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In-Depth Energy Analysis and Consumption Prediction of India

Mudasir Ahmad Wani[1], Er. Dharminder Kumar[2], and Dr Satish Saini[3]

[1]M. Tech Scholar, Department of Electrical Engineering, RIMT University, Mandi Gobindgarh, Punjab, India
[2]Assistant Professor, Department of Electrical Engineering, RIMT University, Mandi Gobindgarh, Punjab, India
[3]Professor, Department of Electrical Engineering, RIMT University, Mandi Gobindgarh, Punjab, India

Correspondence should be addressed to Mudasir Ahmad Wani; wanimudasir382@gmail.com

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 the world temperature to rise by less than 2°C by the end of this century. It is crucial that, we include a trustworthy forecasting tool that can be used to estimate the energy consumption 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 coal is influenced by population and coal price, but demand for oil is influenced by GNP per capita. The GNP and power price both affect how much electricity is demanded. The projected demand for electricity, coal, oil, and natural gas in India from 2030 to 2031 results in a total energy need of 22.944 1015 kJ.

KEYWORDS- Energy Consumption, India, Prediction, Renewable, 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 consumption is discovered to be a sign of society change. Over the past forty years, the Indian energy industry has grown dramatically. At the moment, commercial energy sources including coal, oil, natural gas, and electricity account for 70% of global energy consumption. 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 276.81 billion tonnes, while the projected lignite reserve was 39.9 billion tonnes (mospi.nic.in). The nation imported 159.26 million tonnes of crude oil in 2009–2010, which is equivalent to 80% of its domestic crude oil consumption. The current situation calls for careful planning of energy resources to close the supply-demand mismatch. Figure 1 shows India's use of coal, oil, natural gas, and electricity during the previous three decades. Consumption of coal, oil, and 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 (at prices from 2004–2005) and population were examined. The GNP per capita is discovered to have an exponential trend because, whereas the population growth rate is linear, the GNP rises exponentially. Figure 2 displays the energy per person and the energy intensity (energy consumption/GNP). Even while the energy consumption per person is rising, it is still quite low when compared to other emerging nations. However, it is encouraging to see that the energy intensity practically followed a straight line until 1991–1992, after which it began to decline.

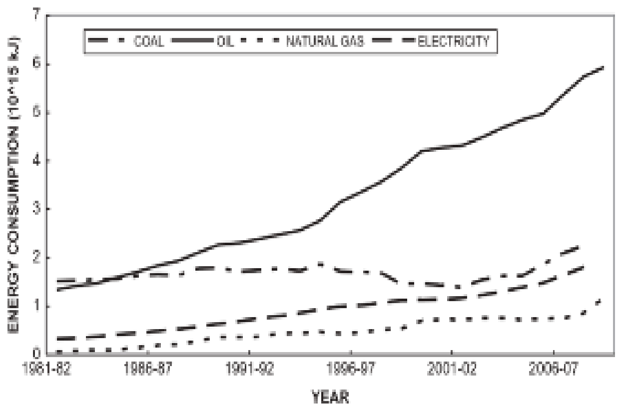

Figure 1: Commercial energy consumption for India

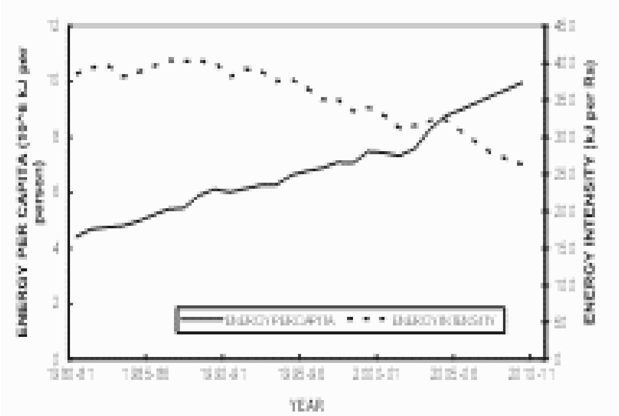

Figure 1: Energy per capita and energy intensity for India

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.

