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Revolutionizing Energy Predictions: Unleashing The Potential of Hybrid Machine Learning for Accurate Household Appliance Consumption and Peak Demand Forecasting

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Abstract: Accurate forecasting of electrical appliance usage and peak demand is crucial for effective planning, maintenance, and the development of automation in electrical power systems. Discrepancies between actual appliance consumption and energy demand may arise from various factors, such as losses in lines and appliances, as well as mismanagement of energy demand. A groundbreaking approach for forecasting household electric appliance consumption and peak demand through a hybrid machine learning (ML) framework is presented here. To address these variations, a thorough examination of smart meter data is essential to pinpoint the key attributes and primary causes of differences between electrical appliance consumption and customers' peak demand. Understanding these intricacies is vital for optimizing power system operations and implementing strategies to enhance efficiency and reliability. The study employs a comprehensive dataset spanning multiple households, ensuring the generalizability of the proposed methodology. Results demonstrate superior predictive capabilities compared to traditional models, offering significant advancements in energy demand forecasting precision. This hybrid approach not only captures nuanced relationships within the data but also adapts dynamically to changing environmental and behavioral factors. As the energy landscape evolves, our innovative methodology stands poised to revolutionize how we understand and anticipate household electricity consumption, providing valuable insights for policymakers, utility providers, and consumers alike.

***Index Terms* - Machine learning, Data filtering, Electrical appliance consumption, Peak demand, Smart meters**

I. Introduction

In the age of intelligent power grids, maximizing energy use is crucial for sustainable and effective management of power [1]. This study explores the complexities of predicting electricity usage and peak demand for household appliances [2], employing a cutting-edge hybrid ML approach [3]. With the integration of smart meters and advanced algorithms, our research aims to close the difference between anticipated and real energy consumption. Smart grids, characterized by their dynamic monitoring and control capabilities, play a pivotal role in this paradigm, facilitating real-time data collection and analysis [4]. Forecasting consumer demand becomes more nuanced as we explore the multifaceted relationships between variables such as weather patterns, socio-economic factors, and historical usage trends. This research not only addresses the challenges posed by traditional forecasting methods but also pioneers a data-driven approach that leverages the potential of ML to enhance the precision and adaptability of household electric appliance consumption and peak demand predictions.

II. LITERATURE REVIEW

Lee et al. [5] compared temporal data analysis, artificial intelligence, and combination approaches for predicting maximum power demand in Korea, favoring LSTM-based hybrids. Syed et al. [6] introduced a highly effective hybrid deep learning (DL) model for smart building energy consumption forecasting, outperforming existing models. Chou et al. [7] introduced a robust hybrid system for 1-day-ahead air conditioner electricity consumption forecasting, outperforming conventional models significantly. Alhussein et al. [8] introduced a hybrid model for forecasting peak load days, achieving a 70% accuracy and potential cost savings. A powerful hybrid energy forecasting model based on machine learning, outperforming existing models with an R-squared of 0.9212 was introduced by Khan et al. [9]. Liu et al. [10] put forward a robust HW-ELM hybrid model for ultra-short-term residential electricity consumption predictions, outperforming existing methods significantly. Sajjad et al. [11] aimed at studying a hybrid CNN-GRU energy forecasting model, offering superior accuracy and efficiency compared to existing methods. introduced A scalable hybrid clustering-based DL model for Short-term Load Forecasting, showing superior accuracy and reduced training time was put forward by Syed et al. [12]. Kiprijanovska et al. [13] put forward a HousEEC, a deep residual neural network performs exceptionally well in forecasting residential energy consumption one day in advance, integrating contextual data for enhanced accuracy. Zhou et al. [14] innovatively addressed building demand prediction complexity using ML and presents an effective hybrid controller for enhanced energy flexibility. Bedi et al. [15] introduced a DL framework for electricity demand forecasting, addressing long-term dependencies and outperforming existing models. Pallonetto et al. [16] compared LSTM and SVM for short-term load forecasting, highlighting LSTM's superior accuracy with sufficient data while favoring SVM with limited data and lower time costs.

III. MATERIALS AND METHODS

In this study, we employ a novel hybrid ML approach that integrates clustering and classification techniques to enhance the accuracy of forecasting electrical appliance consumption and customers' peak demand [17]. The methodology incorporates the faster k-medoids clustering algorithm to derive three distinct clusters from the experimental dataset, subsequently utilized in the classification process. Following cluster identification, optimal features are selected and employed in the classification method [18]. The proposed framework's workflow is illustrated in Fig. 1, providing a clear visualization of the systematic approach implemented in this research.

