adjust usage patterns in advance to avoid high-cost periods. Finally, continuous monitoring and adjustment of energy consumption in response to real-time tariff changes ensure optimal usage and cost savings. Therefore, this pricing-based approach is an effective way to reduce peak demand and manage the energy consumption judiciously. In this approach, modulation of energy price and updating of information provided to the users are most important steps to be taken care of. Due to the increase in the price of energy in energy shortage, consumers are bound to reduce their consumption in peak hours and use renewable energy.

To suggest a tariff structure based on the three parameters—Optimum use of RES, optimized value of total energy consumption over the entire day and optimum waiting time for household appliances—we need to approach the problem as a multi-objective optimization problem.

1. Encouraging the Efficient Use of Renewable Energy: The first criterion focuses on maximizing the use of renewable energy. The tariff structure should incentivize consumers to operate high-energy-consuming appliances, such as washing machines and air conditioners, when renewable energy sources (like solar or wind power) are abundant. Additionally, excess renewable energy should be stored using Energy Storage Systems to reduce stress on the grid during peak hours. This approach ensures efficient use of renewable energy and helps to balance the supply-demand equation, especially during peak consumption periods. Moreover, by encouraging consumers to participate in the electricity trade market, they can both save costs and contribute to the efficient functioning of the energy system, further promoting the use of renewable sources.

2. Minimizing Waiting Time for Appliance Scheduling: The second criterion emphasizes judicious load scheduling. The tariff should encourage consumers to operate their appliances with minimal waiting time, meaning household appliances should be scheduled in such a way that energy consumption is optimized without long delays. This can be achieved through accurate forecasting and strategic planning of future energy needs, ensuring that consumers can use electricity efficiently while minimizing inconvenience.

3. Optimizing Total Energy Consumption: The third criterion addresses the need to keep overall energy consumption within an optimum level, reducing waste. This can be achieved through a combination of proper load management, efficient use of daylight and energy-efficient building designs. By reducing unnecessary energy use, consumers can maintain a fair and permissible level of consumption.

These three factors—encouraging renewable energy use, minimizing waiting time for appliance scheduling and optimizing total energy consumption—are given the highest priority in the proposed tariff structure. Together, they aim to create a “Tri-Optimized Tariff” system that ensures efficient, sustainable and cost-effective energy management over 24-hour periods.

By utilizing a combination of tariff incentives, AI-based load management and AI-based ESS scheduling utility companies can spread energy demand more evenly throughout the day, reducing the strain on the grid during peak hours. This not only prevents grid overloads but also minimizes the need for emergency power sources, making the overall system more efficient. Here, the formulation of an objective function, constraints and the optimization technique have been shown in Figure 5.2.

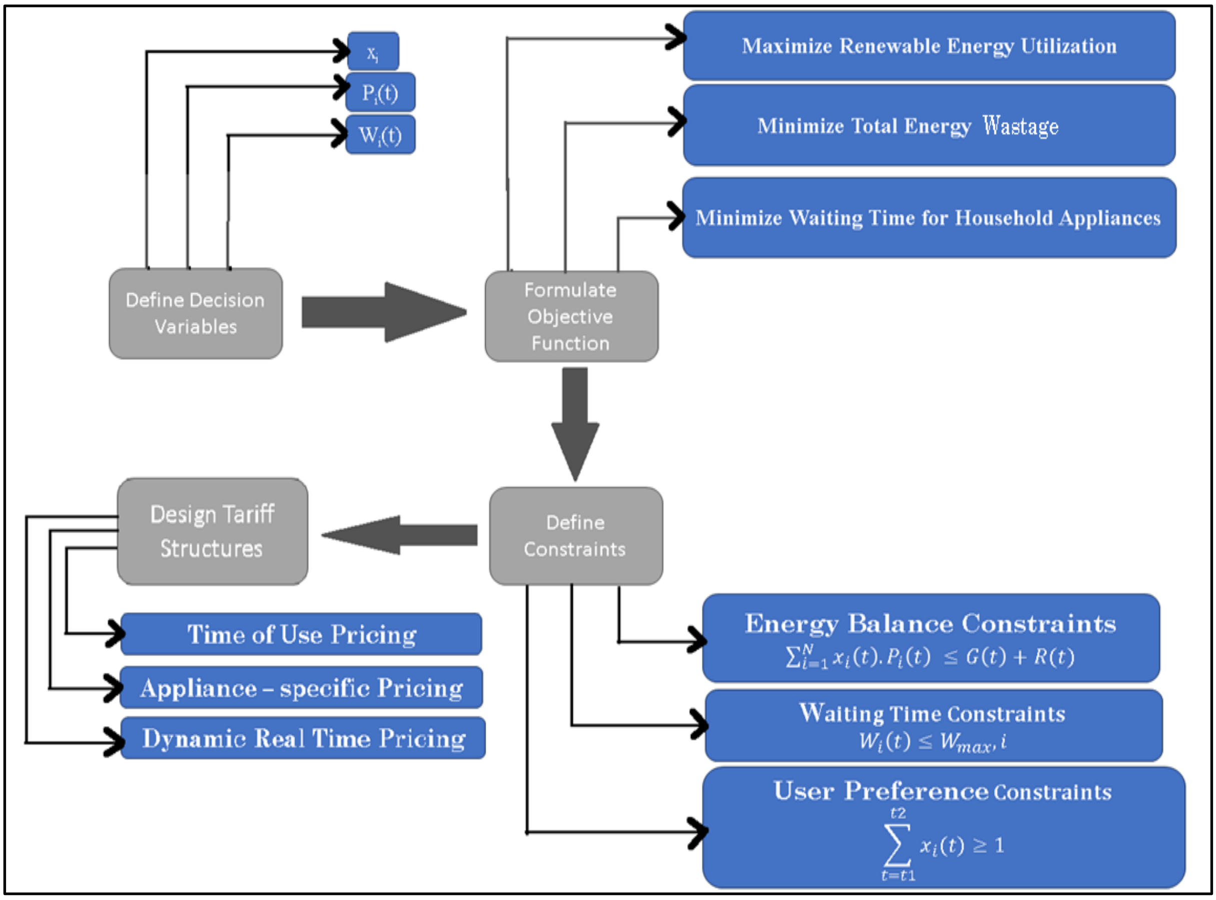


Figure 5.2 TOT Workflow

The steps have been discussed in the following section.

1. Define the Decision Variables

The key decision variables will be linked to:

- x_i: Binary variable representing the state (ON/OFF) of the household appliance i at a specific time t.
- $P_i(t)$: Power consumption of appliance i at time t.
- $W_i(t)$: Waiting time before appliance i can be operated at time t.

2. Formulate the Objective Functions

In this case, we have three objectives: renewable energy utilization, total energy consumption and waiting time for household appliances.

Objective 1: Maximize Renewable Energy Utilization

This objective encourages households to use appliances when renewable energy is available. The function can be modelled as:

$$\text{Maximize } F_1 = \sum_{t=1}^{T} \sum_{i=1}^{N} \min \left(\mathrm{R(t)}.\, x_i(t).\, P_i(t)\right).\, \Delta t \tag{5.1}$$

Where:

- R(t) is the RE available at time t.
- $x_i(t)$ is a binary variable (1 if appliance i is on at time t, 0 otherwise).
- $P_i(t)$ is the power consumption of appliance i at time t.
- Δt is duration of the time interval (in hours).

Subject to:

1. $$\sum_{i=1}^{N} \left(x_i(t).\, P_i(t)\right).\, \Delta t \leq R(t).\, \Delta t,\ \forall t \tag{5.2}$$

2. $$\sum_{t=1}^{T} x_i(t)\ .\, \Delta t = T_i^{ON},\ \forall i \tag{5.3}$$

3. $$\sum_{t=1}^{T} \left(x_i(t).\, P_i(t)\right).\, \Delta t \geq E_i,\ \forall i \tag{5.4}$$

Objective 2: Minimize Total Energy Consumption

Minimizing total energy consumption incentivizes consumers to reduce overall energy usage. The objective function is:

$$\text{Minimize } F_2 = \sum_{t=1}^{T} \sum_{i=1}^{N} x_i(t).\, P_i(t).\, \Delta t \tag{5.5}$$

Where T is the total number of time periods in a day and N is the number of appliances.

Objective 3: Minimize Waiting Time for Household Appliances

To reduce consumer inconvenience, the model minimizes the waiting time for appliances to operate, represented by:

$$\text{Minimize } F_3 = \sum_{i=1}^{N} \sum_{t=1}^{T} w_i(t) \tag{5.6}$$

Where, $w_i(t)$ is the waiting time for appliance i at time t.

3. Define the Constraints

Energy Balance Constraints

The total energy consumption at any time should not exceed the available grid energy and renewable energy combined:

$$\sum_{i=1}^{N} x_i(t).P_i(t) \leq G(t) + R(t) \quad (5.7)$$

Where G(t) is the grid energy available at time t.

Waiting Time Constraints

Certain appliances have time limitations (for example, dishwashers should run within a fixed time window).

$$W_i(t) \leq W_{max}, i \quad (5.8)$$

Where W_{max}, i is the maximum allowable waiting time for appliance i.

User Preferences Constraints

Ensure that the appliances run at least once during the user's preferred times (for example, between 6:00 PM and 10:00 PM):

$$\sum_{t=t1}^{t2} x_i(t) \geq 1 \quad (5.9)$$

Where t1 and t2 are the start and end of the preferred time window.

4. Tariff Structure Design Based on Optimization Results

Once the optimization is performed, the resulting tariff structure could be defined in terms of dynamic pricing.

A. Time-of-Use (TOU) Pricing

Electricity rates vary depending on the time of day and renewable energy availability:

- Peak hours: Higher tariff due to higher grid energy demand.
- Off-peak hours: Lower tariff, encouraging appliance use when renewable energy is abundant.

Here in this section, the flow chart to design the TOU: first part of our proposed tariff structure for domestic consumers has been discussed in Figure 5.3.

$$\text{Total Cost}=a+bx+c(xt) \quad (5.10)$$

Here, ‘a’ comprises of meter rent and monthly variable cost adjustment (MVCA) etc. is a fixed charge independent of maximum demand and energy consumption. ‘b’ depends on maximum demand (kVA) or sanctioned demand (kVA). ‘c’ depends on energy consumption (kWh).

$$\gamma=\gamma_C+\gamma_R \quad (5.11)$$

Here, γ_C and γ_R have been considered as the cost of energy from main grid and renewable energy (fixed) respectively. Here E indicates the total energy consumption over 24 hours and t indicates hour, which varies from 1 to 24.

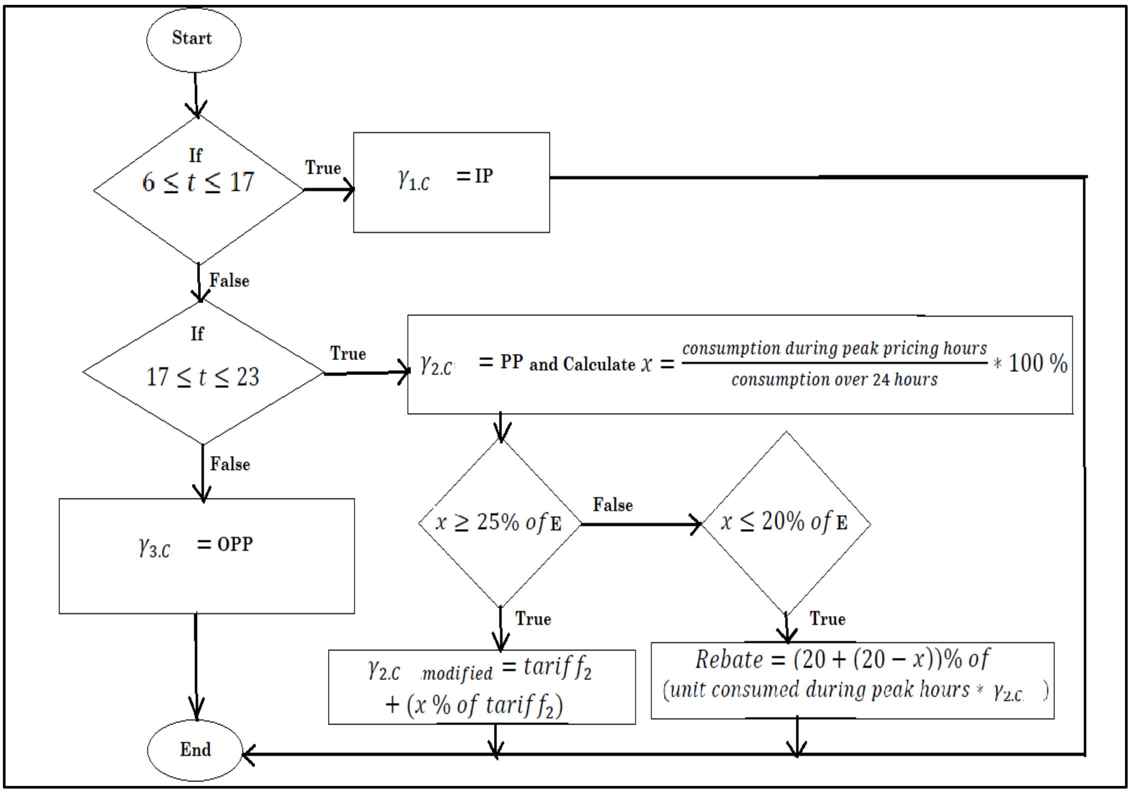


Figure. 5.3 Flow-chart for proposed dynamic tariff

where PP, OPP, IP have considered as unit energy price in peak, off-peak and intermediate hours respectively. This tariff structure is based on three key factors aimed at optimizing energy usage and promoting sustainability.

B. Appliance-Specific Pricing
Incentivize users to run specific high-consumption appliances during times of high renewable energy availability by offering discounted rates.

C. Dynamic Real-Time Pricing
Tariffs are adjusted in real-time based on current grid and renewable energy availability, dynamically changing to encourage optimal appliance usage.
Therefore, tariffs play a crucial role in domestic energy management by providing economic incentives for consumers to modify their behaviour. When combined with AI systems, the potential for cost savings, improved grid stability and environmental benefits is greatly enhanced. This approach leads to more sustainable and efficient energy consumption at the household level, ensuring that the growing energy demands are met in a more reliable and environmentally friendly way. The detailed tariff structure has been provided in Appendix B section B1 for detailed reference.

As mentioned in the previous section, decision-making is a crucial aspect of an energy management system. It involves the process of ensuring the optimum use of energy, m**inimizing waste** and making the **most efficient use of renewable energy**. This is achieved through the **judicious scheduling** of energy storage systems and the **smart management of load or demand** to reduce stress on the grid while also lowering the **carbon footprint**.

Effective decision-making ensures that energy is used efficiently by incorporating **robust yet flexible Optimization technique, which** helps to manage various aspects of the energy system, including:

1. **Maximizing the use of renewable energy**: Decision-making should focus on the benefits of utilizing renewable energy sources like solar and wind power to reduce reliance on non-renewable sources and decrease environmental impact.

2. **Optimizing energy storage**: Efficient scheduling of energy storage systems (ESS) ensures that surplus renewable energy is stored and used during peak demand hours, reducing the burden on the grid.

3. **Encouraging judicious load scheduling**: Incentives can be provided for consumers to shift energy consumption to off-peak hours, reducing grid stress and ensuring a balanced energy supply.

4. **Maintaining total energy consumption within permissible limits**: Decision-making should aim to keep total energy usage within a fair and acceptable range, promoting energy conservation and efficiency.

5. **Penalties for violations**: To ensure compliance, penalties should be imposed for violating energy consumption limits or failing to adhere to optimal scheduling practices.

The results were obtained by applying load scheduling using PSO and the proposed tariff structure to three households with different demand patterns. The implementation led to significant reductions in monthly electricity expenses, as summarized below:

- **Household 1**: Expenses decreased from ₹3597.80 to ₹2440.55, resulting in a **32% savings**.
- **Household 2**: Expenses reduced from ₹3953.67 to ₹2810.47, achieving a **29% savings**.
- **Household 3**: Expenses dropped from ₹2332.15 to ₹1499.10, yielding the highest savings of **36%**.

The pseudocode for PSO based load scheduling algorithm is provided in Appendix A section A4 for detailed reference. Additionally, a graph has been generated to demonstrate the corresponding reduction in total energy consumption across these households, showcasing the effectiveness of the proposed tariff structure in optimizing electricity usage and reducing monthly electricity bill, shown in Figure 5.4 and Table 5.1.

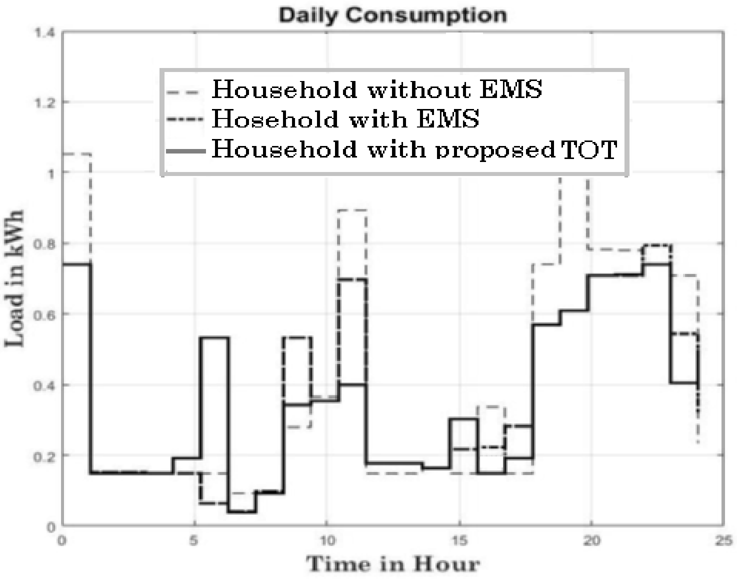


Figure. 5.4 Reduction in daily consumption with existing EMS and proposed TOT

Table 5.1: Savings in Monthly Electricity Bill

Consumers	**Monthly Electricity Expense**			**Savings in monthly electricity expense (in %)**
	With existing Block-Rate Tariff Structure	**With dynamic tariff structure [82]**	**With proposed TOT**	
House-hold 1	3597.80	3347 (approx.)	2400	33%
House-hold 2	3953.67	3521(approx..)	2795	29%
House-hold 3	2332.15	2107 (approx..)	1477	37%

In summary, decision-making in an energy management system is about balancing efficiency, sustainability and flexibility while encouraging renewable energy use, efficient energy storage and responsible consumption which can be achieved with an efficient Optimization technique.

5.3 The Critical Impact of Optimization in Residential Load Management

Optimization techniques are essential for enhancing the efficiency, cost-effectiveness and sustainability of Energy Management Systems (EMS) in homes and commercial buildings. These techniques, including linear programming, integer programming, dynamic programming, heuristic algorithms and machine learning, enable precise control over energy use. They help reduce costs by shifting usage to off-peak times, integrate renewable energy sources and maintain grid stability through demand response. By leveraging real-time data and predictive analytics, EMS can adapt to consumption patterns and optimize energy distribution, ultimately reducing greenhouse gas emissions and promoting sustainable energy practices.

5.3.1 Proposing a new Hybrid Synergistic Swarm Approach

This proposal introduces a cutting-edge hybrid optimization algorithm that leverages the strengths of both Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), with a specific focus on addressing Knapsack problems. The foundational concept of the PSO algorithm involves creating a swarm of particles navigating through the problem space, akin to a flock searching for the optimal resting place in their environment. This process involves each particle searching for an optimal position based on its fitness function, embodying the principle of natural selection where the environment influences the individuals' choices. Two key ideas underscore the optimization properties of this algorithm. Firstly, individual particles assess their current positions not only based on personal exploration knowledge but also benefit from insights shared by other particles within the swarm. Secondly, the incorporation of a stochastic factor in each particle's velocity propels them through unknown regions of the problem space. This unique property, combined with a well-orchestrated initial distribution of the swarm, facilitates extensive exploration and significantly enhances the likelihood of efficiently discovering optimal solutions.

The hybrid algorithm draws inspiration from the Ant Colony Optimization algorithm, which is rooted in the way ants select the shortest path to reach a food source or transport food to their nest. The proposed optimization technique seamlessly integrates the principles of both ant colony and particle swarm optimization, creating a dynamic synergy.

In this integrated approach, particles representing birds or fish at the furthest distances from the food source emulate the Ant Colony Optimization technique. These distant particles initiate pursuit, chasing their nearest group member based on the principles of Ant Colony Optimization. The probability of selecting the shortest path to chase the nearest group member is influenced by the same principle as ants following the concentration of pheromones to efficiently transport food to their nest.

In each iteration, the last member of the flock follows the most probable shortest path and subsequently, the entire group converges to follow conventional PSO. This iterative dynamic ensures a cohesive and effective optimization process.

In conclusion, this proposal unveils a pioneering hybrid optimization algorithm that seamlessly integrates the strengths of PSO and ACO, inspired by the principles of Ant Colony Optimization. The subsequent sections will delve into the intricacies of the algorithm, exploring implementation details, parameter tuning strategies and empirical validations, with the overarching goal of establishing this hybrid approach as a potent and versatile tool for a diverse range of optimization challenges.

