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Sustainable Energy Consumption Analysis through Data Driven Insights

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Abstract:- Energy is the backbone of our society, supporting our daily activities and driving progress. It plays a crucial role in shaping our modern way of life. The future of global energy consumption is influenced by many factors, including demographics, economic dynamics, technological developments, political actions, environmental demands and geopolitical considerations. As the world's population continues to grow and urbanize, the demand for energy is increasing. At the same time, rapid technological innovations are shaping the energy landscape and changing production, distribution and consumption patterns. In the midst of this development, it is very important to optimize energy consumption, accurately anticipate needs, curb climate change, limit emissions of greenhouse gasses, fight against pollution and promote sustainability. This study includes an in-depth analysis of historical consumption trends, assessing the multiple benefits of renewable energy integration, estimating carbon emissions, formulating practical policy recommendations and providing empirically informed insights. The work is based on various data obtained from platforms such as Kaggle and using advanced visualization techniques such as Power BI dashboards. The study provides invaluable perspectives on future energy needs, the penetration of renewable sources into the energy mix, and the strategic needs to achieve sustainable energy use.

Keywords:- *Energy Consumption, Demand Forecast, Sustainable Development, Analysis, Renewable Energy, Carbon Emissions, Kaggle, Power BI, Future Energy Requirements, Policy Recommendations.*

I. INTRODUCTION

Growing concerns about climate change and the environmental impacts of human activities have created a growing need for renewable energy sources. These phenomena lead to sudden changes in ecosystem processes and properties, some of which can be irreversible and leave profound effects [1]. In recent years, global energy use and electricity consumption have shown constant growth, which is due to population growth, economic development and technological development, among others. This growth is influenced by several factors, some of which are listed below:

- ***Challenges with conventional energy sources:*** Non-renewable resources such as coal, oil and natural gas are finite or finite natural resources that deplete over time. Once their reserves are used up, they are non-renewable and thus cannot be used to meet the growing energy demand. Burning them also pollutes the environment a lot, and their costs can be very high because only a few countries have a monopoly on obtaining them.
- ***Population and Rapid Urbanization:*** World population growth and rapid urbanization have increased the concentration of people in cities, which have increased the need for infrastructure, transportation and residential energy. The standard of living in the world has also improved, and with it the demand for more energy-intensive systems. Sectors such as agriculture, transport, IT, healthcare and industry are highly dependent on energy consumption.
- ***Impact of Technological Advances on Energy Consumption:*** IT data centers, servers and electronic equipment require a lot of energy to run and cool. The computational demands of AI and ML algorithms used for data analysis and pattern recognition increase the energy consumption of the IT sector. Online platforms, social media, streaming services and other digital services are also significantly increasing their energy footprint due to their reliance on data centers and network infrastructure.
- ***Issues with Inefficient energy consumption:*** Excessive consumption of natural resources such as fossil fuels, which are limited and non-renewable, is due to inefficient use of energy. Due to the increase in mining and processing activities, it not only worsens environmental pollution, but also increases the scarcity of natural resources. Current methods of energy consumption are quite inefficient, leading to wasted money and increased costs. Due to inaccurate forecasts and optimization tactics, energy demand cannot be met efficiently, resulting in shortages or overconsumption.

The only viable way to solve the problems listed above is to increase the use of renewable energy. The availability and cost-effectiveness of renewable energy sources have increased the possibilities for their integration into existing energy systems.

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However, this requires careful planning and analysis to ensure a reliable and stable energy supply while maximizing the benefits of renewable energy sources. Sustainable energy options use renewable natural resources such as sunlight, wind and water and provide a more sustainable and sustainable energy supply.

Paper [4] suggests a positive relationship between R&D (RandD) spending and renewable energy adoption, indicating the importance of R&D investment in promoting the transition to sustainable energy systems.

Table 1: Renewable Energy Characteristics

Energy Source	**Characteristics**	**Capacity**	**Environmental Impact**	**Cost**
Small Hydro	Low to high head turbines and dams. Run of river.	Intermittent to base load.	Low impact on ecosystems, potential fish migration disruption.	Initial investment can be high, but low operational costs.
Wind	Horizontal and vertical axis wind turbines. Wind Pumps.	Variable, 20 to 40%.	Minimal land use, visual impact, and emissions. Noise concerns in densely populated areas.	Initial investment decreasing, operational costs moderate.
Solar	Photovoltaic. Active thermal (low to high temp for heat or electricity). Passive thermal.	W/o storage: <25%, intermittent; W/thermal storage: 40 to 60%, intermediate.	Low emissions, land use concerns for large-scale installations.	Declining costs, varying with technology and scale.
Geothermal	Cycles: Dry steam, Flash, and Binary	High, base load.	Minimal emissions, potential subsurface environmental impact.	High initial investment but low operational costs.
Bioenergy	Combustion. Fermentation. Digestion. Gasification. Liquefaction.	Intermediate, peaking also possible.	Emissions depend on feedstock and technology. Land use concerns and potential competition with food production.	Costs vary with feedstock availability and conversion technology.

Table 1 provides a detailed comparison of various renewable energy sources, including small hydro, wind, solar, geothermal, and bioenergy.

Each energy source is evaluated based on several characteristics, such as its technological capabilities, current status, power generation capacity, environmental impact, cost considerations, efficiency and deployment flexibility.

This in-depth analysis aims to provide insight into the strengths and limitations of each renewable energy option to inform decision-making processes as we move towards more sustainable and diverse energy systems

II. LITERATURE REVIEW

To gain a deeper understanding of the subject, we conducted a comprehensive and systematic literature review. This review focused on summarizing and analyzing some selected literature on existing theories, tools and techniques used to predict infectious diseases.

- Mostafa et al. (2022) demonstrate the effectiveness of a penalized learning model in the field of smart grid analysis, achieving a remarkable 96% accuracy in predicting system stability. A comparative analysis of classification algorithms identified a convolutional neural network (CNN) as the most accurate classifier with an accuracy and

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computational efficiency of 87%. These predictive models provide important opportunities to improve the stability of the smart grid and optimize different power configurations. Despite the data size limitations, the study effectively uses cloud computing and storage to simulate real-time incident analysis, which demonstrates the practicality of the proposed framework. In general, Mostafa et al. work is a valuable contribution to smart grid renewable energy management by combining BDA and ML.[5]

- Yao et al. (2022) emphasize the urgent need to switch to sustainable energy sources, due to the harmful effects of burning fossil fuels on greenhouse gasses and global temperature. Accelerating this change will require advances in energy technology, infrastructure and policy. Machine learning (ML) is a transformative tool to address these challenges by predicting material properties, designing new materials, analyzing renewable energy usage patterns, and optimizing energy management at the device and network level. ML has enormous potential to revolutionize sustainable energy technologies, especially in material discovery and device optimization. As the field continues to develop, there is compelling evidence that it can accelerate energy technology adoption, promising significant progress toward a sustainable energy future. [6]
- Neumann et al. (2023) examine the effect of weather data transformations on the accuracy of energy time series forecasts, focusing on electricity demand, solar energy, and wind energy. According to the study, appropriate weather data transformations significantly improve forecast accuracy, and interpolation transformations are favorable for station-based weather data, while statistical transformations outperform grid-based data. While both station-based and grid-based weather data benefit from optimal changes in energy demand forecasts, solar forecasts are improved by grid-based data and wind energy forecasts by station-based data. Future research directions include evaluating transformations using multiple weather variables and exploring advanced autoencoder techniques for further improvements. [7]
- Calvo and Valero (2022) address the critical issue of strategic resource availability and future assessments in the field of renewable energy. They highlight the growing demand for elements such as lithium, cobalt and nickel in renewable energy technologies and highlight the challenges of resource dependency and limited recycling options. Labor supports a stricter legal framework, more research and development and a shift to more sustainable economic models to reduce the risks of resource depletion. Calvo and Valero propose a comprehensive framework that includes regulatory reforms, technological innovation, and sustainable economic practices, emphasizing the importance of addressing resource availability issues to ensure the sustainability of renewable energy. [8]
- Morse et al. (2022) evaluate the replacement of coal plants with wind and solar power in the ERCOT region and outline the potential health and environmental benefits. The study shows that on-grid wind and solar projects can replace coal generation with adequate transmission infrastructure and reliable operation of existing resources. Despite the intermittency of wind and solar power, strategies such as adjusting electricity demand to the availability of renewable resources can mitigate reliability problems. However, ensuring a reliable electricity supply also depends on a strong transmission infrastructure and flexible use of available resources. The study recommends additional research to explore energy storage options and expand transmission capacity to support the integration of renewable energy, which is essential to Texas' long-term viability. [9]
- Michaelides (2023) emphasizes the need to switch to renewable energy. energy in electricity production. Focus on Texas as a case study for reducing CO2 emissions. The study quantitatively analyzes the infrastructure needed to reduce carbon emissions to meet current energy demand and outlines the technological feasibility of the transition. However, significant investment is needed in renewable energy blocks and energy storage, which are projected to increase electricity prices and will disproportionately affect poor citizens. The document proposes to introduce energy subsidies for disadvantaged population groups and invest in renewable electricity production to eliminate inequality and promote sustainable energy transitions. [10]
- Moa and Go (2023) provide a comprehensive safety and risk assessment. Large-scale energy storage systems (LSS) and battery energy storage systems (BESS) provide information on potential threats and mitigation strategies. Their study recommends BESS capacity for different LSS sites and analyzes the worst-case fire hazard and BESS damage. STPA-based analysis identifies the root causes of barrier failures, leading to proposed mitigation measures designed to reduce equipment damage and benefit stakeholders, LSS owners, and emergency responders. The proposed security framework should facilitate the deployment of battery storage systems in large solar power plants in line with global energy transition goals. [11]
- Hamdan et al. (2023) present research on predicting future global temperatures and greenhouse gas emissions using long-short-term memory (LSTM) models, predicting significant increases by 2100. Although LSTM models offer promise for predicting climate variables, their limitations, including data, must be considered . sensitivity and challenges in recording extreme events. The research paper develops a mathematical model based on RNN and LSTM algorithms, which shows better prediction accuracy and reliability compared to the RNN algorithm. The research underscores the urgent need for action to curb climate change and highlights significant challenges to future global temperatures and human-caused greenhouse gas emissions. [12]

