A Load Classification Strategy using NILM and DNN for Potential Demand-Side Management

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ABSTRACT Uncoordinated and unplanned increases in electricity demand have become a critical concern in recent times due to growing population and appliance utilization. Significant focus has been placed on optimizing load patterns for appliances and capitalizing on the potential for savings in domestic energy management. This paper develops a low-cost demand-side management system for residential applications through smart energy meters, combined with non-Intrusive load monitoring (NILM) and machine learning for accurate load disaggregation. It also presents a real-time consumption-based dynamic pricing algorithm that exploits the use of deep neural networks (DNN) for classifying of essential and non-essential loads, utilizing real-time collected datasets. The system provides live energy monitoring through Modbus RTU and RS485 protocols, with data stored in Postgre SQL database, enabling data visualization on a Power BI dashboard. The dashboard highlights real-time advice on energy optimization. The proposed approach demonstrates an effective demand response (DR) mechanism, shifting electricity consumption to off-peak hours throughout the day without reducing overall energy use. This enhances optimizing the load curve metrics and improves energy efficiency.

INDEX TERMS demand side management, deep neural networks, energy efficiency, NILM, real-time energy monitoring, smart energy meters

I. INTRODUCTION

Due to the increased population and growing consumption of electrical appliances, the requirement for electricity has dramatically escalated, especially in the countries like Pakistan. Some reports have shown a notable difference in generation capacity and demand, leading to blackouts and load-shedding. This situation poses formidable challenges both for power grids as well as for energy suppliers. Moreover, skewed load utilization patterns among consumers causes significant economic challenge due to the difference of cumulative energy production and installed capacity. Classic energy management systems are normally unable to cope up with the intertemporal variance in demand, which leads to peak load problems and higher energy costs for consumers. Optimization of load patterns and appliance utilization in domestic environments is essential for smooth maintenance and cost savings of the grid. Thus, optimization of these factors forms the prime focus of researchers and industry professionals. The process of improving the load usage patterns and improving load curves is commonly known as Demand Side Management (DSM).

This proposed method was tested to demonstrate a low-cost, real-time load identification mechanism for residential consumers using smart energy meters. The meters use the exchange of data communication protocols such as Modbus

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RTU and RS485. Corresponding data is visualized by an interactive Power BI dashboard, and stored in a PostgreSQL database. The database and visualization are demonstrated to assist the consumer realize the energy consumption and gives hints to optimize this load.

Furthermore, the proposed mechanism classifies the appliances as essential and non-essential, using Nonintrusive Load Monitoring (NILM) algorithm and Deep neural network (DNN). The classification can be used to define dynamic pricing algorithms to encourage users to shift non-essential loads during off-peaking hours, hence flattening the load curve.

The rest of this paper is organized as follows: Section II presents a detailed literature review, comparing the proposed work with existing solution in area. Section III describes the methodology and provides a step-by-step account towards how the solution was developed. Section IV presents the results obtained from the proposed system. Section V concludes the paper with highlights of main takeaways from this work.

II. LITERATURE REVIEW

DSM methods have been well explored for reducing energy consumptions and changing demand from peak to off-peak hours [1]. Latest developments also depict those intelligent systems with real-time data inputs for load shifting do indeed result in a successful automation process. DSM combined with real-time feedback and dynamic pricing yields significant energy savings. The fact, however, is that traditional DSM still requires human intervention at times, which lowers the efficiency.

DSM makes consumers, through real-time load monitoring, load control and incentives/penalties from utility, shift their levels of energy consumption at the right time. The major goal is shifting the load from peak times to off-peak times, while fulfilling the overall energy demand and suitably ensuring the consumers' comfort. However, the effectiveness of DSM relies on efficient load patterns detection and proper mechanism of identifying the nature of loads [2]. So that shifting of only those loads can be strategized which does not disrupt consumers' necessities. In this regard, advances in smart metering, and corresponding learning mechanism of load natures using machine learning tools can potentially play a pivotal role [3].

