JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

LOAD MONITORING, FORECASTING AND MANAGEMENT SYSTEM FOR PEAK LOAD REDUCTION AND RENEWABLE ENERGY INTEGRATION

Thesis submitted by

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Doctor of Philosophy (Engineering)

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STATEMENT OF ORIGINALITY

I, **Mr. Ayandeep Ganguly**, registered on **19th June 2019**, do hereby declare that this thesis entitled **"LOAD MONITORING, FORECASTING AND MANAGEMENT SYSTEM FOR PEAK LOAD REDUCTION AND RENEWABLE ENERGY INTEGRATION"** contains a literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

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Dedicated to

- *My Parents and Teacher*

ABSTRACT

The growing demand for energy, the need to reduce greenhouse gas emissions and the pursuit of achieving the sustainable development goal of ensuring affordable and clean energy to everyone have necessitated the development of energy management systems. These energy management system models seek to provide the best ways to ensure the comfort of the consumers, reduce energy cost, ensure peak load reduction and explore the avenues to integrate renewable energy sources in the present energy mix. Forecasting the future load demand and renewable energy availability is a very important part of any energy management system. The forecasting methods should be robust, computationally efficient and hardware friendly to ensure the best possible energy management operation. Thus, artificial intelligence-based techniques have gained importance in designing forecasting models. However, the real-world data acquisition is plagued with the problems of missing, redundant and insufficient data and requires pre-processing to ensure optimum operation of the forecasting models. Also, the relationships between the electrical load demand of any region and the numerous factors that affect it such as weather, economy and demography are highly non-linear showing various trends which vary in the range of days, weeks and seasons. The above factors somewhat limit the otherwise impressive abilities of artificial intelligence-based forecasting. One of the main challenges of energy management systems is to tackle the variation in the electrical load demand which is significantly large across different regions due to factors such as population density, industrial activity, climate, and access to energy resources. These regions using electricity as their main source of power can be classified as urban, semi urban and rural. The electricity demand of the urban regions is characterized by the highest electricity load due to dense populations, high-rise buildings, commercial centers, and industrial activities, spikes occurring in electricity demand during certain periods, especially during work hours (daytime for commercial and industrial users) and evenings (for residential users) and also during extreme weather conditions, such as summer cooling and winter heating. The contributing factors to the urban energy consumption are extensive use of heating, ventilation and air conditioning systems, high demand from commercial establishments like offices, shopping centers, and hospitals, public infrastructure, data centers and other tech-based industries. The semi-urban regions generally experience moderate electricity demand, with a mix of residential and small commercial loads. The demand pattern here follows both urban and rural characteristics with spikes occurring during early mornings and evenings, when people are home after work and schools. The main contributors to the energy consumption are large residential areas with electric heating, cooling, and household appliances, growing reliance on electric vehicles (EV) leading to increased demand for charging infrastructure, localized small-to-medium scale businesses, schools, and healthcare facilities and seasonal demand variations, especially for cooling in summer and heating in winter. The rural regions typically have lower electricity demand due to sparse population and fewer industries. However, demand can be higher in agricultural areas with irrigation systems or in regions with mining or other resource-based industries. Peaks are often tied to farming or industrial cycles, with demand increasing during certain times of the year, such as the harvesting season when irrigation and machinery use is high. Thus, it is evident that each demographic region has very distinct factors affecting their electricity consumption. The robustness of an energy management system can be measured by its ability to provide the best results irrespective of such demographic variations. A robust energy management system should be able to handle the demographic variations in

energy consumption separately as well as the combined energy demand of a mixed demographic region. It should be able to ensure the best possible outcome for each individual region and the combined regional power demand. With the increasing push towards clean energy, the integration of renewable energy sources in the primary energy mix of the society has become of paramount importance. Energy management systems face significant challenges in handling the complex nature of renewable energy integration in the already highly complex problem of efficient energy management. For urban regions, load balancing is critical due to constant high demand. Integrating renewable sources such as rooftop solar photovoltaic (PV), urban wind turbines, and energy storage helps manage peaks and reduce strain on the grid. For rural regions, there is more potential for decentralized renewable energy systems, including small-scale solar, wind, and bioenergy. Microgrids and local energy storage play a key role in balancing variable demand and improving energy access in these regions. The sub-urban regions can benefit from both centralized grid power and localized renewable sources like community solar projects and home energy storage systems, allowing for a flexible response to changing load demands. Understanding these variations is crucial for designing energy management systems that can efficiently distribute electricity, especially as the share of renewables in the energy mix grows. Energy cost also plays a vital role in determining the efficiency of the energy management systems. Proper tariff system can be leveraged to encourage the consumers in aligning their demand with the generation from the renewable sources. Any power demand profile can be differentiated into peak, valley and flat periods which are different for urban, semi urban and rural regions. So, a common tariff system will not be able to capture the demographic differences and will be inefficient in demand management. Thus, the present research work proposes a properly designed time of use tariff plan to capture the regional variation in demand allowing better demand generation alignment. The present research work proposes an efficient method of load and renewable energy forecasting, monitoring and management system for peak load reduction and renewable energy integration. An artificial neural network-based model has been proposed in this work for electrical load demand forecasting. It makes use of different input factors such as historical load demand data and weather parameters. The set of historical data used as input has been determined through correlation analysis selecting the values which show the highest correlation to the day for which the forecasting has to be done. The different parameters of the weather were investigated to find the parameter which exerts the highest influence in determining the efficiency of the forecasting method. It was found that while temperature shows significant impact, humidity does not play a crucial role in increasing the efficiency of the forecasting model. Further improvement in the efficiency of the forecasting model was achieved by incorporating wavelet transform in the artificial neural network model. The wavelet neural network so formed showed satisfactory performance in short and medium term forecasting with the mean absolute percentage error remaining within 4%. This work further investigates the design and optimization of an energy management system that caters to urban, semi urban and rural regions, addressing the distinct challenges and opportunities of each. It explores the integration of renewable energy, such as solar and wind into local and regional energy systems, with a focus on balancing supply-demand dynamics, reducing energy wastage, and enhancing grid resilience. A model is presented where several regions are combined together based on the demand profile of the regions segregated as urban, semi urban and rural along with the flexibility to schedule loads on the basis of availability of renewable energy sources within the area of the regions. The main focus is on a detailed forecasting based on neural network and then developing a load management system to manage load during peak hours and off-peak period based on availability of distributed generation capacity and available tariff system. The major contribution of this work is providing a detailed model in which the loads are mapped to their probable supplies based on the region wise classification of Urban, Semi-Urban and Rural. The model is capable of identifying the type of region and consumer category to be addressed from the load demand profile of the region. The output of the model provides an hourly percentage of the total load demand which can be supplied by the available renewable energy. This data was incorporated in increasing the efficiency of the energy management system proposed by this work. A robust and sustainable demography driven energy management system was developed which is capable of optimizing the energy consumption of each region individually as well as in a combined energy community mode. The urban regions are considered to be both grid connected and having available photovoltaic power sources whereas the rural regions are considered to be mostly relying on distributed energy resources and a centralized storage system with uncertain grid connection. The grid connection available to rural region participants is considered to be unreliable and prone to power cuts. The output of the fuzzy logic based source load mapping was used to determine the potential contribution of renewable energy by the participants in the community. The battery system was used to supply power during the non-solar hours and in case of power cuts to the rural area. The participants are free to sell their excess renewable energy to the grid or to the community as required for maximization of social welfare and minimization of their energy costs. Mixed integer linear programming was used to implement the energy management system with automatic rescheduling of flexible loads as required for achieving the optimization goals and incorporating the inequality and equality constraints as required to ensure the logical operation of the system. The efficiency of the proposed regional energy management system has been measured against the sustainable development goals of universal energy access, eco-sustainability through greenhouse gas reduction and improvement of grid health. A demography load clustering-based tariff system was also implemented to exploit the energy usage pattern difference among urban and rural areas to increase the efficiency of the model. The payback period of the infrastructure was done and was found to be in satisfactory range.

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Chapter 1
Introduction

1.1 Introduction

The three main components of conventional power system can be classified broadly as generation, transmission and distribution. All the three components are interconnected to facilitate smooth transfer of power from the generating stations to the load centers. The generation of power is done through conventional thermal power plants and renewable energy power plants. Conventional thermal power plants use coal as their main fuel for generating power while there are many developing non-conventional sources being used for power generation such as solar, wind, hydel, geothermal, tidal and biogas energy respectively. The power generated by these power plants are transferred to the consumers using transmission lines which accounts for further transmission losses during the process. At the load centers the power is distributed among the consumers by different distribution utilities. These utilities have different tariff schemes which are used for billing the consumers. As per the statistics released by the Central Electricity Authority of India in its General Report of 2024 there are 151 companies, power corporations and management boards and 11 electricity departments in states and Union territories in India which are engaged in generation, distribution and transmission of power. The rapid urbanization and industrialization of the country along with the vigorous push for rural electrification and energized irrigation pump sets have increased the overall electricity demand by a great extent. The overall energy consumption in India has registered a growth of almost 11% in the last decade. This can be well understood by increase in the per capita energy use shown in Fig. 1.1. This growth in the energy demand has been mainly due to the contribution of the industrial, domestic, agricultural and commercial sector respectively as shown in Fig. 1.2. Domestic electricity consumption, standing at 25%, contributes substantially to the total electricity demand. This increase in domestic electricity consumption is partly due to the fact that high importance has been given in the last few years to the implementation of rural electrification. As per the official statistics 100% electrification of the Indian villages has already been achieved.

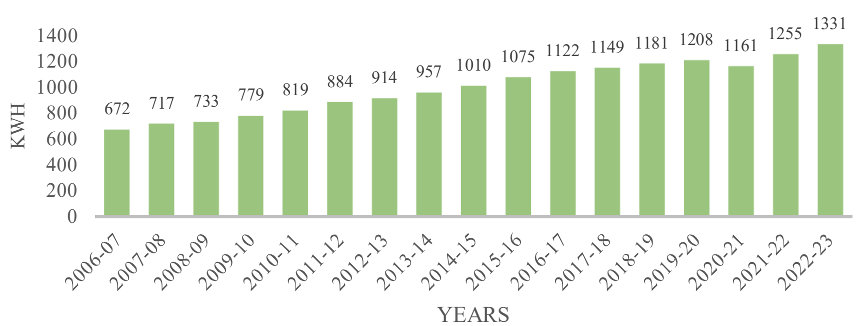


Fig.1.1 Per capita energy consumption growth in India

However, the increase in consumer demand requires increase in generation capacity also. Increasing the conventional generation through thermal power plants require the consumption of more fossil fuel which is reducing very fast over the last decades with only a few years of known deposits left. The sector wise coal consumption for September 2022 and September 2023 is shown in Fig. 1.3 which shows an increase in the percentage share of energy

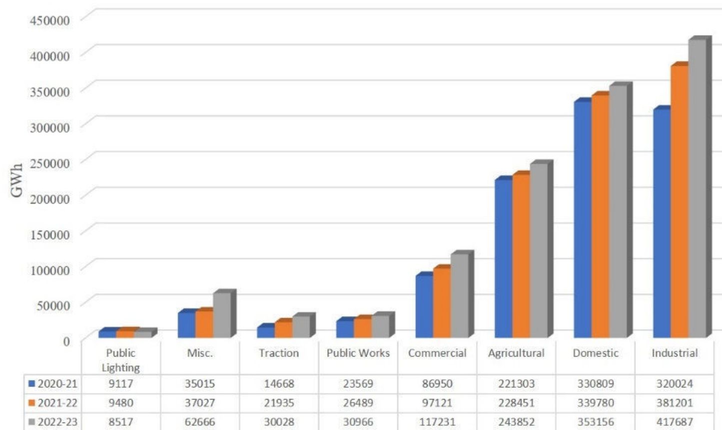


Fig.1.2 Growth of category wise electricity consumption in the past 3 years

production in coal. The coal reserves of India are limited and so the country relies heavily on imported coal. The coal imports of India stand at 268.24 million tonne (MT) among which 10% of the coal is used for power generation causing an economic impact of 0.38 lakh crores.

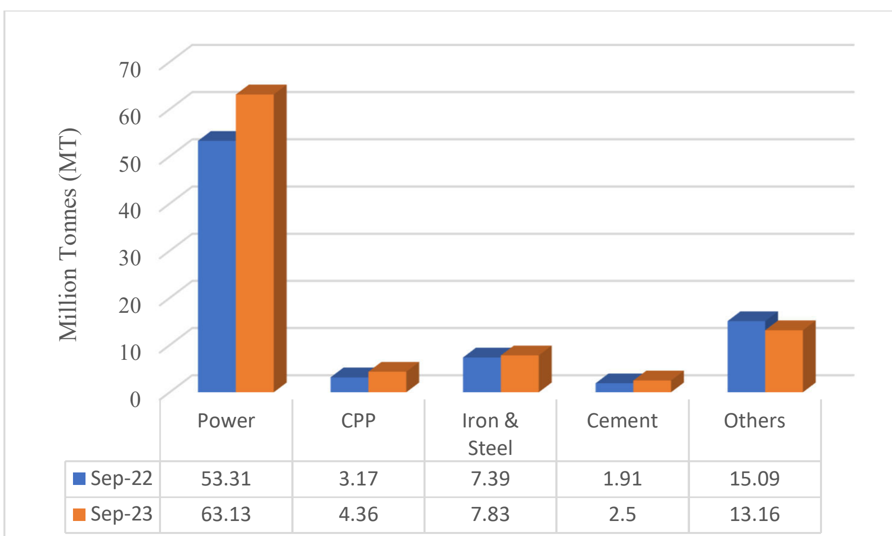


Fig.1.3 Sector wise coal consumption during September FY23-FY24

The use of fossil fuels for power generation is also responsible for addition of substantial levels of Green House Gases (GHG) in the environment. The contribution of power sector in the greenhouse gas emission in 2019 stands at 75.81% as shown in Fig. 1.4. and the sector wise distribution of GHG emissions for 2022 is shown in Fig. 1.5. The emission of greenhouse gases poses a substantial threat to the environment of the planet and has been identified categorized as a significant contributor to global warming.

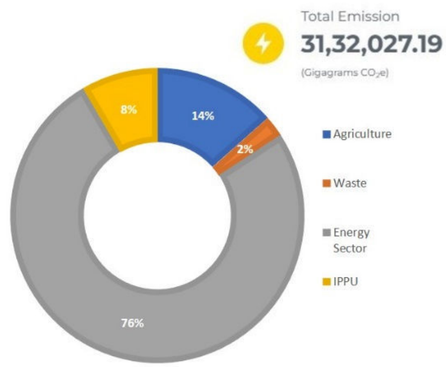


Fig.1.4 Sector wise emission of CO2 in India

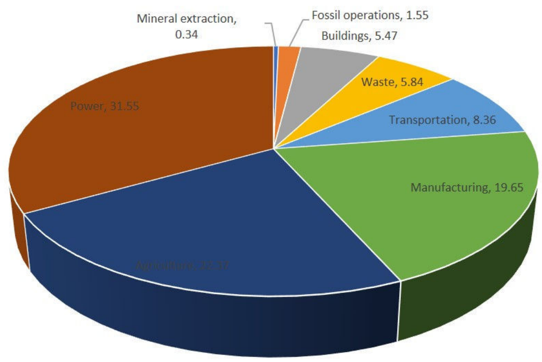


Fig.1.5 Distribution of sectorwise percentage of greenhouse gas emissions in India in 2022

The rate at which the temperature of our planet is increasing due to global warming is quite alarming. In the recent years the harmful impact of climate change has been felt quite strongly through increased occurrences of natural calamities. With the threat to the continued existence of human beings on earth evident, the world leaders at the United Nations adopted 17 sustainable development goals (SDG) in 2015 to bring peace and prosperity for the people and the planet while tackling climate change and preserving the ecosystem of the planet. The emission of greenhouse gases poses a substantial threat to the environment of the planet and has been identified categorized as a significant contributor to global warming. The rate at which the temperature of our planet is increasing due to global warming is quite alarming. In the recent years the harmful impact of climate change has been felt quite strongly through increased occurrences of natural calamities. With the threat to the continued existence of human beings on earth evident, the world leaders at the United Nations adopted 17 sustainable development goals (SDG) in 2015 to bring peace and prosperity for the people and the planet while tackling climate change and preserving the ecosystem of the planet. Among these 17 sustainable goals, SDG 7 is dedicated to ensure affordable, reliable, sustainable and modern energy for the people of the world. The important postulates of SDG 7 along with their indicators are as follows

1. By 2030, ensure universal access to affordable, reliable and modern energy services measurable by
    i. Proportion of population with access to electricity
    ii. Proportion of population with primary reliance on clean fuels and technology
2. By 2030, increase substantially the share of renewable energy in the global energy mix measurable by
    i. Renewable energy share in total final energy consumption
3. By 2030, double the global rate of improvement in energy efficiency measurable by
    i. Energy intensity measured in terms of primary energy and Gross domestic product (GDP)
4. By 2030, expand infrastructure and upgrade technology for supplying modern and sustainable energy services for all developing nations measured by
    i. Installed renewable energy generating capacity in developing and developed countries (in watts per capita)

India, being one of the members of United Nations and avid promoter of sustainable technologies has been playing a key role in ensuring clean energy supply to its citizens through different policies. The Government of India also enumerated the key objectives of India's climate action plan in the Conference of the partied (CoP) 26 held in Glasgow, United Kingdoms from 31st October to 12th November 2021. The five key elements of the declaration are as follows-

a) Reach 500 gigawatt (GW) non-fossil energy capacity by 2030.
b) 50% of its energy requirements from renewable energy by 2030
c) Reduction of total projected carbon emissions by one billion tonnes by 2030
d) Reduction of the carbon intensity of the economy by 45% by 2030 over 2005 levels
e) Achieving the target of net zero emissions by 2070

In pursuit of these goals, India has stepped up the development of renewable energy capacity to supply power to the citizens as can be seen in Fig. 1.6.

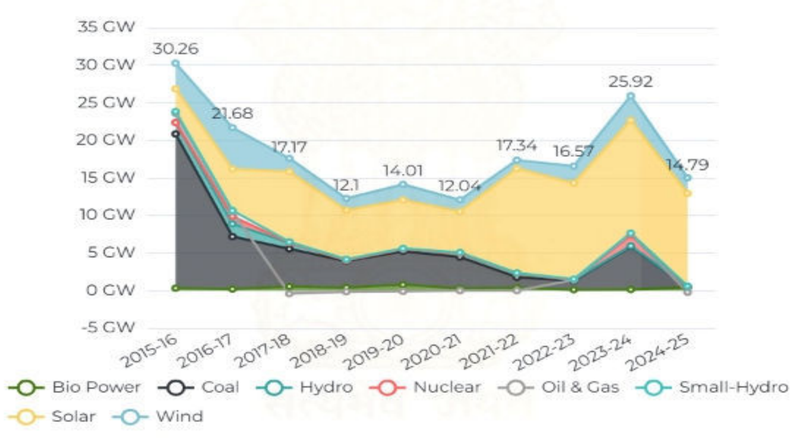


Fig.1.6 Source wise yearly net capacity addition (GW)

From Fig. 1.6 it is quite evident that there has been significant capacity addition to renewable energy power generation from 2019 to 2024. According to official statistics the present scenario of Indian power sector is as follows-

i. The total power generating capacity of India is 440 GW as of March 2024
ii. The renewable energy capacity installed in India is now 43% of the total installed capacity against the set target of 50% by the end of 2030.
iii. The percentage of solar installation among the generating sources is 82 GW (18.55%), hydro is 47 GW (10.63%), wind power is 46 GW (10.41%) and others 16 GW (3.62%)

From figure 1.6 it can be seen that the maximum capacity addition has been done for solar energy. This is due to the fact that integration of photovoltaic power into the present power scenario can be done more easily than the other sources through rooftop solar panels and solar farms on available lands where no other productive work is done. This is made possible due to availability of solar irradiation throughout the country at substantial quantity. From the demand side perspective, it is visible from Fig. 1.7 that domestic consumers comprise almost 1/4th of the total energy consumption whereas agriculture and commercial together comprise another 1/4th of the total power consumption.

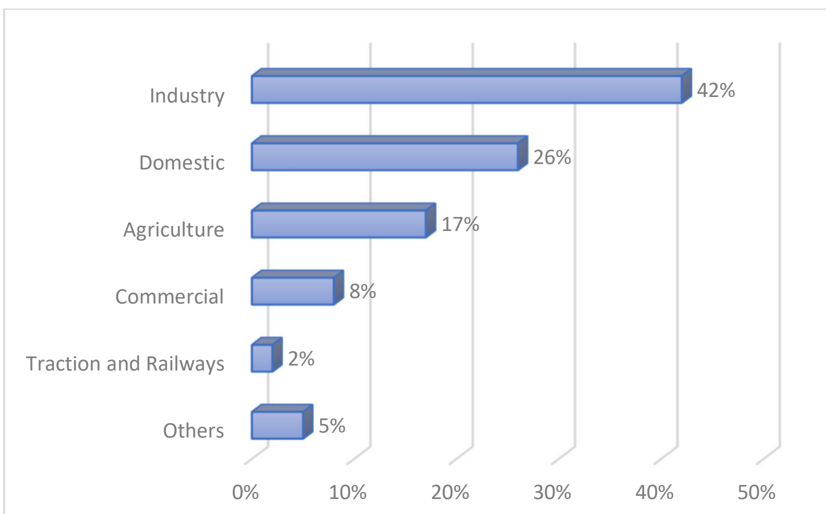


Fig.1.7 Sector wise distribution of energy consumption in India in financial year 2023

The gradual integration of renewable energy resources in these three sectors can result in the percentage increase of renewable energy in the primary energy mix of up to 50% which will further help the country to reach the SDG 7 goals. However, even though the percentage share of renewable energy in the installed capacity has increased its percentage in the primary energy source mix is still very low as shown in Fig. 1.8.

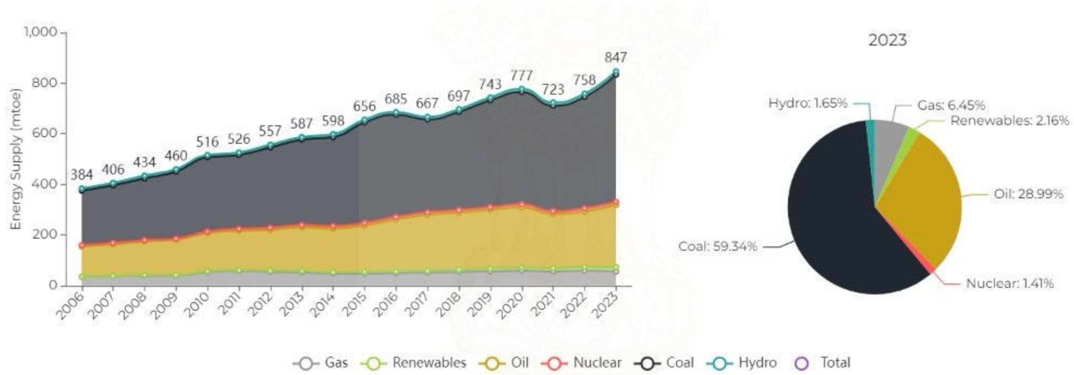


Fig.1.8 Source wise primary energy supply

These statistics show that the average electricity consumer in India still relies heavily on the power generated by thermal power plants. This reluctance of the consumers to adopt renewable sources for their electricity consumption can be attributed to the following possible reasons

a) Capital cost of renewable energy installation
b) Intermittency of renewable energy
c) Mismatch of peak generation and peak demand periods
d) Lack of communication between the power supply utilities and the consumers regarding the variation of energy utilization preferences in urban, rural and semi urban regions

The solutions to these problems can be found by understanding the structure of the traditional power system planning employed in the present power sector and the operational challenges faced by it with the increase in electrification and modernization of the traditional grid. Traditional power systems are designed on the premise of centralized power production in generating stations and its delivery to the points of distribution via transmission systems. The power system planning required for the conventional systems consisted of the following elements

1. Long term demand forecasting – Traditionally, forecasting has been mainly done with the limited objective to gain prior knowledge of the annual energy sales and annual peak demand. Based on this information generation capacity increase and system expansion projects were undertaken as required. The lead times required for such projects being very long, the forecasting horizons ranged from a few years to a decade. Such long-term forecasting although sufficient for the traditional power system planning fails to meet the requirement of the modernized power system with renewable integration. The integration of renewable energy sources in the primary energy source mix requires far more robust forecasting techniques to overcome the consumer inconvenience caused by their highly intermittent nature.

2. Unit Commitment – Unit commitment in the tradition power system infrastructure is the process of determining the best combination of the production from a set of generators to either maximize the revenue from energy production or meet the energy demand at minimum cost, keeping in mind system stability and reliability. However, the present unit commitment determination methods have been developed for controllable generation where the energy production can be controlled according to the load demand. However, such methods are not suitable for scenarios where the generation is dependent on random

variables such as the weather. Instead of unit commitment methods, generation-demand mapping methods are required to be developed to facilitate the adoption of renewable energy sources by the power consumers.

3. Demand Side Management – Demand Side Management (DSM) refers to efforts for managing energy demand by persuading customers to change their usage habits. This is especially important during peak load periods, when electrical demand exceeds supply capacity. The value of DSM lies in its capacity to optimize available resources while deferring or eliminating the need to build new power plants. By properly regulating consumer demand, DSM helps to lower power prices for both utilities and customers, increase grid resilience, and create a more sustainable energy environment. Traditional DSM methods only focused on peak reduction and valley filling. However, for effective integration of renewable energy sources demand must be managed according to the availability of renewable power making it a much more complicated process requiring energy management systems for smart control of appliances through home automation.

4. Monitoring – Presently, power system monitoring is done through legacy Supervisory Control and Data Acquisition (SCADA) systems where a centralized communication infrastructure is combined with hardware and software infrastructure to facilitate reliable operation of the power systems. However, with the restructuring of the electric power industry and the integration of renewable resources the complexity of the required communication infrastructure required has become very high. Thus, new and sustainable monitoring solutions are required to cater to the needs of the modernized power grid.

5. Feeder lines - The most prevalent distribution system in India is through radial distribution feeder. Feeder separation in power distribution divides the system into distinct feeder lines to enhance reliability, reduce outages, and improve maintenance efficiency. In the present power system network the feeder lines are segregated based on the type of loads i.e. residential, commercial, industrial and agricultural. However, the shift from conventional generation sources to renewable generation sources might require a different classification of the feeder lines according to their link with the distributed generation sources and demographical characteristics of the load demand which they are catering to.

In order to effectively utilize available resources without further need to install thermal power plants, it is important to harness energy from renewable energy as a replacement. The present centralized approach to electricity production and distribution is one of the main hurdles in the path of effective renewable energy integration. Due to the unpredictable nature of the climatic factors affecting the generation of power from renewable energy sources, large centralized renewable energy production facilities can lead to inefficient and unreliable power production. Thus, decentralization of the power system infrastructure leading to increased penetration of distributed generation can be a robust and sustainable solution to the present challenges faced in the modernization of the traditional grid. The benefits of distributed generation penetration are shown in Figure 1.8.

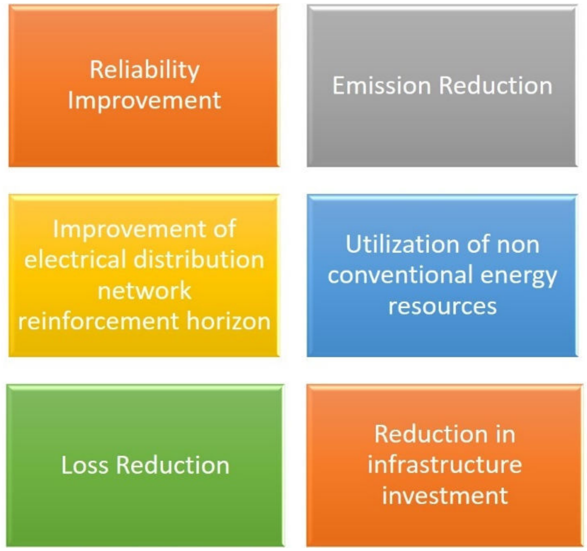


Fig.1.9 Benefits of Distributed Generation penetration

The optimal operation of a decentralized system with distributed generation can only be ensured through the development and implementation of effective power system planning solutions by mitigating the challenges faced by the traditional methods. Such solutions will be required to facilitate the seamless integration of solar, wind, and other renewables in the present power system structure without compromising grid stability. As such, both generation planning through conventional or renewable sources and demand side management will both be important components of it by which we can effectively manage our energy crisis. This paradigm shift required in power system planning to facilitate clean and renewable energy source integration can be provided by artificial intelligence (AI). With the recent leaps made in its development, the application of AI can be a game changer in the development of modern power system planning solutions. The advanced analytical capabilities of AI can analyze the past, optimize the present and predict the future to mitigate most of the challenges being faced in the restructuring of the present power system such as the weather dependent variations in wind, photovoltaic and hydroelectric generation. AI algorithms can contribute in all the aspects of power system planning in the following ways:

1. Renewable Energy (RE) Forecasting

   a. AI based machine learning systems can generate accurate predictions of weather patterns
   b. The advance prediction of renewable energy capabilities by AI is capable of providing utility companies with information about when to use renewable energy
   c. The accuracy of AI generated weather prediction models make power generated from renewable sources more predictable thus increasing its adoption value

2. Demand Side Management

   a. AI can perform advanced analysis to find the correlation between several factors influencing the variation of power demand thus helping in understanding and optimizing consumer behavior

b. It can help operators and utilities to develop knowledge about the appliance usage pattern of consumers at specific times over a certain time period
c. AI can be used to develop intelligent home and institutional energy management systems
d. With the help of AI, systems can be developed to allow incentivization of large consumers of electricity when decreasing their energy requirements on short notice in order to stabilize the grid and generate cost savings for the consumers and grid operators
e. Overall, it can result in better control and operation of demand response applications

3.Monitoring and Control

a. Machine Learning (ML) applications can be deployed to analyze the data generated by advanced sensors, smart meters and other intelligent devices to increase grid resilience by recommending the best possible solutions for mitigating any problem that arises
b. Smoothening energy flow from the distributed generation sources to consumers by intelligent demand side flexibility can be made possible with AI applications
c. AI integration in the active management of the electricity grid can improve accessibility of renewable energy sources
d. Overall, integration of AI in the monitoring and control of the power grid will result in a flexible, resilient and decarbonized grid.

4. Energy Management Systems – Energy management systems (EMS) are expert systems which combine all the aspects of forecasting, demand side management as well as monitoring and control to decide the optimal utilization of available resources. Apart from efficient resource allocation these systems also take into consideration consumer comfort and priorities. With proper incentive schemes, EMS systems have the capability to encourage consumers to become prosumers by installing small scale renewable power generation sources. This can again give rise to an energy trading among the prosumers which can cater to the local load demand. Thus, energy management systems are going to play a key role in the modernization of the grid and transition of the power systems from centralized to distributed generation. However, the functions required to performed by EMS in a decentralized power system with distributed generation sources is extremely complex. Only the use of AI can handle the immense amount of complex data that needs to analyzed at very high speeds by the EMS to actually be effective.

By the above facts, it is already established that AI is dynamic, innovative, smart and better and renewables are the vanguard of the new and smart power generation technologies. The integration of such smart solutions in the present power infrastructure will lead to the transformation of the traditional grid into smart grid and the advent of microgrids. Such a transformation will facilitate the inclusion of renewable sources in the primary energy mix by mitigating intermittence drawback and reinforcing security of supply across the entire electricity system. A brief comparison between the traditional power infrastructure of today and the required power infrastructure of tomorrow is shown in Fig. 1.10. To delve further into the research work required to achieve the aforementioned transformation it is required to understand the relation between smart grid and microgrids. Microgrid can be defined as a subset of Smart grid as shown in figure 1.11. A brief comparison of their characteristics is given in table 1.1

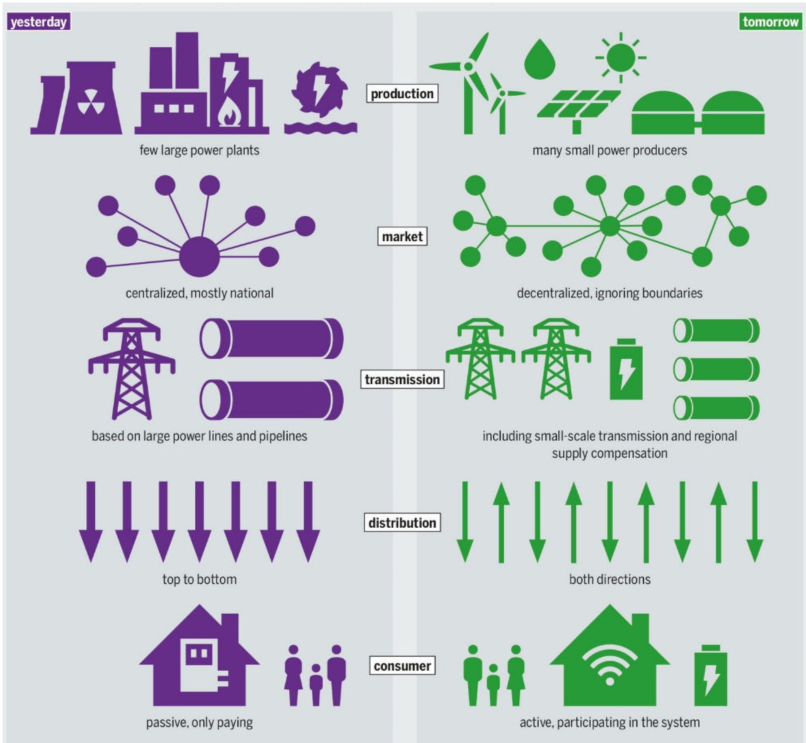


Fig.1.10 Transition of power infrastructure from present to future

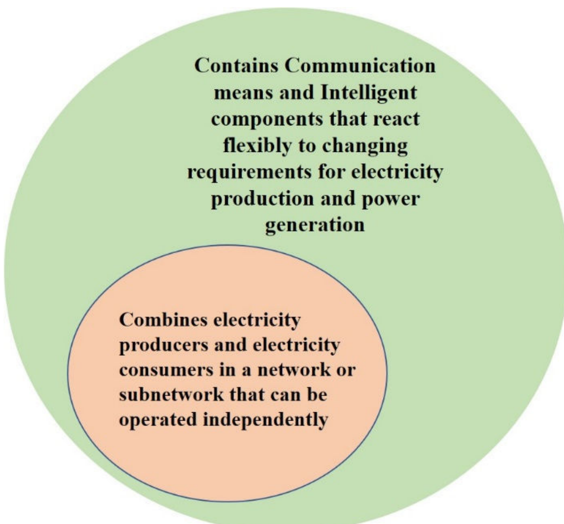


Fig.1.11 Salient property of Microgrid and Smart grid

Table 1.1 Comparative study of Smart grid and Micrograds

Microgrid	Smartgrid
It is a small-scale power supply designated to provide power for a small community	It is a large-scale power supply network that is designated to provide power for a large community
It enables local power generation for local loads	It enables local power generation for local as well as outstation loads
Size of the microgrid may range from housing estates to municipal regions	Size of smart grids are always bigger than municipal regions
Microgrid permits distributed generation at small scales as compared to smart grids	Smart grid permits distributed generation at a larger scale as compared to microgrids
Small substations at individual microgrids monitor and control power distribution using AI based energy management systems	Distribution of total generation carried out economically along with load dispatch centers
Installation cost is economical	Installation cost is very high
Microgrids are smaller in scale, requires fewer decision makers and have faster implementation	Smart grids operate at the utility and national grid level, involving large transmission and distribution lines
Microgrids can be considered as a subset of smart grid	Smart grid can be composed of a number of micro grids
Microgrid considers the utilization of distributed energy systems in order to improve the reliability and flexibility	Smart grid aims to combine intelligent techniques with electricity to improve the convenience and reliability of the whole electricity supply network
Microgrid is equivalent to small smart grid	Smart grid is equivalent to smart macro grid
Microgrid consists of interconnected loads and distributed energy resources within a clearly defined electrical and geographical boundaries which act as a single controllable entity with respect to the main grid	Smart grid is any electrical grid combined with ICT/IT/sensor technology at all levels

Thus, it can be seen that the major distinction between micro grids and smart grids lies in their scale and communication complexity. However, to increase the integration of renewable sources in the primary energy mix emphasis should be given to region based generation for catering to the local load demand. This falls more towards the zone of micro grids than smart grids. As such, a detailed discussion on the components of micro grid is given in section 1.2.

1.2 Microgrid

The definition of Microgrid appears in [1] as "A low-voltage and/or medium-voltage grid equipped with additional installations aggregating and managing largely autonomously its own supply- and demand-side resources, optionally also in case of islanding." Simply put, microgrids are localized energy systems that can operate independently or connect to the main grid. The general architecture of microgrid is shown in Fig. 1.9.

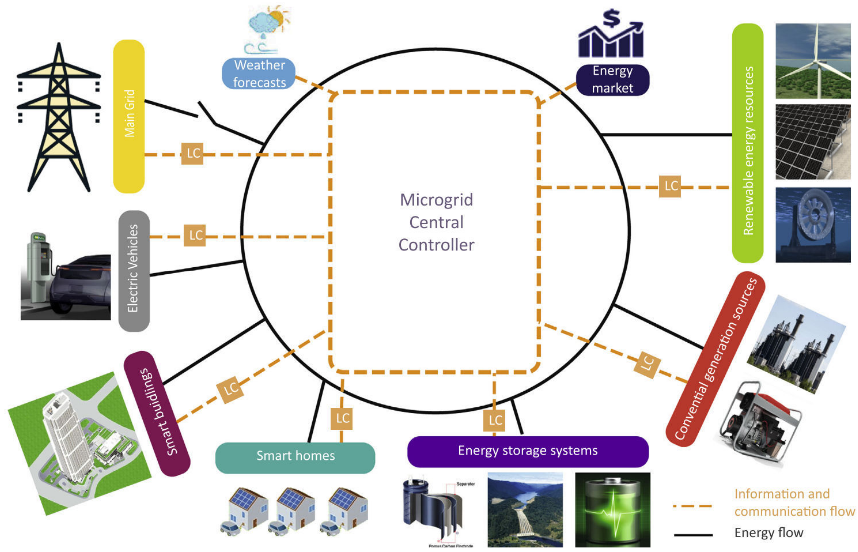


Fig.1.12 General Architecture of Microgrid

As classified in IEEE standard 1547.4, the main properties that a power system should have to be classified as a microgrid are as follows [2]

a. The planning of the system should be purposeful
b. The system should be capable of performing well without being connected to the power grid
c. It should contain local energy sources
d. It should be an integrated system consisting of distributed energy sources and loads

An overview of the systems included in a microgrid can be obtained from the figure 1.12.

1.2.1 Renewable energy sources

A. Solar Photovoltaic

Photovoltaic power is generated from the irradiance of the sun. It is the fastest growing form of renewable energy in the World and India. Solar power plants use semiconductor material which exhibit photovoltaic effects to generate electricity from sunlight. Fig. 1. 10 shows the image of Bhadla Power plant set up in Rajasthan, India. It is the largest solar power plant in the world. The following equations can be used model the operations of the PV panels. For maximum power extraction from PV panels, maximum power point tracking (MPPT) methods are used. Normally, PV panel voltage and current are increased by connecting solar cells in series and parallel, respectively. Subsequently, PV panels are also connected in series and parallel combinations for having required power production from PV system. However, PV systems are not able to meet load demand at all times due to the intermittent nature of solar energy and non-availability of sunlight at nights. Hence, additional DERs need to be installed with PV systems.

Fig.1.13 Bhadla Solar Park – World's Largest Solar Power Plant in Rajasthan, India

B. Wind Energy

Wind power is a significant renewable energy source in India, contributing to the nation's clean energy goals. As of 2024, India has an installed wind power capacity of over 44 GW, making it the fourth-largest wind power producer globally. The country's wind energy potential is estimated at 695 GW at 120 meters hub height, concentrated mainly in states like Tamil Nadu, Gujarat, Karnataka, Maharashtra, and Rajasthan. Tamil Nadu leads with the highest installed capacity, followed by Gujarat. Wind power accounts for about 10% of India's total installed power capacity. The government supports wind energy through initiatives like Generation-Based Incentives (GBI), capital subsidies, and Renewable Energy Certificates (RECs). Offshore wind potential along the Indian coastline is also being explored, with projects planned in Gujarat and Tamil Nadu. Challenges include land acquisition, grid integration, and variability in wind speeds. Despite this, wind energy remains a key component of India's renewable energy transition, aimed at achieving 500 GW of non-fossil fuel capacity by 2030.

C. Hydropower

Hydropower is a vital renewable energy source in India, contributing over 46 GW to the country's total installed capacity. It provides clean, reliable, and flexible electricity, playing a crucial role in balancing grid operations. In remote and hilly regions, small and micro-hydropower plants are pivotal in forming microgrids, supplying energy to off-grid communities. These microgrids enhance rural electrification, reduce dependence on fossil fuels, and support local development. India's vast hydropower potential is estimated at 145 GW, with a significant share remaining untapped, especially in the northeastern and Himalayan regions. However, challenges like land acquisition, environmental concerns, lengthy clearances, and displacement of local populations hinder growth. Seasonal variability in water flow due to monsoons and climate change further impacts generation reliability. High upfront costs and financing hurdles also pose barriers to new projects. Despite these challenges, hydropower remains crucial for India's renewable energy targets and grid resilience.