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- Mollick, Hashmi and Sabuj (2024) discuss the unpredictability of climate change. production of wind turbines. in coastal areas by analyzing ML models for short-term wind speed forecasting. The Cat Boost model looks promising, with regression coefficients exceeding 50-60% in one dataset and over 85% in the other. Site-specific feasibility studies are presented and Weibull model parameters show differences in wind power density. However, errors in the data and the complexity of model training are acknowledged. Future research aims to improve forecast accuracy and incorporate other environmental factors into robust project planning for wind energy projects.[13]
- Loganathan et al. (2022) present a study assessing energy resources and policies in South India, focusing on Andhra Pradesh, Tamil Nadu, Kerala, Karnataka and Odisha. They present a "thermoelectric framework" for alternative energy production using thermoelectric generator (TEG) technologies to harness solar energy. The study highlights the role of renewable energy in reducing carbon dioxide emissions and promoting sustainability, and encourages collaboration between stakeholders on solar energy solutions. Overall, the study provides an overview of the renewable energy landscape in South India and highlights the potential of innovative technologies such as the thermoelectric platform. Collaboration and research in this area can lead to a more sustainable and environmentally friendly energy future for the region. [14]
- Desai (2021) examines the integration of renewable energy sources (RES) into power grids, focusing on Gujarat, India. . As renewable energy prices become competitive at Rs 2.50-3.00/kWh, the paper discusses the challenges of integrating intermittent energy into modern grids. Case studies illustrate methods and project capacity and energy production for 2019-20 and 2029-30. By 2046, renewable energy, including hydropower, could provide 35 to 40 percent of electricity, with coal still the dominant source. Strategies such as green energy corridors and renewable energy control centers enable planned renewable energy production. In Gujarat, initiatives such as feed separation and flexible use of coal-fired power plants are being used to achieve renewable energy production of up to 40% on average and 100% on certain days. The research emphasizes the integration of renewable energy sources into sustainable and environmentally friendly energy systems based on international cases and Gujarati experiences. [15]
- Bouchard et al. (2023) investigated the integration of renewable energy sources into the energy network of the city of Hamburg Mitte, emphasizing the use of real-time data from the city's energy network operator and the "Entso-E" platform. The study highlights the changing nature of renewable energy sources such as solar and wind compared to established sources and emphasizes the need for efficient technology to sustainably balance energy supply and demand. Cost analysis determines the optimal technology combinations for a reliable and environmentally friendly energy grid and evaluates the efficiency and impact of smart grid technologies. The research uses a systematic literature review, historical energy data analysis, real-time demand studies, forecasting, simulation modeling and infrastructure assessments. [16]
- Alkhayat et al. (2021) provide a comprehensive overview of the latest research in the field and classify forecasting methods based on various parameters such as forecast horizon, data usage and estimation methods. The main results are the prevalence of hybrid prediction models and the use of recurrent neural networks (RNN) models such as long short-term memory (LSTM) and Gated Recurrent Unit (GRU) and convolutional neural networks. (CNN). Challenges of deep learning-based energy forecasting are discussed, such as the impact of variability in meteorological data on model accuracy at different locations. Also examples of statistical tests used in model estimation, such as Diebold and Mariano tests, Friedman test, Pearson correlation and ANOVA. [17]
- Almaghrabi et al (2022) investigate the application of the wavelet transform (WT) in photovoltaic (PV) capacity forecasting and address issues arising from its non-uniform and non-linear nature as affected by weather. conditions and markets. Dynamic strategies include dividing time series data into detail and approximation components using WT, reconstruction using inverse wavelet transform (IWT). Various forecasting models are evaluated, including statistical (ARIMA, LR, ES) and machine learning models (NNs, SVR, RF, LSTM, CNN), and machine learning models offer advantages in learning non-linear relationships. Evaluation using the stationary wavelet transform (SWT) reveals models such as RF that are effective in predicting solar energy. The paper evaluates the performance of the model at different accuracy levels (hourly and monthly) and examines the sensitivity of forecasting methods in WT settings, emphasizing the need to optimize parameters to improve accuracy. [18]
- Yuanzheng et al. (2024) delve into the complex world of artificial intelligence (AI)-based renewable energy system operations (RPSO), providing technical insights and factual data to support their argument. It highlights the operational challenges raised by the increasing integration of renewable energy (RE) into power systems, emphasizing variability and intermittency among others. Artificial intelligence techniques, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), are used as tools to improve power system forecasting, distribution, management, and markets in the context of RPSO. ML techniques enable accurate forecasting of renewable energy production to balance electricity supply and demand, while RL methods deal with the computational complexity of optimizing energy transmission to minimize costs. Accurate forecasting, which is critical for a reliable RPSO, includes forecasts such as renewable energy production, demand and electricity prices. AI-based technologies offer solutions to operational challenges by providing real-time control

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signals to effectively manage voltage and frequency fluctuations. Deep learning methods shine with accurate production forecasts that support supply and demand balance. [19]

- Abisoye et al. (2023) provide a comprehensive overview of the application of artificial intelligence (AI) techniques in renewable energy systems. It emphasizes the use of techniques such as Artificial Neural Networks (ANN) and Radial Basis Function (RBF) Neural Networks to optimize photovoltaic (PV) systems and identify temporal characteristics of solar collectors. Artificial intelligence techniques such as ANN and genetic algorithms are used to optimize and forecast renewable energy production, improve performance and reduce costs. The successful deployment of AI in renewable energy systems depends on strong infrastructure support, including access to big data, high computing power and global network communication where big data plays a critical role. Various AI technologies have shown significant achievements in renewable energy applications, such as accurately predicting solar system operating conditions and saving power generation systems on isolated islands. [20].

III. METHODOLOGY

A. Literature Review:

During the study, more than 22 scientific articles and the works of well-known scientists and analysts were examined. Of those 22, the volume includes a literature review of more than 16 articles. The literature review covers predictive modeling, renewable energy integration, weather data analysis, and the transition to sustainable energy. It highlights the importance of machine learning (ML) in smart grid management, material discovery and energy management optimization. The review also discusses the replacement of coal with renewable energy, focusing on the advantages of wind and solar over coal in the ERCOT region. It also discusses Texas' transition to renewable energy and proposes initiatives to address investment challenges and disparities. The review also looks at renewable energy policies and integration efforts in various regions such as Gujarat, Hamburg Mitte and South India. Renewable energy forecasting methods are also discussed, including hybrid forecasting models and deep learning techniques. The review says these studies will significantly advance renewable energy technologies, smart grid management and climate change mitigation strategies.

B. Analysis:

Our goal is to gain meaningful insights and observations that allow us to draw reasonable conclusions about energy consumption patterns. Using various data visualization techniques such as charts, graphs and maps, we analyze trends in energy consumption across sectors and geographies. By presenting the data visually, we try to identify patterns, anomalies, and correlations that may not be immediately apparent from the raw data alone. In addition, our analysis delves into the drivers of energy consumption, including economic activity, population growth and technological development. We examine how these factors affect energy consumption patterns over time and across different economic sectors. In addition, we study the impact of energy consumption on environmental sustainability, including greenhouse gasses and climate change. By displaying data related to energy consumption and its environmental effects, we want to emphasize the urgent need for sustainable energy solutions. Through this data-driven research and visualization process, we seek to uncover insights that help draw conclusions about energy consumption trends, drivers and consequences. With the help of visualized data, we aim to provide valuable insights that can guide future energy policy decisions and sustainable development initiatives.

C. Policy Formulation and Recommendation:

This work offers practical advice to policy makers dealing with the key challenges of energy transition and sustainability. First, it underlines the importance of conducting in-depth research to understand resource availability, predict future needs and mitigate risks in the renewable energy supply chain. Second, it is proposed to assess the feasibility of wind and solar energy as alternatives to coal, and to propose ways to promote their adoption and facilitate the transition. In addition, the paper highlights the value of case study-based policy interventions that emphasize energy efficiency, demand management and power management to achieve sustainable energy goals. These recommendations help policymakers navigate the complexities of energy toward a more sustainable, efficient, and environmentally friendly energy future.