NILM breaks up household electrical consumption into individual appliances without requiring a sensor for every device, which reduces costs and complexity. Hart [4] was the pioneer of NILM in terms of signal processing techniques applied to determine appliances by their power signatures. NILM has been implemented in a large number of smart energy management systems in order to gain detailed insights into residential energy usage [5]. A survey has shown that NILM algorithms, indicating that advanced machine learning models have become considerably more accurate compared to early ones in the domain of load disaggregation. More recent highlights have shown deep learning algorithms in the form of convolutional neural networks (CNN) and Long Short-Term Memory (LSTM) networks are to enhance the accuracy of NILM [6]. This combines NILM with Machine Learning techniques in real-time classification of the other loads that would improve feedforward accuracy and optimize the usage of energy [7].

Machine learning is utilized in the optimization of energy systems, including load disaggregation and dynamic pricing. A study took into account the role of machine learning in the residential energy forecast, where ANNs and SVMs may help in the enhancement of energy consumption prediction [8]. DNNs are currently trending in load classification and has been applied for residential appliances classification, with high accuracy in load disaggregation [9].

Dynamic pricing forms part of the DSM systems which comprise incentives and rewards for the customers to adjust their energy consumption in direct accordance to price signals at any time. Dynamic pricing is acclaimed to reduce peak loads by as much as 30% depending on pricing model and consumer involvement [10]. In addition, Demand Response management (DRM) is needed for DSM to have improved efficiencies [11]. This work utilizes dynamic pricing in the form of a real-time consumption-based algorithm, hence prompting users to shift some of their non-essential loads to off-peak periods. The proposed system integrates DNN based load classification with dynamic pricing, encouraging users to better optimize the energy consumption levels without losing the overall consumption.

Real-time consumption monitoring is quite vital for a good DSM technique. Smart meters and monitoring systems are handled in such a manner that they can contribute to helpful data towards developing the consumption pattern and adjusting appliance use [12]. Real-time data is of paramount importance for optimizing consumption, most specifically in the residential sector, where consumer behavior varies greatly [13]. Integration of real-time visualization tools along with dynamic pricing have a considerable effect on the behavior of the consumers, saving 20% of the consumed energy. Based on these, this paper extends previous works in the literature on demand side management (DSM), non-intrusive load monitoring (NILM), and load disaggregation using machine learning with various contributions that distinguish it [14], [15]. Rather than classic DSM schemes that need human help for solutions, an intense DNN system employed for the real-time differentiation between essential and non-essential loads to carry out proficient load disaggregation [16]. Moreover, the real-time dynamic pricing algorithm, which is integrated into a Power BI dashboard to offer instantaneous feedback through the trained model, convinces users to move non critical loads towards off-peak times. This real-time approach enhances energy efficiency and demand response capabilities that optimize the load curves without compromising the user comfort.

III. METHODOLOGY

The flow of steps in this work comprises of systematized installation of smart meters in residential facilities, their data collection, and corresponding energy consumption analysis. Installed Smart meters installation communicated the load parameters in the MODBUS RTU protocol. This data is collected, processed and fed into machine learning models for disaggregation of load use. The learning outcome is then used to detect the number and nature of appliances in runtime data and its display on dashboard. The detailed steps are as follows:

1. The SME 104D Smart Meter was installed to measure voltage, current, power and energy levels inside the residence.
2. USB to RS-485 converter was used to transmit real-time data using the MODBUS RTU protocol. The parameters for reliable data communication were also configured.

3. The data employed in this research are divided into two categories:
    - Publicly accessible online NILM datasets, and
    - The data gathered with the new hardware system. The hardware was implemented in a home setting to record various home appliances mentioned in Figure 2 over a minimum period of three months.
    - The system was modeled to capture appliance-level power consumption profiles via smart meters with Modbus RTU/RS485 communication, with the captured data stored in a PostgreSQL database for subsequent analysis and training of the DNN-based NILM model.
4. The captured data was stored in the HMI memory and then in the PostgreSQL database. The pre-processing Steps are
    - **Data Cleaning:** This includes correcting the erroneous entries. Errors or missing values because of communication latency or sensor noise were identified and corrected. Outliers and spurious peaks in the data were smoothed out with a moving average filter, while missing values were interpolated with linear interpolation to maintain continuity within the time series.
    - **Normalization:** Scaling the numerical data to improve the performance of the model. To bring all numerical features to the same level of scale and improve model convergence, normalization techniques were employed. Namely, Z-score normalization was used to normalize values such that they are centered at zero mean and unit variance. For certain bounded features, min–max scaling was employed to rescale data to the [0,1] range.
    - **Feature Extraction:** Meaningful features to be extracted, such as mean power, peak load time. Significant features were extracted from preprocessed signals to facilitate the classification process. They are statistical and temporal features such as mean and variance of power usage, peak load time, load duration, and switching event rate. They contain discriminative information on appliance usage patterns that facilitate effective appliance classification through NILM and DNN models.
5. Classification of the usage data, using a wide variety of machine learning algorithms with a focus on Deep Neural Networks Training Process
    - Dataset Split: Training 70% and validation/testing 15% each
    - Loss Function and Optimizer: Categorical cross-entropy and Adam optimizer.
    - Performance Metrics: Accuracy, predicted class probabilities, confusion matrix.
6. Real-time dynamic pricing model based on live data from PostgreSQL.
    - DNN to distinguish between critical and non-critical loads.
    - System recommendation to shut down the loads that are not critical during peak pricing.

