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NON-INTRUSIVE LOAD MONITORING AND IDENTIFICATION USING EUCLIDEAN ANALYSIS

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ABSTRACT

Effective energy cost management and load optimization are pivotal challenges in the 21st century. The intricate nature of electrical loads, coupled with the limitations of existing methods, have fuelled significant research interest in non-intrusive load monitoring (NILM) systems of high accuracy and efficiency. In this study, we proposed an innovative approach for NILM based on Euclidean difference. By meticulously matching real time measurement of load events with predefined dataset connected loads were accurately identified using Proteus software simulations. The system was implemented with Arduino micro-controller and featured liquid crystal display (LCD) for load dis-aggregation feedback. Remarkably, the algorithm achieved 98% accuracy by enhancing load pattern identification and precisely dis-aggregating loads. This research not only optimizes energy consumption but also leads to substantial cost savings for consumers while alleviating strain on the power grid. By harnessing the power of Euclidean difference, we bridge the gap between accurate load dis-aggregation and practical implementation, offering a promising avenue for future advancements in energy efficiency.

KEYWORDS: Non-intrusive load monitoring (NILM), Euclidian analysis, Energy efficiency, Electric load, Smart grid.

1. INTRODUCTION

In recent years, many researchers have developed synthetic approaches for providing a solution to non-intrusive load monitoring (NILM) system. As technology advances and strong interest of research in this area, the concept is getting clearer. The work in[1] highlighted the usefulness of using NILM approach as the best in both energy management and cost effectiveness. However, having a severe drawback and challenges due to the complexity and non-linearity of electrical loads such as industrial, commercial and residential loads, which pose significant challenges due to their varying power factors, harmonic distortions, and intermittent operation, making it essential to develop advanced NILM techniques that can effectively address these complexities and ensure accurate load identification and energy disaggregation. Researchers in,[2] a Convolutional Neural Network (CNN) framework that effectively leverages unlabelled data to enhance supervised and semi-supervised learning was presented, achieving state-of-the-art performance on the Public Library of Appliance Identification Data (PLAID) and outperforming existing methods while reducing the need for labelled data and hyper parameter tuning. As technology advanced, researchers have explored the use of graph theory-based methods for load event matching in NILM systems. As noted by,[3] load event matching is a crucial step in NILM systems, and can be achieved through graph theory-based methods, enabling the classification of load events by their features and improving load identification performance. This approach has shown promising results in improving the accuracy of load identification, and highlights the potential of graph theory-based methods in NILM research. The use of NILM proposals in residential environments is a promising approach to reduce electricity costs, as it enables the monitoring of voltage and current measurements at the home entrance, and identifies equipment status and power consumption. By leveraging a statistical tool and machine learning algorithms, the system was able to identify areas of energy inefficiency and provide insights for cost reduction.[4] The work in[5] used a hybrid method for appliance load signature analysis in NILM systems, which uses a combination of current, harmonic, active and reactive power, and V-I curve geometry features to identify electrical appliances and disaggregate their power consumption. The simulation results demonstrate the effectiveness of this approach in identifying various types of electrical appliances, including resistive, inductive, capacitive, linear, non-linear, electronic, and non-electronic devices, even those with low power consumption.

The study in,[6] presents the Reference Energy Dis-aggregation Data Set (REDD), a public data set for energy dis-aggregation research. The study discussed previous approaches, described their data collection setup, and test a Factorial Hidden Markov Model (FHMM) technique. While the FHMM shows promise, there is room for improvement, and further research could explore modifications such as incorporating hard constraints on device signals, exploring more complex features of the power signal, and semi-supervised techniques for dis-aggregation to enhance accuracy and effectiveness. In,[7] an approach for household appliance identification and classification of household Activities of Daily Living (ADLs) using residential smart meter data was presented, leveraging deep learning techniques and a framework for mapping identified appliances to ADLs. While it demonstrates effectiveness through experimental results and publicly available data sets, there are areas for improvement, including a more detailed explanation of the deep learning algorithm and hyper-parameters, additional comparisons with existing approaches, and consideration of potential data quality issues.

A smart energy management system was developed and simulated using Proteus Visual Design software and Arduino Mega 2560 board. The system measures and analyses load power consumption for single-phase and three-phase loads, and displays the results in a user-friendly format. The system aims to provide a cost-effective and user-friendly solution for smart energy metering and automatic load control, and has the potential to contribute to energy-saving goals.[8] The work reported in,[9] proposes a deep learning approach for energy dis-aggregation, which is the task of separating the total energy consumption of a building into individual appliance usage. Unlike previous methods that learn a single layer of dictionary for each device, this approach learns multiple layers of dictionaries for each device using deep sparse coding. Experimental results on two benchmark datasets show that this method outperforms state-of-the-art techniques. However, the approach has limitations, including not being suitable for real-time dis-aggregation, and future work includes incorporating additional assumptions and exploring practical applications such as dis-aggregating specific loads.

Research has shown that smart energy management systems can significantly reduce energy consumption. Researchers in[10] presented a promising approach using Proteus Visual Design software, but its limitations, such as being simulation-based, warrant further investigation.

Future studies should focus on hardware implementation and comparative analysis with existing solutions.

