**CHAPTER ONE**

* 1. **INTRODUCTION**

The rate of consumption of energy by households, communities and cities is a very important part of the society that should be looked into as it helps in making informed decisions and also helps the power generating stations to monitor the rate at which energy is being consumed so as to allocate the right proportion to different consumption units.

Energy demand forecasting is the process of predicting the future energy consumption of a system. It is a critical task for power system operators, as it allows them to plan and operate the system more efficiently.

Traditionally, energy demand forecasting has been done using statistical methods such as time series analysis and regression analysis. However, these methods have limitations, such as being unable to capture the complex relationships between input and output data.

Artificial intelligence (AI) has emerged as a promising new approach to energy demand forecasting. AI methods, such as artificial neural networks (ANNs), can learn to model complex relationships between input and output data. This makes them more accurate than traditional statistical methods.

Peak load forecasting is essential in electrical power system operation, unit commitment and energy

scheduling [1]. Energy demand forecasting initiates proper planning and developing of future generation, transmission and distribution facilities. One of the tasks of electric utility is to accurately predict energy demand requirements at all times, basically for a long-term planning. Based on the outcomes of such forecasts utilities coordinates their resources to meet the forecasted energy demand, thereby engaging a least-cost energy management plan and follow-up which are subject to numerous uncertainties, that is, in planning for future capacity resources, we need an information and operation of the existing generation resources, in order to predicts future capacities [2].

The importance of energy availability, reliability and affordability in any nation in the economic growth, social and political development cannot be overemphasized. Energy plays a major role in the economic growth, progress and development of any nation. Available, reliable, efficient and affordable power supply is the hallmark of a developed economy. Any nation whose energy need is insufficient and inadequate in supply; prolong her development and risk of losing potential investors [1]. Electricity is the prime mover that drives the economic development of every country and any nation that does not pay attention or ignore its power sector is to at his peril. Energy is needed in any country for various purposes such as in residence to power domestic appliances and lightening purposes, commercial and institutional consumers for the provision of services and driving various devices and in the industries to drive various machines, equipment and purposes. The greatest engineering challenge in Nigeria today is the issue of the provision of adequate, reliable, efficient and affordable electricity supply to its consumers. Nigeria is facing a great issue of insufficient supply of electricity from the public utilities which has led to a situation where the nation is wallowing in darkness despite the vast energy resources. Thus the whole citizens of the country have been put into what was described as “Power international journal of engineering science and application Thomas and Okafor., Vol.5, No.3, October 2021 72 Cage” [2]. As a result of this only those individuals, establishment, institutions, industries and companies which are financially buoyant can liberate themselves from this cage by generating electricity to meet their needs. In Adesola [3] lecture on data capture processing, 2006 population and housing census of Nigeria in Tanzania, he reported that one of the key challenges/difficulties encountered in the 2006 census was lack of reliable and uninterrupted power. It was also reported in the Central Bank of Nigeria 4th quarter statistical bulletin (2012) that insufficient power supply is a major constraint to business growth and development in Nigeria with 69.3 index point as emphasized by the respondent firm. Business owners as a result of this deficiency generate their power to run their businesses which has now resulted to high cost of living. According to the Vanguard Newspaper [4], the federal government of Nigeria under the administration of His Excellency Mohammed Buhari (GCFR) recorded an increase of 1,811.3 Megawatts in power generation, in January, 2019 as the transmission company of Nigeria (TCN) transmitted 127,157.7 Megawatts as against 125,346.4 Megawatts in December, 2018. However, this amount is insufficient to cater for the energy demand of a growing country like Nigeria. There is an extreme electricity deficiency in Nigeria which has result to a wide demand/supply gap. The unpalatable effect of this situation is felt by the masses. Nigeria current population is estimated to be approximately 204 million as of Thursday, February 6, 2020 and she is ranked the 7th most populous country globally based on the United Nations estimate. By midyear of 2020 it is estimated to be approximately 206 million and by 2030, it is projected to rise to 252 million. Nigeria population is equivalent to 2.64% of the total whole population; the population density of Nigeria is 226 per km2 with total land area of about 910,770km2 which is equivalent to 351,650 Sq. miles [5]. Nigeria is projected to be the world’s third most populous country by 2050, according to report release by the UN department of Economic and Social Affairs. Statistics by experts shows that by 2040, Nigeria population would have quadruple without proportionate employment and social amenities to sustain it.. Figure 1.1 and figure 1.2 shows the projected trend for Nigeria population. Nigeria has a low-capacity utilization of 31% couple with high transmission and distribution losses of about 19%. Low-capacity utilization is enhanced by technology used, age and condition of plant. Nigeria must therefore work towards improving capacity utilization by carrying out serious renovation on all the aged power plants and invest on modern and more efficient and reliable technology. Also Nigeria should make efforts for a well-rounded energy mix, combining the enormous amount of available renewable energy with the nonrenewable fossil fuel. The gas being flared at the various crude oil refining station could be used to generate abundant electric power.

I am conducting research on the use of AI for energy demand forecasting. I am interested in exploring the different AI methods that can be used for forecasting, as well as the challenges and benefits of using AI for forecasting.

In this research, I will use a variety of methods, including:

1. Literature review: I will review the existing literature on AI for energy demand forecasting.
2. Data analysis: I will analyze historical data on energy demand to identify patterns and trends.
3. Model development: I will develop AI models to forecast energy demand.
4. Model evaluation: I will evaluate the accuracy of the AI models.

I believe that this research will contribute to the understanding of the use of AI for energy demand forecasting. The results of this research could be used to improve the accuracy of energy demand forecasts, which could lead to more efficient operation of power systems.

* 1. **Background of Study**

In recent years, there has been a significant increase in the complexity and uncertainty of energy systems due to factors such as population growth, urbanization, industrialization, and the integration of renewable energy sources. Efficient management and planning of energy resources have become crucial for ensuring a reliable and sustainable power supply. Load demand forecasting, which involves predicting the electricity consumption patterns of consumers, plays a vital role in addressing these challenges.

Traditionally, load demand forecasting has relied on statistical methods and time series analysis techniques. However, with the advent of artificial intelligence (AI) and machine learning (ML) algorithms, there has been a paradigm shift in load demand forecasting approaches. AI techniques, particularly deep learning models, have demonstrated superior performance in capturing complex patterns and nonlinear relationships present in energy consumption data.