- Possible savings with the loads' reduction

7. Provides an energy consumption Power BI dashboard in real-time and costs. It reflects current usage and gives an estimate of what the future costs will be.

IV. RESULTS AND DISCUSSIONS

A. SMART METER INSTALLATION AND COMMUNICATION

The SME 104D smart energy meter was installed as shown in Figure 1, and used to measure the key electrical parameters, namely, voltage, current, power, and energy, in a residential setting. Figure 3 shows an HMI that captures all the required parameters. Various home appliances, such as an air conditioner (AC), personal computer (PC), resistive bulb, and washing machine, were used as test loads. Data communication between the meter and a PC was achieved via a USB to RS-485 converter, which transmitted data in real-time through the MODBUS RTU protocol. The configuration of the communications parameters, including the device address, baud rate, stop bits, and parity, on the meter helps establish reliable and efficient data transfer.

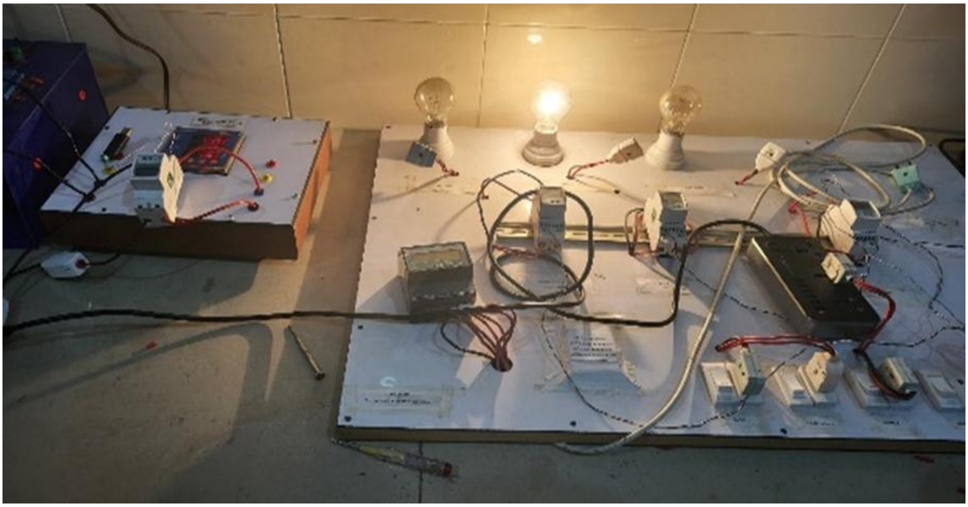

FIGURE 1. SME 104 smart meter collecting data

Data Collected for One Month (August)
Using SME 104 D Smart Meter and RS485 to USB Converter

Appliance	Power (W)	Weekly Usage (Hours)
Air Conditioner (AC)	1300	42
Washing Machine	3500	3
Bulb	100	119
PC	400	21