5.3.2 Mathematical Model

The main concept is that we have particles of a swarm moving in a problem space and evaluating their positions through a fitness function. Once a problem space is defined a set of particles is spawned in it and their positions and velocities are updated iteratively according to the specific PSO algorithm. Even though PSO has been proven to be an efficient algorithm with good results it is not by design one that guarantees that the best solution is found, since it relies on visiting and evaluating problem space positions. Even though many variations exist usually all have a fitness function. The specification of this function depends on the problem being optimized (especially in its dimensions) and as such we will simply refer to it as $f(x_n)$ i.e. $f(x_{n,0}, x_{n,1}, x_{n,2},\ldots\ldots x_{n,d})$, where n is the particle index and d represent the dimension in multi-dimensional space.

The current position of nth particle is x_n i.e. $x(x_{n,0}, x_{n,1,\ldots\ldots,}x_{n.d})$ and velocity of the same is v_n i.e. $v(v_{n,0}, v_{n,1,\ldots\ldots,}v_{n.d})$. In this algorithm we have a completely connected swarm, meaning that all the particles share information, any particle knows what is the best position ever visited by any particle in the swarm. Each particle has a position and a velocity which are calculated as follows:

$$x^{(I+1)}_{n,d} = x^{I}_{n,d} + v^{(I+1)}_{n,d} \tag{5.12}$$

where I represent the number of iterations.

$$v^{(I+1)}_{n,d} = \omega * v^{I}_{n,d} + \mu * R1 * \left[Pbest^{I}_{n,d} - x^{I}_{n,d}\right] + \vartheta * R2 * \left[Gbest^{I}_{n,d} - x^{I}_{n,d}\right] \tag{5.13}$$

where ω represent the inertia

μ represent the acceleration constant for cognitive component
ϑ represent the acceleration constant for social component
R1 and R2 represent stochastic component of algorithm a random value between 0 and 1.
$Pbest_{n,d}^{I}$ represent the local best for nth particle in dimension d.
$Gbest_{n,d}^{I}$ represent the global best for all particle in dimension d.
At each iteration pheromone values are updated by n particles.

$$\rho_{n,d} = (1-\gamma)\rho_{n,d} + \sum_{k=1}^{n} \delta * \rho_{k,d} \tag{5.14}$$

$\delta * \rho_{k,d}$ quantity of pheromone laid on edge by swarm particle k which varies from 1 to n.

$$\delta * \rho_{n,d} = \begin{cases} \frac{Constant}{Dn}\ ,\ if\ n\, particles \\ used\ edge\ in\ their\ path \\ \\ \quad\quad 0,\ otherwise \end{cases} \tag{5.15}$$

At the end of each iteration the current position, local best, global best and quantity of pheromone are updated.
Let the position of particle m in d dimension at the end of I iteration is $x_{m,d}^{I}$ and fitness function value for the same is $f\left(x_{m,d}\right)$.

$$x_{m,d}^{(I+1)} = \begin{cases} x_{m,d}^{I} + v_{m,d}^{(I+1)} \pm \lambda_{m,d}\ , \\ if\ x_{m,d}\ is\ the\ furthest\ position\ with\ respect\ to\ Global\ best \\ \\ x_{m,d}^{I} + v_{m,d}^{(I+1)},\quad otherwise \end{cases} \tag{5.16}$$

Where $\lambda_{m,d}$ is the traversed distance by swarm particle m in d dimension towards particle j if τ is minimum.

And $\tau_{m,j=}f(x_{m,d} - x_{j,d})$ (5.17)

$\lambda_{m,d}$ = min [$\epsilon_{mj,d}$]=min [$\epsilon_{mj,0}$, $\epsilon_{mj,1}$, ... $\epsilon_{mj,d}$] (5.18)
and
$\epsilon_{mj,d} = [(x_{m,1} \sim x_{j,1}), (x_{m,2} \sim x_{j,2}), \dots \dots, (x_{m,d} \sim x_{j,d})]$ (5.19)

While traversing λ distance of particle m toward particle j, the probability of selecting a path towards j,

$$P_{mj} = \rho_{n,d}^{\sigma} * \varepsilon_{n,d}^{\emptyset} \tag{5.20}$$

where σ and $\emptyset$ control the relative importance of pheromone versus heuristic information and $\varepsilon_{n,d}$ represent heuristic information.

This method has been tested using a mathematical equation to determine the minimum value of a random function as well as in IEEE 33 bus system to find out the optimal location for RE integration. Here the result with the following function has been shown in Figure 5.5 and Table 5.2.

Fitness Function: $\min f(x) = \sum_{i=1}^{4} x_i^2$

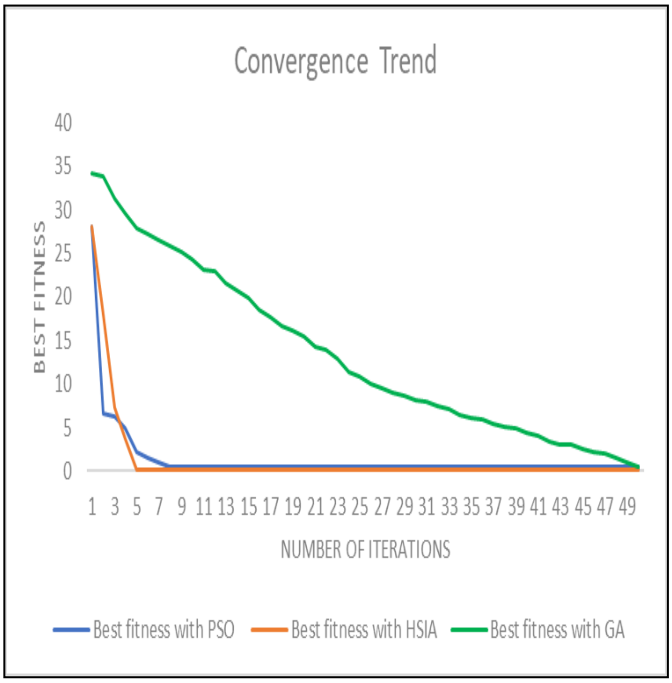


Figure. 5.5 Convergence Trend

Table 5.2: Convergence Trend

Number of Iterations	PSO	HSSA
	Global Best	Global Best
1	28.13	28.13
2	6.57	17.95
3	6.25	7.26
4	4.93	3.76
5	2.15	0.21
6	1.5	0.21
7	1.07	0.21
8	0.3	0.21
9	0.3	0.21
10	0.3	0.21

Based on this the following comparison has been done among PSO, ACO and proposed HSSA for optimization in Table 5.3.

Table 5.3: Comparative Study

Feature	PSO	ACO	HSSA
Search Approach	Continuous, global optimization	Combinatorial, local optimization	Combines global (PSO) and local (ACO) approaches.
Exploration vs. Exploitation	Balances using velocity updates and stochastic factors	Balances using pheromone trails and heuristic information	Enhances exploration with ACO-inspired chasing and strengthens exploitation with PSO.
Behaviour of Outliers	Moves randomly or guided by swarm dynamics	NA	Outliers "chase" neighbors using probabilistic ACO principles.
Convergence	Faster but may get trapped in local minima	Slower but more robust to local minima	Faster convergence with improved robustness against local optima.

The previous section introduced a proposed optimization technique for managing domestic loads effectively. The efficiency of this technique in finding optimal solutions for domestic load management will be discussed further in the next chapter, which includes a case study on a large residential complex. Additionally, its application extends to other fields, as demonstrated in the following section. The same method has been used to determine the optimal size and placement of renewable energy sources in an IEEE 33-bus system, aiming to reduce transmission losses by allocating renewable energy to the distribution section.

This allocation is carefully designed to minimize losses while ensuring efficient distribution of available renewable energy sources based on an assumed penetration level. By optimizing the placement of these energy sources, the system achieves multiple goals: reducing transmission losses, meeting energy demand and providing cost-effective solutions for consumers. The technique not only identifies the optimal size of PV-based energy sources but also pinpoints the most beneficial locations (the number of buses) for integrating renewable energy. The proposed system has been thoroughly tested using MATLAB programming and Simulink, confirming its effectiveness in real-world applications on the standard IEEE 33-bus model, leverages the simplicity and compactness of the system, making it ideal for clear and accurate performance evaluations.

5.3.3 Objective Function Formulation

Here, our aim is to minimize the estimated value of transmission loss. The calculation of transmission loss has been shown in Figure 5.6.

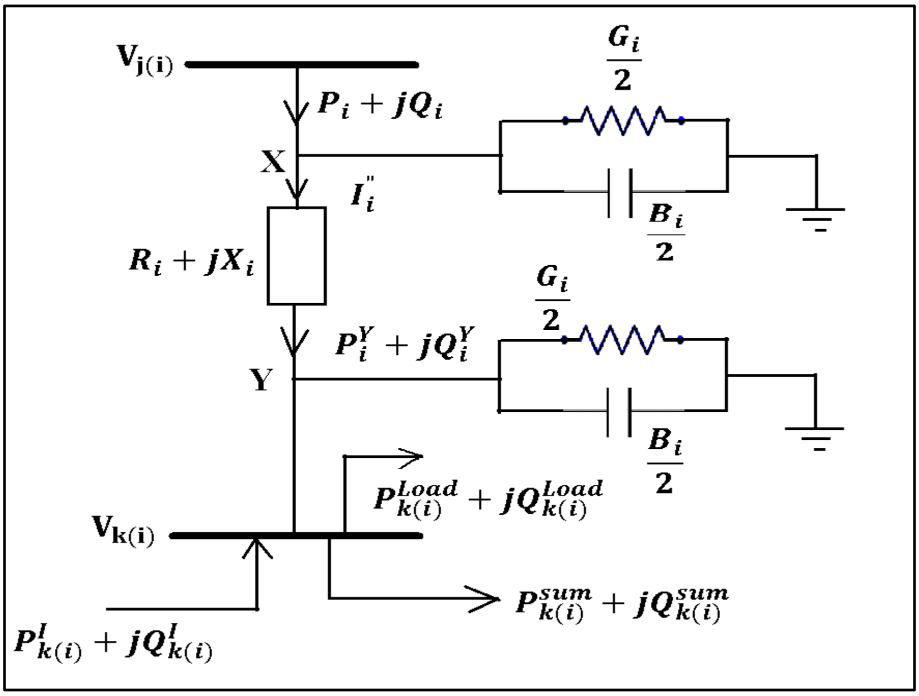


Figure 5.6 Load flow analysis between bus j and k

Load flow analysis in IEEE 33 bus system is solved using Newton Raphson algorithm, where we have considered two buses; bus j and bus k.

Real and Reactive load power at bus k: $P_{k(i)}^{Load} + jQ_{k(i)}^{Load}$

Real and Reactive injected power at bus k: $P_{k(i)}^{I} + jQ_{k(i)}^{I}$

Sum of the Real and Reactive power flow through all downward branches connected to bus k(i): $P_{k(i)}^{sum} + jQ_{k(i)}^{sum}$

$$P_i^Y + P_{k(i)}^I = P_{k(i)}^{sum} + P_{k(i)}^{Load} + (V_{k(i)}^2 * \frac{G_i}{2}) \quad (5.21)$$

$$I_i^{"2} = \frac{(P_i - \frac{V_{j(i)}^2 * G_i}{2})^2 + (Q_i + \frac{V_{j(i)}^2 * B_i}{2})^2}{V_{k(i)}^2} \quad (5.22)$$

$$P_i = P_i^Y + I_i^{"2} * R_i + \frac{V_{k(i)}^2 * G_i}{2} \quad (5.23)$$

$$Q_i^Y + Q_{k(i)}^I = Q_{k(i)}^{sum} + Q_{k(i)}^{Load} + (V_{k(i)}^2 * \frac{B_i}{2}) \quad (5.24)$$

$$Q_i = Q_i^Y + I_i^{"2} * X_i - \frac{V_{k(i)}^2 * B_i}{2} \quad (5.25)$$

$$V_{k(i)}^2 = V_{j(i)}^2 - 2\left\{\left(P_i - \frac{V_{j(i)}^2 . G_i}{2}\right) * R_i + \left(Q_i + \frac{V_{x(i)}^2 . B_i}{2}\right) * X_i\right\} + I_i^{"2}\left(R_i^2 + X_i^2\right) (5.17)$$

$$P_i^{Loss} = \frac{V_{j(i)}^2 . G_i}{2} + I_i^{"2} * R_i + \frac{V_{k(i)}^2 . G_i}{2} \quad (5.26)$$

$$Q_i^{Loss} = \frac{V_{j(i)}^2 . B_i}{2} + I_i^{"2} * X_i - \frac{V_{k(i)}^2 . B_i}{2} \quad (5.27)$$

For n number of branches,

$$P_{Loss} = \sum_{i=1}^{n} P_i^{Loss} \quad (5.28)$$

$$Q_{Loss} = \sum_{i=1}^{n} Q_i^{Loss} \quad (5.29)$$

$F(P^I, Q^I)$ be the power losses which depends on location of PV based DG, RE availability (solar irradiation) and load model at a particular time slot ‘t’.

$$P\left(f\left(SI^t, PV_{DG_{location}}, Load^t\right)\right) = P(SI^t) * P\left(PV_{DG_{location}}\right) * P(Load^t) \quad (5.30)$$

Total probable estimated power loss,

$$P_{Loss}^{Estimated} = \sum_{k=0}^{n} P_{Loss}^t * L^t \quad (5.31)$$

where,

$$\mathrm{P_{Loss}^{t} = F\left(SI^{t}, PV_{DG_{location}}, Load^{t}\right) * P(SI^{t}) * P\left(PV_{DG_{location}}\right) * P(Load^{t})} \quad (5.32)$$

The **Fitness Function is** $\mathbf{min}(\boldsymbol{P_{loss}^{Estimated}})$

Number of RES and ESS unit constraints

$$N_{PV} > 0 \quad (5.33)$$

$$N_{ESU} > 0 \quad (5.34)$$

RES and ESS Capacity Constraints

$$PV\_DG_{capacity}^{min} \leq PV\_DG_{capacity} \leq PV\_DG_{capacity}^{max} \quad (5.35)$$

$$ESS_{capacity}^{min} \leq ESS_{capacity} \leq ESS_{capacity}^{max} \quad (5.36)$$

Constraints on Load supplied by RES and ESS

$$PV_{O/P} : Load\ Demand = K = penetration\ level \quad (5.37)$$

$$(K - 5\%\ of\ K) \leq K \leq (K + 5\%\ of\ K) \quad (5.38)$$

$$PV_{O/P}{}^{t} \leq (L_{l}^{t} + P_{level\_max}) \quad (5.39)$$

Constraints on Voltage level at buses

$$V_{min} \leq V_{Y}^{E} \leq V_{max} \quad (5.40)$$

Constraints on Power Flow

$$P_{i} = P_{I}' + I_{i}'^{2} * R_{i} + (V_{x(i)}^{2} * G_{i}/2) \quad (5.41)$$

$$Q_{i} = Q_{I}' + I_{i}'^{2} * X_{i} + (V_{x(i)}^{2} * B_{i}/2) \quad (5.42)$$

Constraints on ESU Parameter

$$SOE^{min} \leq SOE \leq SOE^{max} \quad (5.43)$$

In conclusion, this research underscores the significance of load management in distribution systems (DSM) and showcases the versatility of the proposed optimization technique. The following section will detail the implementation process in the IEEE 33-bus system to identify the optimal size and placement of renewable energy sources. The results offer a comprehensive analysis of the technique's effectiveness in load management and highlight its potential for real-time application.

5.4 Performance Evaluation of Hybrid Synergistic Swarm Approach with IEEE 33 Bus System

IEEE 33 bus system is the network of IEEE standards and consists one generator, several load points shown in Table 5.4. Due to its easy data availability, IEEE33 bus has find wide application in various research works.

Specification:

Table 5.4 IEEE 33 Bus system Specification

Radial distribution system
No. of buses = 33
No. of lines = 32
Voltage level = 12.66kV
load size = 3.715MW and 2.3MVar.
DG unit voltage = 12.66kV.
Fixed penetration level (30%)

The IEEE 33-bus system serves as a versatile testbed for conducting research in power system analysis and control, offering opportunities to explore and advance various aspects of power system operation, including power flow analysis, voltage stability studies, optimal power flow and control algorithm development. By leveraging the IEEE 33-bus system, researchers can develop innovative solutions to address current and future challenges in the electric power industry.

The IEEE 33-bus system is commonly used for power flow analysis due to its moderate size and complexity, making it manageable for testing different algorithms and techniques. Researchers often analyze power flow under different operating conditions, such as varying loads, generation levels and network configurations, to assess system stability and reliability.

We have used the proposed optimization technique to locate the optimal position for RE integration in the IEEE 33 bus system. The proposed hybrid Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithm offers several benefits when solving complex optimization problems like the optimal size and location of PV-based Distributed Generation (DG) in the IEEE 33-bus system. A detailed pseudocode implementation of this method is included in Appendix A section A5. Below are the key advantages of this hybrid approach:

1. Combining Strengths of PSO and ACO:
   - PSO's Exploration Capabilities: PSO is highly efficient in exploring the solution space globally. It helps particles (solutions) search for optimal positions by updating their velocities based on their personal best and global best positions. This prevents the algorithm from getting stuck in local optima early on.
   - ACO's Exploitation and Convergence: ACO is particularly strong in exploiting the search space through pheromone-based mechanisms, which encourages particles to follow the best solutions found so far. This allows for fine-tuning and faster convergence to an optimal solution, especially in complex search spaces.

2. Improved Convergence Rate:

The hybrid approach enhances the convergence speed of the optimization process. PSO can quickly explore a large portion of the solution space and ACO can fine-tune the solutions by guiding particles towards promising regions. This synergistic approach helps in reaching the global optimum faster compared to using either PSO or ACO alone.

3. Balanced Exploration and Exploitation:
   - Exploration (PSO): In the early stages, PSO allows for wide exploration of the solution space, ensuring that the algorithm does not miss out on potentially good solutions by getting stuck in local optima.
   - Exploitation (ACO): As the algorithm progresses, ACO helps to refine the search around the best solutions, leveraging the pheromone mechanism to intensify the search around optimal areas.

4. Better Handling of Complex, Multi-Dimensional Problems:

Problems like optimal DG placement and sizing involve multiple dimensions (size, location and operational constraints) and nonlinear relationships (such as minimizing power loss and voltage deviation). The hybrid algorithm handles these complexities more effectively because:

- PSO handles the multiple dimensions well, allowing for simultaneous optimization of DG size and location.

- ACO's probabilistic path selection further improves solution refinement by encouraging paths with better solutions, making it suitable for complex grid optimization scenarios.

5. Flexibility and Robustness:
The hybrid algorithm is flexible and can be adapted to various types of optimization problems, whether the objective is to minimize power loss, improve voltage profiles, or optimize cost efficiency. The algorithm is robust and can handle uncertainty in data or problem constraints (such as load demand or renewable energy fluctuations), which are often seen in real-world grid operations.

6. Handling Discrete and Continuous Variables:
  - PSO: Can easily manage continuous variables, such as the size of DG units.
  - ACO: Particularly useful for managing discrete decisions, such as selecting the optimal bus location for DG placement.

This makes the hybrid algorithm well-suited for the mixed nature of the problem, where both continuous (DG size) and discrete (bus location) variables need to be optimized.

7. Improved Solution Quality:
By combining PSO’s global search with ACO’s local refinement, the algorithm is likely to find higher-quality solutions compared to traditional methods. This is particularly useful in power systems where suboptimal DG placement can lead to increased power losses, poor voltage profiles, or inefficiencies in energy distribution.

8. Scalability:
The hybrid approach is scalable and can be applied to larger systems beyond the IEEE 33-bus system. With the ability to efficiently search large solution spaces, it can be adapted to other power grids or optimization problems in energy management systems.

9. Dynamic Adaptability:
  - PSO: Can adapt to changes in the environment, such as fluctuations in demand or renewable generation.
  - ACO: Can dynamically adjust the search space by updating pheromone trails, making it responsive to the evolving conditions in the grid.

This adaptability is crucial for DSM (Demand-Side Management) and renewable energy integration, where conditions change frequently.

10. Improved Decision-Making for Utility Operators:
The hybrid algorithm provides utility operators with more reliable, cost-effective and environmentally sustainable solutions for DG placement and sizing. This can lead to:

- Lower operational costs: By reducing power losses and improving voltage stability.
- Increased grid resilience: By optimizing the placement of DG units, the grid becomes more resilient to disruptions or peak demand scenarios.

5.4.1 Voltage Profile at each bus

Through optimal allocation of PV integration, we significantly improved the voltage profile at each bus in the system. Additionally, the adoption of optimal PV generation locations led to a noteworthy reduction in transmission losses.

The Load Flow Analysis of the designed model has been carried out using Newton Raphson method. It has converged in 6 iterations. From Figure 5.7 it can be concluded that by using the proposed Optimization technique the voltage profile has been significantly improved at bus number 18,26 and 33.

