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Prediction and Utilization of Different Energy Sources in India

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***Abstract*:**Today's world requires extremely efficient energy consumption. Demand is rising as a result of the industrial sector's quick advancements, making energy efficiency initiatives essential to reducing energy waste and satisfying demand. According to the study of numerous scenarios utilized by policy makers, at least a 50% reduction in industrial energy use is required for world temperature for rising less than 2°C by end of century. This is crucial to include a trustworthy forecasting tool which is used for estimating energy utilization based on numerous anticipated elements to remain on track with these scenarios and to meet the desired objectives. Energy is recognized as a crucial component for every country's economic development. Energy is one of the main forces behind economic progress in India, a growing nation. According to the review, socioeconomic factors like GNP, energy prices, and population are all related to energy usage. The impact of socioeconomic factors on energy consumption is examined in this article using econometric models. The R2, SE, test is used to discover the best fit and to identify the important factors affecting energy consumption. It has been shown that demand for thermal power is influenced by population and price, but demand for it is influenced by GNP per capita. The GNP and power price both affect how much electricity is demanded. The projected demand for thermal, hydro, and nuclear power consumption in India from 2030 to 2031 results in a total energy need of 22.944 1015 kJ.

Keywords: India, Conventional energy, prediction , Machine learning

I. INTRODUCTION

A country's success is determined by its level of environmental effect, standard of living, and economic growth. All of them are intimately related to the nation's usage of energy and how well it transforms it into productive activity. Thus, the increase rate of energy utilization is discovered as a sign of society change. Over the past forty years, the Indian energy industry has grown dramatically. The augmentation of resources and expansion of the energy supply, however, have not been able to keep up with the rising demand. India continues to experience severe energy shortages, which have made it largely reliant on imports.

On March 31, 2010, the estimated coal resource was about 276.81 billion tonnes, while the projected lignite reserve was 39.9 billion tonnes. Nation imported about 159.26 million tonnes of the crude oil in 2009–2010,that is equivalent to about 80% of domestic crude oil utilization. The current situation calls for careful planning in energy resources to close supply-demand mismatch. Utilization of coal, oil as well as natural gas in this study does not include energy used to produce electricity. The graph unequivocally demonstrates the exponential growth of oil use.

The previous six decades' GNP at factor cost and population were examined. GNP per person is discovered to have exponential trend, as opposed to population growth rate is linear, the GNP rises exponentially. Figure 2 displays the energy per person and energy intensity . Even even while resource use per population is increasing, it is still fairly low to rest emerging nations. But , it is encouraging to see that energy intensity practically followed a straight line until 1991–1992, after which it began to decline.

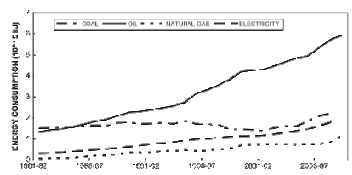


Figure 1 India's conventional energy use

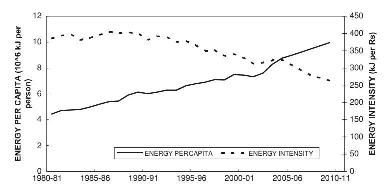


Figure 2 India's energy consumption and level.

Energy planners are under pressure to offer high-quality energy at reasonable rates because of the growing population, the booming economy, and the desire for enhanced quality of life. It is necessary to look at the factors that influence the energy demand.

Multiple linear regression (MLR) and ANNs are used to predict the long-term electricity consumption in India using above selected economic factors. These same models, but based on principal component analysis (PCA), are also used. The MLR method with PCA is referred as PCR and ANN with PCA is referred as PC-ANN. PCA was first proposed by Hotelling in 1933. PCA is a multivariate statistical method widely used in data analysis in diverge fields, because it is simple, nonparametric method. PCA is a variable reduction procedure. It involves a mathematical procedure that transform number of (possibility) correlated variables into a smallest number of uncorrelated variables called principle components (PC). The mathematical technique in PCA is called Eigen analysis: solve for the Eigen values and Eigen vectors of a square symmetric matrix with sums of squares and cross products. The Eigen vectors associated with the largest Eigen values have the same direction as the first PC.

