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# To Analyze Energy Consumption on BESCOM and Classify using ML Approach

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## I. ABSTRACT

Karnataka, a rapidly developing state in India, faces significant changes in energy demand due to population growth, urbanization, and industrialization. This study analyzes Karnataka's energy consumption patterns, particularly focusing on the Bangalore Electricity Supply Company Limited (BESCOM) area, and explores the application of Machine Learning (ML) for classification. It examines historical data, projections, and the impact of initiatives like the Gruha Jyothi Scheme, which provides free electricity to eligible households. The research highlights the need for accurate energy forecasting and efficient management to address consumption trends and ensure sustainable energy distribution. ML methods offer promising tools for predicting consumption, identifying patterns, and improving operational efficiency within the energy sector. The Gruha Jyothi scheme offers up to 200 units of free electricity each month for eligible households.

## II. KEYWORDS

Energy Consumption, BESCOM, Classification, Gruha Jyothi.

## III. INTRODUCTION

Energy is crucial for economic growth and improving quality of life. India exhibits diverse energy consumption patterns across states, broadly categorized into sectors like Industries, Transport, Buildings, Municipalities, Distribution Companies, Agriculture, and Fisheries. There's a recognized need for sector-specific energy efficiency strategies. For instance, states with less urbanization might focus on transport or agriculture, while industrial energy demand, constituting over 30% in most states, requires commensurate efficiency initiatives. Energy providers constantly forecast consumption to ensure reliable power supply, considering factors like historical data, GDP, and consumer behavior.[1].

Policy frameworks, like the Energy Policy Act of 1992 in the US, emphasize efficiency across various sectors. Residential energy consumption is driven by activities like lighting, cooking, and appliance use. Factors like building size and income level influence residential energy use. Globally, household energy needs are projected to grow significantly. While energy consumption is technological, conservation is societal. Developing nations, despite housing a large population percentage, account for a smaller share of global energy use.[2]. Karnataka faces challenges in meeting its power requirements, with past warnings of significant deficits. Electricity is the primary energy carrier in its residential and commercial sectors. Raising awareness about energy-efficient technologies and providing government support are crucial. Projections indicate a steady rise in Karnataka's energy consumption and peak demand through 2031-32. The state utilizes a diverse mix of energy sources, including coal, hydro, solar, wind, biomass, and nuclear, with a growing emphasis on renewables like solar. The Energy Policy Act of 1992 contains provisions for energy efficiency as it relates to buildings, utilities, appliance and equipment energy efficiency standards, industrial facilities, state and local energy conservation programs and federal agency energy management. Karnataka Uses Energy Sources like, Coal, Oil, Electricity.

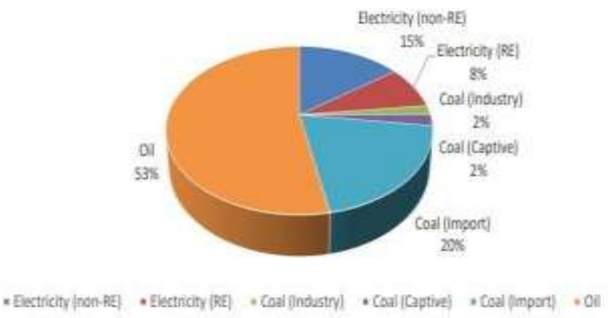


**Fig 1: Karnataka Energy sources (Magwatt).**

The importance of energy is a crucial ingredient in economic growth as well as in any strategy for improving the quality of human life. Energy consumption in the residential sector is usually because of cooking, lighting, water heating, space heating and electric appliances. The energy use in the residential sector is an essential zone for battles to monitor energy. Energy sparing in the home makes benefits for the family unit as lower vitality bills and for the network everywhere as lower imports. As such, these actions provide an opportunity to integrate the promotion of efficient energy use and development with the practice of environmental review and oversight under NEPA and the CAA.[2].