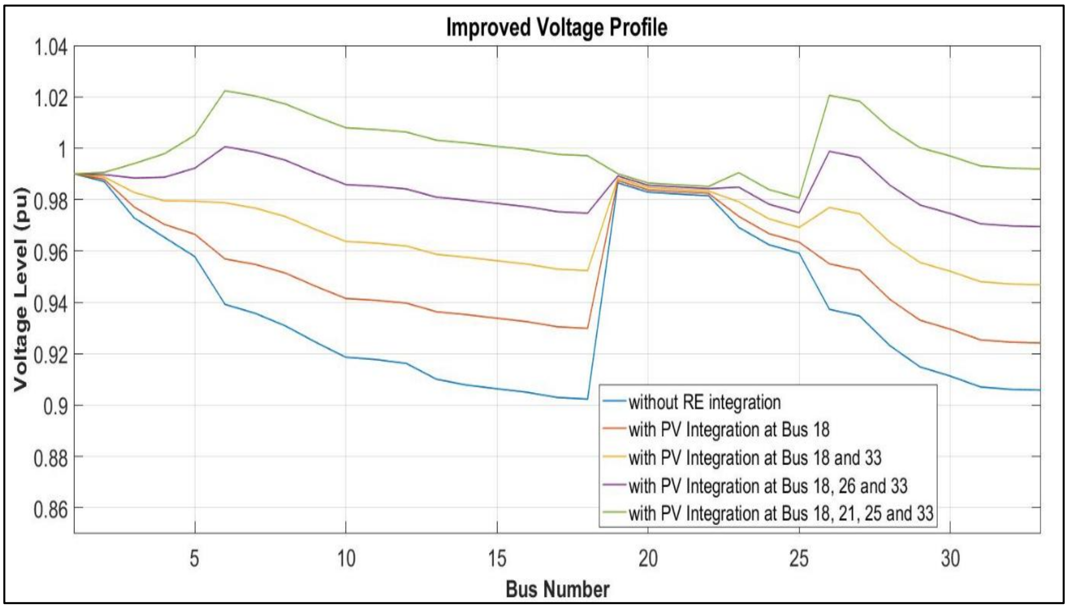


Figure 5.7 Voltage profile

5.4.2 Transmission Losses

The amount of reduction in transmission losses due to optimal placement of PV sources has been tabulated in Table 5.5.

Table 5.5 Transmission Losses due to optimal number, size and location

Conditions	Optimal number and size (PV)	Optimal Location (Bus No.)	Power loss		Percentage Reduction in Power Loss		Minimum voltage (PU)
			Real Power in kW	Reactive Power in KVAR	Real Power in kW	Reactive Power in KVAR	
Fixed Load	Without PV integration	-	206.63	137.8	-	-	0.903
Peak Hours		-	243.5	163.1	-	-	
Fixed Load	1*1.31 MW	18	121.46	79.6	41.22	42.24	0.924
Peak Hours		33	153.45	99.6	36.98	38.93	
Fixed Load	2*1.31 MW	18, 26	68.2	48.7	66.99	64.66	0.943
Peak Hours		26, 33	87.9	61.1	63.9	62.54	
Fixed Load	**3*1.31 MW**	**18, 26, 33**	**66.1**	**50.6**	**68.01**	**63.28**	0.969
Peak Hours		**18, 26, 33**	**74**	**55.9**	**69.61**	**65.73**	
Fixed Load	4*1.31 MW	18, 21, 25, 33	114.7	85.2	44.49	38.17	0.996
Peak Hours		18, 21, 25, 33	111.4	83.61	54.26	48.74	

These findings underscore the effectiveness of the proposed optimization technique in enhancing energy efficiency and system performance while minimizing adverse impacts on consumers. It can be concluded that the proposed optimization technique is performing efficiently and has significant potential for real-time applications, which is crucial for improving the optimal usage of our designed energy management system, SRLMS.

5.5 Chapter Summary

This chapter presents advanced strategies for optimizing residential load management, focusing on innovative tariff systems and novel optimization techniques. We propose a new tri-optimized-tariff system designed to balance energy demand by incentivizing usage during off-peak and intermediate hours. This system aims to reduce energy costs for residents, reduce stress on the electrical grid and promote efficient energy consumption. Detailed calculations for determining peak, off-peak and intermediate hour tariffs are provided, highlighting the potential for significant cost savings and improved load distribution.

Additionally, we introduce a hybrid synergistic swarm approach to further enhance the efficiency of residential load management. This innovative method combines the strengths of various optimization techniques to achieve superior performance. We present the mathematical model underlying this approach and outline the algorithm used to dynamically adjust to changing energy demands and consumption patterns. The design of a Smart Residential Load Management System (SRLMS) incorporating this novel optimization technique is also described, demonstrating its potential to effectively manage residential loads.

The performance of the proposed system is evaluated using the IEEE 33 Bus System. We examine the voltage profile at each bus to ensure stability and reliability and analyze the reduction in transmission losses achieved by the optimized load management system. The results show significant improvements in grid efficiency and overall performance, validating the effectiveness of the proposed methods.

In summary, this chapter offers a comprehensive approach to enhancing strategic residential load management system (SRLMS) through tariff optimization and advanced optimization techniques. and the hybrid synergistic swarm approach provide innovative solutions for reducing energy costs, improving grid stability and promoting sustainable energy consumption, with detailed calculations and performance evaluations demonstrating their efficacy.

Significant Findings from this chapter are:

- Achieved reduction in monthly electricity expense by 30% using proposed Tri-Optimized-Tariff structure which is a major concern for prosumers.
- Achieved reduction in transmission losses by 69% in IEEE 33 Bus system using proposed Hybrid Synergistic Swarm Approach.

In the next chapter, we have presented a case study on the virtual sustainable adoption of a 30-acre residential complex, located at Kolkata, near E M Bypass. We have applied all the proposed techniques discussed so far and validated the approach integrating IEEE 33 Bus system to assess its effectiveness in real-time, large-scale environment and the performance has been evaluated.

Related Publication:

The research work presented in this chapter has contributed to the following publications.

- Kuheli Goswami, Arindam Kumar Sil, “Renewable Energy based Dynamic Tariff system for Domestic load management”, Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), indexed by Scopus, approved by UGC, Vol. 25, No. 2,pp 626-638, February, 2022, ISSN: 2502-4752, DOI: 10.11591/ijeecs.v25.i2.pp626-638.

This publication focuses on a proposal of new tariff structure resulting consumers benefit by reducing monthly electricity expense discussed in section 5.2

CHAPTER 6

Microgrid Integration in a Residential Complex: A Case Study

6.1 Introduction to Sustainable Living

Sustainable living encompasses various aspects of daily life, including energy use, transportation, food production, housing, consumer choices and community engagement. It involves making conscious decisions to reduce one's ecological footprint and contribute positively to the health and resilience of the planet and its inhabitants.

As individuals, communities and societies increasingly recognize the urgency of addressing environmental challenges such as climate change, biodiversity loss and resource depletion, sustainable living offers a pathway towards a more resilient, equitable and thriving future for all. Strategic and efficient energy planning for our community can lead us toward a cleaner environment and ensure a sustainable energy future for generations to come. Here, we present a case study focused on a residential complex located in Kolkata. In the following section, we will examine the demand profile of the residential complex and conduct a performance analysis of our designed Residential Load Management System through virtual adoption within the complex.

6.2 Overview of Residential Complex

The 30-acre residential complex is envisioned as a modern and sustainable community nestled within a serene and green landscape. Situated on a sprawling plot of land, the complex harmoniously blends contemporary design with nature-inspired elements to create a vibrant and welcoming environment for its residents. The detailed distribution of the 30-acre land has been represented in the pie chart Figure 6.1 and Table 6.1.

Overview of 30 acres land area

Table 6.1: Specification of 30-acre plot

Plot Area	1,21,406 square meters (30 acres)
Floor Space Index	3.4
Built-up Area	60,703 square meters
Area for Residential Buildings (32,253 square meters) Number of Residential Towers: 7 Number of Floors on each Tower: 14 Number of Residential Units: 1078 Area for Amenities (28,450 square meters)	
Open Space Area	48,562 square meters
Road, Footpath and Pedestrian Walkway (29,138 square meters) Area for Microgrid setup (4,500 square meters) Green Belt (14,924 square meters)	
Not Useable Land	12,141 square meters

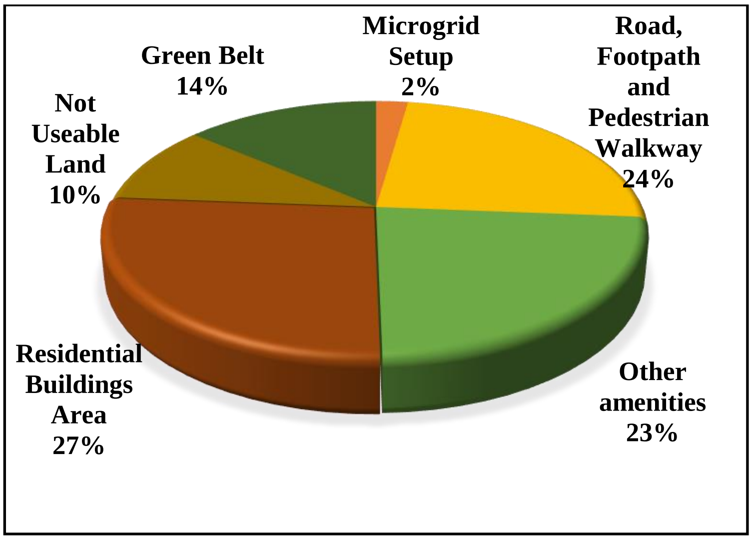


Figure 6.1: Area distribution

Total Built-up Area in the mentioned land is of 60,703 square meters. The area for residential buildings consists of 588 number of 3BHK apartments, each of 280 square meter area with a balcony of 20 square meter area and 490 number of 4BHK apartments, each of 480 square meter area with 20 square meter balcony. Detailed specifications are mentioned in Table 6.2 and 6.3.

Table 6.2: Overview of 3BHK Apartment

Bedroom 1	**4.5 meters x 4.0 meters**
Bedroom 2	4.0 meters x 3.5 meters
Bedroom 3	4.0 meters x 3.5 meters
Living Room	8.0 meters x 6.0 meters
Kitchen	4.0 meters x 3.0 meters
2 Bathrooms	approximately 2.5 meters x 2.0 meters
Balcony	5.0 meters x 4.0 meter

Table 6.3: Overview of 4BHK Apartment

Bedroom 1	**5 meters x 4.5 meters**
Bedroom 2	4.5 meters x 4 meters
Bedroom 3	4.5 meters x 4 meters
Bedroom 4	4.5 meters x 4 meters
Living Room	10.0 meters x 7.0 meters
Kitchen	5.0 meters x 4.0 meters
3 Bathrooms	approximately 3 meters x 2.5 meters
Balcony	5.0 meters x 4.0 meter

The 30-acre residential complex exemplifies a modern, sustainable living environment that balances contemporary design with the natural landscape, providing a high-quality living experience for its residents. The commitment to sustainability is evident in the integration of green building practices, renewable energy sources and efficient energy management systems, ensuring a reduced environmental footprint. The well-planned infrastructure fosters a strong sense of community and enhances the overall well-being of its inhabitants. This residential complex not only meets the immediate needs of its residents but also paves the way for a greener, more sustainable future.

6.3 Energy consumption Analysis

Understanding the energy consumption patterns of a residential complex is crucial for optimizing resource use, reducing costs and minimizing environmental impact. This analysis delves into the hourly energy demands of a 3 BHK and 4 BHK apartment during the summer months. By examining typical usage patterns across various household activities—such as cooling, lighting and appliance use—we aim to provide a comprehensive overview of energy needs. This insight will facilitate the implementation of efficient energy management systems and the integration of renewable energy sources, ultimately contributing to a more sustainable and cost-effective living environment for residents.

6.3.1 Residential Demand Analysis

Here is a revised breakdown of energy usage over a 24-hour period during the summer months, including estimated energy consumption for each time-period:

For 3BHK Apartments

1. **Off Peak Period (11:00 PM - 6:00 AM):**
    - Energy consumption: 6.85 kWh
    - Usage:
        - Air conditioning and Celling Fan: 6.26 kWh
        - Lighting: 0.4 kWh
        - Kitchen appliances (Refrigerator, coffee maker, toaster etc.): 0.2 kWh
        - Electronics and Other appliances (Computer, TV, Charging Devices etc.): 0.09 kWh
2. **Intermediate Period (6:00 AM - 5:00 PM):**
    - Energy consumption: 5.34 kWh
    - Usage:
        - Air conditioning and Celling Fan: 2.36 kWh
        - Lighting: 0.8 kWh
        - Kitchen and Cooking appliances (Refrigerator, oven, microwave, Mixer-grinder etc.): 1.34 kWh
        - Electronics and Other appliances (TV, computer, Washing Machine etc.): 0.84 kWh
3. **Peak Period (5:00 PM - 11:00 PM):**
    - Energy consumption: 6.6 kWh
    - Usage:
        - Air conditioning and Celling Fan: 3.6 kWh
        - Lighting: 0.68 kWh
        - Kitchen and Cooking appliances (Refrigerator, oven, microwave etc.): 0.96 kWh
        - Electronics and Other appliances (TV, computer, Charging Devices etc.): 1.4 kWh

These estimates are based on energy usage patterns, which are acquired from physical survey dataset in a 3 BHK apartment during summer, assuming moderate to high temperatures necessitating frequent use of air conditioning. This data has been used for other 588 3BHK apartments though actual energy consumption for each may vary based on factors such as appliance efficiency and individual habits.

For 4BHK Apartments

1. **Off Peak Period (11:00 PM - 6:00 AM):**
    - Energy consumption: 11.85 kWh
    - Usage:
        - Air conditioning and Celling Fan: 11.17 kWh

        - Lighting: 0.4 kWh
        - Kitchen appliances (Refrigerator, coffee maker, toaster etc.): 0.2 kWh
        - Electronics and Other appliances (Computer, TV, Charging Devices etc.): 0.08
2. **Intermediate Period (6:00 AM - 5:00 PM):**
    - Energy consumption: 5.72 kWh
    - Usage:
        - Air conditioning and Celling Fan: 2.3 kWh
        - Lighting: 1.2 kWh
        - Kitchen and Cooking appliances (Refrigerator, oven, microwave, Mixer-grinder etc.): 1.35 kWh
        - Electronics and Other appliances (TV, computer, Washing Machine etc.): 0.87 kWh
3. **Peak Period (5:00 PM - 11:00 PM):**
    - Energy consumption: 9.53 kWh
    - Usage:
        - Air conditioning and Celling Fan: 6.33 kWh
        - Lighting: 0.88 kWh
        - Kitchen and Cooking appliances (Refrigerator, oven, microwave etc.): 0.92 kWh
        - Electronics and Other appliances (TV, computer, Charging Devices etc.): 1.4 kWh

These estimates are also based on energy usage patterns, which are acquired from physical survey dataset in a 4BHK apartment during summer, assuming moderate to high temperatures necessitating frequent use of air conditioning. This data has been used for other 490 4BHK apartments though actual energy consumption for each may vary based on factors such as appliance efficiency and individual habits.

6.3.2 Commercial Load Analysis

The commercial load analysis involves examining the energy consumption of all commercial amenities and facilities within the 30-acre residential complex. This includes lighting, cooling, appliances and other electrical equipment used in various common areas and services. However, as we are proposing a residential load management system in this research, our focus is solely on the residential loads within the complex. The following case study is therefore based exclusively on the analysis of residential energy consumption.

6.4 Microgrid Implementation

In this case study, we explore the implementation of a microgrid in a residential complex spread over a 30-acre land area. The complex comprises approximately 588 three-bedroom (3 BHK) apartments and 490 four-bedroom (4 BHK) apartments. To achieve better energy management and reduce the stress on the main electrical grid, we have proposed a virtual implementation of a microgrid system within this residential complex.

6.4.1 Space allocation

To generate 500 kW of solar power (considering 2500 kWh generation in 5 peak sunlight hours per day), we need to determine the area required for installing the solar panels. This calculation is based on standard efficiency and spacing requirements for solar panel installations. We have assumed that average efficiency of solar panels is 15-20% and power generation capacity per square meter: ~150-200 watts. Thus, the area required to install solar panels to generate 500 kW of power is approximately 3,333 square meters.

In addition to the solar panel installation, we need 1000 square meters space for other setup and distribution panels to ensure efficient energy management and distribution within the complex.

6.4.2 Cost Assessment

To estimate the overall installation cost for generating 500 kW of solar power, several factors must be considered, including the cost of solar panels, inverters, mounting structures, electrical components, labour and other miscellaneous expenses.

Total Cost (in approx.) = Solar Panel Cost + Battery Cost + Inverter Cost + Mountain Structure Cost + Electrical Components Cost + Labour and Installation Cost + Miscellaneous Cost (permits, transportation etc.)
=₹6 crores

Thus, the overall installation cost for a 500-kW solar generation system is approximately ₹6 crores approximately. This comprehensive setup ensures efficient energy generation and management within the residential complex, contributing to cost savings and sustainability. By implementing the microgrid, each of the 1000 apartments in the complex can benefit from significantly reduced electricity bills. The monthly expense per apartment as maintenance costs is estimated to be between ₹100 and ₹150. This demonstrates the economic advantage of integrating a microgrid system.

6.4.3 Cost Benefit Analysis

A Cost Benefit analysis for the 30 acres land Residential Complex has been shown in this section.

- Solar PV System: 500 kW capacity generating 2,500 kWh/day during 5 hours of peak sunlight.
- Battery Storage: 2,500 kWh capacity:
  - Charges during 5 hours of solar generation (500 kW output stored directly).
  - Discharges over 6 peak hours (416.67 kW discharge rate).
- Current Grid Usage: 808,500 kWh/month, with 25-30% consumed during peak hours.
- Grid Tariff: ₹7.25/kWh.
- Penetration Level: 12% ~ 15%

1. Cost Assumptions

Total assumption for microgrid implementation in 30 acres Residential complex considering 30% solar penetration level has been shown in Table 6.4.

Table 6.4 Cost Calculation

Component	**Unit Cost**	**Total Cost (₹)**
Solar PV System (500 kW)	₹50,000/kW	₹2,50,00,000
Battery Storage (2,500 kWh)	₹15,000/kWh	₹3,75,00,000
Installation Costs	10% of CAPEX	₹62,50,000
Annual OPEX (Solar)	2% of Solar CAPEX	₹5,00,000/year
Annual OPEX (Battery)	3% of Battery CAPEX	₹11,25,000/year
Miscellaneous Costs	Grid connection, permits	₹25,00,000

Total Initial Investment (CAPEX): ₹6,87,50,000 (₹6.875 Crore)

2. Energy Generation and Savings

Solar Energy Generation

- Daily Solar Generation: 2,500 kWh/day × 30 = 75,000 kWh/month.
- Monthly Savings from Solar: 75,000 kWh × ₹7.25/kWh = ₹5,43,750/month.

Battery Operation During Peak Hours

- Energy Supplied by Battery: Discharging 2,500 kWh/day × 30 = 75,000 kWh/month.
- Monthly Savings from Battery: 75,000 kWh × ₹7.25/kWh = ₹5,43,750/month.

3. Benefits

1. Total Monthly Savings (Solar + Battery): ₹5,43,750 (solar) + ₹5,43,750 (battery) = ₹10,87,500/month.
2. Carbon Reduction:
    - Annual energy offset: 150,000 kWh/month × 12 = 1,800,000 kWh/year.
    - CO_2 saved: 1,800,000 × 0.85 kg/kWh = 1,530 tons/year.
    - Carbon credit revenue at ₹1,000/ton = ₹15,30,000/year.

4. Payback and Feasibility Metrics

Timeframe for Analysis: 20 years (solar PV lifespan), with a battery replacement after 10 years.

- Initial Payback Period: Initial CAPEX / Annual Savings = ₹6,87,50,000 / (₹10,87,500 × 12) ≈ 5.3 years.
- Battery Replacement Cost (after 10 years): ₹3,75,00,000.

5. Additional Metrics

LCOE (Levelized Cost of Energy)

Total costs over the project lifespan divided by total energy generated:

- Total Lifetime Costs:
    - Initial CAPEX: ₹6.875 Cr.
    - Battery replacement after 10 years: ₹3.75 Cr.
    - OPEX (20 years): Solar: ₹1 Cr; Battery: ₹2.25 Cr.
    - Total: ₹13.875 Cr.
- Total Energy Generated:
    - 75,000 kWh/month × 12 months × 20 years = 18,000,000 kWh.
- LCOE: ₹13.875 Cr / 18,000,000 kWh = ₹7.7/kWh.
- Resident Participations: ₹65,000

6.5 Designing Smart SRLMS with Novel Optimization Technique

Formulation of a fitness function for optimizing total electricity expense considering conventional energy consumption from the grid, renewable energy consumption, energy storage systems and dynamic tariff involves several steps.

Renewable energy utilization benefit

Encouraging the use of renewable energy during peak and intermediate hours can further reduce expenses. We can adjust the fitness function to reflect the benefit of using renewable energy during these periods.

$$UB_{RE} = (C_{IH}^{RE} * CET_{IH}) + (C_{PH}^{RE} * CET_{PH}) - (C_{IH}^{RE} + C_{PH}^{RE}) * RET \tag{6.1}$$

Energy Storage System Utilization Benefit

Since energy storage is available, the fitness function should encourage storing excess renewable energy during off-peak hours and utilizing it during peak hours. We can modify the fitness function to include the cost of energy storage and the benefit of using stored energy during peak hours.

$$UB_{ESS} = \left((C_{IH}^{RE} * RET) + \left(C_{OPH}^{CE} * CET_{OPH}\right) + \left(C_{PH}^{CE} * CET_{OPH}\right) + \left(C_{IH}^{CE} * CET_{IH}\right)\right) - \left((C''^{RE}_{IH} + C_{PH}^{RE}) * RET_{ESS} + \left(C''^{CE}_{OPH} * CET_{OPH}\right) + \left(C''^{CE}_{PH} * CET_{PH}\right) + \left(C''^{CE}_{IH} * CET_{IH}\right)\right) \tag{6.2}$$

where,

Renewable Energy Tariff with ESS = (ESS installation cost + (maintenance cost * service life of ESS)) / (RE consumed using ESS per cycle * service life of ESS) (6.3)

Load Scheduling Benefit / Incentives

The fitness function should incentivize scheduling loads to off-peak and intermediate hours. We can introduce a term that rewards shifting consumption to these periods.

$$UB_{LS} = \left(C_{IH}^{RE} * (RET_{ESS} \sim CET_{IH})\right) + \left(C_{OPH}^{RE} * (RET_{ESS} \sim CET_{OPH})\right) \tag{6.4}$$

Total Energy Consumption Constraints

We are introducing a term that penalizes the deviation from the maximum allowable limit of energy consumption in Peak hours (E_a).