Photovoltaic power forecasting is a vital feature for large-scale integration into the conventional energy system that is both reliable and cost-effective. Furthermore, photovoltaic (PV) power forecasting is necessary for reorganizing and installing large PV producing stations, power system stabilization, green power business, and power disturbance warning on self-governing power systems. As of February 28, 2021, India's installed solar power capacity, which includes both ground and roof-mounted plants, was 39,083 MW. From April 2019 through March 2020, solar power output totalled 50.1 TWh, or 3.6 percent of total power generation. In January 2022, renewable energy generation reached 13.15 billion units (BU), up from 11.51 BU in January 2021.

By 2030, the government hopes to have installed renewable energy capacity of around 450 gigawatts (GW), with solar accounting for roughly 280 GW (almost 60%) [3]. Malaysia's yearly average daily solar radiation, on the other hand, ranges from 4.21 kWh/m2 to 5.56 kWh/m2. During the forecast period of 2022–2027, the Malaysia renewable energy market is predicted to grow at an annual rate of 8.5 percent. The COVID-19 epidemic has had a minor impact on Malaysia's renewable energy sector, since the government has postponed ambitious solar bids, including a 1 GW procurement in 2020 [4, 5]. These countries intend to increase their contribution to renewable energy (RE) over time. Because of its abundance, solar energy is the focus of renewable energy. In order to assess and analyse PV performance in terms of forecasting output PV power with minimal error, the impacts of important environmental factors on PV performance must be examined.

The historical data of power load are an ordered collection sampled and recorded at a particular time interval, so they are a time series. As a branch of artificial intelligence, soft computing technology aims to gain more reliable and accurate systems and has proven to be an excellent tool for solving various energy applications problems. We have used machine learning to predict the integrated energy consumption of power sources that are thermal, hybrid and nuclear.

II. LITERATURE REVIEW

Diedrich et. Al [3] The study used weekly and monthly data from a home used exclusively for studies. The authors were able to examine the effect of information gathering frequently on model accuracy because of this variation in time length. Sunlight and the ambient temperature were independent factors. Energy use was the reliant variable. We examine quadratic linear regression, simple and multiple linear regression. This was done to see whether the improved quality findings outweighed the abstraction layer that quadratic regression introduced.

Vincenzo Giorgio,et.al [4] It was found that a crucial element in influencing the model's quality was the time interval. The quality of the estimate increases with the length of the time period. The authors hypothesized that this is because energy usage anomalies exhibit significant disparities when data is gathered over a longer period of time. The abnormalities equal out with each time period as more data were gathered over a longer length of time. The estimation coefficient was raised by employing a multiple linear regression model. However, this approach had a negative impact on the root mean square error (RMSE). Multiple regression was shown to have the overall greatest quality of insights when both of these criteria were taken into account. Additionally, the optimum estimated values were produced by daily time intervals.

III. OBJECTIVES

- Determine the literature significance of the energy consumption prediction using Machine learning.
- To study and analyse linear different sources of energy including Hydro, nuclear and thermal.
- To use linear regression and predict the consumption of these resources in India.
- To study energy consumption by these resources throughout the country
- To check the accuracy of the model and compare the results
- To compare the actual and the estimated energy consumption

IV. METHODOLOGY

In this thesis, we present a method for forecasting energy consumption that combines Algorithms for machine learning algorithms regression modelling. The data gathered by several Vocational Psychological Tests around the nation will be the main focus of this thesis. Medium- and small-sized firms' industrial energy is assessed by the Occupational Assessment Center. The difficulty with reducing energy use in these businesses is the inability to detect usage trends, according to our conversations with plant staff throughout several inspections. This is mostly caused by the small quantity of data that plant managers have access to for study. Building energy usage is influenced by two elements, per the [20]:

1. Atmospheric depending on factors, such as the outside temperate, the intensity of ultraviolet irradiance, the humidity, the wind speed, etc.

2. Artificial requirements, such as the opacity ratio, the type of illumination employed, the quantity of units generated, the alignment of the object, etc.

We found that firms lack the manpower or resources needed to assess such a broad variety of data. Finding a greater predictive tool is crucial when working with datasets that contain significant factors that are monitored over time. The IAC databases has publicly accessible annual data for a number of variables (described in the model sections). With the goal of forecasting small- and medium-sized firms' energy use, this study tried to fit a prediction model to the collection. The frameworks utilized in this thesis are all briefly theoretically explained below.