FIGURE 2. Real-Time data collection duration

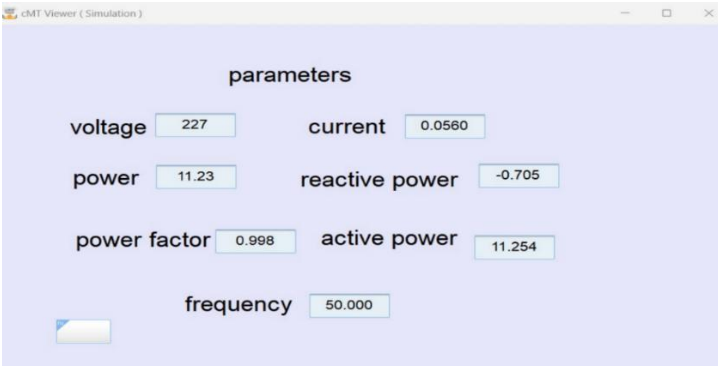

FIGURE 3. Collected features of appliances

B. MACHINE LEARNING FOR LOAD DISAGGREGATION

The energy usage data acquired from the SME 104D smart energy meter was classified and analyzed using a variety of machine learning algorithms. Since DNNs are adept at capturing complex data patterns and yielding high classification accuracy, most attention was given to these. The DNN model was trained on a labeled dataset; each entry of data was tagged with either being an essential load or not. Training was primarily divided into following

1) DATASET SPLITTING

The dataset was divided into training, validation, and testing subsets to test the performance of the model. In normal cases, 70 percent of the data would be used for training, 15 percent for validation, and 15 percent for testing.

2) EPOCHS AND BATCH SIZE

Training the model was done by running it on several epochs, an epoch being simply one run through the training dataset. The batch size was decided to keep track of samples processed before the model updated its weights. The DNN was tested on the test dataset after it has been trained to evaluate its performance given in Figure 4 that shows the model losses and how well it handles data in each epoch.

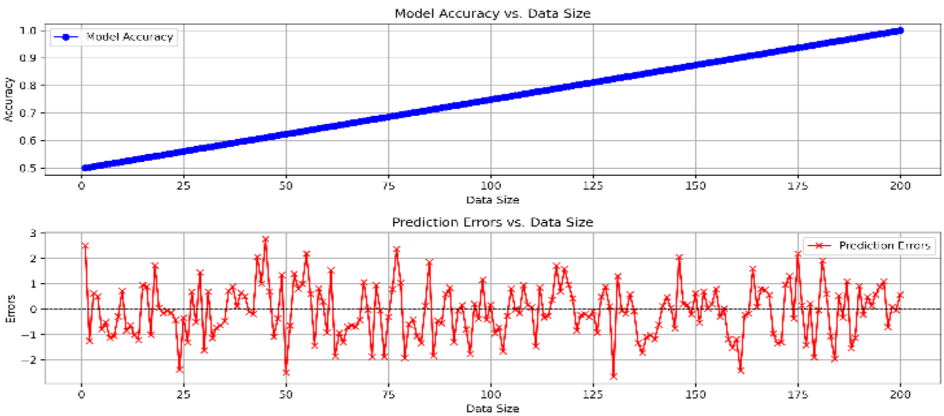

FIGURE 4 . Model error losses while handling dataset

This is the accuracy rate of number of correct predictions made by the model out of the total number of predictions. Similarly, the appropriate loss function which is categorical cross entropy is used for the training of the model. That has been deployed for evaluation of model performance. In Figure 5 that shows model accuracy vs loss over the given data. The Adam optimizer was used to update the weights of the model according to the computed gradients during back-propagation.

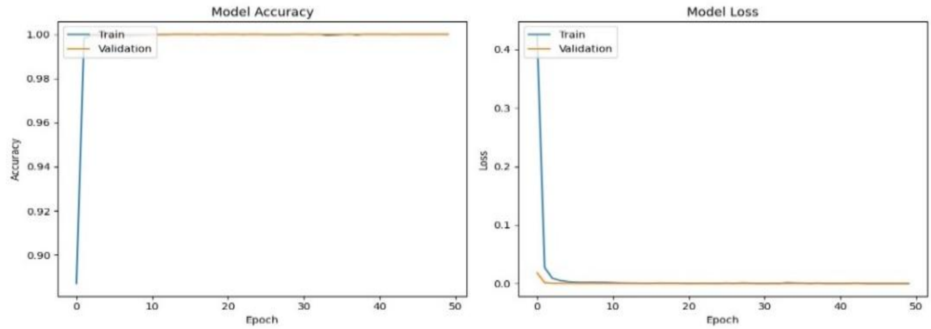

FIGURE 5. Model Loss and Accuracy

The model's predicted class probabilities shown in Figure 6 for every class illustrate the confidence of classifying essential and non-essential loads.

