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Low-cost fuzzy logic-controlled home energy management system

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Abstract

This paper presents a low-cost method for real-time energy management in residences. Light, motion, temperature, and sound sensors are system inputs. Lighting, heating, and cooling output powers are set according to sensor data and consumer conditions. The system is controlled by using three different fuzzy logic inference engines together with a microcontroller, sensors, and Nextion HMI display. The lighting, cooling, and heating can be precisely controlled according to the conditions of the house. This ensures that energy consumption is minimized while maintaining an appropriate level of comfort for the users. This shows that the system is designed as user-friendly and can be operated easily by the consumer. Thus, whether the consumers are at home or not, the consumption of electricity, water, and natural gas is controlled, and unnecessary consumption is prevented. The results show that such systems can effectively reduce energy consumption while maintaining user comfort, and this system could be an essential component of home energy management systems.

Keywords: Energy consumption, Home energy management systems (HEMS), Fuzzy logic, Microcontroller, Smart home

Introduction

Energy management involves the planning, monitoring, and control of energy-related processes to protect both energy resources and the environment. Energy efficiency is closely linked to sustainable development, the selection of optimal fuel sources, the use of renewable energy sources, and environmental awareness and safety [1].

The growth of population and urbanization has led to an increase in energy consumption in households worldwide. Many countries are actively pursuing the implementation and development of energy management systems for their own benefit [2–4]. Managing energy in residential settings requires a complex application procedure due to the many interdependent variables involved. To effectively manage energy, an efficient energy management system is necessary to reduce total energy consumption without compromising the comfort of the home's occupants. Many studies have been conducted on home energy management systems (HEMS), examining their impact on energy consumption, user behavior, and energy cost savings [5, 6]. Recently, there has been a significant increase in interest in energy management systems that employ advanced artificial intelligence techniques [7–9]. However, the need

for large amounts of data, the complexity of neural network models, and the difficulty of interpreting the results make these approaches difficult to apply.

Fuzzy logic is increasingly being utilized in energy management applications to reduce energy costs. Kontogiannis et al. [10] studied the design of fuzzy systems to achieve minimum energy consumption in residential settings. Arabul et al. [11] developed a fuzzy logic controller for an off-grid smart home system to improve sustainable energy usage. Atefand and Eltawil [12] proposed a fuzzy logic controlled approach for heating, ventilation, and air conditioning systems to reduce consumption during peak loads in smart grids. This study was compared with four different scenarios, and the simulation results showed improved system performance. Baniyounes [13] conducted a simulation study to determine the occupancy level of a building and its effect on energy consumption using fuzzy logic-based controllers. Christopoulos et al. [14] proposed a new fuzzy logic model to improve cost, power consumption, and CO_2 pollution for users. While there was no significant reduction in energy consumption, their model resulted in a substantial decrease in CO_2 emissions. Garrab et al. [15] designed a system that enhances energy efficiency during high power consumption demands of smart grids in residential settings. Colatta and Pau [16] used Bluetooth Low Energy in a wireless network to coordinate communication between household appliances using fuzzy logic. Overall, fuzzy logic-based approaches have proven to be a useful tool for energy management applications by reducing energy consumption and improving energy efficiency in residential buildings.

It is noteworthy that in some studies, fuzzy logic and intelligent optimization algorithms are used together. Behrooz et al.[17] presented an integrated approach that employs fuzzy logic and a genetic algorithm to control a building's automation system. Fayaz and Kim [18] utilized a fuzzy controller and optimization algorithms to maximize occupant comfort and minimize power consumption in residential settings. The authors compared the performance of the genetic algorithm, particle swarm optimization, and bat algorithm, with the recommended approach. Khalid et al. [19] performed energy management for smart homes by combining a fuzzy controller and optimization techniques. Jarndal [20] designed an adjustable smart home system that utilizes Genetic Algorithm-Fuzzy Logic-Neural Networks techniques to detect human behavior patterns and predict the user's next behavior.

The other studies focus on optimizing electricity usage in smart homes and microgrids, prioritizing the reduction of energy consumption and enhancement of energy efficiency. They cover various approaches to energy management and demand response, incorporating both renewable energy sources and energy storage systems [21, 22]. Han et al. [23] proposed a system based on ZigBee and PLC-based renewable energy gateway (REG) that optimizes home energy use. Anvari-Moghaddam et al. [24] developed a multi-objective nonlinear programming model for optimum energy use in smart homes. Erol-Kantarcı ve Mouftah [25] proposed an energy-saving system using wireless communication between grid-supplied or locally produced power. Bolurian et al. [26] investigated the efficiency of HEMS by incorporating demand forecasting and renewable energy. Zunnurain et al. [27] proposed an advanced Demand Side Management framework for microgrids that utilizes an integrated Demand Response strategy.

While the use of artificial intelligence techniques and hybrid methods in energy management systems offers significant advantages, it has some difficulties, especially in terms of cost and ease of implementation. Additionally, the installation and maintenance procedures for these systems may require advanced technical skills. Moreover, there is still a need for more research on the real-time applications of these technologies. In this study, a real-time low-cost, and user-friendly energy management system using fuzzy logic is designed. The system is controlled by a microcontroller and uses three different fuzzy inference engines. These engines operate independently according to sensor data and control all conditions such as cooling–heating status, electricity price, lighting status, consumer status, electricity, water and natural gas usage, and date-time. The Nextion HMI screen is used to monitor and control all these conditions. The system was tested by assembling all the components on a model house. The lighting system allows 25%, 50%, 75%, and 100% step adjustments according to the house conditions. Similarly, the cooling and heating systems have a 33%, 50%, and 100% step setting. The system, which can detect whether there are people or animals in the house, prevents unnecessary consumption by controlling the use of electricity, water, and natural gas when no one is present. The developed energy management system, being cost-effective and easy to apply to residences, provides a reduction in energy bills. In addition, the user-friendly system enables it to reach a wider audience of homeowners and expands energy management.