II. LITERATURE REVIEW

Machine learning methods are currently being used in various fields as replacements or in association with classical regression/statistical models to predict future using past data. For an extensive reading on the practical applications of machine learning, one might refer to. Several machine-learning algorithms, including but not limited to random forests [5], support vector machines [7] and neural networks [9] are currently being used to predict energy consumption. There are several publications that suggest that machine learning algorithms, are at least on par with classical approaches.

After training the model, it was tested on 17 blocks of flats. The model was found to be highly accurate with an R2 value of 0.9744. It was also found out that 90% of the computed values had relative errors of 20% or under. also compares the model to multiple dynamic solutions and states that the proposed model runs faster while giving comparable results. From, we learn that when generating models for datasets with smaller number of variables, regression is the best approach in terms of model quality and also speed. Since this thesis will also deal with smaller number of independent variables due to lack of complex data availability with SMCs, [23] was an important resource to establish how a regression model can be built.

III. METHODOLOGY

Regression is a technique used for analysing the impact of change in one or many variables on the change of another variable and it's used in variety of science and engineering disciplines for the same [1]. A simple linear regression is used to analyse the relationship between bivariate data i.e., the impact of one variable change on another variable change. Multiple regression is used for analysing the impact of change in multiple variables on the change of one variable. The variable(s) which impact(s) another is called predictor variable (generally denoted by Xs) and the variable which is impacted is called response variable (generally denoted by Y) [4]. In this thesis, we will be dealing with multiple regression since our dataset involves multiple predictor variables and a single response variable. One of the most common methods of establishing a correlation between variables is determining a "best fit" regression equation to go through the dataset consisting of multiple independent variables and a dependent variable. The best fitting equation to a set of data points would be the equation that is closest to all or most of the data points [7]. This can be achieved by determining the equation with least total vertical distance from the data points. This vertical distance can be defined as the "random error" generated due to the generalization of the whole dataset into an equation. Random error can be both positives and negatives, resulting in several values cancelling out or affecting other values. To avoid this discrepancy, the random errors are squared and summed. This resulting value is called "sum of squared errors" [4]. The goal of regression is to minimize this value "sum of squared errors."

Essentially, the process of determining the best fit equation is minimizing the sum of squared errors of the equation from the actual values. The equation with the minimum sum of squared errors shall be declared the regression equation for the dataset. By plugging in the values of expected independent variables in the future, it is possible to predict the value of dependent variable. This is one form of energy prediction that will be dealt in this thesis. A common example of a regression equation is as follows:

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

y is the independent variable, x are dependent variables, β_0 is the intercept and all other β are coefficients of different variables

Below are the estimates for least square functions [7]:

$$L = \sum_{i=1}^{n} (\in_i)^2$$

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

$$L = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ij}\right)^2$$

y_i is the original value of y at i.

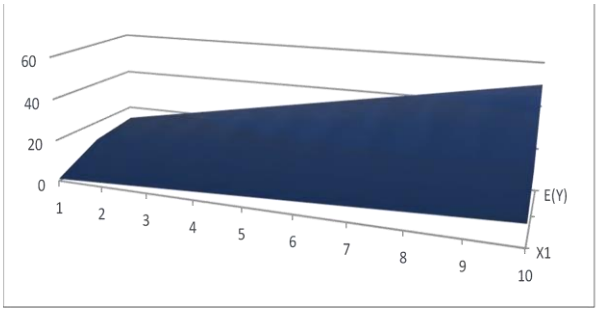

Figure 3: Regression model with two independent, one dependent variable y = 2x1 + x2 A

machine learning algorithm, random forests, is another form of energy prediction that is of interest in thesis.

A. Machine learning

Machine learning can be defined as computational methods used to improve performance metrics and predict future scenarios. Any machine learning algorithm uses data from the past to perform these activities. 'Data' includes any information available electronically to the user which one might use to train his algorithm [41]. The most important attributes of data used in machine learning are quality and size, both contributing to the level of learning and accuracy of the prediction. Machine learning has been used in several fields of study over the past few decades starting from weather prediction, stock market analysis. Machine learning can be used for one of the following standard tasks [1]:

- Classification: Classification tasks deal with assigning each element to a particular category. These tasks are used when there are multiple variables that decide what qualitative variable will be the output. For e.g., in electricity bills, demand charges are calculated only for manufacturing facilities. So, based on electricity bills from the past, a machine learning algorithm can classify the customer as a manufacturing facility if the customer is paying for demand charges. In classification problems, there is no real measure of how far an output is from the real-world scenario. There is only a pass or fail result of the machine learning algorithm [41].
- Regression: Regression in machine learning denotes any prediction in which a real value is the output. Machine learning does not use conventional regression formulas, regression here just denotes that a real value is predicted using past or known data. For e.g., predicting a future electricity bill using past and present bills, consumption data. This thesis will focus on regression using machine learning algorithms. In regression problems, there is a measure for how far an output is from the real-world scenario. This can be useful in calculating a penalty proportional to the measure. Similar to how a regression equation will change when new data points are added, even a machine learning algorithm will keep learning from new data points. This makes accommodating new data easy [1].
- Ranking: Ranking tasks include arranging items according to the users' requirements, priority, deadlines etc. Common examples are web searches that arrange search results according to a keyword, calendar applications that arrange one's tasks according to time, natural language processing systems that rank words according to relevance etc. [7].
- Clustering: Clustering problems involve grouping of a set of items on a dataset together based on homogeneity. Clustering can be done based on area, gender, sex or any common factor. A lot of clustering problems are on social media: clustering profiles to help users identify other people within a particular organization or community. Like classification problems, there is no real measure of how wrong these algorithms might be. The output can only be classified as a pass or fail based on real world scenarios [2].
- Dimensionality reduction, also known as manifold learning: These problems involve transforming a preliminary representation of items into a lower order representation. These algorithms also preserve the properties of the preliminary representation. One can explain it by comparing it to digital copies of older version of cameras [5].

B. Support Vector Regression

Support vector regression is a form of machine learning regression. Support vector regression has been used extensively in the past for energy prediction. Support vector machines work on the principle of structural risk minimization [6]. As discussed earlier, statistical regression works on the principle of least squares estimate. On the other hand, support vector regression works on the principle of least maximum error threshold. This means that the algorithm works to keep the maximum error from a data point within a particular range or desired value [2]. Figure 4 is a simple illustration of a support vector regression based on the principles mentioned on [4].

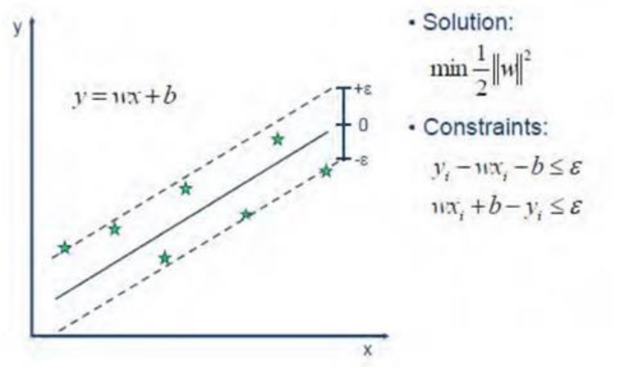

Figure 4: Support Vector Regression underlying optimization model

C. Random Forests

Random forests fall into the category of classification machine learning algorithms.

Random forests have also been used in a few cases for quantitative output determination but will not be discussed in this thesis. The basic output behaviour of random forests was discussed in the second chapter. This chapter will discuss the underlying working mechanism and explain why a particular feature called *wrapper aspect* would be useful in our case study. Random forests are a combination of decision trees, with each tree depending on the values of a random vector of the training dataset sampled independently. The forest then infers value from the several decision trees that are part of it. The efficiency of a random forests depends upon the strength of each tree that is part of the forest [3]. A simple illustration of a decision tree is shown below: in figure 5.

