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Predictive Modelling for Smart Home Energy Optimization using Appliance-Level Data

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***Abstract*— With the rise of smart home technologies, optimizing energy consumption is crucial for reducing costs and environmental impact. This research establishes a predictive modeling approach that examines appliance- level energy data to predict usage patterns and to detect inefficiencies. Employing machine learning, it makes smart scheduling suggestions, taking voltage variations and bandwidth information into account for increased precision. An interactive dashboard will provide actionable insights, assisting homeowners with energy optimization methods, thus reducing electricity bills and minimizing carbon signatures. This research also investigates combining IoT with renewable energy for smart home energy management.**

***Keywords*— Predictive Modelling, Smart Home Energy Optimization, Machine Learning, Appliance- Level Data, Sustainability.**

I. Introduction

The quick adoption of smart home technology has created new opportunities for energy optimization, allowing homeowners to manage consumption of electricity more efficiently and sustainably. Smart homes constantly produce vast amounts of data on appliance usage, voltage fluctuations, energy usage patterns, and network bandwidth. All this data gives an ideal platform for application of machine learning algorithms in order to create predictive models that can enhance energy management. By analyzing energy consumption at the appliance level, these models can predict consumption patterns, identify inefficiencies and offer intelligent suggestions on how to best utilize energy such as moving energy -intensive tasks to off -peak periods, coordinating appliance usage with dynamic electricity prices. Adding voltageand bandwidth data further enhances the precision of these projections by considering current conditions of smart homes.

The objective of this project is to create a predictive modeling platform that provides actionable energy insights via an interactive dashboard. This platform will enable users to make smart energy decisions, save on electricity bills, and aid in sustainability initiatives by mitigating peak demand and overall grid stability. Even though plenty of data is being created in smart homes, homeowners do not possess the tools to properly understand and leverage this data for energy optimization. Conventional energy monitoring systems offer only minimal feedback and no predictive analysis or intelligent scheduling as a function of real time conditions and dynamic pricing models.

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There is a clear need for a system that: A) Accurately forecasts appliance-level energy consumption using machine learning techniques. B) Identifies energy inefficiencies and provides actionable recommendations. C)Supports intelligent scheduling of appliance usage based on non-peak hours and tariff changes. D)Presents energy data in a user-friendly dashboard for real-time monitoring and decision- making. E) Encourages environmentally conscious behavior and integrates potential for renewable energy sources. This project addresses these challenges by designing a comprehensive predictive modelling solution for smart home energy optimization using appliance-level data.
The paper is organized as follows. Section II details about literature survey. The proposed work and experimental results are discussed in sections III and Section IV respectively. The paper is concluded in Section V.

II. LITERATURE SURVEY

The literature review is carried out by considering the existing works on predictive modeling and machine learning approaches, optimization algorithms and load scheduling, IOT enabled and vision-based control systems and integration of smart grids and broader systems.
The work in [1] Cîrnaru and Căuniac employ traditional regression methods—Linear Regression, Random Forest Regression, and Gradient Boosting—to model energy usage in smart homes. Their hybrid predictive approach balances user convenience with energy reduction, ensuring accurate energy forecasts for efficient scheduling.
In [2] Akibor et al. integrate a Genetic Algorithm (GA) with a Long Short-Term Memory (LSTM) network, forming a GA- LSTM model—to optimize energy consumption forecasts. Their method improves prediction accuracy over a baseline LSTM model by incorporating external factors such as weather conditions, thus enhancing energy management strategies.
Kumar and Sundaram in [3] utilize machine learning methods, specifically the Stochastic Gradient Descent (SGD) algorithm, to optimize energy usage. While this study acknowledges challenges like data privacy, accuracy, and associated costs, it reinforces the potential of data-driven methods for dynamic energy optimization in smart homes.
Optimization techniques are central to achieving cost-effective energy management in smart homes. Meta-heuristic algorithms and linear programming approaches are common themes in literature. Ikram et al. [4] investigate load scheduling using two meta-heuristic optimization techniques. Their simulation results show that strategic appliance scheduling can reduce electricity costs by 4.5% while simultaneously enhancing user comfort.
Linear programming offers another robust strategy. Autuori et al. [5] develops a simulation model using linear programming and the CPLEX solver to optimize the integration of photovoltaic (PV) panels and battery storage systems. This model efficiently manages energy flows, ensuring that renewable sources are utilized to their maximum potential.
Expanding the scope to multiple smart homes, Prum et al. in [6] introduce a Mixed-Integer Linear Programming (MILP) approach. By integrating Battery Energy Storage Systems (BESS), PV panels, and Electric Vehicles (EVs), their scheme achieves a notable cost reduction of 46.38%. This MILP model illustrates how collective management is of energy resources can result in huge savings across interconnected houses.
Real-time monitoring and control of energy are crucial for smart homes, and IoT technology plays a central role here. Khan in [7] introduces an OCF-IoT connectivity empowered controls system that not only optimizes the energy usage but also regulates the indoor environment to achieve improved comfort. Through the integration of prediction aided control with an enhanced Firefly algorithm the system realizes energy savings of 36.82% with quick response time.
Additionally, new computer vision methods are burgeoning in energy environment. Chenguang in [8] suggests a vision-based method using the YOLOv5n algorithm for face recognition integrated on the Jetson Nano platform. This process not only maximizes energy efficiency but adjustment according to presence of residents and identity but also increases home security thus bringing safety together with efficiency.
Sathya et.al [9] emphasizes the need to incorporate smart home energy management into extended smart grid infrastructures.
Through the use of IoT technologies and smart grid interfaces, their research illustrates how scheduled energy management as a coordinated effort can intensely lower operational costs and emissions in residential as well as commercial structures.

