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Smart Control of Household Appliances using Wireless Communication and PSO based Optimal Power Consumption Control

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***Abstract*— This study presents a system for real-time monitoring and control of household appliances utilizing the ESP32 (Wroom-32) module and Wi-Fi technology. The system employs the ACS712-20A current sensor module to measure the total output current, which the ESP32 wirelessly transmits to a dedicated webpage. This webpage is specifically designed to display the total current, the number of connected devices, and the duration of usage, allowing users to control the appliances via a relay module. Furthermore, users can view the total power consumption and the corresponding billing amount based on a various tariff-plans for ease of understanding. The analysis was conducted on four electrical appliances, generating a 24-hour dataset of power consumption and billing amounts to examine the optimal load curve. Subsequently, a Particle Swarm Optimization (PSO) algorithm was developed to determine the optimal operating duration for each appliance, ensuring that the total billing amount be lower making maximum demand and average power consumption be almost equal. The study utilized four electrical bulbs rated at 60, 24, 22, and 18 watts to assess accuracy over durations of 6, 12, and 24 hours, with specified runtime hours provided to the PSO algorithm during the optimization process.**

Keywords—Smart Home Automation, Particle Swarm optimization, ESP32, Power Control, Internet of Things

I. INTRODUCTION

In the context of computational intelligence and the proliferation of Internet of Things (IoT) [1] devices, smart home automation has emerged as a significant field of inquiry. This innovative technology addresses the limitations of traditional metering systems, which required manual readings and billing calculations. The implementation of smart metering techniques enables users to monitor real-time electricity consumption and manage electrical appliances via smartphone applications. Furthermore, a bidirectional communication network is established between service providers and consumers, facilitating real-time billing calculations and related data exchange through microcontroller devices or MATLAB/Simulink. [2-5]

Among the various wireless technologies employed in the initial phases of smart metering, Bluetooth has gained prominence. Koay et al. [6] proposed an Automatic Meter Reading system and an Automatic Polling Mechanism, which present a novel framework for remote energy monitoring, highlighting the simplicity of integration and wireless communication within energy management systems. The integration of smart meters [7] within residential settings necessitates effective communication systems such as Zigbee, Ethernet, and Wi-Fi for the transmission of energy consumption data. However, challenges persist in the seamless incorporation of smart meters into domestic environments. Electricity theft poses a significant challenge within smart metering technology. M. Anas et al. [8] investigated the potential of smart meters within Advanced Metering Infrastructure to mitigate electricity theft, proposing various protocols and mathematical models aimed at detecting and preventing non-technical losses within the electrical grid. Additionally, M. Saha et al. [9] introduced an activity detection technology utilizing smartphones in conjunction with electricity meters for user annotation. This system enhances energy consumption insights and analysis in smart homes and buildings by providing information on usage duration and location through smartphone applications. M. Collotta et al. [10] introduced a solution based on Bluetooth Low Energy technology for energy management in smart homes, utilizing fuzzy logic systems to minimize energy consumption and enhance the operation of household appliances. This approach incorporates consumer participation in the decision-making process regarding the activation and deactivation of appliances, thereby proposing a fuzzy logic-based framework to effectively manage consumer feedback. An extension of this research was detailed in [11], which presented a system for home automation and real-time monitoring, aimed at improving energy usage control. The ESP8266, a Wi-Fi module utilizing the TCP/IP protocol, has been identified as a key component in the implementation of IoT devices, particularly in smart metering applications. W. Hlaing et al. [12] applied this module within a single-phase electrical system, promoting efficient energy management in both residential and industrial environments. To enhance communication over extended distances, Santos et al. [13] proposed an IoT-based smart metering technique that emphasizes sustainable energy management through real-time monitoring, data analysis, and remote control of energy consumption in smart buildings. In one of the earlier works, a smart grid infrastructure based on renewables and smart metering system for smart control of the appliances for an university was proposed [14]. Ghosh et.al implemented Cascaded Cuckoo Search Algorithm to establish the wireless network based communication infrastructure for communicating the data from the smart appliances [15]. R. Amudhevalli et al. [16] developed a smart metering system that enables real-time monitoring of electricity usage and bill generation, employing Power Line Communication systems to oversee domestic loads, thus facilitating remote energy management and load analysis for optimized household energy consumption. Additionally, the research addressed the critical issue of electricity theft detection. O. Munoz et al. [17] provided a comprehensive account of the design, construction, and validation of a smart meter with load control features aimed at home automation, which offers