The model types section will talk about the mathematics utilized and the characteristics utilized.

A. Regression

The analysis of the effects of changing one or more elements on changing another measure is done using the regression approach, which is utilized in many scientific and technical areas [21]. To investigate the link between two values, or the impact of one variable change upon that given variable, a basic multiple regressions is utilized. To investigate the impact of changes in various factors on changes in an independent condition, multiple regression is utilized. Factors (often represented by Xs) are factors that affect another variable, while regression models (typically represented by Y) are parameters that are impacted by other parameters [4]. We shall deal with multiple regression in this project since our collection comprises several regression models.

Among the most popular techniques for determining a correlation between variables is to choose a coefficient of determination that "best fits" the dataset, which consists of several independence elements and a dependent variable. The best fit to a dataset is the equations that most closely approximates all of the data points [40]. By identifying the model with the smallest total vertical distance between the information points, this is achieved. When the full dataset is generalized into an algorithm, the maximum distance is the resulting "random mistake." Random mistake may be both positive and negative, which can make certain numbers cancel each other out or have an impact on others. The random mistakes are cubed and combined together to prevent this mismatch. The "sum of squared errors" is the name given to this outcome [4]. Regression aims to lower this quantity, referred to as the sum of the squared errors.

By reducing the average squared defects of the theory from the actual amounts, the best fit equation is effectively found. The predictor variable with the smallest square error sum fits the collection the best. By entering the values of anticipated regressors in the ahead, it is feasible to forecast the value of the dependent variable's value. This thesis will discuss a particular sort of energy modeling. A typical illustration of a regression equation is the one shown below:

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_k x_k$

X are significant factors, y is a variable, 0 is the vector, and the remaining are coefficients for various variables.

Below are estimates for least square functions [40]:

n

$L = \sum(\in i)2$

$i=1$

L is least squares function. $\in_i$ *is the distance of the fitted line from point "i"*

$L = \sum^{n}_{i}=1(yi - \beta_0 - \sum^{k}_{j}=1\ \beta_j x_{ij})^2$

y_i *is the original value of y at i.*

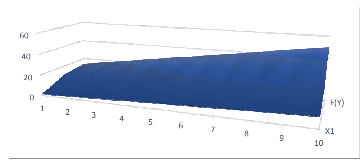


Figure 3. Regression model with two independent, one dependent variable y = 2x1 + x2 A

The machine learning method known as random forests is a further type of estimation that is relevant to our thesis.

B. Machine Learning

Machine learning is described as a collection of computer techniques for enhancing performance indicators and predicting potential future events. Any machine learning algorithm uses past data to do these goals. Any electronic content that is accessible to the user and may be utilized to train his engine is referred to as "data" [41]. The two most crucial aspects of data utilized in machine learning are quality and quantity, both of which affect the depth of knowledge and precision of predictions. Machine learning has been applied in several academic disciplines over the past decades, from stock exchange research to meteorology. The seven frequent tasks can each benefit from the machine learning approach.

- Each constituent is classified by giving it a place in a certain category. These tasks are employed when a number of factors interact to decide which quantifiable attribute will be the outcome. For instance, demand charges are exclusively factored into power bills for manufacturing firms. A machine learning system can therefore identify a customer as a factory site if they are paying demand charges based on their prior power bills. In categorization difficulties, there is no actual method to determine how distant an output is from the real-world scenario. Only a pass or fail outcome is produced by the algorithm of machine learning [41]..

- Regression: Any forecast that yields a true value is referred to as regression in machine learning. Regression in pattern recognition simply implies that a real wealth is estimated using prior or know data; it does not require conventional regression model. For instance, data was utilized to forecast a future power cost from previous and current invoices. Such a thesis will focus on machine learning techniques for classification. How far a response departure from the normal case in classification issues may be measured. Using this, a penalty corresponding to the metric may be calculated. Similar to how an equation changes when data units are introduced, a machine learning system will try to learn from latest data bits. Due of this, it is simple to add new information

- In order to rank objects, they must be arranged according to user needs, prioritization, deadlines, etc. Examples include keyword-organized web searches, task-based calendar apps, relevance-ranked word lists produced by natural language analysis systems, and more [4].