The confusion matrix provides detailed classification result for each class as shown in Figure 7, and it depicts the true positive and false positive rate for every class.

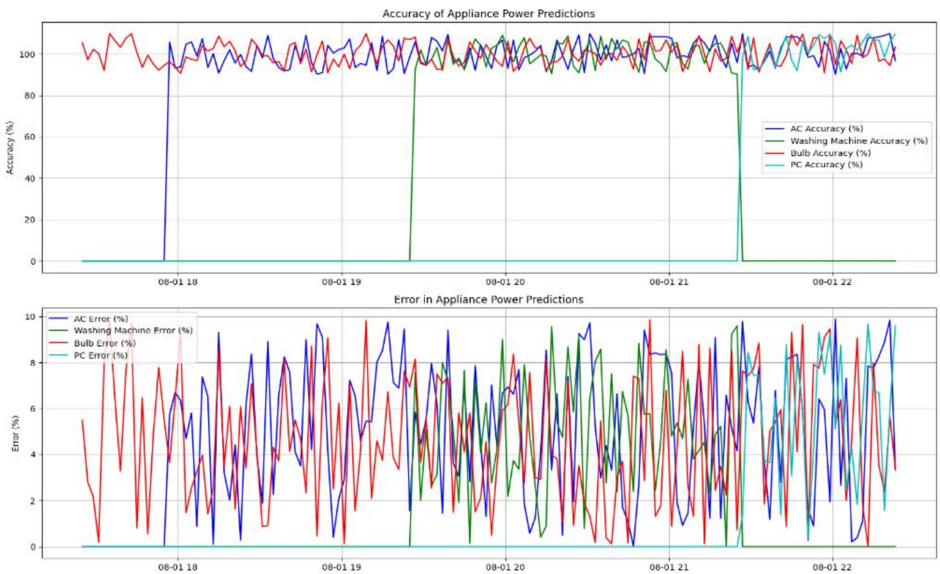

FIGURE 6. Probability and acuuracy for predicting appliances

Figure 7. Confusion matrix

First, the DNN was trained on the pattern of signatures of individual appliances. The different appliances had different characteristics with regard to energy consumption, thus allowing for learning and accurate recognition of their specific operating patterns. Figure 8 shows the individual appliance disaggregation among total power consumed**.** In this training, a labeled set had to be made to indicate when each appliance in a dataset was in use.