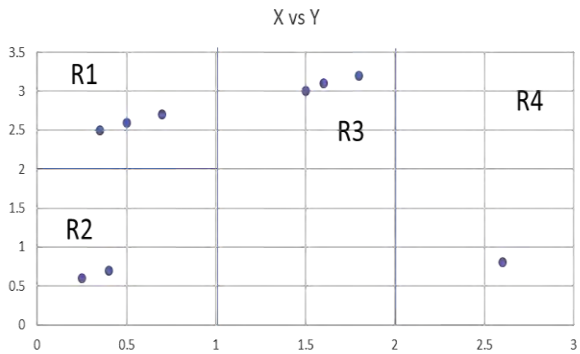

Figure 5: A simple classification problem

From the illustrated example below figure 6, it is seen that the decision tree is able to group the data points of interest by first selecting the variable that has the potential to make the biggest possible classification. In the case of the illustrated example, the condition "Is X > 2" has the potential to directly assign data points into R4. No other condition can directly contribute a first order classification without further checking for another condition. In other words, the algorithm tries to create the shortest decision tree possible to complete the classification problem. This means that the major classifying feature is selected to be the first feature of importance, in this case, X. It is seen that out of the 3 decisions taken by decision tree, 2 decisions are based on the feature X, further adding value to the premise that X is the first feature of importance for this particular problem. While trying to fit a prediction model on dataset with several independent features that have a high range, it is important to group the data points into several subsets and then try to fit in a prediction model. This grouping will make sure that the skewness in the entire dataset will not affect the prediction model results. Random forest classification will give us an output that says what the important features are in a dataset, along with specifying the percentage importance. Based on the percentage importance, the user can divide the primary dataset into smaller localized datasets of a variable. Localized datasets are expected to give better fitting models due to lesser skewness.

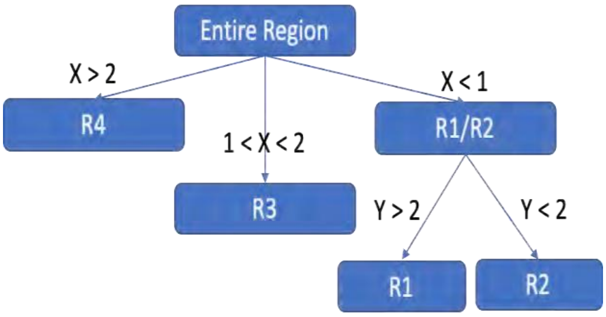

Figure 6: Working of decision trees to classify the data points into region of interest

It is to be noted that the random forest algorithm does not assess the variable importance individually as done by *f* or *p*-test in regression modelling. The variables are assessed jointly assessed for all the variables that are part of the dataset. Then the variables are ranked based on the strength on association with the output variables. This feature of random forests is called 'wrapper aspect' [5]. In this study we use this aspect of random forests to select the input variables to be used as the basis of classification for the regression models. The random forests have been used to find the features of importance ranked one by one so that grouping of the data points can be done based on those features. Each level of division has been done based on a particular variable. The top most classification has been done on the variable of most importance and so on. A detailed flowchart of how the division has been done is presented in the next chapter in this thesis

Energy modelling is an essential component of energy planning. It assists administrators in developing policies and framing strategies. Since the oil crisis of the 1970s, research on energy demand analysis has gained momentum. The fluctuating energy prices because of India's heavy dependence of oil import, energy market security, burgeoning economy, and environmental impact call for a detailed energy demand analysis. Econometric models analyse demand at the aggregate level and identify significant relationships between demand and the socioeconomic variables. The variables used in this research to develop the econometric models for coal, oil, natural gas, and electricity demand are:

Dbest = Best fit equation for demand obtained using time series models

D t−1 = Previous year's demand

Pi = Wholesale price index (i = coal, oil and gas, electricity) @2004–2005 prices = 100 Pop = Population

GNP = Gross National Product Index (GNP at factor cost @2004–2005 prices = 100)

Y = Forecasted energy demand—coal, oil, natural gas, electricity

The best fit Dbest is obtained from the five time series models—linear, logarithmic, quadratic, power, and exponential. The best fit from among the above models is determined using R2 and squared error (SE). Econometric models are developed to identify the influence of these variables on energy demand for Indian conditions. The models developed and considered for the study are given in Appendix 1. Additive and multiplicative models were developed. A total of 92 models for coal, oil, natural gas, and electricity demand were formulated. The top 10 models for each source were selected based on a composite ranking considering R2, SE, and Durbin Watson (DW) statistic. Among the top 10 models selected, t test was performed. Using the results of the 't' test, the influencing variables for coal, oil, natural gas, and electricity demand were identified for Indian conditions. The best fit econometric model for coal, oil, natural gas, and electricity was selected.

