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Study on Energy Consumption Forecasting Using Machine Learning

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ABSTRACT- An Energy consumption forecasting platform that provides the functionality to predicting the consumption of energy. The system allows registered users to log in and new users to register to the application. System helps forecasting and predicting the future energy usage patterns based on historical data and various influencing factors. This concept is a web application. It allows choose the date and time, location, region. All information is recorded in the database. The goal of is to develop model that can anticipate the demand for energy over specific time periods, such as hours, days, or months. To overcome this issue, a model to forecast the electricity bill of houses based on their previous consumption details, trends and usage patterns by making use of data science and machine learning has been proposed.

KEYWORDS- Energy Consumption, Machine Learning, Historical Data, Database.

I. INTRODUCTION

In today's Time, energy consumption is increasing day by day but the production rate is less as compared to consumption rate .energy consumption can be measured by looking at how much energy a production process consumes, for example, by making car parts. This will include water, electricity; gas… any energy source needed to transform the raw material into the final product.Muhammad Ridwan Fathin, et al. has made a study to help electricity providers in taking decisions by doing medium and long-term forecasts using the Auto-Regressive Integrated Moving Average (ARIMA) method, ARIMA is the best for tactical decisions (medium-term) regarding electrical energy consumption. Ni Guo Wei Chen, et al has proposed a model ARIMA-SVR in comparison to ARIMA, ARIMAGBR, LSTM and GRU for power consumption prediction of an office building.The project provides most of the basic functionality that predict the consumption of energy, by Date, Day, Time , by the historical data you can also predict the future energy consumption.Especially after the relaxation of lockdown in a country such as India where the population is high, every household was worried mostly about a common situation i.e. electricity bills. Our idea is to help people have a long-term analysis on the usage of electricity to help cut down unnecessary costs in bills. So, a time-series model has been implemented to accurately predict the future month's bill. Initially, each module makes use of the historical data of the consumer, then it constructs a prediction system to forecast the future value. The predicted value is displayed to the user giving them an idea what will be the usage of their electricity in the next month. Electricity is also non-storable, whatever is produced needs to be consumed immediately . Proper production planning is required for this purpose. Forecasting methods are being employed by various agencies to identify the demand and to produce only what is required.Every industry strives towards leaving a low carbon footprint and conventional power consumption techniques lead to a lot of pollution. With proper demand in mind, the agencies can limit themselves to produce only the required amount. Identifying demand also helps these agencies to provide quality power without swells and outages. ARIMA is a time series forecasting technique widely in use. It considers the previous history of the data and tries to identify a pattern within the distribution. This ensures nearly accurate predictions on test data. We have used the ARIMA model to train the data and to predict the future consumption.

In a world struggling with the twin challenges of urbanization and environmental protection, the importance of efficient energy management cannot be overstated. Accurate prediction of electricity consumption, especially for buildings, is caught between technological innovation, statistical modeling, and the imperative of sustainability. In this academic terrain, we address the methods, opportunities, challenges, and wider societal implications of using nonlinear time series regression models to predict electricity consumption in buildings . As the 21st century brings an unprecedented increase in urban population and an increased focus on sustainability, predicting electricity consumption in buildings using advanced nonlinear regression models is not only of scientific interest but a global necessity. Estimate electricity consumption (kW) in a building given data measurement taken from January 1, 2010, 01:15 a.m. to February 17, 2010, 23:45. This measurement also includes the outdoor air temperature of the building for the same time frame. To aid predictions, the outdoor air temperature of the building is available for February 18, 2010. Two forecasts were made for power consumption on February 18, 2010, and this projected energy usage in the building is arrived at from the following viewpoints:

- Taking the outdoor air temperature of the building into perspective and predicting the expected energy usage.

- Predicting the expected energy usage without taking into effect the outdoor air temperature of the building into perspective.