1.2.2 Weather and Demand Forecast

As discussed before, accurate weather and demand forecasting is required efficient power planning for the renewable source integrated modern grid systems. The generation capacity of the renewables and consumer power demand varies on several climatic factors such as solar irradiation, wind speed, humidity, temperature, precipitation etc. Economic activities, population growth and appliance ownership trends are also driving factors behind the increase in consumer power demand. The integration of weather and demand forecasting is highly essential in a decentralized power system model for aligning generation based on weather dependent renewable sources with demand, optimizing charging/discharging cycles of energy storage systems and maintaining equilibrium between supply and demand. Based on prediction horizon forecasting methods can be divided into –

a. Short Term Load Forecasting (STLF) – Ranging from minutes to hours, STLF is used for real time operations and dispatch
b. Medium Term Load Forecasting (MTLF) – Ranging from days to weeks, medium term forecasting is used for unit commitment and maintenance scheduling
c. Long Term Load Forecasting (LTLF) – With a forecasting horizon ranging from months to years, it aids in capacity planning and policy making

Conventional forecasting techniques consist of multiple linear regression and autoregressive integrated moving average (ARIMA) models, which, while useful, may struggle to capture the non-linear and complex nature of load data. Conversely, machine learning approaches such as artificial neural networks (ANN), support vector machines (SVM), long short-term memory (LSTM) networks, and convolutional neural networks (CNN) have gained prominence due to their ability to manage non-linearities and improve forecasting accuracy. A detailed explanation of these methods of forecasting have been given in Chapter 2.

1.2.3 Battery Energy Storage Systems

Battery converts electrical energy into chemical energy during charging, which is reversed in case of discharging. The depth of discharge (DOD) defines amount of energy capacity consumed and state of charge (SOC) defines amount of energy capacity left. The battery cycle usage has adverse impacts on battery lifetime. For better battery lifetime, it is preferred to use a narrower interval of SOC. Batteries are divided into two main types: primary and secondary batteries. Primary batteries are not rechargeable, while secondary batteries can recharge themselves. Batteries are also divided in terms of electrodes and electrolyte materials, like Nickel-Cadmium, Lead-Acid, and Li-ion batteries.

1.2.4 Smart Homes and Buildings

Smart homes and buildings are the future of sustainable living. They not only improve the quality of life for occupants but also contribute to global efforts to reduce energy consumption and environmental impact. By integrating advanced technologies and focusing on user centric design, smart buildings pave the way for a more efficient and connected world. The benefits of smart buildings can be listed as reduction in energy bills through efficient energy management, less maintenance costs and reduction in carbon footprints. The application of smart homes and buildings can be in the residential, commercial, industrial or healthcare sectors. The implementation of smart automation systems in homes and buildings is essential for their integration in microgrids and smart grids.

1.2.5 Conventional Power Sources

It will take some time to reduce the dependency of the power sector on conventional sources. Till then, conventional power sources will remain an integral part of the energy status. Thus, for a seamless transition, effective integration of conventional and renewable sources is required with the help of intelligent technologies to enhance grid efficiency, reliability and flexibility. Smart grids and micro grids use conventional sources to balance the variability of renewables, ensuring a stable power supply during intermittent generation. Conventional power sources can also work in conjunction with energy storage systems, ramping up and down based on grid needs.

1.2.6 Energy Management Systems

An energy management system works as the controller of the microgrid incorporating data from weather stations, smart homes, grid and energy storage systems to forecast the energy use patterns of the consumers and renewable energy availability to inform the consumers about the optimal scheduling of their appliances to minimize their energy use costs. The appliances of the consumers can be divided into different degrees of freedom ranging from fixed to flexible. An appliance whose operation can be scheduled at any time of the day is called a flexible or schedulable appliance whereas those appliances whose operations cannot be even slightly moved from their designated hours without discomforting the user are denoted as fixed or non-schedulable appliances. Any appliance whose operation can be shifted but within fixed predefined ranges are called partially flexible appliances. The proper designation of the appliances operating within the regional microgrid is very important to ensure the maximum efficiency of the energy management system being employed to operate the microgrid. The grid connected regional microgrid also helps the prosumers within the system to sell their excess generation to the grid thus further increasing their profit and in turn helping the system to obtain the net zero emission goals of the SDG.

With microgrids aiming to revolutionize electrification through decentralization and localized generation to cater to the local load demand along with active participation of the consumers the traditional way of looking at the utility consumer relationship is required to change. Traditionally, the power demand supplied by the utilities has been divided into residential, commercial, industrial, agricultural and public works. In view of the present infrastructure it is logical as in a centralized system a broader classification of the loads to be supplied is enough for system planning as the only information required would be the annual increase in peak load and revenue earned. However, for a more localized approach such as microgrids aiming to tackle the demand supply issue on an hourly basis a regional system planning is required. For a microgrid to operate efficiently, it would require a power system planning tailored to fit the generation and demand pattern of the region it is catering to. It can be understood by the present scenario of low adaptation of renewables as the primary source of energy by the consumers that a fit for all solution will not be an effective approach. The territory supplied by the traditional grid can be broadly classified as urban, semi urban and rural whose power demand characteristics and per capita energy consumption are quite different from each other. This difference arises from the demographic, climatic and socio-economic variations. A brief description of the characteristics of each region is given below:

Urban Region-

- Rapid growth in population with substantial increase in energy requirement
- High living standards with use of high energy consuming devices such as air conditioner (AC), Geyser etc
- Booming commercial sectors with retail malls, hotels, offices, Information technology (IT) parks, large apartment clusters
- Industries and warehouses

Semi urban Region –

- Growing electrification and economic development
- Increasing appliance penetration with increase in lifestyle
- Growing number of micro, small and medium enterprises (MSME)
- Growth in commercial sectors of business, education and healthcare facilities
- Challenges in power reliability
- Financial stress on distribution companies (DISCOMS)
- Energy efficiency prioritization

Rural Region –

- Intermittent and unreliable power supply
- Power infrastructure inadequate
- Significant agricultural sector consumption and subsidized electricity
- Distribution losses
- Increase in MSME
- Increasing demand for household electrification

In conclusion, the modernization of the present grid to smart grid will transform it into a combination of many regional microgrids supplying to the local as well as outstation loads. The regions encompassed by these microgrids can be demographically classified as urban, semi urban and rural or mixed demographic regions. The weather patterns of these different regions as well as appliance ownership, appliance use patterns appliance usage priority and per capita energy consumption of the consumers or prosumers will be significantly different. Understanding this diversity and developing an approach based on the demographical power generation and demand patterns will be key to ensure the optimal operation of the microgrids and subsequently the smart grid.

The increased penetration of renewable sources in India also face the following challenges:

- The intermittency of the renewable sources
- Variability of power supply and uncontrollable ramp rate during increased consumption
- The renewable generation is not coincident with peak load.
- The uncertainty in the generation of renewable resources does not allow load-generation balance
- Plants connected at remote locations with weak transmission networks

- Energy storage devices are costly to acquire and maintain thus, making it inaccessible for the less financially stable consumers

The measures that can be adopted for the mitigation of the above problems are as follows:

- Flexible load demand and ancillary services for supply balancing
- Better demand side management strategies based on regional characteristics for load balancing needs to be developed
- Sectorial forecasting of load demand to capture the differences between regional power consumption is required
- Policy and regulatory advocacy for power-balance market and pricing mechanism is needed.

This work focuses towards increasing the acceptance of renewable sources as primary power sources among the general population. It aims to do so by addressing the problem of load-supply balance acting as a major barrier in the adoption of renewable energy sources. To this end it strives to develop an effective forecasting and demand side management technique incorporating the demographic power demand characteristics which define the power consumption trend of the region in question.

Based on the above discussions some shortfalls in the present power system planning can be identified required to be addressed for the proper integration of renewable energy sources and modernization of the present power system. The identified shortfalls have been enumerated below:

- The development of an energy management system incorporating demand side and resource allocation management based on per capita energy consumption is yet to be explored
- The total number of power consumers supplied by any utility can be categorized as urban, semi urban and rural consumers
- The per capita energy consumption varies with the demography of the region under consideration namely urban, semi urban and rural
- Another aspect that is yet to be addressed is the continuous integration planning of renewable resources in both urban and rural regions
- With increasing penetration of renewable energy in the primary mix of energy supply it is critical to develop an energy management system which can adjust its parameters with the increasing renewable resource integration to present a long-term sustainable solution to regional energy management

The objectives of this dissertation as provided in section 1.8 makes an attempt to address these shortfalls and develop an improved power system planning approach suitable for addressing the power system modernization challenges on a demographic basis.

1.8 Objectives of Dissertation

i. Study and determine the difference in power consumption patterns of different urban, semi urban and rural regions and determine the appliance usage priority, functional window and functional duration to develop synthetic power consumption profiles of urban, semi-urban and rural consumers

ii. Develop an appliance use priority based artificial intelligence driven algorithm to select the percentage of hourly power consumption of an urban, semi urban or rural consumer that can be supplied by the hourly available renewable energy of the region
iii. Develop a robust yet simple forecasting method to perform short and medium-term electrical load demand forecasting for the domestic, commercial, industrial and public lighting sectors of different regions
iv. Determine a tariff scheme based on the characteristics of the regional power consumption for a grid connected regional energy community with options of power trading within the community and the grid.
v. Develop an efficient energy management system by identifying the load pattern and renewable energy generation of different regions and align the daily power demand with renewable supply based on tariff with emphasis on peak load reduction

1.9 Outline of the dissertation

The dissertation is organized in the following manner. It consists of an abstract and keywords followed by:

Chapter 1 contains the introduction of the thesis. It explores the present power scenario of India and presents the statistics of power consumption, primary energy mix, sector wise greenhouse gas emission along with the sustainable development goals and the actions needed to be taken by the country to obtain its climate action objectives as determined in COP26. It describes the importance of adopting the renewable energy resources in the primary energy mix through the formation of grid connected microgrids and the technologies being used to implement that.

In Chapter 2 the previous research works done for development of energy management systems. It explores the research works done in the field of forecasting, load monitoring and demand side management for increasing the efficiency of aligning the renewable generation with the consumer demand through implementation of different tariffs, incentives and involvement of the consumers.

In Chapter 3 the motivation of the work and the selection of the area of work is explained. The regional differences in demographics and power consumption of the urban, semi urban and rural areas are enumerated. The opportunity to use the regional difference in power consumption in the development of an efficient wide area energy management system is explored.

In Chapter 4 description of the research work performed in the field of forecasting is explained.

In Chapter 5 description of the research work done in the field of implementing artificial intelligence to determine the hourly percentage of load that can be supplied by the available renewable energy of the urban and rural areas in different seasons is explained.

In Chapter 6 description of the research work done in the development of a regional energy management system using different tariff structure, MILP based model predictive control with the implementation of different constraints is explained

In Chapter 7 conclusions, contributions and proposal for the future work are discussed.

Chapter 2
Literature Review

2.1 Literature Review

India's energy consumption is heavily reliant on fossil fuels, with coal and oil comprising 74% of the total energy supply. However, in recent years, the Indian government has committed to transitioning toward cleaner energy sources. The country has set ambitious targets, including achieving 175 GW of renewable energy capacity by 2022, with specific targets of 100 GW from solar energy, 60 GW from wind energy, 10 GW from bio-power, and 5 GW from small hydropower. India ranks fourth globally in installed wind capacity and fifth in solar capacity, with renewable energy accounting for approximately 21% of the total installed power capacity. This shift is crucial for meeting the United Nations Sustainable Development Goal 7 (SDG 7), which promotes increasing the share of renewable energy in the global energy mix. Despite progress, the country still faces several challenges, including high initial investment costs, technological limitations, and inadequate infrastructure for integrating renewable energy sources into the national grid [3]. Additionally, the country's reliance on coal for energy security poses a challenge in meeting SDG 7's targets for sustainable energy. A significant challenge in expanding renewable energy is integrating intermittent sources such as wind and solar into the grid. Due to the fluctuating nature of these energy sources, ensuring grid stability is a critical issue, necessitating advanced storage solutions and infrastructure development. By 2040, renewable energy consumption in India is expected to increase substantially, with an estimated solar potential of 750 GW and wind potential of 410 GW. In this projected scenario, renewables are expected to become the second-largest source of energy, overtaking gas and oil, thereby contributing to a more sustainable and diversified energy system [3]

As the global energy landscape shifts towards a more sustainable future, integrated energy systems (IES) and demand-side management (DSM) strategies have emerged as essential components for achieving energy efficiency, reliability, and economic operation. Accurate load forecasting is crucial for the efficient operation of smart grids and energy management systems. Recent advancements in machine learning and deep learning models have significantly improved forecasting accuracy. The technique developed by Rana & Koprinska is the AWNN model, which uses wavelet transforms and neural networks for short-term load forecasting. The model decomposes electricity load data into different frequency components and predicts them separately, achieving high accuracy in both one-step and multi-step ahead predictions [4]. An adaptive fuzzy model was proposed for short-term load forecasting by Cerne et al. Their approach solves the problem of daily load forecasting by breaking it down into smaller subproblems, each addressed with a Takagi-Sugeno fuzzy model. This method improves forecasting accuracy by combining the results of the subproblems [5]. Machado et al. proposed a feed-forward neural network (FFNN) model with an error correction step to enhance load demand forecasts. Their model uses a second FFNN to predict initial forecast errors, improving overall forecast accuracy [6]. A hybrid model that combines convolutional neural networks (CNNs) and gated recurrent units (GRUs) for hourly load forecasting was introduced by

Eskandari et al. Their model extracts load and temperature features using CNNs and feeds them into GRU units, resulting in improved short-term load forecasting performance [7]. LSTM networks have gained popularity for addressing time-series problems due to their ability to capture long-term dependencies in sequential data. A hybrid deep learning model was proposed by Farsi et al. that integrates long short-term memory (LSTM) networks and CNNs for short-term load forecasting. The model, called parallel LSTM-CNN Network (PLCNet), demonstrated superior performance in predicting electricity consumption patterns using real-world data sets from Malaysia and Germany [8]. A novel ensemble model for load forecasting that incorporates feature extraction, a densely connected residual block (DCRB), and bidirectional LSTM units was proposed by Chen et al. Their model effectively captures the randomness and trend characteristics of electricity load data, resulting in improved forecasting performance compared to CNN-based models [9]. Goudah et al. developed an LSTM-based model for predicting residential and industrial energy consumption. By considering the historical consumption data and adjusting for weather conditions, the model demonstrated robust accuracy for both daily and monthly predictions, proving particularly effective for handling time-varying load profiles influenced by temperature fluctuations [10]. An LSTM model was leveraged to enhance forecasting accuracy by including appliance consumption data in the model by Kong et al. The study demonstrated that the inclusion of such granular data improves prediction outcomes, particularly in scenarios with highly volatile consumption patterns, such as residential buildings with varying usage habits [11]. Unlike short term load forecasting, long-term load forecasting requires different strategies, particularly when dealing with large datasets and fluctuating demand patterns. Yiyan et al. addressed this issue with a data-driven linear clustering (DLC) method that pre-processes substation load data and clusters it for modelling with autoregressive integrated moving average (ARIMA) models. This method showed promise in improving the accuracy of long-term predictions by reducing the complexity of load fluctuations in large datasets [12]. An ensemble method for aggregated load forecasting using sub profiles derived from smart meter data was proposed by Wang et al. By clustering these sub profiles and applying ensemble methods, their model improved the accuracy of aggregated forecasts, demonstrating that fine-grained data can provide valuable insights for large-scale load prediction [13]. Apart from the methods mentioned in the previous works, fuzzy models have also been applied to address uncertainties in load forecasting. Cerne et al. presented a Takagi-Sugeno fuzzy model for solving daily load forecasting problems by dividing them into smaller subproblems. The use of fuzzy clustering improved accuracy by allowing for the better handling of nonlinearities and uncertainties present in energy consumption data [5]. In probabilistic load forecasting, Rafiei et al. proposed a hybrid method using generalized extreme learning machines and wavelet neural networks. Their approach accounted for data noise and model uncertainties, delivering probabilistic intervals rather than single-point forecasts. This method was validated with data from the Ontario and Australian electricity markets, showcasing its potential for improving reliability in highly variable markets [14]. In large, geographically distributed power systems, localized forecasting models offer greater accuracy than centralized models. Liu et al. proposed a distributed load forecasting method based on local weather information. Their approach divided a bulk power system into subnets and developed separate models for each subnet, improving forecasting accuracy by considering local variations in weather and load patterns [15]. The need for more granular forecasting also extends to smart homes and buildings, where monitoring systems like NILM (Non-Intrusive Load Monitoring) play a key role. As discussed by Anon. (2016), NILM systems disaggregate the overall energy consumption into individual appliance profiles, allowing for more precise energy management at the residential level. This method improves the accuracy of predictions by focusing on appliance-level data, thus providing more detailed insights into consumption patterns. Recent studies emphasize the value of hybrid models that combine various deep learning techniques to improve prediction accuracy. Farsi et al. introduced the Parallel LSTM-CNN Network (PLCNet), a hybrid model that integrates long short-term memory (LSTM) networks with convolutional neural networks (CNNs). Tested on real-world datasets from Malaysia and Germany, PLCNet was found to significantly outperform traditional models in short-term load forecasting by capturing both temporal and spatial dependencies in electricity consumption data [8]. Similarly, Chen et al. proposed an ensemble model comprising a feature extraction module, a densely connected residual block (DCRB), and bidirectional LSTM (Bi-LSTM) layers. This four-stage model extracts both basic and derived features (such as temperature and load data), addressing multi-scale input challenges and providing more reliable forecasts than CNN-based models. This highlights the importance of incorporating both historical and derived features for better performance in STLF [9]. Accurate forecasting of renewable energy generation, particularly from PV systems, is critical for effective energy management. Kim et al. (2021) address the challenge of predicting PV module temperatures, a key determinant in energy generation. By developing a new equation that reduces prediction errors to within 1.64°C, they significantly improve the precision of PV energy generation forecasts, which is crucial for optimizing energy usage in grid-connected and off-grid systems [16].

After forecasting the load demand and other parameters the most basic process of demand side management is to obtain the objective of reducing electricity consumption through the optimization of the consumption profile of the consumer. The connected loads can be divided into flexible or non-flexible. The flexible loads are scheduled in a way so that the peak load is reduced and the off-peak valley is filled. Load profile optimization plays a crucial role in integrating renewable energy into isolated and off-grid systems. Ciabattoni et al. developed a high-resolution model based on a fuzzy logic inference system (FIS) to simulate domestic electricity use. The model uses occupancy patterns and domestic habits as input data to predict the starting probability of each appliance, helping to optimize energy use at the household level [17]. Tan et al. proposed a linear programming model for load scheduling that minimizes energy costs while providing flexibility to end-users, such as the ability to define multiple time intervals for appliance operation. This flexibility is critical for DSM in smart grids, where users can choose between interruptible and non-interruptible operations based on their preferences [18]. Prinsloo and Johannes conducted a scoping exercise to determine load profile archetypes for solar co-generation models in rural African villages. This work underscores the importance of load profile management in enhancing the performance of renewable energy systems, especially in regions with limited grid access [19]. Jindal et al. explored data-driven demand response management schemes for the residential sector, focusing on reducing peak load demand while maintaining consumer comfort and willingness to participate. Their approach demonstrates how utilities can manage residential loads effectively to minimize demand-supply gaps in the electricity market [20]. Effective demand response (DR) strategies are essential for managing energy consumption and enhancing grid stability. Dynamic pricing mechanisms have been identified as effective tools for managing peak demand and promoting energy efficiency. Idrissi et al. developed a collective energy consumption scheduling (CECS) algorithm for residential sectors using a bi-level game theory approach. Their model aimed to reduce peak load demand by implementing load-shifting and time-activation cycling for controllable appliances such as electric vehicles and high voltage AC (HVAC) systems [21]. Yang et al. investigated time-of-use (TOU) pricing models that aim to improve power quality and reduce power losses in the electrical distribution system. Their model optimizes pricing structures to encourage energy-efficient behaviors among consumers, ultimately contributing to reduced energy demand during peak hours [22]. Non-intrusive load monitoring (NILM), or energy disaggregation, plays a vital role in the smart grid ecosystem, providing valuable insights into the power consumption patterns of individual appliances by analyzing aggregate energy consumption at the mains. Advances in NILM, particularly through deep learning, edge computing, and optimization techniques, have significantly improved the accuracy and efficiency of load disaggregation, energy planning, and demand-side management. Shahab et al. (2023) propose a deep-learning and edge computing approach that builds upon the seq2-point CNN model, introducing a seq2-[3]-point CNN for home-level and site-level NILM problems. Their model achieves notable accuracies of 94.6% for home-NILM and 81% for site-NILM, using the REDD dataset and the REFIT dataset, respectively. In addition, they extend this work to appliance identification using pre-trained 2D-CNN models (AlexNet, ResNet-18, and DenseNet-121) with Wavelet and short-time Fourier transform (STFT)-based 2D electrical signatures. Their approach achieves an impressive 88.9% accuracy in appliance identification using ResNet [23]. Similarly, Rottondi et al. (2019) present an optimization algorithm for NIALM that focuses on minimizing the discrepancy between total energy consumption and the sum of individual appliance contributions. Their approach, tested against combinatorial optimization and factorial hidden Markov models from the NILMTK framework, demonstrates superior performance under certain conditions, offering a competitive alternative for energy disaggregation [24]. The increasing penetration of renewable energy sources, such as photovoltaic (PV) systems, have not only opened up new horizons of DSM but have introduced new challenges for grid operators. Energy management systems (EMS) have become increasingly important in managing distributed generation (DG) and demand response (DR) programs. The dynamic nature of energy demand and renewable energy generation necessitates advanced methodologies that account for varying consumer behaviors, renewable uncertainties, and system constraints. Over the years, research has focused on integrating machine learning, optimization techniques, and forecasting models to enhance energy management systems' efficiency, particularly in demand-side management (DSM), distributed generation, and smart grids. The integration of distributed generation (DG) and DR programs into energy management systems plays a crucial role in ensuring grid stability and reducing energy consumption costs. As such, Rahman & Begum reviewed renewable energy resources in Bangladesh and proposed DSM strategies for addressing the country's power crisis [25]. Debnath & Mourshed (2018) provide a comprehensive review of 483 energy planning models, evaluating forecasting methods based on accuracy, spatial-temporal applicability, and policy relevance. Among the methods reviewed, artificial neural networks (ANNs) are the most widely used, accounting for 40% of the models. Computational intelligence (CI) methods such as support vector machines (SVM), genetic algorithms (GA), and particle swarm optimization (PSO) also demonstrate strong performance, particularly for variables with high variability. The review highlights the advantages of hybrid methods in improving forecasting accuracy, especially for long-term energy planning [26]. Paracha & Doulai highlight the importance of various load management techniques in power systems, arguing that global utilities can provide reliable and economical services by adopting these methods [27]. Gong et al. highlighted the role of home energy management (HEM) techniques in addressing the challenges posed by PV energy penetration, such as the "duck curve." Their study demonstrated the potential of electric water heaters as low-cost energy storage systems to support load shifting and peak shaving, thereby improving grid stability [28]. Xu et al. developed a novel energy management system that optimizes the scheduling of household appliances to maximize utility and minimize energy costs. Their model addresses the uncertainty of renewable energy production by applying probability theory to transform the uncertain optimization problem into a convex optimization problem. This approach enhances the efficiency of renewable energy and storage systems [29]. Pereira et al. proposed a methodology for scheduling DG and DR resources by considering various approaches for DR program remuneration, such as Steps, Quadratic, Constant, Linear, and Elastic models. This approach is particularly beneficial for Virtual Power Players (VPPs) who aggregate small-sized consumption resources, enabling their participation in DR programs. This methodology offers flexibility in managing resources and optimizing their participation in response programs [30].

The integration of artificial intelligence into energy management systems has opened new avenues for optimizing energy distribution and demand response. Jarmouni et al. introduced artificial neural networks (ANN) for multi-source energy management in smart grids. Their work highlights the potential of ANN in predicting energy demand, optimizing energy use, and improving overall grid stability [31]. Cimen et al. focused on non-intrusive load monitoring (NILM) systems, which use machine learning techniques to analyze household energy consumption patterns. These systems enable utilities to better understand load profiles, identify energy-saving opportunities, and tailor demand response strategies to individual users [32]. Pombo et al. emphasized the importance of reference systems as platforms for evaluating new technologies and methods in energy management. These systems provide a framework for comparing various energy management strategies before real-world implementation, helping to mitigate risks and ensure the effectiveness of new approaches [33]. Palaniappan et al. discuss the integration of data mining techniques in demand response management, focusing on the electricity consumption patterns of consumers. By utilizing K-means clustering, their study segments consumer load data into meaningful categories that can then be used to predict demand and optimize load scheduling. Advanced classification models such as support vector machines (SVM) and logistic regression are employed to improve the accuracy of consumption prediction. This approach enhances demand response strategies, allowing for more precise control of load distribution in smart grids [34]. Truong and Jeenanunta introduce a Fuzzy Mixed Integer Linear Programming (MILP) model for large-scale monthly unit commitment (MUC), addressing the uncertainties in fuel prices that impact electricity generation decisions. The application of fuzzy logic to accommodate these uncertainties provides a more resilient framework for national power systems. Sensitivity analysis using a national-level planning dataset in Thailand confirms the effectiveness of the proposed model in managing the complexities of MUC [35]. The advancement of energy disaggregation techniques, particularly through deep learning, is explored by Virtsionis-Gkalinikis et al. Their research incorporates an attention mechanism into neural networks to enhance computational efficiency in appliance energy consumption estimation. The proposed self-attentive neural network architecture demonstrates comparable performance to traditional models while reducing training and inference times, showcasing the potential for machine learning applications in energy management [36]. Vivas et al. focus on a fuzzy logic-based EMS for microgrids with combined battery and hydrogen energy storage systems. The study emphasizes the balance of power supply and demand, integrating renewable energy sources to enhance microgrid performance. The fuzzy logic controller employed in the EMS allows for greater flexibility and expert knowledge incorporation, contributing to the overall reliability and economic viability of microgrid operations [37].

Thus, it has been established that artificial intelligence aided demand-side management (DSM) plays a vital role in improving energy efficiency and aligning energy consumption with supply, particularly in systems with a high share of renewable energy. With the advent of smart grids aiming to move the society away from the conventional power generation and towards an entirely sustainable renewable based power structure, the requirement of demand side management through energy management systems cannot be disputed. Logenthiran et al. applied heuristic optimization techniques for DSM in smart grids. Their work focuses on the application of evolutionary algorithms to optimize load distribution, reduce peak demand, and improve the overall efficiency of the grid [38]. Cruz et al. explored how DSM can leverage data-driven decision-making to optimize appliance scheduling, resulting in bill savings and more efficient energy usage. They validated their DSM approach across three use cases, demonstrating its applicability in both renewable and non-renewable energy systems [39]. Smart homes, equipped with schedulable loads, can also contribute to reducing peak load demand, thus supporting grid stability. Mansouri et al. proposed a tri-objective optimization framework for energy management in microgrids, considering the role of smart homes and demand response (DR) programs. This framework was implemented on an 83-bus distribution system with 11 microgrids, showcasing the potential of coordinated scheduling in improving grid performance [40]. Panda et al. developed a dynamic load-priority-based residential energy management system (REMS) that utilizes the Adaptive Salp Swarm Algorithm (ASSA) to manage uncertainties in renewable energy availability. By prioritizing loads based on consumer preferences and optimizing appliance operation, their system effectively reduces peak loads and facilitates cost-effective electricity use, outperforming traditional scheduling techniques [41]. Sorour et al. present a robust EMS designed for domestic photovoltaic (PV) and battery applications, emphasizing the reduction of absolute net energy exchange with the utility grid. By employing Mixed-Integer Linear Programming (MILP) and utilizing two-day-ahead forecasts for energy demand and PV generation, the proposed system significantly increases self-consumption and reduces energy costs. The real-world application at Swansea University demonstrated a remarkable reduction in operating costs and energy bills compared to existing solutions, thus showcasing the potential of optimized energy management in residential settings [42]. The influence of DSM on power systems stability is assessed by Wang and Milanovic, who introduces a composite stability index to evaluate the impact of advanced DSM on angular and frequency stability. Through various case studies, the critical factors influencing system stability are identified, providing valuable insights for deploying DSM strategies effectively [43]. Wu et al. present a low-complexity fuzzy logic controller for residential grid-connected microgrids, focusing on minimizing grid power fluctuations. The controller's design parameters are optimized for microgrid behavior, demonstrating the feasibility of implementing such systems in real-world residential settings [44]. Youssef et al. explore the application of leader beluga whale optimization (LBWO) and original beluga whale optimization (BWO) in implementing DSM schemes. Their findings indicate significant reductions in electricity costs and peak-to-average ratios, emphasizing the effectiveness of optimization strategies in enhancing the economic viability of residential energy management [45].

The integration of advanced energy management systems (EMS) and innovative strategies for optimizing energy consumption and generation has become increasingly crucial in addressing the challenges posed by rising energy demands, fluctuating renewable energy sources, and the growing prevalence of electric vehicles (EVs). Various optimization techniques have been explored to enhance the efficiency of DSM systems and renewable energy integration. Ramu et al. introduced an enhanced reinforced binary particle swarm optimization (RBPSO) technique for managing solar PV power distribution. This DSM strategy leverages solar PV generation forecasts to adjust load consumption schedules, thus reducing peak energy demand and improving user comfort. The effectiveness of this method was demonstrated by comparing its results to a conventional genetic algorithm [46]. Wang et al. proposed a multi-objective optimization approach to manage the flexibility of air-conditioning systems. By incorporating a flexibility factor along with operational energy consumption, the study aimed to reduce energy use during peak periods while maintaining occupant comfort. The entropy-grey technique was used for decision-making in a day-ahead operation, providing valuable insights for energy management in office buildings [47]. In another study, Mansouri et al. developed a multi-objective model for designing energy hubs, incorporating power-to-gas (P2G) technology and demand response programs. This model, formulated as a mixed-integer non-linear programming (MINLP) problem, optimizes energy resource allocation while considering the variable efficiency of converters, equipment degradation, and load growth [48]. Xu et al.

also introduced a two-stage multi-objective optimization framework for enhancing demand response programs in grid-connected microgrids. The first stage focuses on the economic optimization of energy management, while the second stage addresses demand-side flexibility. They proposed the Average Power Flexibility during Peak Period Index (APFDPPI) to assess the energy flexibility of DR programs [49].

Fuzzy logic and heuristic optimization techniques have gained traction in energy management systems due to their ability to handle complex decision-making processes. Khalid et al. developed an energy management controller using fuzzy logic to regulate appliances while employing heuristic algorithms, such as BAT-inspired and flower pollination algorithms, to schedule shiftable appliances. Their hybrid BAT-pollination optimization algorithm proved effective in reducing costs, energy consumption, and peak-to-average ratio (PAR) [50]. Sumaiti et al. proposed an integrated approach using random willingness factors and load profile attributes can mitigate uncertainties in customer behavior. Their study used three models—linear, exponential, and nonlinear—to represent customer willingness, incorporating a fuzzy inference system (FIS) to handle nondeterministic behaviour [51]. Deka et al. discuss supply-side management (SSM) techniques, specifically the design and testing of control devices to regulate power flow at the consumer end, emphasizing the value of automated solutions [52]. Wang et al. provide further insight into demand response (DR) models for electric and thermal loads in integrated energy systems (IES). Their work highlights the role of scheduling elasticity (SE) in guiding users toward more economical energy use [53]. Similarly, Yang et al. explore integrated demand response (IDR) within regional energy systems (RIES), detailing the importance of price-based and alternative response mechanisms in stabilizing load fluctuations and optimizing energy use [54]. Yuan et al. introduced a risk-adjusted, data-driven approach for managing energy in microgrids. By integrating demand response aggregators with renewable energies, their model reduced energy management risks while promoting optimal energy use [55]. Similarly, Zhuo et al. tackled the stochastic nature of energy management in power systems by proposing a response surface method (RSM) for solving computational intractabilities, making energy management more efficient [56]. Afzal et al. presented a distributed demand-side management system that integrates the Internet of Things (IoT) and smart meters. Their model allows users in community microgrids to optimize their daily energy consumption by playing a game that minimizes individual and collective energy costs. This system is particularly relevant in the context of renewable energy sources, where real-time energy trading among users and shared community microgrids helps reduce overall consumption costs [57]. Arcos-Aviles et al. emphasize the increasing penetration of RES in utility networks and the growing importance of effective EMS to manage microgrids efficiently. To tackle the challenges associated with the stochastic nature of RES, they propose an offline-trained fuzzy logic control (FLC) methodology. This method reduces computational complexity while optimizing the power exchanged between the microgrid and the utility network. By minimizing power peaks and fluctuations, the EMS ensures stable system operation. The study compares FLC with various nature-inspired optimization algorithms, demonstrating that approaches such as particle swarm optimization and differential evolution enhance performance and system stability [58]. Similarly, Dandoussou and Kenfack develop a fuzzy logic-based smart switch controller for load shedding prevention in hybrid systems. Their system incorporates three energy sources—photovoltaics, batteries, and the grid—to make real-time decisions on energy switching based on environmental and system inputs. The smart switch enhances system reliability by dynamically selecting the most appropriate energy source, thus minimizing system disruptions due to load shedding [59]. Meje et al. focus on the implementation of real-time fuzzy logic controllers for hybrid renewable energy systems (HRES), specifically in rural applications in South Africa. Their study demonstrates the feasibility of using fuzzy logic to manage power flows between diesel generators, batteries, and renewable energy sources. The real-time EMS efficiently stores excess energy while ensuring that power is supplied based on the varying demands of the system. This work emphasizes the importance of real-time optimization in hybrid systems, laying the foundation for future applications in hardware-in-the-loop testing [60]. Shuvo and Yilmaz address the growing impact of electric vehicle (EV) charging on the distribution grid, proposing a customer-feedback-based EV charging scheduling method. Their approach minimizes the peak load on distribution transformers while extending their lifespan through a deep reinforcement learning-based maintenance policy. This dual approach provides a comprehensive solution for efficient capacity planning, highlighting the potential for AI-driven optimization in managing EV integration into the grid [61]. The challenge posed by the increased adoption of EVs on traditional electricity grids is tackled by Tulabing et al., who propose a non-wire solution using Localized Demand Control technology. This approach enables localized grids to adhere to preferred demand curves through coordinated actions of flexible loads. Real-world validation and simulations suggest significant improvements in peak demand reduction and network efficiency, highlighting the importance of localized strategies in modern energy systems [62]. The increasing penetration of distributed energy resources (DERs) and flexible loads, such as EVs, has led to new challenges in grid stability and congestion management. Khan et al. (2023) propose a deep deterministic policy gradient reinforcement learning approach for congestion management, which operates without requiring probabilistic models of controllable loads. Their model, tested on the IEEE 33-bus system, proves to be more effective in reducing electricity costs and improving peak-to-average ratios compared to conventional congestion management methods [63]. Similarly, Karimi et al. (2023) present a multi-objective optimization framework aimed at improving the efficiency of demand response programs in distribution networks. By enhancing demand-side flexibility and optimizing energy management in grid-connected microgrids, their model achieves significant reductions in operational costs and peak loads, while improving energy flexibility by introducing a novel index, the Average Power Flexibility during Peak Period Index [64]. Mahmud et al. (2018) introduce an advanced decision-tree-based control algorithm for managing peak loads in residential distribution networks, particularly by coordinating electric vehicles (EVs), photovoltaic (PV) units, and battery energy storage systems (BESSs). Their approach not only reduces peak demand but also improves the overall load factor, demonstrating the effectiveness of real-time control in distributed energy systems [65].

As energy systems become more decentralized, peer-to-peer (P2P) energy exchange and multi-agent systems are gaining prominence. Huang et al. designed a joint clearing process for electric energy and reserve markets that considers interruptible loads. Their model aims to maximize social welfare by incorporating interruptible loads into the joint market under a bilateral mode, demonstrating the effectiveness of their approach through simulation results [66]. Thirugnanam et al. explored P2P energy exchange strategies within multi-microgrids and hybrid AC/DC microgrids. Their research focused on improving energy management in commercial buildings and maximizing energy exchange efficiency between interconnected microgrids [67] [68]. Shi et al. proposed a distributed energy scheduling model for integrated energy system clusters, with P2P energy transactions facilitating optimal energy use [69]. Tofighi-Milani et al. proposed a model which ensures that local agents within a multi-agent distribution system independently schedule their resources to maximize their own profits, taking into account network constraints such as line loadings and losses [70]. These approaches promote a more flexible, decentralized energy market while ensuring system stability. Afzali et al. introduce the concept of holacracy as a new social structure applied to energy management, shifting away from traditional hierarchical systems to a more autonomous, self-organized system. The application of holacracy in energy management empowers consumers (or prosumers) to participate actively within energy communities, optimizing local energy supply while fostering self-organization. The introduction of a "community convenience index" allows for the inclusion of prosumer preferences in energy management, leading to enhanced system convenience and higher hosting capacity in smart microgrids. This novel approach aligns with the movement toward decentralized energy systems, enabling more democratic governance and decision-making in local energy communities [71]. Deng et al. propose an analytical stochastic dynamic programming (SDP) algorithm for managing community energy storage systems in price-maker markets. Their approach considers the price-smoothing effect of energy storage and its impact on consumer costs and producer revenues. The proposed method maximizes both energy arbitrage and community welfare, optimizing storage operations while reducing computational complexity. By evaluating the marginal values of current and future storage use, the SDP framework provides efficient energy storage management, leading to more sustainable community energy practices [72]. Finally, Zahraoui et al. discuss the establishment of a Local Energy Market (LEM) for multi-microgrid systems, highlighting the potential for improved energy trading and social welfare maximization. Their decentralized clearing algorithm demonstrates the viability of protecting participant privacy while ensuring efficient energy exchange within the community [73].

Thus, from the above discussion, it can be concluded that load forecasting, monitoring and management is a well-researched area. However, the in future, the modernization of the grid advocates a shift from the present centralized structure to a decentralized and localized structure. In such a structure, the operational efficiency of the system will have major dependence on the energy usage characteristics of the consumers and the generation characteristics of the local renewable sources. The consumers of electricity can be broadly classified as urban, rural and semi urban. The energy usage characteristics of these three categories vary considerably as has been explained in chapter 3. In a centralized structure having the security of supply from fossil fuels, the main focus is on meeting the peak load demand and revenue earned. As such, the combined characteristic of the area being supplied takes precedence over the individual characteristics of these three categories of urban, rural and semi urban consumers. However, in a decentralized structure with the integration of renewables, the consumer power usage characteristics and the local renewable generation characteristic need to be minutely adjusted to prevent any inconveniences or system failure. From this point of view, with the advent of micro grids and smart grid, the approach towards developing demand management systems by regional classification of power consumers have become even more important. By analysing the present research solutions on demand management systems, it has been found that an approach towards the development of a system incorporating the regional classification of the consumers in urban, semi urban and rural according to their per capita energy consumption has not yet been made. The implementation of consumption pattern-based energy management systems would also require a tariff system based on the consumption patterns as a means to control their usage of power to ensure maximum efficiency of energy utilisation. The present solutions do not explore this avenue thus leaving room of improvement which has been attempted in this work. The present solutions also do not consider the effect of pre-allocation of the available renewable resources towards self and community consumption according to appliance utilization characteristics of urban, rural and semi urban power consumers. The pre-allocation of resources can play a crucial role in increasing the efficiency of energy management systems as it allows for pre-informed demand response management which can reduce power wastage and supply uncertainty. This can result in a more inclusive demand response system which is critical in ensuring affordable, reliable and modern supply to urban, rural and semi urban regions being catered to by the energy management system. Another aspect that is yet to be addressed is the continuous integration planning of renewable resources in both urban and rural regions. With increasing penetration of renewable energy in the primary mix of energy supply it is critical to develop an energy management system which can adjust its parameters with the increasing renewable resource integration to present a long-term sustainable solution to regional energy management.

2.2 Chapter Conclusion

From the above discussion, it can be understood that there is room for improvement in the development of demand response management systems in the decentralized power system structure. The work presented in this thesis attempts to address these issues through a regional demography-based approach by categorizing the consumers of power into urban, rural and semi urban according to their per capita energy consumption. Detailed explanation of the approach can be found in the following chapters.

Chapter 3

Problem Identification and Research Motivation

3.1 Introduction

Electricity has become indispensable in today's world. In India, the energy demand is consistently rising with urbanization, rural electrification programs, increase in population, industrial expansion, and modernization. The per capita electricity consumption in India increased from 15 kWh in 1950 to 1,255 kWh in 2022 as shown in Fig 3.1.

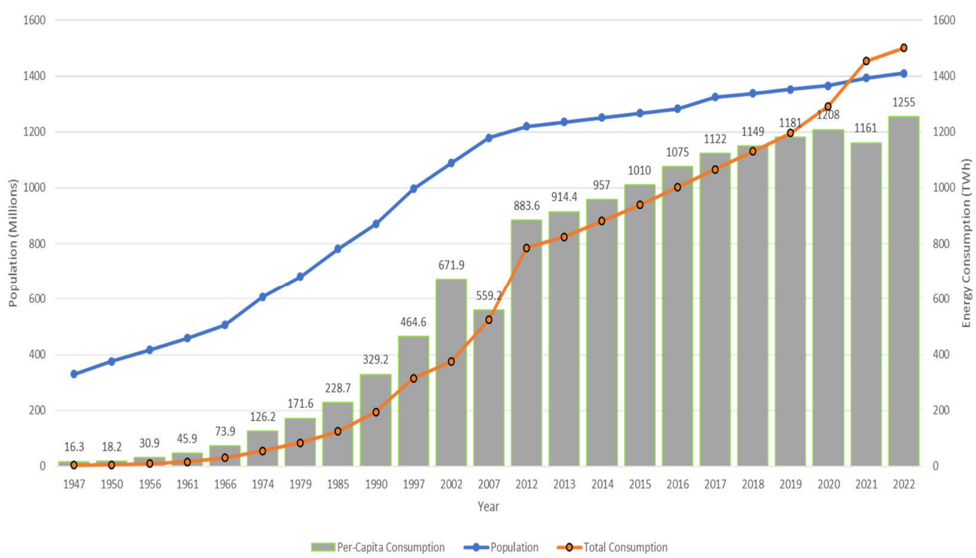


Fig. 3.1 Population and Per Capita Energy consumption growth from 1947 to 2022

The electricity consumers of the country can be demographically divided into urban, semi urban and rural categories. There is significant difference among the power usage characteristics of these categories. The per capita energy consumption is high for urban area households compared to their semi urban and rural counterparts. Fig.3.4 shows that there is a considerable difference in appliance ownership levels between the urban and rural regions of the country even for the lowest income group (Q1).

