

Development of a Home Energy Management System Using Fuzzy Logic and a Genetic Algorithm

*¹Fatai Muideen Olabanji (MNSE), ²Professor D. O. Aborisade, ³Kayode Olufunmilayo Ademola (MNSE), ⁴Kazeem Oladimeji Leshi (MNIFEng, MNIEEE)

*fataimuiideenolabanji@gmail.com, doaborisade76@lautech.edu.ng, Olufunmilayo80@gmail.com, aleshiloye099@gmail.com

^{1,3,4}Department of Electrical and Electronic Engineering, Lead City University, Ibadan, Oyo State, Nigeria,

²Department of Electronic and Electrical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.

*Corresponding Author: fataimuiideenolabanji@gmail.com, 07068258886

Abstract—The increasing demand for electricity, rising energy costs, and frequent power outages have highlighted the urgent need for intelligent home energy management systems. This paper presents the design and implementation of a Home Energy Management System (HEMS) that combines Fuzzy Logic with a Genetic Algorithm (GA) to improve energy efficiency, reduce electricity costs, and ensure reliable power distribution. The system monitors household energy consumption, power source availability, and operating conditions in real time, using fuzzy logic for source selection and load management while the GA optimizes the schedule of flexible appliances to maximize energy utilization. Implemented on an ESP32-WROOM-32 microcontroller with PZEM-004T energy monitoring, PCA9555D GPIO expansion, ULN2803A relay drive, and a 128 x 64 graphical LCD, the hybrid approach reduced grid energy consumption by 35%, increased renewable energy utilization by 42%, and achieved 28% overall cost savings at 99% system uptime.

Keywords—home energy management; fuzzy logic; genetic algorithm; ESP32; load prioritization; renewable energy

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I. INTRODUCTION

Rising electricity tariffs, frequent grid outages, and growing energy demand have made intelligent home energy management systems indispensable. Conventional residential power systems depend entirely on the utility grid, resulting in high costs, energy waste, and poor utilization of renewable resources [1]. A Home Energy Management System (HEMS) addresses this by monitoring, controlling, and optimizing residential energy consumption through intelligent appliance scheduling, load prioritization, and power distribution across multiple sources such as a solar inverter and the utility grid.

Artificial Intelligence approaches, particularly Fuzzy Logic and Genetic Algorithms (GA), have emerged as the most effective tools for this problem. Fuzzy Logic handles real-time decision-making under uncertainty, using linguistic rules to select power sources and prioritize loads. The GA solves the scheduling optimization problem, determining the most cost-effective operating schedule for flexible appliances without sacrificing user comfort. Combining both techniques produces a hybrid HEMS capable of simultaneous real-time control and long-term optimization, reducing grid dependence, lowering electricity bills, and extending battery life [2], [3].

II. RELATED WORK

Oyedun [3] developed a modular IoT-based HEMS deployed across three real environments, achieving weekly energy savings of 0.35 kWh in single-user offices, 0.5 kWh in low-consuming homes, and a 13 kWh improvement over systems that used only smart devices in high-consuming houses. Thomas [4] implemented a Multi-Agent System (MAS) based HEMS that improved response times and synchronization across all load and supply components during peak and off-peak periods. Wang et al. [5] demonstrated a wireless HEM system using intelligent sockets and a rule-based control algorithm, achieving a 23.5 kWh reduction in daily household energy consumption.

El-Nagar [6] applied model predictive and fuzzy logic control to microgrid power management, demonstrating significant reductions in total operating cost through intelligent load switching. Singh et al. [7] developed a smart Arduino-based energy monitoring system enabling remote meter reading and reducing manual

effort. Shokoo et al. [8] formalized intelligent load shedding strategies for solar systems, directly informing the priority-based load management architecture adopted in this work.