As noted by,[11] NILM provides households with cost-effective, real-time monitoring to understand consumption patterns and contribute to energy conservation. Recent reviews highlight NILM's potential, discussing state-of-the-art algorithms, performance metrics, benchmarking frameworks, public datasets, and future research directions, underscoring the need for more accurate algorithms, scalability solutions, and explorations of new applications. NILM has emerged as a crucial aspect of energy management, posing significant challenges in recent years. To address this, researchers have explored deep learning solutions, particularly Convolutional Neural Networks (CNNs). A notable study by[12] proposed a CNN-based approach for NILM, leveraging layer-to-layer structures and feature extraction from power consumption (PC) curves of household appliances. Using the Reference Energy Disaggregation Dataset (REDD), the study achieved a remarkable 96.17% mean accuracy in load disaggregation for four households. This approach outperforms existing methods, demonstrating the effectiveness and efficiency of CNNs in identifying and distinguishing electrical appliances (EAs) and disaggregating total home PC. The study's findings underscore the potential of deep learning in resolving NILM challenges, offering a promising solution for energy management. Researchers have proposed a novel Maximum Power Point Tracking (MPPT) tactic to enhance Photovoltaic (PV) system efficiency under challenging irradiance and load conditions[13] which was validated using MATLAB and Proteus simulations. The technique demonstrated high convergence speed, locating the Maximum Power Point in less than 9.6 milliseconds and 0.24 microseconds, outperforming traditional Perturb and Observe and Incremental Conductance Maximum Power Point Tracking methods by up to six times. Comparative studies have evaluated the effectiveness of different NILM approaches. For instance, researchers in[14] demonstrated the superiority of their proposed method using reconstructed voltage-current trajectory images and CNNs over existing methods. Studies on NILM have investigated various load signature extraction techniques, with[15] proposing a promising approach that utilizes smart meter data and clustering algorithms. However, further evaluation is needed to assess the scalability and generalizability of this method.

The work reported in[16] demonstrates the effectiveness of two-component descriptors in generating Euclidean difference maps using sequential algorithms. These maps accurately represent the shortest difference from each pixel in binary images to the nearest background or object pixel. Notably, the study shows that maps with negligible errors can be produced through two picture scans, incorporating forward and backward movement for each line. The rapid urbanization of developing countries and the resulting surge in high-rise buildings and power consumption necessitate efficient energy conservation programs, which require real-time monitoring of end-use appliances' energy consumption. NILM has emerged as a viable solution, leveraging smart-meter data to estimate appliance-specific power consumption from aggregate building readings. The integration of collaborative deep learning and NILM has gained resistance, with reference[17] proposing a Collaborative and Privacy-Preserving NILM (CPP-NILM) framework. This approach enables effective appliance-level energy consumption analysis.

In this study, we propose a novel approach for energy dis-aggregation in NILM systems. The proposed method focuses on steady-state loads and employs Euclidean analysis. We simulate our method using Proteus software, demonstrating its effectiveness in energy dis-aggregation. The flexibility of our approach allows for easy adaptation to different research scenarios. The proposed system identifies loads by comparing their features or values with a predefined dataset. The load label is displayed for user convenience. The hardware implementation includes current and voltage sensors, with a micro-controller converting analog sensor values to digital and performing the necessary arithmetic for load dis-aggregation. By accurately identifying connected loads from aggregated data, the proposed method enhances cost-effectiveness and overall energy management. This research contributes to the field of NILM and opens avenues for further investigation

2. MATERIALS AND METHOD

2.1 Description of the experimental set-up

NILM was simulated using Proteus Visual Designer (PVD). Among the available Arduino boards in the visual designer, we selected the Arduino Uno for this application. The Arduino Uno features 32kB of memory and 14 digital input/output pins. PVD provides users with two modes of connections: using wires or terminals. While the former can become messy with numerous connections, the latter involves adding default terminal pins and giving them matching names. In our design, we utilized both methods for neatness. Proteus software was employed in this simulation to rigorously test the model approach to addressing the NILM problem of load detection. The connected load was identified based on predefined datasets, which were derived from real load measurements. Consequently, the predicted outcome of this simulation was achieved within the specified limits.

An Arduino Uno was utilized due to its promising memory capacity and versatile applications. Four distinct loads were employed to represent real-world scenarios: a security light, an electric iron, a heater, and an electric stove. Each of these loads was distinct. Three major electrical loads namely current consumption, supply voltage, and consumed power were used as parameters in this simulation. The load current and supply voltage were the input parameters to the microcontroller, while the power was calculated internally within the microcontroller. A 240-volt supply voltage was assumed in this simulation. The current drawn by the individual loads used in this simulation was measured using an ACS712 Hall effect current sensor. Individual load current consumption was measured and recorded to form the predefined dataset, which was subsequently used against the measured values to evaluate the efficiency of the simulation. Resistors were used as the resistive loads, and a 240-volt single-phase power supply was used for voltage measurement. A current sensor was used for load current measurement and a voltage transformer for supply voltage measurement. Each of these measured values was analog, and the microcontroller was used to convert them to digital.

Given that four distinct loads were used, we measured 16 different load consumption combinations to obtain the set data values. For instance, load one was on while loads two, three, and four were off; load one and two were on while loads three and four were off, and so on, until the table 1 below was obtained. Proteus was used in this project along with the Arduino IDE for coding.

The initial step involved arranging the components and implementing the voltage transformer. Using the transformer, a full-bridge rectifier, and a potential divider, we obtained the supply voltage reading. The Arduino was used as the brain of the complete system, responsible for calculations and actions carried out. An LCD display was used to show the current, power, and voltage readings for data visualization during set up while during result taking its used to show the connected load labels. The Arduino IDE software was used to code the Arduino, where all the code used to control the microcontroller was written. The complete circuit setup is shown below. During the simulation, a switch was used to turn the loads on and off so that the actions taken by the microcontroller could be observed and noted during the simulation execution. Complete circuit diagram of the experimental set-up is shown in figure 1.