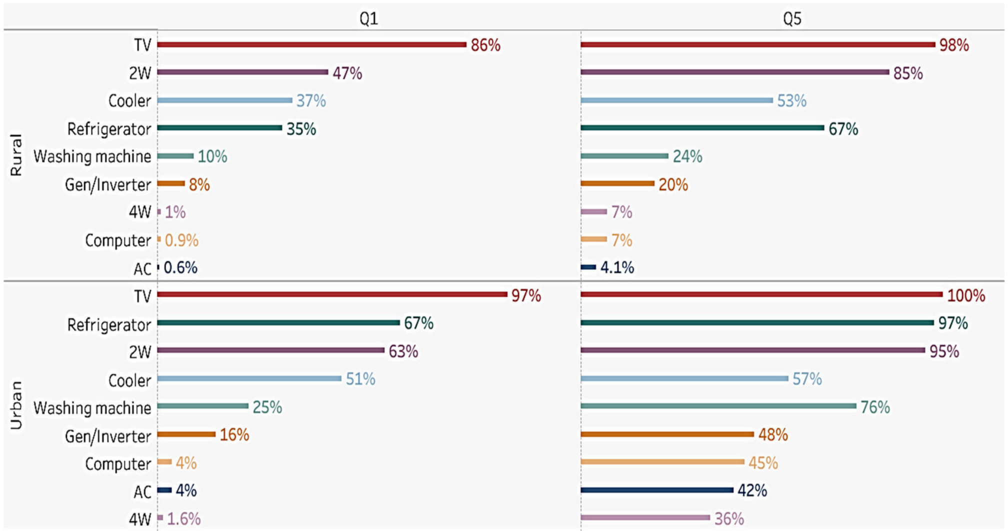


Fig. 3.2 Percentage of appliance ownership comparison between urban and rural households of the lowest (Q1) and highest (Q5) income groups in 2019

Thus, with the advent of microgrids where localization of demand supply is the keystone, an approach to tackling the issue of demand and supply different from that of the traditional residential, commercial, industrial, agricultural and public works division of load will be required. This difference in approach can be provided by the demographical classification of power demand in the urban, rural and semi urban. A brief analysis of the power demand characteristics based on the demographical classification is provided in section 3.2.

3.2 Demographical Region Power Demand Characteristics

3.2.1 Urban Area: Increasing Urbanization and Demand Growth

India's urban power scenario is marked by a unique blend of opportunities and challenges due to rapid urbanization, growing electricity demand, and the transition towards sustainable energy systems. With increasing population density, industrial activity, and the rise of smart cities, the country's urban power landscape is experiencing significant shifts. India's urban population is growing rapidly as shown in Fig 3.3 to Fig 3.5, contributing significantly to the country's overall energy consumption.

Fig. 3.3 Urbanisation in India – The 7 Largest Cities in India. Source: India Infographics

Cities such as Delhi, Mumbai, Bengaluru, and Hyderabad are among the top consumers of electricity. This urbanization drives higher demand for reliable electricity, as cities account for a substantial share of commercial, industrial, and residential electricity use.

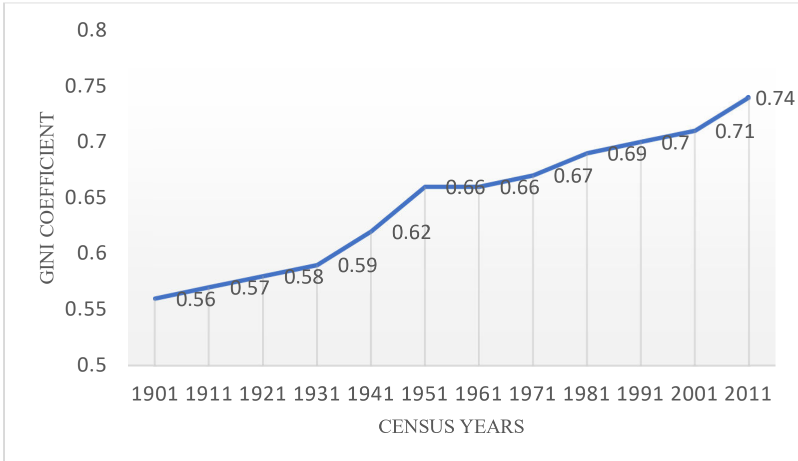


Fig. 3.4 Gini Coefficient for population distribution between size classes of cities (Class I to Class VI) (1901–2011).

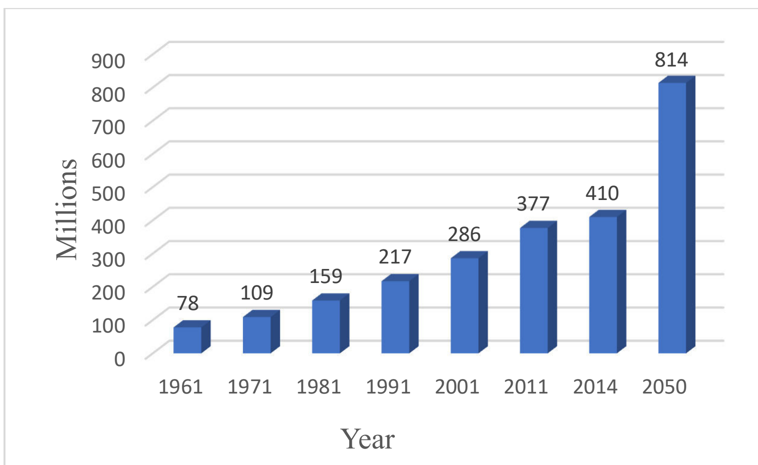


Fig. 3.5 Urban population growth in India 1961-2050. Source: Census of India 1961-2011. The figures of 2014 and 2050 are taken from UN DESA, 2014

The residential sector in urban areas is characterized by rising living standards, increased use of household appliances, and the demand for air conditioning, leading to higher electricity consumption. The commercial sector, driven by retail, offices, and IT parks, also places significant pressure on urban power infrastructure.

A. Transition to Renewable Energy

India has set ambitious renewable energy targets, and urban areas are playing a pivotal role in achieving these goals. Urban power infrastructure is increasingly incorporating renewable energy sources, particularly solar power. The government's push for rooftop solar installations is a major focus in urban settings, where space is a constraint but energy needs are high. India aims to install 40 GW of rooftop solar by 2022, a large portion of which is expected to come from urban areas. Although the uptake has been slower than anticipated, cities are making steady progress in adopting solar energy, reducing dependence on traditional power sources. Some cities are implementing hybrid systems, combining grid electricity with renewable energy sources such as solar and wind, alongside energy storage systems, to ensure reliable power during peak hours.

B. Smart Grid and Energy Efficiency Initiatives

Smart grid initiatives are becoming central to managing the complexity of urban power systems in India. These technologies aim to improve grid reliability, reduce losses, and enhance the integration of renewable energy. Key components include:

Smart Meters: The deployment of smart meters is a crucial part of modernizing urban power distribution systems. These meters enable real-time monitoring, improved billing accuracy, and help in demand-side management. States like Maharashtra, Delhi, and Uttar Pradesh are leading in the deployment of smart meters.

Energy Efficiency Programs: The Perform, Achieve and Trade (PAT) scheme and initiatives by the Bureau of Energy Efficiency (BEE) are aimed at improving energy efficiency in urban sectors like industry, buildings, and transport. Urban areas are also seeing an increase in energy-efficient appliances, such as LED lighting and energy-efficient cooling systems.

C. Challenges in Power Distribution

While India has made strides in improving electricity access in urban areas, several challenges persist:

Aging Infrastructure: Many Indian cities face issues with aging power distribution infrastructure, leading to frequent outages, technical losses, and inefficient power delivery. Upgrading the grid and reducing Aggregate Technical & Commercial (AT&C) losses are top priorities in many urban centers.

Financial Health of DISCOMs: Urban power distribution companies (DISCOMs) continue to face financial difficulties, largely due to inefficiencies, unpaid bills, and subsidized electricity rates. Despite efforts like the Ujwal DISCOM Assurance Yojana (UDAY) to improve the financial health of DISCOMs, challenges remain in ensuring sustainable power delivery.

Grid Reliability: Ensuring uninterrupted power supply in urban areas, especially during peak demand periods, remains a critical challenge. Issues related to load shedding, voltage instability, and the inability to meet peak demand continue to affect urban power supply.

D. Electric Mobility and Urban Power Demand

The Indian government is pushing for the adoption of electric vehicles (EVs), which could have a transformative impact on urban power demand. The National Electric Mobility Mission Plan (NEMMP) and Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) schemes promote the use of EVs, which require the development of a robust charging infrastructure in urban areas.

EV Charging Infrastructure: As EV adoption grows, cities need to expand their charging networks, which could place additional demand on urban power grids. However, this also presents opportunities for load management through time-of-use (TOU) pricing and the integration of EVs as distributed energy storage units.

E. Role of Smart Cities

The Smart Cities Mission, launched by the Government of India, is designed to improve infrastructure and sustainability in select urban centres. Power management is a key component of this initiative, and many smart cities are incorporating cutting-edge technologies like:

Distributed Generation: Cities are moving towards distributed energy generation systems, where renewable sources are located closer to the point of use, reducing transmission losses and enhancing reliability.

Energy Storage Solutions: Battery storage technologies are gaining attention as a means to address the intermittent nature of renewable energy sources like solar and wind. Urban centers are increasingly exploring battery storage options to stabilize the grid and manage peak loads. As India's urban population grows, the pressure on the power sector will continue to intensify. Urban power systems will need to evolve to accommodate the rise of EVs, the integration of more renewable energy, and the demand for smarter, more reliable grid infrastructure. As solar PV and wind energy become more cost-competitive, Indian cities are expected to see higher integration of these sources, supported by energy storage systems. Technologies for peer-to-peer energy trading, virtual power plants, and advanced energy management systems will likely be adopted to better manage urban energy needs. Demand-side management programs, where consumers play an active role in managing their electricity consumption, will become increasingly important as cities move towards smarter and more sustainable power systems.

3.2.2 Semi Urban Areas

Semi-urban areas in India represent the transitional regions between rural and urban areas, often characterized by a mix of agricultural, residential, and small-scale industrial activities. As these regions rapidly urbanize, the demand for reliable electricity has surged, leading to unique challenges in power supply and consumption. The semi-urban power landscape is marked by a growing dependence on electricity for both economic and domestic purposes. This review explores the key aspects of power supply, infrastructure, consumption patterns, and challenges specific to semi-urban areas in India.

A. Power Supply in Semi-Urban Areas

Infrastructure and Grid Connectivity: Semi-urban areas in India generally have better grid connectivity compared to rural regions, with most areas being connected to the national electricity grid. However, the quality of infrastructure in these regions varies significantly. Distribution Companies (DISCOMs) often struggle with maintaining and upgrading infrastructure due to financial constraints, resulting in frequent outages and voltage fluctuations. These power disruptions are common, particularly during peak demand periods or during extreme weather conditions. Many semi-urban areas rely on aging transmission and distribution networks that were originally designed for rural use and are now overburdened by the growing energy demands of expanding populations and industries. Efforts to modernize these grids are underway, but the pace of infrastructure upgrades remains slower than the pace of development in semi-urban regions. These regions also struggle with frequent power thefts, power outages and equipment malfunction.

B. Renewable Energy Integration

Semi-urban areas are increasingly looking towards renewable energy sources, particularly solar power, to supplement their electricity needs. The availability of rooftop space and the relatively lower cost of land compared to fully urbanized areas make semi-urban regions well-suited for solar energy projects. State and central government incentives for rooftop solar installations have led to a rise in the adoption of solar panels in these areas. Small and medium industries, residential complexes, and even government buildings in semi-urban areas are adopting rooftop solar to reduce their dependence on unreliable grid power and mitigate electricity costs. However, the high upfront cost of installing solar panels and the lack of financing options remain barriers for widespread adoption among lower-income households and small businesses.

C. Consumption Patterns in Semi-Urban Areas

Household Consumption: With growing electrification and economic development, household electricity consumption in semi-urban areas is rising steadily. The proliferation of consumer electronics, electric fans, refrigerators, televisions, and air conditioners is driving up demand. Appliance penetration in semi-urban households is increasing, particularly as incomes rise and aspirations align more with urban lifestyles. Many semi-urban households still consume less electricity than their urban counterparts, but the gap is narrowing as households in these areas gain access to more appliances and shift to modern lifestyles. Seasonal variations in electricity demand are prominent, especially during the summer months when the use of air conditioners and fans spikes.

Industrial Consumption: Semi-urban areas also have a growing number of micro, small, and medium enterprises (MSMEs) that contribute significantly to electricity consumption. Industries such as textiles, food processing, and small manufacturing units require reliable power for their operations. As these businesses expand, so too does their demand for uninterrupted and quality power supply. Power outages and voltage fluctuations are especially detrimental to small industries, leading to downtime, equipment damage, and increased operational costs.

Commercial and Public Services: Semi-urban areas are also experiencing growth in the commercial sector, with the establishment of shops, small markets, educational institutions, and healthcare facilities. These establishments require reliable electricity for lighting, cooling, and daily operations, adding to the overall demand. Public services like street lighting, municipal water pumps, and health clinics in semi-urban areas also contribute to the electricity consumption profile. The electrification of public services has improved significantly in recent years, but challenges remain in ensuring consistent supply, especially in smaller towns with limited resources.

D. Challenges in Power Supply and Consumption

Power Reliability: Despite improvements in grid connectivity and electrification rates, semi-urban areas continue to face challenges in power reliability. Load shedding, especially during peak demand periods, remains common in many regions. Inadequate grid infrastructure, overloaded transformers, and poor maintenance practices lead to frequent outages, affecting both domestic and commercial consumers.

Financial Stress on DISCOMs: Many semi-urban DISCOMs operate under financial strain due to high transmission and distribution (T&D) losses, power theft, and the provision of subsidized electricity to agricultural consumers. The financial health of these DISCOMs often limits their ability to invest in necessary infrastructure upgrades, perpetuating the cycle of poor service quality. Unmetered consumptions leads to inefficient electricity use and significant financial losses for utilities. Although metering has improved in many areas, the practice of subsidizing electricity continues to create financial difficulties.

Energy Efficiency: Energy efficiency remains a low priority in many semi-urban areas, particularly in households and small businesses. The lack of awareness about energy-efficient appliances and the relatively higher cost of these products deter their widespread adoption. Programs like the Ujala Scheme, which promotes the use of LED lighting, have helped improve energy efficiency in semi-urban areas, but more concerted efforts are needed to encourage the use of energy-efficient air conditioners, refrigerators, and other high-consumption appliances.

E. The Role of Renewable Energy in Semi-Urban Areas

Renewable energy, particularly solar power, is gaining traction in semi-urban areas as an alternative or supplementary source of electricity. Rooftop solar installations and solar microgrids are being explored as solutions to address the challenges of unreliable grid power, especially in regions where the existing infrastructure is insufficient to meet growing demands. Government subsidies and incentives under schemes like the Grid-Connected Rooftop Solar Programme have encouraged the adoption of rooftop solar installations in semi-urban areas. These systems provide households and businesses with a reliable source of power, reduce dependency on the grid, and help lower electricity bills.

3.2.3 Rural Areas

The rural power supply and consumption scenario in India has undergone transformative changes in recent years, driven by ambitious government schemes and rapid infrastructure development. The number of rural households using electricity as their primary source of energy has reached very close to the urban areas over the last three decades as shown in Fig. 3.4. As over two-thirds of the Indian population resides in rural areas, ensuring reliable and affordable electricity in these regions is essential for economic growth, poverty alleviation, and improved quality of life. Despite significant progress in rural electrification, challenges persist regarding power reliability, financial sustainability, and equitable access. This review examines the current state of rural electrification, major initiatives, challenges in rural power supply, consumption patterns, and the role of renewable energy. However, despite progress in electrification, several challenges continue to hamper the efficient supply of electricity in rural India.

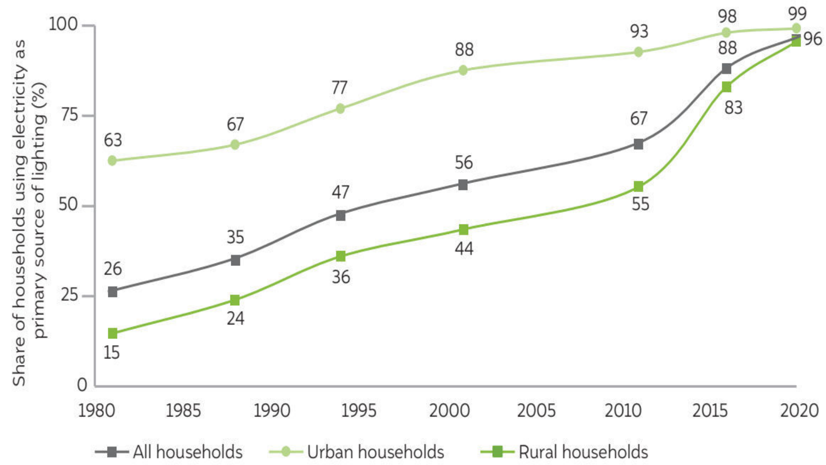


Fig. 3.6 Households using electricity as primary source in the urban and rural areas of India. Source: CEEW State of Electricity Access in India

A. Intermittent Power Supply

As shown in Fig. 3.5 compared to urban areas, rural areas often face power outages and voltage fluctuations, which affect the daily lives of residents and hinder agricultural productivity. The supply of electricity, especially in peak seasons such as the summer and during harvesting periods, is often unreliable. This is due to a combination of technical issues such as overloaded distribution lines and inadequate maintenance of rural power infrastructure.

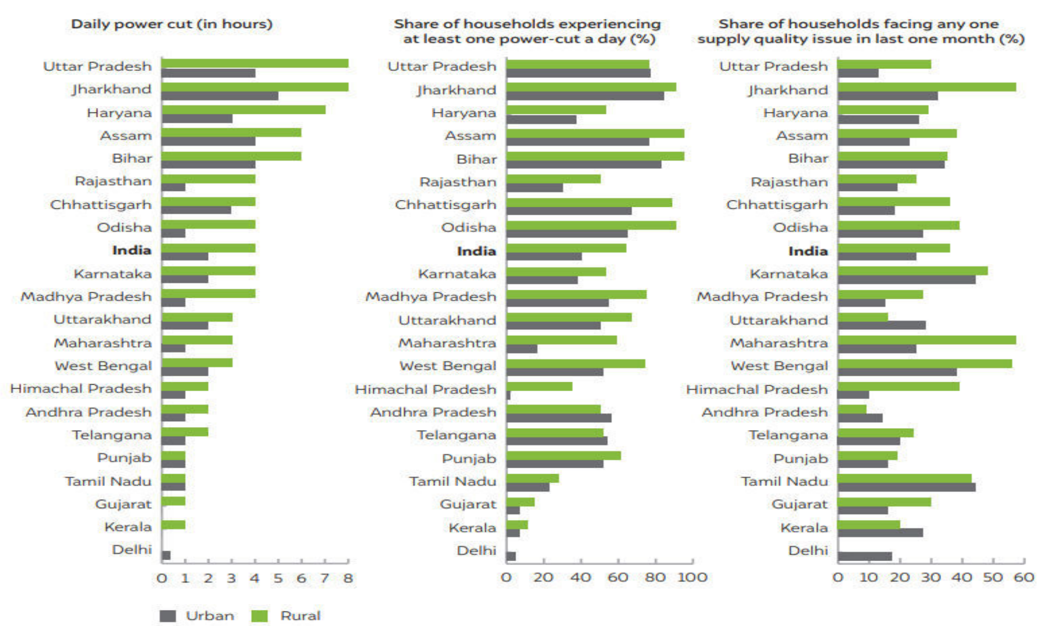


Fig. 3.7 Power cut duration, frequency and gaps in supply quality variation across different states in India. Source: CEEW State of Electricity Access in India

B. Agricultural Power Subsidies and Financial Strain on DISCOMs

A significant proportion of rural electricity is consumed by the agricultural sector, particularly for irrigation. Free or highly subsidized electricity for farmers, while beneficial for agricultural productivity, has led to financial difficulties for Distribution Companies (DISCOMs). These subsidies distort pricing mechanisms, making it difficult for utilities to recover costs, and contribute to high transmission and distribution losses. Moreover, agricultural electricity usage is often poorly metered, leading to inefficiencies in both water and energy usage.

Distribution Losses: High technical and non-technical losses in rural areas, driven by aging infrastructure, theft, and inefficient transmission lines, exacerbate the financial woes of power companies. Despite the efforts of initiatives like the Ujwal DISCOM Assurance Yojana (UDAY), which aimed to revive ailing DISCOMs, rural power distribution continues to face issues related to sustainability.

Inadequate Infrastructure and Capacity: Many rural areas still rely on outdated power infrastructure that is not equipped to handle increasing electricity demand. Furthermore, low voltage levels and limited capacity of rural transformers often result in uneven distribution of power across villages. The infrastructure in rural areas needs to be upgraded to support the growing demands of households, agriculture, and small industries.

C. Consumption Patterns in Rural India

Rising Demand for Household Electrification: With the expansion of rural electrification, electricity consumption in households has seen a steady increase. The traditional low-consumption profile of rural households is changing as access to appliances such as fans, televisions, and refrigerators is becoming more widespread. However, per capita electricity consumption in rural areas remains significantly lower than in urban regions, indicating room for further growth as rural electrification deepens.

Agricultural Consumption: Agriculture remains a dominant consumer of rural electricity, particularly for water pumping for irrigation. However, the lack of metering and free electricity policies has encouraged inefficient energy usage. This has led to over-extraction of groundwater in some regions and contributed to the financial distress of state utilities.

Energy Use in Rural Enterprises: Beyond agriculture and households, rural areas are seeing an increase in energy demand from micro, small, and medium enterprises (MSMEs). The availability of electricity has led to the expansion of rural industries, which in turn boosts economic activities in these regions. However, power outages and voltage fluctuations still affect the productivity and competitiveness of these enterprises.

D. Renewable Energy and Rural Electrification

India's push toward renewable energy offers significant potential for transforming the rural power landscape. Decentralized renewable energy (DRE) systems, particularly solar power, have emerged as key enablers in areas where grid access is difficult or unreliable.

Solar Power for Rural Areas: Solar energy, especially in the form of microgrids and solar rooftop systems, is being promoted in rural areas as a reliable and sustainable solution to electrification challenges. Programs like PM-KUSUM (Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyan) aim to encourage the use of solar pumps for irrigation, reducing dependence on grid electricity and diesel. This not only helps alleviate strain on the grid but also provides farmers with a clean energy alternative.

Decentralized Energy Systems: Decentralized energy systems, such as biogas and small-scale wind, can also play an important role in supplementing rural electricity supply. Biogas plants, particularly those powered by agricultural residues and livestock manure, are being promoted as a renewable source of energy for both households and small industries in rural regions.

E. Challenges in Renewable Integration

High Initial Costs: Despite long-term savings, the upfront costs of renewable energy technologies like solar panels can be prohibitive for many rural households and farmers, particularly in low-income areas.

Maintenance and Local Capacity: The lack of local technical expertise for the maintenance and operation of renewable energy systems can hinder their long-term viability.

3.3 Chapter Conclusion

India's power scenario is rapidly evolving, with a strong emphasis on renewable energy, smart grid technologies, and efficient distribution systems. The power supply and consumption patterns in semi-urban areas of India reflect a complex and evolving landscape. India's rural power supply and consumption scenario has made significant strides, particularly in achieving near-universal electrification. Government schemes have played pivotal roles in expanding access to electricity in rural areas, and the integration of renewable energy presents new opportunities for enhancing energy security. However, as these areas continue to develop, demand for electricity is rising, driven by a combination of residential, agricultural, and industrial needs. With the focus towards modernization of the grid into smart grid, avenues to meet this rise in power demand through the formation of localized microgrids is being explored. This is possible only through the implementation of decentralized and distributed generation controlled by AI based systems to ensure that the local load demand is met in an efficient and consumer centric way. This implementation of distributed generation can be done by conversion of consumers to grid connected prosumers through proper power system planning and incentivization. This will also result in greater renewable energy integration ensuring long-term energy access and sustainability in India. A reduced capacity of conventional sources along with battery storage systems may be implemented on a community basis to increase the power supply security and reliability. However, to make this transition seamlessly, a demographical approach towards demand response and generation planning is required. For a centralized system, the local variations of demand are mostly not discernible as the area supplied by the utilities are vast combining many urban, rural and semi urban regions. So, the power demand characteristics seen from the utility side becomes an amalgamation of the characteristics of all these regions resulting in the loss of any individual differences. This is sufficient for the present infrastructure as such minute details are not very essential for fossil fuel-based generation where the generation can be controlled by the operators. Only, the peak demand and revenue earned are of only concern with shortages of power being dealt through power cuts and load shedding. But, in case of microgrids connected to a smart grid, renewable sources are being considered as the primary sources of generation. As, this type of generation is by nature uncontrollable and required to be distributed, a very sophisticated demand response method will be required to be able ensure the reliability and security of power supply. A demographic approach where the demand response management is done according to the power consumption characteristics of the urban, semi urban and rural consumers has the capacity to be a potential solution to this problem. This will not only be able to cater to the load demand of the consumers on a regional basis but also lead to a better management of the distributed resource allocation and increase consumer satisfaction thereby inspiring us to take up the challenge to identify loads based on demographic categorization like urban, rural and semi urban. All these three types of load segregation will require an accurate forecasting about the load profiles of these areas. Then, as per the forecasted load profile, an effective solution is developed, where renewable energy availability and its its integration to grid becomes inevitable for successful design and development of an energy management system. The next chapter proposes a detailed analysis of the same as our research work that is under discussion.

Chapter 4

Forecasting Techniques for Development of an Efficient Regional Community Energy Management System

4.1 Introduction to Forecasting Techniques

The future knowledge of any event allows us to devise better management plans for the situation. It becomes more important in the presence of uncertainty of certain parameters of the event. In case of developing an energy management system, the uncertainty of the consumer power demand and the availability of renewable energy needs to be considered. The development of an efficient forecasting algorithm is very important to ensure the maximum efficiency of the energy management system. Several research works have been conducted to this end. A brief discussion on the different techniques available for forecasting power demand and generation is given from section 4.1.1 to 4.1.5.

4.1.1 Autoregressive Integrated Moving Average /ARIMAX

The Autoregressive Integrated Moving Average (ARIMA) model is used for time series forecasting. It combines autoregression with moving averages to handle non-stationary data. The regression technique predicts future values based on prior observations, making it beneficial in circumstances with clear connections between present and historical values. An ARIMA model consists of three components: autoregressive (AR), integrated (I), and moving average (MA). The AR component shows that the variable of interest is regressed against its previous values, whereas the MA component denotes the incorporation of delayed forecast errors in the prediction model. The integrated component entails differentiating the data to eliminate trends and establish stationarity, which is critical for the model's success. However, while ARIMA models are useful for some types of time series data, they do have limits. They presume linear connections and may struggle with datasets that reveal nonlinear behaviors or structural fractures. Furthermore, determining the right model parameters may be a difficult undertaking, requiring careful evaluation of many diagnostic techniques and criteria. The ARIMAX model, which stands for Autoregressive Integrated Moving Average with exogenous inputs, is a more complex version of the ARIMA model. This approach expands on the classic ARIMA framework by incorporating exogenous factors that impact the time series under analysis. This capability enables the ARIMAX model to give a more robust and accurate forecasting mechanism by including extra information beyond the target variable's historical data. ARIMAX is particularly suitable for applications where external factors significantly affect the dependent variable.

4.1.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are strong regression analysis techniques that allow for the prediction of continuous numerical values using one or more independent variables. Because of its multi-layer design and activation functions, ANNs may learn complicated, non-linear correlations that classic linear regression cannot. This adaptability enables ANNs to be used in a variety of sectors, including banking, healthcare, and engineering, where anticipating numerical objectives is critical. ANNs have an input layer, one or more hidden layers, and an output layer. Each layer is made up of neurons (or nodes), which process inputs using weighted connections and activation functions. The hidden layers bring nonlinearity into the model, increasing its ability to learn complex patterns in the input. For regression tasks, the output layer usually uses a linear activation function to ensure that the final result is continuous. One of the most significant advantages of employing ANNs for regression is their ability to simulate complicated, non-linear connections between features and targets. This capacity differs from typical regression approaches, which generally make linear assumptions. Furthermore, ANNs can manage big datasets, responding to fluctuations in the data while offering reliable forecasts.

4.1.3 Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks are a form of recurrent neural network (RNN) that is primarily developed to address the issues of sequence prediction, particularly in regression applications. These networks are particularly good at processing time series data, where prior knowledge is crucial for forecasting future results. The core design of an LSTM consists of memory cells that use three gates: the input gate, the forget gate, and the output gate. These gates control the flow of information, allowing the network to retain or forget information over lengthy periods of time and successfully learning long-term dependencies. The design guarantees that key data is maintained while irrelevant information is removed, which is critical for regression jobs that rely on past data patterns for prediction. Their ability to handle sequential data while retaining critical temporal information makes them ideal for these types of applications.

4.1.4 Support Vector Machines

SVMs are increasingly used in prediction tasks in different fields due to their effectiveness in handling complex data structures. Their main benefit is their capability to model both linear and non-linear relationships while efficiently managing high-dimensional datasets. The use of SVMs can significantly improve prediction accuracy, making them a popular option in tasks like time series analysis in finance and environmental science. SVR is a variation of the SVM algorithm specifically designed for regression tasks. In SVR principles of SVM are applied, but the focus is on predicting continuous outputs rather than classifying discrete categories. SVR aims to identify a hyperplane that effectively fits the data while also keeping a margin of tolerance determined by a specified error threshold.

4.1.5 Fuzzy logic

Fuzzy logic is a mathematical approach for modelling ambiguity and uncertainty in decision-making processes, which makes it ideal for forecasting applications. Fuzzy logic, which allows for partial facts, may successfully manage the imprecision that frequently develops in electrical load forecasting. Fuzzy logic is advantageous for predicting because it can handle uncertainty and provide a more robust interpretation of time series data. Fuzzy logic provides significant advantages over standard forecasting approaches. Its ability to adapt to non-linear data patterns and incorporate expert knowledge via fuzzy rules enables it to outperform traditional models. Despite the benefits, using fuzzy logic in predicting is not without its obstacles. These may include the complexity of setting accurate membership functions and criteria, as well as the computing costs of processing enormous datasets. Furthermore, fuzzy models may not always give the degree of precision necessary, especially in highly volatile contexts where data patterns might change fast.

Among all the techniques described above, artificial neural network (ANN) has emerged as an efficient forecasting system for the time series data which can satisfactorily map the non-linearities between the different input parameters and the required output. ANN models have been found to work efficiently for both linear and non-linear forecasting. Wavelet neural network has emerged as an advance neural network model which combines the advantage of traditional neural networks with the diverse information provided by the wavelet decomposition of the time series data. The wavelet decomposition allows the user to extract more data from the available time series data for different resolutions. With the help of wavelet decomposition method redundant data and white noise can be removed thus reducing the computational burden and increase the efficiency of the forecasting algorithm. The different architectures of neural networks have been developed for different specialized requirements. The general architecture of Artificial Neural Networks is given in Fig. 4.1.

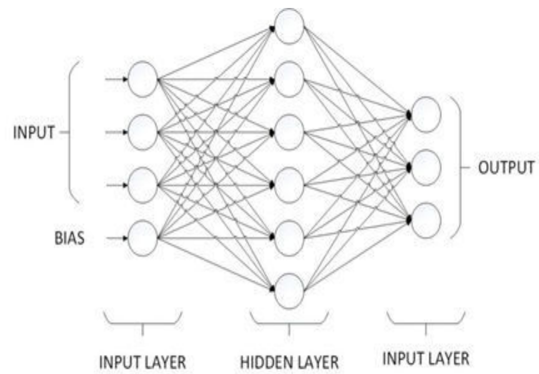


Fig. 4. 1 The general architecture of artificial neural network

The Neural network architecture can be divided into the following categories

a. Feedforward neural networks – Commonly used for pattern recognition, the information in this architecture moves in one direction from input to output. The input and output layers are connected through hidden layers and no feedback loop is present. The weights connecting each layer to the other is determined by training the network using multiple sets of input and output data.
b. Convolutional neural network – The convolutional neural networks, specialized in detecting edges and textures are predominantly used for image processing. They have kernels, each of whose parameters are determined by training. The activation map for image processing is created by the convolution of the kernels and the image.
c. Recurrent neural networks – The recurrent neural networks involve a feedback loop which is used to provide feedback from the outputs of the previous steps in determining the forecast value of the present step. They are mainly used for time series forecasting where previous values can influence the output of the next step. The degree of correlation between the feedback value with the prediction value needs to be determined for optimum functioning of the model.
d. Generative Adversarial Networks (GAN) – It is composed of a generator and a discriminator competing with each other, and is commonly used for generating realistic data.

The training of a neural network model with historical data is required before its implementation. The choice of activation functions for mapping the relation between the input and the output is very critical. It is also important to choose the proper activation function to make the training of the neural network most effective and thus increase the efficiency of the neural network. The activation functions introduce non-linearity into the operation of the neural networks thus allowing the artificial neural network models to move beyond the aspect linear operation. The activation functions have been enumerated Fig. 4.2.

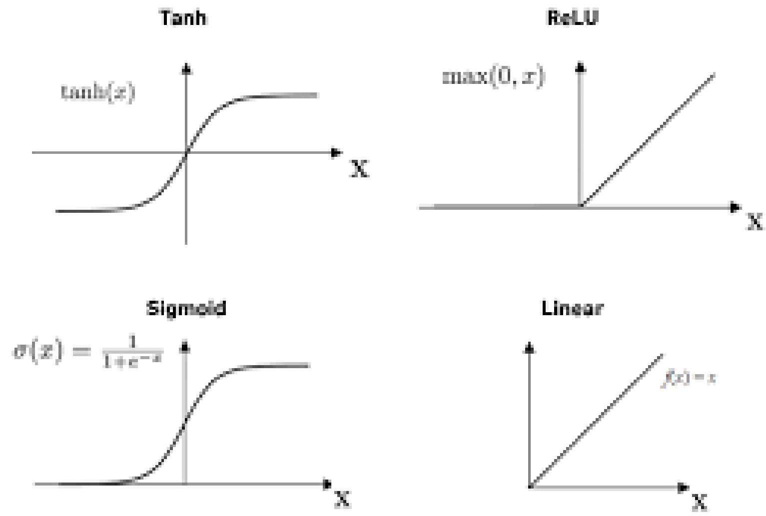


Fig. 4.2 Graphical representation of the activation functions of neural networks

a. Sigmoid activation function – converts the inputs to a value between 0 and 1. The shape of the sigmoid function resembles an 'S'. It converts large negative numbers to values close to zero and large positive numbers to values close to one. Though very popular in the initial neural network models, it has the drawback of the vanishing gradient problem which hampers the learning of the neural network. The sigmoid function can be expressed using the equation (4.1)

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.1}$$

b. Hyperbolic tangent (tanh) activation function – An upgrade to the sigmoid function, tanh converts the input values to a range between -1 to +1. It has a stronger gradient compared to sigmoid functions and it can deal with negative values more effectively. Being centered at zero, unlike the sigmoid function, the tanh function provides a symmetric output around the origin of the coordinate system. However, despite these advantages, the tanh activation function suffers from vanishing gradient problem. The mathematical function to express the tanh activation function is as given in equation (4.2)

$$f(x) = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})} \tag{3.2}$$

c. ReLU (Rectified Linear Unit) – The ReLU function returns a value of zero for negative input values and a linear value between 0 to 1 for the positive input values. The non-linearity of the ReLU function helps the neural network to learn complex patterns. The ReLU function is guided by equation (4.3)

$$f(x) = \max(0, x) \tag{3.3}$$

The choice of the right activation function is very critical for the proper operation of the neural network model.

Wavelet Transform – Wavelet decomposition is a method to break down any time series data into sub series using a selection of mother wavelets. The use of wavelet decomposition can help in extracting critical data from time series data. Wavelet decomposition can be of two types i.e. continuous wavelet transform and discrete wavelet transform. Wavelet transform helps in analyzing signals which contain both time and frequency information. The power demand signals are non-stationary signals with their frequency changing with time. The analysis of these signals using wavelet transformation can result in better extraction of data from the hourly power demand signals. This will lead to better forecasting accuracy as both time and frequency information are available from the wavelet transformed signals. This has led to the development of wavelet neural networks which combines the advantage of the data extraction capability of wavelet transformation with the non-linear adaptation capability of neural networks. The wavelet decomposition mother wavelets that are used can be enumerated as Haar, Daubechies, Coiflets, Symlets and Mexican Hat. The continuous wavelet decomposition is done for continuous time signals while for the discrete time signals the discrete wavelet decomposition is used. The information from the actual time series data is extracted by convoluting the selected mother wavelet with the actual signal.

Wavelet Neural Networks – In wavelet neural networks the wavelet functions such as morlet, daubechies etc are used in the place of conventional activation functions. The parameters of the wavelet activation functions that are required to be adjusted are scale and translation. The WNN model adjusts both these parameters along with the weights of the neural network layers during the learning process. The wavelet neural network has the advantage of time frequency localization, allowing the model to effectively capture the transient and local patterns which may not be otherwise detected. This model has been used to develop effective forecasting techniques for predicting power demand for different consumers. [4]

4.2 Feature Extraction for Efficient Forecasting

Feature extraction plays a crucial role in improving the efficiency and accuracy of forecasting models, especially for time series data. By identifying and selecting the most relevant features, the forecasting model can focus on key patterns and relationships, reducing noise and improving predictions. Below are some methods and techniques for feature extraction aimed at efficient forecasting:

a. Time Series Decomposition
    i. Trend, Seasonality, and Residuals: Decompose the time series into its components: trend (long-term movement), seasonality (cyclical patterns), and residuals (random noise). Extracting these components separately can help the model better capture patterns and improve forecasting.
    ii. Moving Averages: Use simple or exponential moving averages to extract smoothed versions of the data, which highlight trends.

b. Lag Features
    i. Autoregressive Lags: Time series data often depends on previous values. By including lag features (e.g., the value of the series 1, 2, or 5 steps back), the model can learn autocorrelation in the data.
    ii. Rolling Statistics: Calculate rolling statistics like rolling mean, rolling standard deviation, or rolling median for different window sizes. These features summarize the behaviour of the series over recent periods.
c. Differencing
    i. First-order Differencing: Helps remove trends or seasonality by subtracting the previous time step's value from the current time step, making the series stationary (necessary for some models like ARIMA).
    ii. Seasonal Differencing: In case of strong seasonality, subtract the value from the same time in the previous season (e.g., the value one year ago if the seasonality is yearly).
d. Fourier and Wavelet Transforms
    i. Fourier Transform: Useful for extracting frequency-domain features, especially when the time series exhibits periodic behaviour. The dominant frequencies can serve as input features.
    ii. Wavelet Transform: Wavelet-based decomposition can capture both time and frequency information. It is particularly effective for handling non-stationary signals, allowing you to extract time-localized features.
e. Feature Engineering for Seasonality
    i. Calendar-based Features: If the data exhibits periodic patterns, extract features like the day of the week, month, quarter, or holidays. These are especially helpful when the series has seasonal cycles based on the calendar.
    ii. Cyclic Features: For cyclic data (e.g., hourly, weekly), encode time information as cyclical features using sine and cosine transformations. This ensures that time features wrap around smoothly.
f. Statistical Features
    i. Summary Statistics: Extract descriptive statistics such as mean, median, standard deviation, skewness, and kurtosis over rolling windows to capture changing characteristics over time.
    ii. Autocorrelation Features: Calculate autocorrelations and partial autocorrelations at different lags. These features reveal relationships between current and past values.
    iii. Volatility: For financial forecasting, volatility features (e.g., the rate of change or rolling standard deviation) are important to capture market dynamics.
g. Domain-Specific Features
    i. External or Exogenous Variables: Often, external factors (weather, economic indicators, etc.) influence the variable being forecasted. Including these as additional features can greatly improve model performance.
    ii. Business-Specific Indicators: For businesses, metrics like sales targets, promotions, or customer behaviour data can be helpful features.

h. Principal Component Analysis (PCA)

PCA is a dimensionality reduction technique that transforms the feature space into a smaller set of uncorrelated components. PCA is useful when you have a large number of input features (e.g., from decomposing time series data), and you want to extract the most important information while reducing redundancy.

i. Clustering-Based Feature Extraction
   i. K-Means Clustering: Cluster the data based on patterns and assign cluster labels as features. This can help the model understand different regimes or behaviours within the time series (e.g., high-demand vs. low-demand periods).
   ii. Time Series Clustering: Segment the time series into similar chunks based on dynamic time warping (DTW) or other clustering methods to group similar patterns together.

j. Feature Selection Techniques
   i. Correlation Analysis: Calculate the correlation between features and the target variable. Features with high correlation to the target (positive or negative) are often more useful for forecasting.
   ii. Mutual Information: Measure the mutual information between input features and the output to determine the most relevant features.
   iii. Recursive Feature Elimination (RFE): Iteratively remove the least important features and re-train the model to find the most significant features.

4.3 Short Term Forecasting with Artificial Neural Networks

The forecasting horizon required for an energy management system can be classified as short term, mid-term and long term forecasting. The short term forecasting can range from a few hours to a day ahead. Mid term forecasting can encompass the period from a few months to a year and long term forecasting ranges from one year to a few years. Each of these forecasting techniques have their own importance. The information obtained from short term load forecasting can be used to develop an efficient demand side management technique to schedule customer demand according to the availability of energy and relevant constraints. Mid term load forecasting data can be used to develop new techniques for efficient energy management for the predicted load demand. Long term load forecasting can be used to detect the trend in power usage and subsequent infrastructure development.