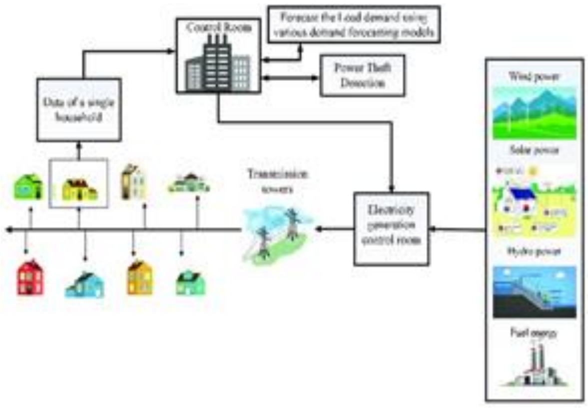

Figure 1: Energy Consumption Forecasting Architecture

Figure Reference : https://images.app.goo.gl/T9NAZEgUq87RyALv5

II. OBJECTIVE OF THE STUDY

The objectives of an energy consumption forecasting project typically :

A. Accurate Prediction:

Develop models that accurately predict future energy consumption patterns, allowing stakeholders to plan and allocate resources effectively. Implement a machine learning model capable of accurately forecasting short-term and long- term energy consumption patterns.

B. Resource Optimization:

Enable energy providers to optimize the allocation of resources, reducing inefficiencies and minimizing operational costs. And also enable distribution based on the predicted demand, ensuring efficient utilization of available resources.

C. Grid Stability :

Assist in managing grid stability by forecasting peak demand periods, facilitating proactive measures to ensure a reliable energy supply.

D. Cost Reduction :

Contribute to cost reduction initiatives by aligning energy production and distribution with anticipated demand avoiding unnecessary expenditures. And provide accurate and timely energy consumption forecasts to aid in strategic planning, budgeting, and resource allocation for energy-related projects.

E. Sustainability :

Support sustainable resource management by promoting efficient energy use and reducing environmental impact through informed decision-making and supporting the integration of renewable energy sources based on forecasted demand.

F. Operational Efficiency:

Improve the operational efficiency of the energy sector by minimizing waste, optimizing load distribution, and enhancing overall system performance.

G. Regulatory Compliance :

Assist in meeting regulatory requirements by providing accurate and timely information to regulators, helping organizations adhere to energy consumption standards and guidelines.

H. Resilience:

Enhance the resilience of the energy infrastructure to adapt to changing demand patterns and external factors, ensuring a robust and responsive energy grid.

Figure 2: Energy Management

Figure Reference: https://images.app.goo.gl/SKJkmqL8wFb5NKTYA

III. LITERATURE REVIEW

The literature on web-based platforms encompasses electricity consumption and its various influencing factors have garnered much attention in recent literature. The work by Ahmed et al. offers an in-depth analysis of electricity consumption in Australia, emphasizing the role of clean energy in mitigating CO2 emissions. Their findings reveal a strong correlation between the uptake of clean energy sources and the reduction of CO2 emissions, indicating that clean energy adoption significantly aids Australia's environmental goals. While Australia's efforts lean towards clean energy adoption, Ghana's electricity consumption shows a different dynamic. Ansu-Mensah and Kwakwa delve into the association between electricity consumption in Ghana and financial development indicators. Their research suggests a nuanced relationship wherein economic and financial advancements play crucial roles in shaping the electricity consumption patterns in the country. Electricity consumption and its various influencing factors have attracted much attention in the recent literature. The work of Ahmed et al. provides an in- depth analysis of electricity consumption in Australia and highlights the role of clean energy in reducing CO2 emissions. Their results show a strong correlation between the use of clean energy sources and reductions in CO2 emissions, suggesting that the adoption of clean energy significantly supports Australia's environmental goal.The consumption patterns within urban households and smart buildings also offer valuable insights. Bakó et al. investigate electricity consumption habits within Hungarian urban households.

Their study highlights the varying consumption patterns influenced by socioeconomic factors, urban infrastructure, and public policy measures Similarly Arteconi and Arteconi assess smart buildings energy efficiency and flexibility attributes. They argue that with advancing technology and growing awareness of energy consumption, smart buildings are evolving to become more adaptive and energy efficient .