Penalty ∞ |RE Consumption + Conventional Energy Consumption – E_a| (6.5)

Penalty = K * |RE Consumption + Conventional Energy Consumption – E_a| (6.6)

K = Penalty co-efficient which determines the magnitude of the penalty (6.7)

If RE Consumption + Conventional Energy Consumption > E_a then Penalty is applied.

Otherwise for (RE Consumption + Conventional Energy Consumption) $\leq$ E_a, zero penalty is applied.

RES Capacity Constraint

$$PV\_DG_{capacity}^{min} \leq RE_{IH} \leq PV\_DG_{capacity}^{max} \qquad (6.8)$$

$$PV\_DG_{capacity}^{min} \leq RE_{PH} \leq PV\_DG_{capacity}^{max} \qquad (6.9)$$

Energy Storage System Constraint

$$ESS_{capacity}^{min} \leq ESS_{capacity} \leq ESS_{capacity}^{max} \qquad (6.10)$$

$$SOE^{min} \leq SOE \leq SOE^{max} \qquad (6.11)$$

Constraints on Load supplied by RES and ESS

$$(PV_{O/P} + ESS_{O/P}) : Load\ Demand = K = penetration\ level \qquad (6.12)$$

$$(K - 5\%\ of\ K) \leq K \leq (K + 5\%\ of\ K) \qquad (6.13)$$

Finally, the **fitness function** incorporating the above-mentioned factors becomes,

$$\min f(x) = \sum Electricity\ Expenses - UB_{RE} - UB_{ESS} - UB_{LS} + Penalty \qquad (6.14)$$

This objective function represents a Strategic Residential Load Management System (SRLMS), the design of which is based on the strategic use of RES with ESS, AI based tariff-TOT and AI based Optimization technique.

6.6 Performance Analysis of SRLMS using Microgrid

The dataset for this case study has been obtained from physical survey and online survey. Based on these data sets an efficient MATLAB SIMULINK model has been designed and developed. The efficiency and effectiveness of the model has been evaluated based on proposed optimization technique, dynamic tariff and ESS scheduling to figure out the improvements over the existing system. The efficiency of the model has also been analyzed in the following sections based on the monthly electricity bill, EPI [109], PAR and carbon emission.

6.6.1 Savings in monthly Electricity Expense

The reduction of daily or monthly electricity expense has been achieved based on two parameters; i) smart and intelligent scheduling of household appliance, ESS and ii) newly proposed, ToU, RTP based three-part dynamic tariff. Daily load requirement, ratings of appliances and the best suited tariff scheme need to be declared by prosumers a day ahead. Based on their requirement, the Utility company would suggest a demand profile to be followed. The benefits of using this approach have been shown in Figure.6.2 and Table. 6.5.

Table 6.5 Savings in monthly electricity bill

Consumers	Monthly Electricity Expense		Savings in monthly electricity expense (in %)
	Without SIEMS	With SIEMS	
3 BHK consumers	4376	3164	27.7%
4 BHK consumers	6601	4722	28.5%
Staff Quarters	1629	1351	17%

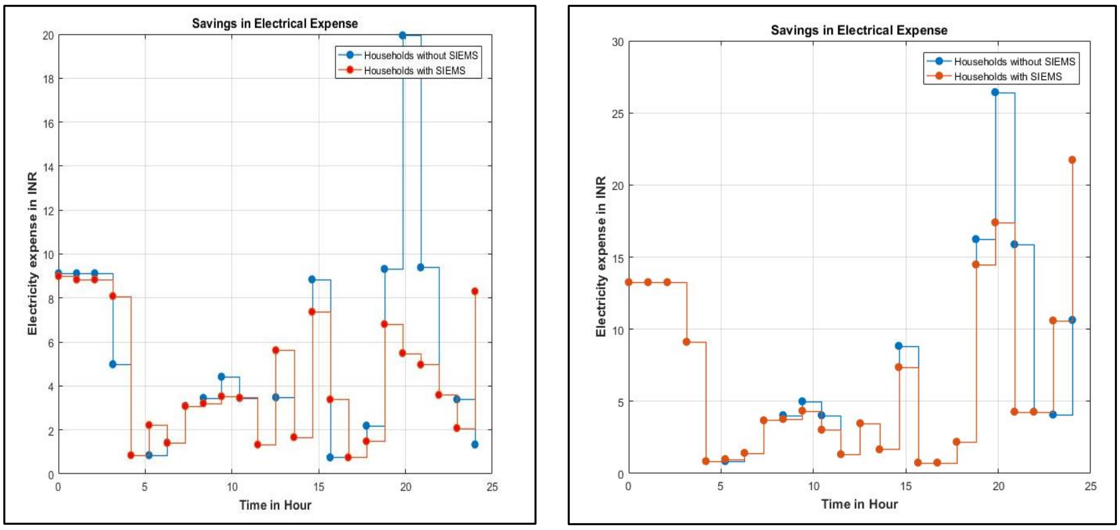


Figure. 6.2. Savings in daily electrical expenses for 3 BHK and 4 BHK apartments

6.6.2 EPI Improvement

Based on the daily energy consumption result shown in Figure 6.3, it can be concluded that due to the reduction in energy consumption, an EPI reduction by 1 or 2 unit can be achieved.

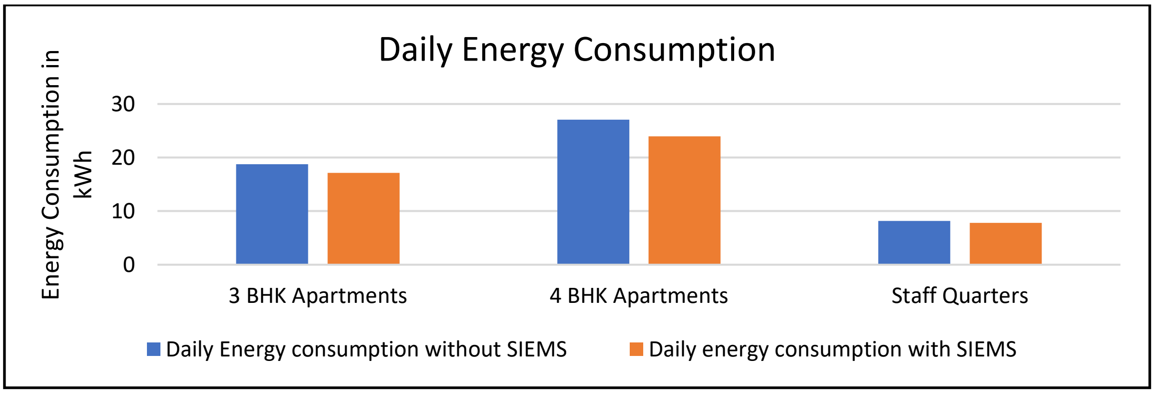


Figure 6.3. Reduction in energy consumption

This in turn may improve the star rating of the considered residential complex, which will help to get more subsidies from the Federal Agencies.

6.6.3 PAR Improvement

PAR is the ratio of the maximum aggregated load consumption over a certain time-period and the average of the aggregated load. The high value of PAR affects the stability of grid stability and increases cost effective energy consumption. Reduction in PAR using the proposed approach has been shown in Fig. 6.4 and Table 6.6.

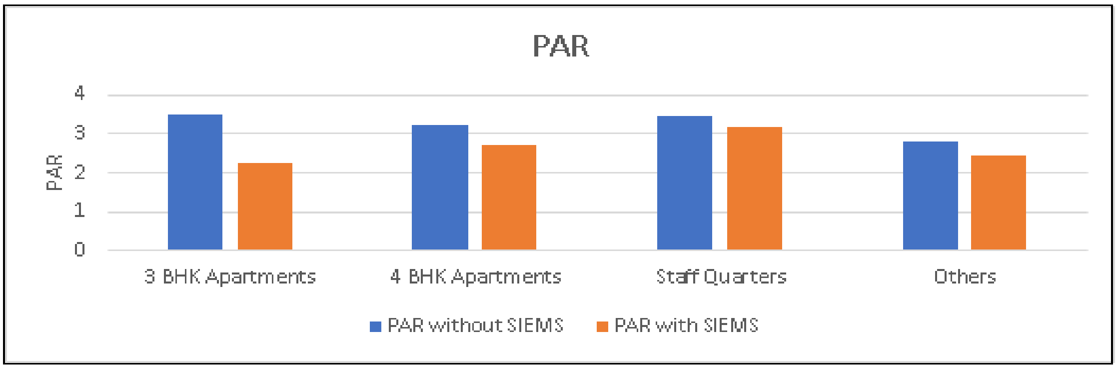


Figure. 6.4. Reduction in PAR

Table 6.6 PAR Reduction

Consumers	PAR		
	PAR without SRLMS	PAR with SRLMS	Reduction in %
3BHK Apartments	3.515	2.245	36%
4BHK Apartments	3.229	2.738	15%
Staff Quarters	3.47	3.2	8%
Others	2.7957	2.4378	13%

6.6.4 Reduction in Carbon Footprint

An estimation says that 1 kWh generation produces 0.935 kg CO_2. Here, in this case study, approximately each day 2.5 tonne of CO_2 emission can be reduced using the proposed approach, which can be absorbed by a tree in 100 years. It also means that 1 acre forest can absorb 2.5 tonne CO_2 per year.

6.7 Performance Analysis of SRLMS on IEEE 33 Bus System

The IEEE 33-bus system was analyzed in detail to assess the impact of RE integration and load modifications. The study involved the following key steps:

1. Load Flow Analysis: To analyze the performance of the power system under the given load and RE conditions, a load flow analysis was performed using the Newton-Raphson method. This iterative computational technique was employed to calculate voltage magnitudes and phase angles at all buses, line losses and power flows through the

network. The results provided a comprehensive understanding of the system’s operational characteristics and stability. Refer to Appendix A section A7 for the pseudocode of Load Flow analysis.

2. Bus Load Modification: Following the baseline analysis, the load data for specific buses was modified to simulate real-world scenarios. A 30-acre residential complex was added at Bus 18 to represent a substantial new load on the system. The integration of this new load was carried out with careful consideration of its impact on the local and overall power system.

3. Renewable Energy Integration at Bus 18: To support the new residential load and reduce dependency on the grid, a renewable energy penetration level of 15% was implemented at Bus 18. This localized RE integration was modelled to study its effects on the demand profile and overall grid stress. The integration highlighted the importance of distributed generation in managing localized demand surges.

4. Demand Profile Analysis: The demand profiles for the entire system, Bus 18 and the neighbouring Bus 19 were generated and analyzed. The profiles illustrated in fig 6.8, 6.9 and 6.10 the hourly variations in load demand and the impact of RE integration. Refer to Appendix A section A6 for the pseudocode of SRLMS performance evaluation on IEEE 33 Bus system. These demand profiles showed:
    - A significant reduction in grid stress due to RE integration (Figure 6.5).
    - Enhanced load management capabilities for Buses 18 and 19, with Bus 19 benefitting indirectly from the changes at Bus 18 (Figure 6.6).

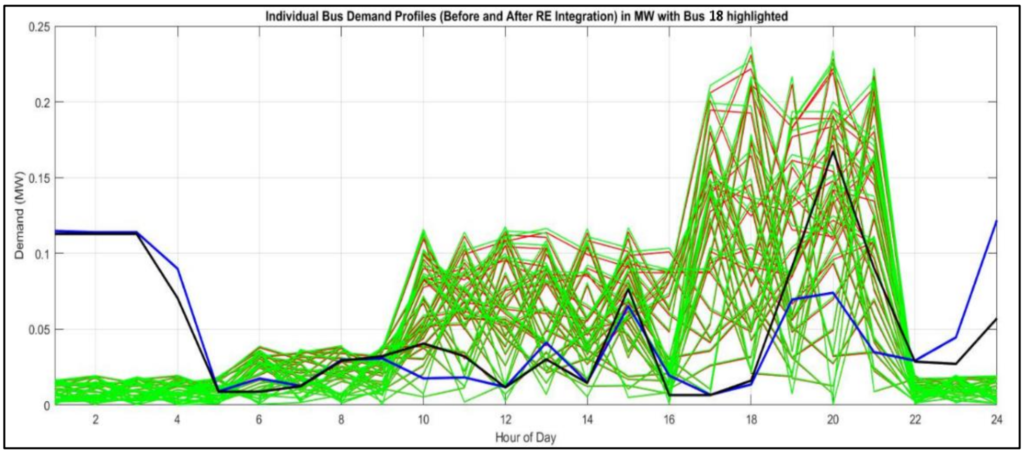


Figure 6.5 Individual bus Demand Profile before and after RE integration (Highlighted: Bus 18)

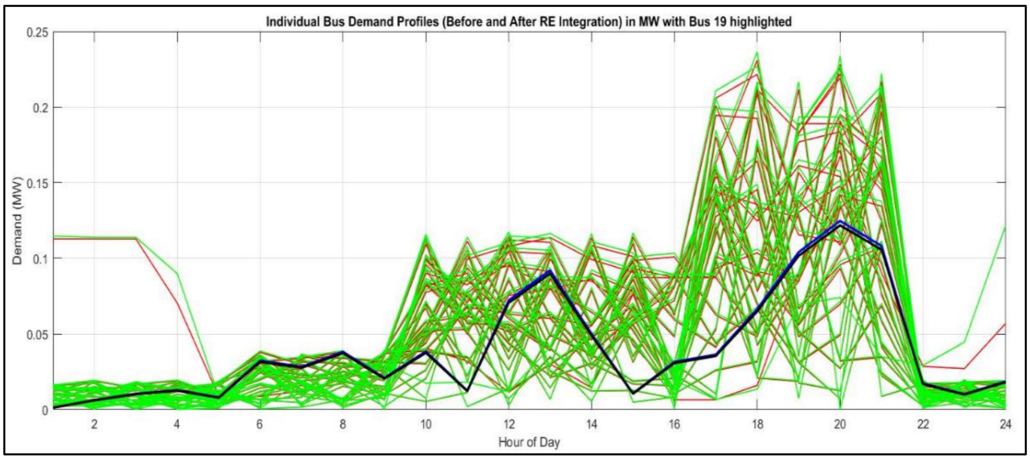


Figure 6.6 Individual bus Demand Profile before and after RE integration (Highlighted: Bus 19)

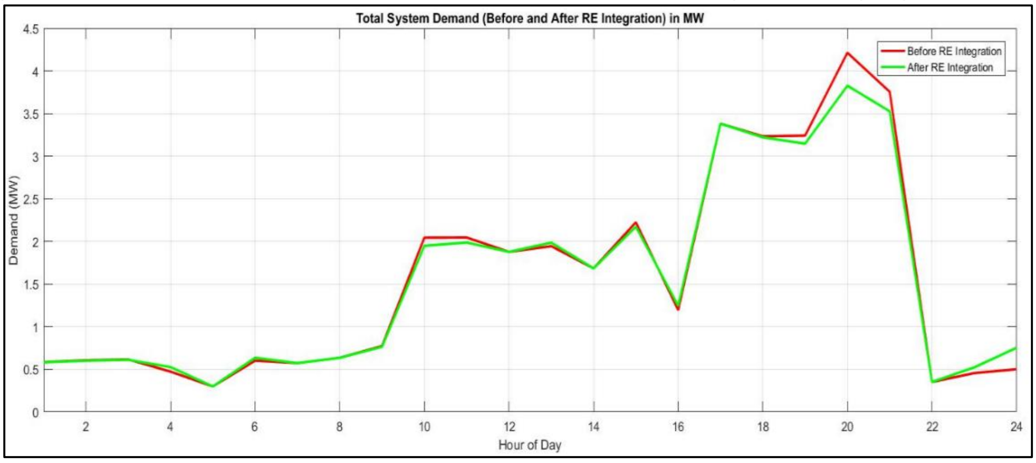


Figure 6.7 System Demand Profile for 24 hours before and after RE integration

5. Key Observations:
    - The addition of the residential complex at Bus 18 created a noticeable increase in localized demand; however, the 15% RE penetration at the same bus helped mitigate this impact.
    - The system’s load flow analysis showed improved efficiency, with reduced line losses and better power distribution after RE integration. System demand profile has been shown in Figure 6.7.

The study demonstrated that strategic RE integration at both the system and local levels can significantly enhance the resilience and performance of the power grid. By reducing peak demand and grid dependency, the RE integration also paves the way for more sustainable energy management practices. The demand profiles clearly indicated a reduction in grid stress, validating the effectiveness of the proposed modifications and highlighting the role of renewable energy in modern power systems.

6.8 Designing of User-centric Smart Application

The "Demand Management Application" was designed to create an interactive and user-centric platform for analysing residential energy consumption patterns and suggesting optimization strategies.

6.8.1 Development Environment

To design this application MATLAB App Designer has been selected for its robust environment that supports graphical user interface (GUI) development with integrated computational capabilities. This choice facilitates seamless embedding of algorithms for energy consumption analysis and cost optimization directly within the application.

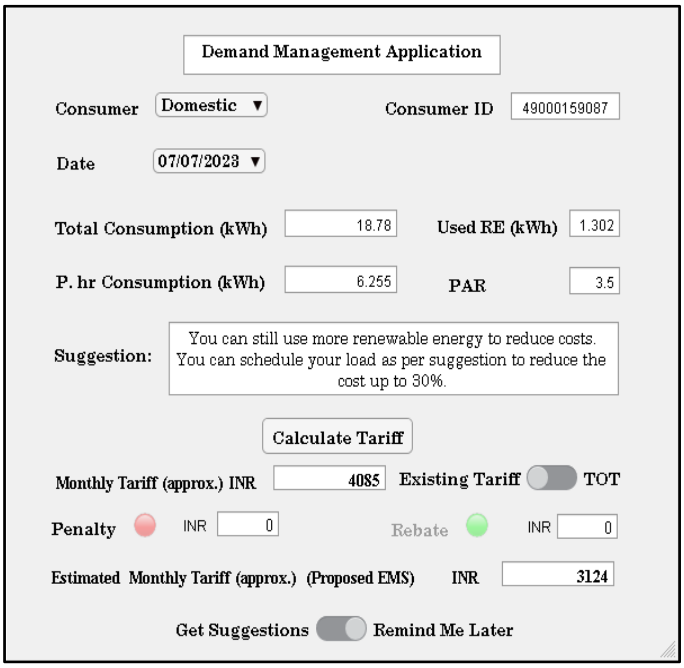
6.8.2 User Interface Design

The GUI was developed to provide a clear and intuitive layout for users. It consists of input fields for total consumption, peak-hour consumption, renewable energy usage and dynamic parameters such as penalties and rebates. The application dynamically calculates and displays the Peak-to-Average Ratio (PAR), estimated monthly tariffs under both current and proposed energy management systems and renewable energy contributions. Key elements like suggestion prompts and interactive toggles enhance the user experience, offering actionable insights to manage energy use more efficiently.

Visual Layout

The GUI of the "Demand Management Application" is organized into distinct sections to streamline user interaction and improve accessibility. The interface includes the following:

1. Input Section: Fields for entering data such as total energy consumption (kWh), peak-hour consumption and renewable energy contribution which can be measured and recorded by using smart plugs.
2. Results Section: Displays calculated outputs such as Peak-to-Average Ratio (PAR), monthly tariff estimates and suggestions based on renewable energy usage.
3. Actionable Insights: A suggestion box provides users with customized recommendations, such as increasing renewable energy usage or optimizing load scheduling to reduce costs shown in Figure 6.8.

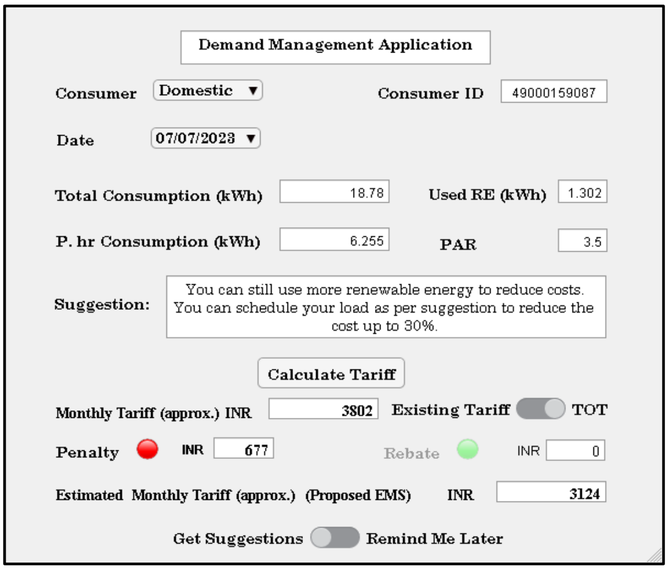


Consumer Domestic
Consumer ID 49000159087
Date 07/07/2023
Total Consumption (kWh) 18.78
Used RE (kWh) 1.302
P. hr Consumption (kWh) 6.255
PAR 3.5
Suggestion: You can still use more renewable energy to reduce costs. You can schedule your load as per suggestion to reduce the cost up to 30%.
Monthly Tariff (approx.) INR 4085
Penalty INR 0
Rebate INR 0
Estimated Monthly Tariff (approx.) (Proposed EMS) INR 3124

Figure. 6.8 User Centric GUI Application

Interactive Features

- Toggle Buttons: Users can enable or disable specific options, such as calculating tariffs under different tariff systems (existing versus Proposed Tri-Optimized -Tariff).
- Calculation Triggers: A "Calculate Tariff" button initiates computations, enabling users to receive instant results based on the provided inputs shown in Figure 6.9.
- Dynamic Updates: The app dynamically updates outputs when any input field is modified, ensuring real-time feedback.