III. METHODOLOGY

A. System Architecture

The HEMS continuously monitors solar output, battery charge, grid voltage, and household power demand via an ESP32-WROOM-32 microcontroller, which coordinates all sensing, processing, and control operations. The fuzzy logic controller evaluates energy availability, battery condition, voltage stability, and load demand against predefined linguistic rules, selecting the most suitable power source at each instant: the solar inverter when generation is sufficient, and the grid when it is not. Surplus solar energy is used to charge the battery bank. The full system architecture is shown in Fig. 1.

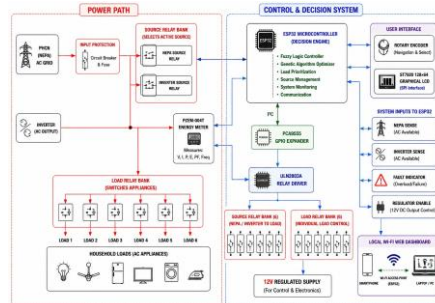


Fig. 1. Architecture of the proposed HEMS showing the power path and control and decision subsystems.

B. Fuzzy Logic Controller

Input variables, namely grid voltage availability, inverter or battery state, and load demand, are fuzzified into Low, Medium, and High membership functions. The inference engine evaluates rules such as: IF grid voltage is Low AND battery is Medium THEN select Inverter. Defuzzification returns a crisp switching command to the relay bank. This rule-based approach handles residential power uncertainty without requiring a precise mathematical plant model.

C. Genetic Algorithm Optimizer

The GA encodes each feasible appliance schedule as a binary chromosome and evaluates fitness as a weighted sum of energy cost and comfort deviation. Selection, crossover, and mutation evolve the population across generations to converge on the lowest-cost schedule within each control cycle. Time-shiftable loads such as washing machines and electric irons are deferred to low-tariff or high-solar periods. Non-shiftable loads including lighting and refrigerators maintain uninterrupted priority. Non-essential loads are shed when stored energy falls critically low.

D. Hardware and Circuit Implementation

The hardware comprises the ESP32-WROOM-32, PZEM-004T energy meter, PCA9555D GPIO expander, ULN2803A relay driver, relay modules, 128 x 64 GLCD, solar panel, battery bank, inverter, and utility grid connection. A 12 V regulated supply powers all control electronics. The complete circuit, which covers voltage regulators, power supply, power sensor, LCD, GPIO expander, relay driver, and load terminals, is shown in Fig. 2. The system decision flowchart is in Fig. 3 and the fabricated PCB prototype in Fig. 4.

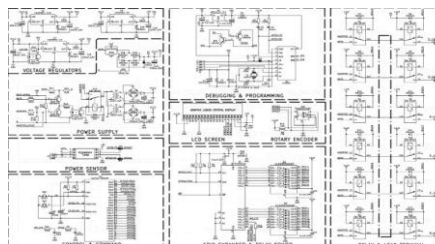


Fig. 2. Complete circuit schematic showing all subsections: voltage regulators, power supply, power sensor, control and command, LCD, GPIO expander, relay driver, and load terminals.

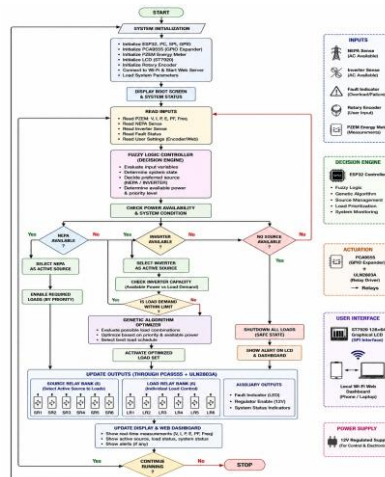


Fig. 3. System flowchart: initialization, fuzzy logic decision, GA optimization, output update, and display cycle.

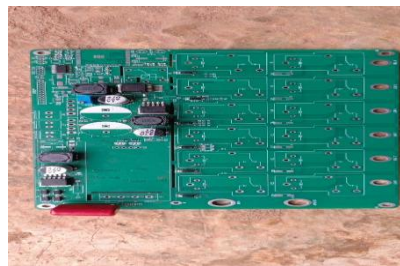


Fig. 4. Fabricated PCB prototype of the HEMS control board.