III. PROPOSED WORK

System design is one of the major steps for developing any model as depicted in figure 1.

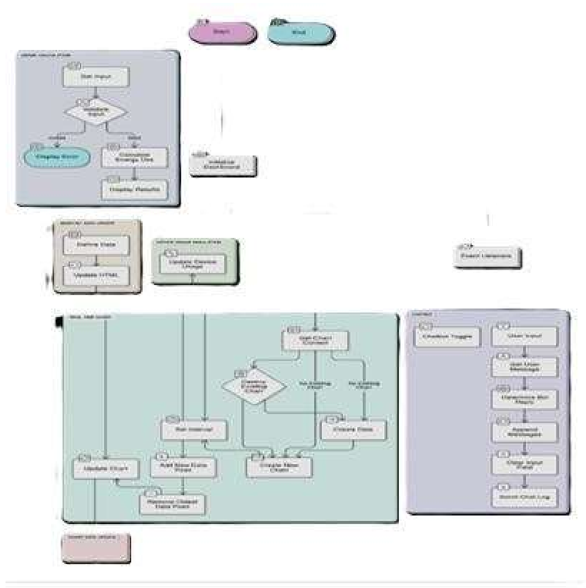

Figure 1. System Architecture

This flow chart represents the structure of a Smart Home Dashboard system. It starts with the dashboard initializing. The model contains modules for usage calculation, device simulation, data updates, real-time charting and chatbot interaction. The usage input is authenticated before calculating and displaying energy use. The charting functions are driven by the monthly data updates and simulated device usage data which are updated in real time. Already existing chart if any is recreated with new information while the old one gets deleted. The chatbot module handles user inputs, decides responses and updates the chat log. The event listeners act as synchronizing agents between modules thus offering an interactive and responsive smart home user interface. The dataset used is from the UCI Machine Learning Repository – specifically, the "Appliances energy prediction" dataset: https://archive.ics.uci.edu/ml/datasets/Appliances+energy+pre diction.

The dataset contains measurements of energy use in a smart home over time, along with environmental variables (temperature, humidity, visibility, etc.). The goal is to predict appliance energy consumption based on these features and improve energy optimization using advanced models like ARIMA and anomaly detection. The dataset contains 19,735 rows (time-stamped data collected every 10 minutes for around 137 days).