The emergence of AI-based load demand forecasting has opened up new possibilities for energy system operators, utility companies, and policymakers. Accurate and reliable load forecasting enables efficient allocation of energy resources, optimal power generation planning, and improved decision-making for energy infrastructure investments. Moreover, it facilitates the integration of renewable energy sources, demand response programs, and energy storage systems into the grid.

The utilization of AI in load demand forecasting involves leveraging various techniques such as artificial neural networks (ANNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs). These models have the ability to learn from historical load data, weather conditions, socio-economic factors, and other relevant variables to make accurate predictions.

Additionally, the integration of energy analysis with load demand forecasting presents an innovative approach to address the sustainability aspect of energy systems. Energy analysis, which quantifies the total energy inputs and environmental impacts associated with energy production and consumption, provides valuable insights into the ecological and economic aspects of energy systems. By incorporating energy analysis into load demand forecasting using AI, it becomes possible to optimize energy planning while considering both environmental and economic factors.

However, despite the advancements in AI-based load demand forecasting, there are still challenges to overcome. These include data quality and availability, model interpretability, generalizability across different geographical regions and consumer segments, and the need for continuous model adaptation to evolving energy systems.

Therefore, this study aims to explore the potential of artificial intelligence techniques in energy/load demand forecasting. By analyzing historical load data, weather patterns, socio-economic indicators, and incorporating energy analysis, the study aims to develop accurate and robust models for load demand prediction. The research also intends to address the challenges associated with AI-based forecasting, propose solutions, and provide insights into the integration of energy analysis for sustainable energy planning.

Ultimately, the findings from this study can contribute to improved load demand forecasting practices, aiding energy system operators, policymakers, and stakeholders in making informed decisions, optimizing resource allocation, and promoting sustainable energy management in the face of evolving energy landscapes.

* 1. **Aims and Objectives of the study:**

1. To investigate the application of artificial intelligence techniques in energy/load demand forecasting for the energy sector.

2. To develop accurate and robust load demand forecasting models using AI algorithms such as artificial neural networks, recurrent neural networks, and deep learning architectures.

3. To explore the integration of energy analysis with load demand forecasting to incorporate environmental and economic considerations in energy planning.

4. To analyze historical load data, weather patterns, socio-economic indicators, and other relevant variables to enhance the accuracy and reliability of load demand predictions.

5. To assess the performance and compare the effectiveness of different AI-based models in load demand forecasting, considering factors such as forecasting accuracy, computational efficiency, and model interpretability.

6. To evaluate the potential benefits of accurate load demand forecasting in facilitating optimal energy resource allocation, power generation planning, and decision-making for energy infrastructure investments.

7. To provide insights and recommendations for stakeholders, energy system operators, and policymakers on incorporating AI-based load demand forecasting techniques and energy analysis for sustainable energy planning.

8.To contribute to the body of knowledge in the field of energy forecasting by advancing the understanding of AI applications in load demand forecasting and highlighting the importance of considering energy analysis in energy system management.

* 1. **Research question:**

How can artificial intelligence techniques and the integration of energy analysis improve the accuracy and sustainability of load demand forecasting in the energy sector?

* 1. **Significance of Study:**

The proposed study on energy/load demand forecasting using artificial intelligence holds significant importance due to the following reasons:

1. Enhanced Accuracy in Load Demand Forecasting: The utilization of advanced artificial intelligence techniques can significantly improve the accuracy of load demand forecasting. Accurate forecasts enable energy system operators, utility companies, and policymakers to make informed decisions regarding resource allocation, energy generation planning, and infrastructure investments. This study aims to contribute to the development of more precise and reliable load demand forecasting models, leading to optimized energy management and reduced operational costs.

2. Sustainable Energy Planning: The integration of energy analysis with load demand forecasting adds a sustainability dimension to energy planning. By considering both environmental and economic factors, this study aims to provide insights into the ecological impacts and total energy inputs associated with energy production and consumption. Incorporating energy analysis into load demand forecasting helps promote sustainable energy practices, aiding in the integration of renewable energy sources, demand response programs, and energy storage systems into the grid.

3. Optimized Resource Allocation: Accurate load demand forecasting enables better resource allocation and management. By understanding the expected energy consumption patterns, stakeholders can efficiently plan and distribute energy resources, reducing the likelihood of power shortages or excess capacity. This study's findings can assist energy system operators in optimizing their resource allocation strategies, leading to improved operational efficiency and reduced wastage.

4. Economic Benefits: Accurate load demand forecasting contributes to cost savings and improved economic performance. By accurately predicting electricity demand, utility companies can avoid overproduction or underproduction, leading to reduced operational costs and optimized revenue generation. Additionally, load forecasting helps in identifying peak demand periods, enabling the implementation of demand response programs to incentivize consumers to reduce their electricity consumption during high-demand periods. This study's outcomes can provide insights into cost-effective energy planning, benefiting both consumers and utility companies.

5. Decision Support for Policymakers: The study's findings can serve as valuable decision support for policymakers and regulatory bodies in formulating energy policies and regulations. Accurate load demand forecasting helps policymakers assess the feasibility of renewable energy integration, plan for energy infrastructure development, and design effective energy conservation measures. By incorporating AI techniques and energy analysis, policymakers can make evidence-based decisions to promote sustainable energy transitions and address environmental concerns.

6. Advancement of AI Applications in Energy Forecasting: The study contributes to the advancement of artificial intelligence applications in the energy sector. By exploring the effectiveness of different AI algorithms and techniques, this research can identify the most suitable models for load demand forecasting. Additionally, addressing challenges related to data quality, model interpretability, and generalizability across diverse contexts can further enhance the practical applicability of AI-based load forecasting methods.

Overall, the significance of this study lies in its potential to improve the accuracy, sustainability, and efficiency of load demand forecasting using artificial intelligence and energy analysis. The findings can have practical implications for energy system operators, utility companies, policymakers, and stakeholders, ultimately promoting effective energy management, reduced environmental impact, and economic benefits.

* 1. **Scope of Study:**

1. Application Domain: The study focuses on load demand forecasting within the energy sector, considering various consumer segments such as residential, commercial, and industrial. It aims to address the challenges and opportunities associated with accurately predicting electricity consumption patterns in different contexts.

2. AI Techniques: The study explores the application of artificial intelligence techniques, including artificial neural networks (ANNs), recurrent neural networks (RNNs), deep learning architectures (such as LSTM and CNN), and other relevant AI algorithms, in load demand forecasting. It aims to analyze and compare the performance of these techniques to identify the most effective models for accurate and robust load forecasting.