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The energy required by ESCOMs of Karnataka for the Financial Year 2021-22 is 67919.26 MUs considering STU loss of 3.10%. The ESCOM wise energy requirement is shown in as Table-1

| **ESCOMs** | **Energy requirement in MUs** |
|---|---|
| BESCOM | 29955.95 |
| GESCOM | 8911.00 |
| HESCOM including Hukkeri Society & AEQUS | 14491.67 |
| MESCOM Including MSEZ | 6499.74 |
| CESC, Mysore | 8060.89 |
| TOTAL | 67919.26 |

**Table 1 : ESCOM wise Energy Requirement**

National Building Code of India 2016 by Bureau of Indian Standards (BIS) with a chapter on approach to sustainability included Association for Development and Research of Sustainable Habitats (ADaRSH) for small stand-alone buildings, Leadership in Energy and Environ ment Design (LEED India) by the Indian Green Building Council (IGBC), Eco-Housing rating system developed for Pune, Energy efficiency labeling programs and the enact ment of the Energy Conservation Act 2001.
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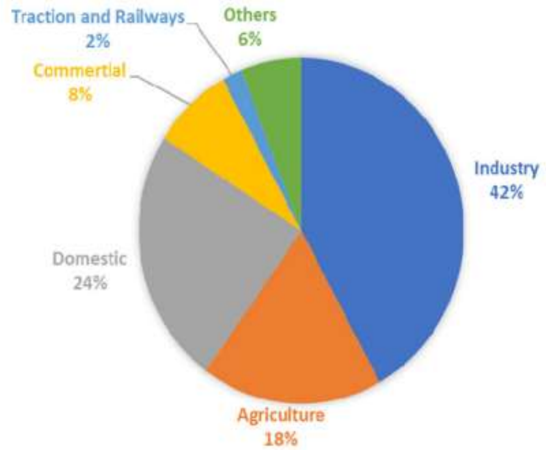


**Fig 2: Industrial Infrastructure Karnataka**

## IV. EXISTING MODELS

### Random Forest Algorithm:

The random forest classification algorithm will be used, same like the decision tree algorithm. The set of decision tree classifiers is what we will take into account when we discuss the random forest. Thus, various random subsets of the independent variables will be plotted, and we will make them categorize on their own. The internal model correctness for every decision tree will be recalculated using the Gini technique. Randomness of Features: Only a random subset of features should be taken into consideration for splitting at each decision tree node. As a result, there is less correlation between the trees and more unpredictability. The number of trees in the forest, the trees' maximum depth, and the size of the random feature subsets are among the hyperparameters of random forests that can be adjusted. A common technique for determining the ideal hyperparameter combination is cross-validation.

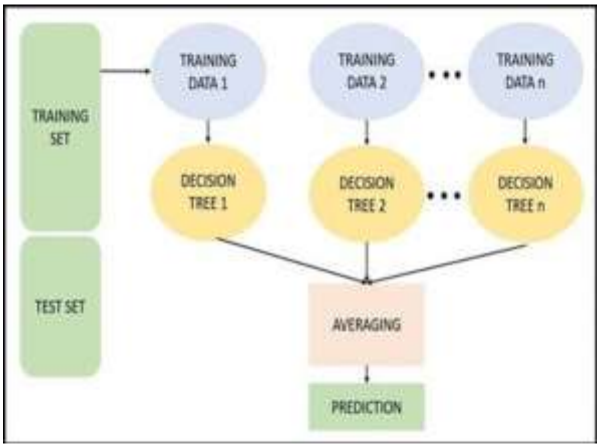


**Fig 3 : Random Forest**

**K-Means Clustering:**

The K-Means algorithm is used to see the efficiency and simplicity in electricity load profiles problems. The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K. The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity. The algorithm has three steps, it starts by (1) giving the algorithm a set of data points and a value of K as a number of clusters, then (2) randomly select K centers of clusters, (3) calculate the distance between each data point and the centers of the clusters K by using one of the distance measurements, (4) assign each data point to the closest center, (5 update the centers, 6) loop through 3-5 until convergence. Euclidean distance metric has been used to calculate the distance between the data points and cluster centers, the calculation of Euclidean distance is shown in Fig 4 where c is the center of the cluster, p is the datapoint and i is the counter to make sure that we covered all the centers and data points.

$$d(p,c) = \sqrt{[\textstyle\sum_{i=1}^{n} (ci - pi)^{2}]}$$

**Fig 4 : Calculation of Euclidean distance**

The K-Means Clustering is used to group energy consumption data, Fig 5 Represents how the K-Means Clustering works.