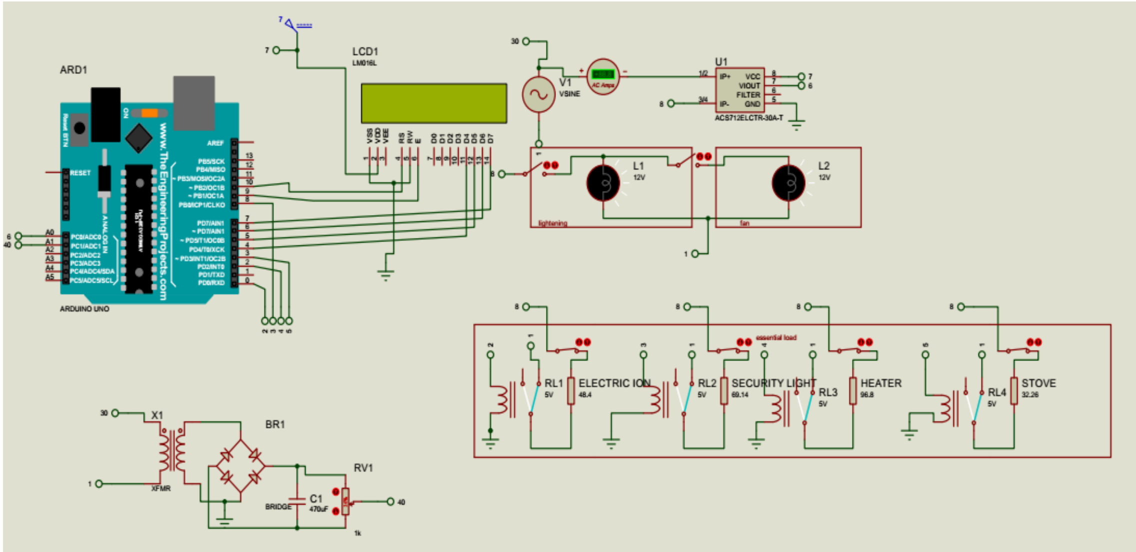

Figure 1: Circuit schematic of the complete system.

2.2 Power supply

This section is responsible for powering the whole system in order to achieve the desired output. 9V DC was used to power both the Arduino, LCD, sensor and other component.

Sensing unit: This section comprises the ACS712-30-amp hall-effect current sensor and a voltage transformer for current and voltage measurement respectively. The ACS712 30-amp Hall-effect current sensor is positioned at the load entrance of the house to measure the total load. We chose the 30-amp sensor due to its capacity.

Additionally, the supply voltage is measured using a voltage transformer connected to the main power supply of the house. The system achieves an accuracy of 95% within the voltage range of 180V to 220V, which is the most common power supply voltage range in Nigeria. The design is based on the rectification method. The output of the voltage transformer ranges from 0V to 5V, which is fed to the micro-controller for analog-to-digital conversion (ADC). To step down the 240V RMS supply voltage to 9V (a 23.4:1 ratio), we employed full bridge rectification. A variable resistor was then used to adjust the output to a maximum of 4.5V to prevent damage to the micro-controller when voltages above 5V are fed into it. The ADC conversion code was implemented accordingly.

2.3 Display unit

The LCD unit, specifically an LCD 16x2, is connected to an Arduino Uno. The VCC pin of the LCD is powered by the 5V pin on the Arduino, while the GND pin is connected to a ground terminal. The D1-D4 pins handle data communication, and the EN pin enables data transmission. Additionally, the R/W pin determines read/write mode, and the RS pin selects between command and data modes. Remember to check your specific LCD model’s pin-out for accurate connections. The LCD display unit shows the connected load in terms of logic display. For example:

“0010” indicates that load 1 is OFF, load 2 is OFF, load 3 is ON, and load 4 is OFF.

“1001” indicates that load 1 is ON, load 2 is OFF, load 3 is OFF, and load 4 is ON.

Microcontroller unit: An Arduino Uno, is deployed for this simulation. To practically apply Euclidean analysis for NILM, we overcome the limitations of some existing approaches. The principle of operation involves using a predefined data-set stored on the micro-controller and real-time measured values of current, voltage, and power to distinguish the connected load. The display then shows the best matching load pattern or load value.

3 Methodology

3.2 Instantaneous method of power calculation

The instantaneous power was calculated to analyze the average load pattern for the sample electric load used during the simulation. RMS voltage and current were employed to determine the power of each distinct load. This instantaneous power data was then utilized to establish the baseline parameters for the entire experiment. Firstly, we calculate the load power using the measured RMS voltage and current, as shown in Equation 1. The predefined data-set is obtained through a logical combination of four bits, as described in table 1.

$$P = \sum_{i=1}^{n} \frac{V(t)_i \times I(t)_i}{n} \qquad (1)$$

$$for\ n = 1,2,3 \ldots \infty$$

where P is the total power of the connected load, V is the supply voltage, and I is the current consumed by the connected load

Table 1: Reference power ratings for different load combinations (ON =1, OFF=0).