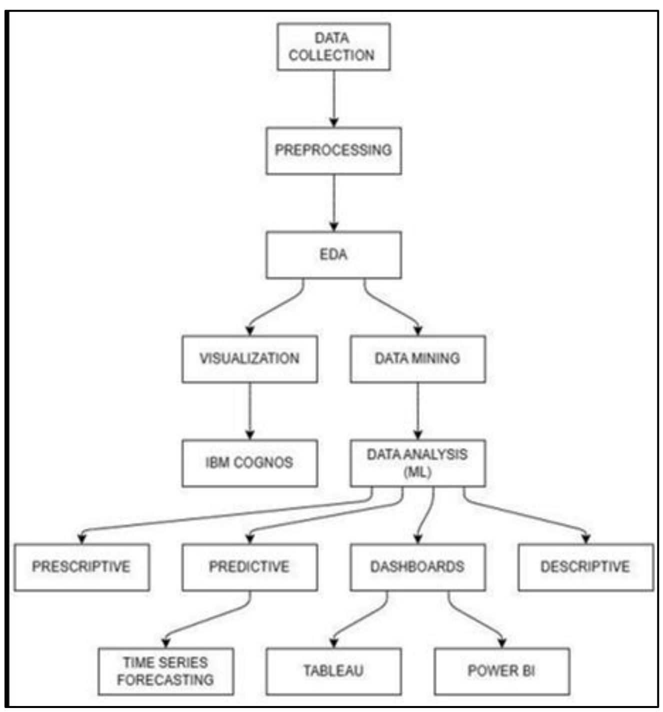

Fig 1: Methodology Flowchart

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Figure 1 Demonstrates the Detailed Workflow of the Methodology used in this Study

D. Datasets Used:

- *World_Energy_Data (D1):* The dataset provides a broad overview of global energy trends from 1900 to 2021, covering 123 countries. With 128 columns packed with information, this is a valuable resource for researchers and analysts. This dataset covers major energy sources such as coal, gas, oil and renewables and provides information on their production, consumption and changes over time. It doesn't just provide raw numbers; it also includes more detailed metrics such as percentage changes, per capita figures and the share of each energy source in the total energy source of the country. In addition, it dives into renewable energy with solar and wind data to support analyzes of the transition to sustainable energy sources.
  Source:[Energy Dataset Country-Wise (1900-2021) (kaggle.com)]

- *Global Data on Sustainable Energy (D2):* A dataset providing a comprehensive overview of sustainable energy indicators and related drivers in 176 countries in the years 2000-2020. This dataset provides valuable information on global energy consumption patterns from 2000 to 2020. the last two decades. We used this dataset to track progress towards SDG 7, compare countries and explore potential use cases from energy consumption forecasting to renewable energy investment strategies. By facilitating cross-country comparisons and highlighting industries, this dataset is an important resource for promoting the sustainable energy transition and addressing pressing environmental issues worldwide.
  Source:[Global Data on Sustainable Energy (2000-2020) (kaggle.com)]

- *World Energy Consumption (D3):* The dataset provides a comprehensive picture. 306 rows and 129 columns show how countries around the world use energy. This includes important aspects such as population, GDP, biofuel consumption, carbon content of electricity and use of renewable energy. This data set is a valuable tool for understanding how energy consumption affects the environment and economy around the world. By looking at trends in fossil fuel use, renewable energy adoption and greenhouse gas emissions, researchers can identify areas for development and track progress toward sustainable energy goals. Detailed information on electricity generation sources and per capita consumption enables an in-depth analysis of energy systems in different regions.
  Source: [World Energy Consumption (kaggle.com)]

- *Ontario Electricity Demand (D4):* The dataset provides an overview of the hourly electricity demand and price in Ontario, Canada, managed by the Independent Electricity System Operator (IESO). The IESO has a key role in balancing electricity demand and supply to ensure the reliable operation of the electricity grid. This dataset covers the years 2003-2023 and provides a comprehensive picture of electricity demand and price trends over time. Hourly demand data represents total electricity consumption in kilowatt hours (kWh), while Average Hourly Price, also known as Hourly Ontario Price (HOEP), is measured in Canadian cents per kWh.
  Source: [Ontario Energy Demand (kaggle.com)]

- *Carbon Emission Data (D5):* The dataset aggregates data from the US Energy Administration in 1980. century to 2020, which facilitates the analysis of factors affecting CO2 emissions worldwide. It includes key indicators such as energy consumption and production of major energy sources by country, as well as indicators such as GDP, population, energy intensity per capita and energy intensity per GDP. Energy intensity measures the inefficiency of an economy in terms of energy use, either per capita or per unit of GDP. The data also provides an overview of CO2 emissions and measures the environmental impact of energy consumption. It has functions classified by country, energy type and year to provide a comprehensive picture of energy-related dynamics.
  Source:[Countries CO2 Emission and more... (kaggle.com)]

- *Energy Dataset Country-Wise (D6):* The dataset provides comprehensive information on energy consumption and production by country, including a set to facilitate comparison. Each row corresponds to a country and provides information on different aspects of energy production and consumption. The data includes details such as changes in coal, gas and oil production, measured in both annual percentage changes and terawatt hours. In addition, it includes the consumption of primary energy, the use of biofuels, the carbon intensity of electricity production and greenhouse gasses. In addition, electricity generation from various sources such as coal, gas, nuclear, hydro, solar and wind is described, facilitating a detailed analysis of energy generation trends. Other metrics are also included, such as energy consumption per unit of gross domestic product, energy consumption per capita and fossil fuel consumption, enabling a comprehensive assessment of each country's energy landscape.
  Source:[Energy Dataset Country-Wise (1900-2021) (kaggle.com)]

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- *CO2 Emissions by Sectors (D7):* The dataset provides a comprehensive overview of carbon emissions across countries and sectors, a valuable resource for researchers and policymakers interested in environmental impacts. Organized by country, date, sector and emissions value, the data allows users to examine emissions trends over time and across sectors.
Source: [CO2 Emissions by Sectors (kaggle.com)]

- *Smart Meters in London (D8):* The dataset provides comprehensive data collection to monitor household energy use in England, Wales and Scotland. Thanks to the government's initiative to install smart meters in every home by 2020, this dataset provides valuable information on energy usage patterns. The data covers a sample of 5,567 London households that took part in the Low Carbon London project run by UK Power Networks between November 2011 and February 2014. It focuses mainly on electricity consumption and includes information on household characteristics such as ACORN rating data and tariff information.
Source: [Smart meters in London (kaggle.com)]

- *Solar Power Generation (D9):* The dataset contains data collected from two solar power plants in India over 34 years. hours days The data set consists of pairs of files, each containing one power generation data set and one sensor reading data set. Electricity production data is collected at the inverter level, where each inverter is connected to multiple solar array lines. On the other hand, sensor data is collected at the facility level using an array of sensors strategically placed within a single facility.
Source:[Solar Power plant Dataset (kaggle.com)]

- *Global Energy Consumption & Renewable Generation (D10):* The dataset contains various datasets that provide insights into global energy. trends in consumption and production of renewable energy. It includes data on the number of terawatt hours (TWh) produced from both renewable and non-renewable sources and highlights the top 20 countries for renewable energy. The dataset also includes a timeline from 1997 to 2017 that describes the progress of the renewable energy sectors (eg hydro, wind, biofuels, solar and geothermal) that are important in the renewable energy production dataset. Additionally, the Top 20 Country Electricity Generation dataset includes national data for each category of renewable energy. In addition, the dataset includes global TWh figures from both renewable and non-renewable sources, helping to understand global energy consumption patterns. Two new datasets have been added to the latest version, providing global consumption indicators at national and continental/international group levels. These additions provide context for changing energy needs over time and the transition from non-renewable to renewable energy sources.
Source:[Global Energy Consumption & Renewable Generation (kaggle.com)]

IV. RESULT AND ANALYSIS

As renewable energy becomes central to solving global energy needs and environmental problems, the following images provide an in-depth analysis of its consumption trends and trends. The accompanying images illustrate the evolving landscape of renewable energy use and highlight key insights gleaned from the data analysis performed. The results of our in-depth research provide valuable insights into the complex dynamics of global energy systems. Our analysis of historical energy consumption data illuminates not only regional differences, but also temporal trends and highlights changing energy demand in response to economic, social and technological factors. By researching the integration of renewable energy, we discover not only the promising growth paths of solar and wind power plants, but also the need for innovative solutions to address challenges such as power outages and grid integration problems.