- • The homogenous collection of a set of objects on a dataset is a grouping issue. Clustering may be done using any common thread, including geography, gender, and sex. On social media, there are several clustering challenges, such as aggregating or clustering profiles to help users find other people within a particular organization or community. As with categorization issues, it is impossible to determine how incorrect these methods are. The result may only be categorized as passing or failing based on real-world situations [1].

- • Dimensionality reduction, also known as manifold learning: These problems require the transformation of a preliminary representation of items into a lower order representation. These algorithms also keep the preliminary representation's properties. It can be explained by comparing it to digital copies of older camera models [13].

In this study, we collected historical sector-wise electricity consumption data from ‘energy statistics’ reports in 2020, 2018 and 2009 by the National Statistical Office, Ministry of statistics and programme implementation, Government of India. The data was collected for the years between 1970 and 2018 (Figure 1).

For sector-wise modelling of electricity consumption simple regression analysis was used to find the relation

Table 1. Equations of four regression models

Regression type	Equation	$R2$
Linear regression model	$y = 7663.7x - 48{,}788$	0.7382
Logarithmic regression model	$y = 93121 \ln(x) - 133{,}936$	0.4369
Power regression model	$y = 10319x0.775$	0.7436
Exponential regression model	$y = 25564e0.0557x$	0.9575

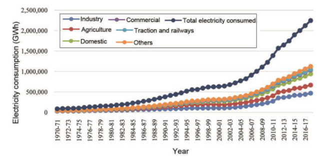


Figure 4electricity consumption (GWh) by sectors (1970–2018).

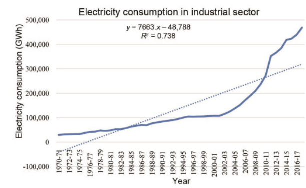


Figure 5Linear regression model.

ship between dependent and independent variables, and thereby the future values of dependent variables. We analysed the past and present data to establish the relationship between electricity consumption and period (1970–2018). The advantage lies in the simplicity of the analysis and the forecast is based on the available data.

. Each regression model generates a modelling equation and their respective $R2$ values were estimated. Microsoft Excel was used for modelling. The derived equations were then used for predicting the future values of electricity consumption by each sector. Also, their corresponding errors were estimated.

C. Modelling Energy consumption

For each sector, i.e. industry, agriculture, domestic, commercial, traction and railways, others and total electricity consumed, regression analysis was carried out. The regression models with the highest $R2$ and lowest mean absolute percentage error (MAPE) values was selected.

For instance, regression analysis for the industrial sector is explained below. The analysis includes plotting of data, finding the best-fit line and calculating errors. Table 1

shows the equations of the four regression models along with their $R2$ values. Table 2 shows the errors of the four regression models which give the best-suited model based on MAPE values. Figures 2–5 show the trendline of each model.

$R2$ is the coefficient of determination used to find the most suitable model. A higher $R2$ suggests better accuracy. MAPE is the average of the ratio of absolute error to actual value of historical data. The regression model having the lowest MAPE value was selected. Smaller values of MAPE suggest better prediction. Table 3 shows the results of regression analysis for each sector.

Table 2. results of regression analysis for each sector

Regression type	ME	MAE	Mean absolute percentage error (MAPE)	Mean square error
Linear	– 1504	51,817.45	0.5086	3,977,114,600.36

V. SYSTEM ARCHITECTURE

Time series models have been created for the utilization of coal, oil, natural gas, and hydropower. Out of the forecasting models, the model Dbest with the best fit is picked. The best fit was determined to be quadratic in every instance. This demonstrated that although the prices of coal, natural gas, and electricity have been rising regularly, the rate of growth has been rapid. Oil consumption is rising at an accelerated pace. To ascertain how demographic factors affect energy use, quantitative models were being created.

Using past information, empirical models were created for populace, GNP, energy price, and intake of coal, oil, natural gas, and light. R2, SE, and DW were computed for each of the 92 models in order to identify the one that suited the data the best. The simulations were ranked using R2, SE, and DW. The top 10 coal models are shown below in order of their performance rating, which takes into consideration all three factors (R2, SE, and DW).