Loads				Power (watt)
Load 1	Load 2	Load 3	Load 4	
0	0	0	0	0
0	0	0	1	1017.40914
0	0	1	0	712.6779
0	0	1	1	1730.08704
0	1	0	0	502.6725
0	1	0	1	1520.08164
0	1	1	0	1215.3504
0	1	1	1	2232.75954
1	0	0	0	1519.188
1	0	0	1	2536.59714
1	0	1	0	2231.8659
1	0	1	1	3249.27504
1	1	0	0	2021.8605
1	1	0	1	3039.26964
1	1	1	0	2734.5384
1	1	1	1	3751.94754

In this study, we utilized four distinct loads: an electric iron with a power rating of 1200 watts, an electric stove rated at 1000 watts, a 500-watt heater, and a 700-watt security light. Each of these loads exhibits linear behavior with a proportional current waveform in a single state. The dataset was generated using a 4-bit truth table format based on AND and OR logic gates, as described by Equation 2. The resulting dataset is presented in Table 1 below.

Table 2: Ratings of the sample loads used in the experiment.

Loads	Voltage (volt)	Current (amp)	Power (watt)
Electric ion	223.41	6.80	1519.18
Electric stove	223.41	2.25	502.67
Heater	223.41	3.19	712.68
Security light	223.41	4.55	1017.41

3.3 The euclidean method

Euclidean distance was employed to determine the shortest path between two points or parameters (data-set and instantaneous load consumption). This metric was chosen due to its inherent simplicity and accuracy, which are critical for effective non-intrusive load monitoring and identification within smart grid systems. The Euclidean approach facilitated the precise identification of loads by leveraging the shortest distance to match power consumption patterns accurately. This method proved to be particularly effective in pinpointing the load that most closely replicated the observed power consumption, thereby enhancing the reliability and efficiency of the monitoring system.

In this approach, Euclidean difference formula was used to calculate the difference between the power drawn by the connected load(s) with the reference value stored in the micro-controller using equation 2.

$$d_{\min} = \sqrt{(P_i - P_m)^2 - (V_i - V_m)^2 - (I_i - I_m)^2}$$

where

d_{min} is the difference between the reference power stored in the microcontroller and that drawn by the connected load(s)

Where P_i, V_i and I_i are values of Power, Voltage (rms) and Current (rms) of dataset

Where P_m, V_m and I_m are the real measured values of Power, Voltage (rms) and Current (rms) of dataset

If the difference is small, it indicates that the data-set values closely match the real measurements. The formula represents the minimum Euclidean difference between two points in a three-dimensional space. For this context, it relates to comparing the data-set values (denoted by P_i, Vi, and I_i), with the real measured values (denoted by P_m, V_m, and I_m). The formula computes the Euclidean difference using the Pythagorean Theorem in three dimensions. In which case, if the data-set values closely match the real measured values, the difference will be small (approaching zero). Interpretation of Euclidean difference for load identification shown in table 3 below (the rms value of the voltage is maintained at 220V for all cases of V_i and V_m).

Table 1: An Illustration of Load Monitoring and Identification Using Euclidean Analysis for the Sample Loads.

Test Load		Reference Values for the Sample Loads		
Current (amp)	**Power (watt)**	**Current (Amp)**	**Power (Watt)**	**Differences**
6.5	1521	6.8	1519.188	1.836667
		2.27	503.168	1017.841
		9.07	2024.34	503.3466
		3.2	713.788	807.2187
		10	2234.96	713.9686
		5.44	1216.99	304.0118
		12.97	2527	1006.021
		4.5	1521.1	2.002498
		11.3	2527	1006.011

		6.77	1521.1	0.287924
		13.57	3042	1521.016
		7.7	1720.1	199.1036
		14.5	3241.2	1720.219
		9.97	2234	713.0084
		16.77	3744.44	2223.464
Euclidean distance			0.287923601	
The minimum of which corresponds with the connected load monitored			6.77 amp and 1521.1 watt	

The complete circuit diagram was shown in figure 1. Our simulation model for NILM includes several stages: the sensing unit, power supply unit, microcontroller unit, load unit, and display unit. The system is based on single-phase (220V/50Hz) power, with distinct simple electric loads to avoid the unusual load patterns introduced by inductive loads. We analyzed the approach for distinguishing and identifying the attached loads using a fed data-set, considering four distinctive resistive loads.

4 RESULT AND DISCUSSION

4.2 Results

In figure 2 below, we utilize a sample with current of 6.5A, power of 1521W, and voltage of 221V. The Euclidean difference is calculated for each data point, resulting in a minimum difference of approximately 0.2879. This minimum difference corresponds to the label with a current of 6.77A and power of 1521.1W. Notably, if we visually inspect the figure, we can observe that this specific data point aligns precisely with the calculated minimum difference.