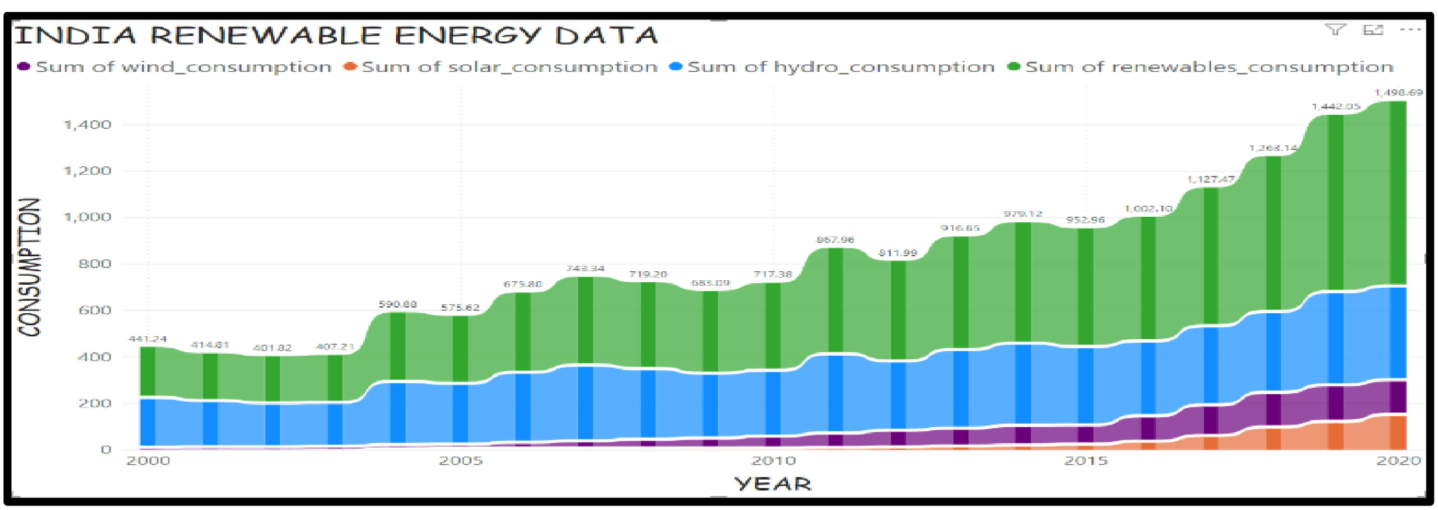

Fig 2: Consumption of Renewable Sources of Energy in India

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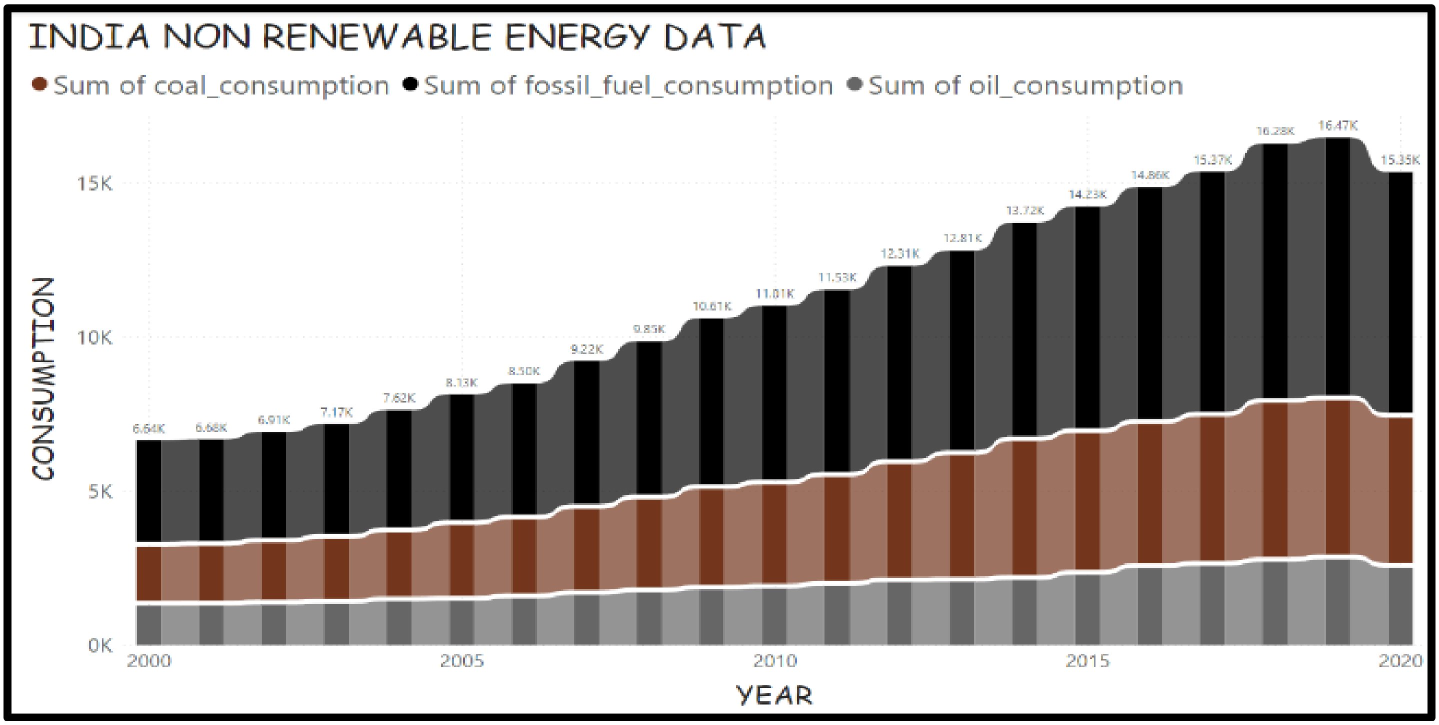

Fig 3: Consumption of Non-Renewable Sources of Energy in India

Figure 2 shows a significant upward trend in renewable energy consumption, with hydropower being the most important component of renewables as solar and wind power increase in later years.

From Figure 3, we conclude that the growth of fossil consumption is stronger compared to renewable energy. [D6]

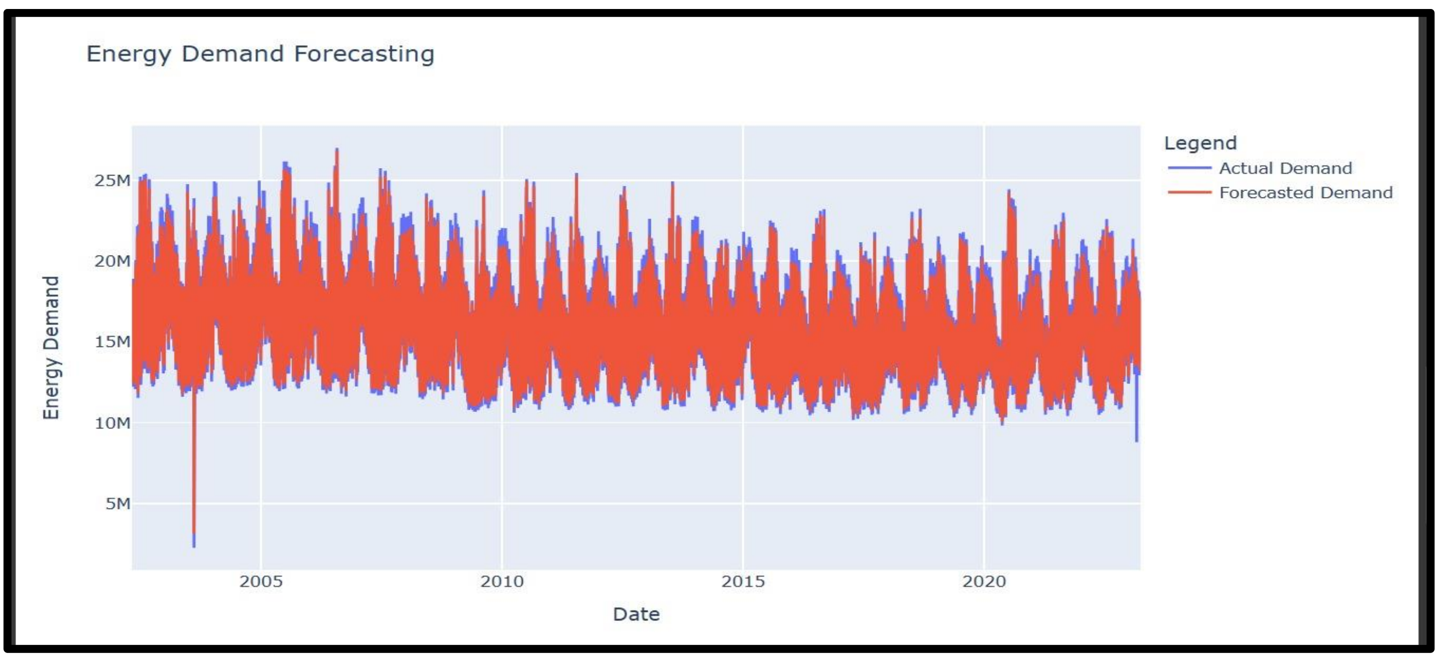

Fig 4: Energy Demand Forecasting

Figure 4 shows a line graph of energy demand over time. The blue line is the actual demand and the red is the forecasted demand. Very small deviations from the predicted values indicate a high accuracy of the model.[D10]

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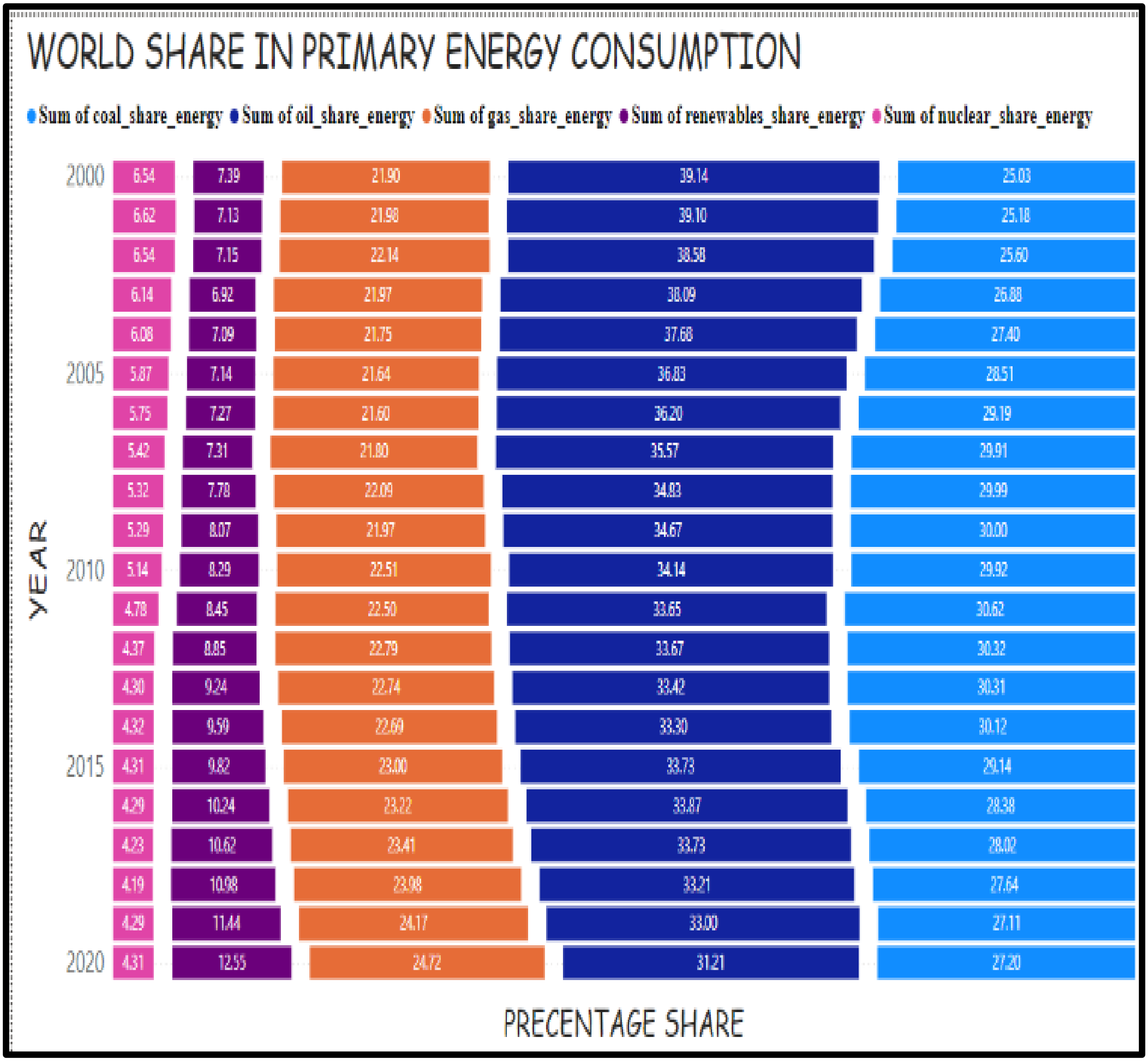