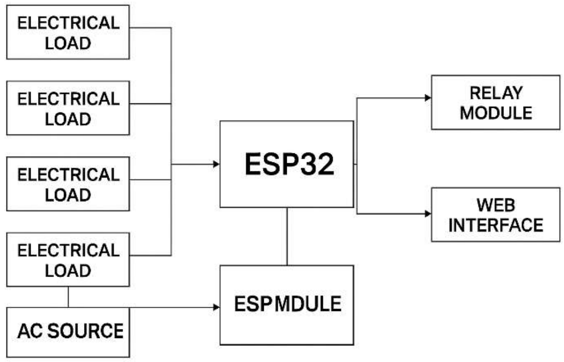

Fig. 1 Block-diagram of proposed work

real-time monitoring and improves energy efficiency in domestic settings.

This study presents a real-time smart home automation system based on the ESP32 platform, utilizing Wi-Fi technology. The system incorporates four electrical components, with the total current output measured via an ACS712 -20A current sensor. This data is displayed on a dedicated website linked to the ESP module, enabling the monitoring and recording of real-time current, power consumption, and the generation of electricity bills. Furthermore, the same website facilitates the wireless control of all components through a relay module integrated within the switchboard, allowing for the assessment of load consumption variations when multiple devices are simultaneously connected to the system. Following the collection of various readings, all data was transferred to MATLAB [18-20]. By analyzing the operational duration of each component in variable hour format, the system was optimized to minimize electricity costs using a two-part tariff, employing Particle Swarm Optimization (PSO). The structure of this paper is organized as follows: Section II details the components and mathematical tools utilized in this research; Section III presents the processed data alongside the optimized values for each component; and Section IV provides the conclusions of the study.

II. Methodology

In this study, a prototype of a smart energy meter utilizing the ESP32 platform is presented, shown in Fig. 1. The assembly of components includes a switchboard connected to the main electrical line, along with four separate outlets designated for measuring load consumption. For the purpose of result analysis, the setup incorporates one tungsten bulb, one compact fluorescent lamp (CFL), one night lamp, and one LED (light emitting diode) light. The specifications for each component are detailed in Table I. All devices were connected to the outlets, and their current consumption was monitored through controlled switching, allowing for subsequent data processing and electricity bill calculations. The pricing structure for electrical energy supplied to consumers is based on a two-part tariff system. The fixed charge is determined by the maximum power demand of the consumer, while the variable charge is contingent upon the units consumed. The total cost is computed using the formula [a*kW + b*kWh], where ‘a’ represents the charge per kW of maximum demand and ‘b’ signifies the charge per kWh of energy consumed. The

TABLE I. SPECIFICATIONS OF ELELCTRCIAL APPLIENCES USED IN THIS WORK

Load number	Load type	Wattage
L1	Tungsten blub	60 Watt
L2	CFL	25 Watt
L3	CFL	22 Watt
L4	LED	18 Watt

comprehensive details of this work are elaborated in the following sections.

A. Current measurement using ACS712

The ACS712 is a Hall-effect current sensor capable of measuring both alternating current (AC) and direct current (DC), shown in Fig. 2. In this study, the ACS712 was utilized for sensing currents up to a maximum of 20A, with a sensitivity of 100mV/A. It produces an analog voltage output that is directly proportional to the current flowing through it and operates on a 5V power supply. The sensor is well-suited for applications that require rapid and precise current measurements, boasting an accuracy of ±1.5% and a response time of 5µs. However this sensor has lack of electrical isolation and shows poor performance on temperature changes.

B. 4 Channel Relay Module

A relay module, shown in Fig. 3, functions as an electronic switch designed to manage the flow of AC power (250V-10A) through a low-voltage digital DC signal (5V-20 mA). Specifically, a 4-channel relay module consists of four independent switches integrated onto a single board, powered by a 5V DC supply and equipped with four digital control pins. When a HIGH signal (5V) is applied to these pins, the corresponding relay activates, creating a short circuit across an AC supply terminal, which enables current flow and effectively turns the AC circuit on. Conversely, when a LOW signal (0V) is supplied to the relay module, it disconnects the AC supply, thereby switching the AC circuit off. This mechanism allows for the control of AC power using a simple DC supply, as illustrated in Fig. 2.