Consumer Domestic
Consumer ID 49000159087
Date 07/07/2023
Total Consumption (kWh) 18.78
Used RE (kWh) 1.302
P. hr Consumption (kWh) 6.255
PAR 3.5
Suggestion: You can still use more renewable energy to reduce costs. You can schedule your load as per suggestion to reduce the cost up to 30%.
Monthly Tariff (approx.) INR 3802
Penalty INR 677
Rebate INR 0
Estimated Monthly Tariff (approx.) (Proposed EMS) INR 3124

Figure. 6.9 User Centric GUI Application

Visual Aesthetics

- Colour Coding: Specific indicators, such as red for penalties and green for rebates, ensure clear communication of actionable data.
- Alignment and Font Design: Consistent font style and size, coupled with structured alignment of fields, enhance readability.
- Date Selection Field: Allows users to select specific dates for historical or future consumption analysis.

These GUI features combine functionality with user-friendly design, ensuring that the application is both practical and accessible to residential consumers seeking to optimize their energy management.

Functional Algorithm Integration

Behind the interface, the app integrates computational algorithms to process input data and generate outputs in real-time. The algorithms account for consumer-specific parameters such as renewable energy usage, existing tariffs and penalties to calculate cost savings. Conditional logic is implemented to provide personalized suggestions for load scheduling and renewable energy utilization, further aligning user behaviour with optimal demand-side management practices, shown in Figure 6.10 and Figure 6.11. User can have detailed suggestion for scheduling the load to avoid the Penalties using proposed TOT scheme.

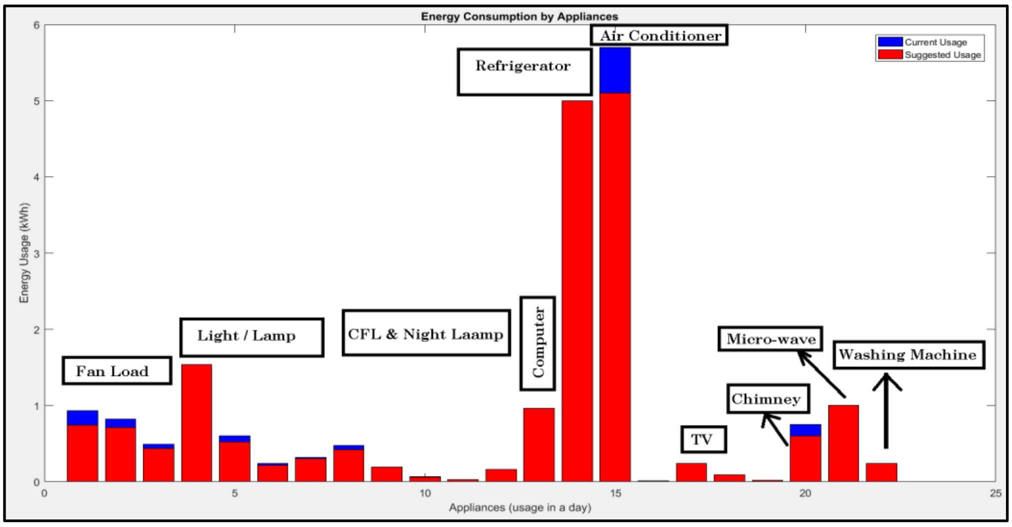


Figure. 6.10 Suggestion by Utility through User Centric GUI Application

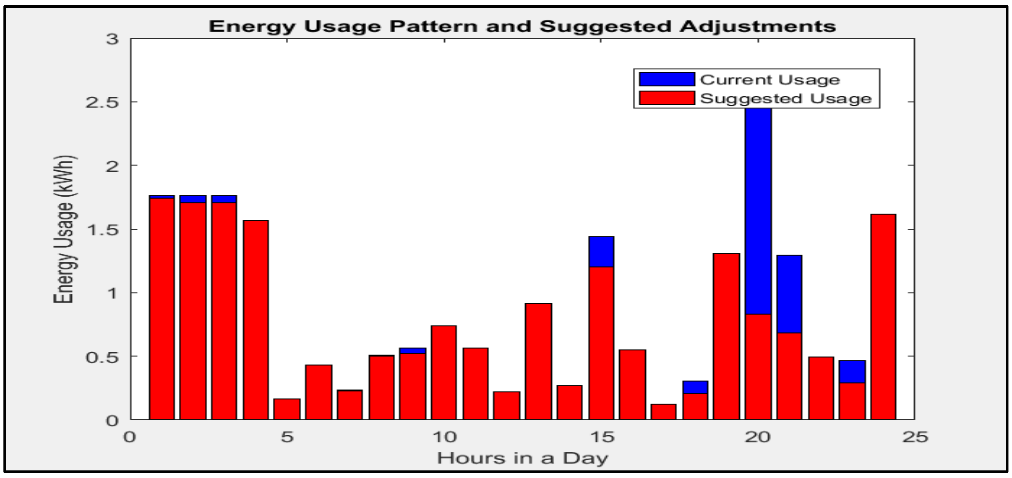


Figure. 6.11 Suggestion by Utility through User Centric GUI Application

The modular architecture of the app allows for future scalability, including IoT integration and real-time data analytics for enhanced functionality.

6.9 Chapter Summary

Implementing a microgrid in the 30-acre residential complex not only offers significant cost savings but also enhances energy reliability and sustainability. With a substantial reduction in electricity bills for residents and a lower environmental impact, the microgrid system demonstrates an effective approach to modern energy management in residential communities. This case study underscores the potential benefits and feasibility of microgrid implementation in large residential complexes with user centric application.

Significant Findings from this chapter are:

- Achieved reduction in monthly electricity expense by 25% using proposed SRLMS in large-scale application.
- Achieved improved EPI and Star level of the adopted Residential Complex by 1 unit (minimum) by implementing SRLMS with microgrid.
- Achieved more than 15% reduction in grid stress (IEEE 33 Bus system).
- Achieved 2.5 tonne reduction in CO_2 emission.

In the next chapter, we have provided the conclusion and discussion of our research work. Key findings are summarized along with insights into the implications of the results and opportunities for future advancements.

Related Publication:

The research work presented in this chapter has contributed to the following publication.

- Kuheli Goswami, Arindam Kumar Sil, "Improvement of Energy Performance Index for Domestic Prosumers Based on Newly Proposed Dynamic Tariff and Rule-based Strategy," International Transactions on Electrical Energy Systems (ITEES), indexed by Scopus, SCIE, approved by UGC, Vol. 2022, Article ID: 5087908, August, 2022, https://doi.org/10.1155/2022/5087908.

This publication focuses on a case study to improve Energy Performance Index of a large residential complex by implementing proposed SRLMS, discussed in section 6.2, section 6.3, section 6.4, section 6.5 and section 6.6.

CHAPTER 7

Conclusion and Future Scope

7.1 Thesis Conclusion

It is crucial to address the current power crisis and propose efficient and effective energy planning to reduce energy consumption, especially during peak hours. Reducing energy usage during peak times can be achieved by utilizing renewable energy sources. However, integrating renewable energy into the main grid is difficult and challenging. Therefore, implementing local solutions to meet local demand would reduce stress on the main grid. This can be accomplished by using microgrids powered by renewable energy-based distributed generation, which not only addresses energy challenges but also reduces carbon footprints, contributing to environmental sustainability—a pressing issue for developing countries. Given the current power scenario and energy crisis, it is essential to focus on renewable energy availability, which motivates the proposal of a flexible, robust and efficient energy management system for microgrids.

According to the government, over 25% of total energy is consumed by domestic sectors, highlighting the need to design an energy management system for residential prosumers and large residential complexes based on renewable energy availability.

This approach allows prosumers to participate in the electricity trade market, either directly or indirectly and by proposing optimized and dynamic tariffs, the system can encourage consumers to enhance energy efficiency. It also helps to maintain a healthy relationship between utilities and prosumers while significantly contributing to reducing carbon emissions and fostering a more sustainable energy future.

Despite significant advancements in energy management systems and microgrid technology, several gaps remain, particularly in efficiently managing renewable energy sources within local grids. While much research focuses on the technical feasibility of microgrids, comprehensive solutions that address the real-time variability of renewable energy availability, especially in domestic and residential sectors, are lacking. In this research work, we aim to tackle this issue by integrating renewable energy sources with energy storage systems for the domestic sector. With the detailed understanding of the load characteristics, we have designed a load management and scheduling system using advanced feature selection techniques to optimize energy use. These techniques allow us to prioritize household appliances based on consumer preferences, ensuring efficient load scheduling. Additionally, we have proposed an optimal strategy for managing energy storage systems, which improves the overall integration, utilization and management of renewable energy in domestic and residential settings. This approach offers a more effective solution for addressing the challenges of renewable energy variability and its application in real-world scenarios.

Another important issue is that most of the existing energy management system (EMS) models are not designed for large-scale applications, leaving a gap in tailored approaches for distributed systems like microgrids serving residential consumers or communities. In this research, we propose an AI-based optimization technique to address this gap. The EMS we designed uses this technique to find the optimal solution for reducing energy consumption, peak demand and carbon footprints, while also minimizing electricity costs for consumers and prosumers. This approach benefits both the consumers and utility sectors, encouraging the adoption of different schemes such as the Energy Performance Index (EPI). **Using the proposed energy management system (EMS), we achieved an improvement in the Energy Performance Index (EPI), which in turn elevated the star rating of the residential complex by one or two units, promoting the initiatives by utilities and federal agencies to save more energy to make an eco-friendly system and simultaneously maintain a healthy relationship between the utility company and prosumers.**

Our research shows that the proposed EMS not only improves the EPI but also enhances system efficiency and sustainability. We tested this proposed AI-based optimization technique on individual domestic consumers, prosumers and large residential complexes to assess its versatility. Additionally, we applied this technique to the IEEE 33-bus system to determine the optimal size and location for renewable energy-based distributed generation (DG) thereby reducing the transmission losses. **In this case, we achieved a reduction of 69% in active power losses and 65% in reactive power losses, respectively in IEEE 33 Bus system.** This ensures that the system remains robust, flexible and efficient. The results demonstrate that the proposed optimization technique can operate effectively at both small scales (single residential consumers or prosumers) and larger scales, such as the IEEE 33-bus system, highlighting its versatility and ability to function in real-time scenarios.

The findings from this thesis can be structured into two distinct sections to emphasize the dual focus of the research: small-scale applications and large-scale applications in real time environment.

Small-Scale Applications

In the small-scale application, we concentrated on individual households, analysing demand data for seven households. The proposed SRLMS has been implemented by integrating rooftop photovoltaic (PV) systems, introducing energy storage systems (ESS), implementing a dynamic, AI-based tariff structure and designed a MATLAB-based application to enable users to monitor, control and plan their energy usage on a day-ahead basis.

Using proposed optimization techniques, we scheduled household loads to reduce energy wastage, improve energy efficiency and minimize the Peak-to-Average Ratio (PAR). The system also ensured that energy consumption during peak hours was curtailed by prioritizing renewable energy utilization. The benefits extended to consumers, achieving over 32% savings in monthly electricity expenses while reducing PAR by 40% which have been shown in table 7.1 and table 7.2 respectively. While a single household's PAR reduction directly reflects on its energy profile, its contribution to the overall grid PAR depends on the number of such households implementing similar EMS strategies. These results can serve as a reference model for similar implementations, showcasing how targeted EMS strategies can improve residential energy efficiency and sustainability.

Table 7.1: Reduction in Monthly Electricity Expense (small scale application)

Consumers	Monthly Electricity Expense without SRLMS	Monthly Electricity Expense with SRLMS	Savings in Monthly Electricity Expense (in %)
Household 1	3597.80	2440.55	32
Household 2	2203.21	1664.81	24
Household 3	2332.15	1499.10	36
Household 4	1852.41	1371.00	26
Household 5	3953.67	2810.47	29

Table 7.2: Reduction PAR (small scale application

Consumers	PAR without SRLMS	PAR with SRLMS	Reduction in PAR (in %)
Household 1	2.85	1.64	43
Household 2	3.64	2.16	41
Household 3	3.11	2.07	33
Household 4	3.69	2.46	33
Household 5	3.63	2.37	35

By prioritizing renewable energy sources and deploying ESS, the proposed SRLMS improved system efficiency and reliability while reducing carbon emissions.

To validate and complement this framework, a practical **Daylight and Occupancy Sensor-Based Control** was implemented at a smaller scale. This experiment aimed to analyze the tangible benefits of sensor-driven automation in real-time environments by focusing on specific zones within households, such as the **living room, kitchen, and bedroom** etc.

The sensor system responded to real-time daylight availability and human presence to reduce unnecessary energy usage. As a result, the observed energy savings were notable in the following figures.

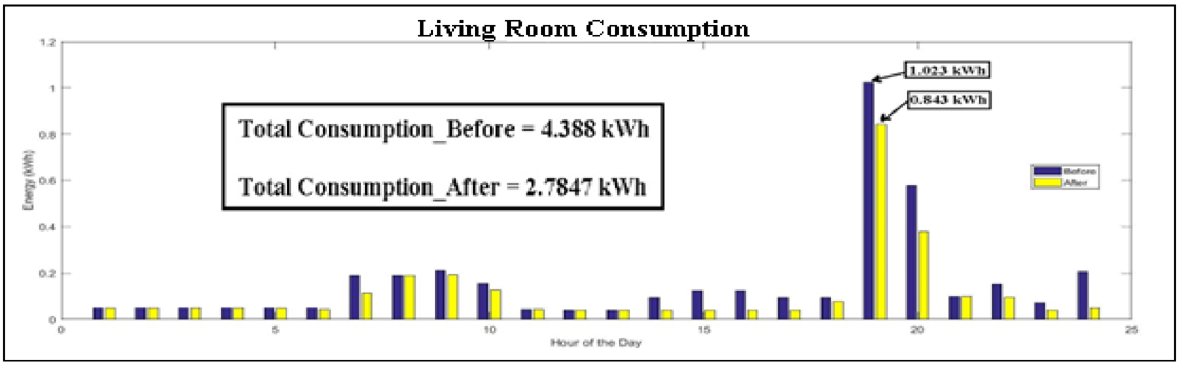


Figure 7.1 Reduction in Living Room Consumption with Day light and Occupancy Sensor based Control

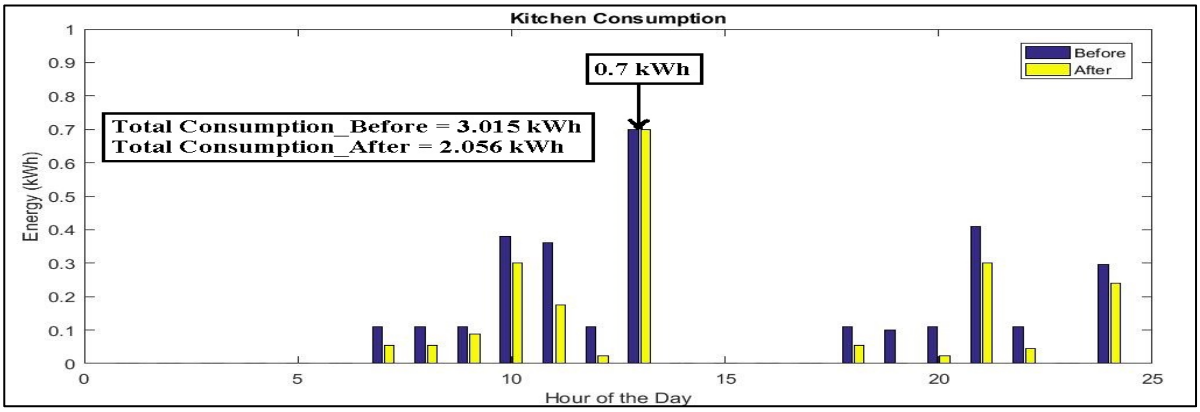


Figure 7.2 Reduction in Kitchen Consumption with Day light and Occupancy Sensor based Control

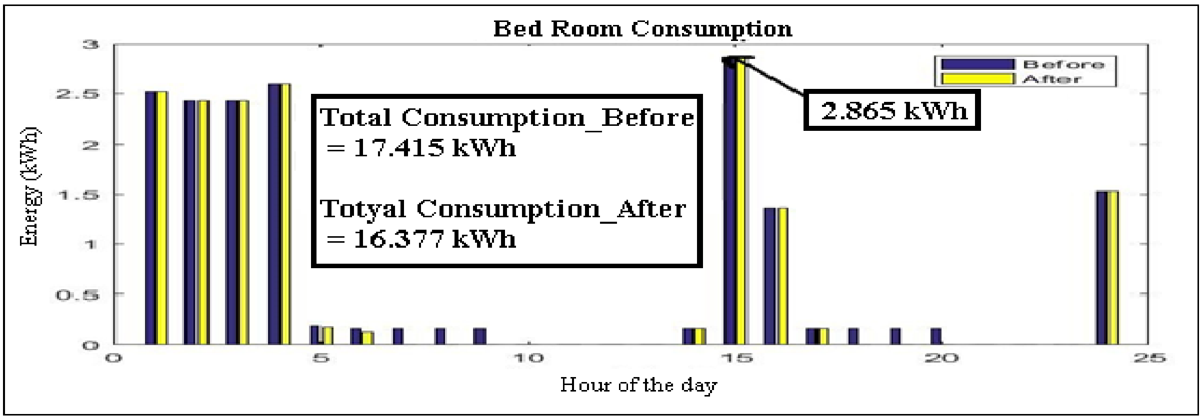


Figure 7.3 Reduction in Bedroom Consumption with Day light and Occupancy Sensor based Control

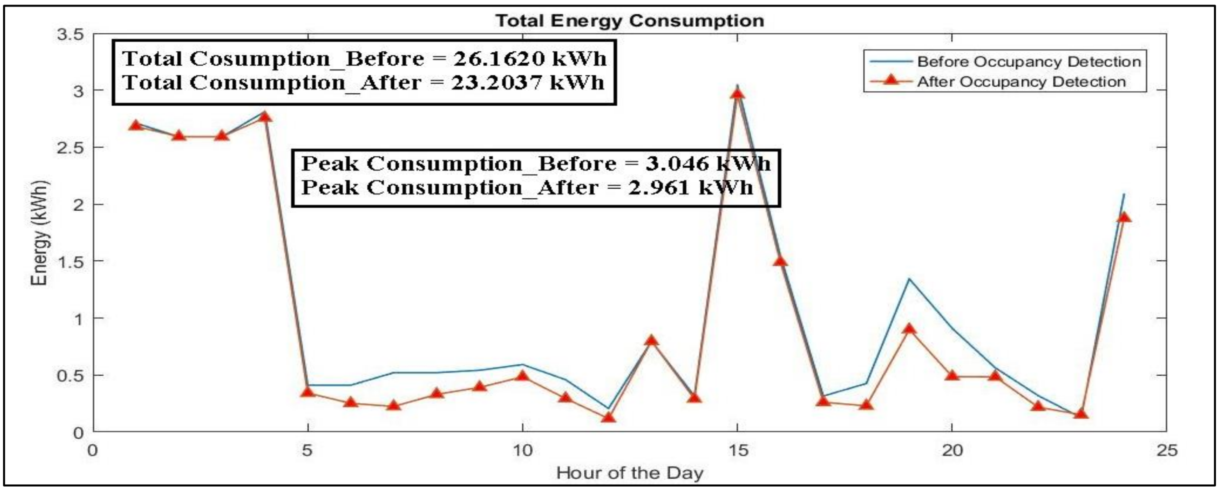


Figure 7.4 Reduction in daily energy consumption with Day light and Occupancy Sensor based Control

Figure 7.1 to Figure 7.4 clearly illustrate these reductions and validate the sensor-based approach as a valuable complement to the core SRLMS. This small-scale implementation confirms the effectiveness of combining smart sensing with

AI-based energy planning and highlights the potential for further scalability and integration.

Large-Scale Applications

In the large-scale application, the focus shifted to the integration of microgrid powered by PV within a 30-acre residential complex, considered to be situated at bus 18 in IEEE 33-bus system. For the residential complex, we have analyzed demand data, integrated a microgrid powered by renewable energy sources, deployed ESS with optimized charging and discharging strategies and designed a MATLAB-based application to enable users to monitor, control and plan their energy usage on a day-ahead or week-ahead basis.