Material and methods

Efforts to enhance energy efficiency in homes can be more effective if the following conditions are considered [28]: (a) A higher energy consumption in a house indicates a greater potential for energy savings. (b) Improvements to energy systems are more financially effective when electricity and fuel costs are higher. (c) When the ambient temperatures are closer to the desired temperature, the energy consumption will be lower.

Consumer behavior is highly variable due to human nature. It is crucial to alter behavior in relation to the usage of electrical energy, but people frequently require reminders, making technological interventions the most effective solution. By effectively managing electrical energy, various benefits can be attained, including energy savings, lowered billing costs, and financial savings [29].

In this study, a fuzzy logic-based energy management system is designed for residential homes. Fuzzy logic rules are applied to set air conditioning and lighting, ensuring the most suitable temperature and lighting. The system utilizes various sensors to identify the types of consumers in the homes and establish consumption restrictions for electricity, water, and natural gas based on factors such as whether the consumer is a human or a pet. The system is also capable of detecting when the consumer is not present in the residence. In this way, energy consumption is reduced by increasing energy efficiency, and while energy management is ensured, unnecessary consumption is restricted without compromising consumer comfort. The structure of the proposed system is shown in Fig. 1.

System components

The system uses temperature, light, sound, and motion sensors, as well as a precision clock module and an 18F46K20 microcontroller. It includes a 100-W heating element

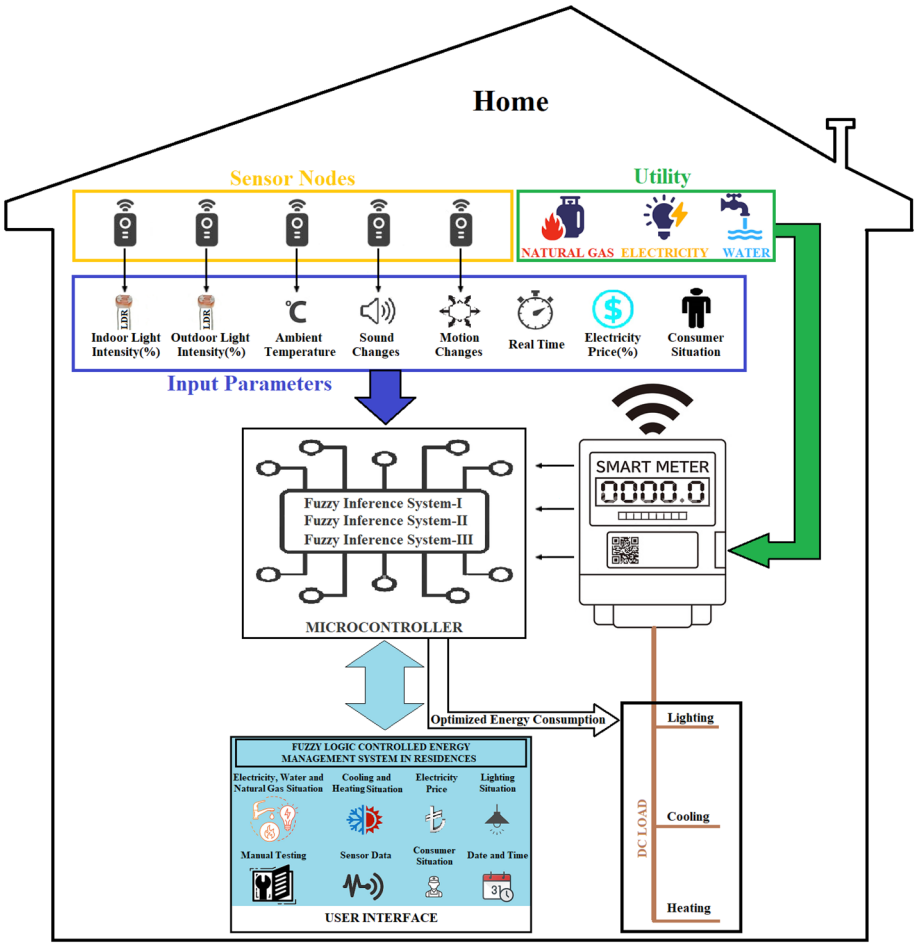


Fig. 1 Overview of the proposed system

for warming, a 310-W Peltier cooler for chilling, and a strip LED for illumination. The 4.3-inch Nextion HMI LED screen allows for manual control, real-time monitoring of results, and automatic control of the system, allowing users to adjust operating conditions as needed. Table 1 presents a list of the system's components and features.