Fig 5: World Share in Primary Energy Consumption

Figure 5 shows the share of different forms of energy in the primary energy consumption of the world from 2000-2020. It is evident that despite some progress towards incorporating renewable energy sources, the overall picture remains bleak. The dominance of fossil fuels, particularly coal and oil, continues to persist, indicating a slow pace in transitioning to cleaner energy alternatives. The limited reduction in the share of fossil fuels suggests a lack of significant commitment to addressing climate change and reducing greenhouse gas emissions. The lack of substantial growth in renewables relative to fossil fuels underscores the challenges and barriers hindering the transition to a more sustainable energy mix.[D1]

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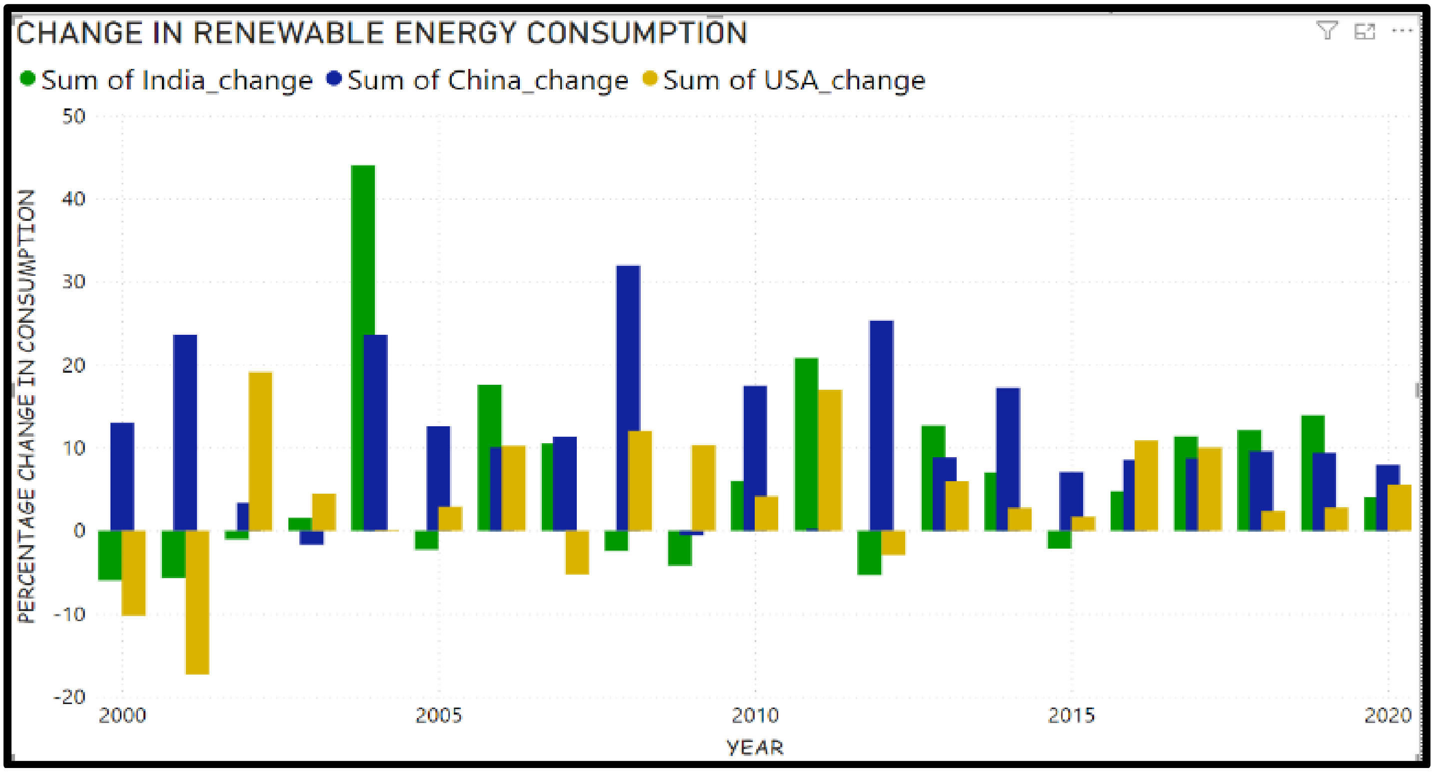

Fig 6: Change in Energy Consumption

Figure 6 is a comparison of India, China and the United States in the percentage change in consumption of renewable energy forms. China's renewable energy consumption has grown significantly over the years.[D6]