The microgrid solution allowed for a more sustainable and cost-effective energy management system. This was extended to the IEEE 33-bus system, with renewable energy integrated at bus 18, representing the residential complex. **The system achieved an 18-20% reduction in PAR at bus 18 and a 10% reduction across the overall IEEE 33 bus system.** Besides these, research on dynamic, real-time pricing models that optimize both energy consumption and production for prosumers, while encouraging better engagement between utilities and consumers has resulted **over 28% savings in monthly electricity expenses and 36% reduction in PAR, highlighting its effectiveness in reducing grid stress and improving system performance.**

A detailed analysis of the following two figures Figure 7.5 and Figure 7.6 highlights the advantages of implementing effective energy planning for microgrids situated within the IEEE 33-bus system, as demonstrated through the proposed research work. The figures provide insights into the benefits of renewable energy integration, optimized load scheduling and the reduction of grid stress, showcasing the practical applications of the proposed energy management strategies for microgrids.

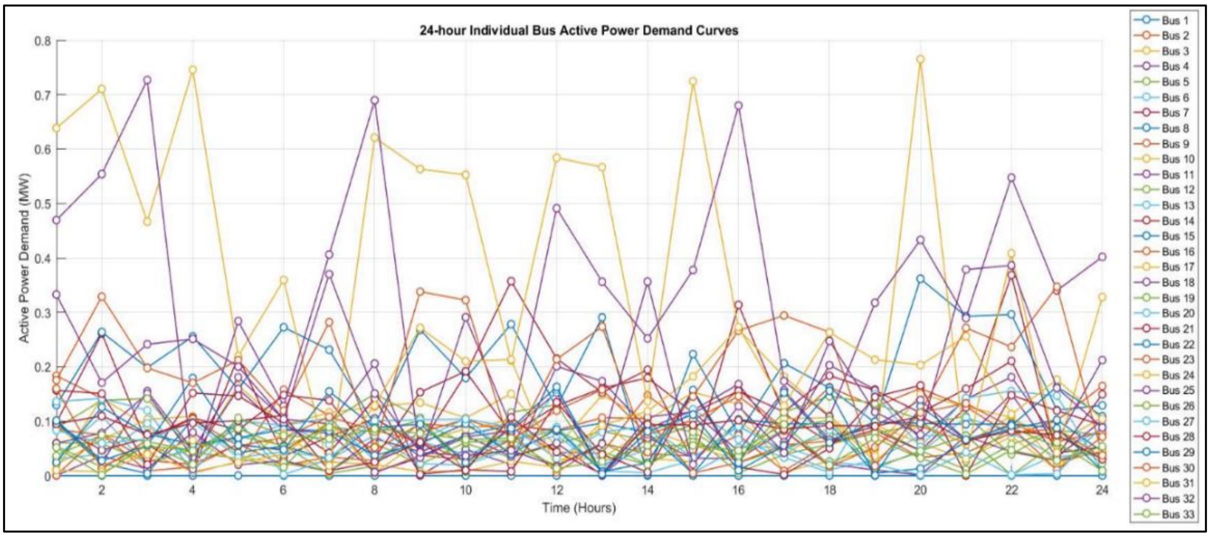


Figure 7.5 Individual Bus Active Demand Profile for 24 hours (without energy planning for microgrid)

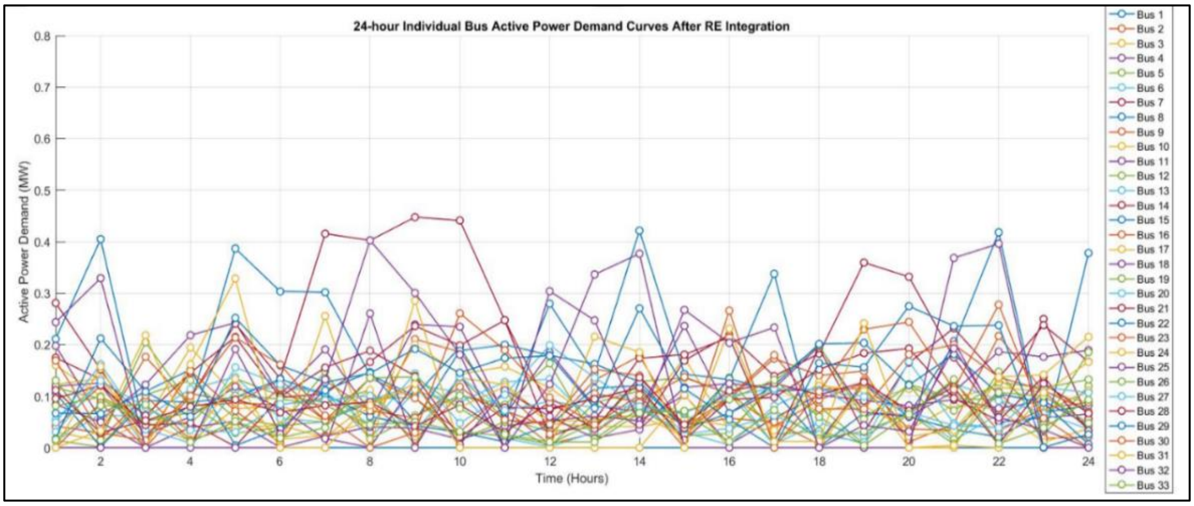


Figure 7.6 Individual Bus Active Demand Profile for 24 hours (with energy planning for microgrid)

Furthermore, the environmental impact of microgrid solutions in reducing carbon footprints is underexplored, especially in developing countries where scalability and economic viability need further investigation. In this research, we have attempted to estimate the reduction in carbon footprint achieved by implementing the proposed energy management system in a 30-acre residential complex with a specific built-up area. **Our findings reveal approximately 2 tonne significant reduction in carbon emissions due to the adoption of this system.** This demonstrates the potential environmental benefits of microgrid solutions, particularly in residential areas. However, further research is needed.

This research highlights the crucial role of SRLMS in optimizing the use of renewable energy in modern power systems. As we transition toward more sustainable energy infrastructures, the application of microgrids offers a promising pathway for decentralized energy systems, reducing dependence on traditional fossil fuels while enhancing grid resilience and energy efficiency.

7.2 Future Scope

This study can be further extended to design a daylight and occupancy sensor-based energy management system and predict the energy consumption with the life cost analysis of the sensors and ESS. The research opens several avenues for further investigation and development:

1. **Scalability:** Future studies could explore the scalability of the proposed microgrid system to larger communities or industrial applications, examining the technical and economic impacts.
2. **Advanced AI Integration:** Continued enhancement of AI algorithms for more sophisticated load management and predictive maintenance, improving system resilience and efficiency.
3. **Hybrid Systems:** Integration of other renewable sources, such as wind and biomass, to develop hybrid microgrids that can further enhance energy security and sustainability.
4. **Policy and Economic Analysis:** Assessing the policy frameworks and economic models that support the widespread adoption of renewable energy-based microgrids, ensuring their viability and attractiveness to stakeholders.

Additionally, further research is needed to explore how microgrids can participate in energy trade markets, enhance consumer involvement and contribute to long-term sustainability goals.

APPENDIX-A

A1. Pseudocode for ARIMAX Model Implementation

```
Step 1: Load Data
    Import time series data y and exogenous variables X1 and X2 from an Excel file.
    Combine X1 and X2 into a single matrix X.
Step 2: Set ARIMAX Model Parameters
    Define ARIMA model orders: p (AR order), d (Differencing order) and q (MA order).
Step 3: Transform Data
    Apply a logarithmic transformation to y to stabilize variance.
Step 4: Define ARIMA Model with Exogenous Variables
    Create an ARIMA model using the defined parameters (p, d, q) and include the exogenous matrix X.
Step 5: Estimate Model Parameters
    Estimate the ARIMAX model using the estimate function.
    Obtain the estimated model, parameter covariance matrix, log-likelihood and additional information.
Step 6: Forecast Future Values
    Prepare future values of exogenous variables in futureX.
    Forecast future values using the forecast function with numSteps steps.
Step 7: Calculate Prediction Error
    For each time step:
        Compute the relative error between observed and forecasted values.
        Square and root the error to get the absolute value.
    Sum the errors and calculate the Mean Absolute Error (MAE).
Step 8: Plot Results
    Create a time vector for plotting.
    Plot observed and forecasted values on the same graph.
    Add titles, labels and legends to the plot.
```

A2. Pseudocode for K-Means Clustering Analysis

```
Step 1: Load Dataset
INPUT number of Areas
LOAD latitude, longitude, demand, generation

Step 2: Combine above Features into a Matrix
COMBINE latitude, longitude, demand, generation into data

Step 3: Normalize Data
INITIALIZE features_normalized as zeros matrix of same size as data
FOR each column in data:
    CALCULATE min_val and max_val of the column
    NORMALIZE column values using formula: (value - min_val) / (max_val - min_val)
    STORE normalized values in features_normalized
END FOR

Step 4: Perform K-Means Clustering
SET optimal K to desired number of clusters
APPLY K-means function on features_normalized with optimal K clusters
OUTPUT i dx (cluster indices) and centroids

Step 5: Visualize Clusters
CREATE 3D scatter plot of features_normalized using latitude, longitude and demand
COLOR points based on cluster indices (idx)
LABEL axes: Latitude, Longitude, Demand
TITLE plot: "K-Means Clustering Results"
ADD grid and color bar

Step 6: Analyze Clusters and Compute DGI
PRINT "Cluster Analysis:"
FOR each cluster k from 1 to optimal K:
```

```
    IDENTIFY data points in cluster K using idx
    EXTRACT cluster data for cluster K from original data

    Step 7: Calculate Cluster Statistics
    CALCULATE mean-Latitude, mean-Longitude, mean-Demand, mean-Generation for cluster data
    COUNT cluster Size (number of areas in cluster k)

    Step 8: Calculate DGI (Demand-Generation Index)
    CALCULATE DGI_K as mean-Generation / mean-Demand

    Step 9: Display Results
    PRINT Cluster statistics: Mean Latitude, Mean Longitude, Mean Demand, Mean Generation
    PRINT DGI and Number of Areas for cluster k
END FOR
```

A3. Pseudocode for Weighted KNN Feature Evaluation

```
Step 1: Load Dataset
  - Load dataset with features and labels.

Step 2: Define KNN Parameters
  - Set the number of neighbours (`k`).

Step 3: Initialize Variables
  - Determine the number of features in the dataset.
  - Create a variable to store accuracy scores for each feature.

Step 4: Feature Evaluation Loop
  - For each feature in the dataset:
    1. Select the current feature as a subset.
    2. Perform cross-validation using K-fold (e.g., 5 folds):
      - Split data into training and testing sets for each fold.
      - Train a Weighted KNN model using the training set.
```

```
      - Test the model using the testing set and calculate accuracy.
    3. Compute the average accuracy for the current feature across all folds.
    4. Store the average accuracy in the accuracy scores.

Step 5: Rank Features
  - Sort features by their accuracy scores in descending order.

Step 6: Select Top Features
  - Identify the indices of the top features based on the sorted accuracy scores.

Step 7: Display Results
  - Print the feature ranking and their corresponding accuracy scores.
  - Display the indices of the top-selected features.

Step 8: Output Selected Features
  - Return the indices of the top features for further use.
```

A4. Pseudocode for Appliance Scheduling Using PSO

```
Step 1: Input Parameters
  - Define total number of appliances (N).
  - Define total number of time periods (T).
  - Input power consumption of appliances (P).
  - Input renewable energy availability (R).
  - Input grid energy availability (G).
  - Define maximum waiting time penalties for appliances (W_max).
  - Specify user preferences for appliances (start and end times).

Step 2: Objective Weights:
  - Define weights for renewable energy utilization (w1), total energy consumption (w2) and waiting time penalty (w3).

Step 3: PSO Parameters:
```

```
  - Initialize the number of particles, maximum iterations, cognitive and social components (c1, c2) and inertia weight (w).
  - Randomly initialize particle positions (x) and velocities (v).
  - Initialize personal best positions (best_particle) and global best position (global_best).
  - Set initial fitness values to infinity.

Step 4: Optimization Loop:
  - Repeat for the specified number of iterations:
    1. For each particle:
      - Reshape the particle's position into an appliance schedule (N x T).
      - Calculate objectives:
        - Renewable energy utilization (F1).
        - Total energy consumption (F2).
        - Waiting time penalty (F3).
      - Compute the fitness function using the weighted sum of objectives.
      - Update the particle's personal best if its fitness improves.
      - Update the global best if the particle's fitness is better than the global fitness.
    2. Update particle velocities and positions using PSO update equations.
    3. Set positions to the valid range (0 to 1).
    4. Reduce inertia weight over iterations.

Step 5: Extract Final Schedule:
  - Reshape the global best position into the final appliance schedule (N x T).

Step 6: Tariff Calculation:
  - Calculate the total energy cost using the final schedule.
  - Display the final appliance schedule and estimated monthly tariff.

Step 7: Output Results
  - Return the final schedule and monthly tariff.
```

A5. Pseudocode for Optimal Location in IEEE 33 Bus System Using HSSA

```
Step 1: Input Data:
  - Load bus and line data for the IEEE 33 bus system.

Step 2: Parameters:
  - Define the number of particles (numParticles) and maximum iterations (numIterations).
  - Specify dimensions (location and size of PV-DG).
  - Define PSO parameters: inertia weight (w), cognitive factor (c1) and social factor (c2).
  - Set ACO parameters: pheromone importance (alpha), heuristic importance (beta), pheromone evaporation rate (rho) and constant (Q).

Step 3: Initialization:
  - Randomly initialize particles (PV-DG size and location) and velocities.
  - Set personal best positions (pBest) and global best position (gBest).
  - Initialize pheromone levels for ACO.
  - Set initial fitness values for personal and global best to infinity.

Step 4: Fitness Function:
  - Define the fitness function to minimize power loss or voltage deviation using input bus data.

Step 5. Optimization Loop
  - Repeat for the specified number of iterations:
    1. PSO Update:
      - Update velocities using PSO equations.
      - Update particle positions.
    2. Fitness Evaluation:
      - Calculate fitness for each particle.
      - Update personal bests and global best based on fitness values.
    3. ACO Update:
      - Identify farthest particles based on distance from global best.
      - Update pheromone levels for farthest particles.
      - Use pheromone levels to guide farthest particles toward nearest particles.
```

```
  4. Convergence Check:
     - Optionally stop if the global best fitness change is below a threshold.

Step 6: Output Results:
  - Display optimal size and location of PV-DG.
  - Return minimized power loss or voltage deviation.

Step 7: Auxiliary Functions:
  - Implement the fitness function to calculate power loss.
  - Create a function to find the nearest particle for ACO updates.
```

A6. Pseudocode for Performance Evaluation of 30-acre Residential complex before and after RE integration on IEEE 33 Bus System

```
Step 1: Initialize System Parameters:
  - Define system base values (V_base, S_base).
  - Input bus data [Bus ID, Type, P_load, Q_load].
  - Input line data [From Bus, To Bus, R, X, B_half].

Step 2: Process Data:
  - Normalize load data (P_load, Q_load) using S_base.
  - Initialize voltage magnitudes (V) to 1.0 pu.

Step 3: Set Convergence Criteria:
  - Define boundaries and maximum iterations.

Step 4: Perform Backward/Forward Sweep Power Flow Analysis:
  - Repeat until convergence or max iterations:
    a. Backward Sweep:
       - Compute branch currents starting from the last branch to the root.
       - Accumulate downstream load currents.
    b. Forward Sweep:
       - Update bus voltages iteratively using line parameters and currents.
```

c. Check Convergence:

- Stop if the change in voltage magnitudes is below tolerance.

Step 5: Output Results:

- Display convergence status, number of iterations, bus voltages and voltage angles.

Step 6: Load 24-hour Demand Profile before RE integration:

- Define time (1–24 hours) and total active power limit (P_system_max).
- load active/reactive power profiles for each bus.

```
demand_before_RE = [Provide the full demand matrix];
number_of_buses = 33;
```

.

Step 7: Plot Results:

- Plot total active power demand over 24 hours.
- Optionally, plot individual bus demand curves.

Step 7: Load renewable energy (RE) generation profile (in kWh).

```
RE_generation_profile = [...];
```

Step 8: RE allocation: Specify the buses where RE is integrated.

```
RE_bus = [18];
RE_capacity = 1.31;
```

Step 9: Apply RE contribution to specified buses.

```
for each_hour = 1:24
    for each_bus = 1:length(RE_bus)
        bus_id = RE_bus(each_bus);
        RE_energy = RE_generation_profile(each_hour) * RE_capacity * RE_contribution_percent / 100;
        demand_after_RE(bus_id, each_hour) = demand_before_RE(bus_id, each_hour) - RE_energy;
        if demand_after_RE(bus_id, each_hour) < 0
            demand_after_RE(bus_id, each_hour) = 0; % Ensure no negative demand.
        end
```

```
    end
end

Step 10: Use a power flow solver like Newton-Raphson or Gauss-Seidel for load flow analysis

Step 11: Evaluate system performance.
peak_demand = max(sum(demand_matrix, 1));
average_demand = mean(sum(demand_matrix, 1));
PAR = peak_demand / average_demand;
PAR_before = calculate_PAR (demand_before_RE);
PAR_after = calculate_PAR (demand_after_RE);
Print result

Step 12: Plot total system demand and individual bus demand.
plot_total_system_demand(demand_before_RE, demand_after_RE);
plot_individual_bus_demand(demand_before_RE, demand_after_RE, bus_id);
```

A7. Pseudocode for Load flow analysis of IEEE 33 bus system with dynamic load

Step 1: Initialization

- Clear previous variables, format display and start timer.
- Define bus data (m) and line data (l).
- Initialize variables such as number of buses (no), number of branches (br) and base values for system parameters (MVAb, KVb, Zb).

Step 2: Per Unit Conversion

- Convert resistance and reactance of lines to per-unit (R and X arrays).
- Convert active and reactive power of loads to per-unit (P and Q arrays).

Step 3: Connectivity Matrix

- Create a connectivity matrix (C) that indicates connections between buses.
- Identify end nodes (buses without outgoing connections) using the connectivity matrix.

Step 4: Path Formation

- For each end node, trace paths back to the root bus (assumed bus 1) and store these paths in matrix g.

- Ensure paths are in order and rearrange them to maintain a consistent format.

Step 5: Adjacency Matrix

- Construct adjacency matrix (adjb) for branches and corresponding buses.
- Ensure no duplicate entries and adjust indices for MATLAB indexing.

Step 6: Voltage and Current Calculations with defined loads

- Initialize bus voltages (vb) with a default value.
- Iteratively compute:
    - Nonlinear currents (nlc) at buses for defined loads.
    - Branch currents (Ibr) considering adjacency matrix paths considering the loads.
    - Voltage drops across branches to update bus voltages based on previous calculations.

Step 7: Power Loss Calculation

- Compute active and reactive power losses (Plosskw and Qlosskw) for each branch.
- Sum the losses to obtain total system power losses (PL, QL).

Ster 8: Visualization

- Plot bus voltage magnitudes against bus numbers.
- Output power losses and optimization results.

Step 9: Display Results

- Present computed results including:
    - Bus voltages and their angles.
    - Active and reactive power losses.

Step 10: Optimization Section

- Define and simulate the impact of distributed generation (DG) integration and find optimal location for RE integration as mentioned in previous pseudocode 5.
- Repeat similar steps for per-unit conversion and system analysis post-DG.