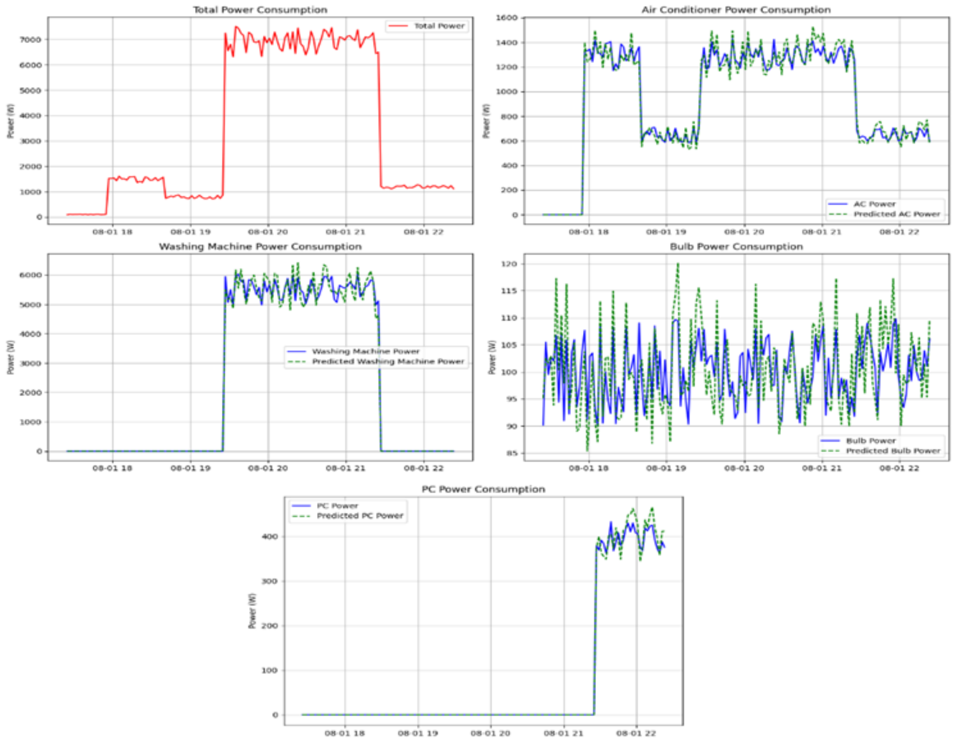

FIGURE 8. Individual appliance contribution of power predicted vs true power

The trained DNN was tested under test scenarios where all appliances were running in sequence. This is necessary as the model would thus estimate the total energy usage in terms of aggregate usage of multiple appliances. Leverage on the knowledge sourced individually from training, DNN ensured a clear distinction of each appliance contribution even when running in tandem, showing the efficiency in load disaggregation. The application of DNNs is of extreme importance to provide a detailed insight into the usage of energy in residential settings. As shown in Figure 9 DNN model successfully disasggregates total house hold power consumption into individual appliance contribution.This enables identification of which appliance are responsible for the majority of energy usage at any given time.It is visible that AC (Air conditioner) is highest contributor in power consumed by house hold. Figure 10 shows quantufying share of each appliance, the system provides consumers with actionable insights for shifting non-essential loads, therby supporting DSM and optimizing overall energy efficiency.