Proposed fuzzy system

In many real-world problems, the inputs can be uncertain and the outputs probabilistic or approximate. It is important to determine the problem-specific algorithm [30]. However, fuzzy logic is particularly useful in real-time control systems as it responds quickly and accurately to uncertainties [31, 32]. In this study, a fuzzy logic method is proposed to optimize energy use in a household by controlling various energy-consuming devices. The system employs three different inference engines, with each engine working independently based on sensor data. The output obtained from the first inference engine is used as input for the second inference engine [33]. The overall structure of the designed system is depicted in Fig. 2. The system's inputs comprise time, motion changes, sound changes, interior lighting light intensity, exterior lighting light intensity, electricity price,

Table 1 System component and specification

Temperature sensor (NTC)	10 KΩ resistor, 5 mm diameter, and 23 mm leg length
Light sensor (LDR)	5 mm body diameter, resistance ranging from 150Ω to 500KΩ
Sound sensor	Microphone with 5 mm body diameter, 150Ω–500KΩ resistance, 2.2KΩ output impedance, 1–10 V operating range, max power 0.5 mA
Motion sensor	Operating voltage range 3.3–15 V, motion detection distance 5 m, output time adjustable between 2.5 s and 1 h
Precision clock module	Operating voltage range 3.3–5 V, 8 gr weight, programmable square wave output, internal AT24C32 memory (32 KB)
HMI LCD	480 × 272 Resolution, 16 MB internal memory, 2 KB RAM, micro sd card slot, 5 V operating voltage
Microcontroller	8-bit, 40 pins, 3.8 KB RAM, 64 KB program memory size
12 V adapter	100–240 V AC input voltage, 12 V output voltage, 29 A output current, 350W
Model house and test cabin	Wooden model house with 40 cm width, 40 cm length, and 25 cm height

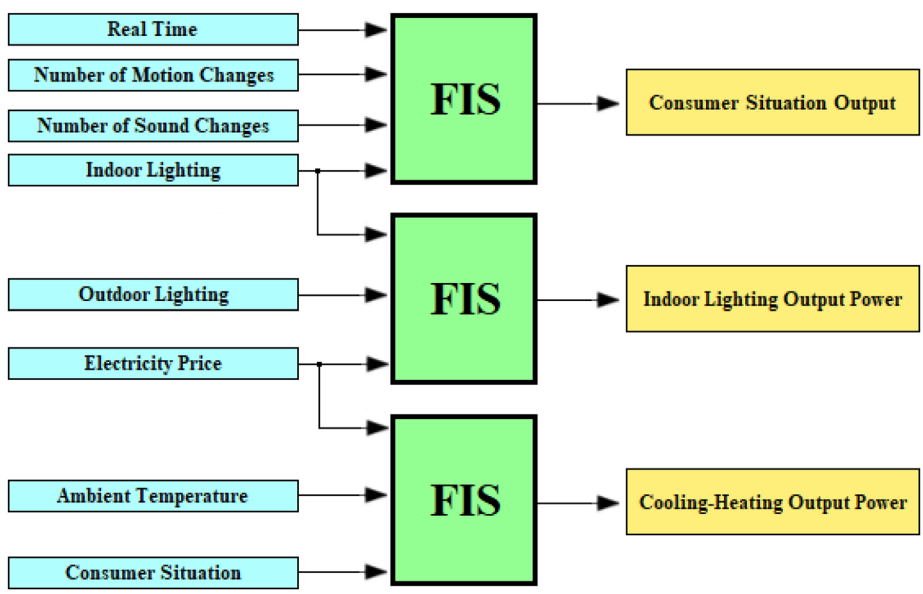


Fig. 2 General structure of the proposed fuzzy system

and ambient temperature. Three output parameters are determined: consumer situation, interior lighting output power, and air conditioning output power.

Fuzzy inference engine I

Fuzzy inference engine-1 consists of 108 rules. Light, sound, motion sensors, and real-time clock data are determined as inputs in the inference mechanism. Consumer situation is determined as output. The system structure is shown in Fig. 3. Examples of the rule base are given below.

If Indoor Light Intensity is LOW, Sound Change is LESS, Motion Variation is LESS, and Real Time is "MORNING", Consumer Situation is "NONE",

...

If Indoor Light Intensity is LOW, Sound Change is LESS, Motion Change is Normal and Real Time is "NOON", Consumer Situation is "HUMAN AVAILABLE",

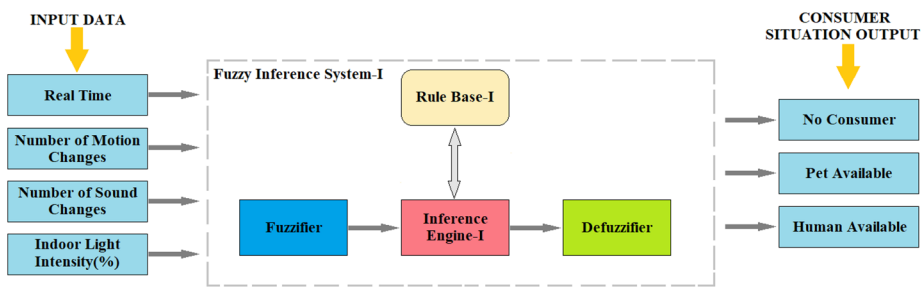


Fig. 3 Fuzzy inference engine I

...