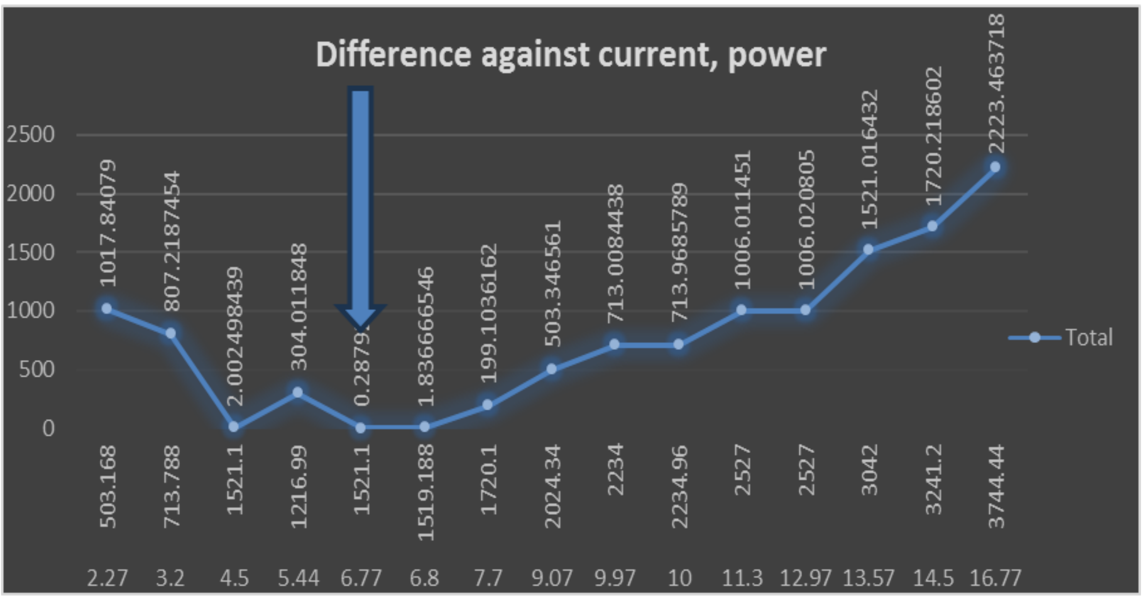

Figure 2: Graph of Calculated Difference against Current and Power for the First Sample.

For the figure 3, we consider a different sample with current of 9.92A, power of 2216.12W, and voltage of 223V. Once again, the Euclidean difference is computed, yielding a minimum difference of approximately 17.8. Remarkably, when we examine the figure, we find that this minimum difference corresponds precisely to the load level with a current of 9.97A and power of 2234W. The consistency of the calculated differences underscores the accuracy and precision of the Euclidean difference formula.

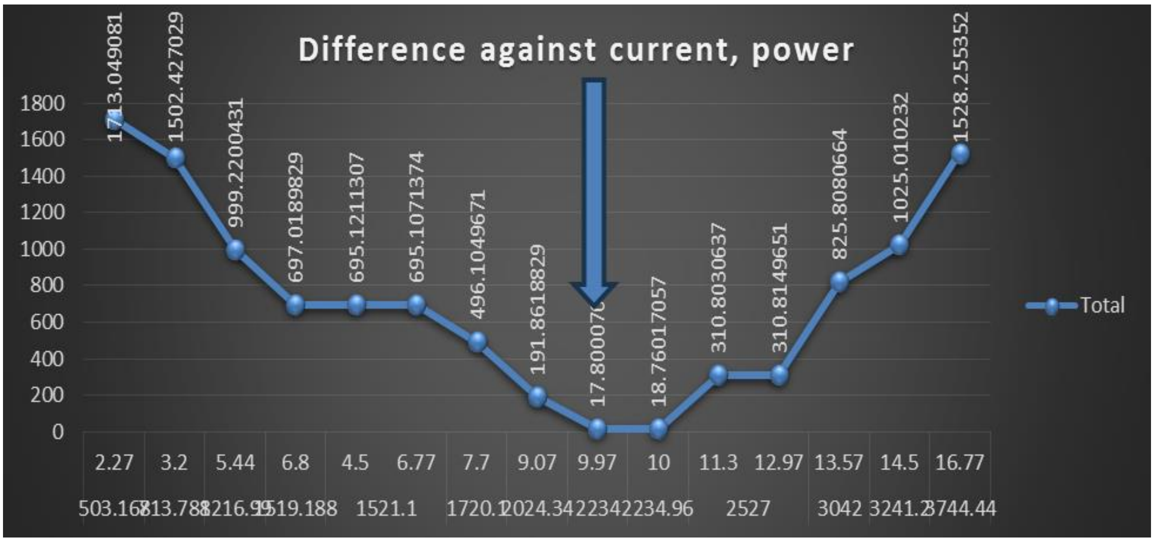

Figure 3: Graph of Calculated Difference against Current and Power for the Second Sample.

The figures illustrate various load configurations and their corresponding statuses. Figure 4 displays the connected load using an LCD display and shows the load power using an ammeter, where “1111” indicates that all loads are connected. Figure 5 indicates that load “0111” is active, meaning load one is off while all the remaining loads are connected. Figure 6 shows that load “0110” is active, implying that loads one and four are off, while loads two and three are connected. Figure 7 indicates that load “0100” is active, signifying that only load two is connected while all the remaining loads are off. Finally Figure 8 demonstrates that load “0000” is active, meaning all the loads are off.