Coal, oil, natural gas, and electricity requirement for India for the next two decades was forecasted

IV. SYSTEM IMPLEMENTATION

Time series models were developed for coal, oil, natural gas, and electricity consumption. The best fit model D_{best} from among the time series models is selected. In all cases it was found that quadratic fit was the best fit. This indicated that even though coal, natural gas, and electricity have a steady increase, the rate of increase is steep. The rate of growth in the consumption of oil is exponential. To determine the influence of the socioeconomic variables on energy consumption, econometric models were being developed.

Econometric models were developed using the past data for coal, oil, natural gas and electricity consumption, GNP, energy price, and population. To identify the best fit model R^2, SE and DW were determined for all the 92 models. The models were ranked based on R^2, SE, and DW. Composite ranking was found considering all the three (R^2, SE, and DW) and the top 10 models for coal are presented below as per their ranking.

$Y = f(D_{t-1}, P_i, GNP, Pop)$ Additive model $R^2 = 0.841$ SE = 70103.65 DW = 2.147

$Y = f(D_{t-1}, P_i, Pop)$ Additive model $R^2 = 0.841$ SE = 70115.08 DW = 2.125

$Y = f(D_{t-1}, P_i, GNP)$ Additive model $R^2 = 0.818$ SE = 75042.17 DW = 2.344

$Y = (D_{t-1}, GNP/Pop, P_i)$ Additive model $R^2 = 0.815$ SE = 75714.14 DW = 2.268

$Y = f(D_{t-1}, P_i, GNP, Pop)$ Multiplicative model $R^2 = 0.820$ SE = 74765.27 DW = 1.946

$Y = f(D_{t-1}, P_i, GNP, Pop)$ Multiplicative model $R^2 = 0.820$ SE = 75576.08 DW = 1.912 (7) $Y = (D_{t-1}, GNP/P_i, Pop)$ Additive model $R^2 = 0.822$ SE = 74247.11 DW = 1.873

$Y = (D_{t-1}, P_i/Pop, GNP)$ Additive model $R^2 = 0.810$ SE = 76745.85 DW = 2.210

$Y = (D_{t-1}, P_i/Pop, GNP)$ Multiplicative model $R^2 = 0.816$ SE = 75545.72 DW = 1.892

$Y = f(D_{t-1}, P_i, GNP)$ Multiplicative model $R^2 = 0.816$ SE = 75597.53 DW = 1.888

Similar analysis was performed for oil, natural gas, and electricity. In the case of coal, it was found that in all the top 10 models the demand is influenced by the previous year's demand and the price of coal. In the case of oil, GNP was the influencing variable while for natural gas, the demand was influenced by the previous year's demand and population. In the case of electricity, the previous year's demand was the influencing parameter. The variables that influence the energy demand source-wise were determined using the 't' test. The test was performed on the top 10 models for coal, oil, natural gas, and electricity. If the 't' value is between −2 and 2 or the significance is above 0.05, the variable is insignificant. The tests of significance obtained for electricity is given in Table 1. Only those models whose variables are found to be significant are considered and ranked. The best fit econometric models for coal, oil, natural gas, and electricity were determined

Table 1: "t" test for econometric models-Electricity

Model	Type	Variables	t
$Y = f(D_{t-1}, P_i, GNP, Pop)$	Additive	Constant	−1.669
		Dt−1	21.582
		P_i	−0.511
		GNP	0.067
		Pop	1.207
$Y = f(D_{t-1}, P_i, GNP)$	Additive	Constant	−1.150
		Dt−1	21.924
		P_i	−2.821
		GNP	1.544
$Y = f(D_{t-1}, P_i, Pop)$	Additive	Constant	−1.725
		Dt−1	24.623
		P_i	−1.285
		Pop	1.986
$Y = f(D_{t-1}, GNP, Pop)$	Additive	Constant	−1.965
		Dt−1	22.148
		GNP	−1.176
		Pop	3.063
$Y = f(D_{t-1}, GNP/P_i, Pop)$	Additive	Constant	0.063
		Dt−1	39.697
		GNP/P_i	−0.961
		Pop	0.924
$Y = f(D_{t-1}, GNP/P_i)$	Additive	Constant	3.738

Coal

Y ¼ 406808 þ 0:566 ðDt1Þ 4305:961 ð ÞþPi 1751:455 ðPopÞ R^2 ¼ 0:841SE ¼ 70115:08 DW ¼ 2:125