If Indoor Light Intensity is LOW, Sound Change is NORMAL, Motion Change is LESS, and Real Time is "MORNING", Consumer Situation is "PET AVAILABLE",

Figure 4a–e displays the membership functions for the inputs and outputs in the fuzzy inference system structure. Triangular and trapezoidal membership functions are utilized to transform inputs and outputs into fuzzy values. The Mamdani minimum inference mechanism is used to obtain final fuzzy values, which are then converted into the output value through the centroid defuzzification method. The resulting output value indicates the consumer state, which is classified into three categories: "No Consumer," "Pet Available," and "People Available."

Fuzzy inference engine II

The consumer situation obtained from the first fuzzy inference mechanism, electricity price, and temperature data is determined as inputs in this inference mechanism. Cooling and heating output power has been determined as output. The system structure is shown in Fig. 5. In the second fuzzy inference system, the rule base consists of 45 rules. Examples of the rule base are given below.

If the Consumer Situation is "HUMAN AVAILABLE ", Electricity Price is "LOW" and Ambient Temperature is "TOO HOT", Cooling and Heating Output Power is "100% COOLING",

...

If the Consumer Situation is "PET AVAILABLE ", Electricity Price is "LOW" and Ambient Temperature is "TOO HOT", Cooling and Heating Output Power is "100% COOLING",

...

If Consumer Situation is "NO CONSUMER", Electricity Price is "LOW" and Ambient Temperature is "TOO COLD", the Cooling and Heating Output Power is "COOLING AND HEATING OFF",

...

If the Consumer Situation is "HUMAN AVAILABLE ", Electricity Price is "HIGH" and Ambient Temperature is "TOO COLD", Cooling and Heating Output Power is "66% HEATING",

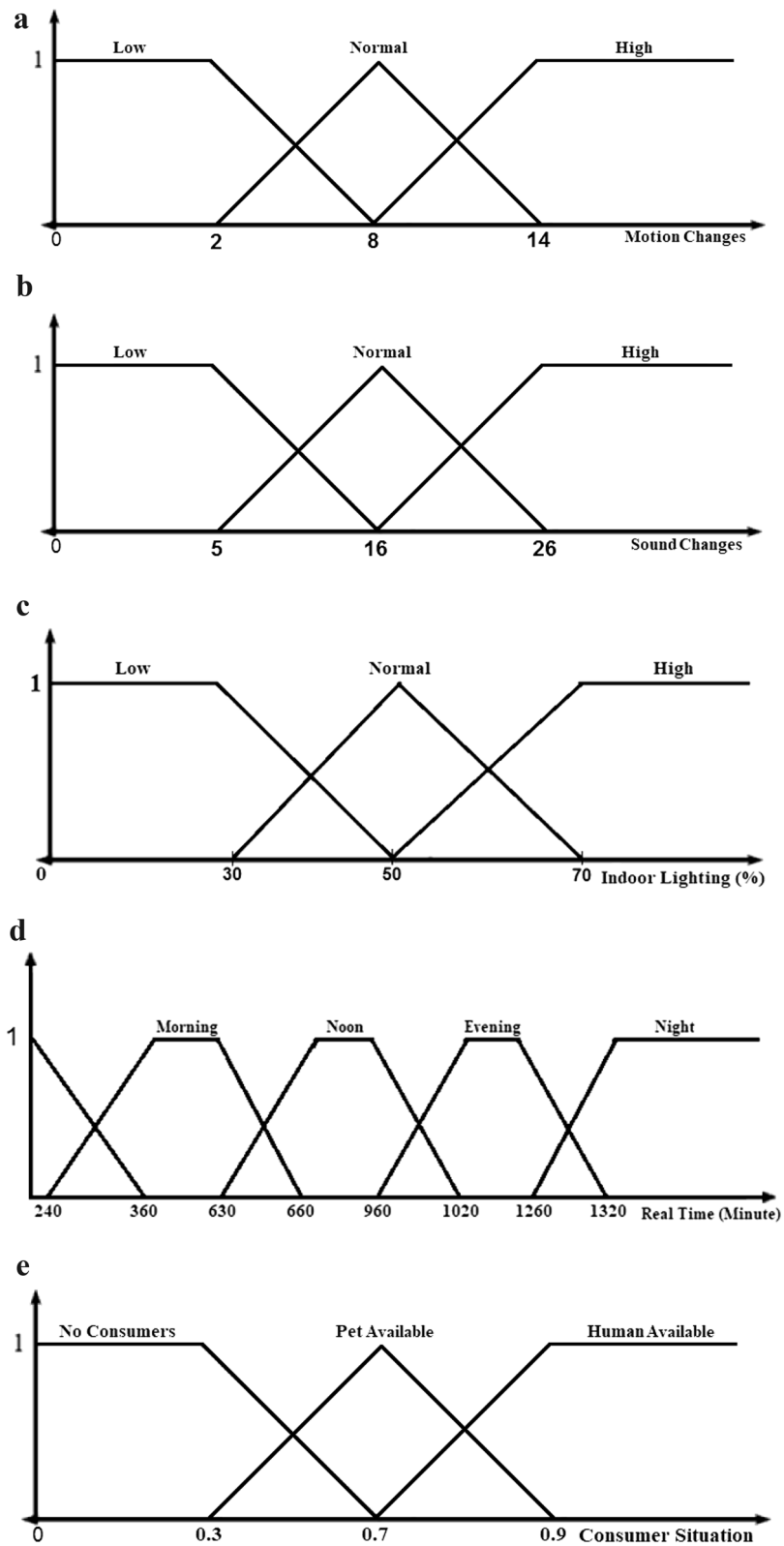


Fig. 4 **a** Motion change fuzzy membership function. **b** Sound change fuzzy membership function. **c** Indoor light intensity fuzzy membership function. **d** Real-time fuzzy membership function. **e** Consumer situation fuzzy membership function

