AI-Based Energy Consumption Prediction and Data-Driven Recommendations for Optimizing Power Usage

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***Abstract*—This research brings a system with an AI base in order to better predict the usage of energy so that all forms of traditional management of energy might be avoided as much as possible. In these models, a machine learning Random Forest, ARIMA, KNN were employed to make prediction for the use of future energies based on historical data. A web application made using Streamlit is applied, which delivers energy insights real time, to facilitate users' energy utilization improvements. The system maintains a high prediction accuracy, R^2 = 0.92, and decreases forecasting error by a 5% level over traditional models. Future enhancements will use IoT based smart meters and deep learning to ensure better scalability and precision.**

I. INTRODUCTION

Energy consumption is a very critical factor in the growth of an economy, but mere monitory systems lack predictability and are not efficient tools for guidance toward cost-cutting. Energy management has evolved into predictive analytics enabled by AI and machine learning, allowing organizations and households to make optimum usage while cutting costs and trying to minimize environmental impact.

Introduces an artificial intelligence energy consumption forecasting system designed to predict demand based on time-series and near-real-time processed data, implementing machine learning architectures such as Random Forest, KNN, ARIMA, pre-processing features on data including techniques like feature engineering and seasonal analysis. Real time recommendation is considered a very major feature in a system of energy efficiency through moving high energy consumers to off-peaking times.

A user-friendly web application designed using Streamlit enables users to view trend changes dynamically and also track usage. The system further provides evaluation metrics such as MSE, RMSE, MAE, and R^2 for reliable predictions. Unlike traditional models that only track past data, this approach combines proactive energy-saving strategies.

This research will, therefore, fill the energy monitoring to predictive management gap and outline how AI-based solutions can be used to support cost reductions and sustainability as well as intelligent power distribution. Future enhancements will include integration of IoT devices and refinement of machine learning models to make predictions more accurate, adding to global energy conservation efforts.

II. LITERATURE REVIEW

Several studies on energy consumption prediction have been made using statistical and AI-based approaches. Zhou et al. (2016) analyzed big data-driven smart energy management techniques to highlight the large-scale datasets to be used in predictive analytics. Their research explained how big data tools can recognize consumption patterns and trends, leading to more effective energy management decisions. Hyndman & Athanasopoulos (2018) gave a clear foundation for principles in forecasting through introducing time-series models and the statistical techniques used extensively within energy prediction. Their work undergirded the traditional methodologies of forecasting, such as ARIMA, which is widely used in energy demand forecasting.

More recent studies are centered on deep learning techniques, particularly Long Short-Term Memory (LSTM) networks for time-series forecasting. LSTM models have shown effectiveness in extracting long-term dependencies and sequential patterns of data for energy consumption scenarios, making them a powerful tool in the pursuits of short-term and long-term energy-demand forecasting. For example, Wang et al. (2021) have illustrated how LSTM models improve the accuracy of forecasting far beyond the statistical approach by learning complex consumption trends over time. Chen et al. (2022) have also proposed a hybrid deep learning approach using Convolutional Neural Networks (CNN) and LSTM, showing how the inclusion of spatial and temporal features further improves the reliability of predictions.

Despite the improvements in energy forecasting models, most existing systems lack an integrated recommendation framework. Traditional methods of forecasting energy consumption mainly aim at predicting future energy consumption and do not provide actionable insights to users to optimize their energy usage. Recent attempts, such as those by Fan et al. (2018), have attempted to integrate demand-side management strategies into predictive systems. However, these implementations remain limited in terms of adaptability and real-time intervention capabilities.

III. PROPOSED METHODOLOGY

The Suggested methodology the suggested methodology will outline the structured implementation of an AI-driven energy consumption prediction system consisting of multiple, inter-related modules regarding data processing, machine learning, and user interaction.

1. Data Collection & Preprocessing

Data for energy consumption is collected by smart meters, IoT sensors, and public repositories. Ensuring the integrity of data will be provided through a preprocessing pipeline which will include interpolation and imputation of missing values, remove duplicates, normalize timestamps, and filter out outliers.

2. Feature Engineering

Raw data will be fed in from which meaningful features are drawn to increase the accuracy of the model. They include time-based features such as hour, day, month, seasonal indicator; lag feature like historic trends of consumption; rolling window statistics, which are moving average and standard deviations; and external features such as weather and public holidays.