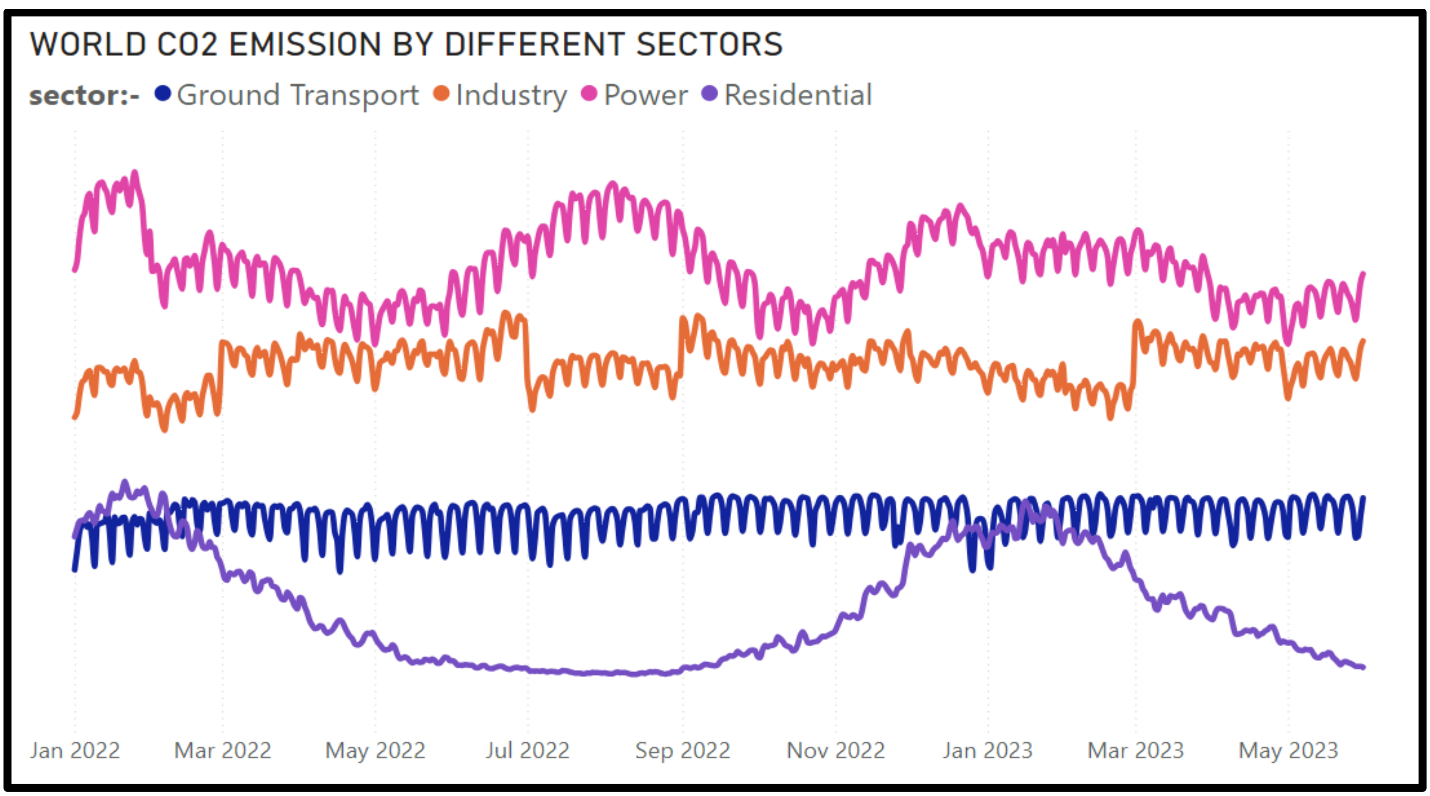

Fig 7: Co2 Emission by Different Sectors

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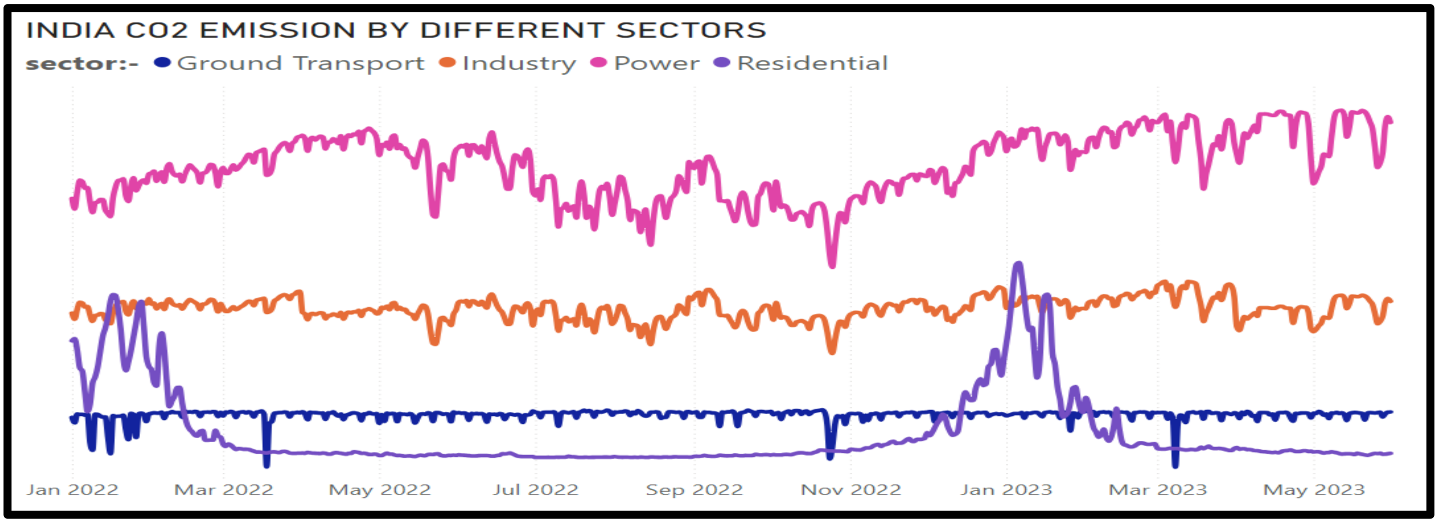

Fig 8: Co2 Emission by Different Sectors in India

Figure 7 shows world emissions of carbon dioxide from different sectors. The industries are land transport, industry, electricity and housing. Data is from January 2022 to May 2023. The electricity sector is the largest emitter of carbon dioxide emissions, followed by industry. [D7]

Figure 8 shows India's carbon dioxide emissions from various sectors from January 2022 to May 2023. The four sectors shown are land transport, electricity, industry and housing. There are significant fluctuations in the CO2 emissions of the residential area.

Any policy aimed at reducing carbon dioxide emissions must focus on integrating and increasing the share of renewable energy in industry and the energy sector, as they are the largest emitters of carbon dioxide and other greenhouse gases.[D7]

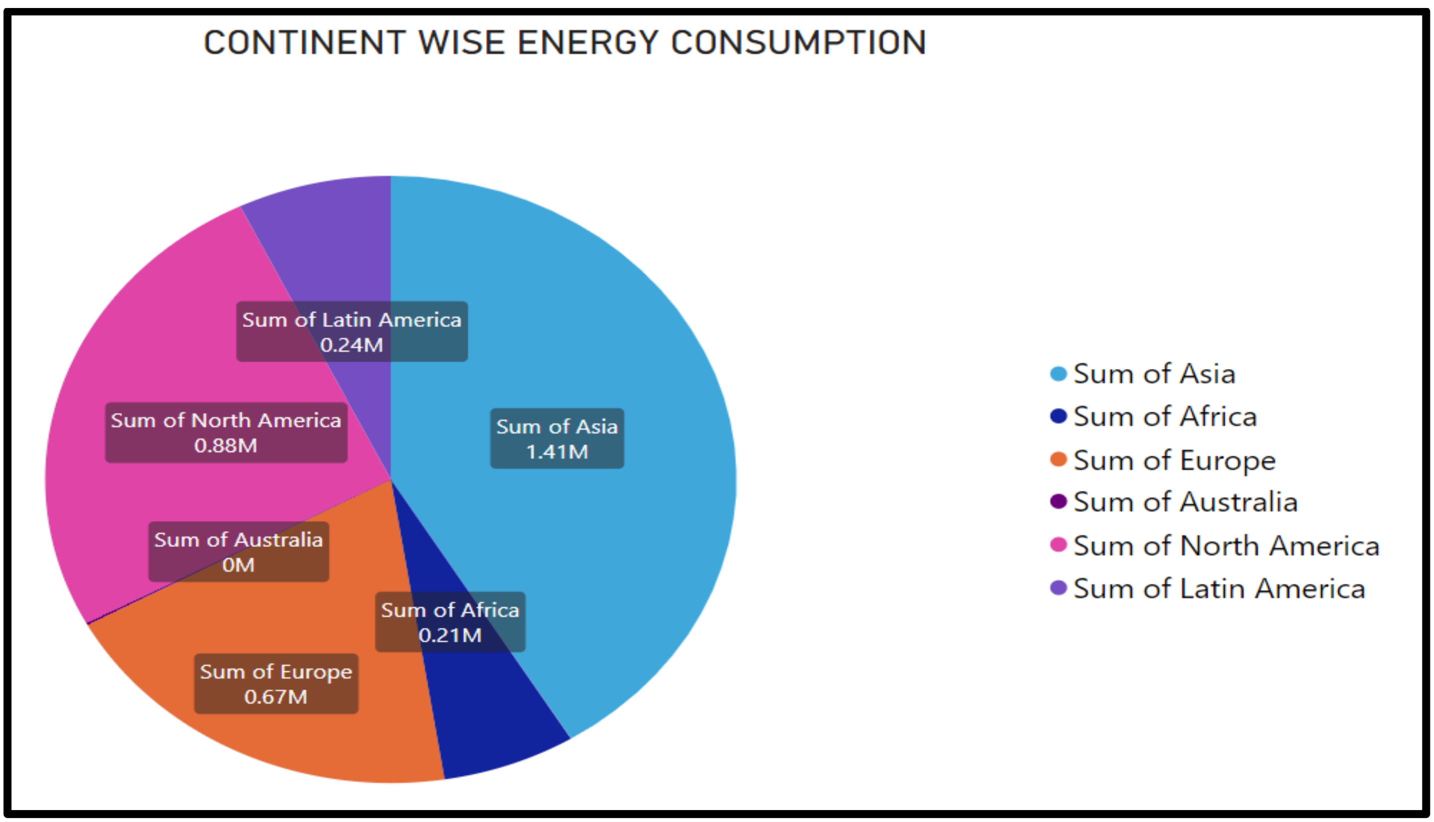

Fig 9: Energy Consumption by Different Continents

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Figure 9 shows the energy consumption of different continents. The continent that consumes the most energy is Asia, followed by North America, Europe, Latin America, Africa and Australia.

Although Asia consumes more than 40% of the world's energy, a comparison of different continents per capita shows that Europe is the largest consumer per capita.[D10]

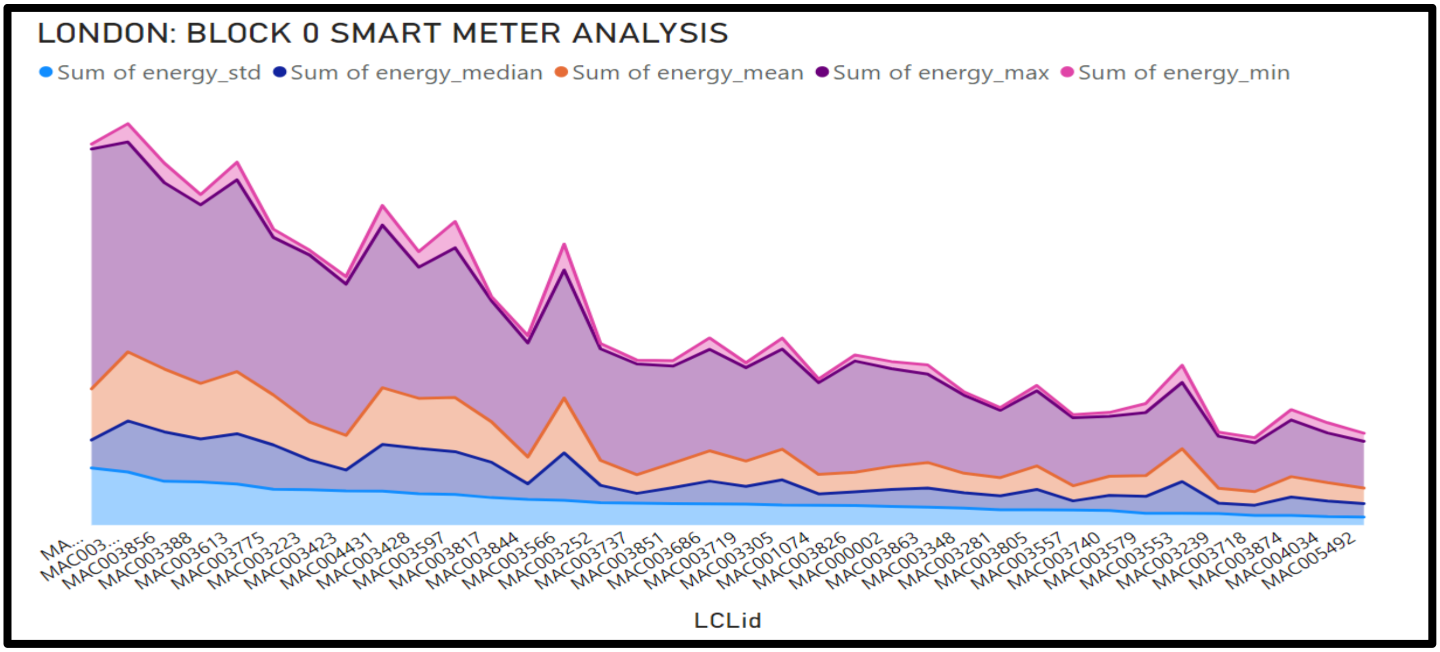

Fig 10: Smart Meter Data (London)