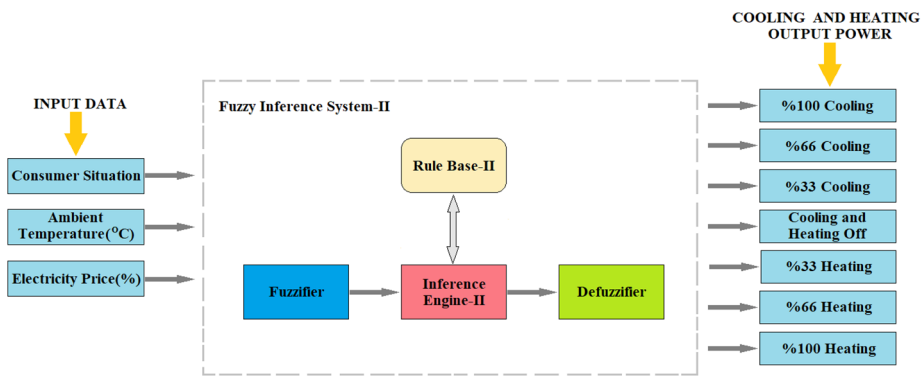


Fig. 5 Fuzzy inference engine II

...

If the Consumer Situation is "HUMAN AVAILABLE ", Electricity Price is "LOW" and Ambient Temperature is "TOO COLD", Cooling and Heating Output Power is "100% HEATING",

The second fuzzy inference engine employs triangular membership functions as shown in Fig. 6a–c. Inputs and outputs are transformed into fuzzy values using triangular membership functions, and their corresponding fuzzy membership degrees are determined. After processing the inputs in the fuzzy decision table, the fuzzy values for the cooling and heating output powers are determined using the Mamdani minimum inference mechanism. The Centroid defuzzification method is then used to convert these values to the output value, and the final output is calculated. The cooling and heating output powers are classified as "100% Cooling," "66% Cooling," "33% Cooling," "Cooling and Heating Off," "33% Heating," "66% Heating" and "100% Heating."

Fuzzy inference engine III

The inputs for this inference mechanism include light data and electricity prices, while the output is the power level for interior lighting. The system's structure is illustrated in Fig. 7. In the third fuzzy inference system, the rule base comprises 27 rules. Examples of rules from the rule base are provided below.

If Electricity Price is "LOW", Indoor Light Intensity is "LOW" and Outdoor Light Intensity is "LOW", Indoor Lighting Output Power is "LEVEL 5",

...

If Electricity Price is "NORMAL", Indoor Light Intensity is "LOW" and Outdoor Light Intensity is "LOW", Indoor Lighting Output Power is "LEVEL 4",

...

If Electricity Price is "LOW", Indoor Light Intensity is "HIGH" and Outdoor Light Intensity is "NORMAL", Indoor Lighting Output Power is "LEVEL 3",

...

If Electricity Price is "NORMAL", Indoor Light Intensity is "NORMAL" and Outdoor Light Intensity is "NORMAL", Indoor Lighting Output Power is "LEVEL 2",

...

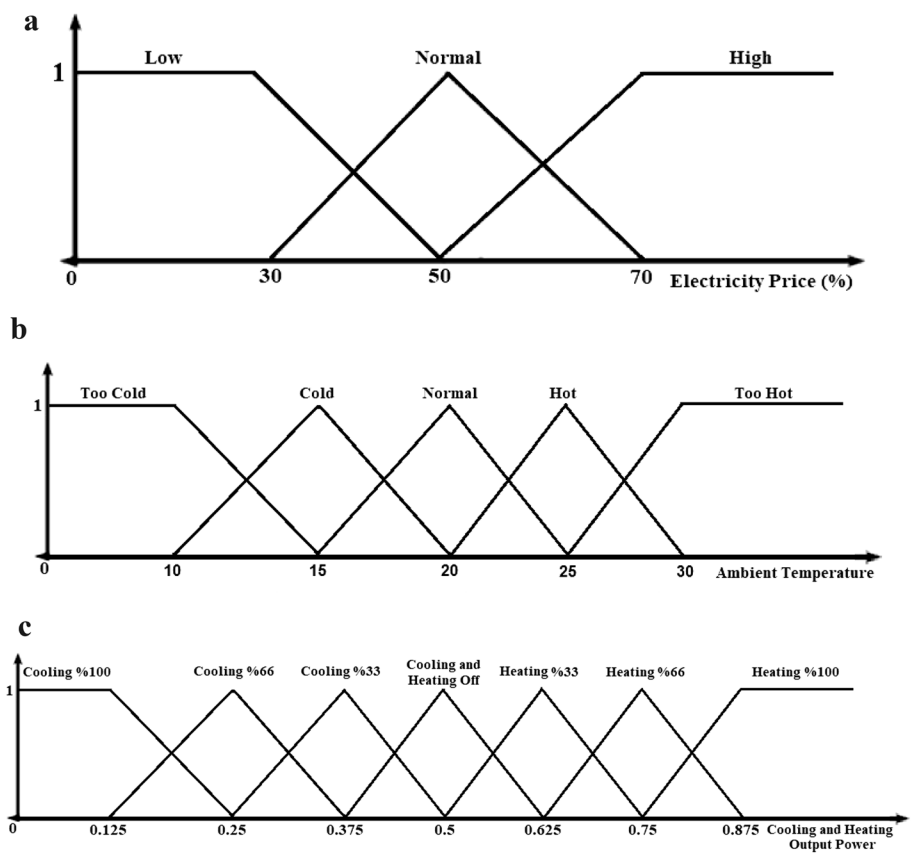


Fig. 6 **a** Electricity price fuzzy membership function. **b** Ambient temperature fuzzy membership function. **c** Cooling and heating output power fuzzy membership function