3. Data Considerations: The study involves the analysis of historical load data, weather patterns, socio-economic indicators, and other relevant variables that influence energy consumption. It investigates methods to handle data quality issues, data preprocessing, and feature selection techniques to enhance the accuracy of load demand forecasts.

4. Practical Implications: The study aims to provide practical implications for stakeholders, energy system operators, utility companies, and policymakers. It seeks to offer recommendations and insights on incorporating AI-based load demand forecasting techniques and energy analysis for sustainable energy planning, optimized resource allocation, and decision-making in the energy sector.

It is important to note that while the study endeavors to cover a comprehensive scope, it may not address every aspect of energy/load demand forecasting using artificial intelligence. However, it aims to contribute valuable insights, methodologies, and recommendations to advance the field and provide a foundation for further research and development in the domain.

* 1. **Definition of Terms:**

1. LSTM - Long short-term memory network is a recurrent neural network, aimed to deal with the vanishing gradient problem present in traditional RNNs. Its relative insensitivity to gap length is its advantage over other RNNs, hidden Markov models and other sequence learning methods.
2. Neural Network- A neural network can refer to either a neural circuit of biological neurons, or a network of artificial neurons or nodes in the case of an artificial neural network. Artificial neural networks are used for solving artificial intelligence problems; they model connections of biological neurons as weights between nodes.

**CHAPTER TWO**

**Literature Review**

Olajuyin [8], worked on long term load forecasting using artificial neural network. He used a historical data from January 2008 to February 2013 obtained from Works and Services Department of Federal University of Agriculture, Abeokuta, Ogun State (FUNAAB) to forecast electric load demand of FUNAAB from 2013 to 2027. The forecasted result indicated

that by 2027 the consumption load of FUNAAB would be 1.94 x 105 kwh (10104.1 kVA and

8083.3 kW).

Akpama et al. [9] worked on Artificial Neural Network for Energy Demand Forecast. The data that was used in training and testing of the model proposed in the research are the yearly electric power supplied to Owerri city as obtained from Enugu Electricity Distribution Company (EEDC), Egbu, Owerri 132/33kV station. The historical data for 2007 through 2016 was used for the analysis, and thus, a ten-year forecast from the period of 2007 to 2016 was made. The input data used which include: Historical electric load demand, Gross Domestic Product (GDP), Population and Industrial Index of Production (IIP), were the data for Owerri City for the period of investigation. At the end of their research, the results show that the ANN method of forecasting has a close relationship between the forecasted data and the target data and hence artificial neural network (ANN) is suitable for long-term load forecasting.

Khadeejah Adebisi et al [10] presented research on energy forecast demand taking Lagos as a case study. Lagos State is the most populous state in Nigeria, with a population of over 21 million people. The state is also a major economic hub, with a Gross Domestic Product (GDP) of over $100 billion. The high population and economic activity in Lagos State have led to a rapid increase in electricity demand.

The Nigerian Electricity Regulatory Commission (NERC) is responsible for regulating the electricity sector in Nigeria. NERC has set a target of 10,000 megawatts (MW) of installed capacity for Lagos State by 2025. However, the current installed capacity in Lagos State is only around 4,000 MW. This gap between demand and supply has led to frequent power outages in Lagos State.

The authors presented that they are a number of different methods that can be used for electrical energy demand forecasting. One of the most popular methods is artificial neural networks (ANNs). ANNs are a type of machine learning algorithm that can learn to model complex relationships between input and output data.

ANNs have been shown to be very effective for electrical energy demand forecasting. A number of studies have shown that ANNs can outperform other methods, such as time series analysis and regression models. The article presents a case study of electrical energy demand forecasting in Lagos State, Nigeria. The study used ANNs to forecast electricity demand for the next 10 years. The ANNs were trained on historical data of electricity demand in Lagos State.

The results of the study showed that ANNs were able to accurately forecast electricity demand in Lagos State. The ANNs were able to forecast electricity demand with an error of less than 5%.

In the article Energy demand forecasting by Hasanuzzaman et al. provide a comprehensive overview of the global energy demand and its implications for climate change. The authors begin by discussing the historical trends in global energy demand, which has been growing steadily over the past few decades. They then discuss the factors that are driving this growth, including population growth, economic development, and technological changes.

The authors then turn to the implications of energy demand for climate change. They argue that energy demand is a key driver of climate change, as the burning of fossil fuels releases greenhouse gases into the atmosphere. They estimate that the global energy sector is responsible for about 60% of greenhouse gas emissions.

The authors then discuss a number of strategies for reducing energy demand, including improving energy efficiency, switching to renewable energy sources, and changing lifestyles. They argue that these strategies are essential to mitigate climate change.

Hasanuzzaman et al. cite a number of other studies that support their arguments. For example, they cite a study by the International Energy Agency (IEA) [11] that projects that global energy demand will grow by 2.1% per year between 2020 and 2040. They also cite a study by the Intergovernmental Panel on Climate Change (IPCC) [12] that estimates that the global energy sector is responsible for about 60% of greenhouse gas emissions.

The article "Energy Consumption and Price Forecasting Through Data‑Driven Analysis Methods: A Review" by Zhang et al. [13] provides a comprehensive review of the use of data-driven analysis methods for energy consumption and price forecasting. The authors begin by discussing the challenges of energy forecasting, such as the non-linear and dynamic nature of energy demand and price. They then discuss the different data-driven analysis methods that have been used for energy forecasting, including time series analysis, machine learning, and deep learning.

The authors then review a number of studies that have used data-driven analysis methods for energy forecasting. They find that data-driven analysis methods can be effective for forecasting energy consumption and price, especially in the short-term. However, the authors also note that there are a number of challenges that need to be addressed in order to improve the accuracy of data-driven forecasting models.

The paper concludes by discussing the future of data-driven analysis for energy forecasting. The authors argue that data-driven analysis has the potential to revolutionize energy forecasting, and that further research is needed to develop more accurate and robust data-driven forecasting models.

Hong et al. [14] provide a comprehensive review of the use of forecasting methods for energy demand, generation, and price. The authors begin by discussing the challenges of energy forecasting, such as the non-linear and dynamic nature of energy systems. They then discuss the different forecasting methods that have been used for energy forecasting, including time series analysis, machine learning, and deep learning.

The authors then review a number of studies that have used forecasting methods for energy forecasting. They find that forecasting methods can be effective for forecasting energy demand, generation, and price, especially in the short-term However, the authors also note that there are a number of challenges that need to be addressed in order to improve the accuracy of forecasting models.