Electricity, natural gas, and oil were all examined in a way similar. In the case of coal, it was found that in all ten of the finest works, the consumption is impacted by the demand from the following year as well as the price of coal. For oil, the determining factor was GNP, but for biogas, the desire is determined by both the demographics and the demand from the preceding year. The requirement from the last year served as the influential framework in the case of electricity. To identify factors that affect energy consumption by source, the 't' test is utilized. Tests were conducted on the top 10 models for coal, oil, natural gas, and electricity. If the 't' value is just 2 and 2 or the value is higher than 0.05, the distribution is defined to be inconsequential. The diverse samples for electricity are displayed in Table 1. Only models with important variables are taken into account and rated. We found the best regression equations for coal, oil, natural gas, and electricity..

Hydro

Y ¼ 406808 þ 0:566 ðD$_t$1Þ 4305:961 ð ÞþP$_i$1751:455 ðPopÞ R^2 ¼ 0:841SE ¼ 70115:08 DW ¼ 2:125

Thermal

Y ¼ 1097830 þ 0:377 ðD$_t$1Þþ 27949:563 ðGNP=PopÞ R^2 ¼ 0:995SE ¼ 66496:02 DW ¼ 1:451

Nuclear

RY ¼ ¼ 0106930$_{:986SE}$ ¼þ 646958$_{29268:12}$:3 ð$_{DW}$Dt¼1=$_1$Pop$_{:866}$Þþ 2388:004 GNP

2

Electricity

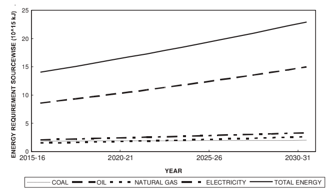


Figure 6 India's need for commodity.

Only admixture models were found to be the best matched designs in each case. Figure 3 depicts the predicted requirement for coal, oil, natural gas, and hydropower during the next 20 years. According to calculations, India will use 22.944 1015 kJ of energy total between 2030 and 2031. It is now widely acknowledged that the bulk of the world's energy requirements are met by oil. India's oil reserves are not very large. As of March 31, 2010, India's " intrinsic reserves of crude oil and natural gas were separately 1206.15 million tonnes (MT) and 1453.03 billion cubic meters (BCM). (mospi.nic.in).Future energy demands cannot be met by the current supplies. India has an abundance of renewable resources, including wind, solar, and biofuels, as it is a tropical nation with a coastlines and lots of sunshine. To some extent, gas managers concentrate on creating unconventional and renewable energy sources to fulfill future requirements for energy. One can use a low-carbon growth plan to increase India's excess calories while also lowering pollutants. Additionally, this would help to save foreign currency.

VI. SIMULATION AND RESULTS

importpandasaspd

importnumpyasnp

importmatplotlib.pyplotaspypl

importseabornassd

Cleaning the dataset

In [3]:

states_df = pd.read_csv('/Users/tahirshowkatbazaz/Desktop/Saima IET/State_Region_corrected.csv')

states_df.head()

Out[3]:

	State / Union territory (UT)	Area (km2)	Region	National Share (%)
0	Rajasthan	342239	Northern	10.55

	State / Union territory (UT)	Area (km2)	Region	National Share (%)
1	Madhya Pradesh	308350	Central	9.37
2	Maharashtra	307713	Western	9.36
3	Uttar Pradesh	240928	Northern	7.33
4	Gujarat	196024	Western	5.96

A. . Data Exploration

1. Number and names of states and union territories in each region.

	unique
Region	
Central	[Madhya Pradesh, Chhattisgarh]
Eastern	[Odisha, Bihar, West Bengal, Jharkhand]
NorthEastern	[Arunachal Pradesh, Assam, Meghalaya, Manipur,...
Northern	[Rajasthan, Uttar Pradesh, Ladakh, Himachal Pr...
Southern	[Karnataka, Andhra Pradesh, Tamil Nadu, Telang...
Western	[Maharashtra, Gujarat, Goa, Dadra and Nagar Ha...