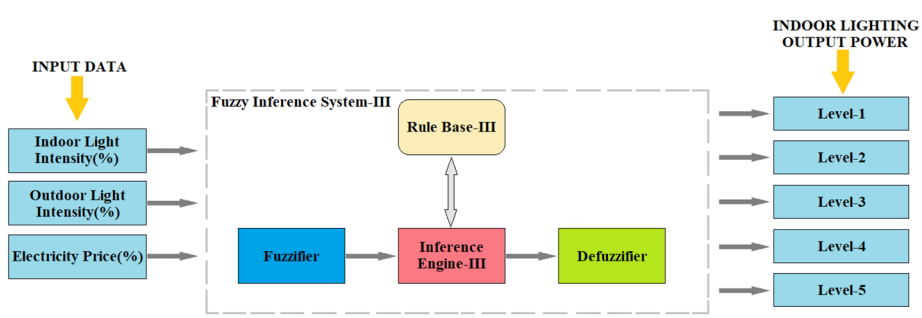


Fig. 7 Fuzzy inference engine III

If Electricity Price is "HIGH", Indoor Light Intensity is "HIGH" and Outdoor Light Intensity is "HIGH", Indoor Lighting Output Power is "LEVEL 1"

The triangle membership functions are illustrated in Fig. 8a–c for input and output variables of the third fuzzy inference engine. Inputs and outputs are transformed into fuzzy values with triangular membership functions and fuzzy membership degrees are obtained. After the inputs are processed, the fuzzy values of the interior lighting output

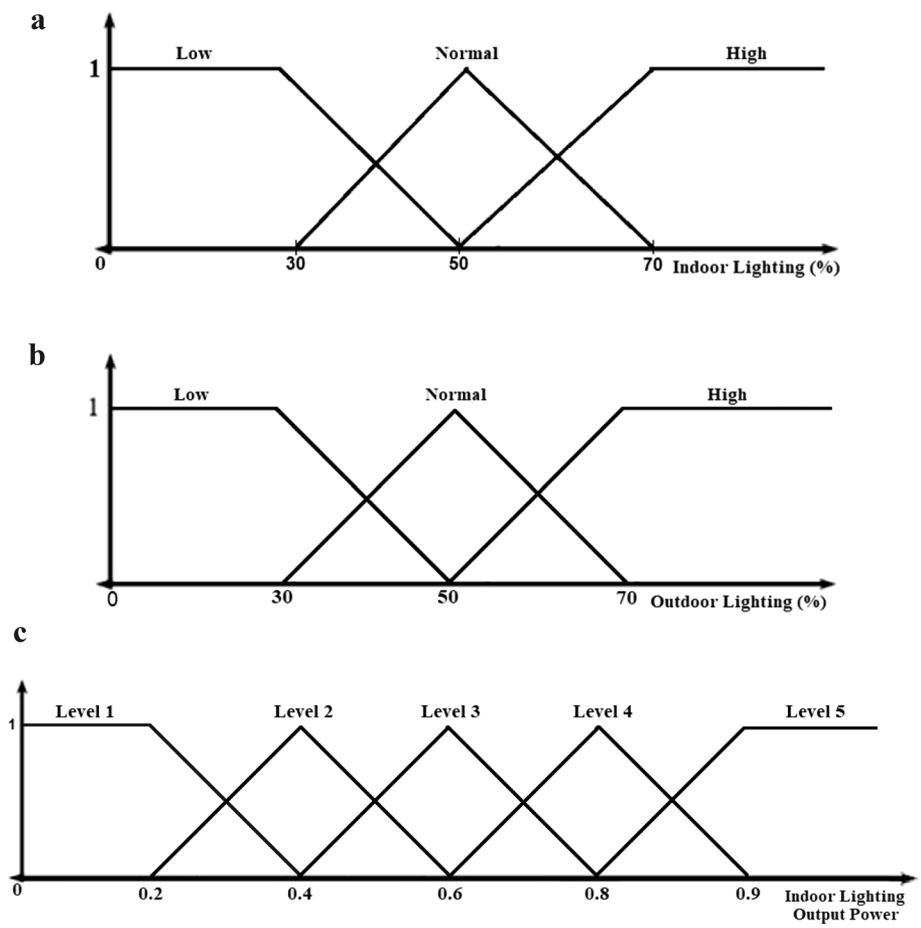


Fig. 8 **a** Indoor light intensity fuzzy membership function. **b** Outdoor light intensity fuzzy membership function. **c** Indoor lighting output power fuzzy membership function

power are determined with the help of the Mamdani minimum inference mechanism. The Centroid defuzzification method is used to convert these values to the output values. The interior lighting output power is classified as "Level 1," "Level 2," "Level 3," "Level 4" and "Level 5." At Level 1, the indoor lighting remains switched off.