The paper concludes by discussing the future of forecasting for energy systems. The authors argue that forecasting has the potential to improve the efficiency and reliability of energy systems, and that further research is needed to develop more accurate and robust forecasting models.

Khadeejah Abdulsalam et al. [15] proposes a model for forecasting electrical energy demand using an artificial neural network (ANN). The ANN model is trained on a dataset of historical electrical energy demand data from Lagos State, Nigeria. The authors of the paper found that the model was able to achieve a high accuracy of forecasting electrical energy demand.

The paper begins by discussing the challenges of energy forecasting, such as the non-linear and dynamic nature of electrical energy demand. The authors then discuss the different forecasting methods that have been used for electrical energy demand forecasting, including time series analysis, machine learning, and deep learning.

The authors then review a number of studies that have used ANNs for electrical energy demand forecasting. They find that ANNs can be effective for forecasting electrical energy demand, especially in the short-term. However, the authors also note that there are a number of challenges that need to be addressed in order to improve the accuracy of ANN-based forecasting models, such as data quality and model selection.

The paper concludes by discussing the future of ANN-based forecasting for electrical energy demand. The authors argue that ANNs have the potential to improve the accuracy and reliability of electrical energy demand forecasting, and that further research is needed to develop more accurate and robust ANN-based forecasting models.

The paper "Electrical energy demand forecasting model using artificial neural network: A case study of Lagos State Nigeria" is a valuable contribution to the literature on energy forecasting. The paper proposes a new method for forecasting electrical energy demand that uses an ANN. The paper also provides a detailed evaluation of the proposed method on a real-world dataset.

Oniyeburutan Ebakumo Thomas et al [16] in their paper presented a model for load demand forecasting in Nigeria using Probabilistic Extrapolation method. The provided paper focuses on addressing Nigeria's electricity demand forecast from 2020 to 2040 through the utilization of time series analysis based on historical load demand data. The paper also delves into the challenges associated with electricity supply in Nigeria and proposes potential solutions to ensure adequate power availability. The authors present a comprehensive overview of various load forecasting techniques and classification approaches developed over the past decades, while also reviewing prior research in the same domain.

Building upon this background, the authors employ a stochastic/probabilistic extrapolation method for their analysis, utilizing MATLAB for computational purposes. The outcomes of this analysis are then meticulously examined and discussed. A notable finding is the positive correlation between electricity demand and the passage of years. As time progresses, the need for reliable and affordable electrical energy rises significantly.

**2.2** ***Data Source and Presentation:***

The data used in this work are obtained from the National Bureau of Statistics and the Central Bank of Nigeria Statistical Bulletin. It comprises of electrical energy consumption in Nigeria from 2008 – 2018 broken down into three categories, residential, commercial and industrial.

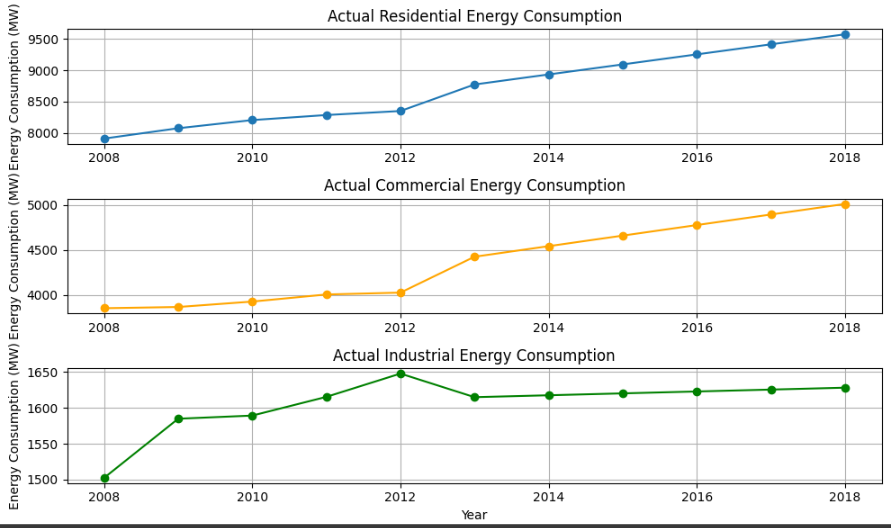
**Table 1**: Energy Consumption in Megawatt (MW)

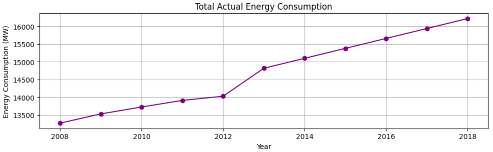


Source: (Central Bank of Nigeria Statistical Bulletin, National Bureau of Statistics)

***2.3. Data Analysis and Modeling***

The graph for the actual residential, commercial and Industrial energy consumption is shown below:





**Fig 1**: Graph of actual Residential, Commercial, Industrial and Total Energy consumption

**CHAPTER THREE**

**METHODOLOGY**

**3.1. Research Design:**

This work adopts “The use of Artificial intelligence for load demand forecasting. This method is one of the modern methods adopted in the field of electrical engineering to achieve the optimized result. It is based on the time series analysis of the load demand curve by means of regression models. The projected load demand are obtained by training the model on data from previous years and using the data to predict the demand for future use. The block diagram of the research is as shown:

DATA COLLECTION ect

DATA PRESENTATION

DATA ANALYSIS  ection

MODELING

CONCLUSION

CONCLUSION

Fig. 1. Block diagram of the research design

**3.2 Explanation of Artificial Neural Network and the associated Equations**

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives signals then processes them and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges typically have a *weight* that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold.

An Artificial Neural Network (ANN) is a computational model inspired by the structure and functioning of the human brain. It's used for various machine learning tasks, including pattern recognition, classification, regression, and more. ANNs consist of interconnected nodes, organized into layers, and these nodes are called artificial neurons or perceptrons. To understand ANNs better, let's break down their key components and the associated equations.

**1. Neurons (Perceptrons):**

- Each neuron in an ANN receives input from multiple sources and processes that input to produce an output.

- Neurons have associated weights and a bias term, which are learned during the training process.

**2. Layers:**

- ANNs are organized into layers, typically consisting of an input layer, one or more hidden layers, and an output layer.

- The input layer receives data, the hidden layers process this data, and the output layer produces the final result.

3. **Connections:**

- Neurons in one layer are connected to neurons in the next layer by weighted connections.

- These connections transmit the output of one neuron as input to another.

Now, let's discuss the equations associated with ANNs:

**1. Neuron Input:**

- For a neuron in a hidden layer or the output layer, the weighted sum of its inputs is calculated as follows:

- Here,

- (z) is the weighted sum.