The Smart Home Energy Dashboard is an interactive, web-based application designed to help users monitor, predict, and optimize energy usage within a smart home environment. The key functionalities of the system include i) Real-Time Energy Usage Monitoring Displays a dynamic line graph showing energy consumption (in kWh) over time. Allows users to visually interpret peak usage periods. Enables better understanding of consumption trends on a daily basis. Users can select an appliance (e.g., Dishwasher, Refrigerator) from a dropdown menu. A slider lets users specify the number of usage hours per day (1 to 24). The system then calculates and displays Daily Energy Usage (kWh), Helps users understand the impact of individual appliances on their energy bills. ii) Predicted vs Actual Energy Usage Visualizes predictions made by an ARIMA model against actual recorded energy usage. Helps in assessing model accuracy and understanding forecast trends. Assists homeowners in planning energy usage based on expected patterns. iii) Smart Home Chatbot (AI Assistant) Provides a text-based interface to ask questions like: “How much energy does the AC consume per hour?”, “How can I reduce my electricity bill?”, Responds with predefined or dynamic answers based on appliance data and logic. Enhances user engagement and acts as a virtual energy consultant. The Backend Data Handling and Forecasting module reads and processes appliance-level energy data from CSV files. It Utilizes machine learning model ARIMA for Forecasting future usage, detecting anomalies in energy patterns, streamlined via Python libraries namely pandas, matplotlib, scikit-learn, and tensorflow. An UI/UX Interactivity dashboard is built using Streamlit, the dashboard provides a clean, responsive, and interactive interface using which the users can interact with sliders, dropdowns, and real-time graphs without needing technical knowledge.

IV. Results

The Smart Home Dashboard successfully demonstrates a user- friendly interface for monitoring and managing household energy consumption. The implementation provided an intuitive visual representation of energy data, enabling users to assess usage patterns, predict future consumption, and estimate associated costs with minimal effort. The below figures from Figure 2 to Figure 10 depict the various visualization plots that are derived.
Figure 2 shows the functionality of a wattage calculator.

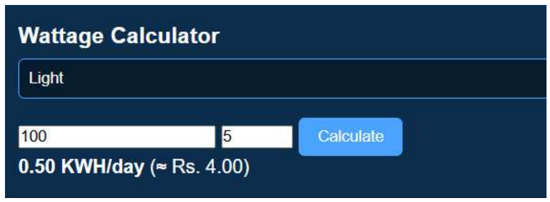

Figure 2. Wattage calculator

Figure 3 shows the functionality of real time updates of the usage of a furnace in the data set for simulated environment.

Figure 3. Real Time update

Figure 4 shows the login page of the application which has the username and password setting mechanism. The authenticity of the user can be verified at the back end.

Figure 4. Login Page

Figure 5 shows the welcome page of the application.

Figure 5. Welcome Page

The below figure 6 shows the daily mean power consumption of an appliance -dishwasher and is clear that the consumption is on an average of 0.04 to 0.06 KW.

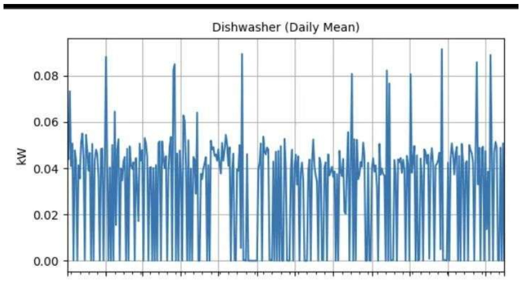

Figure 6. Daily mean power consumption of an appliance -Dishwasher

The figure 7 depicted below indicates the daily mean of a weather parameter, namely wind speed. it is clear that the wind speeds 2.5 mph to 15 mph in normal days affecting the appliances performances due to voltage fluctuation.

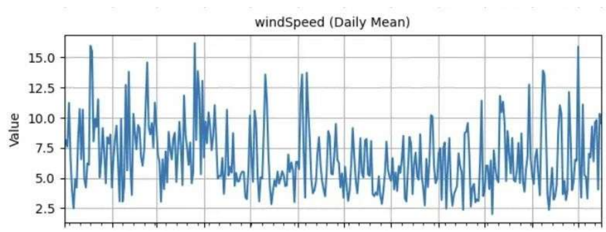

Figure 7. Daily mean value of wind speed

Figure 8 shows the monthly average consumption of the various appliances and the overall home consumption. The figure emphasizes the fact that the consumption of furnaces and fridges contributes more to the overall home energy consumption.

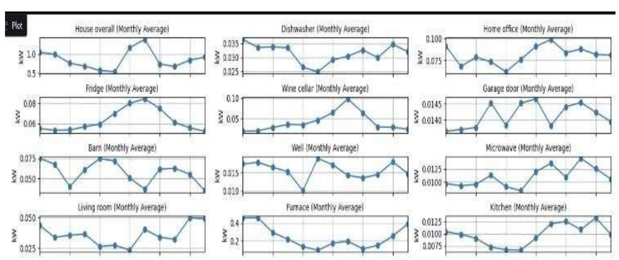

Figure 8. Monthly average consumption

Figure 9 shown below studies the correlation between the daily mean of sum of appliance usage and the house overall consumption.