Short term load forecasting is of primary importance for developing any energy management system. Artificial neural network has emerged as a promising technique for short term load forecasting. A neural network based short term load forecasting model was tested using regional data to determine the applicability of the method in the development of a multiregional energy management system. Backpropagation model is used for the neural network used for short term load forecasting. The backpropagation method is characterized by the repeated application of the chain rule through all the possible network paths. Updating the gradient of each weight with respect to the error in the output by equation (4.4) is the ultimate objective in training the neural network.

$$w_{ij} = w_{ij} - \rho \frac{\partial E}{\partial w_{ij}} \tag{4.4}$$

The following network shown in Fig. 4.3 can be used to develop the equations (4.5) to (4.17)

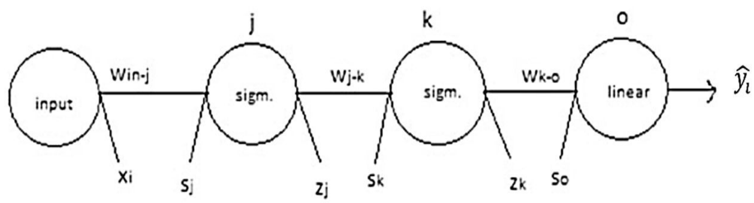


Fig. 4.3 Feedforward network representation

$$s_j = w_1.x_i \tag{4.5}$$

$$z_j = \sigma(in_j) = \sigma(w_1.x_i) \tag{4.6}$$

$$s_k = w_2.z_2 \tag{4.7}$$

$$z_k = \sigma(in_k) = \sigma\left(w_2.\sigma\left(w_1.x_i\right)\right) \tag{4.8}$$

$$s_0 = w_3.z_k \tag{4.9}$$

$$\hat{y}_i = in_0 = w_3.\sigma\left(w_2.\sigma\left(w_2.x_i\right)\right) \tag{4.10}$$

$$E = \frac{1}{2}(\hat{y}_i - y_i) = \frac{1}{2}\left(w_3.\sigma\left(w_2.\sigma\left(w_i.x_i\right)\right) - y_i\right)^2 \tag{4.11}$$

$$\frac{\partial E}{\partial w_{k0}} = \frac{\partial}{\partial w_{k0}}.\frac{1}{2}.(\hat{y}_i - y_i)^2 = \frac{\partial}{\partial w_{k0}}.\frac{1}{2}.(w_{k0}.z_k - y_i)^2 = (\hat{y}_i - y_i)(z_k) \tag{4.12}$$

The updates of other layers can be obtained by equations (4.13) and (4.14)

$$\frac{\partial E}{\partial w_{jk}} = (\hat{y}_i - y_i)(w_{k0})\left(\sigma(s_k)(1-\sigma(s_k))\right)(z_i) \tag{4.13}$$

$$\frac{\partial E}{\partial w_{ij}} = (\hat{y}_i - y_i)(w_{k0})\left(\sigma(s_k)(1-\sigma(s_k))\right)(w_{jk})\left(\sigma(s_j)(1-\sigma(s_j))\right)(x_i) \tag{4.14}$$

Summarizing the above equations, we can present equations (4.15) to (4.17)

$$\Delta w_{ij} = -\rho\left[(\hat{y}_i - y_i)(w_{k0})\left(\sigma(s_k)(1-\sigma(s_k))\right)(w_{jk})\left(\sigma(s_j)(1-\sigma(s_j))\right)(x_i)\right] \tag{4.15}$$

$$\Delta w_{jk} = -\rho\left[(\hat{y}_i - y_i)(w_{k0})\left(\sigma(s_k)(1-\sigma(s_k))\right)(z_i)\right] \tag{4.16}$$

$$\Delta w_{ko} = -\rho\left[\left(\hat{y}_i - y_i\right)\left(z_k\right)\right] \tag{4.17}$$

The neural network is made to learn from the historical data of 2017 hourly load data and average temperatures of West Bengal. To fulfil the objective of forecasting the week-ahead load demand of a day, a program was written in MATLAB utilizing the ANN toolbox in MATLAB. The multilayer feedforward network architecture has four layers consisting of two hidden layers and one output layer (Fig. 4.1). The number of neurons in the hidden layer was varied from 5 to 21 to find the best fit model with the highest efficiency. It was seen that 12 neurons in the first hidden layer and 21 neurons in the second hidden layer gave the best output. The forecasted load of each hour for the target day is obtained from the 24 neurons, respectively, in the output layer of the ANN architecture. The input neurons are used to provide information of the historical load, temperature, and target day, specifically the temperature of the target day and the type of the day. The details of the input and output of the ANN is given in the Table 4.1. The selection of the exogenous and endogenous input features was done by exploring the relationships between the features and the load demand characteristics which are shown in Figures 4.4 to 4.8.

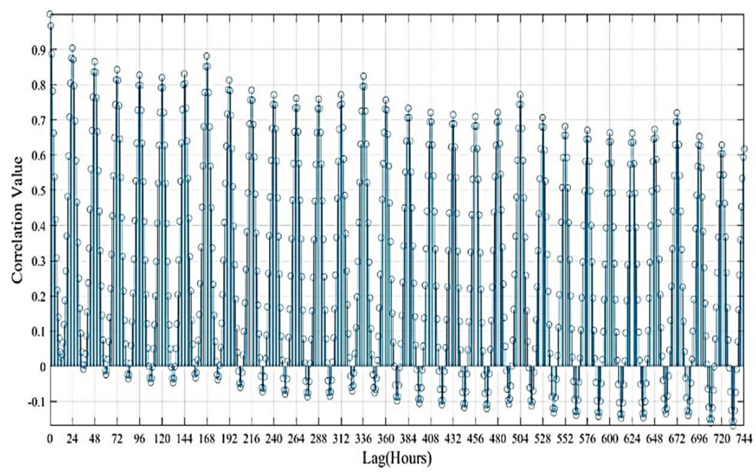


Fig. 4.4 Hourly autocorrelation results of the electrical load demand for the month of January 2017

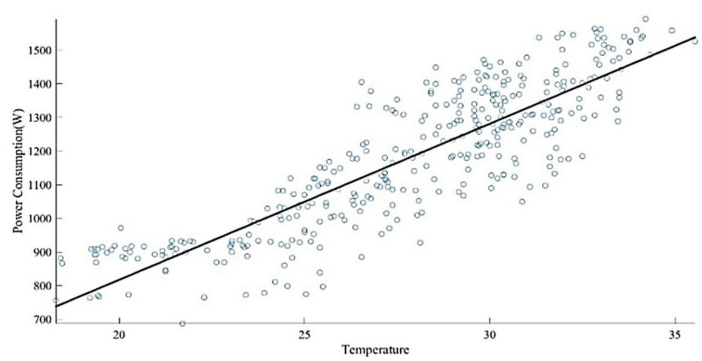


Fig. 4.5 Relationship between average daily temperature and load demand for the year 2017

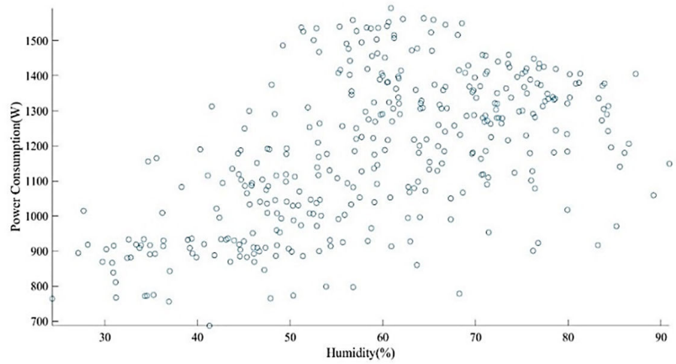


Fig. 4.6 Relationship between average daily humidity and load demand for the year 2017

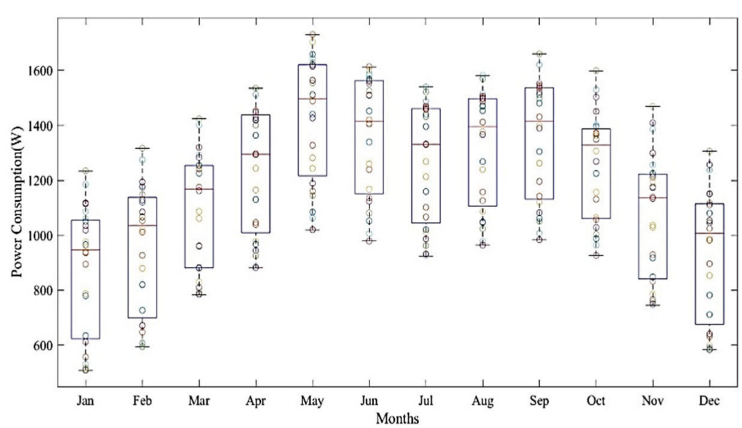


Fig. 4.7 Variation of monthly load demand for the year 2017

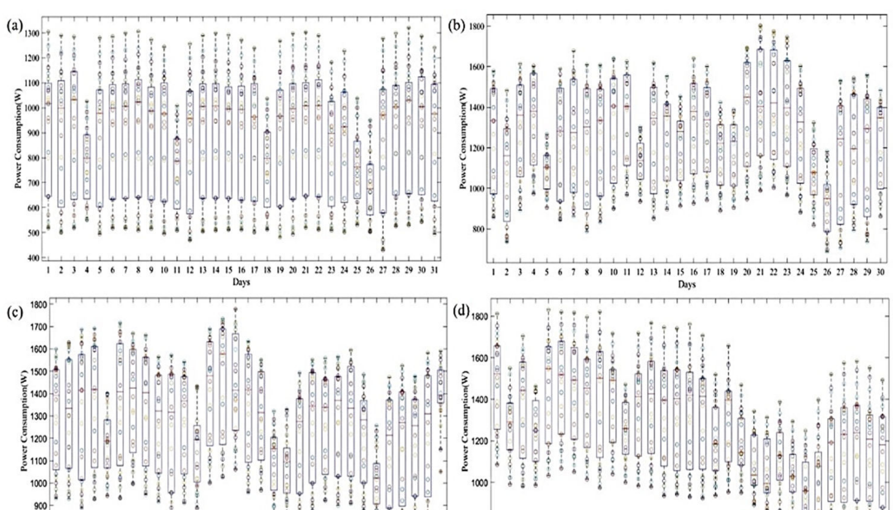


Fig. 4.8 Daily load demand variations of (a) January (b) April (c) July (d) October for the year 2017

From Fig. 4.4, which plots the autocorrelation values, it can be seen that maximum similarity between the present load demand and historical load demands occur at the 168th, 336th, 504th and 672nd hours of the same months which can be translated to 7, 14, 21 and 28 days prior to the present day. From this information a conclusion can be drawn that there is a correlation between the power demand of the same days of every week leading to the selection of (d-7) as the prominent endogenous feature where d is the day for which forecasting is done. From Fig. 4.5 it can be seen that average daily temperature has a marked influence on the daily load demand. As such, the daily minimum, maximum and average temperatures have been considered as an exogenous input for the forecasting. Another important environmental variable is humidity whose relationship with the power demand is shown in Fig. 4.6. It can be seen that there is no marked relationship between humidity and power demand. As such, humidity was not considered as an input variable. Fig. 4.7 and Fig. 4.8 shows the yearly and daily variations of the power demand. A pattern is easy detectable in the figures between the power demand of weekdays and weekends. Thus, the type of day feature distinguishing the day under consideration as weekday or weekend has also been considered as an input for forecasting.

Table 4. 1 ANN inputs and outputs

Inputs	**Description**
1–24	L (d-7, h); h = 1–24
25–27	T_{max} (d-7); T_{min} (d-7); T_{avg} (d-7)
28–30	T_{max} (d); T_{min} (d); T_{avg} (d)
31	Day type
Outputs	**Description**
1–24	L (d, h); h = 1–24

The inputs are scaled using the MATLAB function "prestd" to prevent the saturation of the input neurons. To get the proper output, the process is reversed for the output neurons using the MATLAB function "poststd" and the outputs are scaled back to the original range. The network was trained by backpropagation algorithm using the log-sigmoid activation function for the hidden layer and linear activation function for the output layers. The load and temperature data of West Bengal for a span of 1 year, i.e., 2017 obtained from eastern region load dispatch centre was used for training the proposed neural network. After the training of the network is completed, a separate set of input and target data was used to test the performance of the neural network, keeping the weights and biases of the network obtained after training as constant. One neural network is trained for each day of the week to make a week-ahead forecasting system. The importance of week-ahead forecasting lies in the fact that it gives us enough time to prepare for the upcoming load demand and decide how the load can be optimally dispatched using conventional and renewable sources and decide upon the proper coordination of the available power generation.

The training of the network was done using the historical data for the state of India, West Bengal for 365 days. The total available data was divided into a training (75% of the data) and testing set (25% of the data). The network was trained using the training set and then it was tested with the test set. The error tolerance was set to 1e-5 and the maximum number of iterations was set to 5000. The error of the network output was calculated using the mean absolute percentage error (MAPE) with the formula in equation (4.18)

$$MAPE = \frac{\sum_{i=1}^{N} \frac{|x_i - \hat{x}_i|}{x_i} \times 100}{N} \tag{4.18}$$

Where N is the total time period, $\hat{x}_i$ is the predicted load consumption value at time i and x_i is the actual power demand value at time i. The network was trained using the gradient descent training function with a momentum component. One neural network was trained for each day of the week. The testing and training of the networks were done using only the weekday data. The holidays and the weekends were not involved in this forecasting. The output of the forecast for each day from 31st August 2017 to 6th September 2017 is shown in the figures below. The blue line shows the target value, that is, the original load of the target day while the red line represents the output of the neural network as shown in Fig.4.9 to Fig.4.13. The error values are given in Table 4.2.

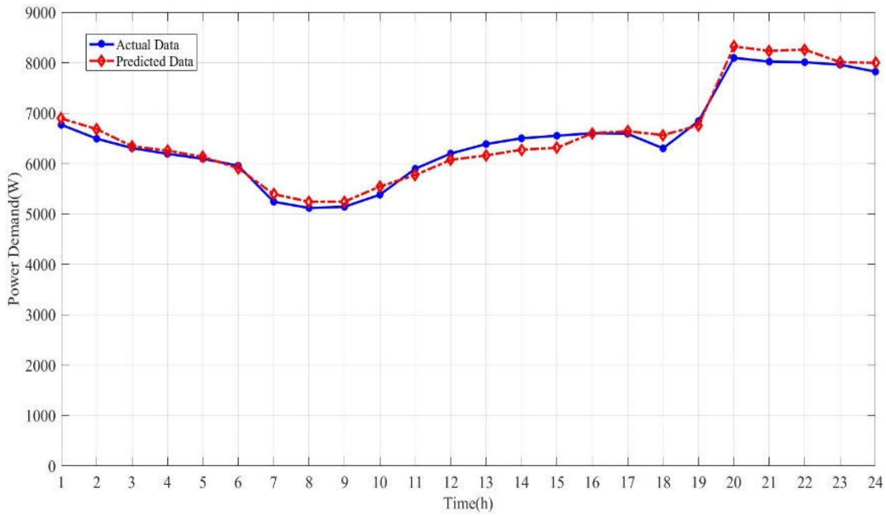


Fig. 4.9 Monday load forecasting

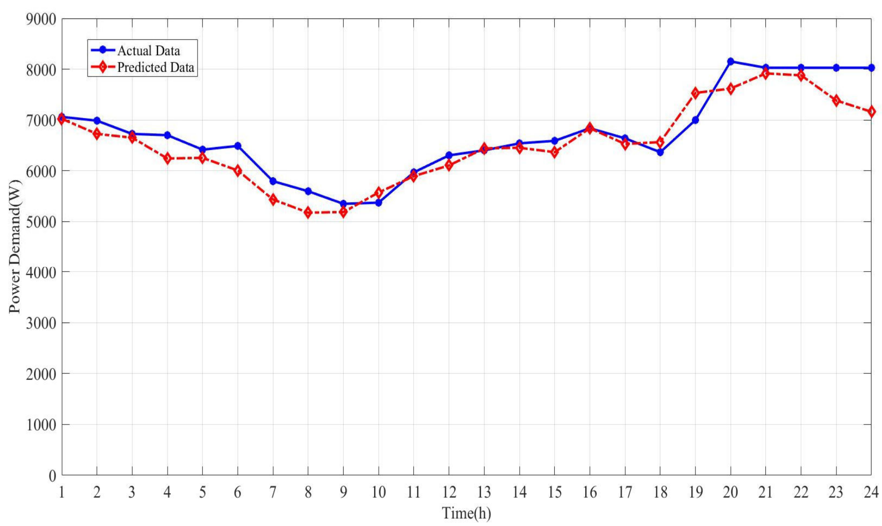


Fig. 4.10 Tuesday load forecasting

The accuracy of the neural network could have been increased further if it was possible to train the network with more data. But as the data available at the source was inconsistent and only for 1 year the training accuracy of the neural network was affected. It was also seen that using a log-sigmoid activation function in the second hidden layer provided better results compared to a tan-sigmoid function.

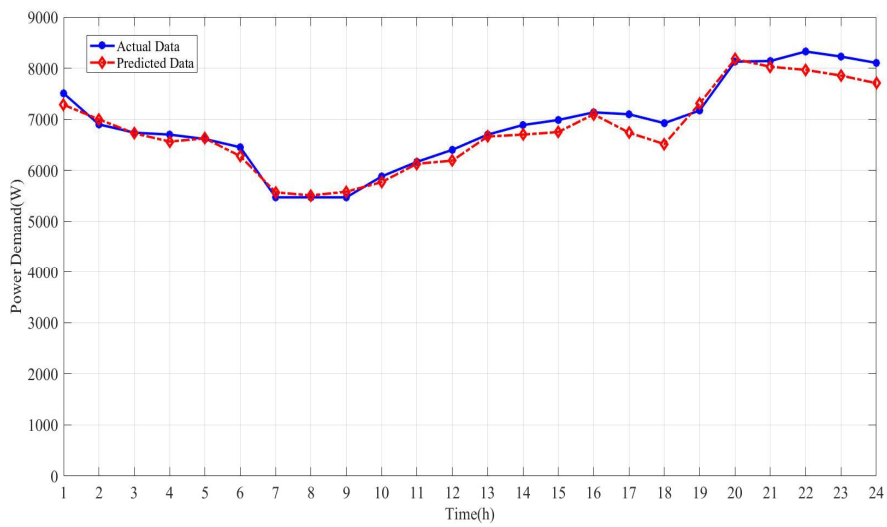


Fig. 4.11 Wednesday load forecasting

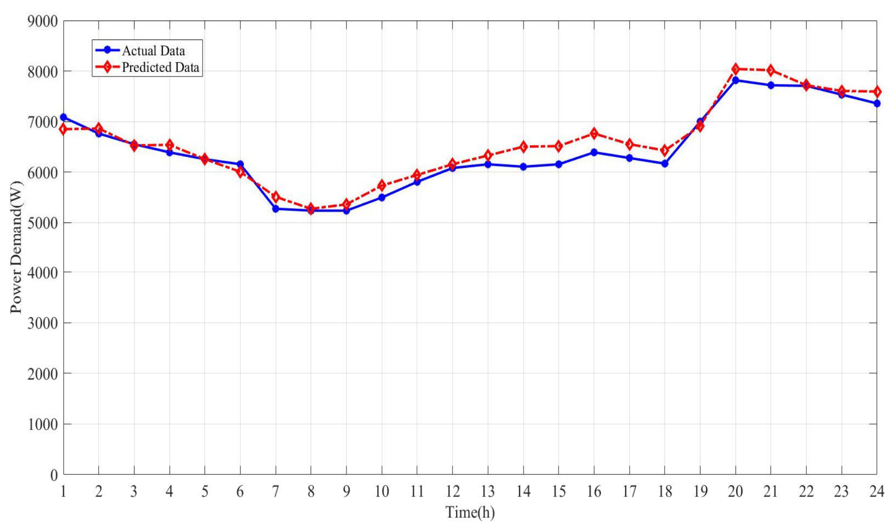


Fig. 4.12 Thursday load forecasting

It was seen that neural network as a tool for load forecasting performs fairly in terms of accuracy. The main advantage of using a neural network is that the architecture is not needed to be modified with change of inputs or span of forecasting. So, this can be considered a suitable tool for a wide range of applications.

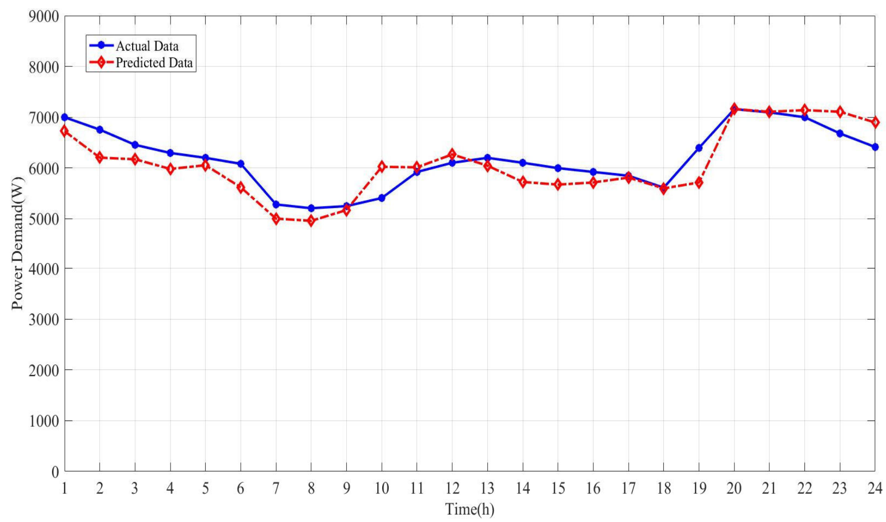


Fig. 4. 13 Friday load forecasting

Table 4.2 Error values between the forecasted and actual demands of each day

Target day	**MAPE**
Monday	2.11
Tuesday	3.62
Wednesday	2.32
Thursday	2.80
Friday	4.32

Using the forecast obtained from this tool a better load dispatch strategy can be formulated and the system response can be automated thus reducing the time of response and margin of error. Any number of factors can be used as the input of the artificial neural network and the training of the network can be done with the help of other artificial intelligence with a goal of increasing the accuracy of the tool.

4.4 Application of ANN technique for Mid Term Load Forecasting as a case study for Peak Load Reduction

To ensure the most efficient performance of any load forecasting method to be used in energy management systems higher granularity is required to identify the trend of the power consumed by different sectors which can be aggregated to form the power demand of the total area. To this end, the artificial neural network technique was tested to determine its effectiveness in midterm forecasting domestic, industrial, commercial and public lighting demands over the span of a year. The forecasts of the different types of load viz. Domestic, Commercial, Industrial, Public Lighting of the urban load demand is shown from Fig 4.14 to 4.19.

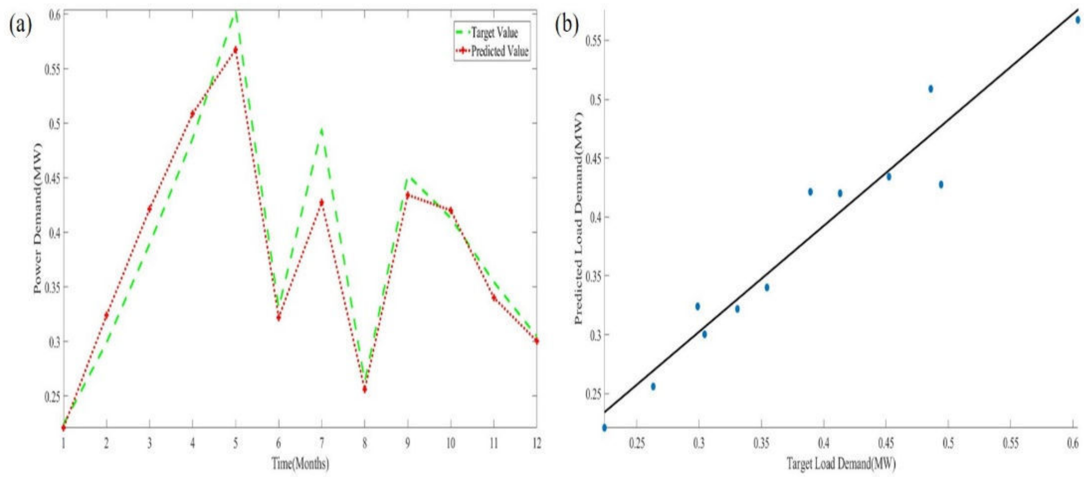


Fig. 4.14 Year ahead domestic load demand forecasting results using ANN showing (a) the actual and predicted load comparison and (b) the actual and predicted value linear fit

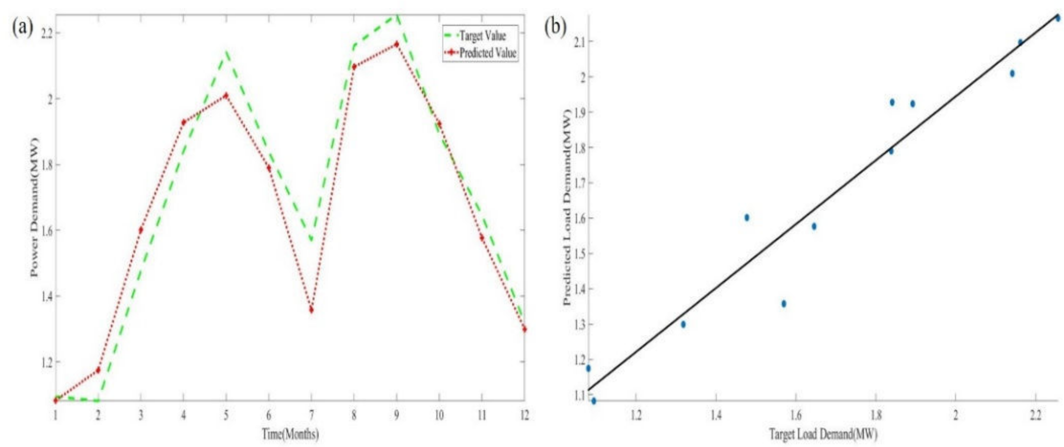


Fig. 4.15 Year ahead industrial load demand forecasting results using ANN showing (a) the actual and predicted load comparison and (b) the actual and predicted value linear fit

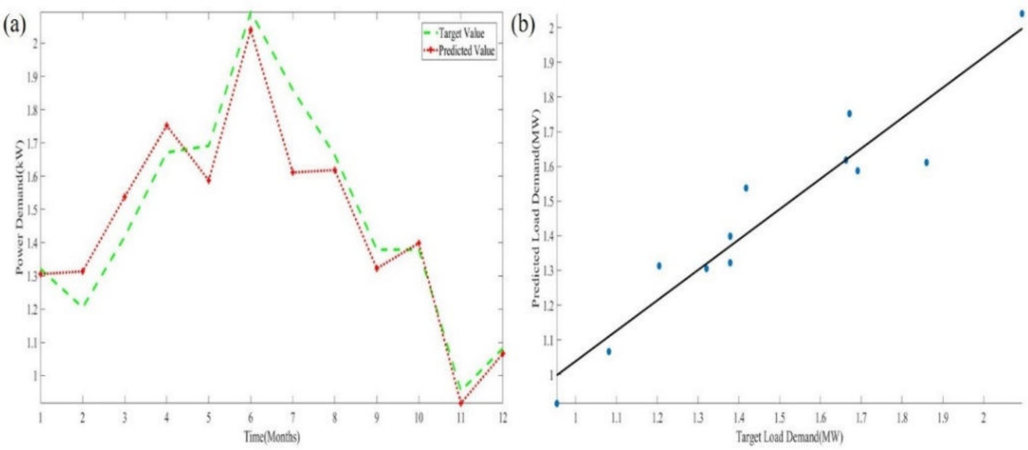


Fig. 4. 16 Year ahead commercial load demand forecasting results using ANN showing (a) the actual and predicted load comparison and (b) the actual and predicted value linear fit

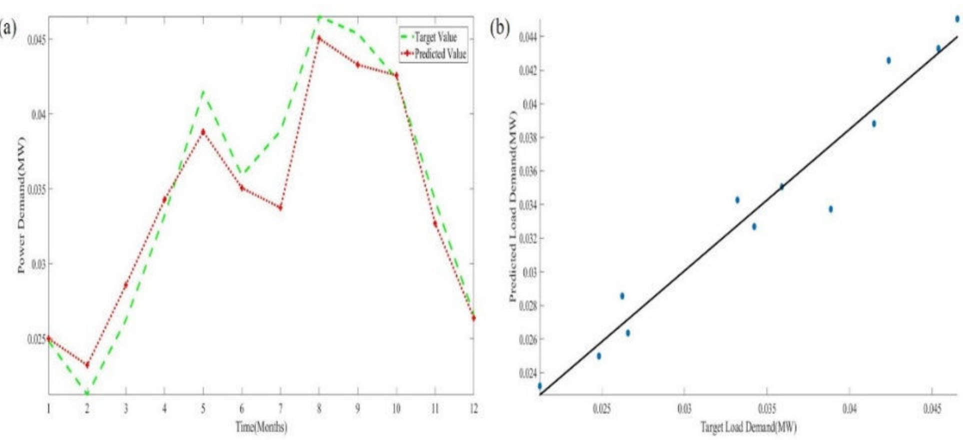


Fig. 4. 17 Year ahead public lighting load demand forecasting results using ANN showing (a) the actual and predicted load comparison and (b) the actual and predicted value linear fit

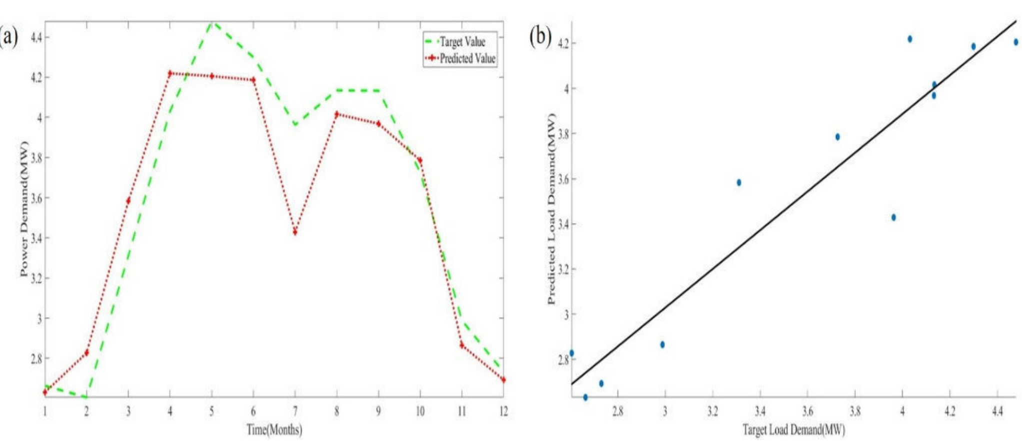


Fig. 4. 18 Year ahead total load demand forecasting results using ANN showing (a) the actual and predicted load comparison and (b) the actual and predicted value linear fit

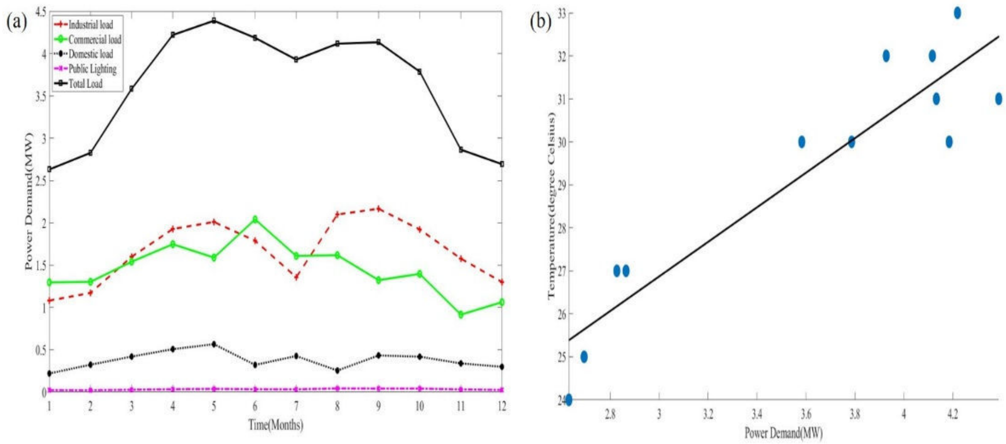


Fig. 4. 19 Year ahead load demand forecasting results using ANN showing (a) all the loads (b) the variation of the total load demand with temperature over the year

Table 4.3 shows the errors of the forecasted load when compared with the testing target load and the variation of the load with temperature of the different months.

Table 4.3 Forecasting errors of the load demand of different sectors by ANN

Type of Load	MAPE	RMSE
Domestic Load	4.96	5.0275
Commercial Load	4.93	5.037
Industrial Load	4.96	5.0798
Public Lighting Load	4.91	4.79

As the forecast has been made for a year in advance so the errors generated is comparatively more than short term load forecasts but it can be seen from the graphs that the possible contribution of each load on the total and peak load has been satisfactorily captured. Table 4.4 shows the variation of different loads with the maximum and minimum temperature change per month. The temperature is given in degree Celsius and the load is in megawatts (MW).

Table 4.4 Variation of Load of different sectors with temperature

2017	Max Temp	Min Temp	Dom Load (KW)	Ind. Load (KW)	Com. Load (KW)	Pub Light (KW)	Latitude	Longitude
JAN	30	10	221.488	1082.2688	1297.145	24.63	22.5744° N	88.3629° E
FEB	33	15	324.744	1172.396	1304.057	23.40		
MAR	35	17	421.031	1599.431	1541.340	28.54		
APR	38	23	508.360	1927.967	1748.170	34.62		
MAY	39	23	567.275	2010.721	1590.089	38.93		
JUN	39	24	322.279	1789.314	2041.034	34.69		
JUL	36	25	427.481	1357.971	1609.370	33.40		
AUG	39	25	255.833	2099.013	1618.219	44.82		
SEP	36	24	434.702	2166.846	1323.680	43.21		
OCT	35	19	419.698	1922.284	1397.750	43.00		
NOV	32	14	340.149	1578.026	916.530	32.68		
DEC	30	10	300.446	1300.948	1063.483	26.25		

Fig 4.19 shows the plot of each forecasted load along with the total forecasted load. It can be seen that there is a notable seasonal variance of the loads. Here artificial neural network has been used to capture the effect of temperature on the load variations over the year. The forecast can be more accurately made with the availability of more data and it is possible to study the effects of the other conditions such as humidity, tariff etc with the same method. This advance information can be used to determine the effect of the different loads on the total load and peak load reduction can be obtained by better management of the load. From this work we can conclude that among the different components of the urban load the commercial and industrial loads have a major share whereas public lighting has a negligible share and contributes little to the total load demand. Whereas the domestic and commercial load curves have more variations compared to industrial and public lighting, the industrial load seems to have a more marked effect on the total load curve. The effect of temperature is quite clear on the commercial and domestic loads and the effects of other factors such as humidity and tariff can be studied using the same neural network technique. This advance study made possible by long term forecasting can be used for better management of loads in obtaining the ultimate aim of peak load reduction.

4.5 Comparison between Wavelet Neural Network and Artificial Neural Network for Peak Load Management through Urban Forecasting

Through the discussion in the previous section it has been clear that ANN can be a very useful tool in the forecasting of load demand for the traditional categorization of loads as domestic, commercial, industrial and public lighting in both short and mid term forecasting. However, ANN in its traditional form cannot distinguish between the demographic categorization of load demand. In order to explore the possible enhancement of forecasting through ANN to capture the urban, semi urban and rural power consumption patterns the load demand data obtained through survey by the Prayas Energy Group was used [74]. From the dataset, specifically the data of Pune City and Kanpur rural has been used as urban and rural data respectively preclassified according to their demographic information. The data available for the urban area is mostly complete whereas several inconsistencies exists in the Kanpur rural data. This may be due to malfunctioning of the smart meters used to collect data or the power cuts prevalent in the rural areas. However sufficient data was gathered to perform the analysis for the month of June 2019. The inclusion of semi urban region was not possible in this case as no specific data for semi urban regions were available. Eight households each of the urban and rural regions were considered, the combined load demand profiles of which are shown in Fig. 4.20.

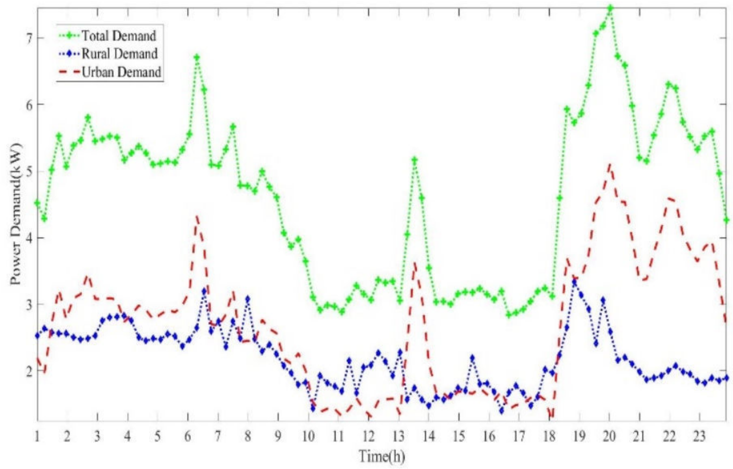


Fig. 4.20 Urban, rural and total load demand

Through appearance the load profiles resemble a combination of waves with different frequencies. So, wavelet decomposition was considered as the best tool to analyse the load demand patterns. At first, continuous wavelet transformation (CWT) was used to confirm the presence of distinguishable variations in the urban and rural load demand patterns. The result of the CWT decomposition is shown through a scalogram in Fig. 4.21. It is evident that stark differences exist between the power usage patterns of the two demographical regions. From Fig. 4.21(a) describing the urban load demand pattern it can be seen that there are intermittent high demand periods ranging from scales 13 to 21 throughout the day with a very pronounced

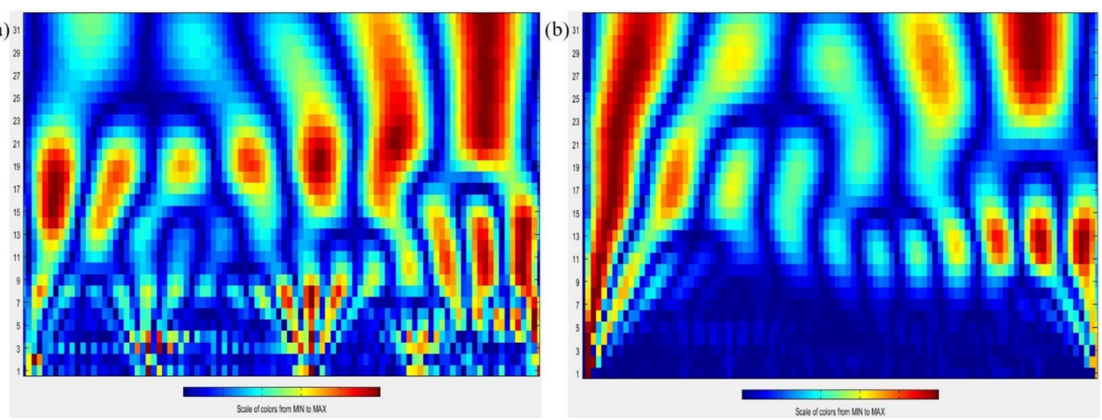


Fig. 4.21 Scalogram of (a) urban region and (b) rural region obtained by CWT decomposition

evening peak period with scales ranging from 13 to 31. The morning peak is very significant in the scale range of 13 to 20. The rural demand scalogram shown by Fig. 4.21(b) shows a more pronounced morning peak with scales ranging from 5 to 31 and a small evening peak with scales ranging from 25 to 31. However, there are smaller oscillations throughout the day compared to urban load demand. Thus, it can be safely concluded that there is a stark difference in the urban and rural power usage patterns which has been captured by CWT decomposition. Now, correlation analysis was performed between the rural, urban and total load demand data to determine how well the urban and rural demand is represented in the total load demand data. The correlation values between the urban and rural load profile with the total load profile is given in table 4.4. It can be seen that the urban load profile receives more representation in the total load profile compared to the rural load profile. Thus, in a demography-based energy management system, the forecasting values obtained using the total demand data in its standard form may face the inconvenience of diluting the information of rural power demand. To overcome this, the discrete wavelet transform of the total demand data was done using ‘daubechies(db)10’ wavelet up to 4 levels. The rural and urban load demand data was smoothened down to its base waveform using moving average function with a window size of 12 hours. The short fluctuations in the load demand of the urban and rural area were obtained by subtracting the smoothened curve from the original curve. Fig. 4.22 shows the comparison of the approximate levels 3 and 4 and detail level 2 with the rural and urban demand curves. The correlation data shown in table 4.4 shows that the rural power demand having less fluctuations is highly correlated with approximation levels 3 and 4 whereas it shows no correlation with detail levels 1 and 2. On the other hand, the urban power demand data shows lesser correlation with approximation level 3 compared to approximation level 4 but it also shows higher levels of correlation with detail level 2 and 1 compared to rural demand. Based on this information, a wavelet decomposed neural network model (WANN) was designed and tested for forecasting accuracy. However, the Prayas dataset could not be used in this regard as there was large inconsistencies in the rural dataset. Alternatively, a dataset obtained from a leading power supply company of Kolkata was used in this comparison. The data was taken from the summer of 2015, specifically the month of June. The data was divided into two parts. One part was used for training the WANN and ANN networks while the other part was used for testing the network. A graphical structure of the proposed WANN network used is given in Fig 4.14.