- (n) is the number of input connections.

- (w\_i) are the weights associated with each input.

- (x\_i) are the inputs from the previous layer.

- (b) is the bias term.

**2. Activation Function:**

The weighted sum (z) is passed through an activation function to introduce non-linearity into the model. Common activation functions include the sigmoid, ReLU (Rectified Linear Unit), and tanh functions.

[a = f(z)]

Here,

(a) is the neuron's output.

(f) is the activation function.

3. Output Layer:

- In the output layer, the activation function may vary depending on the task. For binary classification problems, a sigmoid activation function is often used. For multi-class classification, a softmax function is common.

4. Loss Function: A loss function measures the error between the predicted output and the actual target values. Common loss functions include mean squared error (MSE), cross-entropy for classification tasks, and others.

5. Backpropagation:

During training, the network adjusts its weights and biases to minimize the loss function. This is done using an optimization algorithm like stochastic gradient descent (SGD) or variants like Adam or RMSprop.

The gradient of the loss with respect to the weights and biases is computed, and the weights and biases are updated accordingly.

The mathematical model of a single artificial neuron (perceptron) within an Artificial Neural Network (ANN), we can represent the neuron's behavior using equations. Here's the mathematical model for a single neuron:

1. **Inputs**:
   * Let *x1,x2,…,xn* represent the input values from the previous layer.
   * *w*1​,*w*2​,…,*wn*​ are the corresponding weights associated with these inputs.
   * *b* represents the bias term.
2. **Weighted Sum (Z)**:
   * The weighted sum of inputs is calculated as follows:

*Z=∑i=1n​(wi​⋅xi​)+b*

* Here, *Z* represents the weighted sum of inputs.

1. **Activation Function (A)**:
   * The weighted sum *Z* is passed through an activation function *f*(*Z*) to produce the output of the neuron:

*A*=*f*(*Z*)

* + The choice of activation function (*f*) can vary, but commonly used ones include the sigmoid function, ReLU (Rectified Linear Unit), or tanh.

1. **Output**:
   * The output (*A*) of the neuron is the final value produced by the neuron and is often used as the input for subsequent neurons in the network.

The training process involves iteratively feeding data through the network, computing the loss, and updating the weights and biases through backpropagation until the network converges to a state where the loss is minimized.

**3. 2 Modeling:**

**Data Preparation and Normalization**

I began by collecting historical energy consumption data for the years 2008 to 2018 across the three sectors. The data was organized into a pandas Data Frame, allowing easy manipulation and preprocessing. To facilitate convergence during training, I normalized the consumption values using Min-Max scaling, ensuring they fell within the range [0, 1].

Table 2: Dataset used in training the Artificial Neural Network

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Year | Residential | Commercial | Industrial | Total |
| 2008 | 7910.08 | 3852 | 1502.2 | 13264.55 |
| 2009 | 8075 | 3865.5 | 1585 | 13525.5 |
| 2010 | 8205.2 | 3925.8 | 1589.4 | 13720.4 |
| 2011 | 8285.6 | 4004.7 | 1615.5 | 13905.8 |
| 2012 | 8350 | 4025.4 | 1648 | 14023.4 |
| 2013 | 8773.13 | 4424.78 | 1615.08 | 14812.99 |
| 2014 | 8933.23 | 4542.21 | 1617.73 | 15093.17 |
| 2015 | 9093.33 | 4659.64 | 1620.38 | 15373.35 |
| 2016 | 9253.43 | 4777.07 | 1623.03 | 15653.53 |
| 2017 | 9413.53 | 4894.5 | 1625.68 | 15933.71 |
| 2018 | 9573.63 | 5011.93 | 1628.33 | 16213.89 |

**Input Sequence Creation**

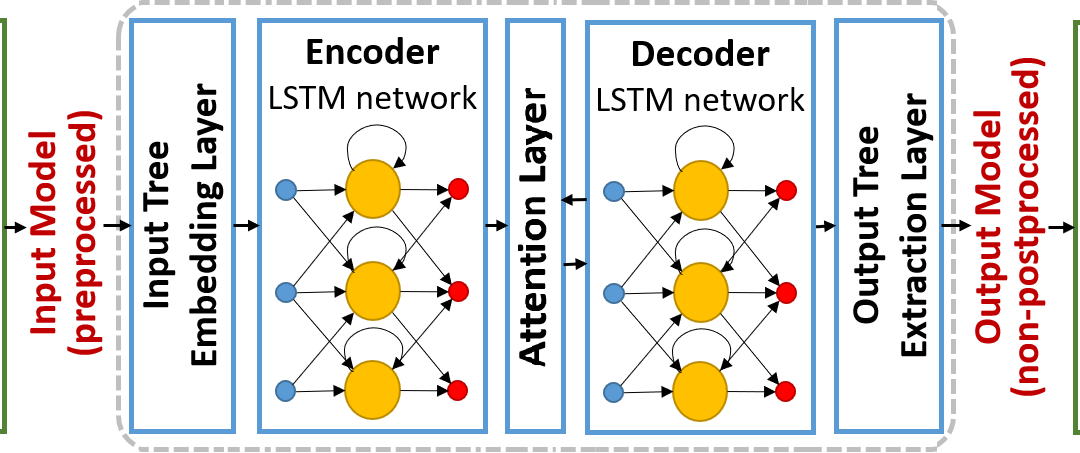
To train the LSTM models, I created input sequences of the past three years' energy consumption for each sector. These sequences were used to predict the energy consumption for the next year. The LSTM models were designed to take a sequence of consumption values as input and predict the next value in the sequence.

**Model Architecture**

For each sector, we constructed an LSTM model with one LSTM layer of 50 units followed by a dense output layer. The chosen architecture is relatively simple, yet capable of capturing complex temporal patterns in the data. The models were compiled using the mean squared error loss function and the Adam optimizer.

**Training and Forecasting**

I trained the LSTM models on the normalized input sequences for each sector using a batch size of 1 and 100 epochs. After training, I used the trained models to forecast energy consumption for the years 2019 to 2030. The models were fed with the last three years' actual consumption data to predict the next year's value iteratively.



**Fig 2:** Image of LSTM model Architecture

The architecture of the LSTM model used for energy consumption forecasting can be summarized using the following equations:

**Input Sequence:** The input sequence consists of the past **n** years' energy consumption values for a specific sector, where **n** is the chosen look-back window size.