Figure 10 shows a line diagram of household energy consumption over time. The diagram shows that energy consumption is highest in the winter months and lowest in the summer months. This is because the household uses more energy for heating in winter. The diagram also shows that energy consumption varies more during the winter months than during the summer months. This is because the weather is more changeable in the winter months, which leads to more fluctuations in energy demand.[D8]

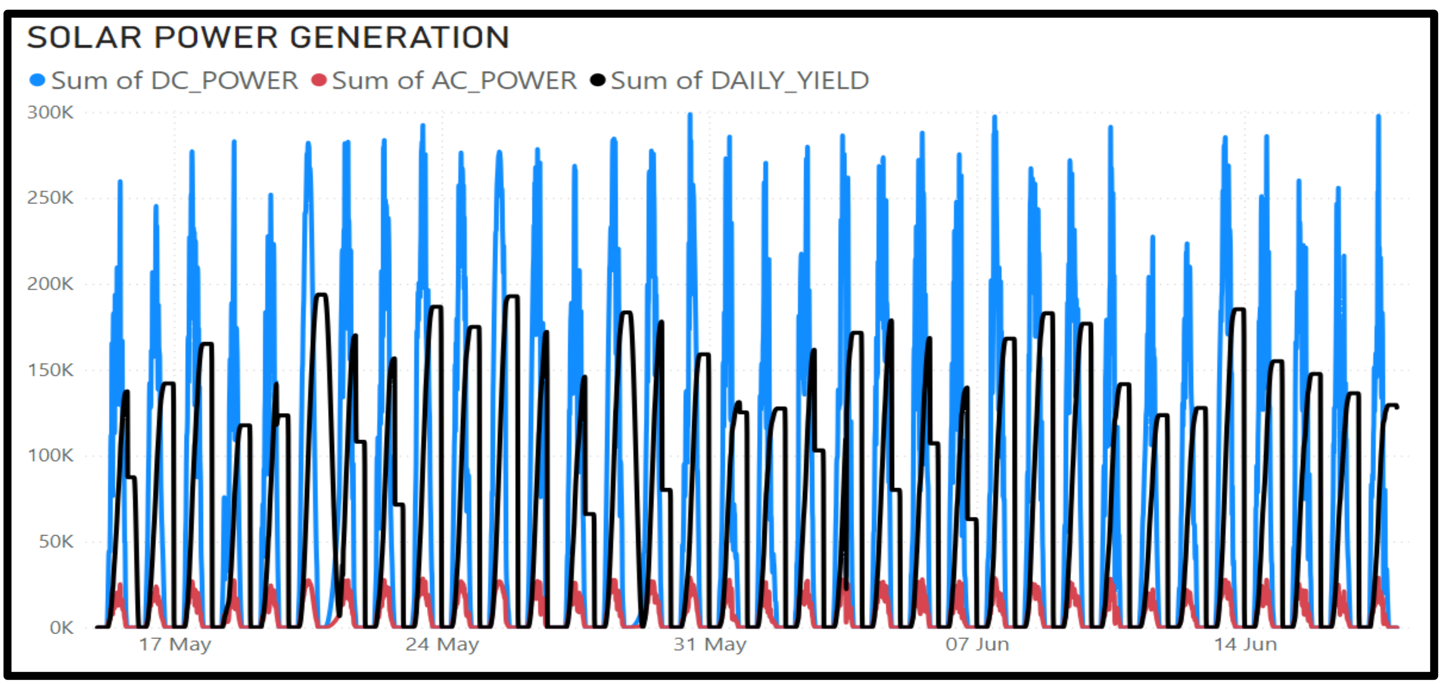

Fig 11: Solar Power Generation (India)

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Figure 11 shows the production of solar energy using solar energy.

The x-axis shows the time in days and the y-axis shows the electricity production in kilowatts.

The blue line shows the DC current, the red line shows the AC current and the black line shows the daily return.

The daily production is the total amount of electricity produced by the solar power plant per day.

Despite the high DC generation, the average daily output of the plant does not indicate inefficiency, as more than 30% of the total capacity is wasted.[D9]

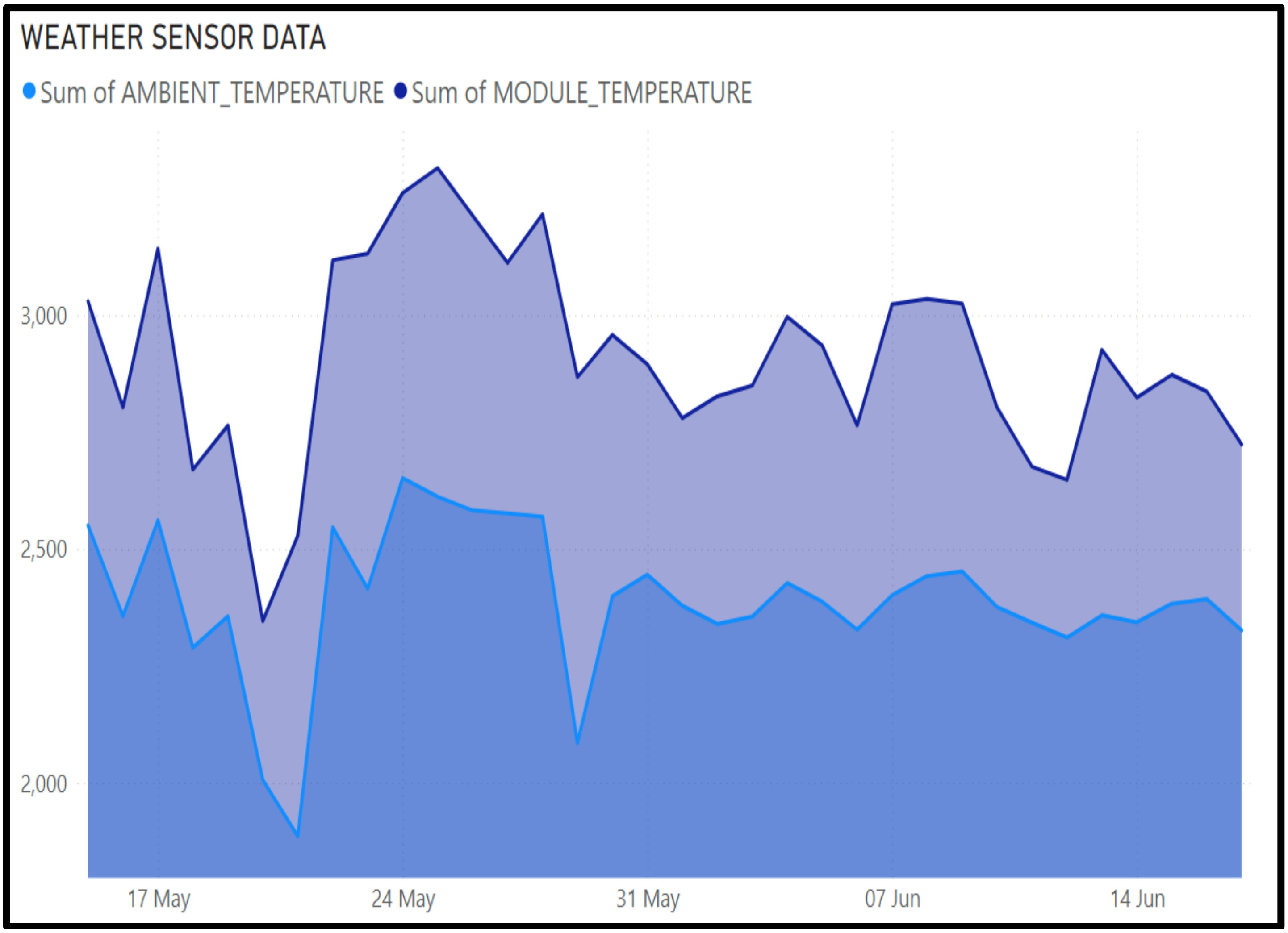

Fig 12: Weather Sensor Data (India)

Figure 12 is a line graph showing the sum of ambient temperature and module temperature over time.

The x-axis shows time in days and the y-axis shows temperature in degrees Celsius.

The sum of the ambient temperature is usually greater than the sum of the module temperature.

This is because the ambient temperature is the ambient temperature of the weather station, while the module temperature is the temperature of the solar panels.