Circuit and visual design

All control is performed through the Nextion 4.3-inch HMI LCD screen. Two separate options have been constructed: a manual test mode and a normal operating mode. The sensors are installed on the model house and connected to the electronic board. In addition to the menu displayed on the Nextion LCD screen, the output powers for the interior lighting, cooling, and heating are also indicated by the level LEDs on the electronic board. Filter capacitors have been included to decrease the impact of any electromagnetic noise that could arise from the microcontroller, sensors, or other circuit components. The 18F46K20 microcontroller, which is responsible for the control, and communication with the Nextion LCD, the DS 3231 precision clock module, and all other management, is programmed utilizing the C programming language. First, circuit simulation tests were conducted in the Proteus program. Following that, the printed

circuit was created by transferring it onto the PCB. The electronic board structure for the system was designed in the Proteus program, and the PCB diagram is presented in Fig. 9.

To conduct experimental studies on the system, a model house was designed, and sensors were installed in appropriate locations. Their physical connections were made to the control card. Analog data collected from the sensors were converted to digital format and processed in the microcontroller. The design of the model house used for experimental studies and the placement of sensors are illustrated in Fig. 10.

The Nextion LCD screen interface, which controls the device's operation, is designed using the Nextion Editor program. The homepage design is displayed in Fig. 11. In this menu, the brightness adjustment of the screen is made from the part hidden in the upper left. Here, it is possible to reach different menus. The instantaneous status of electricity, water, and natural gas is shown to the consumer in Fig. 12. Electricity, water, and natural gas consumption are closed when there is no consumer. If the consumer is a pet, the natural gas valve is closed; water and electricity consumption are activated. If the consumer is human, electricity, water, and natural gas are active. Electricity, water, and natural gas consumption are monitored from this menu.

The consumer situation obtained from the first inference engine, the electricity price selected, and the value of the temperature sensed are instantly monitored and the cooling and heating output power is calculated. Electricity price is shown as a slide bar. Fuzzy results are mathematically calculated based on the user's selection of low, normal, or high electricity prices. In addition, the indoor lighting output power is calculated based on the instantaneous light intensity detected by light sensors installed inside and outside the model house, and the user-selected electricity price. Figure 13 displays the manual test page, which offers manual control of variables such as time, indoor and outdoor light intensity, number of motion and sound detections,