Oil

Y ¼ 1097830 þ 0:377 ðDt1Þþ 27949:563 ðGNP=PopÞ R^2 ¼ 0:995SE ¼ 66496:02 DW ¼ 1:451

Natural Gas

RY ¼ ¼ 0106930:986SE ¼þ 64695829268:12:3 ðDWDt¼1=1Pop:866Þþ 2388:004 GNP
2
Electricity

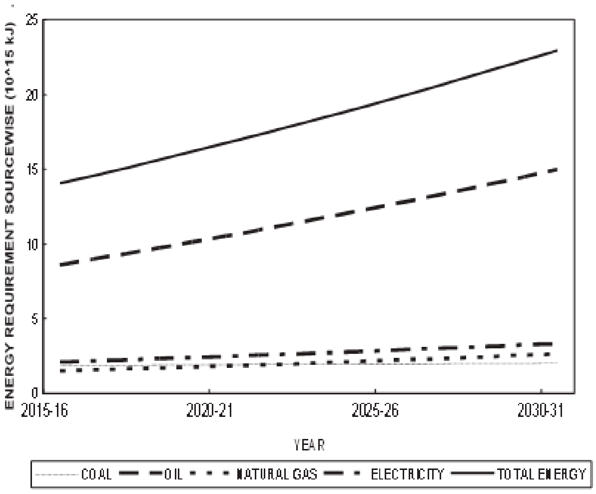

Figure 7: Requirement of commercial energy in India.

In all cases, it was found that only additive models featured as the best fit models. The coal, oil, natural gas, and electricity requirement for the next two decades were forecasted and are presented in Figure 3. It is found that the total energy requirement for India during 2030–2031 is expected to be 22.944×10^{15} kJ. Oil is found to be the major contributor to the energy requirement. The oil reserves in India are very limited. The estimated reserves of crude oil and natural gas in India as of March 31, 2010 are 1206.15 million tonnes (MT) and 1453.03 billion cubic meters (BCM), respectively (mospi.nic.in). The reserves are not sufficient to meet the future energy requirement. India being a tropical country with a vast coastline and strong sunshine, it is richly endowed with renewable energy sources like wind, solar, and biomass. Energy administrators can focus on developing renewable and nonconventional energy sources to meet the future energy demand to some extent. Low carbon growth strategy can be followed not only to reduce emissions but also to improve India's energy reserve position. This would also help in conserving foreign exchange.

V. SIMULATION AND RESULTS

Econometric models were developed using the past data for coal, oil, natural gas and electricity consumption, GNP, energy price, and population. To identify the best fit model R2 , SE and DW were determined for all the 92 models. The models were ranked based on R2 , SE, and DW. Composite ranking was found considering all the three (R2 , SE, and DW) and the top 10 models for coal are presented below as per their ranking in table 2. Similar analysis was performed for oil, natural gas, and electricity. In the case of coal, it was found that in all the top 10 models the demand is influenced by the previous year's demand and the price of coal.