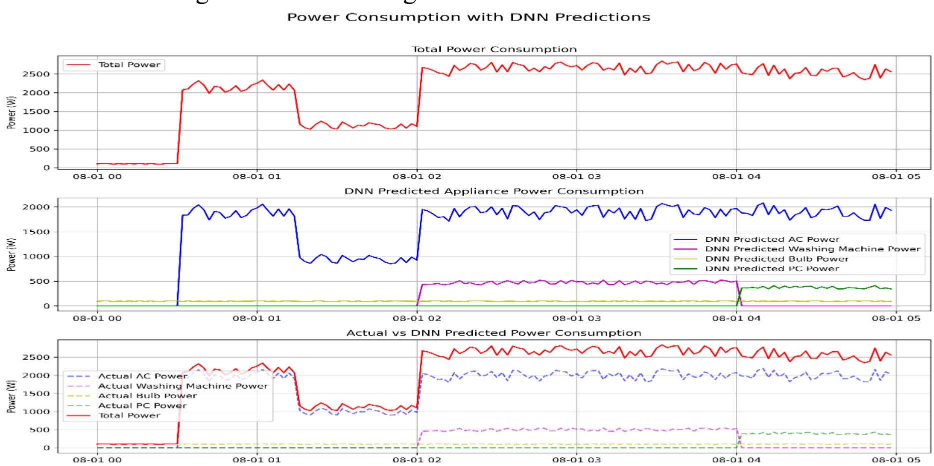

FIGURE 9. DNN predicted each appliance contribution from total power

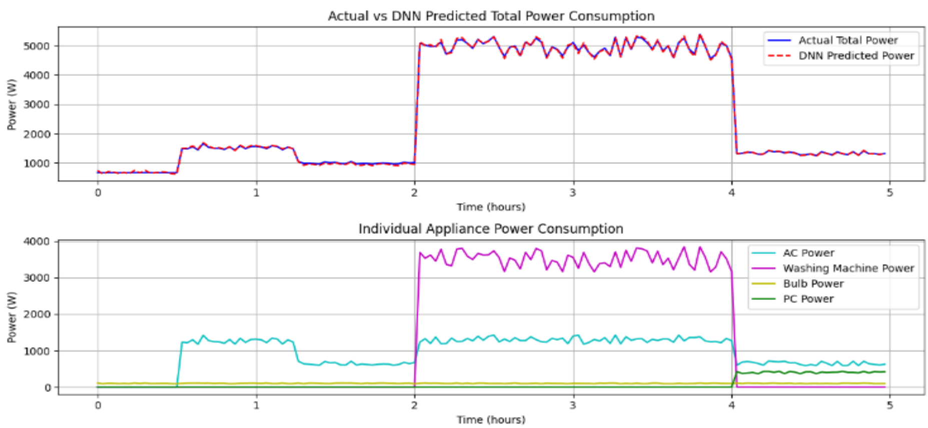

FIGURE 10. DNN predictions based on total power

The architecture of the DNN is a kind of arrangement in the form of a layer of interconnected neurons, functions similarly to that of biological neurons. It processes incoming inputs with the weighted sum and transmits it to an activation function. As shown in Figure 9 the predictions based on the total power and the features which were used to specify trend curve of each appliance. The output layer finally generates predictions telling how likely each appliance will be active at any given time.

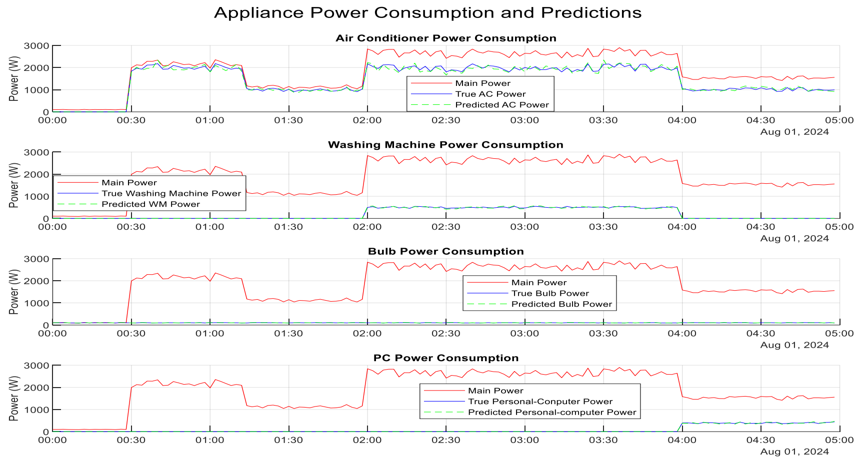

FIGURE 11. DNN predictions based on total power for each appliance

C. DASHBOARD FOR USER ENGAGEMENT

This Power BI dashboard gives real-time data visualization through the monitoring of energy consumption. It fetches its data in real-time from PostgreSQL, reflecting the current voltage and power consumption and the total energy usage shown in Figure 12. In addition, it reflects the current bill and also indicates the estimated charge for electricity for the rest of half an hour based on the consumption pattern as observed at this point in time. Based on this, users can predict their costs and hence avoid unnecessary expenses and ensure efficient management of electricity consumption.

The solution shows these recommendations generated by the DNN model on the dashboard to the users depending on their type: essential and non-essential loads. Hence, the Dashboard prompts users to turn off those devices that they considered non-essential to save energy, thus minimize energy costs. More so, the dashboard provides a list of non-essential loads in operation to allow users to identify which non-essential devices are in operation at a given time shown in Figure 12 is the first page that provides real-time insights of energy consumption through Power BI dashboard where we have added feature for calculating cost against energy consumed by each appliance for user to take actionable decisions based on real data and suggestions .The combination of insights generated from machine learning along with database-driven metrics allows the consumer to be equipped with information to make intelligent use of energy. Dashboard contains a second page shown in Figure 13 which captures running non-essential appliances and if user kept running at this rate how much power consumed and billing cost against it is predicted for user to have clear idea about reduction in cost and user can monitor for how long it is feasible to run a specific appliance.