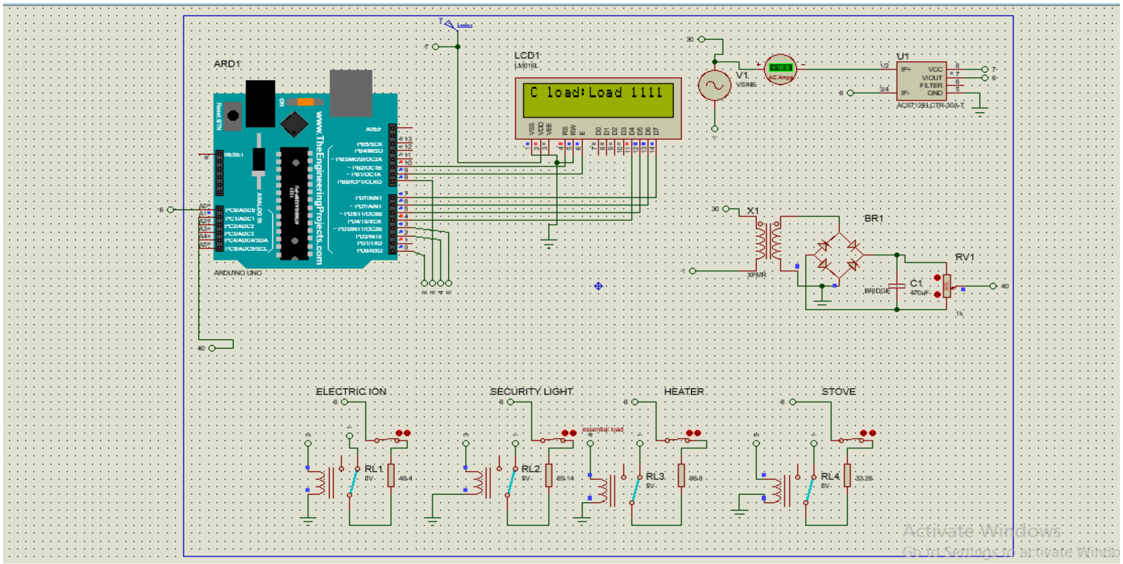

Figure 4: Response of the system when all loads are connected.

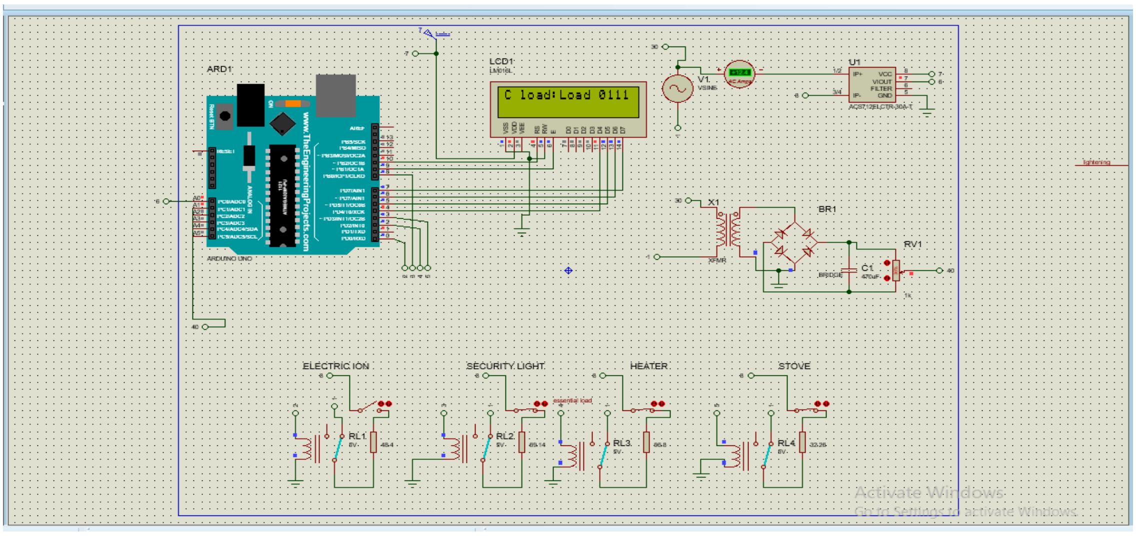

Figure 5: Response of the System when Load 2, 3 & 4 are Connected.

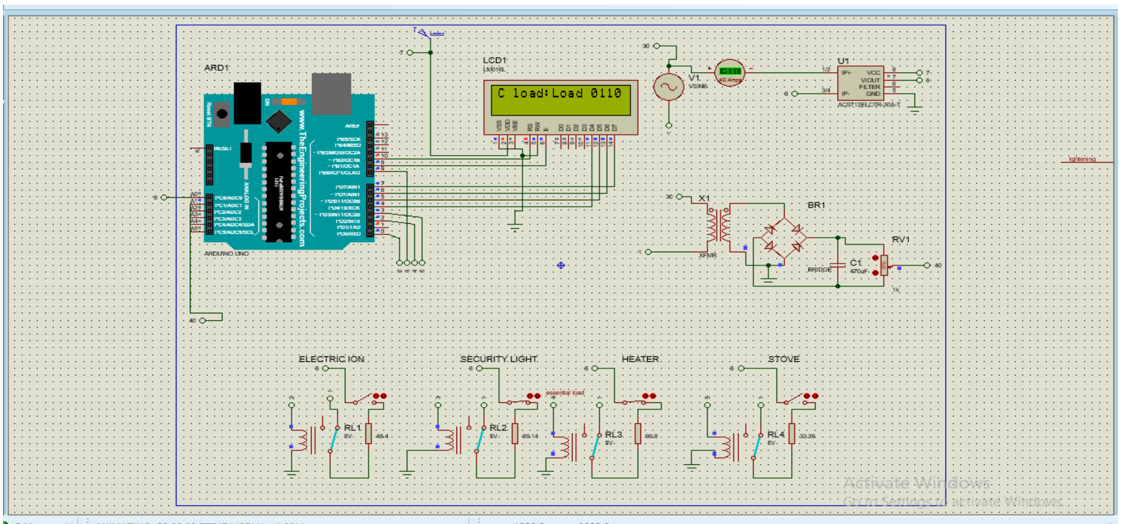

Figure 6: Response of the System when Load 2 & 3 are Connected.