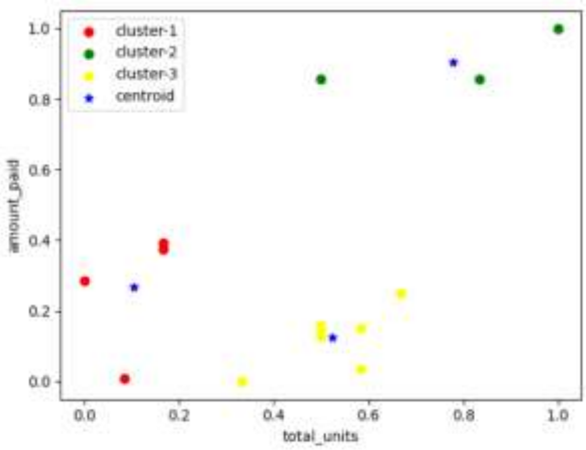


**Fig 5 : K-Means**

**Hierarchical Clustering:**

Hierarchical clustering is a technique used to group similar data points together based on their similarity creating a hierarchy or tree-like structure. The key idea is to begin with each data point as its own separate cluster and then progressively merge or split them based on their similarity.

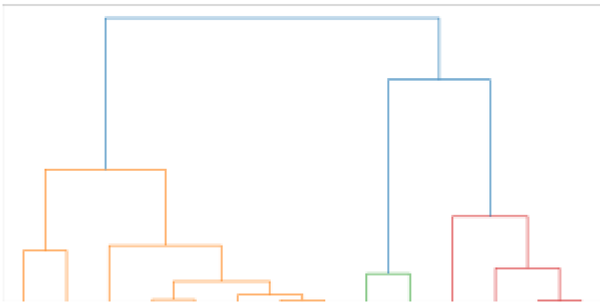

**Fig 6 : Hierarchical**

**V. PROPOSED MODEL**

Although the suggested design appears to be widely implemented, comprehending the dataset is difficult. The Karnataka Legislature (Government of Karnataka) approved the Karnataka Electricity Reforms Act (KERA) in 1999 to enhance the state's electricity sector's performance. It required the

Karnataka Electricity Board to be unbundled (KEB).

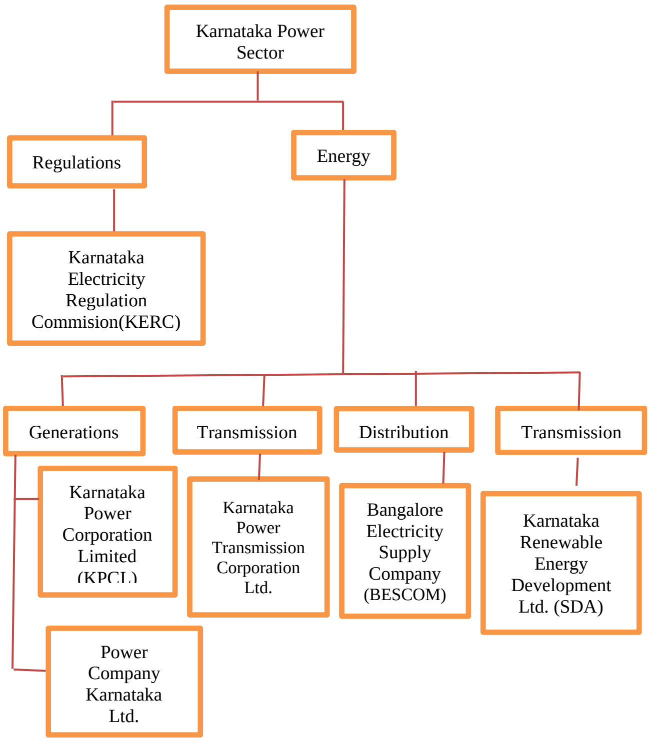


**Fig 7 : Architecture of Karnataka State in energy sector. [4].**

In the Future Energy Demand the Energy consumption will have to increase on a massive scale in order to have global peace, rural and urban development and improvements in many sectors such as tourism, automation, manufacturing, trade, etc. Urban and rural development form the infrastructure and the basis for multi-sectoral industries and economic growth in all countries. Energy planning in Karnataka is not an integrated activity.[4].

The plans for electricity, oil, coal, and firewood are separate exercises. Secondly, the planning activity considers only the demand and projects the demand over a period of years. The efficiency in utilization has scarcely been looked into. This has led to a situation where an input of about 25 units of energy is needed to get a useful output of 1 unit of energy (wasting the remaining 24 units).[1].

Energy resources can be broadly categorised as renewable and depletable. Renewable resources are available every year whereas depletable resources are stored ones whose availability keeps on decreasing depending on use. Fire-wood is in a peculiar position - if our consumption per year equals our annual 'Production', it is a renewable resource; if the consumption exceeds annual growth, then it gets depleted. Since electricity cannot be stored, 'electricity sales' to ultimate consumers is to be considered as the 'electricity consumption' by the different consumer categories Domestic, Industry (low and medium voltage), Industry (high voltage), Commercial, Irrigation and Others.[6].