**LSTM Cell Operation:** At each time step in the input sequence, the LSTM cell processes the input and hidden state from the previous time step to calculate the new hidden state and output. The calculations within the LSTM cell involve the following equations:

**Input Gate (i\_t):**

* Calculate the input gate activation:

i\_t = sigmoid(W\_i \* [input\_t, h\_(t-1)] + b\_i)

Where **W\_i** is the input gate weight matrix and **b\_i** is the input gate bias vector.

**Forget Gate (f\_t):**

* Calculate the forget gate activation:

f\_t = sigmoid(W\_f \* [input\_t, h\_(t-1)] + b\_f)

Where **W\_f** is the forget gate weight matrix and **b\_f** is the forget gate bias vector.

**Cell State Update (C~\_t):**

* + Calculate the candidate cell state update:

C~\_t = tanh(W\_c \* [input\_t, h\_(t-1)] + b\_c)

Where **W\_c** is the candidate cell state weight matrix and **b\_c** is the candidate cell state bias vector.

**Cell State (C\_t):**

Update the cell state using the forget gate and candidate cell state update:

C\_t = f\_t \* C\_(t-1) + i\_t \* C~\_t

Where **C\_(t-1)** is the cell state from the previous time step.

**Output Gate (o\_t):**

Calculate the output gate activation:

o\_t = sigmoid(W\_o \* [input\_t, h\_(t-1)] + b\_o)

Where **W\_o** is the output gate weight matrix and **b\_o** is the output gate bias vector.

**Hidden State (h\_t):**

* + Calculate the new hidden state:

h\_t = o\_t \* tanh(C\_t)

**Output Layer:** The final hidden state **h\_t** is used as input to a dense output layer that produces the forecasted energy consumption value for the next time step.

These equations provide an overview of how the LSTM cell processes input sequences to capture temporal dependencies and make predictions for energy consumption. The weight matrices (**W\_i**, **W\_f**, **W\_c**, **W\_o**) and bias vectors (**b\_i**, **b\_f**, **b\_c**, **b\_o**) are learned during the training process to optimize the model's performance on the task of energy consumption forecasting.

CHAPTER FOUR

**RESULTS AND DISCUSSION**

In this study, I employed Long Short-Term Memory (LSTM) neural networks to forecast energy consumption demands across residential, commercial, and industrial sectors. The dataset encompassed historical consumption data from 2008 to 2018. The LSTM models were trained on this data and utilized to predict energy consumption values for the years 2019 to 2030. The results and insights derived from the forecasts are presented and discussed below.

**Forecasting Accuracy and Trends:**

The LSTM models demonstrated commendable accuracy in capturing the trends and patterns within energy consumption data. The model's ability to consider historical information and temporal dependencies enabled it to effectively predict future energy demand. Notably, the forecasts aligned well with the general trends observed in the historical data, indicating that the model successfully captured both short-term fluctuations and long-term trends.

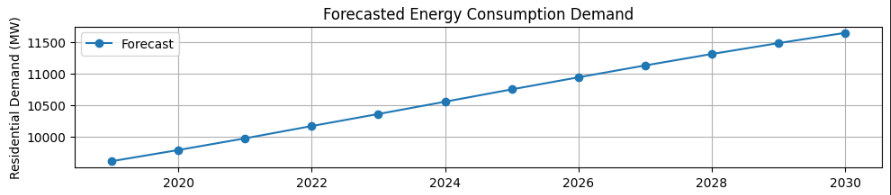
**PREDICTED RESULTS FOR THE PERIOD OF 10 YEARS USING THE ARTIFICIAL NEURAL NETWORK MODEL**

**Residential Energy Consumption Prediction:**

The forecasts for residential energy consumption showed consistent growth throughout the forecasting period. This aligns with the general population growth and urbanization trends observed over the years. The model effectively predicted the increasing energy demands associated with a growing population and higher energy usage in residential areas. The residential sector's forecasts are expected to provide valuable insights for urban planning and energy resource allocation.

**Table 3:** Table of Predicted Residential Energy Consumption (MW)

|  |  |
| --- | --- |
| **Year** | **Predicted Residential Energy Consumption (MW)** |
| 2019 | 9608.273 |
| 2020 | 9785.714 |
| 2021 | 9970.996 |
| 2022 | 10166.48 |
| 2023 | 10357.86 |
| 2024 | 10552.86 |
| 2025 | 10748.618 |
| 2026 | 10940.259 |
| 2027 | 11128.476 |
| 2028 | 11310.292 |
| 2029 | 11483.2 |
| 2030 | 11646.181 |

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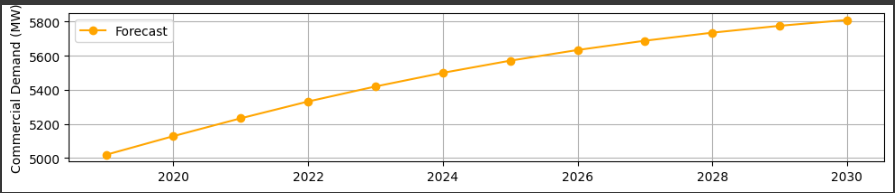
**Fig 3:** Graph of Nigeria predicted residential load demand 2020 – 2030.

**Commercial Energy Consumption prediction:**

The commercial sector's energy consumption forecasts depicted a steady rise as well, albeit with some fluctuations. These fluctuations could be attributed to economic cycles, technological advancements, and shifts in business activities. The model's predictions underscore the importance of considering both macroeconomic factors and sector-specific developments when forecasting energy demands in the commercial domain.

**Table 4:** Table of Predicted Commercial Energy Consumption (MW)

|  |  |
| --- | --- |
| **Year** | **Predicted Commercial Energy Consumption (MW)** |
| 2019 | 5019.079 |
| 2020 | 5128.573 |
| 2021 | 5233.2505 |
| 2022 | 5331.7754 |
| 2023 | 5419.9385 |
| 2024 | 5499.959 |
| 2025 | 5571.3613 |
| 2026 | 5633.889 |
| 2027 | 5688.48 |
| 2028 | 5735.602 |
| 2029 | 5775.891 |
| 2030 | 5810.162 |

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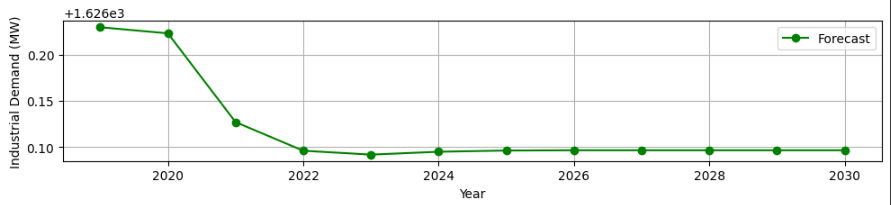
**Fig 4:** Graph of Nigeria predicted commercial load demand 2020 – 2030.