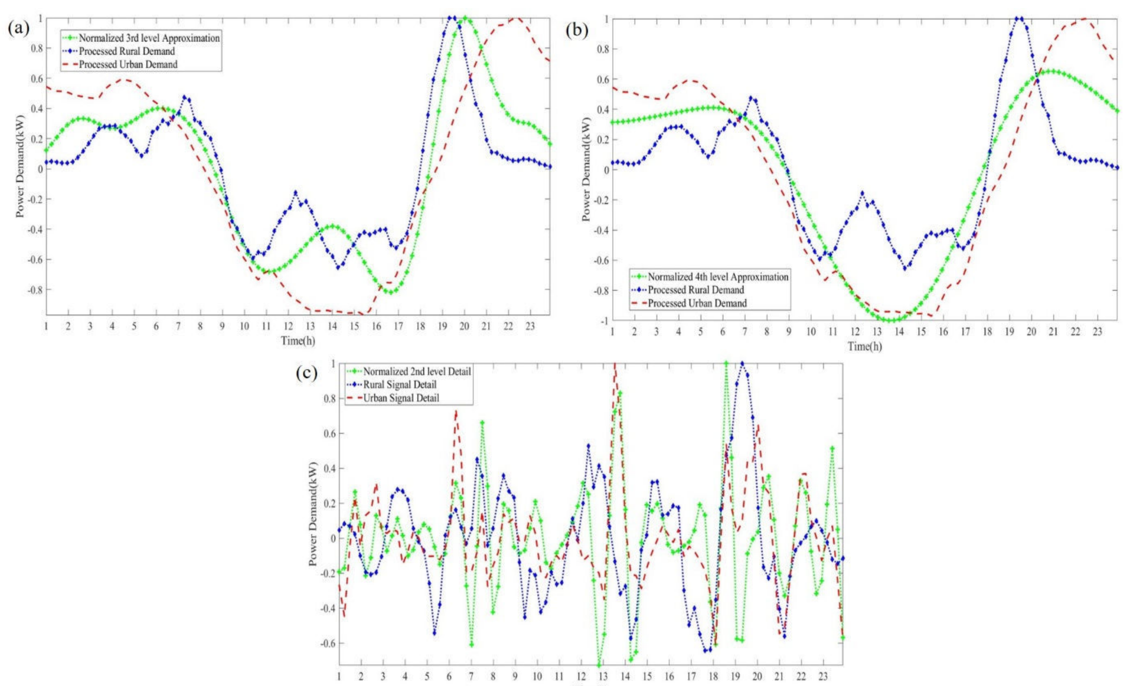


Fig. 4.22 Comparison of the processed rural and urban load demand data with (a) approximation level 3 (b) approximation level 4 and (c) detail level 2 of DWT decomposed total load demand curve

Table 4.5 Correlation values between the processed rural and urban demand data and the wavelet decomposed levels of the total load demand data

	Total Profile	A4	A3	D2	D1
Rural Profile	0.7165	0.7940	0.8816	0.0434	0.0487
Urban Profile	0.9642	0.9548	0.7540	0.6162	0.3419

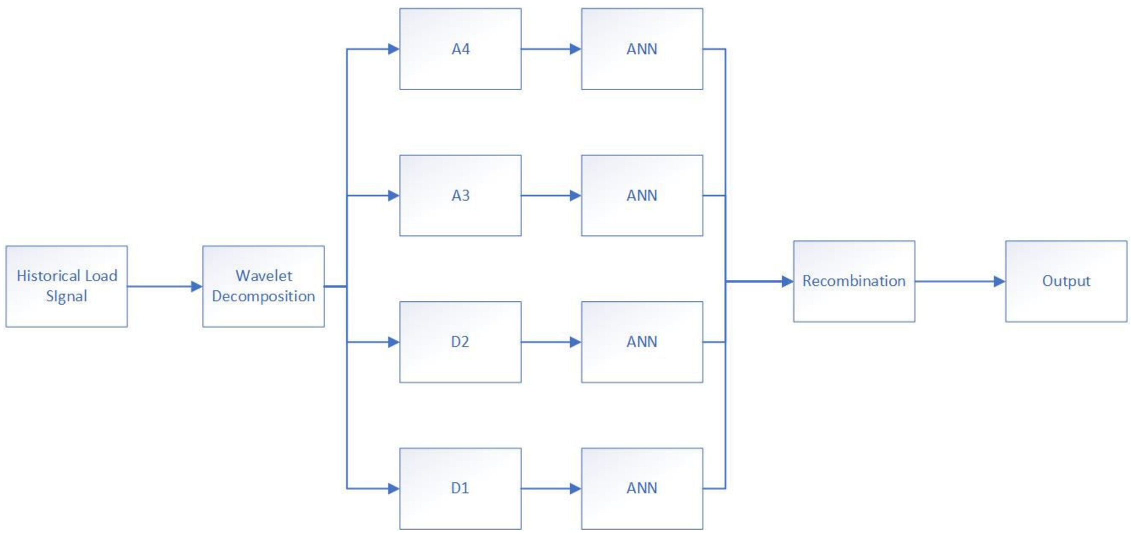


Fig. 4.23 Schematic diagram of the Wavelet Neural Network technique used

The input data to the WANN network was divided into the components of different frequencies by using the 'daubechies 10' wavelet upto the 4^{th} level. The selection of daubechies 10 as the mother wavelet was done after studying several literatures and comparing it with the other wavelet functions of the daubechies family as well as symlets and coiflets family. It was found that using the daubechies 10 (db10) mother wavelet for decomposition yields the best results. The waveform of the daily load profile appears to be most suited for decomposition by db10 as the variation of the profile is less compared to the other wavelet functions and the load profile shape is also similar to db10 compared to symlets and coiflets. The 4^{th} level approximation and the 3rd and 2nd level details were extracted for use. The 3rd level detail was left out as it does not specifically contribute to the peak load demand and represented mostly the random fluctuation of load over time. The approximate and detailed level signals were then reconstructed to be used as input to the ANN network. The ANN structure was taken as a three-layer structure with two hidden layers. The activation function used for the layers was the 'logsig' activation function. The hidden layers had 70 and 24 neurons respectively. The input data comprised of the last two days' load data preceding the day for which forecasting was being done. The ANN network of the structure without wavelet had the same structure but the undecomposed load signal was fed as input to the ANN network. Mean Absolute Percentage Error (MAPE) has been used to measure the accuracy of the two forecasts. The resulting graphs and results are shown below. The error values in percentage is shown in table

4.6. Mean Absolute Percentage Error (MAPE) method shown in equation (4.19) has been used to calculate the respective errors.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \tag{4.19}$$

Where N = Number of observations

A_i = Actual value of the i^{th} observation

F_i = Forecasted value of the i^{th} observation

Table 4.6 MAPE values of ANN and WANN outputs

Day	MAPE (ANN)	MAPE (WANN)
Tuesday	3.7713	3.7655
Wednesday	1.9133	1.9109
Saturday	3.6284	3.6409
Sunday	2.4133	2.4462

The original peak loads and the forecasted peak loads using ANN and WANN for the two weekdays and weekends in the month of June, 2015 for the city of Kolkata have been given in Table 4.7 with the accuracy of the forecast. The outputs of the proposed algorithm are shown in Fig 4.15 to Fig. 4.18

Table 4.7 Peak load forecast error of WANN and ANN

Day	Original Peak Load (in KW)	ANN Peak Load	WANN Peak Load	ANN Error (in %)	WANN Error (in %)	Improvement of WANN over ANN (in %)
Tue	1670	1682	1664	0.72	0.35	0.37
Wed	1700	1636	1657	3.76	2.53	1.23
Sat	1520	1513	1515	0.46	0.33	0.13
Sun	1300	1321	1336	1.62	2.77	-1.15

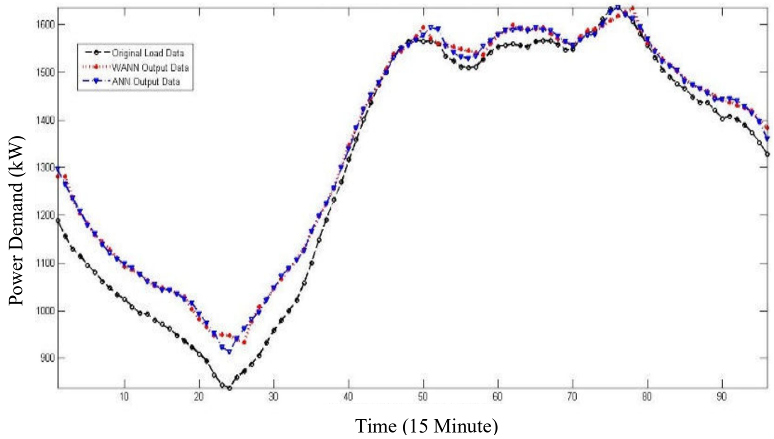


Fig. 4. 24 Comparison between the outputs of ANN, WANN and the original demand for Monday

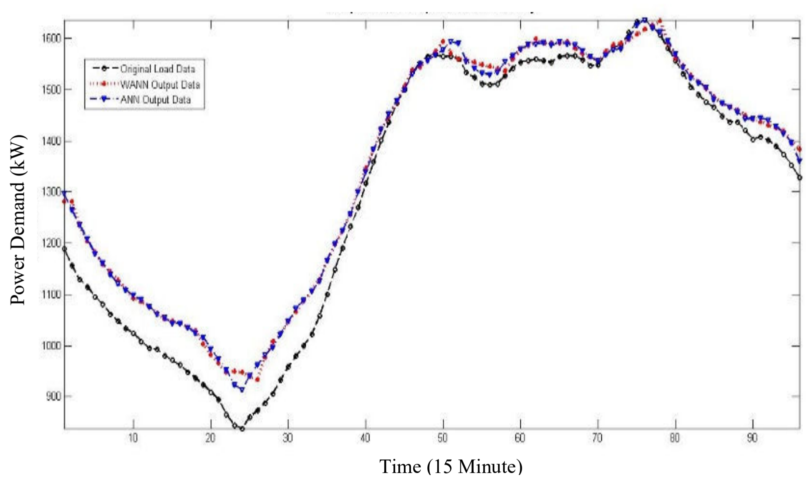


Fig. 4.25 Comparison between the outputs of ANN, WANN and the original demand for Tuesday

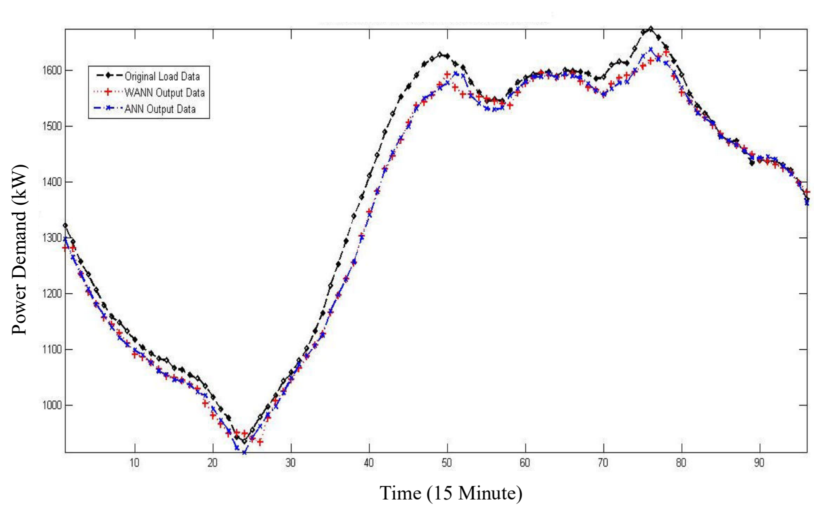


Fig. 4.26 Comparison between the outputs of ANN, WANN and the original demand for Wednesday

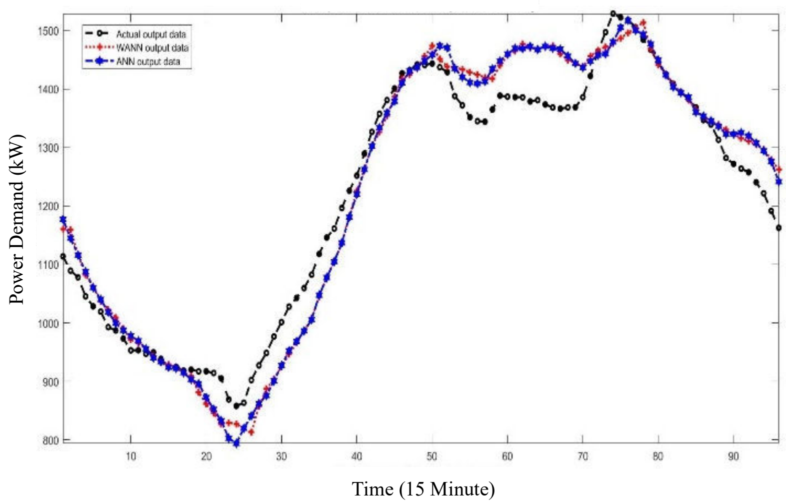


Fig. 4.27 Comparison between the outputs of ANN, WANN and the original demand for Wednesday

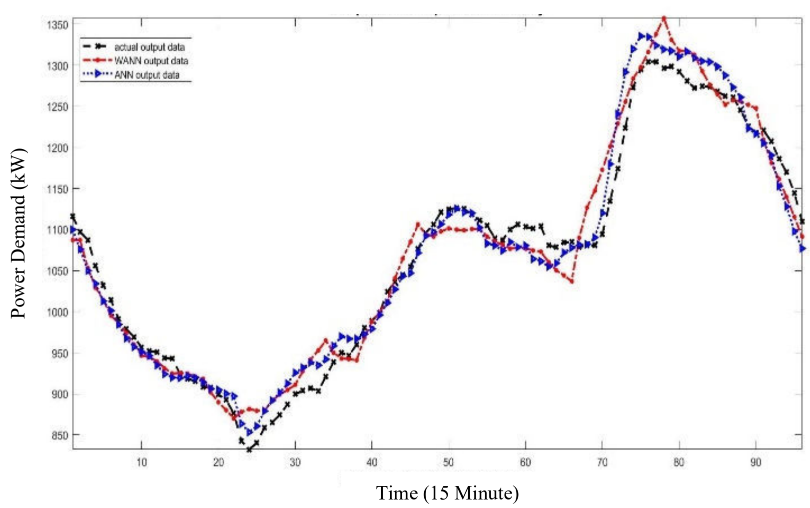


Fig. 4.28 Comparison between the outputs of ANN, WANN and the original demand for Sunday

The data of hourly power consumption was extracted from the eastern region load dispatch center reports and an urban region near Kolkata power consumption from a leading power utility. The data was obtained in two different resolutions of hourly and 15 minutes interval. The resolution used for the training and testing of the ANN was taken as one hour. The 15 minutes resolution was converted to hourly by averaging the four quarterly readings to convert to hourly reading. The daily average, minimum and maximum temperatures of Kolkata was taken as the reference temperatures were used as the input of the neural network. The temperatures were obtained from online weather websites. The midterm forecasting data was extracted from a Calcutta electric supply corporation repository. The dataset contained the power consumption data of several high-tension line consumers from different zones including Kolkata, North 24 Paraganas and Howrah. The consumers are categorized as industries, hospitals, schools, commercial buildings, domestic housings and public lighting. The monthly units consumed for each consumer were logged. The consumers were categorized into domestic load, commercial load, industrial load and public lighting for the purpose of neural network training and testing.

The application of the developed models to any external dataset can be done through a simple process. The dataset has to be pre-processed to remove any outliers or fill up missing data. The dataset has to be normalized and applied to the neural network. For using the wavelet neural network, the dataset has to be wavelet decomposed using db10 mother wavelet. After forecasting the detailed and approximate waveforms separately they need to be analyzed or recombined for further processing.

4.6 Chapter Conclusion

Thus, we can see from the results that WANN has less error in predicting the output of the next day's load compared to ANN. Though the improvement in the error percentage may be small but when the energy is measured in megaunits (MU), this small development can make a significant impact. The peaks are also more prominently predicted by the WANN method compared to the ANN method except on Sunday which is a weekend and which has much lesser peak value compared to the other days. The forecasting has been done for two weekdays and weekends to show the difference between load demand on weekdays and weekends. This prediction will help in renewable integration for both weekdays and weekends. The availability of data was limited for this work. Availability of more data can have significant impact on the output accuracy of the WANN network. It is evident from the above result that WANN can be used as a dependable tool for STLF preserving the urban and rural representations in the total load demand data. It is also concluded that peak load forecasting can be achieved more accurately with higher fluctuations in demand. Considering higher fluctuations involve variation of the regional load demand which aggregates to total demand for the period of 24 hours and these variations are affected by change in weather conditions, season or temperature. Therefore, it can be concluded that WANN can accommodate the variations of the urban, rural and semi urban power demand characteristics and still forecast the peak demand for a day with sufficient accuracy.

Chapter 5

Development of Regional Load Management System based on Rural, Semi Urban and Urban Loads

5.1 Introduction

The rapid increase in population over the last few decades has resulted in substantial increase in power demand. The power demand is still mostly catered by the conventional power sources which account for a major share of the greenhouse gases being emitted which in turn is causing pollution and global warming. The solution to this problem has three parts namely increased use of renewable resources, demand side management and source side management. There has been several research works over the past few decades on the development of efficient energy management systems to tackle the problem of demand and source side management. Several techniques have been used to develop these systems. From the analysis of the past research works it was noted that home energy management has emerged as one of the most widely researched area for reduction of cost and grid stress. Some of the researchers have also proposed commercial and industrial energy management systems. The availability of public domain data for this research sector is very less thus affecting the smooth conduct of research work. So, the development and use of synthetic power demand patterns of the consumers for testing energy management systems has been accepted as necessary. Recently, community energy management systems have emerged as a sustainable solution confirming the advantages of community-based resource generation and utilization over individual efforts. The effect of the demographic differentiation of a community in urban and rural sectors to utilize the power consumption pattern between these sectors are has been explored in this work. Fuzzy logic technique has been used to build appliance level power demand profiles for urban and rural commercial and residential consumers using survey data of rural and urban areas. Fuzzy logic was further used to designate the hourly appliance power demand as grid or renewable compatible to determine the average hourly requirement of renewable power for each consumer.

5.2 Proposed Load Monitoring Strategy

In this section we first present the load switching and rescheduling models of the regional loads and then propose a method to determine the percentage of loads that can be supplied by renewable energy. This process will contribute towards Renewable Energy growth planning based on the composition and growth of load demand in the regions supplied by different utilities.

5.2.1. Model of Switching Schedule of Loads

The area supplied by each utility can be divided into three regions Urban, Semi-Urban and Rural based on the population. The loads of every region can be further subdivided into residential, commercial, industrial, agricultural and public lighting as shown in Fig 5.1(a). It is understandable that each area will have different concentration of loads based on the income and lifestyle of the people and accordingly the percentage of total load as well as loads of individual category that can be supplied with the renewable energy will vary. The loads of each type again comprise of non-shift able and flexible loads. In our work we have taken Residential and Commercial loads of an Urban and a Rural area respectively. To provide an effective model for load to renewable energy mapping first it is required to develop a switching profile of each load and a rescheduling strategy to reduce the peak load and stress on generation facilities. In order to develop a switching profile fuzzy logic has been used in this work. It has been seen that a reasonable modelling of consumption pattern can be done by computational intelligence using individual appliances as basic building blocks [17] . An upper limit on the number of appliances that can be switched on at the same time is provided by a prefixed hourly maximum power consumption value. This value has been determined by forecasting with ANN. ANN was selected for it's efficiency in multivariate forecasting [75, 76] . The fuzzy rule base of the system has been developed after extensive study of the data provided by surveys over multiple cities and towns spread over different regions [77, 78]. The number of urban residential and commercial appliance ownerships are considerably higher compared to the rural areas. The usage patterns of the appliances were used to develop the Fuzzy Rule base an example of which is shown in Table 5.1. The time of the day has been divided into five membership functions namely Early Morning (EM), Morning (M), Afternoon(A), Evening(E), Late Evening (LE). Also, the historical user switching behavior variable (app_{hub}) and their probability to be switched on has been divided into 5 membership functions namely Very High (VH), High (H), Medium(M), Low(L), Very Low (VL). The saturation parameter is given by $(app_{on}/app_{tot}) \times 100$ and it has three membership functions namely High (H), Medium (M) and Low (L). Trapezoidal membership functions have been taken for all the input parameters whereas the output parameter has been modelled by triangular membership functions.

Table 5.1 Fuzzy rulebase for determining the probability of switching on AC with low saturation

Time of Day / **Historical user switching behaviour (app_{hub})**	EM	M	A	E	LE
VH	**L**	**M**	**VH**	**VH**	**L**
H	**VL**	**L**	**H**	**H**	**VL**

M	**VL**	**VL**	**M**	**M**	**VL**
L	**VL**	**VL**	**L**	**L**	**VL**
VL	**VL**	**VL**	**VL**	**VL**	**VL**

The entire day has been divided into T time periods for each of which every appliance is assigned a switching value through the fuzzy logic program as shown in equations (5.1) to (5.7)

$$S_{l,i}^{h} = a, \forall a \in [0,1] \tag{5.1}$$

$$\sum_{i=1}^{h} a_i \neq rt_l \tag{5.2}$$

$$\sum_{\substack{i=1 \\ h}}^{l-1} d_{l.i}^{e,h} + d_{l,i}^{e,h} \leq rf_h^{max} \tag{5.3}$$

$$\sum_{l=1}^{n-1} \mathrm{d}_l^{i} < \emptyset \tag{5.4}$$

$$\mathrm{P_i} = \mathrm{P_i}(.)|\mathrm{P_i}(t) \text{ subject to}(1) \text{ to } (4) \tag{5.5}$$

$$\mathrm{Obj} = \left[\sum_{h=1}^{24}\left(\sum_{l=1}^{N} \mathrm{P_{l,h}} - \mathrm{P_{ref,h}}\right)^2 + \kappa\right] \tag{5.6}$$

$$\kappa = 1000 * \sqrt{[\mathrm{rt_l} - \mathrm{rt_{act}}]^2} \tag{5.7}$$

Where Obj is the objective function and κ is the penalty function incorporated into the objective function to ensure that the appliances complete their runtimes. This has been used as a soft penalty function to allow a small amount of flexibility in the appliance runtimes. This can be justified with the fact that $\mathrm{rt_l}$is the average runtime of the $\mathrm{l^{th}}$ appliance which means some appliances belonging to the $\mathrm{l^{th}}$ set will have less runtimes than the average while some will have more. The best population among multiple runs is selected based on the Obj function value. The structure of the fuzzy system is shown in Fig 5.1(b).

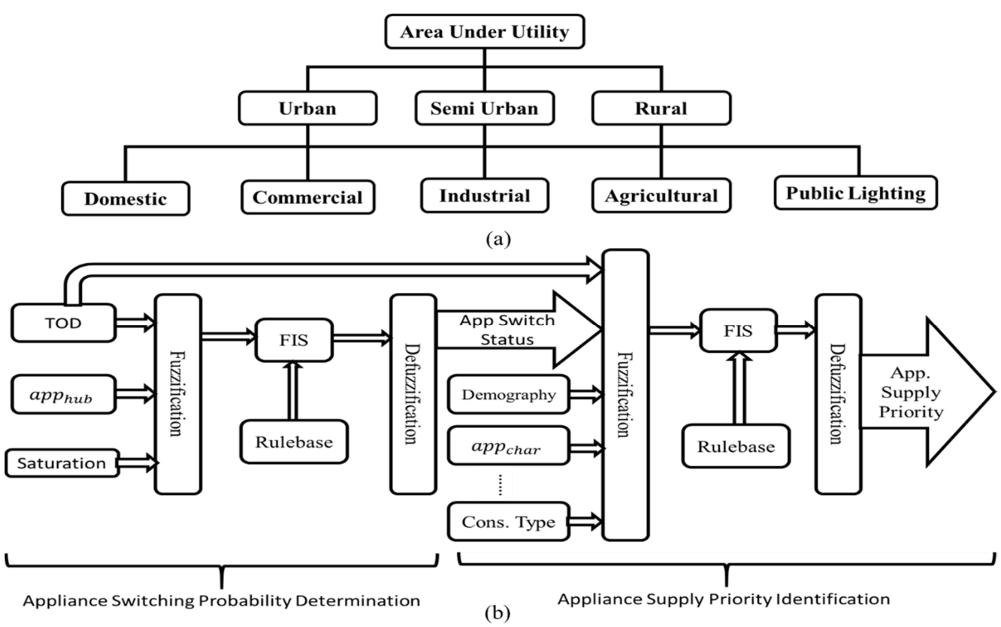


Fig 5.1 Structures of the area division and Fuzzy Logic Process (a) Area and Load Division Structure, (b) Fuzzy Structure

5.2.2. Classification of Regions

The load profiles that were developed using fuzzy logic are utilised to classify different regions based on the correlation between the output of the fuzzy logic program and the actual load demand input or the region. The synthetic load profile L^{XY}_{synth} and the actual load demand profile L_{act} are first normalized using the formulas (5.8) to (5.10)

$$L^{XY,h}_{synth,norm} = \frac{L^{XY,h}_{synth}}{L^{XY,max}_{synth}} \quad (5.8)$$

$$L^{h}_{act,normh} = \frac{L^{h}_{act}}{L^{act}_{max}} \quad (5.9)$$

$$L^{XY,h}_{synth} = \sum_{i=1}^{N} L^{XY,h}_{synth,i} \quad (5.10)$$

Where,

$L^{XY,h}_{synth,i}$ = fuzzy logic output of h^{th} hour of the i^{th} load of Y^{th} type of X^{th} region.

N = total number of loads of Y^{th} type in X^{th} Region.

L^{max}_{act} = maximum value of the input load profile in time period T.

Then the correlation between them is obtained using the equations (5.11) and (5.12)

$$\mathrm{cor}\left(L_{act,norm}, L^{XY}_{synth,norm}\right) = \frac{\mathrm{cov}\left(L_{act,norm}, L^{XY}_{synth,norm}\right)}{\sigma\left(L_{act,norm}\right) * \sigma\left(L^{X}_{synth,norm}Y\right)} \quad (5.11)$$

$$L_{act} \in XY \mathrm{if} \mathrm{cor}\left(L_{act,norm}, L^{XY}_{synth,norm}\right) \geq 0.8 \quad (5.12)$$

where,

$\forall X \in$ [Urban, Semi Urban, Rural]

$\forall Y \in$ [Residential, Commercial, Industrial, Agricultural, PublicWorks]

5.2.3. Rescheduling of Loads for better Load Factor

After formation of the switching profiles each appliance of Y^{th} type in X^{th} region is obtained as $\left[a^{XY}_{i,1}, a^{XY}_{i,2} \ldots, a^{XY}_{i,H}\right] \in R^{M\times N}$ where $M = \sum_{i=1}^{X'} \sum_{j=1}^{Y'} \sum_{k=1}^{A} a^{ij}_{k}$ and $N = H$ where X'= total number of regions, Y'= total number of consumer types and A = total number of appliances in under each consumer type of each region. Each appliance will have a different set of starting and stopping time $\left[t_{start}, t_{stop}\right] \in R^{(M\times 2)}$ between which they can be rescheduled. This start and stop times have been decided by taking into consideration the different user data obtained from surveys and data repositories of utility services. PSO has been used to perform the rescheduling to minimize the objective function shown in equation (5.13)

$$\text{Obj} = \min\left[\sum_{h=1}^{H}\left(\sum_{i=1}^{M} \phi_i^h \times P_i^{rt(h)} - \text{avg. Load}\right)^2\right] \tag{5.13}$$

Where H denotes the maximum time slots the day has been divided into, M denotes the total number of appliances under consideration defined earlier, $\phi_i^h \in [0,1]$ denotes the switching status of the load satisfying the conditions given by equations (5.14) to (5.16).

$$\phi_i^h = [0,1]\ \forall t \in \left[t_{start,i}, t_{stop,i}\right] \tag{5.14}$$

$$\phi_i^h = 0 \forall t \notin \left[t_{start,i}, t_{stop,i}\right] \tag{5.15}$$

$$rt_i^{XY} = a_{i,H}^{XY} - a_{i,1}^{XY} \tag{5.16}$$

$P_i^{rt(h)}$ = the power consumption demand of ith load on the runtime slot corresponding to the h^{th} time slot of the day and $\text{avg. Load} = \frac{1}{H}\sum_{i=1}^{H}\sum_{j=1}^{M} P_j^{rt(i)}$. The function of the load scheduling program is to bring the load demand factor as close to 1 as possible by filling in the valleys and reducing the peaks in the daily demand curve. This serves to ensure that the load consumption is fully optimised so that when the loads are selected for renewable or grid supply there is no wastage of resources due to inefficient load consumption pattern. The demand to be supplied at each time slot can be defined by equation (5.17)

$$\sum_{i=1}^{M} P_i^{rt(h)} = \sum_{j=1}^{J} NSL_j(h) + \sum_{k=1}^{K} CL_k(h) - \sum_{l=1}^{L} DL_l(h). \tag{5.17}$$

Where $NSL_j(h) = j^{th}$ Non-Schedulable Load at h^{th} time slot, $CL_k(h) = k^{th}$ Connected Load at h^{th} time slot which was either already present in the time slot of concern or disconnected from another time slot and connected to the present time slot and $DL_l(h) = l^{th}$ Disconnected Load which has been disconnected from the time slot in concern and shifted to another time slot.

5.2.4. Tagging the scheduled loads to determine which loads can be supplied by Renewable Energy

The loads are tagged in three levels – those which can be supplied by renewable energy, those who can be supplied by grid and those who are interruptible. The division of loads is done by using a fuzzy rule base, an example of which is given in Table 5.2 and Table 5.3. At first the usage priority of the appliance is determined based on the demographical classification, appliance characteristics (app_{char}) which denotes the attribute of the appliance because of which it is used such as temperature for space cooling appliances as shown in Table 5.2. Then the output of the fuzzy inference system in terms of usage priority is fed to another fuzzy inference system to determine whether the appliance being used can be supplied from grid or renewable or does it need to be interrupted using the fuzzy rulebase example shown in Table 5.3. The renewable energy available in the region is classified into three categories: High(H), Medium(M) and Low(L).

Table 5.2 Fuzzy rulebase example for appliance usage priority selection

Time of Day	Temperature (app_{char})	Demographical Classification	Usage Priority
MN	LT	R	L
MN	LT	SU	M
MN	LT	U	M
MN	HT	R	M
MN	HT	SU	H
MN	HT	R	H

Table 5.3 Fuzzy Rule Base for Load Source Mapping with Low Renewable availability

Usage Priority	**Runtime**	**Renewable Availability**	**Power Consumption Level**	**Consumer Type**	**Priority Supply**
L	M	L	LP	res	Int
L	M	L	MP	res	Int
L	M	L	HP	res	Int
M	L	L	LP	res	ren
M	H	L	MP	res	Int
M	M	L	HP	res	Int
M	M	L	LP	res	ren
M	L	L	MP	res	ren
M	M	L	HP	res	Int
M	H	L	LP	res	ren
M	H	L	MP	res	Int
M	VH	L	HP	res	Int
H	M	L	LP	res	ren
H	L	L	MP	res	ren
H	VH	L	HP	res	Int

The power consumption of each load has been classified into three categories: High Power (HP), Medium Power (MP), Low Power (LP) and the time duration of continuous consumption for each load starting from the hour under consideration is divided into five categories: Very High (VH), High(H), Medium(M), Low(L) and Very Low (VL). On every hour the different loads are tagged to be supplied by either renewable energy or directly from the grid based on the equations (5.18) to (5.20):

$$S_i^{XY,h+rt} = f\left(rt_i^{XY,h}, P_i^{XY}, B^R, W_i^{XY,h}\right) \quad (5.18)$$

$$B^R = \sum_{i=1}^{N} \lambda_i^X \quad (5.19)$$

$$\forall S_i^{XY,h} \in [0,1,2] \quad (5.20)$$

where,

$S_i^{XY,h+rt}$ = switch status of i^{th} load of Y^{th} type in the X^{th} region in $(h+rt)^{th}$ hour.

1 = possibility to be supplied by renewable sources

2 = supplied by grid

0 = interruptible

λ_i^X = Available power from renewable source energy of i^{th} type in X^{th} Region

N = total number of Renewable Energy Sources in the Y^{th} region

rt = runtime of i^{th} load of Y^{th} type in X^{th} region

P_i^{XY} = power rating of the i^{th} load of Y^{th} type in the X^{th} region

$W_i^{XY,h}$ = tagged status of i^{th} load of Y^{th} type in the X^{th} region at h^{th} hour

The loads that are tagged each hour for being supplied by a certain source continues to be supplied from that as source for the consecutive hours in which it is in continuous operation. While classifying the different loads at those hours the load that is already tagged due to continuous operation from a previous hour is skipped but provided with the highest priority to be provided from the supply it is already tagged with.

5.2.5. Redistributing the Regional Loads in case of Source Failure

Sometimes a source may fail to deliver in a Region at any hour such that

$$\sum_{i=1}^{N} P(act)_i^{X,h} < \sum_{i=1}^{N} P(pred)_i^{X,h} \quad (5.21)$$

where,

$\sum_{i=1}^{N} P(act)_i^{X,h}$ = Actual available power from renewable sources of the X^{th} region in the h^{th} hour.

$\sum_{i=1}^{N} P(pred)_i^{X,h}$ = Predicted available power from renewable sources of the X^{th} region in the h^{th} hour.

In such a case it is necessary to reorganise the loads projected to be supplied by renewable energy. The loads are redistributed according to their priority and state of operation such that

$$L_i^{XY,h} > L_j^{ZY,h} \text{if} rt_i^{XY} > 0, rt_j^{ZY} = 0 \text{ and } PR_i^{XY} = PR_j^{ZY,h} \tag{5.22}$$

or,

$$L_i^{XY,h} > L_j^{ZY,h} \text{if} PR_i^{XY,h} > PR_j^{ZY} \tag{5.23}$$

$$S_i^{XY,h+rt} = 1 \tag{5.24}$$

$$S_j^{ZY,h+rt} \in [0,2] \tag{5.25}$$

where,

$[0,1,2] \in [\text{switchedoff}, \text{renewablesupplied}, \text{gridsupplied}]$

$L_i^{XY,h} = i^{th}$ load of the Y^{th}type ofX^{th} region in h^{th} hour

$L_i^{ZY,h} = i^{th}$ load of the Y^{th} type of Z^{th} region in h^{th} hour

$PR_i^{XY,h} =$ Priority of the i^{th} load of the Y^{th} type of X^{th} region in h^{th} hour

$PR_i^{ZY,h} =$ Priority of the i^{th} load of the Y^{th} type of Z^{th} region in h^{th} hour

$\forall X, Z \in [\text{urban}, \text{semiurban}, \text{rural}]$

$\forall Y \in [\text{Residential}, \text{Commercial}, \text{Industrial}, \text{Agricultural}, \text{PublicWorks}]$

Based on the mathematical discussion given in section 5.2.5 an algorithm was developed to form a reference template to compare and distinguish between different Regions and Load categories, reschedule them to decrease the load factor and finally categorize them into the loads than can be supplied by renewable and those which need to be supplied by grid. The pseudocode of the proposed algorithm is provided in algorithm 5.1.

Algorithm 5. 1 Algorithm to explain the fuzzy tool to map regional demand to renewable

Algorithm: Fuzzy Tool to Map Demand to Renewable Supply

[appl_no,power_consump] *= func (demographics[Region], consump_pattern[Region]);*
[Region_type] *= max(corr(Region,preGenerated_RegionProfiles));*
[appl_sets, appliance_numbers,appl_switchingProfile]=func(Region_type);
group ←similar appliances switched together;
set limits←min max hours of switching on appliances;
run PSO;
for *h ← 1 to 24* ***do***

appl_usagePriority *= FIS (TOD,* app_{char}*,demography);*

supplySelectFIS_input *=*
func(appl_contRunHours,app_powConsump,perc_RenewAvail, appl_usagePriority);

supplySelectFIS_output *= appl_Supply ∈ [renewable, grid, interruptible];*

Select: dom, comm, ind and agri loads having $max(appl) \in renewable$*;*

Reschedule: appl ∉ [renewable] to hours ∈ [demand_factor ≤ 1];

Supply: selected units and appliances according to their priority level;

Store: excess renewable supply to be used during low availability hours;

end

5.3. Result and Discussion

The output obtained from the proposed fuzzy logic model was compared with the actual load profiles by using the correlation method to find the accuracy and degree of similarity to which the output of the proposed fuzzy regional power profile simulator matches the actual power consumption patterns of the urban and rural regions considered for developing the proposed classifier model. The actual power demand curves for urban and rural regions were obtained from [77] and [19]. The fuzzy regional power profile simulator is used to build up the actual power profile of the urban and rural consumers using the appliances owned and the appliance usage pattern of each consumer. The advantage of this method is that only the approximate running hours, functioning window, rated appliance power and the aggregate power profile is required to develop the daily power profiles of each appliance usage which can be aggregated o form the final daily power demand profile of the user. The urban residential and commercial power demand profiles developed by the abovementioned process is shown in Fig. 5.2 and Fig. 5.3.

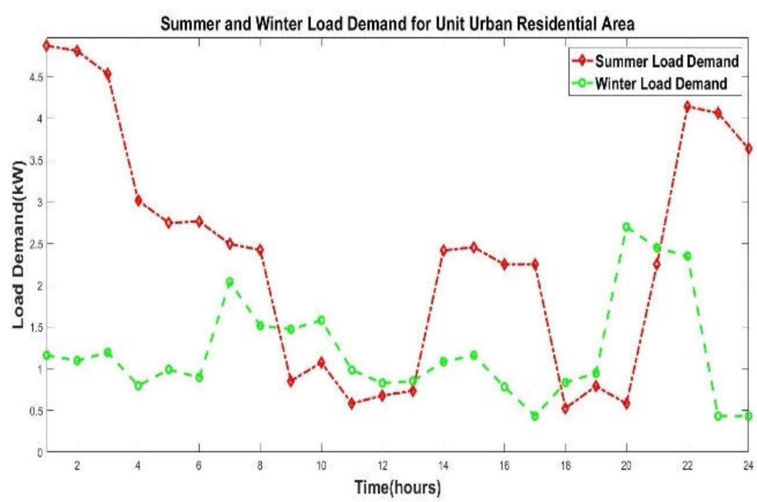


Fig 5.2 The output of the fuzzy tool for developing unit urban residential load demand

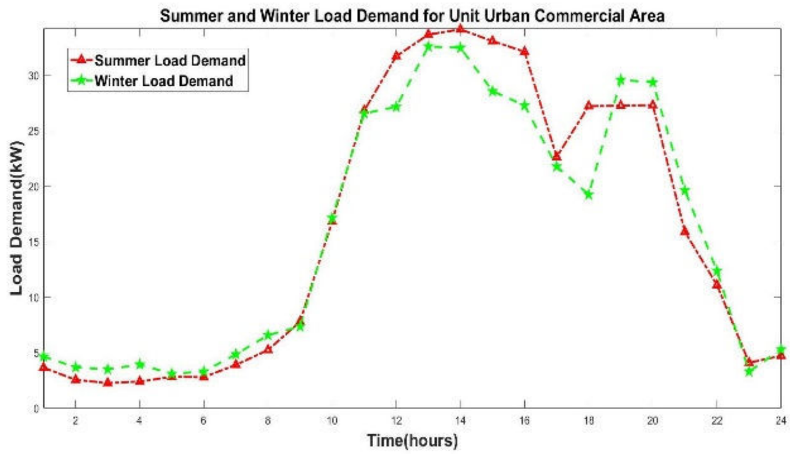


Fig 5.3 The output of the fuzzy tool for developing unit urban commercial load demand

The correlation data given in Table 5.4 was used to verify the accuracy of this method by comparing the aggregate daily power profiles developed from the summation of the appliance usage power profiles of urban residential, commercial and rural residential consumers with the actual average load profiles of the abovementioned consumers obtained from utility reports.

Table 5.4 Correlation data

	Output Data of Fuzzy Tool		
Real Time Data	Urban Residential	Urban Commercial	Rural Residential
Urban Residential	0.8414	-0.7727	-0.1234
Urban Commercial	-0.6735	0.8662	0.2341
Rural Residential	-0.1962	0.2242	0.8551

The diagonal correlation data shows that there is almost 85% similarity between the developed and actual power demand profiles of the consumers. The off-diagonal data of the correlation matrix that shows the correlation between the non-similar profiles. The low and negative values of the elements lead to the inference that there is a considerable difference between the appliance usage patterns of the consumers of different sectors of the urban and rural regions. The purpose of this work is to utilize this difference in the daily power demand pattern arising from the difference in regional appliance usage pattern. Classification of hourly grid and renewable compatible appliance use can be used to develop a renewable and grid power demand pattern which can be used to develop an efficient regional energy management system. To obtain this goal, a mapping system is developed to perform the hourly mapping of the appliances used to grid and renewable power. The knowledge about the availability of the hourly renewable power is crucial to this process. The renewable power availability is forecasted using the technique explained in Chapter 4. Before applying the mapping process the scheduling of the shiftable appliances is needed to be completed. As the intermittency of the renewable sources can cause inconvenience to the consumer in case the available renewable power at a particular hour is less than the forecasted value. If the schedulable appliances are scheduled based on the information of renewable energy availability then the user may not be able to switch on the appliance in case sufficient renewable energy is not available for use. Also, the grid may face a sudden unaccounted for increase in power demand as the consumers would then switch to the grid for the required power. Again, if the scheduling is done to minimize the cost then it may give rise to new peak demand periods which is also not desirable. To overcome this problem, the scheduling of the schedulable appliances was done by taking into consideration both the reduction of cost and keeping the load factor close to one. The scheduling was done with particle swarm optimization (PSO). For developing an effective rescheduling model, the loads of the different consumer categories of a region were classified into shiftable loads and non-shiftable loads. The start and stop times between which each load can be rescheduled was fixed considering the region type, consumer type and load type as these factors are very important in scheduling loads. A load of same type may have different operating schedules based on the region and the consumer who is using it. The output of the PSO algorithm after scheduling the appliances and the original unscheduled load demand pattern is shown in Fig 5.6. Fig. 5.6a shows the scheduled and unscheduled load of the combined regional area and Fig.5.8b shows the scheduled and unscheduled power demand of the rural households for the summer and winter seasons. Though the residential power demand does not show much change after scheduling, the overall regional demand profile can be seen to have become much uniform mostly due to the contribution of the scheduled commercial loads. After scheduling of the loads, the appliance level power demand is passed through a classification algorithm which classifies the power demand of each appliance at each hour as renewable compatible or grid compatible. The inputs to the fuzzy logic model are Regional Demographics in the form of average population per square km of the area under consideration, appliance specific attributes (temperature, illumination etc.), time of day (TOD), power consumption of the appliance, and type of installation i.e. residential or commercial that the appliance user belongs to. The output of the fuzzy inference system provides the priority of the appliances under consideration as $\chi \in [0,1]$ where int $\in [0,0.3]$, renewable $\in [0.25,0.65]$, grid $\in [0.6,1]$. The fuzzy logic membership functions are shown in Fig 5.4 and Fig 5.5.