B. Mean power generation in India,both actual and estimated

In [23]:

mean_power = power_df.groupby(by='Date',as_index=**False**).mean()

mean_power

Out[23]:

989 rows × 8 columns

C. Plotting a graph of all the types of power gernerations in all of India, with total power generation

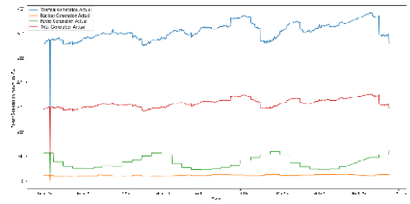


Figure 7 Dominant power over India

Thermal seems to be the most dominanat power generator all over India

1. Actual Power vs Estimated Power

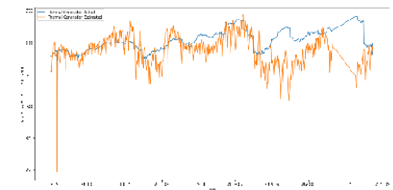


Figure 8 Thermal actual power vs generated power

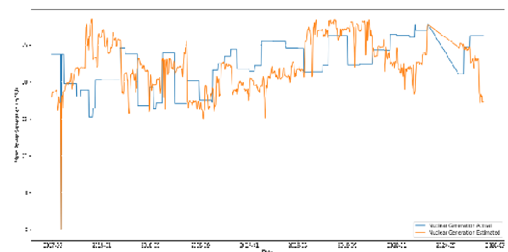


Figure 9 Nuclear Actual power vs generated power

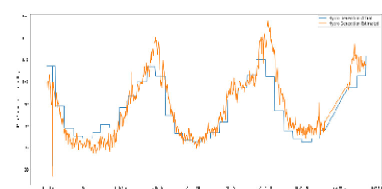


Figure 10 Hydro Actual power vs generated power

Thermal and nuclear seems to fluctuate from itself, but actual and estimated values for hydro trail each other well.

2. Regions that use the most of all power generators

In [27]:

mean_power_per_region = power_df.groupby(by=['Date','Region'],as_index=**False**).mean()

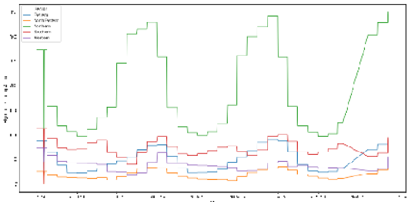
mean_power_per_region

Out[27]:

4945 rows × 9 columns

D. Hydro Generataion

In [28]:



E. *Nuclear Generation*

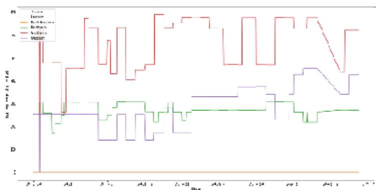
In [29]:

pypl.figure(figsize=(18,9))

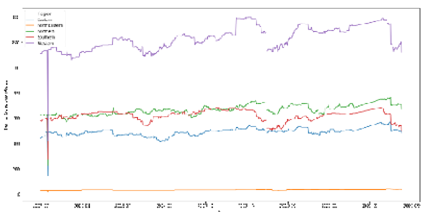
sd.lineplot(x='Date',y='Nuclear Generation Actual',hue='Region',data=mean_power_per_region)

Out[29]:

<matplotlib. axes. _subplots.AxesSubplot at 0x7f967159cad0>



F. *Thermal Generation*



From the following graphs, the northern, southern and western regions uses the thermal, nuclear and hydro energy the most, respectively, over 3 years.

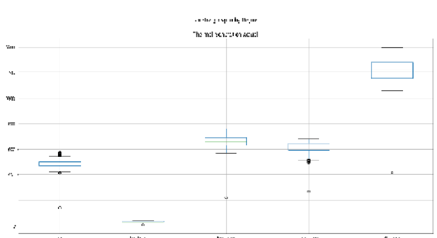
1. *Searching for outliers*

In [31]:

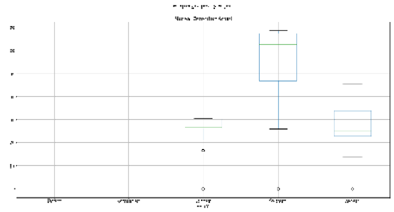
mean_power_per_region.boxplot(by='Region',column=[' Thermal Generation Actual'],figsize=(18,9))

Out[31]:

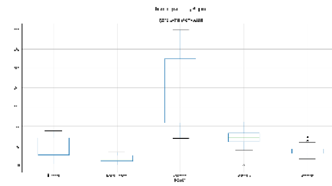
<matplotlib.axes._subplots.AxesSubplot at 0x7f967270e810>