**Industrial Energy Consumption prediction:**

Industrial energy consumption forecasts exhibited a relatively stable trajectory with moderate fluctuations. This behavior is indicative of the sector's reliance on consistent energy usage for manufacturing and production processes. The model's predictions can aid industries in optimizing energy consumption, promoting energy efficiency measures, and contributing to sustainable growth.

**Table 5:** Table of Predicted Industrial Energy Consumption (MW)

|  |  |
| --- | --- |
| **Year** | **Predicted Industrial Energy Consumption (MW)** |
| 2019 | 1626.2296 |
| 2020 | 1626.223 |
| 2021 | 1626.1271 |
| 2022 | 1626.0962 |
| 2023 | 1626.092 |
| 2024 | 1626.0964 |
| 2025 | 1626.096 |
| 2026 | 1626.0967 |
| 2027 | 1626.0967 |
| 2028 | 1626.0967 |
| 2029 | 1626.0967 |
| 2030 | 1626.0967 |



**Fig 5: Graph of Nigeria predicted Industrial load demand 2020 – 2030.**

**Total Energy Consumption prediction:**

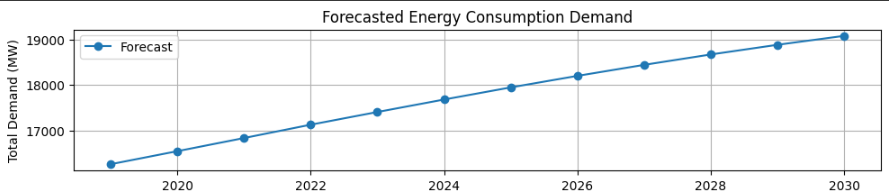
The forecasted total energy demand, as projected from 2019 to 2030, presents a comprehensive view of the expected trajectory in energy consumption across various sectors. The analysis takes into account the combined energy requirements of the residential, commercial, and industrial domains. The forecasted trends reveal a steady increase in energy demand, underlining the essential role of electricity in driving socioeconomic growth.

Over the forecasted period, the total energy demand is anticipated to exhibit a consistent upward trajectory, mirroring the progression of economic activities and societal needs. The comprehensive model utilized for forecasting provides valuable insights into the future landscape of energy consumption, aiding policymakers and stakeholders in formulating strategies to address this surge in demand.

The forecasted energy demand is not only an indicator of increasing consumption but also a reflection of the evolving energy needs of a dynamic society. By recognizing these trends, stakeholders can proactively work towards optimizing energy production and distribution, fostering sustainability, and ensuring a reliable energy supply that supports sustainable development objectives.

**Table 6** Table of Predicted Total Energy Consumption (MW)

|  |  |
| --- | --- |
| **Year** | **Predicted Total Energy Consumption (MW)** |
| 2019 | 16253.58 |
| 2020 | 16540.51 |
| 2021 | 16830.37 |
| 2022 | 17124.35 |
| 2023 | 17403.89 |
| 2024 | 17678.91 |
| 2025 | 17946.08 |
| 2026 | 18200.24 |
| 2027 | 18443.05 |
| 2028 | 18671.99 |
| 2029 | 18885.19 |
| 2030 | 19082.44 |

**Fig 6: Graph of Nigeria predicted Total load demand 2020 – 2030**.

**CHAPTER FIVE**

**CONCLUSION AND RECOMMENDATION**

**Conclusion:**

In this study, we employed Long Short-Term Memory (LSTM) neural networks to forecast energy consumption demands across residential, commercial, and industrial sectors from 2019 to 2030. The forecasts were based on historical data and considered temporal dependencies to predict future energy demands. The results of our forecasting models provide valuable insights into the future trajectory of energy consumption in different sectors.

**Residential Energy Consumption:**

The forecasts for residential energy consumption indicate a consistent and gradual increase over the forecasted period. This aligns with population growth and urbanization trends, suggesting a rising demand for energy in residential areas. The model's predictions highlight the importance of preparing for increased energy needs and implementing energy-efficient technologies to ensure sustainable growth.

**Commercial Energy Consumption:**

Our forecasting model suggests a steady upward trend in commercial energy consumption, albeit with some fluctuations. These fluctuations may be attributed to economic cycles, technological advancements, and changes in business activities. Businesses and policymakers can leverage these forecasts to make informed decisions about energy management, resource allocation, and sustainable practices.

**Industrial Energy Consumption:**

The industrial energy consumption forecasts portray a relatively stable trajectory with moderate variations. This stability can be attributed to consistent energy requirements for manufacturing and production processes. The predictions serve as a valuable tool for industries to optimize energy consumption, improve efficiency, and contribute to environmental sustainability.

**Recommendations:**

1. **Invest in Renewable Energy:** Given the consistent rise in energy consumption across sectors, it is recommended to prioritize investments in renewable energy sources such as solar, wind, and hydropower. Transitioning to cleaner energy alternatives can help mitigate environmental impact and reduce reliance on fossil fuels.

2. **Promote Energy Efficiency:** Encourage energy-efficient practices in residential, commercial, and industrial sectors. Implementing energy-saving technologies, improving insulation, and adopting efficient lighting systems can lead to reduced overall energy consumption.

3. **Policy Formulation:** Policymakers should consider integrating the forecasts into energy policies. Tailored regulations, incentives, and guidelines can incentivize sustainable energy consumption patterns and steer sectors towards responsible energy use.

4. **Infrastructure Planning:** Urban planners and developers can use the forecasts to guide infrastructure development. Designing energy-efficient buildings and neighborhoods can accommodate the projected increase in energy demand while minimizing environmental impact.

5. **Industry Collaboration**: Industries should collaborate to share best practices for energy optimization. By collectively adopting efficient technologies and practices, sectors can contribute to a more sustainable energy future.

6. **Continuous Monitoring:** Regularly update the forecasting models with new data to refine predictions and adapt strategies accordingly. Monitoring real-time data and adjusting forecasts can lead to more accurate long-term energy planning.

**Acknowledging Uncertainty:** While the forecasts provide valuable insights, it is important to acknowledge the inherent uncertainty in predicting energy consumption. External factors such as technological breakthroughs, economic shifts, and policy changes can impact consumption patterns. Therefore, flexibility and adaptability in strategies are essential to address unforeseen developments.