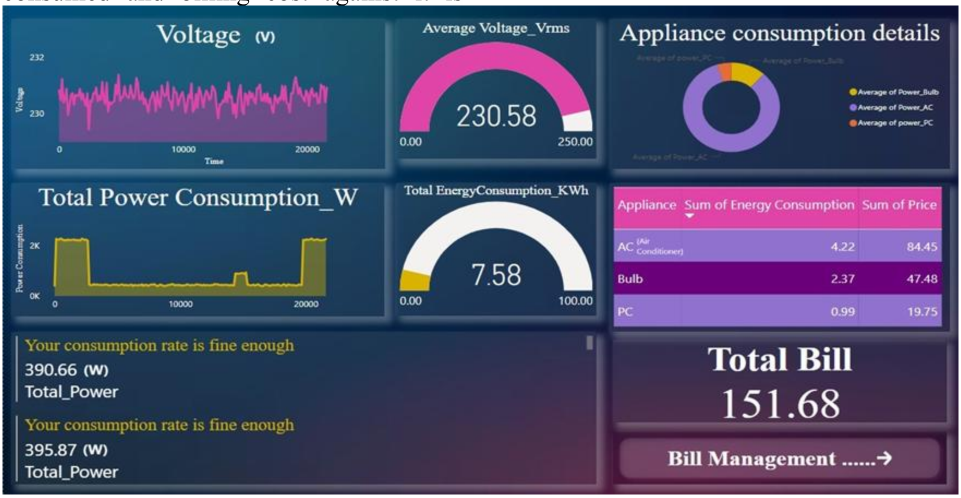

FIGURE 12. Real-Time Power Consumption Visualization

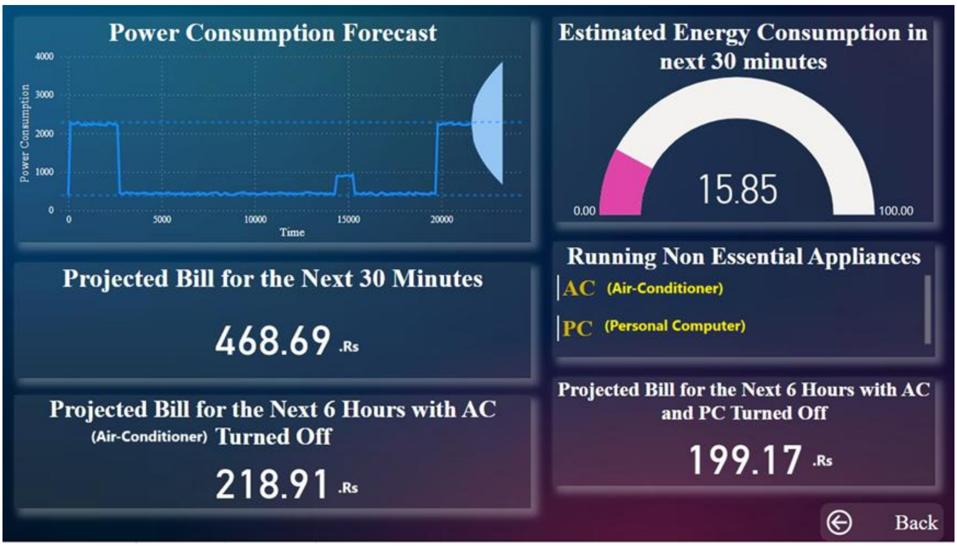

FIGURE 13. Forecasted Bill and list of Non-Essential Loads

D. CONCLUSION

The framework proposed a DSM mechanism for residential loads by integrating smart energy meters, NILM and DNN for identification of shiftable loads in terms of appliances for better energy consumption. The work successfully displayed the monitoring and real-time classification of energy usage. This work also introduces the concept of categorization of essential and non-essential appliances using machine learning so that dynamic pricing strategies are made possible, thus enhancing the potential strategy making for energy efficiency. The methodological approach demonstrates the strength of the DNN in potentially disaggregating load signatures from individual appliances, even if several appliances are running at the same time, and makes an accurate prediction about energy usage. A user-friendly dashboard is also demonstrated to provide real-time insights to the consumers about their energy consumption decisions. This can eventually help reducing electricity costs while maintaining comfort. The framework will encourage proactive practices in energy consumption and ensure stability for the power grid while facilitating the move toward sustainable energy practices.

Future research will focus on expanding the framework through the exploration of larger datasets and extended model training. Particular attention will be given to accommodating appliance energy consumption under varying tolerance levels, addressing nonlinear load behaviors, and improving the practicality of the proposed system for real-world deployment. Furthermore, efforts will be directed toward enhancing scalability, integrating the framework with IoT-enabled smart homes, smart grid platforms and validating its performance across diverse consumer environments to strengthen both robustness and generalizability.

CONFLICT OF INTEREST

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVALIABILITY STATEMENT

The data associated with this study will be provided by the corresponding author upon request.

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