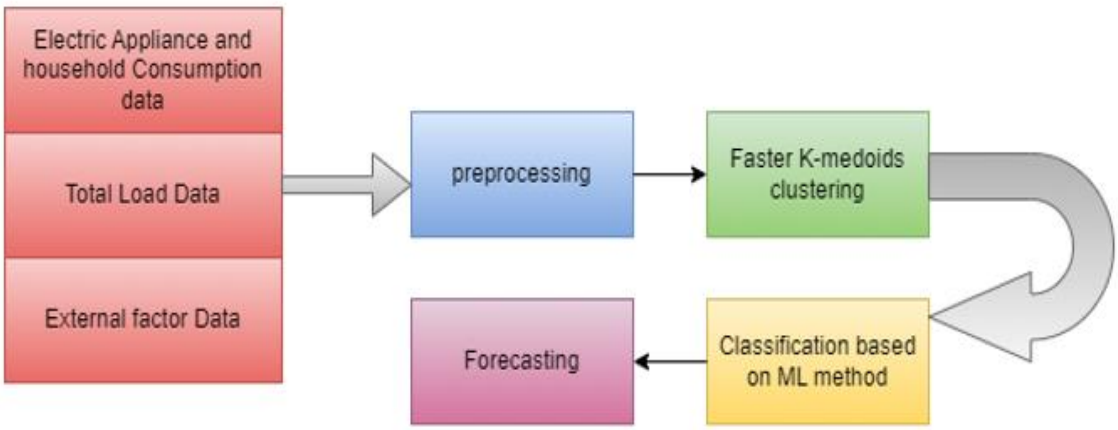

Figure 1: proposed methodology

3.1 Preparation of data analysis

The initial step involves selecting data for ten household appliances, measuring electric consumption in kilowatts (kW) with a 3-minute time interval between samples. The dataset encompasses one year of electricity consumption data, spanning from June 2017 to May 2018. The second main goal is centered on forecasting the highest power usage by customers. Employing the k-medoids clustering method [19], the dataset, sourced from smart meters, includes electric consumption data from 550 households at 30-minute intervals. This dataset comprises unique identifiers for each household, along with customer attributes such as gender and age, alongside 30-minute consumption data in kilowatt-hours (kWh).

3.2 Data Refinement and Optimal Feature Identification

Initial steps were taken to ready the gathered data for precise and effective forecasting. These included identifying missing information, cleaning the data, eliminating noise, applying data filtering, and employing various fundamental preprocessing techniques. The selection of ideal characteristics involved screening the data of electric appliance usage on a daily, weekly, monthly, and annual basis, with a temporal precision of 3 minutes. The identification of optimal features centered on the fundamental, essential, and commonly utilized appliances among customers. Subsequently, ML methods were applied to the raw data.

3.3 k-medoids clustering

The Faster k-medoids algorithm is a clustering method rooted in the principles of the k-mean clustering algorithm. Unlike the traditional k-mean approach, this clustering technique computes the distance matrix just once, utilizing it across all iterative steps to identify new medoids. The algorithm operates in three key steps: first, it computes the gap between two entities, forecasting the starting medoid by picking n objects with the least distance; second, it updates the medoids; and finally, it assigns objects to their respective medoids, resulting in the formation of clusters.

3.4 ML based classification

This study primarily focuses on employing a classification algorithm to predict the annual basis of energy consumption with ten household electrical appliances. Additionally, the algorithm forecasts customers' peak demand for a one-year duration. The Support Vector Machine (SVM) [20], a supervised learning algorithm, is chosen for its effectiveness in classification tasks. SVM utilizes a hyperplane to classify datasets into multiple classes, with the distance from the hyperplane being a crucial factor in classification. The more a point is distant from the hyperplane, the SVM classifier can assign it more accurately to its respective class. Furthermore, Artificial Neural Network (ANN), mimicking the human neural system, is employed. Comprising all layers, ANN processes input to output, with selected ten electrical appliances' consumption serving as input and the ANN's output representing the forecasted customers' peak demand.

4. RESULT AND DISCUSSION

Chosen for forecasting energy consumption were a total of 10 household electrical devices, comprising Refrigerator, Oven, Hair Dryer, Room 1 Lighting, Air Conditioner (A/C)1, Laptop, Water Heater, Television, Iron, and Cloth Dryer. Seven optimal features were chosen based on smart meter measurements, furthermore, data on the average consumption for each device was acquired. is shown in table 1. Data analysis led to the forecast of household electrical appliances consumption, showcasing the yearly consumption of each device in kilowatts (kW) in Fig. 2. The chart illustrates that the A/C has the maximum power usage, followed by the refridge and others.