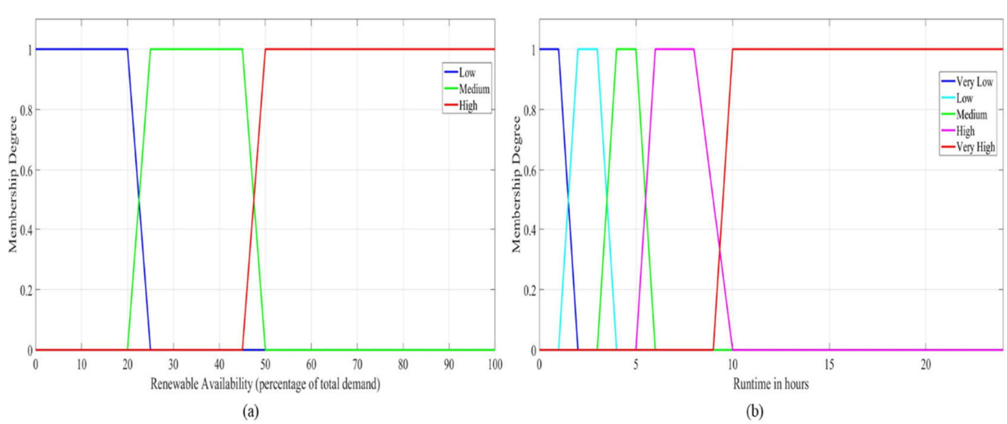


Fig 5. 4 Fuzzy membership functions for (a) renewable availability expressed in percentage of total demand (b) appliance runtime

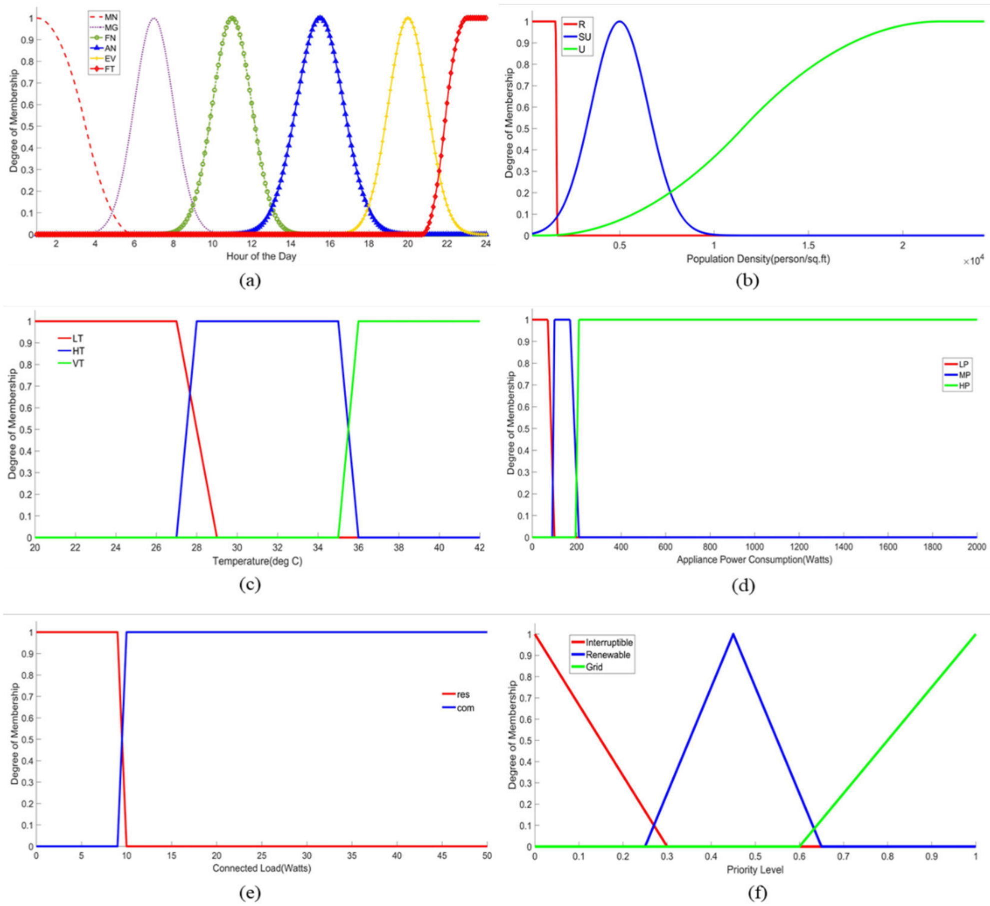
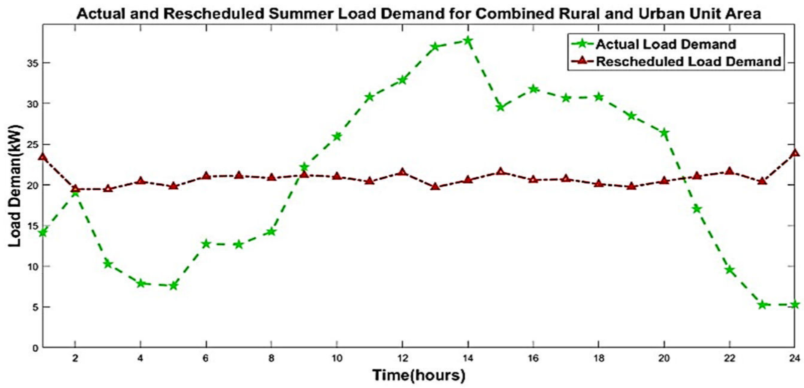


Fig 5.5 Fuzzy membership functions for (a) Time of day (b)Demographic classification (c) Temperature for space cooling (d)appliance power consumption (e) consumer type based on connected load (f) supply selection for appliances

The priority of each appliance considered hourly differs depending upon whether the region is Urban, Rural or Semi Urban. With the uncertain nature of renewable energy sources and the objective of grid energy consumption reduction it is necessary to classify the hourly priority of the scheduled appliances region wise. The output of the Fuzzy System classifies the appliances as Interruptible, Renewable Compatible and Grid Priority respectively towards increasing priority. The output membership function of the Fuzzy Inference System is shown in Fig 5.4 (f). The inputs to the fuzzy inference system are given as Regional Demographics, Temperature for classification of space cooling, Illumination for classification of space lighting priority, Power Consumption of the appliances which has been divided in three levels i.e. low, medium and high, Time of Day where 24 hours have been divided into 6 parts for better management, and the type of load i.e. Residential or Commercial based on the total connected load of the consumer. Some of the membership functions have been illustrated from Fig 5.4 (a) to Fig 5.4(f). Different membership functions were tested to find the combination of membership functions which provided optimum results. The highest priority loads were marked as grid priority as interruption in their operation cannot be afforded due to uncertainty of renewable supply. The main parameter for making this decision was weather conditions and user comfort.

The least priority loads were marked as interruptible. The interruptible loads are considered to get supplied by renewable supply if available, but in absence of sufficient renewable supply these loads are not to be provided with grid supply. Between these two categories lie the loads marked with renewable compatible status. They will receive supply from renewable sources and will be interrupted only if the renewable supply falls short even after interrupting the least priority loads. A sample set of the fuzzy logic rule base has been provided in Table 5.3. The fuzzy rule base of the system has been developed after extensive study of the data provided by surveys over multiple cities and towns spread over different regions [77-78].



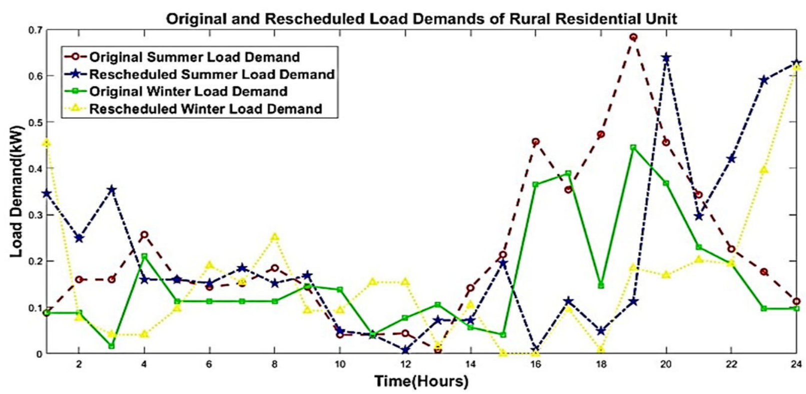


Fig 5.6 Actual and Rescheduled Load of Combined Area and Rural Unit (a) Combined Unit Area Load, (b) Seasonal rural residential unit area load before and after scheduling

The algorithm first determines the region type by correlating the regional power demand profiles to a predetermined average regional power profiles of urban, rural and semi urban regions. After the region type has been determined, the appliance ownership and usage data into the fuzzy appliance profile generator to generate appliance level power demand profiles. After this the appliance scheduling was done using the method detailed in section 5.2.3. The results obtained after scheduling the appliances is shown in Fig. 5.6. Then the hourly classification is done for each appliance. The outputs have been shown in the Fig. 5.7 and Fig. 5.8. This system provides us with a good insight into the characteristics of the load demand both region wise and consumer category wise. The proposed model can be used to classify the appliance level power demand as renewable or grid supply compatible for several renewable energy availability scenarios. Based on the real time availability of the renewable energy, the user can switch between the different classification modes. The grid utility also has a prior information about the range in which the power demand may vary which can help them to stay prepared for any situation arising due to the intermittency of the renewable sources.

Table 5.5 Percentage Load Selected for Renewable Supply per Region and Consumer Category

Season	Consumer Category	Urban	Semi Urban	Rural
Summer	Residential	4.79	10.42	29.1
	Commercial	14.615	14.721	12.88
Winter	Residential	6.09	7.1	31.26
	Commercial	14.13	14.3	17.81

The major contribution of this work is providing a detailed model in which the loads are mapped to their probable supplies based on the region wise classification of Urban, Semi-Urban and Rural. The model is capable of identifying the type of region and consumer category to be addressed from the load demand profile of the region.

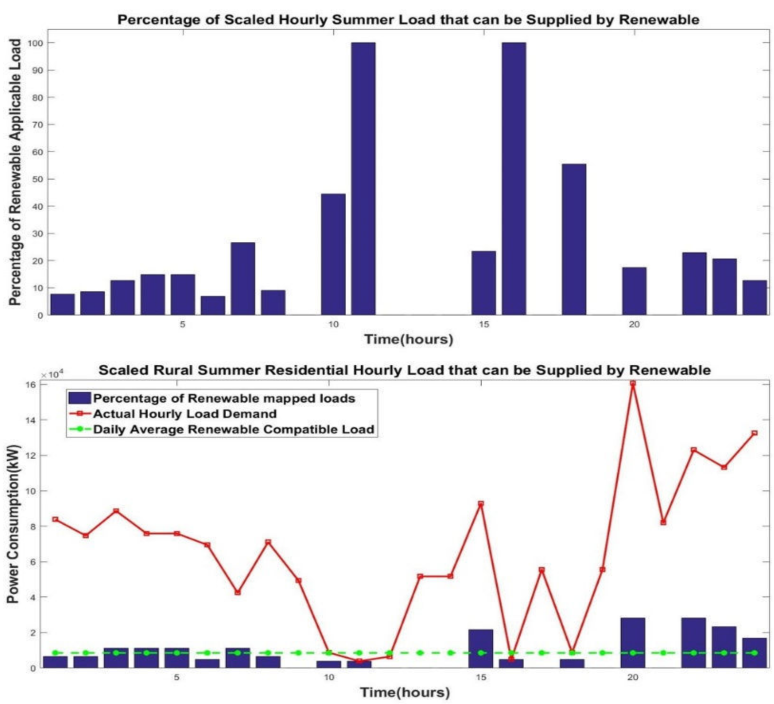


Fig 5.7 Percentage and actual rural residential loads available for renewable supply in Summer, (a) Percentage of rural residential hourly load selected to be supplied by renewable, (b) Actual value of rural residential rescheduled load to be supplied with renewable compared to total demand

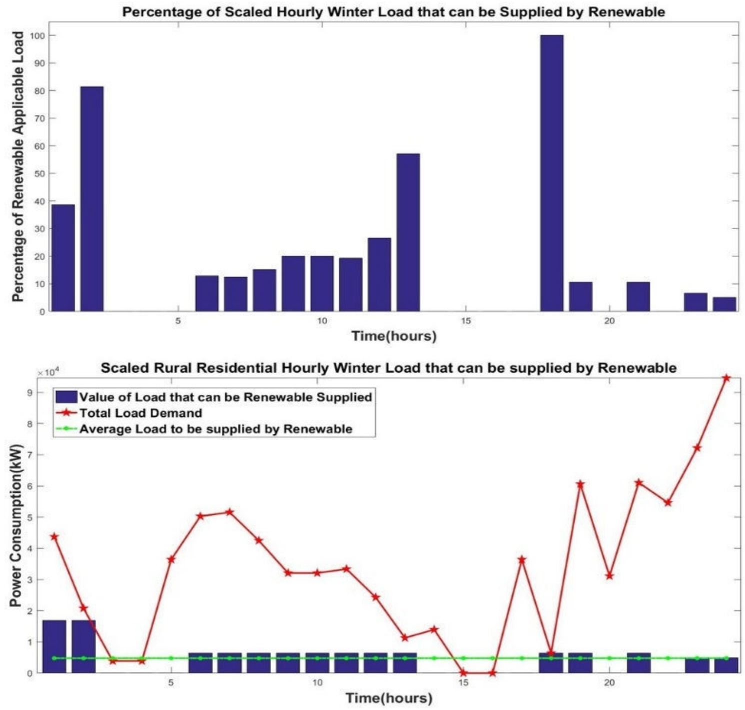


Fig 5.8 Percentage and actual rural residential loads available for renewable supply in Winter, (a) Percentage of rural residential hourly load selected to be supplied by renewable, (b) Actual value of rural residential rescheduled load to be supplied with renewable compared to total demand

This model can be utilized to develop a roadmap for the region wise development of renewable energy sources based on the growth of population and subsequent growth of load demand which depends upon the type of region under question and appliance ownership percentage in such regions. So, this model contributes in diversifying the load management system and tailor solutions to the needs of a particular region based upon the demographic and geographical characteristics of that region. It also provides a future roadmap of renewable energy development based on the load demand characteristic of the urban, semi-urban and rural regions which is very important for sustainable development.

Table 5.6 Demand Supply Variation Data

Season	Supply Level	Urban		Semi Urban		Rural	
		High Demand	Low Demand	High Demand	Low Demand	High Demand	Low Demand
Summer	High Supply	13.99	43.79	13.78	43.47	24.75	47.70
	Low Supply	3.01	8.08	2.96	4.85	5.45	10.81
Winter	High Supply	7.16	19.38	6.50	19.45	7.16	20.96
	Low Supply	1.47	4.35	1.35	4.36	9.32	19.61

The percentage of loads that are tagged for being supplied with renewable energy is found to be largely varying both region wise and consumer category wise. The percentage share of the loads of each region that can be supplied from renewable sources is shown in Table 5.5. The load demand of the regions and the available renewable energy vary with changes in climatic factors. The demand supply variations have been shown in Table 5.6 referencing the values of which we can see a higher percentage of residential loads are selected for renewable supply compared to commercial loads. The reason being that residential units consume less power, are less critical and have more scheduling flexibility. For similar reasons, rural percentage of both the category of loads are higher than Urban and Semi Urban. The values of Urban and Semi Urban regions appear close to each other as the types of appliances used in these regions are nearly the same. The lower values obtained during winter can be attributed to the following two reasons. The first is lesser renewable availability due to decreased solar intensity and shorter days. The second is the reduced use of space cooling appliances resulting in increased percentage share of heavier and more critical loads, which are less likely to be selected for renewable supply by the fuzzy tool, in the total load demand of the region. So, it is evident that the developed tool can distinctly distinguish between the different load profiles.
Also, the performance of the proposed method to suggest a renewable integration approach with distinctly different percentages for the different regions and consumer categories is also satisfactory. Summarising, it can be said that the proposed method is capable of providing a region wise load management solution distinctly capturing the diversity of the load demand characteristics of different regions and consumer categories.

5.3 Grid Integrated Performance

The procedure described in section 5.2 has been tested on a modified grid system developed using a combination of IEEE 14 bus system and IEEE 5 bus system. The schematic representation of the system is given in Fig. 5.9.

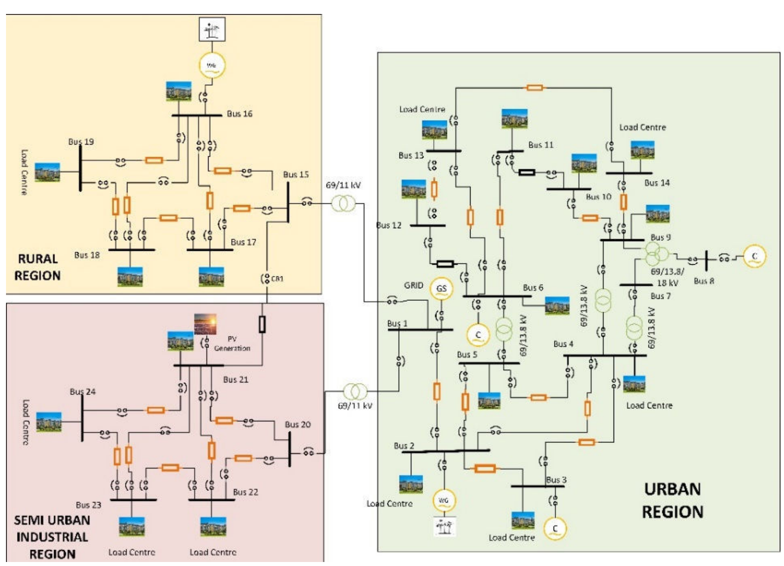


Fig 5.9 Urban, Semi Urban and Rural regional grid system

The original specified parameters of the system are given in Tables 5.7 and 5.8.

Table 5.7 Generation and Demand data for IEEE 14 bus system

Bus No	Generation		Load		Bus No	Generation		Load	
	Real Power (MW)	Reactive Power (MVAR)	Real Power (MW)	Reactive Power (MVAR)		Real Power (MW)	Reactive Power (MVAR)	Real Power (MW)	Reactive Power (MVAR)
1	-	-	0	0	8	0	17.4	0	0
2	40	42.4	21.7	12.7	9	0	0	29.5	16.6
3	0	23.4	94.2	19	10	0	0	9	5.8
4	0	0	47.8	3.9	11	0	0	3.5	1.8
5	0	0	7.6	1.6	12	0	0	6.1	1.6
6	0	12.2	11.2	7.5	13	0	0	13.5	5.8
7	0	0	0	0	14	0	0	14.9	5

Table 5.8 Generation and Demand data for IEEE 5 bus system

Bus No	Generation		Load	
	Real Power (MW)	Reactive Power (MVAR)	Real Power (MW)	Reactive Power (MVAR)
1	-	-	0	0
2	40	30	20	10
3	0	0	45	15
4	0	0	40	5
5	0	0	60	10

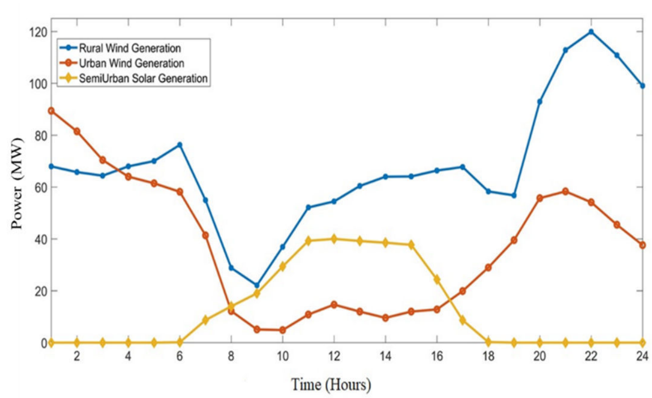


Fig 5.10 Hourly power generation profile of the renewable power sources

For the purpose of testing the proposed methodology the following modifications have been done in the system:

- The PV generator in bus 2 changed to wind power source capable of producing maximum power of 100 MW
- The PV generator in bus 21 changed to solar power source with maximum output of 50 MW
- The PV generator in bus 16 changed to wind power source with maximum capability of 130 MW
- The hourly generation values of the above sources are shown in Fig 5.10.
- Circuit breaker added between tie line connecting bus 15 and bus 21
- Load shedding capability for load 21 and load 22 in the semi urban region is added to simulate the base case of excess demand

The loads consisted of a combination of Residential and Commercial loads in bus nos. 1,6,13,16,17,18 and 19, only commercial in bus nos. 3,4,9 and 14 and only residential in bus nos. 5,10,11 and 12. The semi urban region loads were kept the same as the IEEE data provided to simulate constant industrial load. Only bus no 21 was connected to a variable load to test the effectiveness of peer to peer energy transfer strategy. The number of residential and commercial units per feeder bus was determined by dividing the actual load data by the connected load of the residential and commercial units. These active power demands were made variable by using the actual hourly load profile curves scaled up by the total number of units connected to each feeder bus. The reactive power demand per hour was obtained by taking the power factor of the loads as 0.8. Renewable energy sources are connected to buses 2,16 and 21 providing one source to each region. The urban and semi urban region has wind power plant while the rural region was provided with a PV power plant. The wind and solar energy outputs are calculated using the equations

$$P_w = 1/2 * A * \xi * \Psi^3 * t \tag{5.26}$$

$$P_{WT} = (\eta_W / 100) * P_w \tag{5.27}$$

$$P_{pv} = A_{pv} * r_{pv} * Irr * PR_{pv} \tag{5.28}$$

where, P_w is the wind power energy output, P_{WT} is the turbine output power, A is the swept area of the turbine, ξ is the air density, Ψ is the speed of wind, t is the time over which the operation of the wind turbine is considered, P_{pv} is the power generated by the Photovoltaic Array, r_{PV} is the yield of the connected solar panels, I_{rr} is the hourly average irradiation of the region and PR_{pv} is the performance ratio of the photovoltaic module which was considered as 0.65. The efficiency of the DC to AC converter connected to the PV array was taken as 80% conservatively. The PV power plant is considered to be connected in the Semi-Urban Industrial region. The Wind Energy farm in the rural area was considered to have peak power output of 130 MW as the land availability and the wind speed in the rural areas is comparatively more than the urban area whose wind farm was considered to have peak power of 100 MW. The PV power output was calculated using equation (5.26) [16]. The wind energy calculation is done using equations (5.27) to (5.28) [79]. The system shown in Fig. 5a was used to simulate two case studies. The first case study was done to obtain the load-shedding instances, bus voltage profiles and greenhouse gas emissions without the implementation of the proposed solution. A load shedding system was implemented in the semi-urban region to simulate the over loading of the tie line connecting the semi-urban region to the Grid. The load connected to bus 21 is shed if the collective demand of the semi urban industrial region goes beyond 125 MW but stays within 145 MW. If the demand exceeds 145 MW then load connected to bus 22 is shed. The breaker connecting the Rural region to the semi-urban industrial region is kept open, thus preventing peer to peer energy transfer. There is no renewable source availability in this scenario. It is found that several instances of load shedding occur and the voltage profiles of some buses also go beyond acceptable levels.

Case study II was done after implementing the proposed solution to the same system. The simulation output results showed considerable improvement in all the areas compared to case study I. The bus voltage outputs in per unit (p.u) for Case Study I and II are shown in Tables 5.9 and 5.10. Only those buses whose voltages were out of the tolerable range were taken into consideration and it is quite clear from the values that there was a significant improvement in bus voltages after the implementation of the proposed solution in the system. The switching status of circuit breaker (CB) 1 added between the rural and semi urban region compared with the load shedding status of the loads at bus 21 and 22 are shown in Fig. 5.11. From Figs 5.11 & 5.12 it can easily be observed that the time of closing of the breaker CB1 between rural region and semi urban industrial region coincides with the load shedding profile of loads 21 and 22 in the case without the application of the proposed solution. In Fig.5.12 it can be seen that substantial amount of power being supplied from the rural region to the semi urban industrial region which indicates peer to peer energy transfer and thus efficient utilization of the excess renewable energy present in the Rural region due to the implementation of the proposed solution. The substantial reduction in greenhouse gas emission both overall and hourly basis after implementation of the proposed solution is very clear from Fig. 5.13 thus verifying that the implementation of the proposed solution can provide significant improvement both in the operation of the present power system and environmental impact by reducing greenhouse gas emissions significantly.

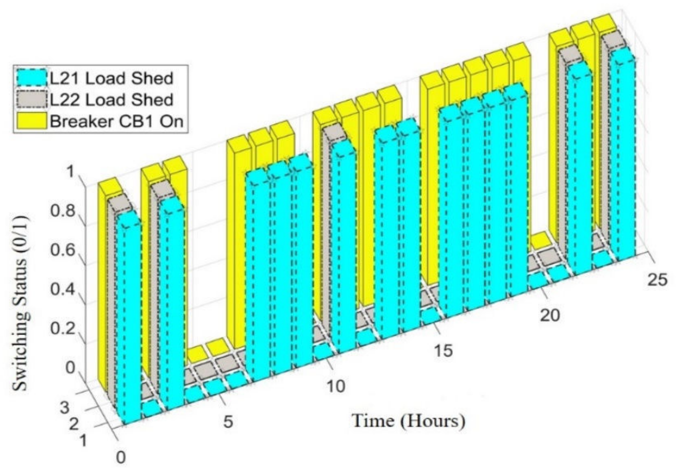


Fig 5.11 CB1 switching and load shedding status of loads at bus 21 and 22

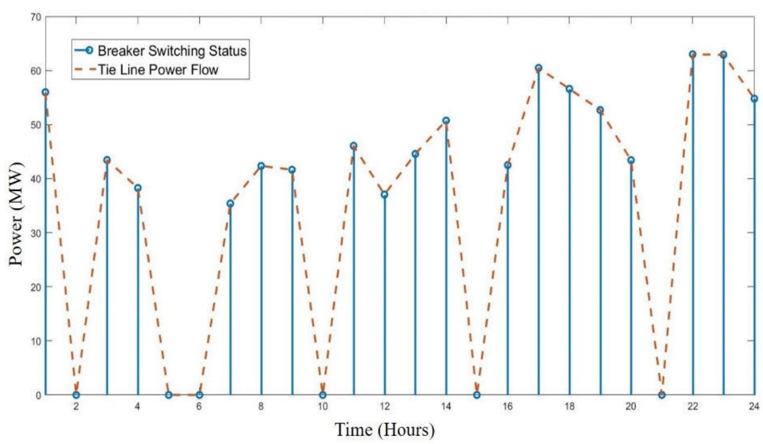


Fig 5.12 CB1 switching and tie line power flow between rural and semi urban region

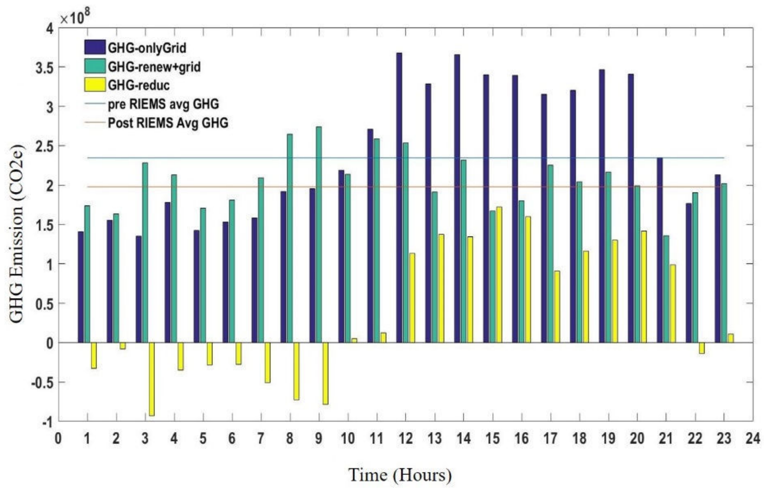


Fig 5.13 Greenhouse gas emissions pre and post implementation of proposed methodology

The CO_2 equivalent emission per 1kWh of energy consumed has been taken as 950g per kWh of power generated by fossil fuel i.e. coal whereas the mean CO_2 emission per kWh of energy generated through fossil fuel so the equivalent percentage reduction in GHG emission was calculated as in equation (5.29).

$$\alpha = (\nu_{pre} * 950 - \nu_{post} * 950 + \vartheta * 12) / (\nu * 950) * 100 \tag{5.29}$$

Where α is the percentage reduction in GHG emission, ν_{pre} is the power consumed before implementation of the proposed solution, ν_{post} is the reduced power consumed from grid post implementation of the proposed solution, ϑ is the amount of renewable power consumed post implementation of the proposed solution.

Table 5.9 Pre and Post Regional Bus Voltages (p.u.) of Semi-Urban Industrial Region

	Bus 16		Bus 17		Bus 18		Bus 19	
Hours	Pre-Regional Renewable Integration	Post-Regional Renewable Integration	Pre-Regional Renewable Integration	Post-Regional Renewable Integration	Pre-Regional Renewable Integration	Post-Regional Renewable Integration	Pre-Regional Renewable Integration	Post-Regional Renewable Integration
1	1.1713	1.1080	1.1754	1.1077	1.1762	1.1082	1.1759	1.1071
2	1.1668	1.0648	1.1704	1.0562	1.1712	1.0556	1.1707	1.0514
3	1.1668	1.0344	1.1704	1.0254	1.1712	1.0247	1.1707	1.0203
4	1.1601	1.0483	1.1630	1.0399	1.1637	1.0393	1.1630	1.0352
5	1.1668	1.0665	1.1704	1.0580	1.1712	1.0574	1.1707	1.0532
6	1.1679	1.0672	1.1716	1.0587	1.1724	1.0581	1.1720	1.0540
7	1.1531	1.0494	1.1553	1.0414	1.1558	1.0408	1.1548	1.0367
8	1.1489	1.0347	1.1506	1.0272	1.1512	1.0265	1.1500	1.0222
9	1.1444	1.0332	1.1456	1.0257	1.1461	1.0250	1.1447	1.0207
10	1.1074	1.0781	1.1048	1.0717	1.1047	1.0712	1.1019	1.0674
11	1.0194	1.0448	1.0084	1.0377	1.0070	1.0371	1.0011	1.0333
12	0.9875	0.9844	0.9736	0.9702	0.9718	0.9687	0.9647	0.9623
13	0.9742	1.1083	0.9591	1.1072	0.9572	1.1076	0.9497	1.1061
14	0.9494	1.0959	0.9321	1.0939	0.9299	1.0941	0.9215	1.0924
15	0.9502	1.1274	0.9330	1.1255	0.9307	1.1258	0.9224	1.1240
16	0.9050	1.1033	0.8839	1.1013	0.8811	1.1016	0.8712	1.0998
17	0.9716	1.1320	0.9563	1.1347	0.9543	1.1357	0.9467	1.1357
18	0.9602	1.1324	0.9438	1.1351	0.9417	1.1360	0.9337	1.1359
19	0.8835	1.0861	0.8606	1.0836	0.8575	1.0838	0.8469	1.0818
20	0.9168	1.0633	0.8967	1.0560	0.8941	1.0557	0.8846	1.0523

21	1.0433	1.1621	1.0345	1.1634	1.0335	1.1643	1.0283	1.1643
22	1.1413	1.1330	1.1422	1.1343	1.1427	1.1353	1.1412	1.1353
23	1.1592	1.1219	1.1619	1.1223	1.1626	1.1231	1.1618	1.1227
24	1.1704	1.1223	1.1743	1.1223	1.1752	1.1230	1.1748	1.1224

Table 5.10 Pre and Post Regional Bus Voltage Values (p.u.) of Rural Region

	Bus 21		Bus 22		Bus 23		Bus 24	
Hours	Pre-Regional Renewable Integration	Post-Regional Renewable Integration	Pre-Regional Renewable Integration	Post-Regional Renewable Integration	Pre-Regional Renewable Integration	Post-Regional Renewable Integration	Pre-Regional Renewable Integration	Post-Regional Renewable Integration
1	0.9930	0.9778	0.9804	0.9538	0.9774	0.9528	0.9664	0.9473
2	0.9796	0.9796	0.9594	0.9594	0.9592	0.9592	0.9652	0.9652
3	0.9930	0.9517	0.9804	0.9277	0.9774	0.9264	0.9664	0.9202
4	0.9258	0.9766	0.9031	0.9541	0.9019	0.9534	0.8997	0.9521
5	0.9822	0.9822	0.9621	0.9621	0.9619	0.9619	0.9684	0.9684
6	0.9668	0.9668	0.9460	0.9460	0.9456	0.9456	0.9493	0.9493
7	0.9668	0.9828	0.9447	0.9607	0.9440	0.9601	0.9438	0.9603
8	0.9108	0.9499	0.8860	0.9256	0.8843	0.9242	0.8762	0.9171
9	0.9108	0.9497	0.8860	0.9253	0.8843	0.9240	0.8762	0.9169
10	0.9770	0.9770	0.9566	0.9566	0.9564	0.9564	0.9619	0.9619
11	0.9873	0.9510	0.9744	0.9266	0.9713	0.9252	0.9591	0.9178
12	0.8537	0.9284	0.8275	0.9040	0.8254	0.9024	0.8160	0.8947
13	0.9716	1.0045	0.9498	0.9824	0.9492	0.9821	0.9498	0.9834
14	0.9352	0.9811	0.9116	0.9576	0.9103	0.9567	0.9053	0.9528
15	0.9783	0.9783	0.9580	0.9580	0.9578	0.9578	0.9635	0.9635
16	0.9776	1.0061	0.9561	0.9842	0.9556	0.9840	0.9573	0.9863
17	0.9197	0.9858	0.8953	0.9618	0.8938	0.9609	0.8867	0.9556
18	0.9375	0.9946	0.9140	0.9711	0.9128	0.9704	0.9081	0.9671
19	0.9108	0.9672	0.8860	0.9429	0.8843	0.9418	0.8762	0.9351
20	0.9207	0.9780	0.8977	0.9553	0.8965	0.9546	0.8937	0.9529
21	0.9858	0.9858	0.9659	0.9659	0.9658	0.9658	0.9730	0.9730
22	0.9983	0.9867	0.9859	0.9630	0.9831	0.9622	0.9733	0.9579
23	0.8592	0.9768	0.8332	0.9526	0.8312	0.9515	0.8223	0.9454
24	1.0100	0.9957	0.9980	0.9728	0.9955	0.9722	0.9886	0.9707

The average GHG emission levels over the period of 24 hours before and after implementation of the proposed methodology are 2.3×10^{8} CO2e and 2×10^{8} CO2e respectively which means a reduction of around 13% in the GHG emissions have been obtained. The grid health index was measured using the voltage deviation index (VDI) [80] of absolute voltage improvement for pre and post implementation of the proposed methodology shown in equation (5.30).

$$VDI_j = \left|1 - V_j\right| \tag{5.30}$$

where VDI_j is the voltage deviation index of the j^{th} bus and V_j is the voltage of the j^{th} bus in per unit (p.u). As shown in Table 5.11 implementation of the proposed regional load monitoring system achieves significant voltage level improvement in the buses in consideration thus sufficiently increasing grid health.

Table 5.11 Pre and Post Regional Bus Voltage Deviation Index Values (p.u.) of Rural and Semi Urban Industrial Region

Bus No.	Pre-Implementation	Post Implementation	Percentage improvement
Bus 16	0.11	0.08	21.47
Bus 17	0.11	0.08	29.01
Bus 18	0.12	0.08	29.62
Bus 19	0.12	0.08	32.68
Bus 21	0.05	0.03	48.04
Bus 22	0.07	0.05	31.15
Bus 23	0.07	0.05	31.44
Bus 24	0.07	0.05	32.42
Average Improvement			32

5.4 Chapter Conclusion

This chapter describes a new approach towards load management and renewable integration method based on regional approach considering the load demand characteristics of different consumer categories. The region classification tool and load selection for renewable supply has been developed using fuzzy logic and the rescheduling of loads using different parameters varying regionally for a better load factor has been done using PSO. The proposed solution assures to contain the entire range of regions and loads as obtained from data available from online repositories and surveys of different organisations. It is shown by the test results that the performance of the proposed method in recognising the type of region and consumer category from the load demand profile is satisfactory and has obtained an overall improvement in the grid health by 32% along with reduction of average GHG emission of 13%.

The next chapter will present the research works carried out to develop a regional power demand based regional community energy management system implementing the fuzzy based hourly appliance classification and regional tariff systems.

Chapter 6
Regional Power Demand Simulation, Energy Management Performance and Impact of Tariff

6.1 Introduction

Substantial amount of research has been conducted over the last few decades on developing sustainable solutions in the field of energy and power. The proposed solutions range from demand side management to supply side management with integration of renewable energy sources in the primary energy mix. Energy communities have emerged as a viable solution to develop an energy efficient sustainable society. It has been found that energy sharing among the participants in the community with the option of selling the excess power to grid can provide sufficient motivation to the consumers for installing renewable energy installations in their residential and commercial installations. The energy use characteristics of the different consumers can be further exploited to maximise the monetary profits and energy savings that can be obtained through the formation of energy communities. The demographic differences of urban and rural regions in terms of appliance ownership and usage pattern can provide a good opportunity

6.2 Simulation Setup and Power Usage Profile Modelling Data

The simulations are performed on energy profiles of two urban and two rural houses together forming an energy community. These load profiles were simulated using LoadProGen simulator in MATLAB 2021a®. The parameters of urban and rural power consumption preferences, appliance ownership and appliance usage time for simulating these load profiles were obtained from surveys conducted on residential houses of rural and urban areas [77] [78] and are shown in Table 6.1 where R denotes Rural and U denotes Urban. The output of the simulations for the load profiles of the four residential houses are shown in Fig. 6.1. The houses are equipped with solar power output with peak value equivalent to 30% of their connected load. Time of day prices of energy has been used for optimization and the day ahead forecasted values of the renewable power availability of each house is obtained by using wavelet neural network (WNN) as explained in Chapter 4. The forecasted PV power output of the four homes of the community are provided for the prediction horizon of 24 hours in Fig. 6.2.

Table 6. 1 Parameters of urban and rural appliance ownership, functioning window, functioning cycle and rated power

Appliance Name	**Average Rated Power Consumption(W)**	**Number**		**Functioning Cycle (hours)**		**Functioning Duration(hours)**		**Functioning Window**	
		R	**U**	**R**	**U**	**R**	**U**	**R**	**U**
TV	127	1	2	1	1	5	6	11-22	18-24
Music System	100	-	2	-	1	-	6	-	24
Refrigerator	150	1	1	1	1	11	24	24	24
Computer	250	-	2	-	1	-	3	-	10-12,18-22
Geyser	2000	-	2	-	1	-	1	-	6-9
Washing Machine	400	1	1	1	1	1	2	8-16	10-15
Water Pump	750	1	1	1	1	2	2	24	24
Iron	1100	-	1	-	1	-	1	-	24
Ceiling Fan	40	1	3	1	1	5	8	24	24
AC	1800	1	2	1	1	5	8	1-7,12-15,18-24	1-6,12-16,22-24
Table Fan	70	-	1	-	1	-	4	-	24
Incandescent Lamp/CFL/LED	97/12/8	2	3	1	1	9	8	5-8,18-24	24
LED Tubes	20	-	3	-	1	-	4	5-8,18-24	18-24
OTG/Microwave	1000	1	1	1	1	1	2	5-11,16-18	8-10,21-24
Cooler	224	1	-	1	-	3	-	24	-

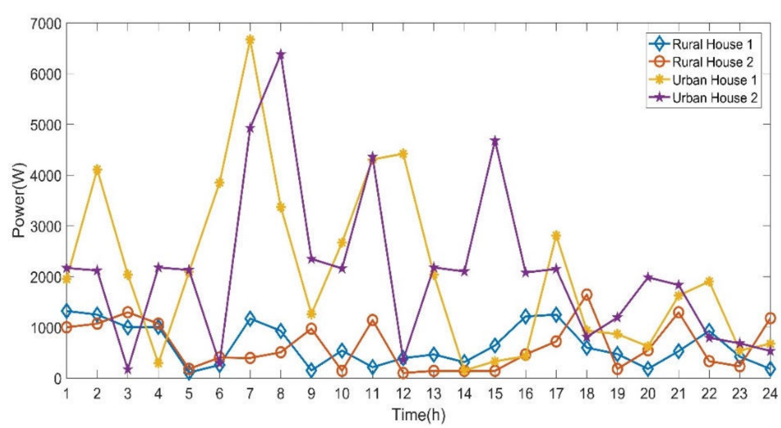


Fig 6. 1 Original Power Demand of the four houses

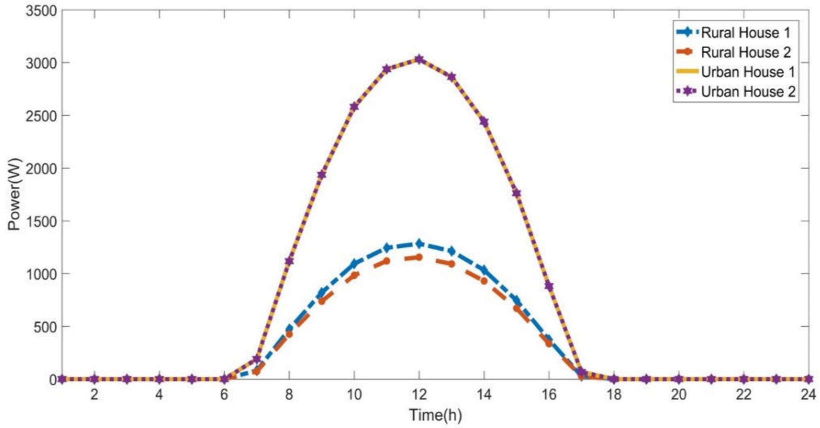


Fig 6. 2 Available PV power from the four houses as considered in different scenarios

The time horizon for performing the simulations is considered as 24 hours. The simulations are performed using MILP based community optimization. The upper and lower limits of the renewable power made available to each house of the community per hour is obtained by using the fuzzy inference method explained in Chapter 5. The control signals for battery banks and flexible loads for both the urban and rural residential units are generated based on the optimized cost function. The simulations are presented for a single season i.e. summer, but with two distinct regional power consumption characteristics and a community TOD tariff system to capture the effect of the regional power usage variation on the operation of AI controlled energy community. This study is crucial for developing a smart energy management system for application to areas encompassing regions having different demographic patterns. The residential units use a time of use tariff for purchasing energy from the grid. The purchasing and selling prices for the interactions with grid are shown in Table 6.2 and that of the community is shown in Table 6.3. This helps in observing the performance of the system under an organized dynamic tariff system. The capping of selling and purchasing power amount has

Table 6.2 Buying and Selling prices for the interaction between home and grid

	Medium Demand Period	**High Demand Period**	**Low Demand Period**
Grid Price (INR/KWh)	7.97	9.51	6.81
Grid Sell Price (INR/KWh)	2.4	2.85	2.04

Table 6.3 Buying and Selling prices for the interaction between home and grid

	Medium Demand Period	**High Demand Period**	**Low Demand Period**
Renewable Buy Price (INR/KWh)	3.99	4.78	3.405
Community buy/sell price (INR/KWh)	3.2	3.8	2.724

been considered as the connected load of each house. A battery has been considered for one urban household having the following characteristics: rated capacity is 10kW, maximum charge/ discharge power is 5kW, ramp up/ramp down power is 2kW and charge/discharge efficiency is taken as 95%. Two and three shiftable appliances have been considered for the rural and urban homes respectively. They are washing machine, iron and water pump for urban homes and washing machine and water pump for rural homes. The restrictions imposed on these appliances are that their total runtimes within the prediction period should be equal to the prescheduled runtime specified by the consumer, they have to remain on for a minimum of one hour every time they are switched on an they cannot be switched on consecutively before a minimum time period has passed in between. The members of the households have the possibility to define the runtime and functioning window of the shiftable appliances.
The implementation is done in MATLAB2021a® and the optimization problem was solved with Gurobi using MATLAB-Gurobi interface. Five case studies are considered for comparison as shown in Table 6.4. For each of these five case studies, nine scenarios are considered for performing the simulations as shown in Table 6.5. These five case studies and nine scenarios are chosen due to their relation with the need to assess the operational gains of an interregional energy community over a non-energy community operation with varying degree of renewable energy production by each household and/or the presence of controlled energy storage capacity and appliances.