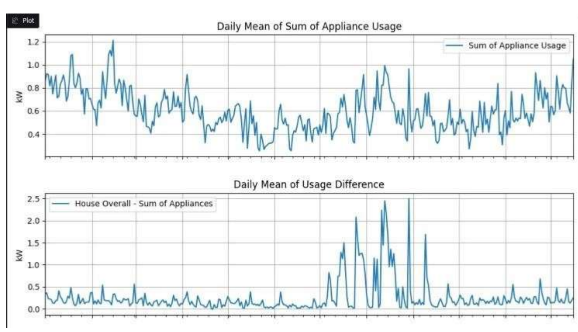

Figure 9. Usage Difference and rolling mean

In Figure 10 the correlation between weather parameters and appliances consumption is presented. The energy consumption of the furnace is mainly dependent on the wind speed which is highlighted in red colour. Likewise, the energy consumption of the air cooler depends on the temperature and apparent temperature which is also indicated in red. The low correlation is between the consumption of furnace and the temperature variance which is indicated in orange color.

temperature_corr	humidity_corr	visibility_corr	apparentTemperature_corr	pressure_corr	windSpeed_corr	cloudCover_corr	windBearing_corr
0.010379	0.011511	-0.002609	0.005560	0.010730	-0.003853	-0.033460	0.011183
-0.015716	-0.001868	-0.008064	-0.014547	0.000211	-0.001672	-0.002395	0.004016
0.011968	-0.006008	0.020638	0.010856	0.027091	-0.017898	-0.039897	0.012427
0.107466	0.030749	0.009019	0.107064	-0.000517	-0.024886	-0.023490	-0.008589
0.289168	0.055541	0.030095	0.288882	0.018494	-0.052860	-0.040467	-0.025930
0.013511	-0.007399	0.002262	0.013578	-0.000276	0.000419	-0.007457	0.012327
-0.017188	-0.002141	0.008376	-0.015189	0.011716	-0.015196	-0.011635	0.006255
-0.004691	-0.006590	-0.001069	-0.004741	0.002994	0.000677	-0.003029	0.004085
0.001369	0.012541	-0.018359	0.002265	-0.001248	-0.006129	0.009580	-0.006218
-0.049781	0.003189	-0.014494	-0.048981	0.013774	-0.013427	-0.009402	0.016713
-0.339845	-0.055172	-0.029998	-0.348868	-0.001174	0.104223	0.010163	0.036634
-0.006106	0.010423	-0.005027	-0.004344	0.003483	-0.010423	-0.007505	0.002839

Figure 10. Correlation table

The second part of the results of the application are the predictive analysis which is presented in the following figures. Figure 11 shows the prediction made by the moving average model with an RMSE value of 0.277 which is having 87% accuracy

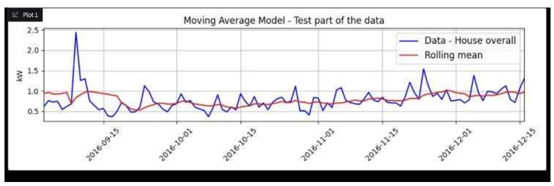

Figure 11. Moving average model

Figure 12 shows the results obtained for persistence algorithm for overall house consumption. The model has RMSE value of 0.388 and 90% accuracy.

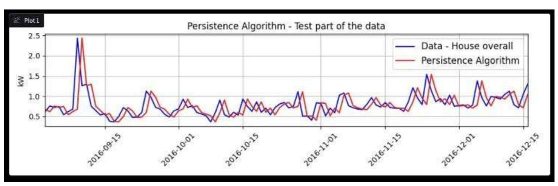

Figure 12. Persistence Algorithm results

Figure 13 shows the tests statistic used for prediction using augmented Dickey-Fuller Test.

Augmented Dickey-Fuller Test Results:

	0
Test Statistic	-2.988
p-value	0.0360301
#Lags Used	10
Number of Observations Used	340
Critical Value (1%)	-3.44973
Critical Value (5%)	-2.87008
Critical Value (10%)	-2.57132

Figure 13. Dickey-Fuller Test Result

In figure 14, the results of ACF and PACF tests are shown in line plots which indicate the correlation between the original and the difference means of the data inputs.