APPENDIX-B

B1. Existing Tariff Structure

Type of Consumer	Existing Tariff Scheme Tariff Scheme	Monthly Consumption in kWH	Energy charge / kWH	Fixed charge in Rs. / kVA / Month
Domestic (urban)	Normal	**First 25 unit**	**4.89**	**15**
		next 35 unit	5.4	
		next 40 unit	6.41	
		next 50 unit	7.16	
		next 50 unit	7.33	
		next 100 unit	7.33	
		above 300	8.92	

B1. Proposed Tariff Structure

	Monthly Consumption			Extra Charge in Peak hours		
Tariff Scheme	**Type of energy consumed**	**Monthly Consumption in kWH**	**Net energy charge in INR / kWH**	**extra % of average consumption during peak hours**	**Penalty/ Rebate**	**Fixed charge in Rs. / kVA / Month**
T.O.D for TOT	**Conventional Grid energy**	**6am - 5pm**	**6.5**	**NA**	**NA**	15 (additional Fixed Charge for total monthly Consumption > 300 units)
		5pm - 23pm	**7.8**	**(> 25% of Total consumption) /(<20% of Total consumption)**	**P / R**	
		23pm - 6am	**5.5**	**NA**	**NA**	
	Renewable Energy	**All unit**	**3.15**	**NA**	**NA**	

APPENDIX-C

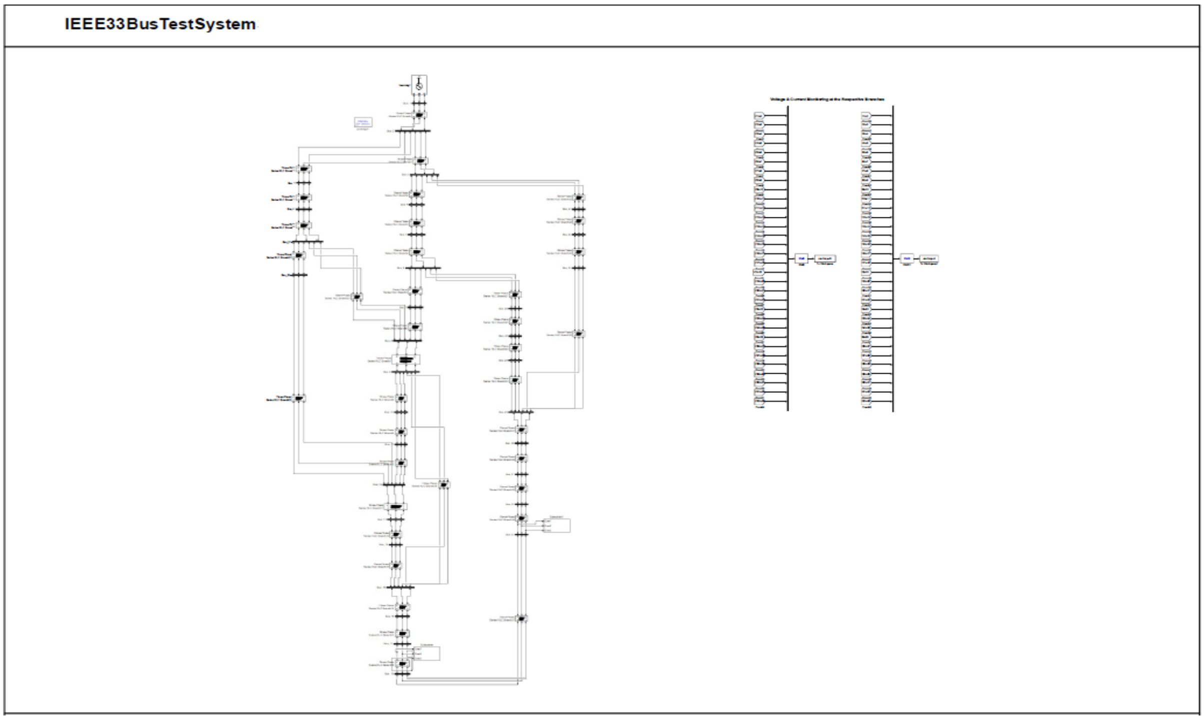


Figure C1: IEEE 33 Bus system in MATLAB SIMULINK

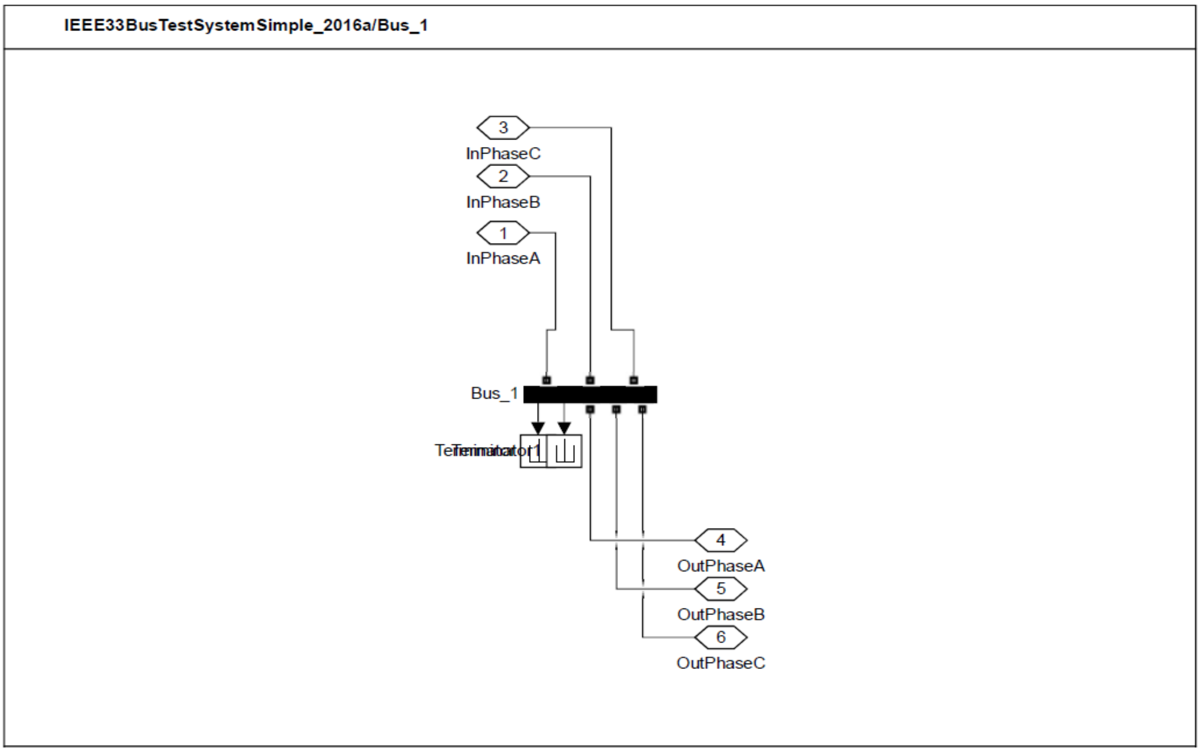


Figure C2: Bus 1_ IEEE 33 Bus system in MATLAB SIMULINK

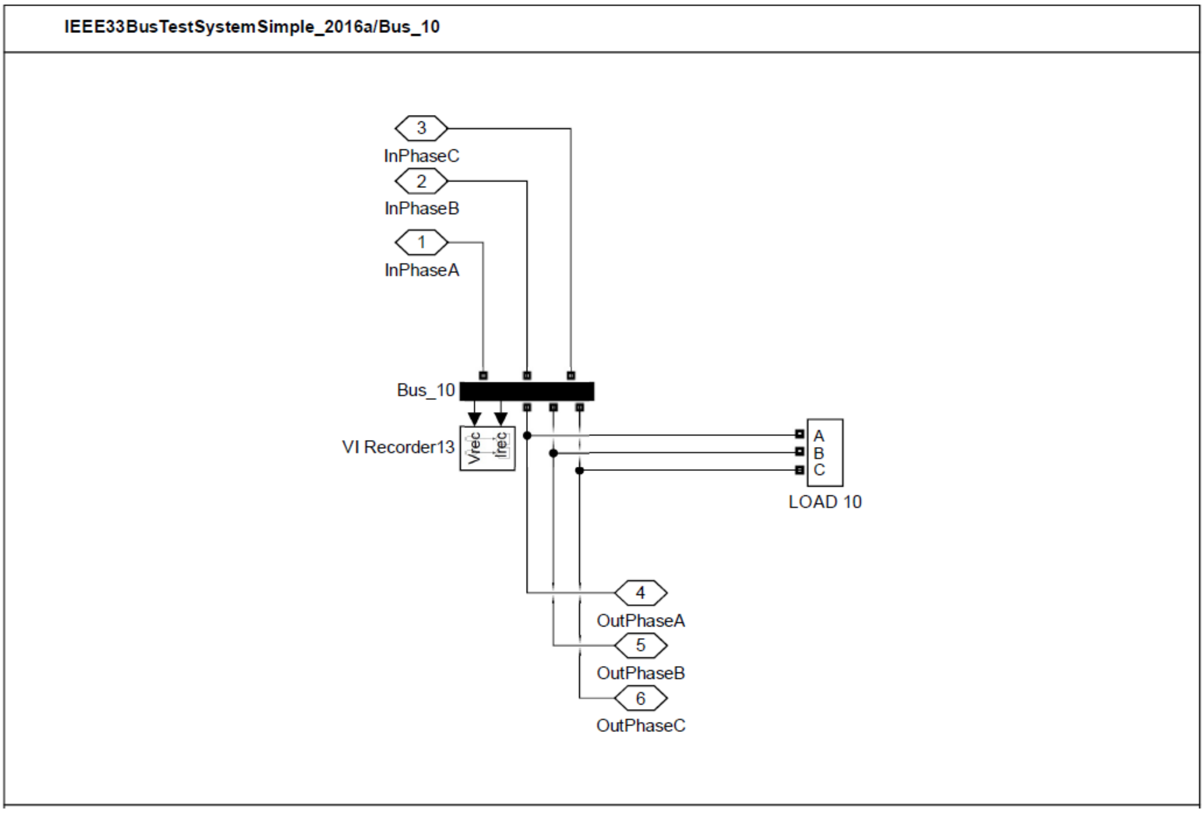


Figure C3: Bus 10_ IEEE 33 Bus system in MATLAB SIMULINK

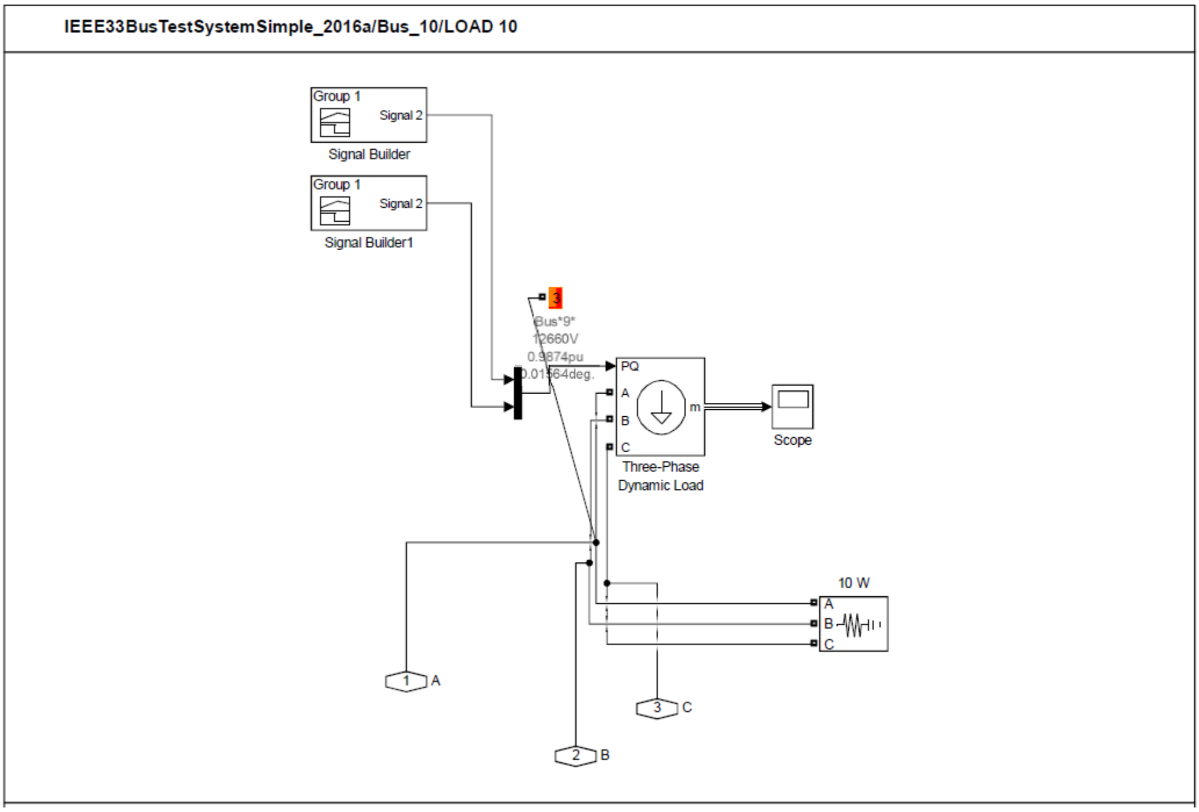


Figure C4: Load at Bus 10_ IEEE 33 Bus system in MATLAB SIMULINK

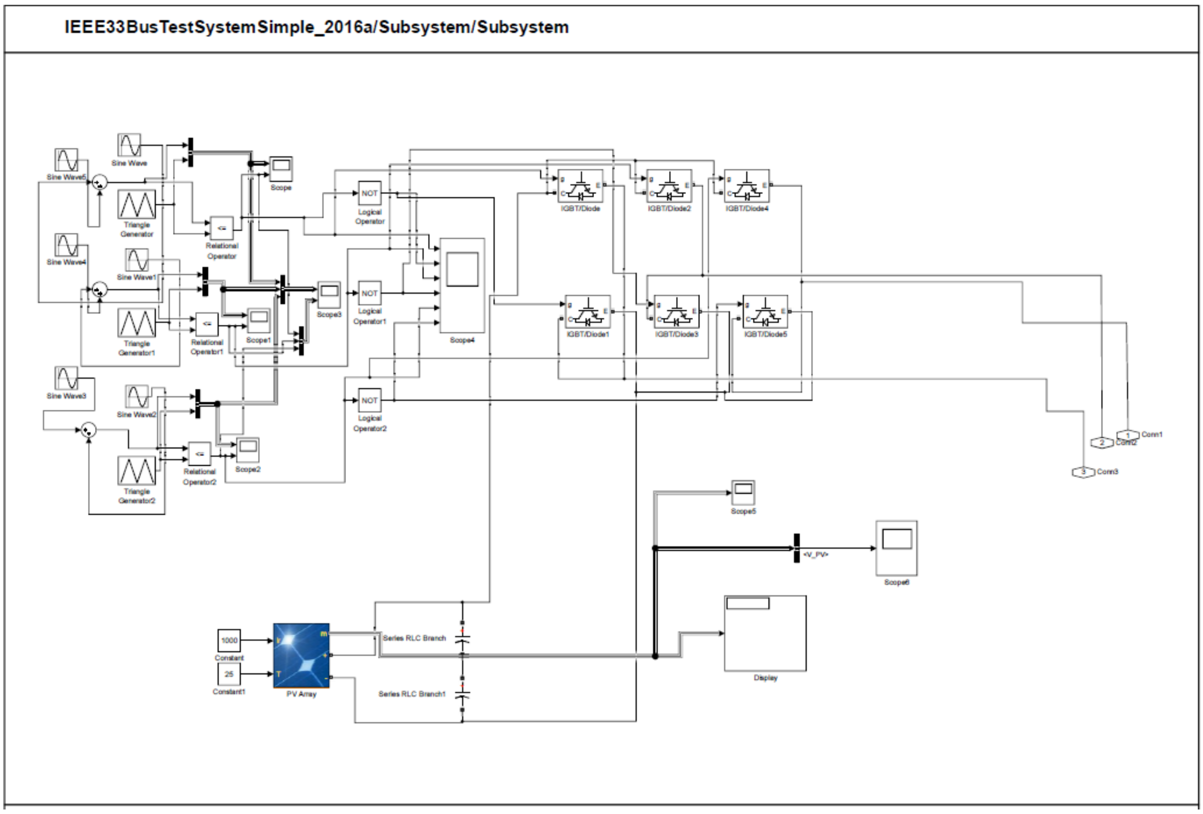


Figure C5: PV system and inverter for RE integration_ IEEE 33 Bus system in MATLAB SIMULINK

References:

[1] Fan, Shu & Hyndman, Rob. (2010). Short-Term Load Forecasting Based on a Semi-Parametric Additive Model. Monash University, Department of Econometrics and Business Statistics, Monash Econometrics and Business Statistics Working Papers. 27. 10.1109/TPWRS.2011.2162082.

[2] Hinojosa, Victor & Hoese, Alejandro. (2010). Short-Term Load Forecasting Using Fuzzy Inductive Reasoning and Evolutionary Algorithms. Power Systems, IEEE Transactions on. 25. 565 - 574. 10.1109/TPWRS.2009.2036821.

[3] Lee, Cheng-Ming & Ko, Chia-Nan. (2011). Short-term load forecasting using lifting scheme and ARIMA models. Expert Syst. Appl.. 38. 5902-5911. 10.1016/j.eswa.2010.11.033.

[4] Al-Hamadi, H.. (2011). Long-term electric power load forecasting using fuzzy linear regression technique. PEAM 2011 - Proceedings: 2011 IEEE Power Engineering and Automation Conference. 3. 10.1109/PEAM.2011.6135023.

[5] Feilat, E.A. and Bouzguenda, M. (2011) Medium-Term Load Forecasting Using Neural Network Approach. 2011 IEEE PES Conference on Innovative Smart Grid Technologies - Middle East (ISGT Middle East), Jeddah, 17-20 December 2011, 1-5.

[6] Hong, Wei-Chiang, 2011. "Electric load forecasting by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm," Energy, Elsevier, vol. 36(9), pages 5568-5578.

[7] Wei-Chiang Hong, Yucheng Dong, Li-Yueh Chen, Shih-Yung Wei, SVR with hybrid chaotic genetic algorithms for tourism demand forecasting, Applied Soft Computing, Volume 11, Issue 2, 2011, Pages 1881-1890, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2010.06.003.

[8] Jianjun Wang, Li Li, Dongxiao Niu, Zhongfu Tan, "An annual load forecasting model based on support vector regression with differential evolution algorithm," Applied Energy, Volume 94, 2012, Pages 65-70, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2012.01.010.

[9] H. He, T. Liu, R. Chen, Y. Xiao and J. Yang, "High frequency short-term demand forecasting model for distribution power grid based on ARIMA," 2012 IEEE International Conference on Computer Science and Automation Engineering (CSAE), Zhangjiajie, China, 2012, pp. 293-297, doi: 10.1109/CSAE.2012.6272958

[10] J. W. Taylor, "Short-Term Load Forecasting With Exponentially Weighted Methods," in IEEE Transactions on Power Systems, vol. 27, no. 1, pp. 458-464, Feb. 2012, doi: 10.1109/TPWRS.2011.2161780.

[11] Montgomery, D. C., Peck, E. A., & Vining, G. G. (2012). Introduction to Linear Regression Analysis. Wiley.

[12] [Guan, Che and Luh, Peter B and Michel, Laurent D and Wang, Yuting and Friedland, Peter B, "Very short-term load forecasting: wavelet neural networks with data pre-filtering", IEEE Transactions on Power Systems, Vol.28, No.1, (2012), pp.30-41

[13] Li, Hongze & Guo, Sen & Zhao, Huiru & Su, Chenbo & Wang, Bao. (2012). Annual Electric Load Forecasting by a Least Squares Support Vector Machine with a Fruit Fly Optimization Algorithm. Energies. 5. 4430-4445. 10.3390/en5114430.

[14] M. M. Ali, P. S. V. Jagadeesh, I. . -I. Lin and J. -Y. Hsu, "A Neural Network Approach to Estimate Tropical Cyclone Heat Potential in the Indian Ocean," in IEEE Geoscience and Remote Sensing Letters, vol. 9, no. 6, pp. 1114-1117, Nov. 2012, doi: 10.1109/LGRS.2012.2190491

[15] Wu, Jie & Wang, Jianzhou & Lu, Helen & Dong, Yao & Lu, Xiaoxiao. (2013). Short term load forecasting technique based on the seasonal exponential adjustment method and the regression model. Energy Conversion and Management. 70. 1–9. 10.1016/j.enconman.2013.02.010.

[16] Sahay, Kishan & Tripathi, Mrinal. (2013). Day ahead hourly load forecast of PJM electricity market and ISO New England market by using artificial neural network. 1-5. 10.1109/ISGT-Asia.2013.6698744.

[17] Hong-ze Li, Sen Guo, Chun-jie Li, Jing-qi Sun, A hybrid annual power load forecasting model based on generalized regression neural network with fruit fly optimization algorithm, Knowledge-Based Systems, Volume 37, 2013, Pages378-387,ISSN-0950-7051, https://doi.org/10.1016/j.knosys.2012.08.015.

[18] Zhao, Zhuang & Lee, Won & Shin, Yoan & Song, Kyung-Bin. (2013). An Optimal Power Scheduling Method Applied in Home Energy Management System Based on Demand Response. Smart Grid, IEEE Transactions on. 4. 1391-1400. 10.1109/TSG.2013.2251018

[19] Y. Goude, R. Nedellec and N. Kong, "Local Short and Middle Term Electricity Load Forecasting With Semi-Parametric Additive Models," in IEEE Transactions on Smart Grid, vol. 5, no. 1, pp. 440-446, Jan. 2014, doi: 10.1109/TSG.2013.2278425.

[20] Koo, Bon-gil and Lee, Heung-seok and Park, Juneho, "A study on short-term electric load forecasting using wavelet transform", IEEE PES Innovative Smart Grid Technologies, Europe, (2014), pp.1-6.

[21] J. -w. Liu, P. Wang, H. Liu and L. Yang, "Time series predictive wavelet neural network control method," The 26th Chinese Control and Decision Conference (2014 CCDC), Changsha, China, 2014, pp. 359-364, doi: 10.1109/CCDC.2014.6852172.

[22] Schachter, Jonathan & Mancarella, Pierluigi. (2014). A short-term load forecasting model for demand response applications. International Conference on the European Energy Market, EEM. 1-5. 10.1109/EEM.2014.6861220.

[23] Sarhadi, Ali & Kelly, Richard & Modarres, Reza. (2015). Snow water equivalent time-series forecasting in Ontario, Canada, in link to large atmospheric circulations.

[24] Lee, Woo-Joo & Hong, Jinkyu. (2015). A Hybrid Dynamic and Fuzzy Time Series Model for Mid-Term Power Load Forecasting. International Journal of Electrical Power & Energy Systems. 10.1016/j.ijepes.2014.08.006.

[25] A.S. Khwaja, M. Naeem, A. Anpalagan, A. Venetsanopoulos, B. Venkatesh, improved short-term load forecasting using bagged neural networks, Electric Power Systems Research, Volume 125, 2015, Pages 109-115, ISSN 0378-7796,

[26] Lahouar, Ali & Ben Hadj Slama, J.. (2015). Random forests model for one day ahead load forecasting. 2015 6th International Renewable Energy Congress, IREC 2015. 10.1109/IREC.2015.7110975.