IV. THE PURPOSE OF THIS PLATFORM

The purpose of the energy consumption forecasting platform is to provide a efficient solution for predicting the future consumption of energy in various fields. The platform aims to offering a user-friendly web application. Key purposes of the platform include:

A. Optimizing Energy Usage:

By accurately predicting energy consumption, stakeholders can better manage energy resources, leading to optimized usage patterns. This can result in cost savings, reduced waste, and improved efficiency.

B. Resource Planning:

Energy suppliers, grid operators, and policymakers can use forecasting models to plan for future energy demand. This includes determining appropriate infrastructure investments, capacity expansion, and resource allocation to meet projected demand.

C. Renewable Energy Integration:

Energy consumption forecasting supports the integration of renewable energy sources, such as solar and wind, into the grid. By predicting energy demand, stakeholders can better match renewable energy generation with consumption patterns, maximizing utilization and minimizing reliance on fossil fuels.

D. Carbon Emission Reduction:

Accurate forecasting enables better planning for demand-side measures aimed at reducing carbon emissions. By aligning energy consumption with low-carbon energy sources and promoting energy efficiency, forecasting models contribute to broader sustainability goals.

E. Consumer Empowerment:

Providing consumers with insights into their energy consumption patterns empowers them to make informed decisions about their usage habits, potentially leading to reduced energy consumption, lower bills, and environmental impact

F. Forecasting:

The trained model is now made to predict the values for next months. The forecasted value has 95% confidence interval within which the value may lie.

V. SCOPE AND METHODOLOGY

A. Scope:

The scope of an energy consumption forecasting project involves predicting future energy usage patterns using historical data and relevant factors. The project typically includes:

- **Data Collection:** Gather historical energy consumption data from various sources, including utility providers. Collect supplementary data such as weather conditions, holidays, and economic indicators, and other relevant factors that influence energy consumption.
- **Data Preprocessing:** Clean and preprocess raw data to handle missing values and outliers, and ensure consistency. Normalize and standardize data to improve model performance.
- **Model Selection:** Choose appropriate forecasting models (e.g., time series models, machine learning algorithms) based on project requirements.
- **Feature Engineering:** Identify and incorporate relevant features influencing energy consumption, such as seasonality and special events. Explore the correlation between external factors(e.g., weather conditions) and energy consumption.
- **Model Development:** Select appropriate machine learning algorithms, considering factors such as accuracy, interpretability, and scalability. Train and develop forecasting models using historical data.
- **Validation:** Validate the accuracy of model performance using testing datasets and appropriate metrics.
- **Integration:** Integrate forecasting models with existing energy management systems or stakeholder platforms.
- **Visualization:** Develop visualization tools and dashboards for presenting forecasted energy consumption trends.
- **Reporting:** Generate regular reports summarizing forecast accuracy and key insights. Test data is provided to trained model and value for next months is obtained from graph.
- **Continuous Improvement:** Establish a robust monitoring system to continuously assess the oerformance of the forecasting model. Implement mechanisms for continuous model monitoring, updates, and retraining based on new data in energy consumption.
- **Scalability and Adaptability:** Design the project to scale with increasing data volumes and adapt to changing energy landscape conditions.

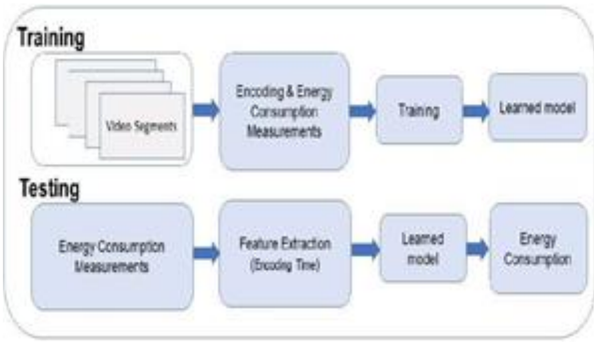

Figure 3: Modelling

Fig_Reference: https://images.app.goo.gl/PbUfYXXU4cwutu567

- **Knowledge Transfer:** Document the entire process, methodology, and implementation details to facilitate knowledge transfer, training, and future enhancement. Facilitate knowledge transfer to stakeholders and end-

users for ongoing system maintenance and improvement.
The overall scope aims to provide accurate energy consumption forecasts, enhance resource planning, and support decision-making processes for stakeholders in the energy sector.