C. ESP-WROOM-32 Wi-Fi module

The ESP-WROOM-32 is a versatile microcontroller module that integrates Wi-Fi, Bluetooth capabilities, suitable for a diverse array of applications, ranging from energy-efficient sensor networks to demanding functions such as MP3 playback and voice processing. Central to this

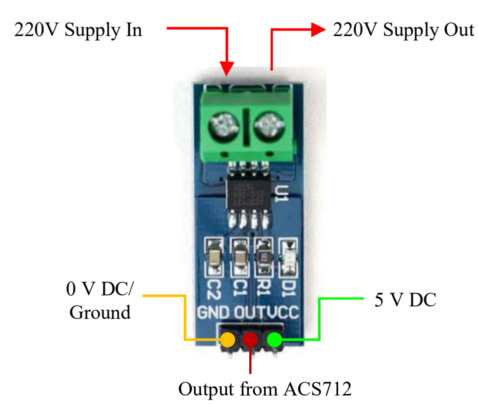

Fig. 2 ACS712 Current Sensor to measure AC current drawn from source

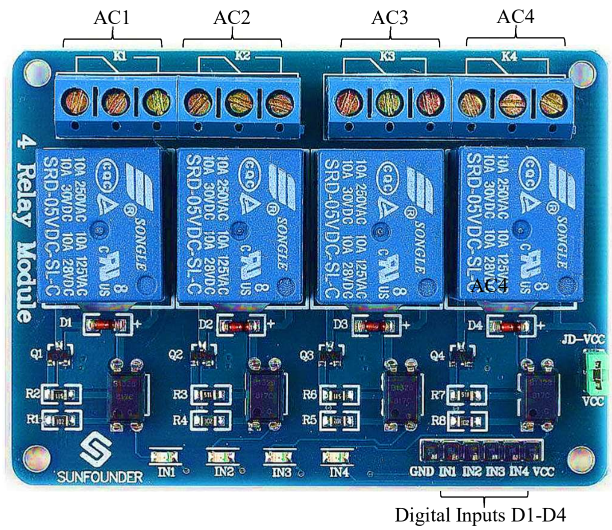

Fig. 3 4-channel Relay module used as digitally controlled switch

module is the ESP32S chip, which boasts dual CPU cores with clock speeds that can be adjusted between 80 MHz and 240 MHz. It is equipped with various built-in peripherals, including capacitive touch sensors, Hall effect sensors, amplifiers, an SD card interface, Ethernet connectivity, and support for multiple communication protocols such as SPI, I²C, and UART. The ESP32 operates in three distinct modes: Access Point (AP), Station (STA), and AP+STA, and it utilizes FreeRTOS along with LWIP protocol support.

The development board (Fig. 4) is furnished with essential components, including a CP2102 USB-UART bridge, reset and boot buttons, an LDO regulator, and a micro-USB connector, facilitating straightforward prototyping with breadboards. The chip is capable of functioning in an ultra-low-power mode, utilizing a dedicated coprocessor to oversee peripherals while the main CPU remains in a low-power state. With data transmission rates reaching up to 150 Mbps and a transmission range supported by an output power of 22 dBm, it is particularly well-suited for IoT applications, wearable technology, and embedded systems. The Bluetooth feature enables connections to smartphones or low-energy beacons, while the Wi-Fi capability provides extensive internet access.

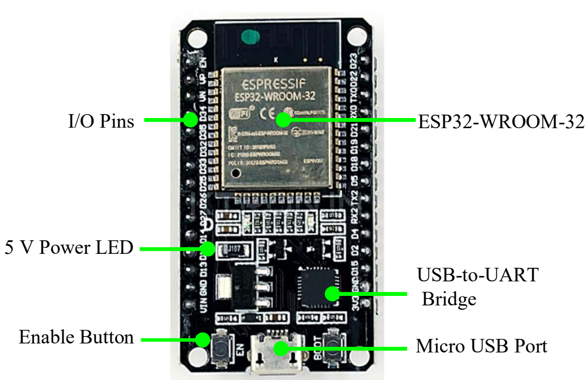

Fig. 4 ESPWROOM32 Module used as primary controlling and communication device

D. PSO based optimization of load consumption

Particle swarm optimization (PSO) [21] represents a sophisticated methodology that leverages the principles of swarm intelligence to enhance the performance of a designated function, referred to as the 'Cost function' (CF). This optimization process aims to either minimize or maximize the discrepancy between the desired and actual solutions through successive iterations. Initially, heuristic values are assigned to the particles within the search space, and these values are iteratively updated to identify the optimal position or solution for each particle, ultimately yielding the best possible output.