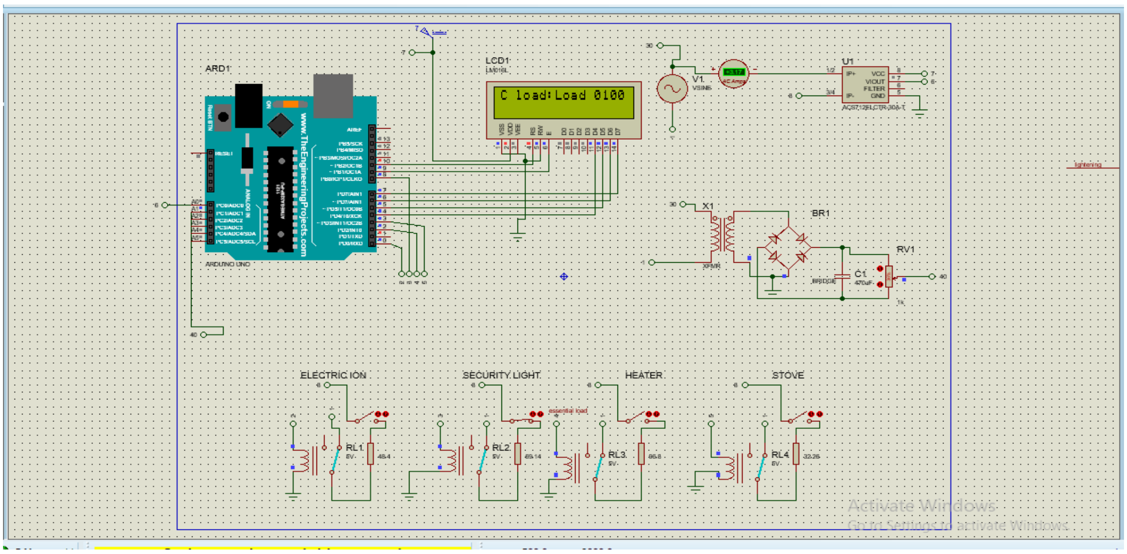

Figure 7: Response of the System when Only Load 2 is Connected.

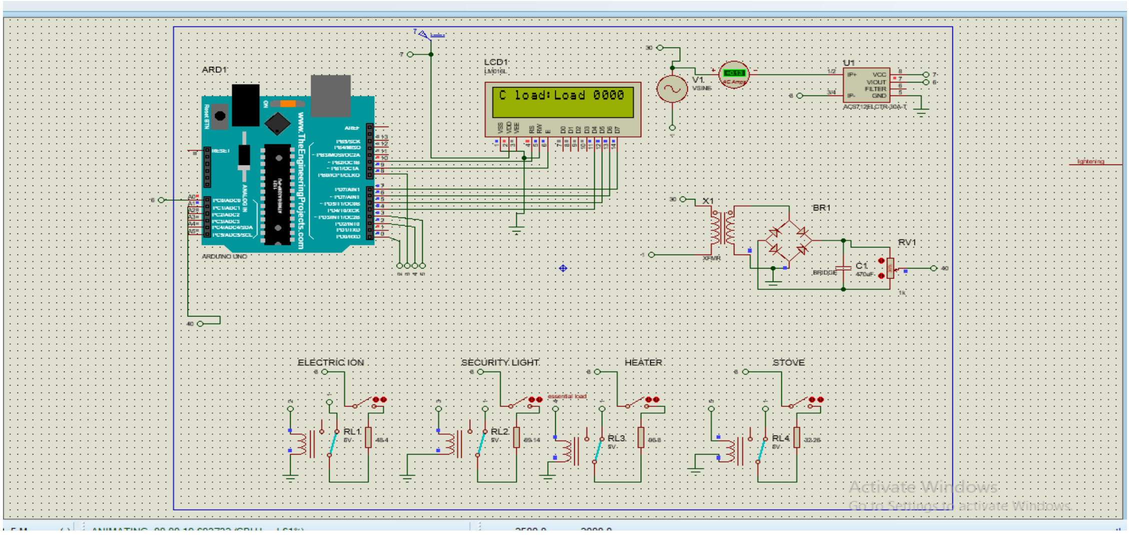

Figure 8: Response of the System when all Loads are Disconnected.

5 DISCUSSION

The overall result of the system simulation is positive. Steady state signatures for NILM system was tested using four loads. The simulation successfully identified connected loads based on Euclidean difference and a predefined dataset fed to the system. Figures 4 through 8 as shown and described above demonstrate the system's functionality by illustrating load detection and classification during testing. The system utilizes Euclidean difference measurements to compare the current load profile against a predefined dataset. This method allows for precise and accurate identification of which loads are active at any given time. This approach provides accurate load detection by matching the observed signal to the closet predefined load profile, and it is straightforward, computationally efficient, and suitable for real-time applications.

6 CONCLUSION

In summary, our work contributes not only to the field of NILM but also to the broader goal of sustainable energy management. As technology advances, our Euclidean-based approach holds promise for a greener, more efficient future. In the face of pressing challenges within the power sector and the growing urgency to adopt sustainable energy solutions, NILM systems emerge as pivotal tools for achieving energy efficiency. This paper introduces a novel approach that hinges on Euclidean analysis, resulting in an impressive 98% accuracy in load identification. By enhancing the precision of load type, class, and pattern identification, our method has the potential to revolutionize energy management practices across residential settings. We propose a novel algorithm based on Euclidean difference to match load events accurately, surpassing existing methods and simplifying the implementation process. The simplicity of our algorithm makes it suitable for both software and hardware integration, paving the way for real-world applications. By accurately disaggregating loads, this approach can optimize energy consumption, leading to cost savings for consumers and reduced strain on the power grid. Sustainability gains arise from efficient energy utilization, aligning with global efforts to mitigate climate change. This research opens avenues for further exploration, including real-time NILM implementation, scalability, and integration with smart grids. Additionally, investigating the impact of our approach in diverse contexts, such as industrial settings and smart homes, would enhance its practical relevance.