## VI. WORKING AND ANALYSIS

The project is centered on the exploration of household electricity usage patterns based on unsupervised machine learning approaches. To begin with, core Python libraries like pandas, numpy, matplotlib, seaborn, and scikit-learn were used for loading the data, preprocessing, clustering, and visualization purposes. The ori.csv dataset was loaded with features such as the number of rooms, household people, average monthly income, number of electricity units used, amount paid, and ownership indicators for appliances (e.g., TV, AC, fridge, washing machine), and a classification of urban or rural area.

During the data preprocessing stage, rows with incorrect entries (zero or negative entries for num_rooms and num_people) were eliminated, and incomplete records in important fields like num_rooms and amount_paid were dealt with by dropping incomplete records. A subset of important features was chosen to provide meaningful clustering. Since clustering algorithms are sensitive to differences in scale among features, the StandardScaler was applied to normalize all features, bringing them to a similar range with mean zero and unit variance.

Hierarchical Agglomerative Clustering was used for segmentation with Euclidean distance as the metric and Ward's linkage method to reduce within-cluster variance. The number of clusters was specified as three, and a dendrogram was created to visually examine how the households coalesced into clusters at different levels. Hierarchical clustering was suitable since it provid

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ed an easy-to-understand view of the dataset structure without needing the number of clusters to be specified in advance.

After post clustering, each household received a cluster identifier (0, 1, or 2), which was added back into the original dataset. Visuals like scatter plots of electricity units consumed against the amount paid, colored by cluster, were used to show differences between the clusters.

These visuals showed distinct separations in consumption and payment trends between different groups of households. The three clusters on analysis constituted different profiles. Cluster 0 comprised mostly lower-consumption, lower-income, smaller-house, rural-household types.

Cluster 1 had households with middle-level consumption and payment levels, generally from mixed urban and rural areas. Cluster 2 included high-consumption, high-payment household types, mainly urban, with large houses and multiple electrical devices like air conditioners, televisions, and washing machines.

This distinct distinction between clusters brought t o the fore the association between income level, appliance ownership, and electricity consumption. The application of hierarchical clustering, and specifically the Ward linkage, worked well in revealing the natural clusters of households in terms of consumption behavior. As opposed to KMeans, which demands predefinition of the number of clusters, hierarchical clustering permitted the ease of exploring the data and determining the best number of clusters by understanding the structure of the dendrogram. Lastly, the project efficiently separated homes using their electricity consumption and associated characteristics.

These observations present actionable suggestions that may be beneficial to the provision of electricity by helping power suppliers develop differentiated energy management systems, encouraging efficient usage among those consumi-ng more energy, and benefiting poor households through necessary interventions.

The integration of solid preprocessing, considerate attribute selection, adequate clustering technique, and proper illustration made the investigation comprehensive and feasible.