In this study, four electrical appliances were utilized, with their specifications detailed in Table I. Two distinct case analyses were conducted: i) a 6-hour timeframe and ii) a 12-hour timeframe, during which the desired operational times for each appliance were input into the system. For the 6-hour duration, the appliances (designated as L1 to L4) were aimed to be activated for 3, 2, 2, and 5 hours, respectively. In the 12-hour scenario, the activation times were 6, 4, 3, and 10 hours, respectively. The algorithm was trained to ensure that the actual usage times closely mirrored the specified times, resulting in total power consumption measured in Watthours (Wh). Consequently, the maximum demand (in watts) was found to be nearly equivalent to the average power consumption over the specified timeframe, thereby maintaining a relatively stable load curve. Minor variations in the usage times of each appliance were deemed acceptable within the PSO framework. Utilizing these initial conditions, the positions and velocities of the particles were adjusted in each iteration according to a specific equation.

$$
\begin{aligned}
y_{k+1}^{i} &= y_{k}^{i} + v_{k+1}^{i} \\
v_{k+1}^{i} &= v_{k}^{i} + c_1 r_1 \left(p_{k}^{i} - y_{k}^{i}\right) + c_2 r_2 \left(p_{k}^{g} - y_{k}^{g}\right)
\end{aligned} \tag{1}
$$

where, y_k^i : particle position; v_k^i : particle velocity; p_k^i : best position retained by each particle (p_b); p_k^g : optimal location recalled by the swarm (g_b); r_1, r_2 : random variables between 0 and 1; c_1, c_2: cognitive and social parameters.

Now, the PSO parameters were used as follows,

- Maximum number of iteration: 2000
- Number of particle: 50
- Learning rate: 0.99
- Cognitive and social parameter: 2

The selection of input parameters were made heuristically using trial-and –error method to achieve better performance (however, the PSO can also be replaced by other optimization algorithms e.g., GA, grey wolf, cuckoo search). In this study, the CF has been segmented into two components: CF1 and CF2. The CF1 component was optimized to align with the total runtime of each appliance. In addition, CF2 was formulated to enhance power consumption under a two-part tariff, ensuring that the maximum demand closely matches the average power usage. The optimization of these two components allows the PSO algorithm to determine the runtime for each appliance during each hour. In this way, the maximum demand reduces which effectively, reduces the total electricity bill, computed by two-part tariff, three-part tariff, or maximum demand tariff, where, huge amount is generated for high

Algorithm 1: Computation of CF used in PSO

Define: $W1_{1\times4}$: represent wattage of all appliances
Define: $RT_{1\times4}$: runtime of each appliances to be input to PSO in Hour
Define: $TA_{1\times1}$: Total number of appliances # *here TA=4*
Define: $T_{1\times1}$: Hour duration # *here T= 6 or 12*
Initialize: $X_{1\times p}$: a matrix of order p(=TA*T) # *optimized based on runtime of each appliance in each Hour, initialized using arbitrary values*
Start
k=1, $a=[]_{TA\times T}$
for $1\leq i\leq 4$
  for $1\leq j\leq T$
    a(*i* , *j*) =X(k)
    k=k+1
# *here matrix 'a' is generated where each column represents runtime of all appliance in each Time-Hour and each row represents runtime of each appliance in Total 12 Hour*
$aWH_{1\times4}$ = sum(a^T)
CF1=abs(sum($(aWH-RT)^T$)) # *used to optimize total runtime of each appliance in 12 Hour, to match them to RT*
$tW_{1\times12}$ = []
for $1\leq i\leq T$
  tW(*i*) = a(: , *i*). * W1 # *computing total wattage consumption of all appliance in each Hour*
Define: maxtW : *maximum of TW*
Define: meantW : *average of TW*
CF2=abs(maxtW-meantW) # *used to optimize two part tariff to match maximum demand to average power consumption*
CF=CF1+CF2 # *final Cost Function, minimized using PSO*
End

 # Output: a (or X)

maximum demand. This details of the algorithm are presented in Algorithm 1.