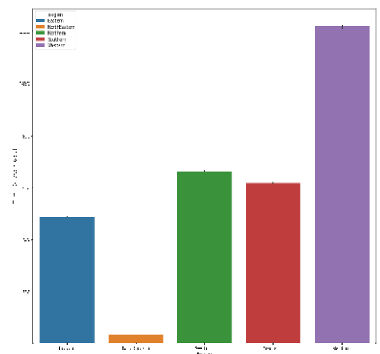
In [32]:

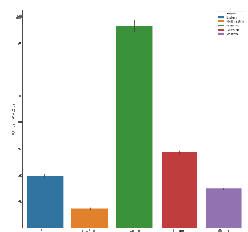


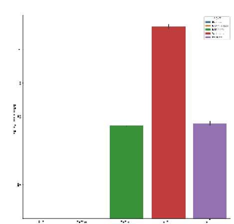
In [33]:



Bar chart of the regions that uses the most power generator







Power usage per area

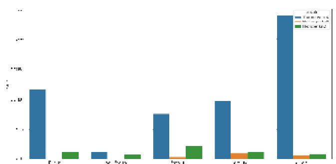
In [37]:

power_share = states_df.groupby(by='Region',as_index=**False**).sum()

power_share

Out[37]:

	Region	Area	National Share
0	Central	443541	13.480
1	Eastern	418336	12.710
2	NorthEastern	262179	7.940
3	Northern	889881	27.193
4	Southern	636251	19.330
5	Western	508042	15.440



Thermal still is the dominant power generator in all of India

G. Linear Regression (for Hydro Generation)

1. Making the dataframe for training and testing data

In [46]:

mean_thermal = mean_power[['Hydro Generation Estimated','Hydro Generation Actual']]

mean_thermal

Out[46]:

	Hydro Generation Estimated	Hydro Generation Actual
0	99.538	113.484
1	99.128	113.484
2	94.610	113.484
3	100.072	113.484
4	94.032	113.484
...	...	...
984	117.900	105.154
985	113.962	105.154
986	113.956	105.154
987	115.826	105.154
988	114.650	122.794

989 rows × 2 columns

Estimated Accuracy is 94%

2. Removing all outliers that might disturb with the model

In [47]:

q1 = mean_thermal['Hydro Generation Actual'].quantile(0.25)

q3 = mean_thermal['Hydro Generation Actual'].quantile(0.75)

iqr = q3-q1

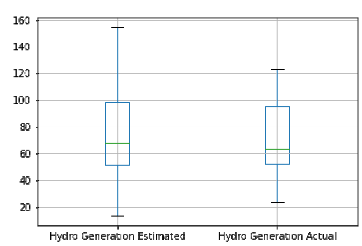
minimum = q1 - (1.5 * iqr)

maximum = q3 + (1.5 * iqr)

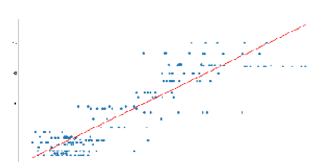
()

Out[49]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f9674a12190>



H. Creating the training and testing data for linear regression



VII. CONCLUSION

A. Conclusion

For the Indian setting, this approach identifies the influencing elements in demand for electricity, coal, wind, oil, and gas and oil. We are experimenting over the use of the the renewable resources such as hydro, nuclear and thermal energies. Policymakers should more strategically prepare for the future energy need with the aid of the identification of key elements. India's overall energy demand is predicted to be 22.944 1015 kJ from 2030 to 2031, of which 14.972 1015 kJ would come from oil. It is discovered that India would have to rely extensively on oil imports in the future. Estimated Accuracy is recorded as 94%.. This needs to stop, and India needs to develop self-sufficiency, in order to guarantee a stable economy. Additionally, relying solely on industrial energy sources like coal and oil are bad for environment.

B. Future scope

Given that India is well-endowed by India has an abundance of renewable energy sources, including wind, solar, and biomass, as it is a tropical nation with a sandy beach and lots of sunshine. With some point, resource managers concentrate on creating unconventional and renewable power sources to fulfill energy requirement. One can use a limited growth plan to increase India's excess calories while also lowering pollutants. Additionally, this would help save foreign currency.. renewable energy resources, policymakers must develop strategies to make the most of these resources

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