Figure 8 shows Acess to electricity vs Year

Figure 9 displays Access to dean fuel and technology Vs Year

Figure 10 shows Access to Energy consumption vs year

Is shown in figure 11 Electricity generator v/s year

Figure 8: Access to electricity vs Year

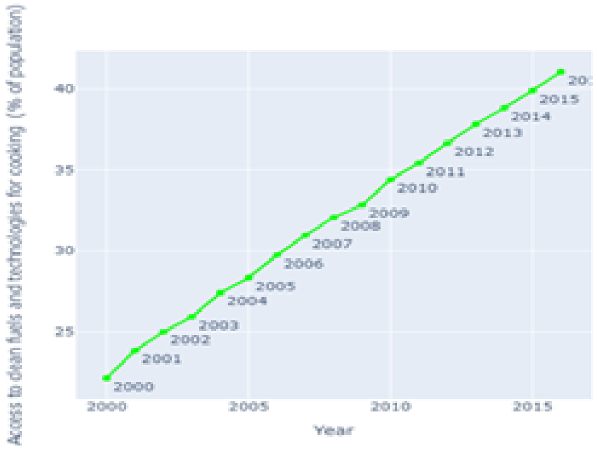

Figure 9: Access to dean fuel and technology Vs Year

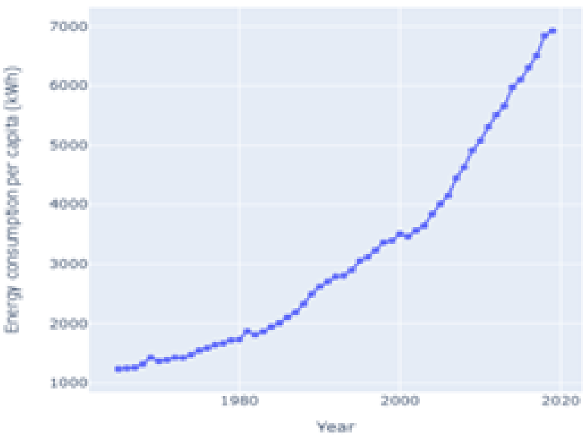

Figure 10: Access to Energy consumption vs year

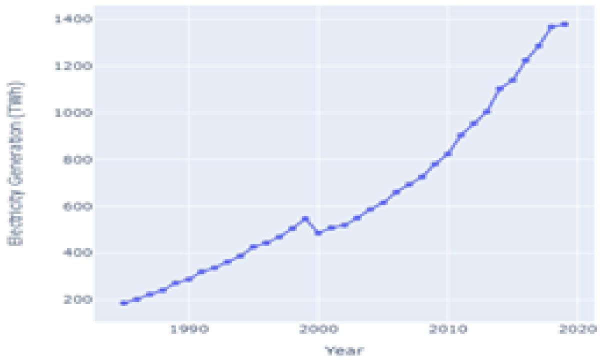

Figure 11: Electricity generator v/s year

Table 2: Energy consumption

	Name	Value
13	Electricity Generation (TWH)	1.935667e+08
9	Biofuels (TWH)	1.030018e+03
7	Wind Consumption – EJ	1.001653e+03
8	Geo Biomass Other – EJ	1.000190e+03
3	Coal Consumption – EJ	9.987561e+02
1	Oil Consumption – EJ	9.986703e+02
2	Gas Consumption - EJ	9.984631e+02
5	Hydro Consumption - EJ	9.984595e+02
6	Nuclear Consumption – EJ	9.968084e+02
4	Solar Consumption - EJ	9.858457e+02
31	Solar (% electricity)	3.260972e+02
39	Renewables (% electricity)	3.063897e+02
34	Nuclear (% electricity)	2.440384e+01
38	Nuclear (% electricity).1	2.397947e+01
25	Nuclear (% sub energy)	2.208656e+01
26	Per capita electricity (kWh)	6.938216e+00
36	Fossil fuels (% electricity)	4.026390e+00
11	Annual change primary energy consumption (%)	2.075461e+00
10	Access to clean fuels and technologies for coo...	-6.004565e-02
0	Year	-3.322192e+00
28	Coal (% electricity)	-8.379437e+00

	Name	Value
22	Energy consumption per GDP (kWh per $)	-9.668844e+00
29	Gas (% electricity)	-1.507793e+01
33	Oil (% electricity)	-3.719828e+01
37	Low-carbon electricity (% electricity)	-4.751077e+01
30	Hydro (% electricity)	-2.573457e+02
32	Wind (% electricity)	-2.574350e+02
35	Other renewables (% electricity)	-3.726915e+02
24	Low-carbon energy (% sub energy)	-5.560379e+02
23	Fossil fuels (% sub energy)	-5.635271e+02
27	Primary energy consumption (TWh)	-9.978044e+02
12	Annual CO2 emissions per unit energy (kg per k...	-1.145332e+03
17	Electricity from other renewables (TWh)	-1.935667e+08
19	Electricity from oil (TWh)	-1.935667e+08
21	Electricity from nuclear (TWh)	-1.935667e+08
15	Electricity from gas (TWH)	-1.935667e+08
14	Electricity from coal (TWH)	-1.935667e+08
16	Electricity from hydro (TWH)	-1.935667e+08
18	Electricity from solar (TWH)	-1.935667e+08
20	Electricity from wind (TWH)	-1.935667e+08

VI. CONCLUSION

For the Indian setting, this approach identifies the influencing elements in the demand for coal, wind, oil, natural gas, and electricity. 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. 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 is bad for the environment. Given that India is well-endowed with renewable energy resources, policymakers must develop strategies to make the most of these resources.

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