III. Results and Discussions

The Particle Swarm Optimization (PSO) method has been employed to determine the optimized operational durations for various appliances, with the results for a six-hour period presented in Table II. According to the data, during the first hour, appliance L1 is activated for 33 minutes, while in the second hour, it operates for 41 minutes. This pattern continues, with each load being activated at different intervals, as detailed in Table II. Initially, the PSO was provided with specific operational requirements for loads L1 through L4, which were set at 3, 2, 2, and 5 hours, respectively. However, the PSO's optimization yielded total operational times of 3.05, 2.0167, 1.9833, and 4.95 hours for these appliances, resulting in a mean absolute error of 1.08% in the overall runtime. Additionally, the total watt-hour (Wh) consumption for all appliances over the six-hour period is summarized in the final row of Table III, indicating a nearly uniform load consumption across each hour. This results in a maximum demand of 60.8971 W, which closely aligns with the average load consumption of 60.8970 W.

A comparable outcome was observed in Case II, which involved a study duration of 12 hours, as presented in Table 3. The loads L1 to L4 were initially designated for 6, 4, 3, and 10 hours, respectively; however, the optimization through PSO resulted in operational times of 6.3, 4.0167, 3.05, and 9.9833 hours for these devices. This adjustment led to a mean absolute error of 1.81% in the total runtime. Furthermore, the cumulative watt-hour (Wh) consumption for all devices during the six-hour interval is detailed in the last row of Table III, revealing a nearly consistent load consumption throughout each hour. Consequently, the maximum demand reached 60.169 W, which is in close proximity to the average load consumption of 60.1328 W. Fig. 5 presents a graphical depiction of the load curve, illustrating both the peak demand and the average power consumption over a 12-hour period, as detailed in Table III.

An analogous analysis was performed for the same load appliances over a 24-hour period, with the resulting load curve displayed in Fig. 6, which also indicates the average power and peak demand. Furthermore, Fig. 7 illustrates the runtime of each appliance as provided to the PSO and the measurements obtained from PSO. It is evident that the PSO yielded results closely resembling the inputs, maintaining a relatively consistent load curve over the 24-hour duration as well.

TABLE II. OBTAINED RESULTS FOR CASE I: 6 HOURS DURATION OF ELECTRICITY CONSUMPTION

Load	Duration of operation of each load calculated in minutes in T-th hour, optimized for 6 hour duration (expressed in min)						Total time (in Hour) output by PSO	Total time (in Hour) provided by PSO
	T=1	T=2	T=3	T=4	T=5	T=6		
L1	33 min	41 min	28 min	31 min	32 min	18 min	3.05	3
L2	0 min	0 min	14 min	33 min	29 min	45 min	2.0167	2
L3	24 min	28 min	24 min	1 min	10 min	32 min	1.9833	2
L4	60 min	28 min	60 min	58 min	47 min	44 min	4.95	5
Total Wh Electricity consumption in each hour								
	60.8971 Wh	60.8971 Wh	60.8969 Wh	60.897 Wh	60.897 Wh	60.897 Wh		

TABLE III. OBTAINED RESULTS FOR CASE II: 12 HOURS DURATION OF ELECTRICITY CONSUMPTION

Load	Duration of operation of each load calculated in minutes in T-th hour, optimized for 12 hour duration (expressed in min)												Total time (in Hour) output by PSO	Total time (in Hour) provided to PSO
	T=1	T=2	T=3	T=4	T=5	T=6	T=7	T=8	T=9	T=10	T=11	T=12		
L1	38	22	34	34	8	30	38	38	31	33	38	34	6.3	6
L2	5	32	0	29	48	12	6	4	30	35	17	23	4.0167	4
L3	16	20	20	14	40	31	27	6	1	8	0	0	3.05	3
L4	46	60	60	31	60	44	29	60	60	37	52	60	9.9833	10
Total Wh Electricity consumption in each hour														
	60.169	60.168	59.985	60.168	60.135	60.166	60.166	60.148	60.078	60.123	60.167	60.121		