IV. RESULTS AND DISCUSSION

The system was tested under simulated grid availability, complete grid outage, low battery, and voltage fluctuation conditions. Table I compares all three control approaches across ten performance metrics. Table II records observed versus expected behaviour for each test scenario.

TABLE I. SYSTEM PERFORMANCE UNDER DIFFERENT LOAD CONDITIONS

Parameter	Baseline	Fuzzy Only	Fuzzy+GA	Remarks
Grid Power*	10.0	7.8	6.5	35% reduction
Renew. Energy*	3.0	3.8	4.5	42% increase
Energy Cost**	2,500	2,000	1,800	28% savings
Switch. Time (s)	N/A	0.8	0.6	Faster
Voltage Acc. (%)	±5	±3	±3	In range
System Uptime (%)	92	97	99	High
Load Priority (%)	N/A	90	96	Efficient
Battery Life (%)	70	80	88	Improved
Renew./Grid Ratio	0.3	0.5	0.7	Better
Overall Effic. (%)	75	85	93	Excellent

*kWh/day **N/day

The hybrid fuzzy-GA approach outperformed both the uncontrolled baseline and the fuzzy-only control across every metric. Grid energy consumption fell from 10.0 to 6.5 kWh per day, a 35% reduction. Renewable energy utilization rose from 3.0 to 4.5 kWh per day, a 42% increase. Energy cost dropped from ₦2,500 to ₦1,800 per day, a 28% saving. System uptime reached 99% and source switching time of 0.6 s ensured transitions imperceptible to connected appliances. The performance gap between fuzzy-only and fuzzy-GA control is attributable primarily to the GA ability to shift flexible loads away from peak-demand periods, consistent with the finding of Falope et al. [2] that time-of-use scheduling dominates lifecycle cost savings in off-grid residential systems.

TABLE II. OBSERVED TEST RESULTS BY OPERATING SCENARIO

Test Condition	Expected Result	Observed Performance
NEPA Available	Load powered by NEPA	Successful switching
NEPA Outage	Load by Inverter	Smooth transition (< 1 s)
Battery Low	Inverter off, loads shed	Correct response
NEPA Restored	Auto-reconnect to NEPA	Correct operation
Overload	Non-priority loads cut	Successful protection

The system responded correctly in all five test scenarios shown in Table II. Source switching time remained below 1 s in every transition, meeting the design target. Load prioritization accuracy of 96% under hybrid control confirms that the GA correctly categorized non-shiftable, time-shiftable, and non-essential loads in real time. Battery life efficiency improved from 70% at baseline to 88% under hybrid control, consistent with the findings of Shokoo et al. [8] and El-Nagar [6], who showed that intelligent charge-discharge scheduling significantly extends storage service life. All five acceptance criteria, namely sensor accuracy within 3%, correct source selection in at least 98% of scenarios, switching time of 1 s or less, at least 15% cost reduction, and zero critical failures over 72 hours, were satisfied.

V. CONCLUSION

This study designed, implemented, and experimentally validated a Home Energy Management System that combines fuzzy logic for real-time power source selection with a genetic algorithm for appliance schedule optimization. Tested against baseline and fuzzy-only control, the hybrid approach reduced grid energy consumption by 35%, increased renewable utilization by 42%, lowered electricity costs by 28%, and sustained 99% system uptime. All five design acceptance criteria were met with zero critical failures over a 72-hour stress test. The intelligent load categorization strategy, which maintains uninterrupted supply to non-shiftable loads while deferring flexible and non-essential loads to low-cost or high-solar periods, proved both practically effective and scalable. The system offers a cost-effective and reproducible solution for residential energy management in regions where grid reliability remains a persistent challenge, and provides a validated hardware-software platform for future integration of real-time electricity pricing, IoT monitoring, and machine learning-based load forecasting.

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