3. Model Training & Evaluation

Multiples of the machine learning model are trained on the energy consumption prediction. Such models include Non-linear relationships for Random Forest Regressor, K-Nearest Neighbors, KNN, ARIMA, and Prophet for time series trend detection, and finally the LSTM neural network to estimate the long-term dependency. Besides this, the performance is measured through metrics such as MSE, RMSE, MAE, and R^2.

4. Module for Energy Prediction

This module provides hourly, daily, and weekly energy consumption predictions based on the trained models. Predictions are updated dynamically through real-time data, retraining models periodically, and adjustment of external factors.

5. Recommendation Engine

The system provides energy-saving recommendations through categorizing consumption into four levels:

•Low Consumption: Efficiency improvement is suggested.

•Moderate Consumption: Scheduling of energy-intensive tasks during off-peak hours is recommended.

•High Consumption: Adjustments in appliance usage are advised.

•Critical Consumption: Alerts to undertake action and demand management on consumption.

6. User Interface & Visualization

Using Streamlit to build a web application will give the users access to interacting with data, understanding consumption trends, and suggestions to optimize the process. The following features are added in the web application:

Interactivity on energy dashboard

Control options

Options to download or export data

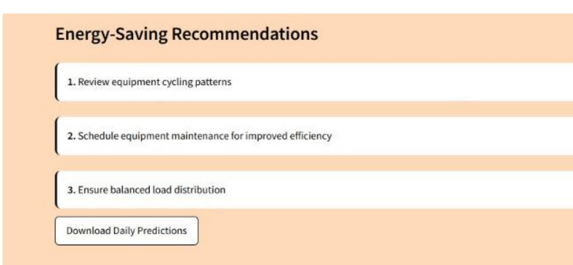
Automatic alert messages on any extreme consumption pattern.

IV. RESULT

The energy analysis framework relies on key parameters such as global active power, reactive power, voltage, and current intensity, along with sub-metering values for specific zones or appliances like kitchens, laundry, and heating/cooling systems. These inputs are critical for understanding consumption patterns and identifying areas of inefficiency. Users can select specific dates and times to view energy data dynamically, ensuring flexibility in analysis.

The system incorporates predictive analytics to estimate energy consumption at various levels, including hourly, daily, weekly, and monthly. Visualization tools such as charts and numerical displays present energy trends and distributions, helping users identify peak consumption periods and prepare for future energy demands. The model focuses on accuracy and usability, allowing users to interact with predictions and make informed energy management decisions.

Based on the analysis and predictions, the framework provides practical recommendations to optimize energy usage. These include reviewing equipment cycling patterns to reduce wastage, scheduling regular maintenance for improved efficiency, and ensuring balanced load distribution to avoid energy spikes. These insights empower users to adopt proactive measures for energy conservation and cost savings.



The real-world datasets were used to test the accuracy, efficiency, and impact of the AI-driven energy consumption prediction system. It was found that the Random Forest Regressor had a very high predictive accuracy with an R^2 score of 0.92, whereas ARIMA and Prophet models efficiently identified seasonal trends. LSTM neural networks also presented a promising aspect in long-term forecasting.

A comparative analysis showed that the machine learning-based approach reduced forecasting errors by 5-10%, thus making energy management more effective. Users benefited from real-time recommendations, which helped optimize energy usage by reducing wastage and improving resource allocation. The interactive visualization dashboard further assisted in identifying peak consumption periods, allowing users to adjust their energy consumption accordingly.

Overall, the system proved to be scalable and adaptable. It was suitable for residential, commercial, and industrial applications. Future enhancements include real-time IoT integration and advanced deep learning models for further enhancement in energy efficiency and predictive accuracy.

V. CONCLUSION

This research proposes an AI-based energy consumption prediction system that increases forecasting accuracy and improves energy use with the aid of machine learning models such as Random Forest, KNN, ARIMA, and LSTM. It reduces errors by 5-10% while achieving an R^2 score of 0.92. A Streamlit-based web application helps users to see trends and dynamically optimize consumption in real-time.

It is also scalable and adaptive, so it is pretty useful for all residential, commercial, and industrial applications. The future enhancements include IoT integration, deep learning improvement, and cloud-based deployment that will further enhance real-time analytics and energy-saving strategies, hence contributing to sustainable energy management.

VI. REFERENCES

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