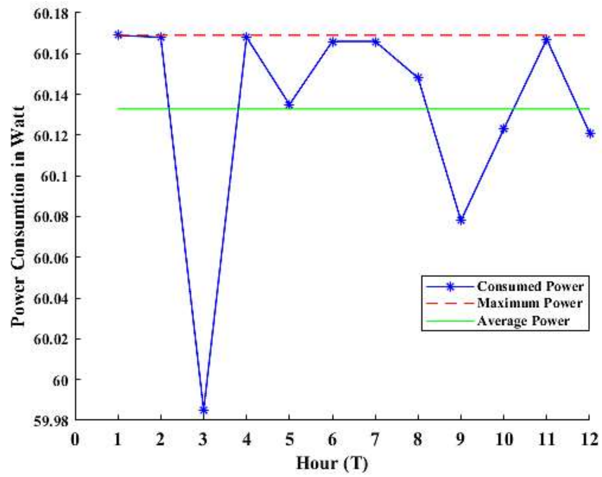

Fig. 5 Load curve showing power consumption in each hour, average power and maximum demand for 12 Hour duration, shown in Table III.

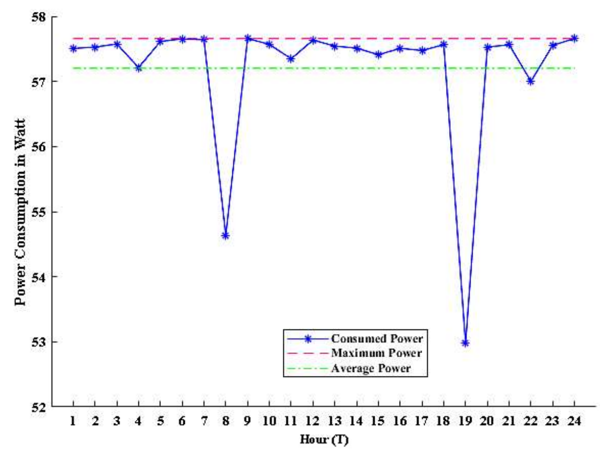

Fig. 6 Load curve showing power consumption in each hour, average power and maximum demand for 24 Hour duration.

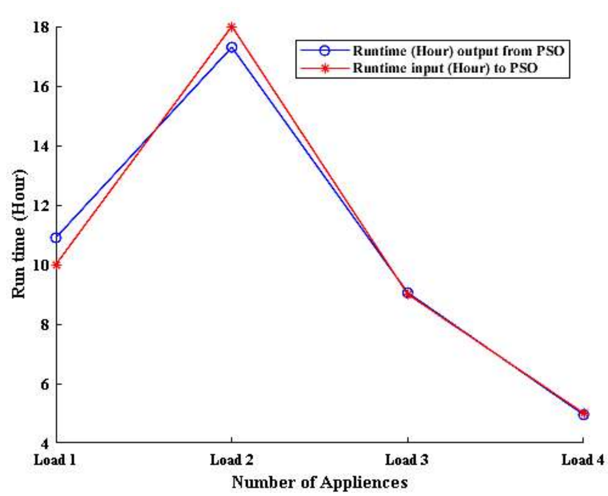

Fig. 7 Runtime (in Hour) of each 4 appliances input and output to PSO algorithm in 24 hour duration shown in Fig. 5.

The complete system over view diagram is shown in Fig. 8 and circuit diagram for the hardware configuration is

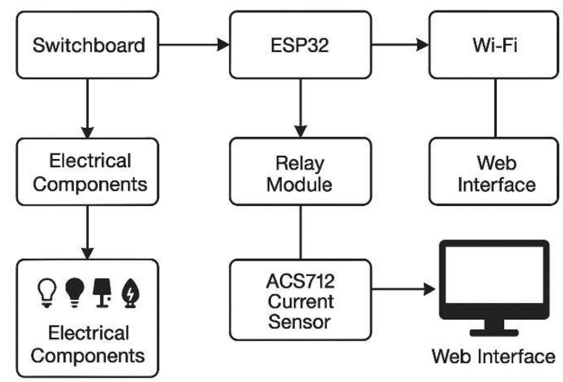

Fig. 8 System- Overview diagram of proposed work.

illustrated in Fig. 9. It features four electrical output connections, equipped with manual switches, linked to a relay module. The relay is operated by the ESP32 module through Wi-Fi communication. Additionally, a graphical user interface has been developed, accessible via an internet browser, to manage all connected loads. The overall current consumption is monitored by the ACS712 sensor, which is subsequently displayed on a 16×2 LCD module.