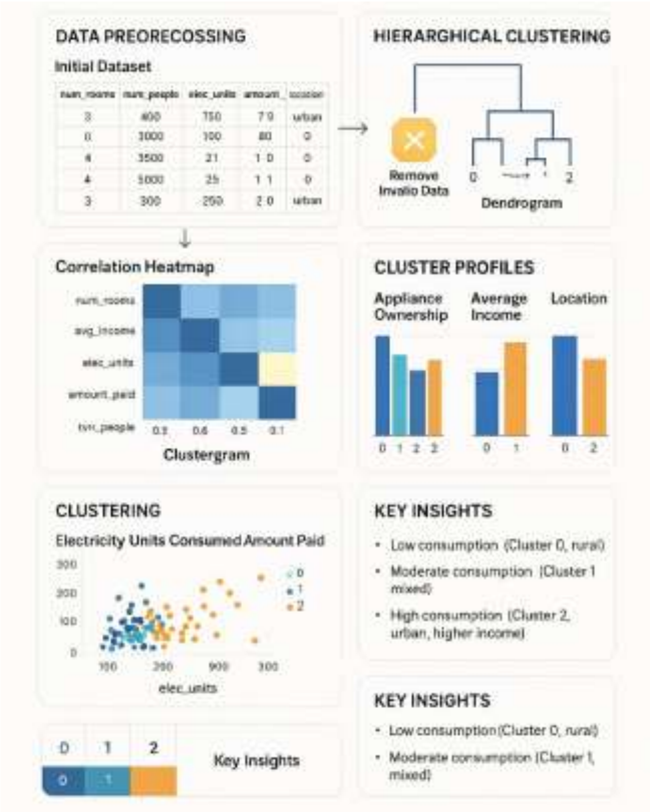
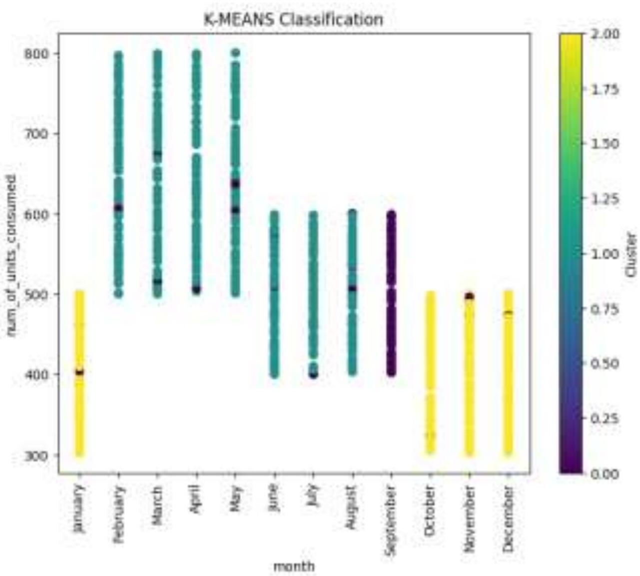
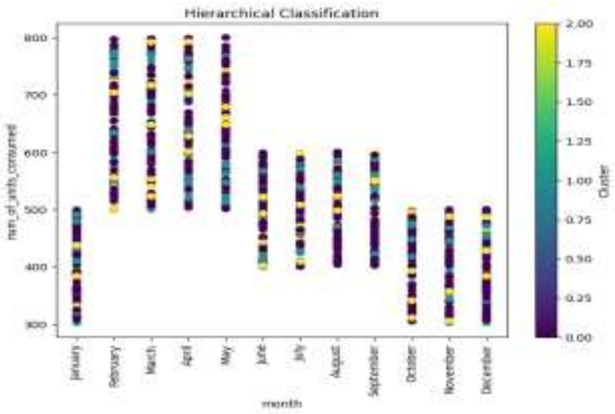
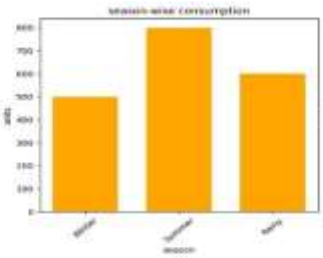


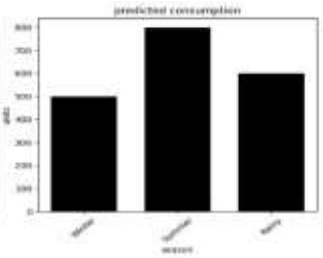

**Fig 8 : Analysis Of Household Electricity Consumption**

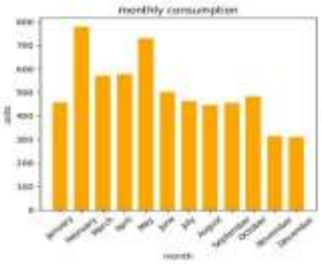
## VII. RESULTS

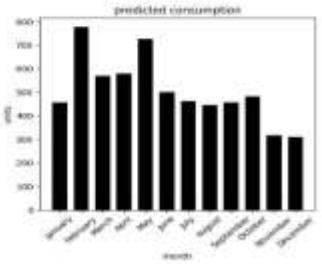










## VIII. CONCLUSION

This study outlines a framework for analyzing energy consumption within BESCOM's jurisdiction using ML classification techniques. Karnataka's dynamic energy landscape, characterized by growing demand and a push towards renewables, necessitates advanced analytical tools. ML models offer the potential to process large datasets, identify complex patterns, and provide actionable insights for energy providers like BESCOM.

By classifying users based on their consumption behavior, this approach can enhance load forecasting accuracy, optimize resource distribution, support targeted energy efficiency initiatives, and contribute to the sustainable management of Karnataka's energy resources.

Addressing challenges related to data quality, model interpretability, and the specific constraints of schemes like Gruha Jyothi will be crucial for successful implementation. Ultimately, leveraging ML can aid Karnataka in balancing energy demand, promoting conservation, and ensuring a reliable and equitable energy supply for its residents.

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