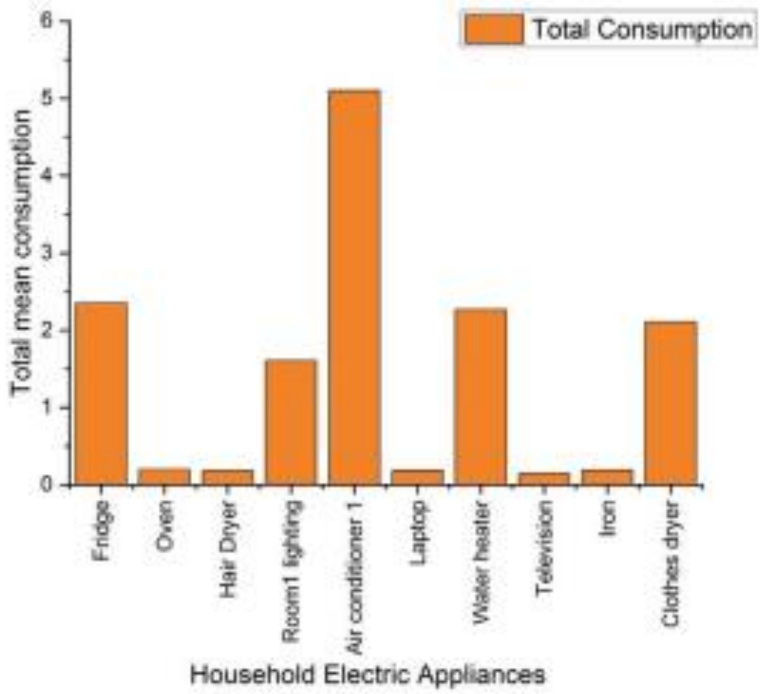

Figure 2: Annual Mean Consumption of Electrical Appliances

In Fig. 3, electric consumption for each equipment is visualized. The consumption pattern over the week, highlighting that the air conditioner consumes the most electric energy. Peak demand periods, characterized by overlapping energy consumption, are crucial for lifestyle assessments. To assess the efficacy of the suggested approach, the error in forecasting was reduced through the use of the ANN technique. The performance of the ANN method was contrasted with different forecasting approaches, such as Random Forest, SMA, and Regression. Fig. 4 demonstrates that the ANN approach yields a lower Mean Absolute Percentage Error (MAPE) compared to other methods.

Table 1: Overview of Mean Values for Seven Electric Appliance Features

Electric appliance	Daily	Weekly	Monthly	Spring	Summer	Fall	Winter	Total
Fridge	0.0832	0.087654	0.0976543	1.43212	1.50678	1.031245	0.754327	2.35276
Oven	0.010632	0.005127	0.009823	0.034176	0.030987	0.025209	0.45825	0.198041
Hair Dryer	0.009365	0.009801	0.013863	0.048163	0.049512	0.048740	0.0490786	0.179241
Room1 lighting	0.116003	0.378002	0.384482	0.430086	0.445012	0.35983	0.35103	1.606804
Air conditioner 1	0.310323	0.814326	0.957234	1.342156	1.402341	0.875198	0.715678	5.098721
Laptop	0.00632	0.008867	0.009899	0.017243	0.020987	0.024207	0.028018	0.186509
Water heater	0.12897	0.159082	0.189563	0.401253	0.370976	0.403487	0.417409	2.26793
Television	0.003345	0.005083	0.008863	0.049972	0.056542	0.074356	0.065628	0.145698
Iron	0.003412	0.0044562	0.008053	0.049765	0.050432	0.046543	0.049712	0.187324
Clothes dryer	0.0682	0.088763	0.099753	1.20982	1.39802	1.198623	1.443207	2.10982

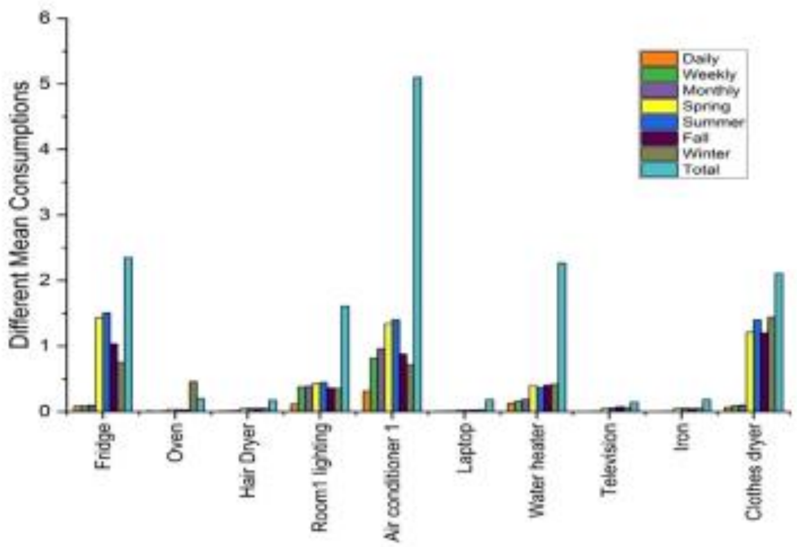

Figure 3: Variation in Mean Consumption Across Electric Appliances

IV. CONCLUSION

A hybrid ML approach, leveraging the Faster k-medoids clustering method, SVM, and ANN predicting the usage of residential electric devices and anticipating the highest power demand was introduced in this study. The proposed method demonstrates impressive accuracy, achieving a 99.2% precision in forecasting electric appliances consumption. Moreover, it significantly reduces Mean Absolute Percentage Error (MAPE) in predicting maximum power requirement. The outcomes confirm the efficiency of our method in enhancing forecasting results. Looking ahead, further investigations and more efficient techniques are recommended to delve into the factors influencing peak consumption by appliances during specific periods. Additionally, efforts should be directed toward shifting peak times to enhance energy conservation further.

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