The primary objective of this study is to enhance the efficiency of load consumption by consumers, thereby minimizing the electric bill in accordance with a two-part tariff structure. Assuming that the average energy consumption remains constant throughout the day, a reduction in maximum demand would consequently lead to a decrease in the consumer's bill. This research addresses this issue by analyzing the load curve over periods of 6 and 12 hours, which were considered as the daily energy consumption in our prototype analysis. The digital-relays can be further replaced by MOSFET or solid-state relays for better accuracy.

IV. Conclusion

The escalating energy consumption in various nations has led to a heightened reliance on fossil fuels. This dependency raises significant concerns regarding the future security of energy supplies, particularly in light of rising oil and gas prices and the potential for shortages, which could adversely impact national economic growth. Furthermore, the increased utilization of fossil fuels contributes to detrimental environmental effects. This study aims to advocate for the adoption of electrical appliances as a means to conserve energy and mitigate negative environmental impacts. Our research will provide consumers with valuable insights into energy usage and pricing, enabling them to better manage their activities and energy expenditures. Ultimately, by optimizing energy consumption, human civilization can reduce its adverse environmental effects.

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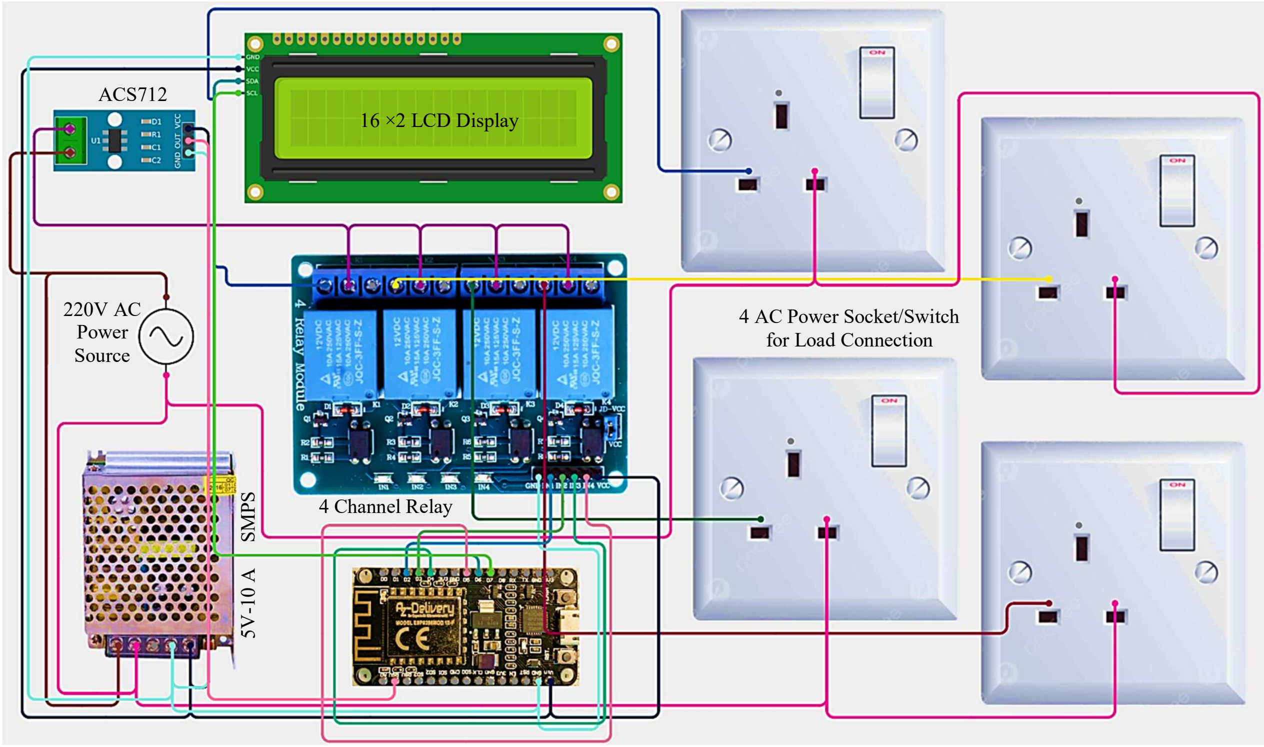

Fig. 9 Circuit diagram of proposed work with 4 socket-switch combination where desired leads were connected.

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