Table 6.4 List of cases explored

# Case Study	Description
Case Study 1	Proposed RCEMS for community operation using individual tariff model
Case Study 2	Proposed RCEMS for community operation with community-based tariff model
Case Study 3	Proposed RCEMS for community operation with separate urban and rural sector tariff model
Case Study 4	Hybrid resource allocation energy community model with community tariff model
Case Study 5	Hybrid resource allocation energy community model with separate urban and rural sector tariff model

An important point to note is that one of the contributions of this work is to minimize the energy cost of the community as a whole with less importance to the cost of individual members. The ideal value of the energy purchased and sold between the entities involved in the optimization at each time period is determined by the program with focus on the minimization of community energy costs.

Table 6. 5 The list of scenarios explored for each case

# Scenario	Description
Scenario 0	No battery no solar power (Each home is optimized separately)
Scenario 1	Rural House 1 has solar power
Scenario 2	Urban house 1 has solar power
Scenario 3	Both urban house 1 and rural house 1 has solar power
Scenario 4	Both the urban houses have solar power

Scenario 5	Urban house number 2 and rural house number 1 has solar power
Scenario 6	Both the urban houses and rural house 1 has solar power
Scenario 7	Both the urban houses and rural house 1 has solar power while rural house no 2 has 50% solar capacity
Scenario 8	Both the urban houses and rural house 1 has solar power while rural house no 2 has 90% solar capacity
Scenario 9	Both the urban houses and rural house 1 has solar power while rural house no 2 has 90% solar capacity and urban house number 1 has battery

6.3 Methodology of the proposed solution

6.3.1 Determination of regional Time of Day (TOD) tariff using period partitioning

A time of day tariff system was developed using the time of use tariff plan provided by the state utility board and the peak, flat and valley period of power demand partitioning method explained in [22]. The process of the tariff determination using the said method has been shown in Fig. 6.2. The mathematical formulation of the process is given by equations (6.1) and (6.2)

$$\min\left\{F\left(P_{fv},P_{pf}\right)=\frac{1}{24}\sum_{\substack{m\in(p,f,v)\\ i\in 24}}\left(P_i-\bar{P}_m\right)^2\right\} \tag{6.1}$$

$$\bar{P}_m=\frac{1}{N}\sum_{i\in m}P_i \tag{6.2}$$

Three tariff scenarios have been developed using the period partitioning model and applied to find the best possible tariff scheme which can be applied to obtain the most efficient results from the proposed regional community energy management system by incentivising the consumers to participate in the energy management system. The peak, valley and flat periods were determined using the period partitioning method for the urban and rural residences considered individually, combining all the four houses to form a community and separate urban and rural clusters which were then combined to form a community as a whole. The peak, valley and flat periods obtained for the power consumption of each urban and rural house separately is shown in Fig. 6.4. The same periods for the community obtained by combining all the residences together is shown in Fig. 6.5 and that of the community formed by separate urban and rural clusters is shown in Fig. 6.6. After separating the power consumption in the three cases the hourly tariff was applied according to the classification of the hourly consumption as peak, valley and flat which was further used for the optimization problem.

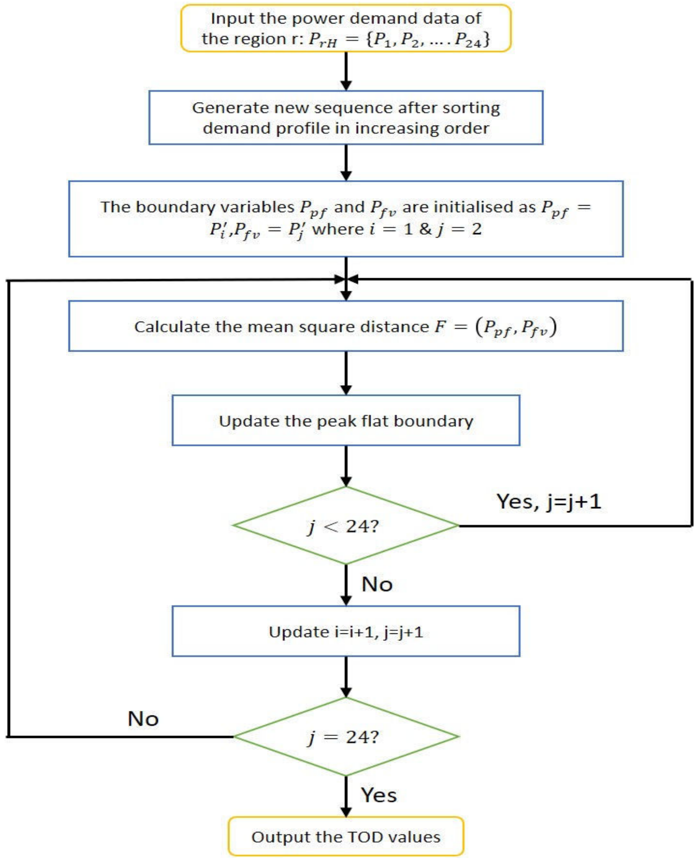


Fig 6.3 Flowchart of the particle partition method to select the optimum tariff for different community combinations

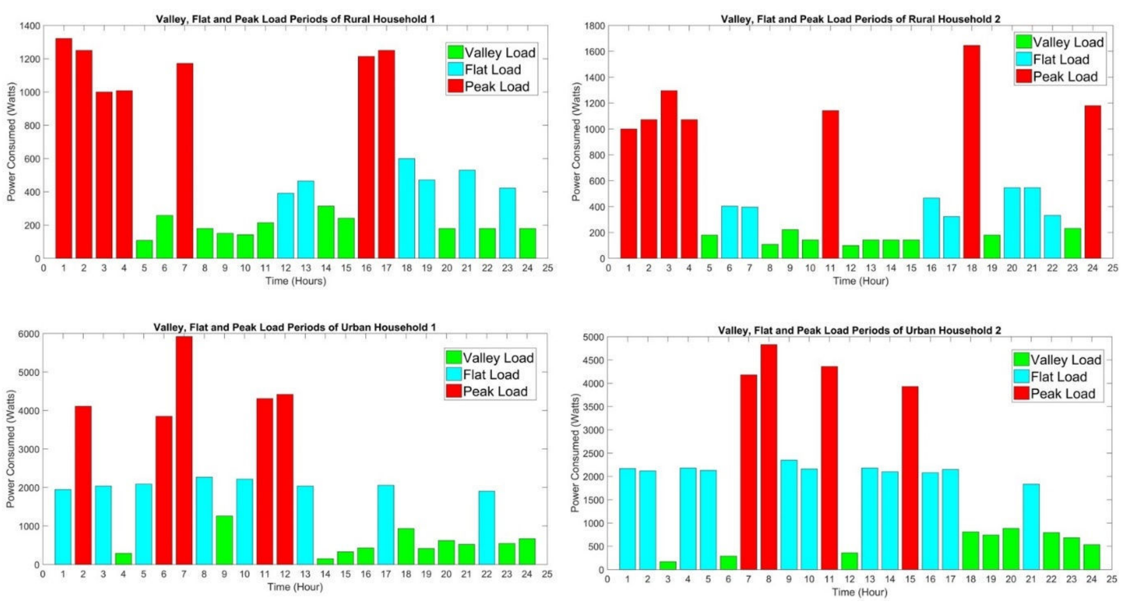


Fig 6.4 Peak, Valley and Flat hours obtained from individual power demand of the individual households

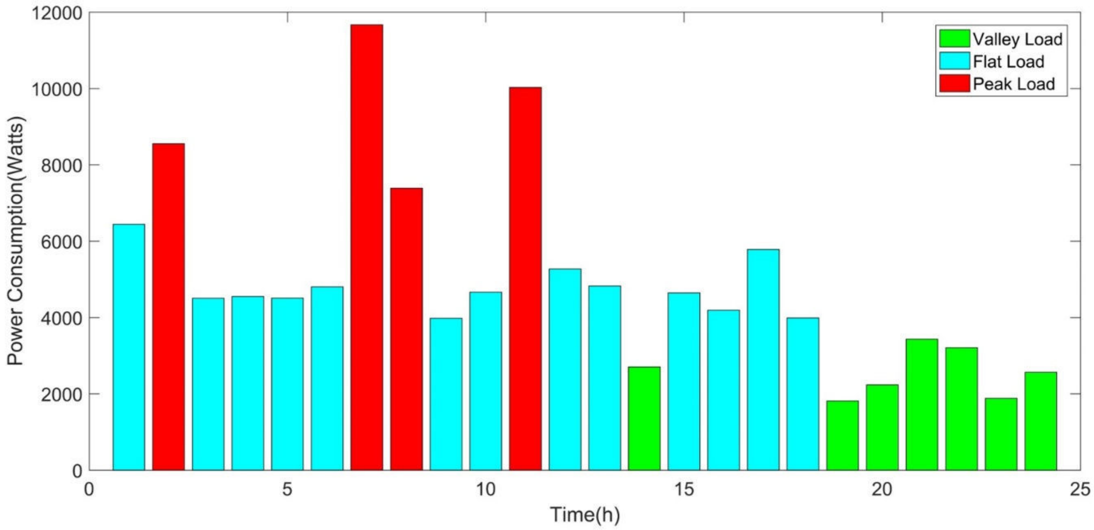


Fig 6.5 Peak, Valley and Flat hours obtained from combined power demand of the community

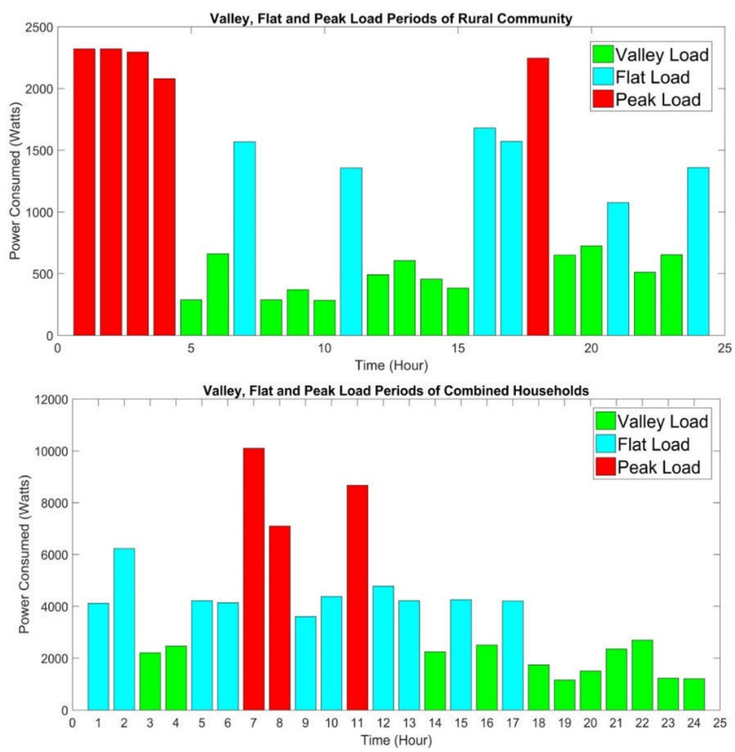


Fig 6.6 Peak, Valley and Flat hours obtained from combined power demand of the rural and urban households taken as separate communities

It shows that there is a marked difference between the peak, valley and flat hours of urban and rural residences. Also, the power consumption of the urban society is much higher compared to the rural society. The concentration of peak and flat hours during the daytime can be explained by the running of the space cooling appliances during the daytime. As these appliances consume a large amount of power, they increase the community energy consumption values by a significant amount.

6.3.2 Formulation of the fuzzy guided Mixed Integer Linear Programming (MILP) based predictive control problem

The proposed mixed integer linear programming based predictive control integrates a fuzzy logic module with an intelligent optimizer. The concept underlying the fuzzy monitored intelligent optimizer for the Regional Community Energy Management System (RCEMS) is presented in the Fig. 6.7. The intelligent optimizer comprises of a fuzzy logic system and a MILP module. The fuzzy logic module combines the weather parameters and consumer appliance preferences to determine the hourly percentage of loads of each prosumer that can be supplied by the renewable sources as described in chapter 5. The output of the fuzzy module is provided as an input to the MILP optimizer along with the following information:

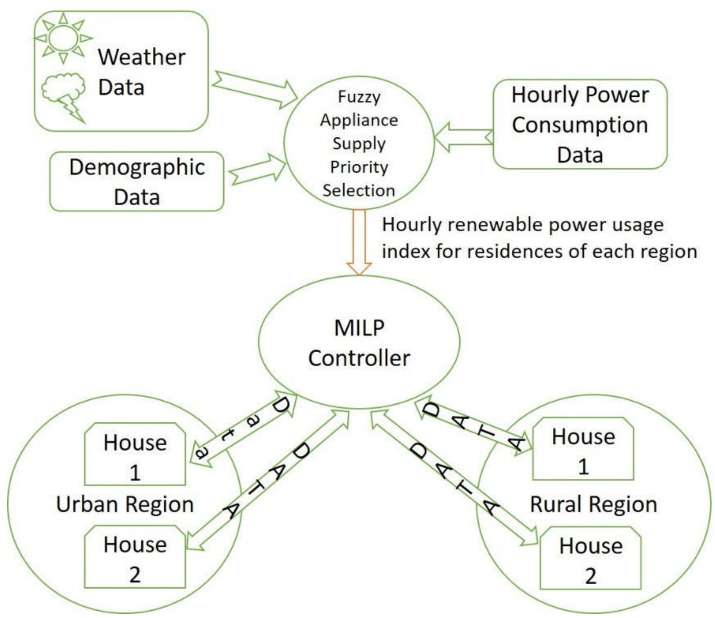


Fig 6.7 Graphical representation of the workflow

- Information related to electrical consumption and appliance use priority of urban and rural residential units.
  - $P_{t,k,r}$ = active power consumption (kW) of the k^{th} house of the r^{th} region at the t^{th} hour of the day
  - $R_{t,k,r}$ = reactive power consumption (VAR) of the k^{th} house of the of the r^{th} region at the t^{th} hour of the day
  - $P^{PV}_{t,k,r}$ = ac power generated by the solar installation of the k^{th} house of the of the r^{th} region at the t^{th} hour of the day
  - Energy storage availability and storage capacity details

- $SoC_{k,t}$ = state of charge of the battery bank of the k^{th} house at the t^{th} hour
- The appliance switching pattern, regional appliance usage priority and the fixed or flexible nature of the appliances of house k in region r

The above information is obtained from each house by the aggregator per hour. In case of schedulable appliances that can be automatically controlled, the number of working hours and the time gap between two consecutive working hours of each schedulable appliance for house k of the r^{th} region is provided to the aggregator. The active power consumption of the k^{th} house of the r^{th} region at the time interval t given by equation (6.3) is composed of the following elements

- Fixed operation appliances that are not monitored and subsequently not controlled automatically ($\bar{M}$, $\bar{C}$)
- Flexible time appliances that are both monitored and controlled by the aggregator (AMC)
- Appliances that are manually controlled by the consumer (MC)

$$P_{k,t,r} = \sum_{j=1}^{N\overline{MC}} P_{k,t,r,j} + \sum_{j=1}^{MC} P_{k,t,r,j} + \sum_{j=1}^{CMC} P_{k,t,r,j} \tag{6.3}$$

The complexity of forming the problem of community energy management is very high. The proposed RCEMS will be able to manage the power consumption of the entire region-based community in order to obtain a solution with the cost of operation minimized to the maximum extent. The complexity of the RCEMS arises from the fact that there are multiple factors to ensure such as the energy balance of each residential unit considered, the energy balance of the demographic regions considered, the balance between the cost reduction and comfort of the users of each region and the energy community as a whole. The state of charge of available energy storage devices, obtaining an economic balance between charging the devices with available renewable or grid energy and the energy balance between the grid and the community under study. At every instant t, the proposed optimizer model solves a Mixed Integer Linear Programming (MILP), with the objective function given as follows by equation (6.4)

$$minC^{comm} = \min \sum_{r=1}^{NR} \sum_{t=1}^{Nt} \sum_{k=1}^{Nh} \left\{ P_{t,k,r}^{grid+} \times CG_{t,r}^{+} + P_{t,k,r}^{ren+} \times CR_{t,r}^{+} + P_{t,k,r}^{comm+} \times CC_{t,r}^{+} - P_{t,k,r}^{grid-} \times CG_{t,r}^{-} - P_{t,k,r}^{comm-} \times CC_{t,r}^{-} \right\} \Delta t \tag{6.4}$$

In equation 4 Nt denotes the prediction period which is 24 hours, Nh denotes the total number of houses in the community from urban and rural regions, NR denotes the total number of regions considered i.e. urban, semi urban and rural, the sampling rate of the program in hours is given by Δt. The sampling rate taken for this work is one hour. $P_{t,k,r}^{grid+}$ / $P_{t,k,r}^{grid-}$ are the forecasts of the active power (KW) bought from the grid/sold to the grid at the time instant of t by house k of region r at time instant t.

$P_{t,k,r}^{comm+}$ / $P_{t,k,r}^{comm-}$ are the estimates of the active power (KW) bought from and sold to the community at the t^{th} hour by the k^{th} house of region r. $CG_{t,r}^{+}$ / $CG_{t,r}^{-}$ denote the cost of buying from and selling to the grid of a region at the time period t. $P_{t,k,r}^{ren+}$ is the renewable energy used by the k^{th} house of the r^{th} region at the t^{th} hour. $CC_{t,r}^{+} / CC_{t,r}^{-}$ gives the cost of buying and selling to the regional community energy grid for the t^{th} hour of the r^{th} region and $CR_{t,r}^{+}$ denotes the cost of using renewable energy generated by the residential unit itself. This cost justifies the fact that there is capital cost involved in setting up a PV generation unit at home and the cost to use the subsequent power generation can be obtained by dividing the capital and monthly maintenance cost by the total units of PV generated power used by the household. Through this method, the objective of minimizing the cost of power bought from the grid and maximization of the cost of power sold to the grid is achieved. However, there are many constraints that are required to be satisfied for the system to work properly.

$$0 \le P_{t,k,r}^{grid+} \le conn\_load_{k,r} \times S_{t,k,r}^{GB} \tag{6.5}$$

$$0 \le P_{t,k,r}^{grid-} \le conn\_load_{k,r} \times S_{t,k,r}^{GS} \tag{6.6}$$

The set of constraints given in equations (6.5) and equation (6.6) ensure that the power bought from and sold to the grid are non-negative variables and the total traded power is less than the contracted power which in this case is equal to the connected load of the residential unit under consideration. $S_{t,k,r}^{GB} / S_{t,k,r}^{GS}$ are the binary variables determining whether the k^{th} house of the r^{th} region is in the mode of buying power or from or selling power to the grid at time instant t. They take the value of 1 if power is being bought at that time instant, otherwise it is 0.

$$0 \le P_{t,k,r}^{comm-} \le conn\_load_{k,r} \times S_{t,k,r}^{CS} \tag{6.7}$$

$$0 \le P_{t,k,r}^{comm+} \le conn\_load_{k,r} \times S_{t,k,r}^{CB} \tag{6.8}$$

The equations (6.7) and (6.8) defines the lower and upper boundary constraints for trading power with the community grid by the k^{th} house of the r^{th} region at time instant t. $S_{t,k,r}^{CB} / S_{t,k,r}^{CS}$ are the binary variables determining whether the k^{th} house of the r^{th} region is in the mode of buying power or from or selling power to the grid at time instant t. $conn\_load_{k,r}$ is the connected load of the k^{th} house of the r^{th} region.

$$\sum_{r=1}^{NR}\sum_{k=1}^{NH} P_{k,r}^{comm+} = \sum_{r=1}^{NR}\sum_{k=1}^{NH} P_{k,r}^{comm-} \tag{6.9}$$

$$app\_S_i^{PV+} + app\_F_i^{PV+} + P_{t,k,r}^{grid-} + P_{t,k,r}^{comm-} + P_{t,k,r}^{RB+} = P_{t,k,r}^{PV} \tag{6.10}$$

$$P_{t,k,r}^{GB+} + P\_app_{t,k,r}^{grid+} = P_{t,k,r}^{grid+} + P_{t,k,r}^{comm+} + P_{t,k,r}^{B-} \tag{6.11}$$

$$S_{t,k,r}^{GB} + S_{t,k,r}^{CS} \le 1 \tag{6.12}$$

$$S\_app_{t,k,r}^{G} + S\_app_{t,k,r}^{R} + S\_app_{t,k,r}^{comm} \le 1 \tag{6.13}$$

$$S_{t,k,r}^{CB} + S_{t,k,r}^{CS} \le 1 \tag{6.14}$$

$$\sum_{t=1}^{Nt}\sum_{i=1}^{n\_app}\left(S\_app_{i,t,k,r}^{G} + S\_app_{i,t,k,r}^{R} + S\_app_{i,t,k,r}^{comm}\right)\times app\_P_{i,k,r} = P_{t,k,r} \tag{6.15}$$

$$\sum_{t=1}^{Nt}\sum_{i=1}^{n\_app} S\_app_{i,t}^{R} \times app\_P_{i,t} \le P_{t}^{PV} \tag{6.16}$$

$$\sum_{r=1}^{NR}\sum_{k=1}^{Nh}\sum_{t=1}^{Nt}\sum_{i=1}^{n\_app}\left(S\_app_{i,t,k,r}^{G} + S\_app_{i,t,k,r}^{R} + S\_app_{i,t,k,r}^{comm}\right) = app\_run_{i,t,k,r} \tag{6.17}$$

Equation (6.9) gives the energy balance in the community grid ensuring power sold is equivalent to the power bought at each time instant t among all the houses NH across all the regions NR. Equation (6.10) provides the implementation of renewable power balance of each house of each region for the time period t. $app\_S_{i}^{PV+}$ and $app\_F_{i}^{PV+}$ are the photovoltaic(PV) power drawn by the i^{th} schedulable and fixed appliances at time t for the k^{th} house of the r^{th} region. $P_{t,k,r}^{RB+}$ is the recharging power drawn by the battery bank at time instant t. $P_{t,k,r}^{PV}$ is the PV power generated by the k^{th} house of the r^{th} region at time t. $P_{t,k,r}^{GB+}$ is the power drawn by the battery bank from the grid for charging at time instant t. $P_{t,k,r}^{B-}$ is the discharging power drawn from the battery bank for supplying appliances at time t. $P\_app_{t,k,r}^{grid+}$ is the power drawn by the appliances of house k from the grid at time instant t. Equation (6.11) gives the power balance of the power consumed by the appliances of each residential unit of each region at every instant of the time period taken into consideration. The households are restricted from buying power from the grid or the community and sell it to the community by the constraints given by equation (6.12) and (6.14). The appliances switched on at a particular period of time can draw power from one of the three sources i.e. the grid, community or renewable source as given by equation (6.13). Constraint equation (6.15) makes sure the fixed appliances switch on as per the choice of the consumer. $S\_app_{i,t,k,r}^{G}$, $S\_app_{i,t,k,r}^{R}$, $S\_app_{i,t,k,r}^{comm}$ are the grid, renewable and community switching variables of the i^{th} appliance of the k^{th} house in the r^{th} region at time t, $app\_P_{i,k,r}$ is the rated power of the appliance and $P_{t,k,r}$ is the total power consumed by the k^{th} house of the r^{th} region at time t .The constraint given by equation (6.16) specifies that a combination of appliances can draw power from the renewable source at time t only if the summation of their rated power is equal or less than the available renewable energy at that same time instant t, the remainder of the renewable energy is sold either to the grid or made available to the community. Equation (6.17) represents the constraint that the summation of all the non-zero value of the switching status of appliance i over the entire period of prediction should be equal to the total runtime of the appliance for the day as specified by the consumer.

The energy balance of the k^{th} house of the r^{th} region at the time period t is considered separately for the renewable energy consumption and the grid power consumption as shown by equations (6.18) and (6.19). n_appS and n_appF are the total number of schedulable and fixed appliances present in the residential unit in consideration.

$$\sum_{i=1}^{n\_appS} app\_S_{i,t,k,r}^{PV+} + \sum_{i=1}^{n\_appF} app\_F_i^{PV+} + P_{t,k,r}^{grid-} + P_{t,k,r}^{comm-} + P_{t,k,r}^{RB+} = P_{t,k,r}^{PV} \tag{6.18}$$

If battery is not available then $P_{t,k,r}^{RB+}$ =0.

$$\begin{aligned} &\sum_{i=1}^{n\_appS} app\_S_{i,t,k,r}^{grid+} + \sum_{i=1}^{n\_appF} app\_F_i^{grid+} + \sum_{i=1}^{n\_appS} app\_S_{i,t,k,r}^{comm+} + \sum_{i=1}^{n\_appF} app\_F_i^{comm+} \\ &+ P_{t,k,r}^{GB+} = P_{t,k,r}^{grid+} + P_{t,k,r}^{comm+} + P_{t,k,r}^{B-} \end{aligned} \tag{6.19}$$

The scheme for battery bank control is shown from equation (6.20) to (6.25):

$$min\_SoC_k^B \le SoC_k^B \le max\_SoC_k^B \tag{6.20}$$

$$SoC_{init,k}^B = SoC_{final,k}^B \tag{6.21}$$

$$SoC_{k,t}^B = SoC_{k,t-1}^B + \eta_c^b \times ch_t + \eta_{dc}^b \times disch_t \tag{6.22}$$

$$P_{k,t}^{B+} - P_{k,t-1}^{B+} \le R_u \tag{6.23}$$

$$P_{k,t-1}^{B-} - P_{k,t}^{B-} \le R_d \tag{6.24}$$

$$S_c^{BG} + S_c^{BC} + S_c^{BR} \le 1 \tag{6.25}$$

The battery is allowed to be charged from all three sources as this allows the battery to take advantage of the off-peak grid tariff and also the renewable availability period to get charged allowing the use of the battery during the peak hours. Equation (6.20) specifies that the state of charge SoC_k^B of the storage system of the k^{th} house should lie between the maximum and minimum values given by $max\_SoC_k^B$ and $min\_SoC_k^B$ respectively. $SoC_{init,k}^B$ and $SoC_{final,k}^B$ are the initial and final charging state of the battery banks. $SoC_{k,t}^B$ is the state of charge of the battery bank B of the k^{th} house at time t. η_c^b and η_{dc}^b are the charging and discharging efficiency of the battery bank. The charging and discharging power being drawn by the battery bank at time t is given by the variables ch_t and $disch_t$ respectively. $P_{k,t}^{B+}$ and $P_{k,t}^{B-}$ and are the charging and discharging power being drawn by the battery of the k^{th} house at time period t .The ramp up and ramp down values for charging and discharging values of the battery are are R_u and R_d. $S_c^{BG}, S_c^{BC}, S_c^{BR}$ are the switching variables of the battery bank for charging from grid, community and renewable sources respectively. Equation (6.21) ensures the level of battery bank that needs to be maintained at the end of the period of prediction. The state of charge of the battery at any instant is given by equation (6.22). The charging and discharging rate cannot be more than the ramp up or ramp down values respectively as ensured by equations (6.23) to (6.24). The equation (6.25) restricts the battery bank to being charged from only one source at a particular time period.

$$0 \le P_{k,t}^{B+} \le P_{k\_max}^{B} \times S_{ch} \tag{6.26}$$

$$0 \le P_{k,t}^{B-} \le P_{k\_max}^{B} \times (1 - S_{ch}) \tag{6.27}$$

$$S_{ch} = S_{c}^{BG} + S_{c}^{BC} + S_{c}^{BR} \tag{6.28}$$

The equation (6.26) to (6.28) ensures that charging or discharging power of the battery banks is non-negative at a particular time.

2.4 The Controllable Loads

The flexible loads have to follow the following restrictions

a. The appliance e.g. the washing machine must operate for the duration specified by the user i.e. $WM_{k,t}$
b. It has to remain switched on for a minimum pre-specified period of time $WM_{k,t}^{SD}$
c. The power demand of the appliance is considered to be constant at its rated power $P\_app_{k,t}^{SD}$

The constraints imposed are

$$WM_{k,t}^{on} - WM_{k,t+x}^{on} \ge TD_{k,t}^{WM} \tag{6.29}$$

$$WM_{k,t,r}^{SD} = P_{WM}^{SD} \times WM_{k,t}^{ON} \tag{6.30}$$

$$\sum_{i=1}^{NS} \left(v_{t,i}^{G} + v_{t,i}^{R} \right) \le 1 \tag{6.31}$$

$$v_{t,i}^{on} + v_{t,i}^{off} \le 1 \tag{6.32}$$

Equation (6.31) ensures at any time instant only one shift able appliance of the k^{th} house of the r^{th} region can be switched on. $v_{t,i}^{on}$ and $v_{t,i}^{off}$ are the switch on and switch off status of the appliance i at time t. $TD_{k,t}^{WM}$ is the time delay between successive switching on time of the appliance washing machine of k^{th} house. The condition of the appliance remaining switched on for the prespecified number of consecutive hours is ensured by the constraint in equation (6.29). Equation (6.30) ensures that the power consumption P_{WM}^{SD} of the appliance is constant and equal to its rating during the period of switched on time of the appliance $WM_{k,t}^{ON}$.The startup and shut down time of an appliance cannot be at the same time instant as ensured by equation (6.32).

The figures 6.4,6.5 and 6.6 show the peak, valley and flat hours determined for individual houses, energy community formed through combination of all urban and rural houses and clustered urban and rural sector houses combined to facilitate interactive energy sharing between each other and the grid. The figures show a marked difference between the peak, flat and valley hours of the community as a whole and that for individual urban and rural clusters. From Fig. 6.4 and Fig. 6.6 it is noticeable that the urban and rural power usage characteristics are different from each other. In the community mode shown in Fig. 6.5 the urban sector will be having more influence on the determination of peak, flat and valley hours as their power consumption is much higher compared to the rural areas. The urban and rural houses taken individually introduces too much variation in the system thus increasing the complexity and computational burden. Whereas, the urban and rural clustering method captures sufficient information regarding the diversity in the power usage nature of the urban and rural regions at a reduced complexity thus allowing the energy management system to be more effectively implemented. The difference is power usage nature of the different regions arise from the variation in appliance ownership trends and appliance usage patterns of the different regions. The proposed work has modelled the RCEMS by considering the hourly usage of each appliance building up to the aggregate power consumption pattern to capture the abovementioned difference. This method allows the energy management system more freedom to efficiently manage the energy usage as the variability of fixed and shiftable power consumption at an appliance level resolution based on user preference can be incorporated in the decision-making structure. The figures show a few peak hours in the morning while the valley hours are seen near the evening. The concentration of peak and flat hours during the daytime can be explained by the running of the space cooling appliances during the daytime. As these appliances consume a large amount of power, they increase the community energy consumption values by a significant amount. It can also be seen that the peak periods of the simulated rural region lie mainly in the early morning and evening hours with intermittent flat periods whereas the peak periods of the simulated urban region lie mostly in the morning hours. The peak periods in the actual regions where this method will be implemented can differ. As this simulation is based on survey data any difference in the simulated profiles and real-life power consumption trends may be due to the inaccurate response of the survey participants. However, this does not affect the performance of the proposed methodology as it is based on the difference in the urban and rural power consumption pattern which is satisfactorily represented in the simulated profiles. The peak periods in the late night and early morning hours correspond to the operation of space cooling devices during summer. Whereas in the urban regions most of the household chores are done in the mid-day hours which correspond to the peak hours as shown in Fig. 6.6.

The simulations are done for one day in the summer season with the survey data obtained from the residents for all the 4 case studies and 9 scenarios with different tariff models. In the case study of community-based tariff with appliance-based resource allocation both the urban and rural sector houses are combined together to form a single community cluster. The peak, valley and flat hours of this combined urban and rural houses are determined and appropriate TOD price is allocated to each hour. For all the case studies the power being sold to the community is characterized by having a higher price than that being sold to the grid. This distinction is made to encourage the consumers with renewable generation resources to sell to the community first and then to the grid. The hourly buying and selling price of power among the community is set as 0.4 times that of the hourly grid price. The hourly selling price of power to the grid is set at 0.3 times that of the hourly grid power cost and the renewable usage price is set at 0.5 times that of the power available from grid. A cost has been put on the usage of renewable power to offset the installation and maintenance costs. Any participant cannot buy and sell from the community at the same time. This model allows more power to be available in the community power pool for utilisation of the other households having complementary power usage. The developed power sharing community functions in an autonomous mode which allows each participant to trade power independently. The power trading and utilisation of each participant is limited only by their own constraints and is not influenced by the other participants of the community. This allows each household to have more control in determining their priority between cost and comfort.

The operational costs for all the four urban and rural houses obtained for case study no.1 using individual tariff scheme obtained by the period partitioning model are shown in Table 6.6. Here, U1, U2, R1 and R2 denote urban household 1, urban household 2, rural household 1 and rural household 2 respectively. Similarly, Table 6.7 to Table 6.10 shows the operational costs outputs of case study no. 2 to case study no. 5 respectively.

Table 6.6 Change in cost for the different scenarios using individual tailored tariff applying proposed model

# Scenario	U1(INR)	U2 (INR)	R1(INR)	R2(INR)	Community Cost (INR)	Percentage reduction in community cost
Experimental Case	419.23	420.29	125.86	122.29	1087.67	-
Scenario 0	420.53	418.67	131.38	130.46	1101.03	-1.23
Scenario 1	415.44	393.46	105.21	130.46	1044.57	3.96
Scenario 2	347.87	391.56	128.61	129.88	997.91	8.25
Scenario 3	336.91	375.67	102.64	126.81	942.04	13.39
Scenario 4	336.08	332.33	116.70	124.59	909.69	16.36
Scenario 5	378.80	338.42	105.21	128.24	950.67	12.59
Scenario 6	323.69	317.05	102.64	120.95	864.34	20.53
Scenario 7	323.03	305.02	102.65	114.64	845.34	22.28
Scenario 8	315.06	301.53	102.64	105.74	824.97	24.15
Scenario 9	293.58	280.39	100.25	104.40	778.62	28.41

Table 6.7 Change in cost for the different scenarios using community usage-based tariff applying proposed model

# Scenario	U1(INR)	U2(INR)	R1(INR)	R2(INR)	Community Cost (INR)	Percentage reduction in community cost
Experimental Case	419.23	420.29	125.86	122.29	1087.67	-
Scenario 0	412.84	413.21	122.91	119.88	1068.84	1.73
Scenario 1	410.78	388.99	93.74	117.66	1011.16	7.03
Scenario 2	339.68	392.16	119.59	116.98	968.41	10.96
Scenario 3	335.41	363.39	93.74	118.20	910.74	16.27

Scenario 4	378.72	327.91	93.74	119.23	919.60	15.45
Scenario 5	329.65	328.44	108.67	114.30	881.06	19.00
Scenario 6	323.96	316.40	93.75	99.87	833.98	23.32
Scenario 7	311.81	308.00	91.58	102.48	813.87	25.17
Scenario 8	314.45	294.31	92.74	91.50	793.00	27.09
Scenario 9	289.28	276.36	90.15	92.30	748.09	31.22

Table 6.8 Change in cost for the different scenarios using separate urban and rural cluster usage-based tariff applying proposed model

# Scenario	U1(INR)	U2 (INR)	R1(INR)	R2(INR)	Community Cost (INR)	Percentage reduction in community cost
Experimental Case	419.23	420.29	125.86	122.29	1087.67	-
Case 0	402.23	403.86	125.13	125.39	1056.61	2.86
Case 1	397.96	379.62	99.94	125.39	1002.92	7.79
Case 2	329.52	380.63	121.69	124.81	956.65	12.05
Case 3	325.26	354.53	99.94	123.23	902.95	16.98
Case 4	320.58	317.42	110.36	120.52	868.88	20.12
Case 5	364.25	321.52	99.94	125.39	911.10	16.23
Case 6	307.92	307.41	94.65	115.51	825.49	24.11
Case 7	307.52	292.53	97.79	109.74	807.58	25.75
Case 8	298.42	289.82	98.93	101.44	788.62	27.50
Case9	278.03	268.54	94.23	101.43	742.23	31.76

Table 6.9 Change in cost for the different scenarios using community tariff applying hybrid resource allocation model

# Scenario	U1(INR)	U2 (INR)	R1(INR)	R2(INR)	Community Cost (INR)	Percentage reduction in community cost
Experimental Case	419.23	420.29	125.86	122.29	1087.67	-
Scenario 0	412.84	413.21	122.91	119.88	1069	1.73
Scenario 1	400.74	397.97	121.11	118.83	1039	4.51
Scenario 2	385.26	380.63	118.26	117.02	1001	7.95
Scenario 3	374.54	361.52	116.12	112.56	965	11.30
Scenario 4	374.54	361.52	116.12	112.56	965	11.30
Scenario 5	346.84	335.79	110.17	108.46	901	17.14
Scenario 6	336.69	319.41	101.36	102.08	860	20.97
Scenario 7	328.73	311.97	99.63	101.47	842	22.61
Scenario 8	321.22	306.68	98.24	100.34	826	24.01
Scenario 9	289.38	280.88	103.40	103.83	777	28.52

Table 6.10 Change in cost for the different scenarios using separate urban and rural cluster usage-based tariff applying hybrid resource allocation model

# Scenario	U1 (INR)	U2 (INR)	R1 (INR)	R2 (INR)	Community Cost (INR)	Percentage reduction in community cost
Experimental Case	419.23	420.29	125.86	122.29	1087.67	-
Scenario 0	402.23	403.86	125.13	125.39	1056.61	2.86
Scenario 1	390.15	388.73	123.49	124.48	1026.84	5.59
Scenario 2	374.70	371.50	120.90	122.91	990.01	8.98
Scenario 3	364.00	352.02	118.97	118.59	953.58	12.33
Scenario 4	336.55	328.96	111.72	112.58	889.81	18.19
Scenario 5	364.00	352.02	118.97	118.59	953.58	12.33
Scenario 6	325.71	309.80	103.24	109.13	847.88	22.05
Scenario 7	316.77	302.04	104.13	107.44	830.39	23.65
Scenario 8	311.03	296.59	101.39	106.46	815.47	25.03
Scenario 9	280.29	271.60	103.73	109.55	765.18	29.65

It can be seen from the results that case study no. 3 where the proposed method was implemented along with urban and rural clustering-based tariff achieves the maximum reduction in community cost whereas in case no.2 where the proposed method was implemented with community tariff model the cost reduction of the rural houses is the most. However, both these cases show considerable reduction in the energy costs of all the residential participants from both urban and rural demographics compared to the other three cases. Thus, it can be understood that due to the variation in energy consumption patterns in demographically different regions, the impact of tariff and resource allocation has to be taken into account for developing an effective energy management system encompassing urban, semi urban and rural areas. The superior performance of the proposed RCEMS arises from the fact that it incorporates both these factors while optimising the energy cost and the allocation of available renewable energy between the participating urban and rural residential units. The novelty of the proposed method lies in the fact that instead of using the aggregate power consumption data of the urban and rural residential units, it considers a ground up approach where appliance based allocation of the available renewable source which is combined to build the final aggregate power consumption data. The selection of the appliances is done using the fuzzy logic technique described in chapter 5. This allows the proposed method to capture the difference in appliance ownership and usage which is the main contributor to the different power consumption profiles between urban, semi urban and rural areas. While the proposed model works with urban and rural household data it can be further extended to include semi urban consumer data also. Though, the community cost steadily decreases over all the scenarios as shown in figures 6.8 and 6.9, it can be observed that in some scenarios such as case 2 scenario 4 there is a slight increase in community price.