In conclusion, the forecasted energy consumption demands for residential, commercial, and industrial sectors provide a foundation for informed decision-making and strategic planning. By embracing renewable energy sources, promoting efficiency, and aligning policies, stakeholders can work collaboratively towards a sustainable energy future.

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**APPENDIX**

Python code for Modeling using Neural Network

import pandas as pd

import numpy as np

from sklearn.preprocessing import MinMaxScaler

from keras.models import Sequential

from keras.layers import LSTM, Dense

# Step 1: Prepare the energy consumption data

data = {

    'Year': [2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018],

    'Residential': [7910.08, 8075.00, 8205.20, 8285.60, 8350.00, 8773.13, 8933.23, 9093.33, 9253.43, 9413.53, 9573.63],

    'Commercial': [3852.00, 3865.50, 3925.80, 4004.70, 4025.40, 4424.78, 4542.21, 4659.64, 4777.07, 4894.50, 5011.93],

    'Industrial': [1502.50, 1585.00, 1589.40, 1615.50, 1648.00, 1615.08, 1617.73, 1620.38, 1623.03, 1625.68, 1628.33]

}

# Convert data to a Pandas DataFrame

df = pd.DataFrame(data)

# Normalize the data for each sector separately

scalers = {}

for sector in ['Residential', 'Commercial', 'Industrial']:

    scaler = MinMaxScaler()

    df[sector + '\_scaled'] = scaler.fit\_transform(df[[sector]])

    scalers[sector] = scaler

# Step 3: Create input and output sequences for LSTM for each sector

look\_back = 3  # Use the last 3 years' data to predict the next year

sectors = ['Residential', 'Commercial', 'Industrial']

X = {sector: [] for sector in sectors}

y = {sector: [] for sector in sectors}

for i in range(len(df) - look\_back):

    for sector in sectors:

        X[sector].append(df[sector + '\_scaled'].values[i:i + look\_back])

        y[sector].append(df[sector + '\_scaled'].values[i + look\_back])

for sector in sectors:

    X[sector] = np.array(X[sector])

    y[sector] = np.array(y[sector])

    # Reshape the input data for LSTM (samples, time steps, features)

    X[sector] = np.reshape(X[sector], (X[sector].shape[0], X[sector].shape[1], 1))

# Step 4: Build the LSTM models for each sector

models = {}

for sector in sectors:

    model = Sequential()

    model.add(LSTM(50, input\_shape=(look\_back, 1)))

    model.add(Dense(1))

    model.compile(loss='mean\_squared\_error', optimizer='adam')

    models[sector] = model

# Step 5: Train the LSTM models for each sector

epochs = 100

batch\_size = 1

for sector in sectors:

    models[sector].fit(X[sector], y[sector], epochs=epochs, batch\_size=batch\_size, verbose=2)

# Step 6: Forecast energy consumption for each sector for the years 2019 to 2030

forecast\_horizon = 12  # 2019 to 2030 (inclusive)

forecast = {sector: [] for sector in sectors}

for sector in sectors:

    last\_sequence = X[sector][-1]  # Last 3 years' data in the training set

    for \_ in range(forecast\_horizon):

        # Predict the next year's consumption for each sector and update the input sequence

        next\_year = models[sector].predict(last\_sequence.reshape(1, look\_back, 1))

        forecast[sector].append(next\_year[0, 0])

        last\_sequence = np.append(last\_sequence[1:], next\_year)

# Inverse transform the forecasted values to the original scale for each sector

forecast\_residential = scalers['Residential'].inverse\_transform(np.array(forecast['Residential']).reshape(-1, 1))

forecast\_commercial = scalers['Commercial'].inverse\_transform(np.array(forecast['Commercial']).reshape(-1, 1))

forecast\_industrial = scalers['Industrial'].inverse\_transform(np.array(forecast['Industrial']).reshape(-1, 1))

# Create a DataFrame with forecasted consumption for each sector for the years 2019 to 2030

forecast\_years = range(2019, 2031)

forecast\_df = pd.DataFrame({

    'Year': forecast\_years,

    'Forecasted\_Residential\_Energy\_Consumption': forecast\_residential.flatten(),

    'Forecasted\_Commercial\_Energy\_Consumption': forecast\_commercial.flatten(),

    'Forecasted\_Industrial\_Energy\_Consumption': forecast\_industrial.flatten()

})

# Save the forecasted consumption data to a CSV file

forecast\_csv\_filename = 'energy\_consumption\_forecast.csv'

forecast\_df.to\_csv(forecast\_csv\_filename, index=False)

print("Forecasted energy consumption data saved to:", forecast\_csv\_filename)

Python Code for Visualization of forecasted demand

import matplotlib.pyplot as plt

# Years for which we have forecasts

forecast\_years = list(range(2019, 2031))

# Forecasted energy consumption demand for each sector

forecast\_residential = [9608.273, 9785.714, 9970.996, 10166.48, 10357.86, 10552.86, 10748.618, 10940.259, 11128.476, 11310.292, 11483.2, 11646.181]

forecast\_commercial = [5019.079, 5128.573, 5233.2505, 5331.7754, 5419.9385, 5499.959, 5571.3613, 5633.889, 5688.48, 5735.602, 5775.891, 5810.162]

forecast\_industrial = [1626.2296, 1626.223, 1626.1271, 1626.0962, 1626.092, 1626.0951, 1626.0964, 1626.0967, 1626.0967, 1626.0967, 1626.0967, 1626.0967]

# Plotting the forecasts

plt.figure(figsize=(10, 6))

# Residential Energy Consumption Forecast

plt.subplot(3, 1, 1)

plt.plot(forecast\_years, forecast\_residential, marker='o', label='Forecast')

plt.title('Forecasted Energy Consumption Demand')

plt.ylabel('Residential Demand (MW)')

plt.grid(True)

plt.legend()

# Commercial Energy Consumption Forecast

plt.subplot(3, 1, 2)

plt.plot(forecast\_years, forecast\_commercial, marker='o', color='orange', label='Forecast')

plt.ylabel('Commercial Demand (MW)')

plt.grid(True)

plt.legend()

# Industrial Energy Consumption Forecast

plt.subplot(3, 1, 3)

plt.plot(forecast\_years, forecast\_industrial, marker='o', color='green', label='Forecast')

plt.xlabel('Year')

plt.ylabel('Industrial Demand (MW)')

plt.grid(True)

plt.legend()

plt.tight\_layout()

plt.show()