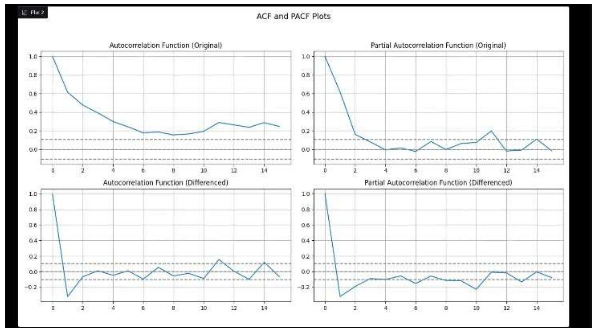

Figure 14. ACF and PACF Plots

The ARIMA Fit result for the training data for annual home energy consumption is as shown in figure 15.

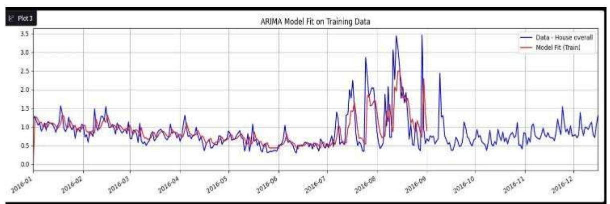

Figure 15. ARIMA prediction for Training data

The performance analysis of ARIMA model for the real test data is presented in Figure 16. The data is for overall house consumption for single cap for a period of 3 months. It is clear from the figure that the prediction is 95 % accurate with RMSE value of 0.585. The rolling forecast is presented in Figure 17.

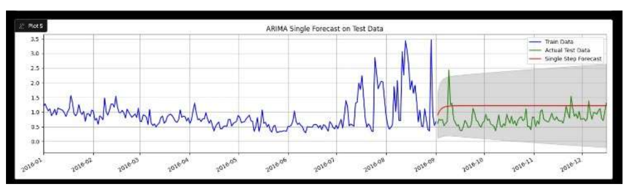

Figure 16. ARIMA prediction for Test data-single cap

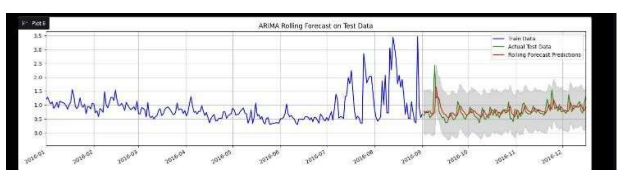

Figure 17. ARIMA prediction for Test data-rolling

The user interaction is provided through the chat application, and the screen shot is presented in figure 18.

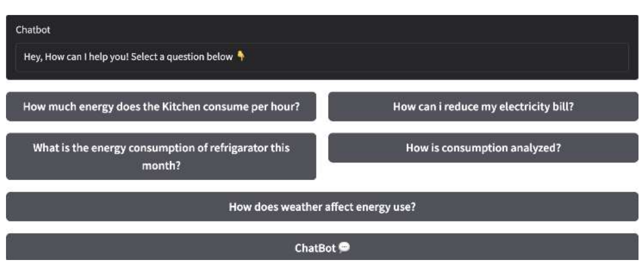

Figure 18. Chat Application

The results clearly state that the proposed solution predicts the energy consumption of appliances used in smart homes with an accurate level of 95%. shown by Random Forest method of 99.79 accuracy percentage.

V. Conclusion

This paper presents a comprehensive smart home energy optimization system that leverages machine learning, deep learning, and IoT-inspired concepts to forecast appliance- level energy usage, detect anomalies, and assist users through an interactive dashboard and chatbot. By utilizing ARIMA for accurate time-series forecasting and reinforcement learning for load balancing, the system not only enhances energy efficiency but also empowers users with data-driven insights and personalized recommendations. The integration of user-friendly visualizations, cost estimations, and a conversational chatbot makes the platform highly accessible and practical for everyday use. As smart homes continue to evolve, this solution lays a solid foundation for future enhancements, including real-time IoT data integration, renewable energy coordination, and mobile support. With continued development, this system has the potential to contribute significantly toward building sustainable, intelligent, and energy-conscious living environments.

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