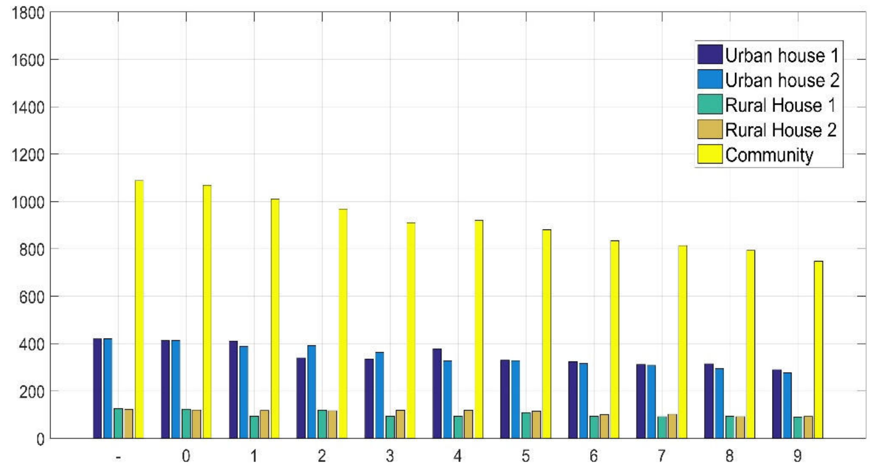


Fig 6.8 All scenarios cost comparison for community and individual houses with community tariff

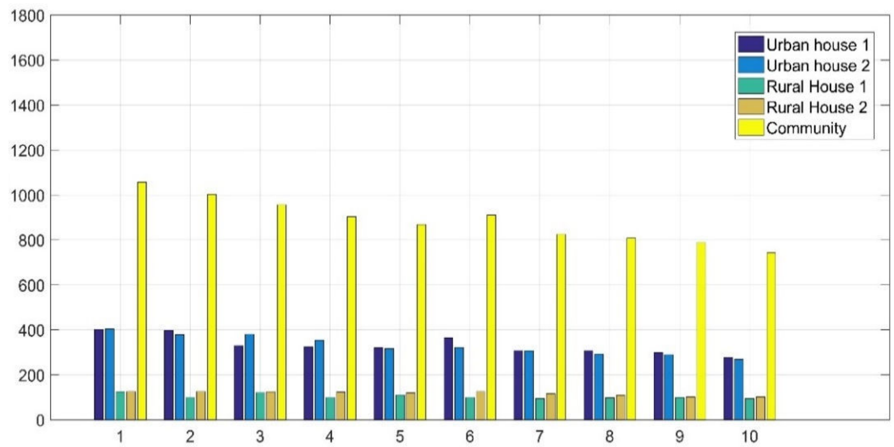


Fig 6.9 All scenarios cost comparison for community and individual houses with separate urban and rural community tariff

In this scenario, both the urban houses have solar power, but they being high power utilising consumers, not much renewable power is left to be sold to other participants or the grid thus increasing the cost of the community. In hybrid resource allocation, the entire available energy of the community is divided between the households in proportion to their hourly power usage. From the operation costs of the abovementioned scenario as shown in Tables 6.9 and 6.10, it can be observed that maximum reduction in community cost can be obtained in appliance utilisation pattern-based resource allocation compared to hybrid resource allocation. The Fig. 6.10 and 6.11 show significant difference in the hourly power bought and sold from and to the community thus confirming the influence of the different tariff models on the optimization of power trading by the proposed RCEMS.

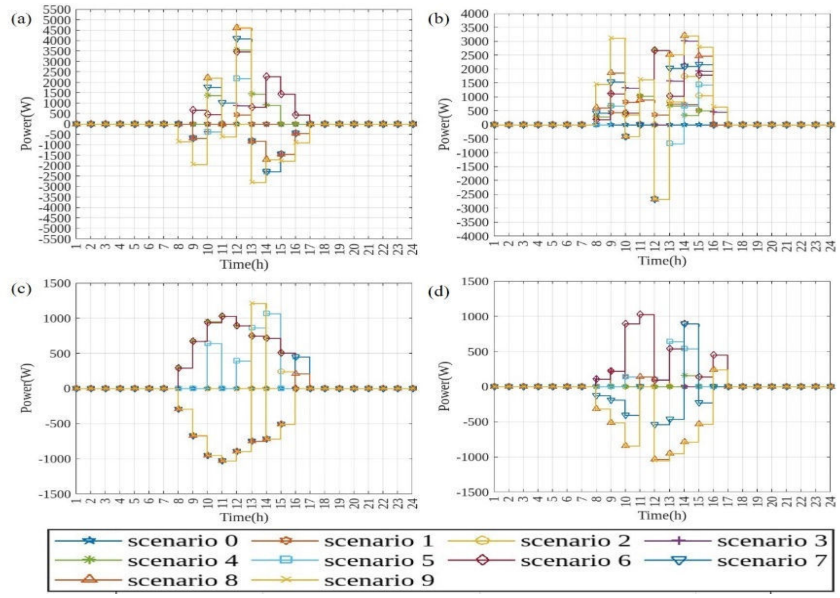


Fig 6.10 Power trading between the four houses over a period of 24 hours for different scenarios considering the regional community tariff formed with all the houses

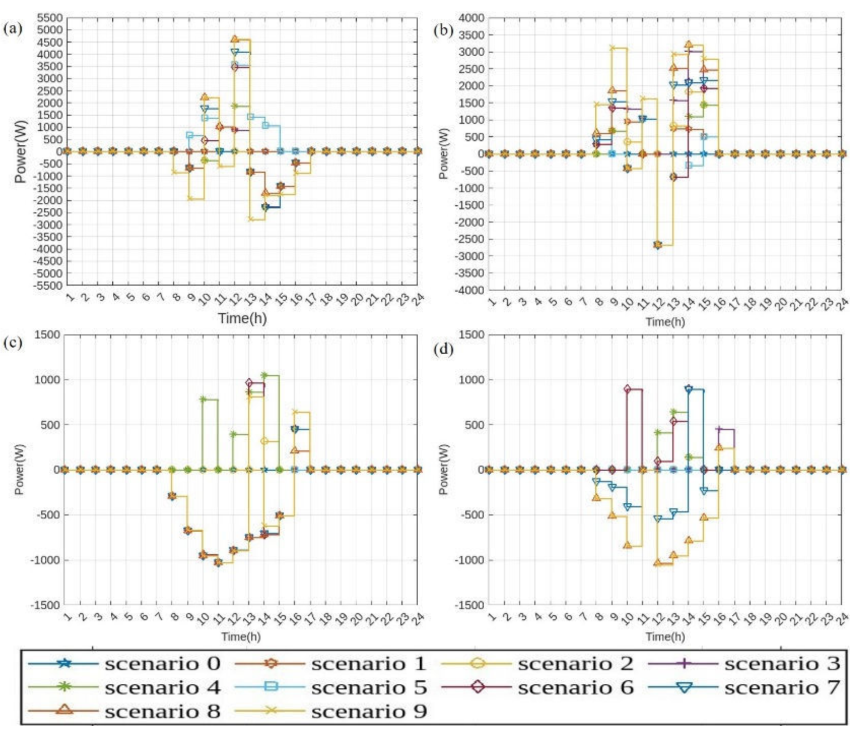


Fig 6.11 Power trading between the four houses over a period of 24 hours for different scenarios considering the regional community tariff formed separately with urban and rural households

It can also be seen that the urban and rural clustering-based tariff provides superior results compared to mixed demographic community tariff. This variation in tariff arises from the difference in hourly power consumption classification explained in art 6.3.1. Fig. 6.12 shows the hourly power consumption from the grid for the best scenarios of the proposed methodology using both all inclusive community and demographically clustered community tariff models. From the figure it can be seen that there has been significant peak demand reduction for the demographically clustered energy communities and also the different urban and rural residential units. The reduction in the peak load is more prominent in urban households than compared to rural households because of them being high energy Users. However, the reduction in the power consumption of all the units during the hours of renewable energy availability is visibly significant compared to the base case scenario. The increase in the load demand in some hours having low cost of grid energy can be attributed to the charging of the energy storage device. Fig. 6.13 shows the power demand curves for all the scenarios and the energy storage charging schedule of case study no 3 which has the best performance. The peak demand points of the original power demand profile are marked along with the final values of the power demand in those hours obtained using the proposed method. A significant demand reduction is observable. A renewable power use peak has been generated in the same hours thus confirming the shift of power demand from the grid to the renewable sources after applying the proposed methodology.

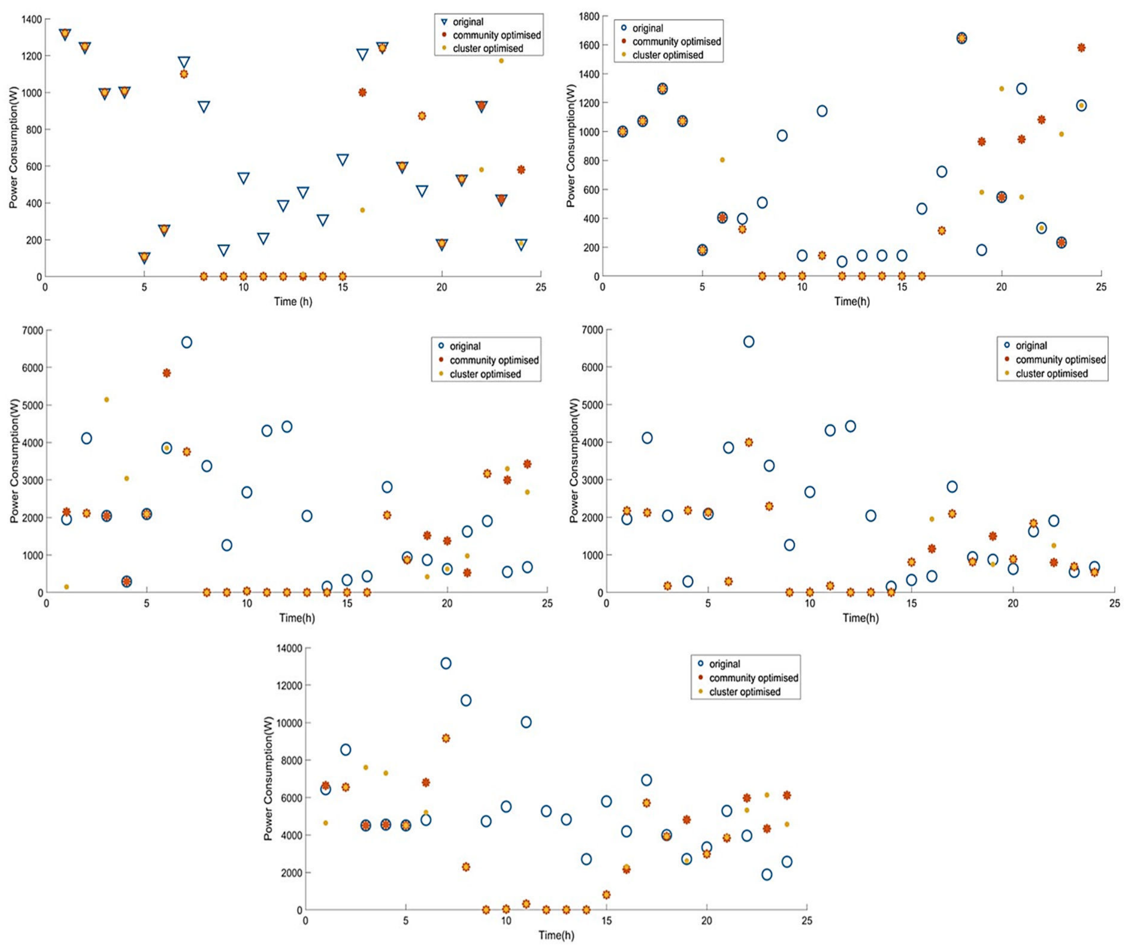


Fig 6.12 Hourly load consumptions from the grid for original consumption, community optimized scenario 9 and cluster optimized energy community scenario 9

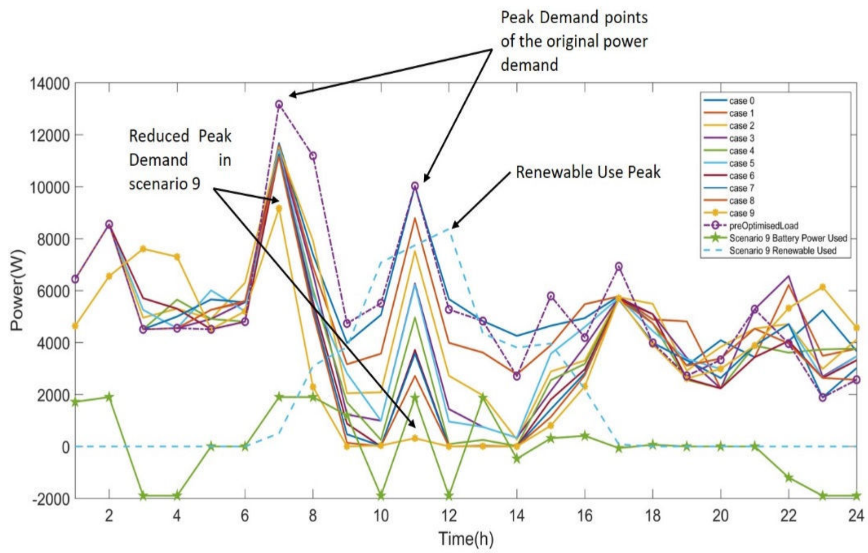


Fig 6.13 All cases for urban and rural regional tariff-based community grid power demand with emphasis on the original consumption and optimized scenario 9 with availability of renewable energy in all houses and one storage device

The comparison between the percentage reduction in cost for all the scenarios of all the models is shown in Fig. 6.14. Here, PMURC represents Proposed Model with Urban and Rural Clustering, PMCC represents Proposed Model with Community Cost, HURC represents Hybrid resource allocated Urban and Rural Clustering and HCC represents Hybrid resource allocated Community Cost.

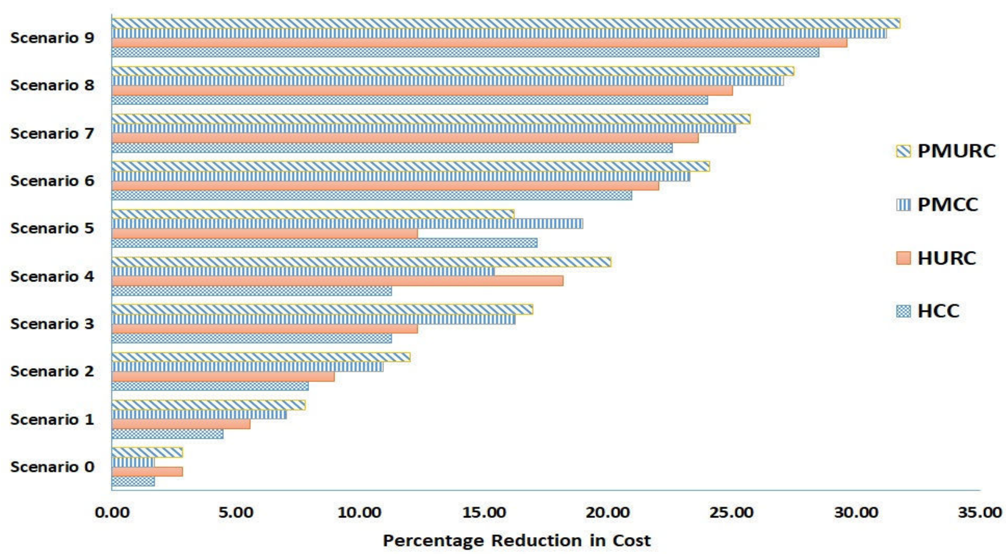


Fig 6.14 Comparison between the percentage reduction in cost by application of different schemes

From Fig. 6.14 it can be clearly inferred that the proposed energy management model using appliance-based resource allocation through fuzzy logic technique and demographical energy pattern capturing hourly tariff model provides the best results. Also, the comparison of the rural and urban greenhouse gas reduction obtained for different scenarios using the proposed method has been detailed in the Fig. 6.15.

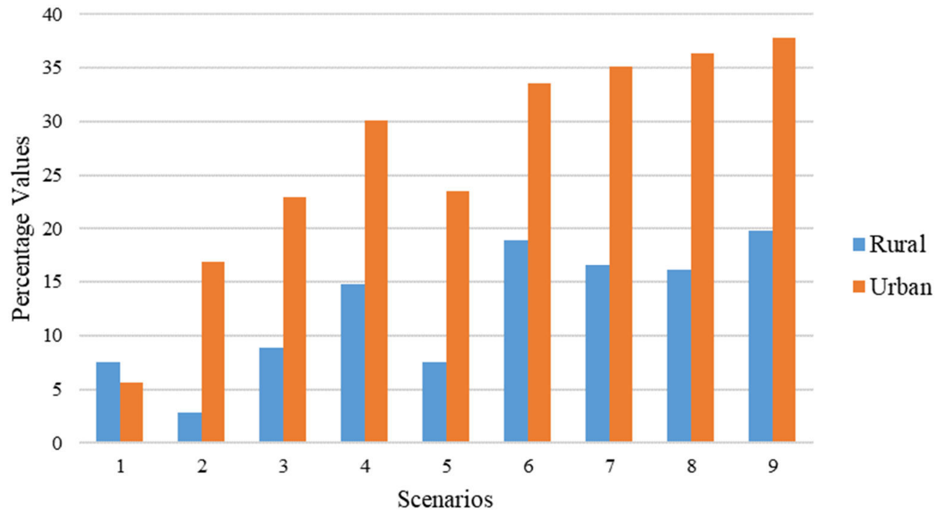


Fig 6.15 Percentage urban and rural GHG reduction obtained by the proposed solution

The increase in the integration of renewable energy in the daily power consumption of the rural and urban households for all the different scenarios explored has been shown in the Fig 6.16. The figure shows the percentage of renewable power integrated in the total daily power consumption by each household during the solar hours.

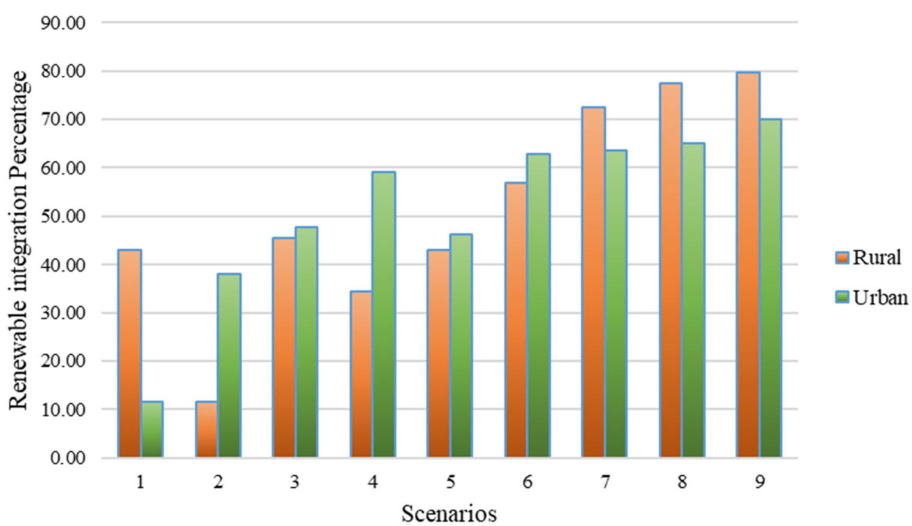


Fig 6.16 Average renewable integration in the daily power consumption of Urban and Rural households

The difference in the percentage energy cost savings by applying the proposed method with the old individual tariff and the new proposed tariff for the rural areas specifically has been shown in the following table:

Table 6.11 Percentage energy cost savings for different scenarios using the proposed method for old and new tariff schemes for the combined rural area household cost only

	Individually Calculated Tariff		Demographic Cluster Tariff		Community Tariff	
	Cost in INR	Percentage Reduction/Increase	Cost in INR	Percentage Reduction/Increase	Cost in INR	Percentage Reduction/Increase
Scenario 0	261.8	-5.5	250.5	-1.0	242.8	2.2
Scenario 1	235.7	5.0	225.3	9.2	211.4	14.8
Scenario 2	258.5	-4.2	246.5	0.7	236.6	4.7
Scenario 3	229.5	7.5	223.2	10.1	211.9	14.6
Scenario 4	241.3	2.8	230.9	7.0	213.0	14.2
Scenario 5	233.5	5.9	225.3	9.2	223.0	10.1
Scenario 6	223.6	9.9	210.2	15.3	193.6	22.0
Scenario 7	217.3	12.4	207.5	16.4	194.1	21.8
Scenario 8	208.4	16.0	200.4	19.3	184.2	25.8
Scenario 9	204.7	17.5	195.7	21.2	182.5	26.5

It can be seen that there is substantial savings in all the tariff schemes. However, for scenario 0 where no renewable integration is done there is a marginal 1% increase in the cost for the demographical clustered tariff whereas the cost increases by 5.5 % when individually customised tariff is used. If this is compared with the results shown in tables 6.6 to 6.8 it can be seen that there is an increase in community cost only for the individually tailored tariff whereas for both community tariff and demographic clustering-based tariff the community cost is reduced. This can be attributed to the fact that the high energy consuming urban users contribute more towards the community cost. So, even though there is an increase in the rural community cost there is a decrease in the urban community cost thus reducing the total combined community cost. However, the demographic clustering-based tariff scheme and the community tariff scheme both perform well in reducing rural energy cost when renewables are integrated. This, can be another incentive to the consumers to make the adjustments required to integrate a higher percentage of renewable energy in their daily energy consumptions.

6.3.4 Calculation of Payback Period

For calculation of the payback period, the developed program is run for 4 days with variable PV availability. The capacity of the urban area PV panel is considered as 3kWp and that of the rural households is taken as 1.2kWp. The PV availability for the 4 days is shown in Fig. 6.15

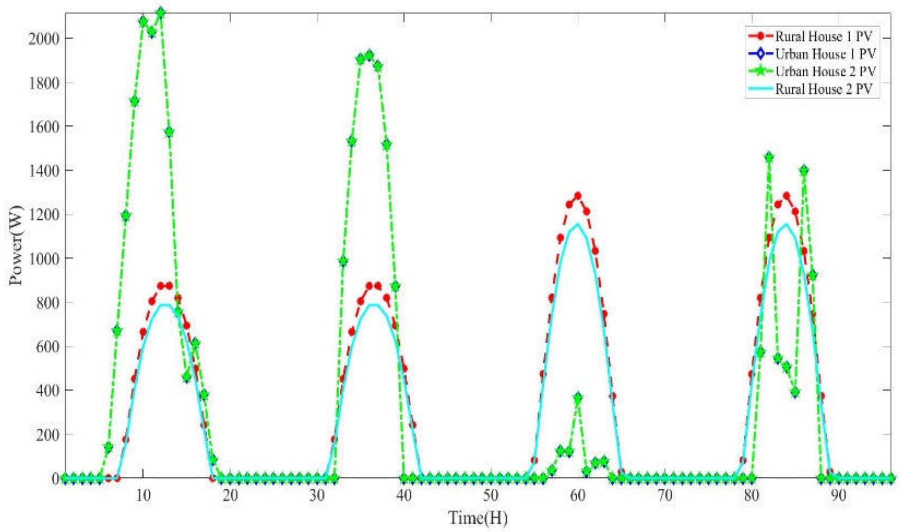


Fig 6.17 PV output of the four prosumers for four consecutive days

The average cost reduction of the urban and rural houses along with the community over the period of 4 days is given in table 6.11

Table 6.12 Monthly cost reduction of prosumers with varying PV conditions

	Present Cost (INR)	Reduced Cost (INR)	Percentage Reduction	Monthly Cost (INR)	Reduction in Monthly Cost (INR)
Urban House 1	1677	1333.65	20.5	11739	2406.5
Urban House 2	1680.36	1365.94	18.71	11762	2200.67
Rural House 1	503.44	337.61	32.94	3524	1163
Rural House 2	489.16	359.95	26.41	3424	904.28
Community	4349.96	3397.15	21.9	30449	6668.33

The payback period for the households and the community for installing hybrid solar systems according to the requirement considered is shown in table 6.12 and Fig. 6.16.

Table 6. 13 Payback periods of the prosumers and the community

	PV Installation Type	PV Installation Cost	Monthly Savings	Approx payback period in months	Approx payback period in years
Urban House 1	Hybrid	372000	2406.5	155	13 years
Urban House 2	On grid	135000	2200.67	61	5 years
Rural House 1	On grid	50400	1163	43	4 years
Rural House 2	On grid	50400	904.28	56	5 years
Community	Combined	607800	6668.23	91	8 years

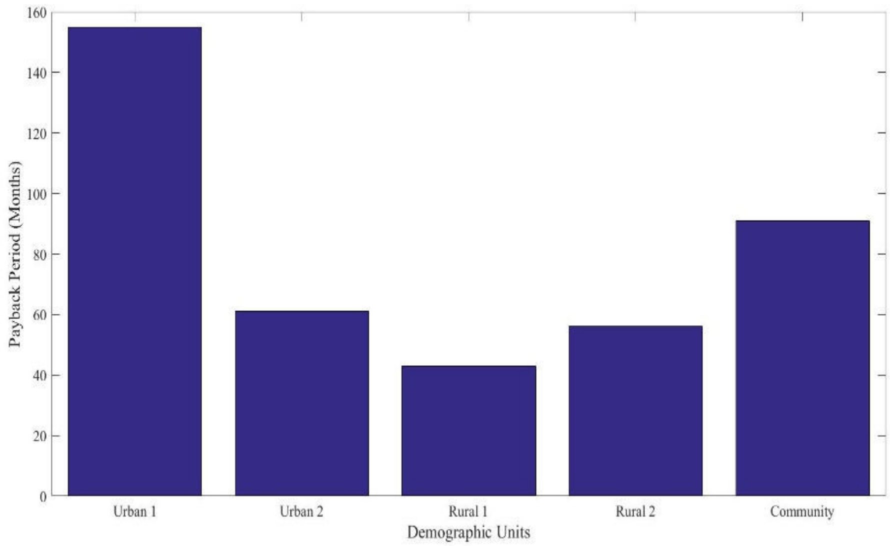


Fig 6.18 Payback periods for the four urban and rural prosumers and the community as a whole

6.4 PSO-MILP based dual optimized PV and battery capacity determination

In order to further explore the development of an urban, rural and semi urban categorization based energy management solution it was important to consider the process of battery and PV sizing for supplying a mixed demographic region with access to community power trading. For this, an PSO-MILP based dual optimization algorithm was developed as shown in Algorithm 6.1. For the rural community grid accessibility was considered to be unreliable with intermittent grid supply. The optimisation algorithm was run for a day where the grid availability of the rural community was considered to be 62.5% i.e. 15 hours of grid supply was available. To ensure constant power supply to the rural community a battery setup was considered for the rural houses only. The maximum capacity of this battery setup was considered to be limited at 60% of the total connected load of all the rural houses. The implementation of PV system was done incrementally starting with one urban house. The individuals are free to sell the excess available power to the grid. The urban community due to the presence of constant grid supply and higher income level is provided with the choice to sell power to either the community or the grid.

Algorithm 6. 1 PSO-MILP dual optimized model for PV and Battery sizing in a mixed demographic model

	Algorithm 2: PSO-MILP dual optimization for PV and battery capacity determination
1	***Input***: *number of consumers, grid availability index, PV availability for each house, battery availability status and battery capacity, appliance ownership, appliance rated capacity, appliance runtime, region type* *[Region_type] = fuzzy_output (per Capita Energy Consumption, population density, connected load)* *[appl_no,power_consump,appl_Switching Profile,appliance runtime]=func(Region_type,consumer_type)* *grid availability index (number of consumers,time steps) ∈ [0,1]*
2	***Output***: *PV and battery sizing*
3	***Initialize outer loop ← PSO***
4	***Initialization of variables:*** *define population size, maximum iterations, assign random values to particles representing battery and PV capacities, set initial particle velocities and best positions (pBest and gBest)*
5	***Evaluate Initial Fitness ←MILP inner loop***
6	***While solution ≠ global minima OR iter < maximum iterations***
7	*Update particle velocity and positions*
8	*Ensure capacities remain within physical bounds*
9	*Evaluate fitness ← MILP inner loop*
10	*Initialize MILP variables ←grid buy, grid sell, community buy, community sell, battery power usage*
11	*hourly community participation index=function (fuzzyOut(region_type, consumer_type,))*
12	*Implement constraints ← local and global power balance equations, appliance specific renewable power consumption restriction, renewable energy consumption and trade balance, total runtime requirement of schedulable appliances, power supply security of rural community*
13	*Return daily cost, unsupplied rural demand, excess community power*
14	*Evaluate fitness = w1*cost+w2*(unsaturated_demand/total_demand)* *+w3*(excess_communityPower/total_PowerAvailable)* *Where w1, w2, w3 are weights to control the outcome choices*
15	*Update pBest and gBest*
16	*End*
17	*End*

The hourly community participation index of the urban houses is determined by the fuzzy logic process explained in Chapter 5. The community power available can be bought by any of the urban or rural participants according to their need. The price matrix is developed according to the urban-rural cluster pricing method explained in Chapter 6. The cost functions to be optimized is shown in equation (6.33)

$$f_{pv,batt} = w_1 \times (\cos t_U + \cos t_R) + w_2 \times \frac{dem\_unSat_R}{Tot\_dem_R} + w_3 \times \frac{comm\_P_e}{comm\_P_a} \tag{6.33}$$

Where $f_{pv,batt}$ is the cost function to be optimized by the outer PSO loop, $\cos t_U$ and $\cos t_R$ are the final power consumption costs of 24 hours obtained by running the inner MILP loop, dem_unSat_R is the total unsaturated demand of the rural region due to unavailability of power from both grid and community, Tot_dem_R is the total demand of the rural region, $comm\_P_e$ is the unused community power available after running the inner MILP optimization loop, $comm\_P_a$ is the total community power available, w_1, w_2 and w_3 are the weight parameters by which the optimization focus can be shifted towards cost optimization, satisfaction of the rural consumers or reduction in wastage of power. The tuning parameters of the outer PSO loop were: population Size: 5, variable size: 1 to 5, inertia weight (w): 0.7, acceleration coefficients (c1, c2): 1.5, 1.5. The total number of variables are taken as five which represents the size of the renewable source required by each of the four houses and the battery size required for the scenarios that has been studied. The program has been tested for incremental penetration of PV with adding PV capability to each consumer one by one and progressively increasing the variables from one to five. The results are shown in table 6.13. The population size could not be increased further due to computational constraints. So, with further investigation, better results are possible.

Table 6. 14 PV and battery installation capacity required in terms of percentage of rural and urban connected loads

Cases	Optimized PV installation and Battery Capacity in Percentage of Connected Load				
	Urban House 1	Urban House 2	Rural House 1	Rural House 2	Battery Capacity
Only Urban House 1 has PV	84	-	-	-	60
Urban House 1 and Urban House 2 have PV	64	43	-	-	60
Both the Urban houses and Rural House 1 have PV	57	21	81	-	60
All the Houses have PV	24	25	74	24	55.8

Thus, it can be seen from table 6.13 that with the increase in PV generation penetration the requirement of Urban houses PV capacity decreases progressively as the community trading requirement decreases. The battery capacity required for the rural community decreases by only 5% even when all the houses have PV capability. This can be attributed to the fact that the grid outages during the non-PV availability period does not allow the rural houses to reduce their dependency on the battery usage. This output has been obtained with equal weightages attributed to cost reduction, unsatisfied demand of the rural region and reduction in excess community power.

6.5 Chapter Conclusion

From the above discussion it can be inferred that the performance of the proposed methodology developed to provide an energy management solution based on the urban, rural and semi urban demographic energy consumption characteristics is promising. Through the utilization of a demographical clustering based tariff system and regional priority based load monitoring and classification it has been successful in reducing the energy cost by a percentage of 31.76 of a mixed demographic energy community with benefits to both the urban and rural participants. The utilization of renewable energy to benefit both the prosumer and the consumer in a participation based demographic energy trading model will also improve the level of renewable source integration in both urban and rural communities. The use of energy storage systems in both urban and rural communities have been explored with a fuzzy logic based predetermined hourly community participation model and it has been successful in extending the renewable installation benefits to non-renewable production hours having higher implications on the customer comfort of the rural areas. Implementation of the PSO-MILP bi-optimization model can provide satisfactory solutions to the PV and BESS sizing required for a mixed demographic energy community. The takeaways from the entire work has been summarized in the next chapter.

Chapter 7
Conclusion and Future Scope

7.1 Conclusion

With the world moving toward a future where green energy will be replacing the conventional sources of power generation, the research on the efficient integration of renewable energy sources with the present consumer base has become significantly important. The main obstacle in the rapid integration of renewable sources in the present power scenario lies in the intermittent nature of the renewable power. The consumers prefer to have sufficient power at their disposal to use whenever it is needed. The inconvenience caused by the intermittency of the renewable sources are preventing them from being a popular source of power among the consumers. Though the cost of renewable energy has come down vastly over the years, the consumers are still not ready to accept the cost to comfort trade off required for the use of renewables. ***To address this problem, several research works have attempted to design an efficient energy management system to align the power requirement of the consumers with the renewable power available.*** To counter the inconvenience of the intermittent nature of the renewable sources, energy storage devices have been included in the energy management system. ***However, the researches have mostly been focused on individual home management or commercial utility management.*** The ability of individuals to install renewable energy generating systems is still low in the country with the relatively high capital cost required for the installation and the long break even point of the investment being the major deterrents. ***This might be overcome through the formation of energy communities.***

An important factor that the present research works have not considered is the variable nature of the power usage of the consumers of different demographic regions. In the formation of energy communities with options to draw power from both available renewable energy and the grid the involvement of different demographic regions cannot be ignored. Thus, ***Monitoring the characteristics of the power consumption pattern of different regions is very important because it reveals various parameters which can be of utmost importance to understanding the power usage, requirement and priority of the consumers of the region.*** The regions having consumers contributing to electrical demand on the grid can be conclusively categorized into urban, semi urban and rural based on the factors such as density of population, per capita energy consumption, daily power demand profiles, dominance of the type of loads and the economy of the region. The consumers of each region can again be divided into domestic, commercial, industrial and public lighting. Each of these consumers again have separate energy usage patterns which varies depending upon the regional characteristics. Thus, ***Monitoring the characteristics of the power consumption pattern of different regions is very important because it reveals various parameters which can be of utmost importance to understanding the power usage, requirement and priority of the consumers of the region.*** The energy management system proposed for the demand management makes an attempt to understanding the appliance ownership and energy usage priority of the consumers of urban, semi urban and rural regions forming the energy community and incorporating them in the development of an energy management system to address their needs. The profiling of the energy demand of the different regions has been done through forecasting using artificial neural network and wavelet neural network. The load demand of any region is again characterized by the appliance ownership, usage pattern and appliance usage priority of the resident consumers. The appliance usage has been graded as non-essential and essential according to the usage priority of the different consumers of urban, semi urban and rural regions. It is quite evident from this work that the aggregated load demand can be conclusively segregated as urban, semi urban and rural patterns with variations between the peak and off-peak hours.

The proposed energy management technique also provides a solution to renewable integration in the primary energy mix of the regions. Fuzzy logic has been used to develop an appliance classification technique which can be used to determine the suitability of the appliances used per hour to be supplied by renewable or grid. The urban regions better grid connectivity is utilized to offset the unreliable grid availability of the rural and semi urban regions. The appliances classified as renewable supply compatible per hour forms the superset from where the appliances are supplied with renewable energy according to their priority of the hour. The membership function limits of the fuzzy logic have been determined using the analyzed energy usage patterns and priority of usage of the urban, semi urban and rural regions. This analysis leads to the allocation of contribution coefficient to each consumer of each region according to which they are expected to contribute to the local microgrid. Whereas the renewable integration in rural and semi urban regions are characterized by solar and wind, the renewable availability in urban areas is mainly through rooftop PV installations. The proposed model allows the consumers to become effective prosumers thus increasing the renewable utilization. To deal with the uncertainties of the renewable sources, a community battery setup has been considered for the regions depending mainly upon the microgrids. The battery charging is optimized according to the availability of the renewable energy and grid availability. The segregation of the regions as urban, semi urban and rural allows the assessment of the contribution of each region to the peak and off-peak power demand on the grid. ***The use of proper tariff plans for different regions is another key factor in encouraging the consumers of that region in participating in the energy community transactions.*** Different tariff models depending upon the energy use pattern of the urban, semi urban and rural regions have been implemented and the urban and rural clustered TOU tariff scheme has been found to yield the best results. This can be attributed to the fact that region-based energy usage tariff encourages the consumers to contribute to the energy optimization schemes thus increasing the efficiency of the methods. ***Mixed Integer Linear Programming (MILP) has been used to develop the optimization algorithm as it overcomes the problem of not finding the best possible solution due to being stuck in the local minima. Several constraints have been integrated in the algorithm, with the results showing increased renewable utilization, GHG emission reduction and decrease in energy usage cost.***

The salient contributions of the dissertation are as follows:

- Artificial Neural Network is found to be a suitable candidate for forecasting the short-term power demand and renewable availability on a regional scale of urban, semi urban and rural with its satisfactory accuracy and ability to capture the non-linearities between the several features such as temperature, day of the week and humidity. Comparing several input features combinations, it was found that more accurate results were obtained with the input combinations of the load demand of the same day and hour of the previous week, type of day i.e. weekday or weekend, minimum, maximum and average temperature of the same day of the previous week and the forecasted values for the day whose power consumption is being predicted. Humidity was found to be redundant as it did not play any role in increasing the accuracy of the forecast. (ETES 2018)

- Artificial neural network was tested to find its suitability in being applied for the mid term load forecasting of the different load types such as domestic, commercial, industrial and public lighting loads. Though it gave satisfactory results, its accuracy was lower than that of the short-term load forecast. This can be attributed to the forecasting horizon being much further at 1 year compared to the forecasting horizon of short-term day ahead forecasting. (ASPCON 2018)

- Wavelet Neural Network was compared with traditional ANN to find the better technique for short term load forecasting. They have been used to forecast the urban load for both weekdays and weekends and their efficiency has been compared to determine their suitability for use in peak load management. It shows that WNN has better capability of capturing the variations in the power demand profiles with better accuracy in predicting the peak load periods. (CALCON 2020)

- Fuzzy Logic has been used to develop a prediction model to determine the hourly power demand of urban, semi urban and rural regions which can be supplied using the available renewable energy of the region to reduce the demand on the grid. The power usage pattern and priority difference of each region has been considered along with the appliance ownership and appliance power ratings. Both the residential and commercial consumers of the areas have been considered for summer and winter seasons. The Fuzzy logic process provided good results in determining the hourly appliance usage share in grid and renewable connected mode of the consumers with relative simplicity in implementation compared to other methods. (BEEI 2022)

- Three different models of tariff were explored to find the model that can be used to obtain the best possible optimization output. The period partitioning model has been used to determine the peak, flat and valley hours of the power usage of the consumers in urban and rural regions. The identification of and application of peak, flat and valley tariffs was done on an hourly basis instead of a continuous period to exploit the difference in the power usage characteristics of the urban and rural consumers. This formulation was applied based on the recognition that the peak period of one region may not be the peak period of another and thus shifting the power consumption consumers of the non-peak region may result in forming a new peak period for the community as a whole. Three models of tariff i.e. individual, community and regional were used and it was seen that the regional tariff scheme provided better result in decreasing the community cost as well as community peak compared to the others. (Fourth International Conference on Emerging Frontiers in electrical and Electronic Technologies, 2024)

Ξ Optimization of cost was done using MILP with several operational constraints imposed. The optimization was done using a ground up model based on the appliance usage priority of the regions instead of the total power consumption. This provided a greater degree of flexibility to the optimization model as the regional differences in power utilization could be explored in a component scale. The proposed model does not rely on the presence of schedulable appliances to reduce the cost of the consumer. Instead, it explores the possibility of power supply to the appliances either from grid or renewable energy on an hourly basis. This results in an energy management technique which integrates renewable energy into the existing daily power usage pattern of the consumers reducing cost and grid reliability without any trade-offs between cost and comfort. This method also reduces the cost of the community as a whole incentivizing the individual consumers to participate in power trading within the community. This method also maintains the advantage of grid security for the consumers at the same time reducing the demand on the grid. Reduction in greenhouse gas emission and betterment of node voltage has also been obtained after testing the system in a modified IEEE bus system. (BEEI 2025)

7.2 Future Scope

The objective of this thesis was to extract knowledge on the usage pattern, characteristics and variation of the power demand of different regions classified as urban, semi urban and rural. The extracted knowledge was used to develop an energy management system to be applied on a regional basis to reduce cost, greenhouse gas emissions and facilitate the increased incorporation of renewable energy in the primary energy mix of the country through formation of regional energy communities. The objective of the study having been achieved, this energy management program can be used for widespread application. However, additional work needs to be done to prepare this method for field deployment removing any limitations that might arise during widespread application. Some of the future work which requires more attention are as follows:

1. The robustness of this regional energy management method must be further tested and generalized by applying several realistic power consumption patterns and regional power use restrictions that can be obtained from the utilities supplying the consumers.
2. The forecasting method needs to be further developed to incorporate consumer preferences and demographic parameters to increase the accuracy of the forecasting technique.
3. The method needs to be further explored through implementation in real time systems to justify the demographic demand.
4. Work needs to be done to implement the developed algorithm in hardware platform to increase its adaptability among the consumers and utility service providers.

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