[27] S.O. Rajankar S. N. Talbar., "An optimum ECG denoising with wavelet neural network," in Pervasive Computing (ICPC), 2015 International Conference on , vol., no., pp.1-4, 8- 10 Jan.2015

[28] A. Gutierrez, "Influence of Wavelets and Boundary Conditions on the Diagnosis of Multiple Sclerosis Using Artificial Neural Networks," in 2015 Annual Global Online Conference on Information and Computer Technology (GOCICT), Louisville, KY, USA, 2015 pp. 6-10.doi: 10.1109/GOCICT.2015.10

[29] Y. -H. Hsiao, "Household Electricity Demand Forecast Based on Context Information and User Daily Schedule Analysis From Meter Data," in IEEE Transactions on Industrial Informatics, vol. 11, no. 1, pp. 33-43, Feb. 2015, doi: 10.1109/TII.2014.2363584.

[30] L. Hernandez et al., "A Survey on Electric Power Demand Forecasting: Future Trends in Smart Grids, Microgrids and Smart Buildings," in IEEE Communications Surveys & Tutorials vol. 16, no. 3, pp. 1460-1495, Third Quarter 2014, doi: 10.1109/SURV.2014.032014.00094.

[31] Olivares, Daniel & Canizares, Claudio & Kazerani, Mehrdad. (2014). A Centralized Energy Management System for Isolated Microgrids. Smart Grid, IEEE Transactions on. 5. 1864-1875. 10.1109/TSG.2013.2294187.

[32] Nguyen, Hung & Song, Ju Bin & Han, Zhu. (2014). Distributed Demand Side Management with Energy Storage in Smart Grid. IEEE Transactions on Parallel and Distributed Systems. 26. 1-1. 10.1109/TPDS.2014.2372781.

[33] Khan, M. & Javaid, Nadeem & Mahmood, Anzar & Khan, Zahoor & Alrajeh, Nabil. (2015). A Generic Demand-Side Management Model for Smart Grid. International Journal of Energy Research. 39. 954-964.

[34] Basit, Abdul & Sidhu, Guftaar & Mahmood, Anzar & Gao, Feifei. (2015). Efficient and Autonomous Energy Management Techniques for the Future Smart Homes. IEEE Transactions on Smart Grid. 8. 1-10. 10.1109/TSG.2015.2504560.

[35] Dudek, Grzegorz. (2016). Pattern-based local linear regression models for short-term load forecasting. Electric Power Systems Research. 130. 139-147. 10.1016/j.epsr.2015.09.001.

[36] Kumar, Sharad & Mishra, Shashank & Gupta, Shashank. (2016). Short Term Load Forecasting Using ANN and Multiple Linear Regression. 184-186. 10.1109/CICT.2016.44.

[37] L. Zhuang, H. Liu, J. Zhu, S. Wang and Y. Song, "Comparison of forecasting methods for power system short-term load forecasting based on neural networks," 2016 IEEE International Conference on Information and Automation (ICIA), Ningbo, China, 2016, pp. 114-119, doi: 10.1109/ICInfA.2016.7831806.

[38] Cheepati, Kumar & Prasad, Talbar (2016). Performance Comparison of Short Term Load Forecasting Techniques. International Journal of Grid and Distributed Computing. 9. 287-302. 10.14257/ijgdc.2016.9.4.26.

[39] S. I. Vagropoulos, G. I. Chouliaras, E. G. Kardakos, C. K. Simoglou and A. G. Bakirtzis, "Comparison of SARIMAX, SARIMA, modified SARIMA and ANN-based models for short-term PV generation forecasting," 2016 IEEE International Energy Conference (ENERGYCON), Leuven, Belgium, 2016, pp. 1-6, doi: 10.1109/ENERGYCON.2016.7514029.

[40] Esther, B. P., & Kumar, K. S. (2016). A survey on residential Demand Side Management architecture, approaches, optimization models and methods. Renewable and Sustainable Energy Reviews, 59, 342–351. doi:10.1016/j.rser.2015.12.282

[41] Rasheed, M.B.; Javaid, N.; Awais, M.; Khan, Z.A.; Qasim, U.; Alrajeh, N.; Iqbal, Z.; Javaid, Q. Real Time Information Based Energy Management Using Customer Preferences and Dynamic Pricing in Smart Homes. Energies 2016, 9, 542. https://doi.org/10.3390/en9070542

[42] Samadi, P., Wong, V.W., & Schober, R. (2016). Load Scheduling and Power Trading in Systems With High Penetration of Renewable Energy Resources. IEEE Transactions on Smart Grid, 7, 1802-1812.

[43] Ma, Kai & Yao, Ting & Yang, Jie. (2016). Residential power scheduling for demand response in smart grid. International Journal of Electrical Power & Energy Systems. 78. 320-325. 10.1016/j.ijepes.2015.11.099.

[44] Zhang, Zhong & Shi, Yiming & Toda, Hiroshi & Akiduki, Takuma. (2017). A Study of a new wavelet neural network for deep learning. 127-131. 10.1109/ICWAPR.2017.8076676.

[45] Khwaja, Ahmed & Zhang, Xiaoying & Venkatesh, B.. (2017). Boosted neural networks for improved short-term electric load forecasting. Electric Power Systems Research. 143. 431-437. 10.1016/j.epsr.2016.10.067.

[46] Abderrezak Laouafi, Mourad Mordjaoui, Salim Haddad, Taqiy Eddine Boukelia, Abderahmane Ganouche, Online electricity demand forecasting based on an effective forecast combination methodology,Electric Power Systems Research, Volume 148, 2017,Pages 35-47,ISSN 0378-7796,https://doi.org/10.1016/j.epsr.2017.03.016.

[47] C. W. Gellings, “Evolving practice of demand-side management,” Journal of Modern Power System and Clean Energy. Springer, vol. 5, pp. 1-9, 2017, doi: 10.1007/s40565-016-0252-1.

[48] Yousafzai, Adnan & Khan, Asif & Javaid, Nadeem & Hussain, Hafiz Majid & Abdul, Wadood & Almogren, Ahmad & Alamri, Atif & Niaz, Iftikhar. (2017). An Optimized Home Energy Management System with Integrated Renewable Energy and Storage Resources. Energies. 10. 549. 10.3390/en10040549.

[49] Ahmad, Sadiq & Ahmad, Ayaz & Yaqub, Raziq. (2017). Optimized Energy Consumption and Demand Side Management in Smart Grid. 10.4018/978-1-5225-2589-9.ch025.

[50] Berk Celik, Robin Roche, David Bouquain, Abdellatif Miraoui. Coordinated Home Energy Management in Community Microgrids with Energy Sharing Among Smart Homes. ELECTRIMACS 2017, Jul 2017, Toulouse, France. pp.1-6. ffhal-01624464f

[51] X. Wu, X. Hu, Y. Teng, S. Qian, and R. Cheng, "Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plugin electric vehicle," Journal of Power Sources, vol. 363, pp. 277–283, 2017.

[52] X. Wu, X. Hu, X. Yin, C. Zhang, and S. Qian, "Optimal battery sizing of smart home via convex programming," Energy, vol. 140, pp. 444–453, 2017.

[53] Celik, Berk & Roche, Robin & Bouquain, D. & Miraoui, A.. (2017). Decentralized Neighbourhood Energy Management With Coordinated Smart Home Energy Sharing. IEEE Transactions on Smart Grid. PP. 1-1. 10.1109/TSG.2017.2710358.

[54] M. J. Sanjari, H. Karami, and H. B. Gooi, "Analytical rule based approach to online optimal control of smart residential energy system," IEEE Transactions on Industrial Informatics, vol. 13, no. 4, pp. 1586–1597, 2017.

[55] Jeddi, Babak & Mishra, Yateendra & Ledwich, Gerard. (2017). Dynamic programming based home energy management unit incorporating PVs and batteries. 1-5. 10.1109/PESGM.2017.8273925.

[56] Sharifi, R., Fathi, S. H., & Vahidinasab, V. (2017). A review on Demand-side tools in electricity market. Renewable and Sustainable Energy Reviews, 72, 565–572. doi:10.1016/j.rser.2017.01.020

[57] Matsila, Hulisani & Bokoro, Pitshou. (2018). Load Forecasting Using Statistical Time Series Model in a Medium Voltage Distribution Network. 4974-4979. 10.1109/IECON.2018.8592891.

[58] F. Tian, W. T. Ming and W. Yun, "Application of Wavelet Fuzzy Neural Network in Real Time Traffic Flow Forecasting," 2018 2nd IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), Xi'an, China, 2018, pp. 1452-1455, doi: 10.1109/IMCEC.2018.8469721.

[59] Ahmad, H., Ahmad, A., & Ahmad, S. (2018). Efficient Energy Management in a Microgrid. 2018 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET). doi:10.1109/pgsret.2018.8685946

[60] Hussain, Hafiz Majid & Javaid, Nadeem & Iqbal, Sohail & Hasan, Qadeer & Khursheed, Khursheed & Alhussein, Musaed. (2018). An Efficient Demand Side Management System with a New Optimized Home Energy Management Controller in Smart Grid. Energies. 11. 190. 10.3390/en11010190.

[61] W. Bao and W. Bin, "Real-time Tide Prediction Based on An Hybrid HA-WANN Model Using Wind Information," 2018 14th IEEE International Conference on Signal Processing (ICSP), Beijing, China, 2018, pp. 604-608, doi: 10.1109/ICSP.2018.8652339.

[62] Killian, Michaela & Zauner, M. & Kozek, Martin. (2018). Comprehensive smart home energy management system using mixed-integer quadratic-programming. Applied Energy. 222. 662-672. 10.1016/j.apenergy.2018.03.179.

[63] Issi, Fatih & Kaplan, Orhan. (2018). The Determination of Load Profiles and Power Consumptions of Home Appliances. Energies. 11. 607. 10.3390/en11030607.

[64] H. Ahmad, A. Ahmad and S. Ahmad, "Efficient Energy Management in a Microgrid," 2018 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), Islamabad, Pakistan, 2018, pp. 1-5, doi: 10.1109/PGSRET.2018.8685946.

[65] Ahmad, Sadiq & Naeem, Muhammad & Ahmad, Ayaz. (2018). Low complexity approach for energy management in residential buildings. International Transactions on Electrical Energy Systems. 29. e2680. 10.1002/etep.2680.

[66] Wang, Yu & Liu, Luyao & Wennersten, Ronald & Sun, Qie. (2019). Peak shaving and valley filling potential of energy management system in high-rise residential building. Energy Procedia. 158. 6201-6207. 10.1016/j.egypro.2019.01.487.

[67] S. A. Malik, T. M. Gondal, S. Ahmad, M. Adil and R. Qureshi, "Towards Optimization Approaches in Smart Grid A Review," 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 2019, pp. 1-5, doi: 10.1109/ICOMET.2019.8673392.

[68] G. Dong and Z. Chen, "Data-Driven Energy Management in a Home Microgrid Based on Bayesian Optimal Algorithm," in IEEE Transactions on Industrial Informatics, vol. 15, no. 2, pp. 869-877, Feb. 2019, doi: 10.1109/TII.2018.2820421.

[69] Hu, Xiaosong & Feng, Fei & Liu, Kailong & Zhang, Lei & Xie, Jiale & Liu, Bo. (2019). State estimation for advanced battery management: Key challenges and future trends. Renewable and Sustainable Energy Reviews. 114. 10.1016/j.rser.2019.109334.

[70] Lu, Qing & Zhang, Zhixin & Lü, Shuaikang. (2020). Home energy management in smart households: Optimal appliance scheduling model with photovoltaic energy storage system. Energy Reports. 6. 2450-2462. 10.1016/j.egyr.2020.09.001.

[71] Jernej Zupančič, Bogdan Filipič, Matjaž Gams, Genetic-programming-based multi-objective optimization of strategies for home energy-management systems, Energy, Volume 203, 2020, 117769, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2020.117769.

[72] Z. Xu, Y. Gao, M. Hussain, and P. Cheng, “Demand side management for smart grid based on smart home appliances with renewable energy sources and an energy storage system,” Mathematical Problems in Engineering, vol. 202020 pages, Article ID 9545439, 2020.

[73] Wang, Xiuwang & Mao, Xinna & Khodaei, Hossein. (2020). A multi-objective home energy management system based on internet of things and optimization algorithms. Journal of Building Engineering. 33. 101603. 10.1016/j.jobe.2020.101603.

[74] Li Tao, Yan Gao, Real-time pricing for smart grid with distributed energy and storage: A noncooperative game method considering spatially and temporally coupled constraints, International Journal of Electrical Power & Energy Systems, Volume 115, 2020, 105487, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2019.105487.

[75] Jo, Jaeyeon & Park, Jinkyoo. (2020). Demand-Side Management With Shared Energy Storage System in Smart Grid. IEEE Transactions on Smart Grid. PP. 1-1. 10.1109/TSG.2020.2980318.

[76] Dinh, Huy & Yun, Jaeseok & Kim, Dong & Lee, Kyu-Haeng & Kim, Daehee. (2020). A Home Energy Management System With Renewable Energy and Energy Storage Utilizing Main Grid and Electricity Selling. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2979189.

[77] Alilou, Masoud & Tousi, Behrouz & Shayeghi, Hossein. (2020). Home energy management in a residential smart micro grid under stochastic penetration of solar panels and electric vehicles. Solar Energy. 212. 6-18. 10.1016/j.solener.2020.10.063.

[78] Kumaravel, Sureshkumar & Ponnusamy, Vijayakumar. (2020). An Efficient Hybrid Technique for Power Flow Management in Smart Grid with Renewable Energy Resources. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. 1-21. 10.1080/15567036.2020.1855274.

[79] Ali, Mohammed. (2021). Evaluation of electrical load estimation in Diyala governorate (Baaquba city) based on fuzzy inference system. International Journal of Electrical and Computer Engineering (IJECE). 11. pp3757-3762. 10.11591/ijece.v11i5.pp3757-3762.

[80] Mansouri, Seyed & Ahmarinejad, Amir & Nematbakhsh, Emad & Javadi, Mohammad & rezaee jordehi, Ahmad & Catalão, João. (2021). Energy management in microgrids including smart homes: A multi-objective approach. Sustainable Cities and Society. 69. 102852. 10.1016/j.scs.2021.102852.

[81] Fathy, Ahmed & Alanazi, Turki & Rezk, Hegazy & Yousri, Dalia. (2021). Optimal energy management of micro-grid using sparrow search algorithm. Energy Reports. 8. 758-773. 10.1016/j.egyr.2021.12.022.

[82] Tostado-Véliz, Marcos & Mouassa, Souhil & Jurado, Francisco. (2021). A MILP Framework for Electricity Tariff-choosing Decision Process in Smart Homes Considering ‘Happy Hours’ Tariffs. International Journal of Electrical Power & Energy Systems. 131. 107139. 10.1016/j.ijepes.2021.107139.

[83] Arevalo, Wilian & Tostado-Véliz, Marcos & Jurado, Francisco. (2021). A Novel Methodology for Comprehensive Planning of Battery Storage Systems. The Journal of Energy Storage. 37. 102456. 10.1016/j.est.2021.102456.

[84] Dalal, Rakesh & Bansal, Kamal & Thapar, Sapan. (2021). Bridging the energy gap of India's residential buildings by using rooftop solar PV systems for higher energy stars. Clean Energy. 5. 423-432. 10.1093/ce/zkab017.

[85] Mohammad Sadegh Javadi, Ali Esmaeel Nezhad, Pedro H.J. Nardelli, Matthew Gough, Mohamed Lotfi, Sérgio Santos, João P.S. Catalão, Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs, Sustainable Cities and Society, Volume 68, 2021, 102792, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2021.102792.

[86] Bishoy E. Sedhom, Magdi M. El-Saadawi, M.S. El Moursi, Mohamed.A. Hassan, Abdelfattah A. Eladl, IoT-based optimal demand side management and control scheme for smart microgrid, International Journal of Electrical Power & Energy Systems, Volume 127,2021, 106674, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2020.106674.

[87] Kumar, Milan & V M, Shenbagaraman & Shaw, Rabindra & Ghosh, Ankush. (2021). Predictive Data Analysis for Energy Management of a Smart Factory Leading to Sustainability. 10.1007/978-981-15-4692-1_58.

[88] T. T. Nguyen, T. T. Ngoc, T. T. Nguyen, T. P. Nguyen, and N. A. Nguyen, "Optimization of location and size of distributed generations for maximizing their capacity and minimizing power loss of distribution system based on Cuckoo search algorithm," Bulletin of Electrical Engineering and Informatics, vol. 10, no. 4, 2021

[89] Tostado-Véliz, Marcos & Icaza, Daniel & Jurado, Francisco. (2021). A Novel Methodology for Optimal Sizing Photovoltaic-Battery Systems in Smart Homes considering Grid Outages and Demand Response. Renewable Energy. 170. 884-896. 10.1016/j.renene.2021.02.006.

[90] Ayşe Kübra Erenoğlu, İbrahim Şengör, Ozan Erdinç, Akın Taşcıkaraoğlu, João P.S. Catalão, Optimal energy management system for microgrids considering energy storage, demand response and renewable power generation, International Journal of Electrical Power & Energy Systems, Volume 136, 2022, 107714, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2021.107714.

[91] Jabeur, Reda & Boujoudar, Younes & Mohamed, Azeroual. (2022). Microgrid energy management system for smart home using multi-agent system. International Journal of Electrical and Computer Engineering. 12. 10.11591/ijece.v12i2.pp1153-1160.

[92] Yang, Ranchen & Xu, Tingting & Chen, Guozhu. (2022). Coordinated energy management for an islanded microgrid with multi-energy and multi-storage units. Energy Reports. 8. 67-74. 10.1016/j.egyr.2021.11.131.

[93] Cortés-Caicedo, Brandon & Ocampo, Jauder & Bolaños, Rubén & Montoya Giraldo, Oscar & Grisales-Noreña, Luis. (2024). A multi-objective PSO for DC microgrids: Efficient battery management to minimize energy losses and operating costs. Journal of Energy Storage. 96. 112550. 10.1016/j.est.2024.112550.

[94] Brillianto Apribowo, Chico Hermanu & Hadi, Sasongko & Wijaya, Franscisco & Setyonegoro, Mokhammad & Sarjiya, Sarjiya. (2024). Optimal sizing and placement of battery energy storage system for maximum variable renewable energy penetration considering demand response flexibility: A case in Lombok power system, Indonesia. Energy Conversion and Management: X. 23. 100620. 10.1016/j.ecmx.2024.100620.

[95] Magda I. El-Afifi, Bishoy E. Sedhom, Abdelfattah A. Eladl, Mohamed Elgamal, Pierluigi Siano, Demand side management strategy for smart building using multi objective hybrid optimization technique, Results in Engineering, Volume 22, 2024, 102265, ISSN 2590-1230, https://doi.org/10.1016/j.rineng.2024.102265.

[96] M. Jagadeesh Kumar, T. Sampradeepraj, E. Sivajothi, Gurkirpal Singh, An efficient hybrid technique for energy management system with renewable energy system and energy storage system in smart grid Energy, Volume 306, 2024, 132454, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2024.132454.

[97] Zhang, Delong & Du, Mingxing & Zhang, Ziyang & Li, Ji & Li, Chao & Liu, Hongli & Shao, Lei. (2023). Effect of multi-energy storage systems on improving the synergy of integrated energy system. 90-93. 10.1109/NEESSC59976.2023.10349231.

[98] Xing, Xueliang & Jia, Limin. (2023). Energy Management in Microgrid and Multi-microgrid. 10.36227/techrxiv.22179344.

[99] Sebastián Taboh, Isabel Méndez-Díaz, Paula Zabala, Heuristics for home appliances scheduling problems with energy consumption bounds, Sustainable Energy, Grids and Networks, Volume 39, 2024, 101511, ISSN 2352-4677, https://doi.org/10.1016/j.segan.2024.101511.

[100] Judith Stute, Sabine Pelka, Matthias Kühnbach, Marian Klobasa, Assessing the conditions for economic viability of dynamic electricity retail tariffs for households, Advances in Applied Energy, Volume 14, 2024,100174,ISSN-2666-7924, https://doi.org/10.1016/j.adapen.2024.100174.

[101] Ahmet Dogan, Analysing flexibility options for microgrid management from economical operational and environmental perspectives International Journal of Electrical Power & Energy Systems, Volume 158, 2024, 109914, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2024.109914.

7] Zhang, Delong & Du, Mingxing & Zhang, Ziyang & Li, Ji & Li, Chao & Liu, Hongli & Shao, Lei. (2023). Effect of multi-energy storage systems on improving the synergy of integrated energy system. 90-93. 10.1109/NEESSC59976.2023.10349231.

8] Xing, Xueliang & Jia, Limin. (2023). Energy Management in Microgrid and Multi-microgrid. 10.36227/techrxiv.22179344.

9] Sebastián Taboh, Isabel Méndez-Díaz, Paula Zabala, Heuristics for home appliances scheduling problems with energy consumption bounds, Sustainable Energy, Grids and Networks, Volume 39, 2024, 101511, ISSN 2352-4677, https://doi.org/10.1016/j.segan.2024.101511.

00] Judith Stute, Sabine Pelka, Matthias Kühnbach, Marian Klobasa, Assessing the conditions for economic viability of dynamic electricity retail tariffs for households, Advances in Applied Energy, Volume 14, 2024,100174,ISSN-2666-7924, https://doi.org/10.1016/j.adapen.2024.100174.

01] Ahmet Dogan, Analysing flexibility options for microgrid management from economical operational and environmental perspectives International Journal of Electrical Power & Energy Systems, Volume 158, 2024, 109914, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2024.109914.

Arindam Kumar Sil
02/06/2025.

Dr. Arindam Kumar Sil
Associate Professor
Electrical Engg Dept.
Jadavpur University
Kolkata - 700 032