Solar panels are heated by the sun, so they are usually warmer than the air around them. Combined with solar energy production data, sensor data shows a relationship where total yield increases as temperature increases. [D9]

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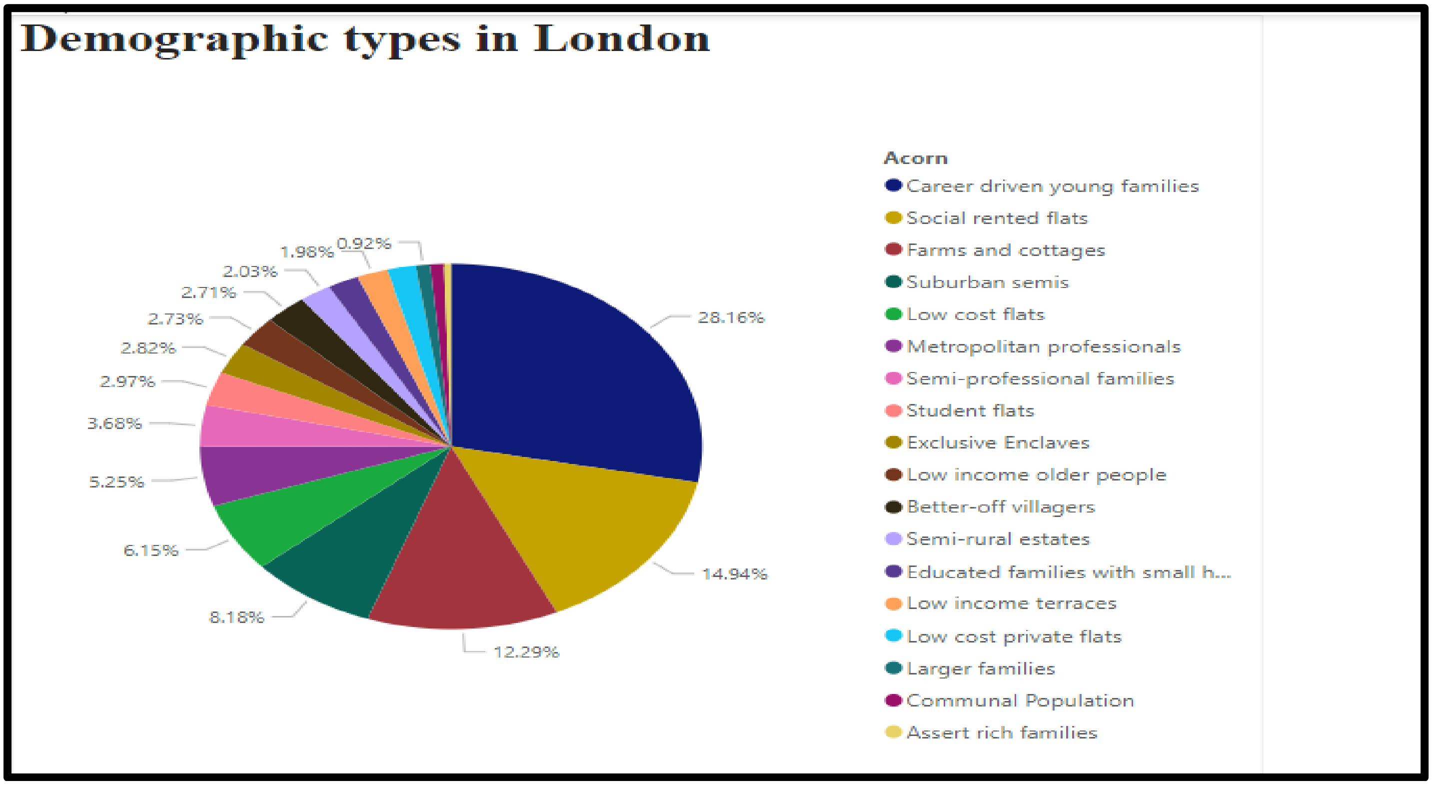

Fig 13: Demographic Types in London

Figure 13 shows a pie-chart in which the people of London were classified into different demographic types based on Acorn data with each group visualized as a percentage of total population.[D8]

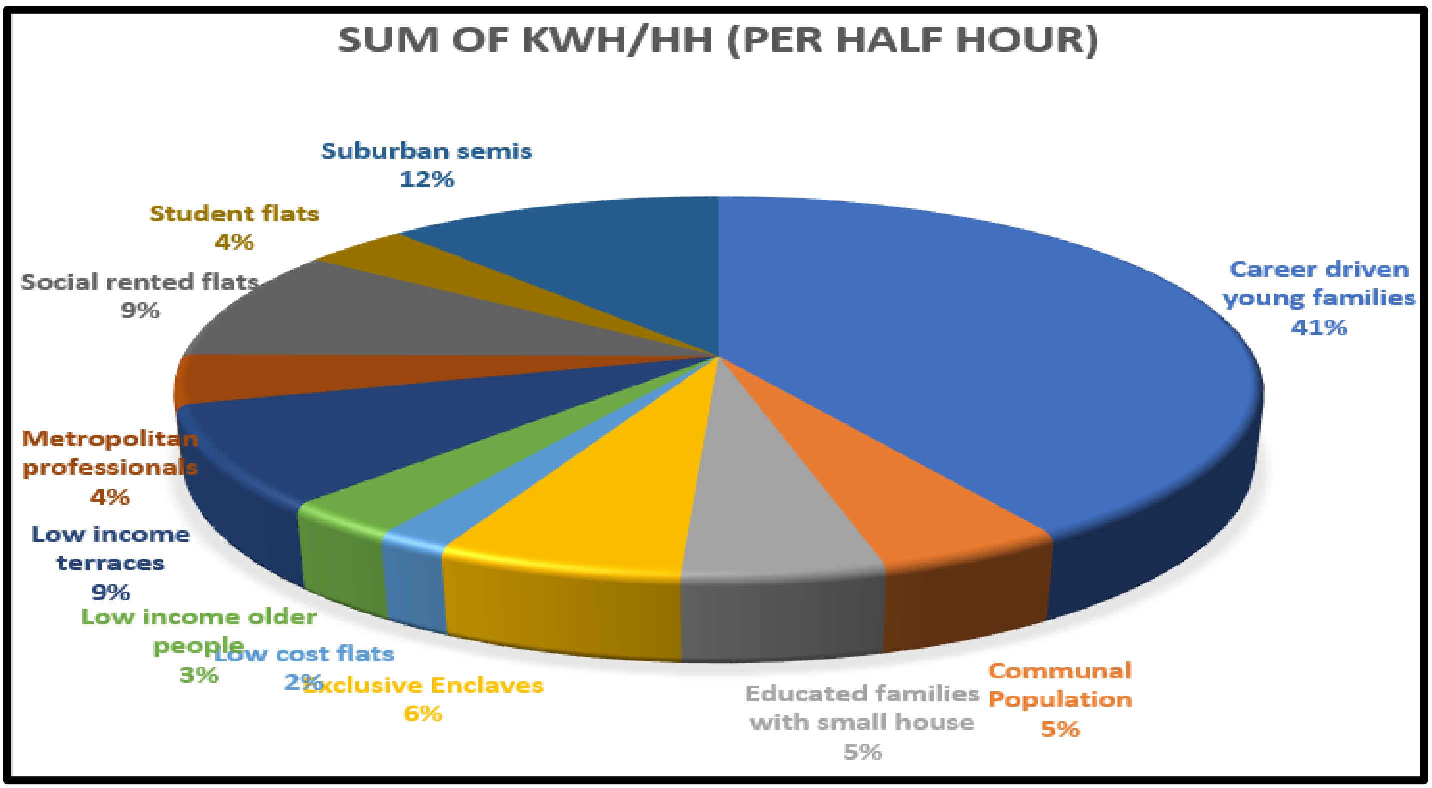

Fig 14: Share in Electricity Consumption in London

Figure 14 shows that career-oriented young families, who make up 28.16% of the population, consume 41% of the total electricity. Exclusive enclaves account for 2.86 percent of the population, consuming 6 percent of total electricity, double the share. Similar findings highlight existing inequalities in energy availability and use.[D8]

V. DISCUSSION

This work explores various aspects of global energy dynamics and highlights key findings from a comprehensive visualization and dataset of renewable energy production, global energy consumption and carbon emissions.

First, it highlights the significant growth of renewable energy consumption in India over the last two years. . for decades. , especially in the solar and hydropower sector, which shows a promising shift to sustainable energy sources. Despite this growth, consumption of non-renewable energy, particularly fossil fuels such as coal and oil, continues to rise, posing challenges to India's energy transition efforts. Second, the analysis of global energy consumption shows the dominance of Asia as the largest energy consumer, mainly due to rapid industrialization and urbanization. In addition, it can be noted that there are opposite trends in energy consumption in large countries, China surpasses the United States as the largest energy consumer, while India's energy consumption is constantly growing along with economic growth.

In addition, the sector-by-sector examination of CO2 emissions highlights land transportation and industry as critical contributors to global carbon emissions. This underscores the urgent need for policies to limit emissions from these sectors and transition to cleaner energy options. In addition, London's smart meter data sheds light on household energy consumption patterns, highlighting seasonal changes and the increasing use of renewable energy sources. This highlights the importance of intelligent energy management systems in promoting energy efficiency and sustainability at the local level. In addition, a study of solar generation data illustrates the diurnal variation of solar generation, highlighting the need for efficient energy storage solutions to maximize the use of renewable energy sources.

VI. CONCLUSION

This work highlights the complex interaction between energy consumption, environmental impacts and policy considerations, and highlights the importance of joint action to promote renewable energy deployment, reduce carbon emissions and promote sustainable energy practices, both locally and globally. With targeted policy action and technological innovation, we can pave the way to a more sustainable and sustainable energy future for generations to come.

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