B. Methodology:

Time series is made using ARIMA for forecasting values over a confidence interval. Time series data can't be split randomly into train and tests. First 85% observation used for training the model and remaining 15% for testing.

- **Data Visualization:** Dataset is plotted with x-axis(date) and y-axis (units consumed kWh). After careful observation a seasonal component is observed repeating every year.
- **ADF Test:** Stationary dataset is given to the model for training. To check for the stationary, trend and seasonality components are observed. For stationarising, trend and seasonal components are removed and ADF test is performed to see if null hypothesis can be rejected or not, for rejecting it p value should be less than 0.05. Differencing is also performed to stationarise the data and differencing with greater order tends to overfit.
- **Autocorrelation and Partial Autocorrelation Function:** The parameters required by ARIMA model represented as**-** p is differencing order i.e. 1 and p, q are obtained from AR and MA models using ACF and PACF graphs
- **Prediction:** The Residual Sum of Squares (RSS) of data is close to 0 it means data is distributed stationarily.

VI. DISCUSSION

In the model for the building we are interested in, it is observed that consumption of energy was higher on conspicuous days rather than on normal days. Also, it is seen that energy consumption during the day is more as compared to nights. It is also believed that the increase in energy consumption are largely due to the nature of activities during that time frame. An important variable in predicting energy consumption are the activities that are carried out in any building. Commercial activities such as in a restaurant/cafe or any production facility with fixed schedules are also associated with energy consumption profile. Additional data on the components of these activity variable are collected and incorporated into an updated model for further increasing the accuracy of the performance and provide better residual values.

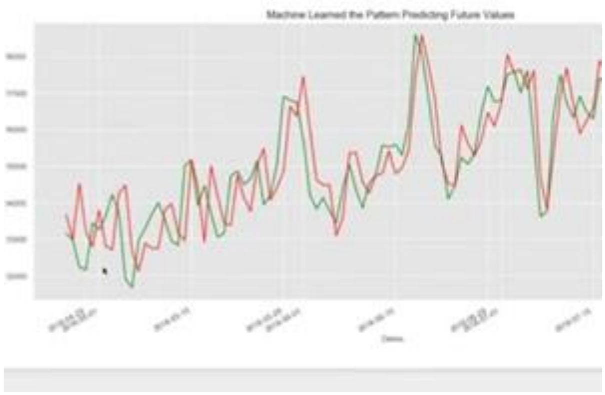

Figure 4: Result of Data Flow

Fig_Reference: https://www.youtube.com/live/rAYFuFNOCic?si=S5EvCs-aD3tpEyne

A. Risk and Mitigation

- **Data Quality Issues:** Implement thorough data cleaning and validation processes.
- **Model Overfitting:** Regularly validate the model's performance.
- **Changing External Factors:** Design the model to adapt to changing environmental and economic conditions.
- **System Integration Challenge:** Collaborate closely with IT teams and conduct thorough testing.

VII. CONCLUSION

In Conclusion The investigations done for the patterns of energy consumptions in our local buildings have revealed some important observations that are relevant for future research and energy management. In recent years, forecasting electricity usage using machine learning approaches has gained popularity as a study topic. Accurately projecting future power consumption is essential for effective energy management, cost savings, and environmental sustainability given the rising demand for energy. It is important to keep in mind that forecasting electricity consumption is a challenging process that calls for careful consideration of a number of variables, including seasonality, time of day, and weather. To make accurate forecasts, it is essential to choose the right characteristics and models. Additionally, predicting energy consumption is a continual process that has to be updated and monitored often to account for changes in consumer behaviour, environmental conditions, and other pertinent variables.

CONFLICT OF INTERREST

The authors declare that they have no conflict of interest.

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