In summary, the work presented in this paper can contributes not only to the field of NILM but also to the broader goal of sustainable energy management. As technology advances, our Euclidean-based approach holds promise for a greener, more efficient future.

REFERENCE

1. S. Henriet, U. Şimşekli, B. Fuentes, and G. Richard, "A Generative Model for Non-Intrusive Load Monitoring in Commercial Buildings", in Energy and Buildings, 2018; 177: 268-278, ISSN 0378-7788, https://doi.org/10.1016/j.enbuild.2018.07.060
2. R. Zhao, J. Lu, B. Liu, Z. Yu, Y. Ren and W. Zheng, "Non-Intrusive Load Identification Method Based on Self-Supervised Regularization," in *IEEE Access*, 2023; 11: 144696-144704, , doi: 10.1109/ACCESS.2023.3337385.
3. Y. Xiao, Y. Hu, H. He, D. Zhou, Y. Zhao and W. Hu, "Non-Intrusive Load Identification Method Based on Improved KM Algorithm," in *IEEE Access*, 2019; 7: 151368-151377, doi: 10.1109/ACCESS.2019.2948079

4. P. R. Z. Taveira, C. H. V. De Moraes and G. Lambert-Torres, "Non-Intrusive Identification of Loads by Random Forest and Fireworks Optimization," in *IEEE Access*, 2020; 8: 75060-75072, , doi: 10.1109/ACCESS.2020.2988366.
5. N. Iksan, J. Sembiring, N. Haryanto and S. H. Supangkat, "Appliances identification method of non-intrusive load monitoring based on load signature of V-I trajectory," *2015 International Conference on Information Technology Systems and Innovation (ICITSI)*, Bandung, Indonesia, 2015; 1-6, doi: 10.1109/ICITSI.2015.7437744.
6. J. Z. Kolter and M. J. Johnson, "REDD: A public data set for energy disaggregation research, Workshop on data mining applications in sustainability (SIGKDD) ", San Diego, CA, 2011; 25: 59-62.
7. M. A. Devlin and B. P. Hayes, "Non-Intrusive Load Monitoring and Classification of Activities of Daily Living Using Residential Smart Meter Data," in *IEEE Transactions on Consumer Electronics*, 2019; 65, 3: 339-348, Aug., doi: 10.1109/TCE.2019.2918922.
8. C. Venugopal, & T. Govender, "Load power and energy management system using Proteus visual design software". in Indonesian Journal of Electrical Engineering and Computer Science, 2020; 20, 2: 1044-1052. doi: http://doi.org/10.11591/ijeecs.v20.i2.pp1044-1052
9. S. Singh and A. Majumdar, "Deep Sparse Coding for Non–Intrusive Load Monitoring," in *IEEE Transactions on Smart Grid*, 2018; 9, 5: 4669-4678, Sept., doi: 10.1109/TSG.2017.2666220
10. C. Venugopal, & T. Govender, "Load power and energy management system using Proteus Visual Design software", in Indonesian Journal of Electrical Engineering and Computer Science, 2020; 20, 2: 1044-1052. doi: 10.11591/ijeecs. v20.i2 pp1044-1052
11. A. Faustine, N.H. Mvungi, S. Kaijage, & K. Michael, "A survey on non-intrusive load monitoring methodologies and techniques for energy disaggregation problem", in Engineering Environmental Science, 2017, doi: 10.48550/arXiv.1703.00785
12. A. Moradzadeh, B. Mohammadi-ivatloo, M. Abapour, A. Anvari-Moghaddam, S. Gholami Farkoush, & S-B. Rhee, "A Practical Solution Based on Convolutional Neural Network for Non-Intrusive Load Monitoring" in Journal of Ambient Intelligence and Humanized Computing, 2021; 12, 10: 9775-9789. https://doi.org/10.1007/s12652-020-02720-6
13. A. Chellakhi, S. El Beid, & Y. Abouelmahjoub, "Implementation of a novel MPPT tactic for PV system applications on MATLAB/Simulink and Proteus-based Arduino board

environments", in International Journal of Photoenergy, 2021, Article ID 6657627. doi: 10.1155/2021/6657627.

14. D. Jia, Y. Li, Z. Du, J. Xu and B. Yin, "Non-Intrusive Load Identification Using Reconstructed Voltage–Current Images," in *IEEE Access*, 2021; 9: 77349-77358, , doi: 10.1109/ACCESS.2021.3082432.
15. M. Dong, P. C. M. Meira, W. Xu and C. Y. Chung, "Non-Intrusive Signature Extraction for Major Residential Loads," in *IEEE Transactions on Smart Grid*, 2013; 4, 3: 1421-1430, Sept., doi: 10.1109/TSG.2013.2245926..
16. P. Danielsson, "Euclidean distance mapping", in Computer Graphics and Image Processing, 1980; 14, 3: 227-248.
17. S. Dai, F. Meng, Q. Wang, & X. Chen. "DP2-NILM: A distributed and privacy-preserving framework for non-intrusive load monitoring" in Renewable and Sustainable Energy Reviews, 2024; 191: 114091, ISSN 1364-0321, doi: https://doi.org/10.1016/j.rser.2023.114091