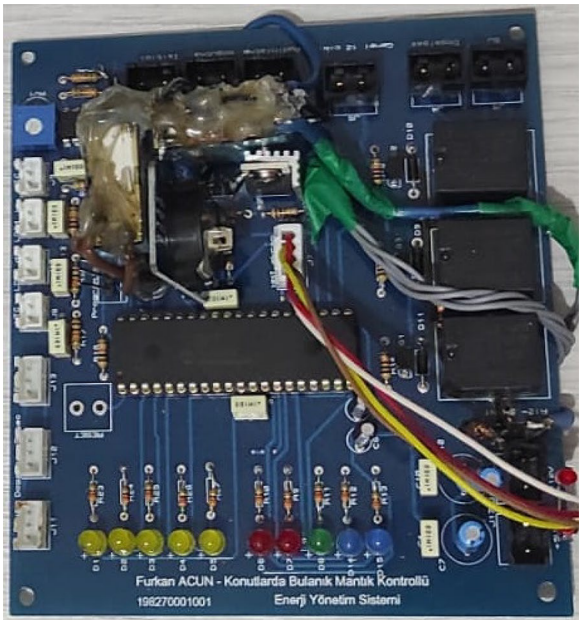


Fig. 9 The designed control card

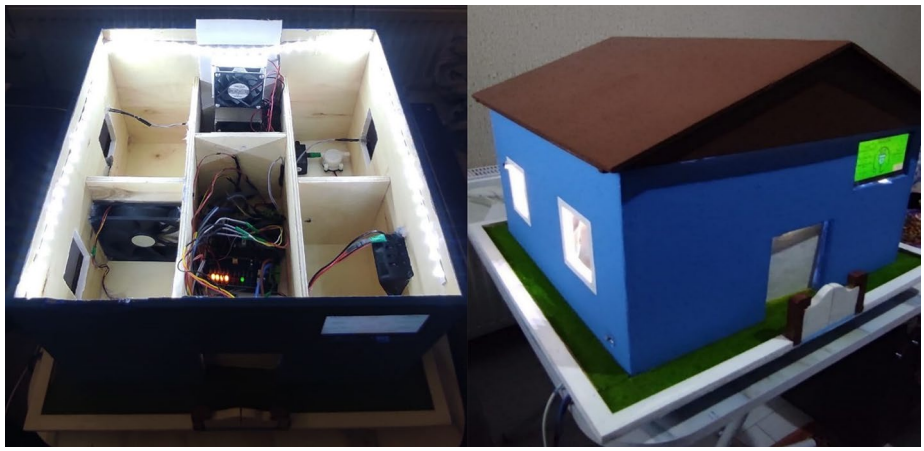


Fig. 10 Model house sensor placement and structure

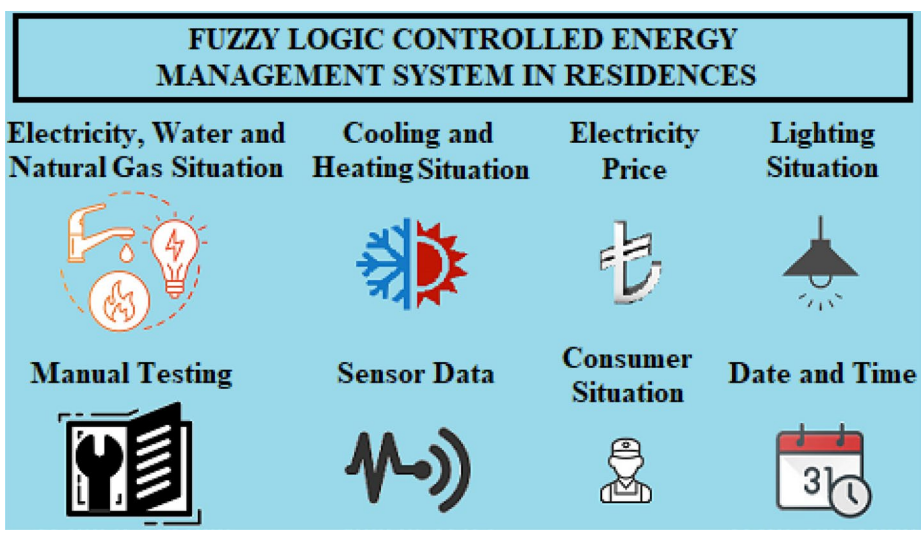


Fig. 11 Nextion LCD screen home section

ambient temperature, and electricity price for each desired test scenario. The page also displays the results of three different inference engines for electricity, water, and natural gas situations on the right-hand side. The first page presents the membership status of the test results as a percentage, while the second page displays the mathematical values of the Centroid defuzzification results."

The fuzzy logic controller's test results menu has been added as a submenu on the manual test menu, as depicted in Fig. 14. This menu allows for instant monitoring and control based on the parameters selected on the manual test page.

There is a Centroid clarification menu added as a subpage within the manual test menu. On this page, the mathematical calculations of Centroid defuzzification are followed and the accuracy of the results of three different inference engines is checked.

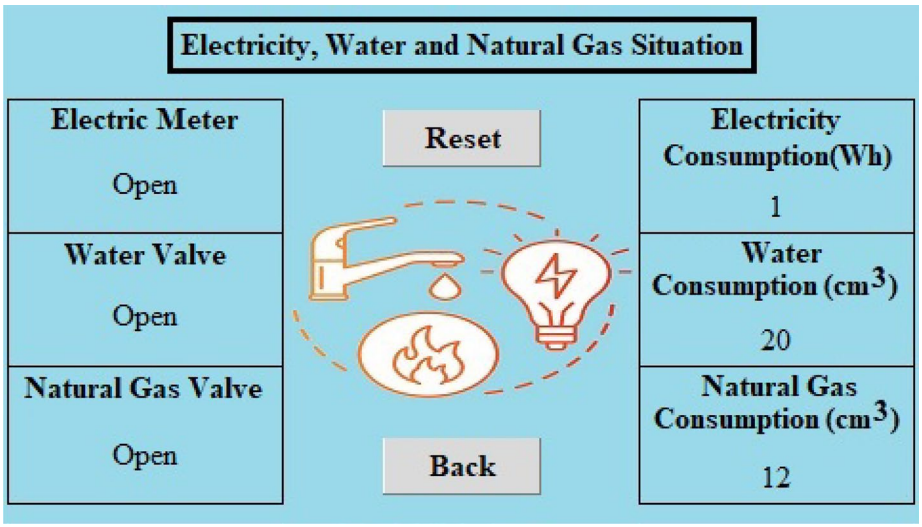


Fig. 12 Interface showing electricity, water, and natural gas

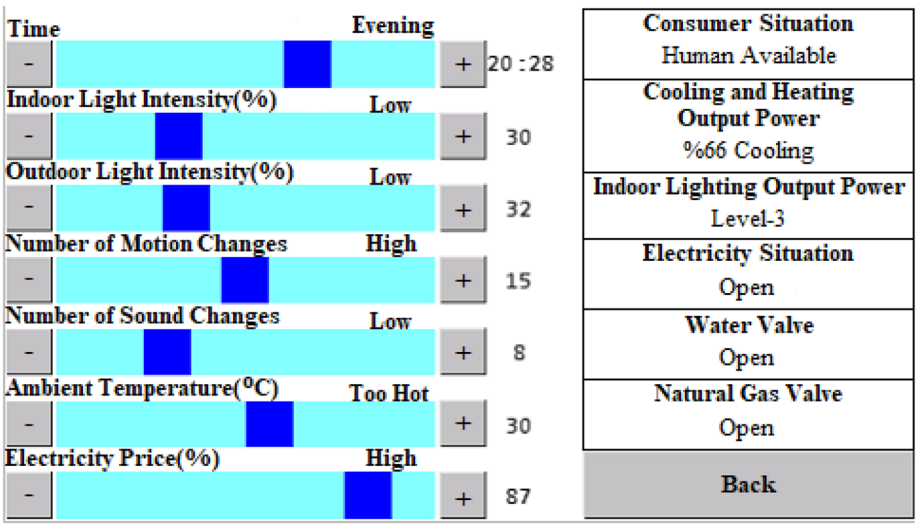


Fig. 13 Manual test interface

Additionally, the sensor data page is updated in real time with information such as time, number of motion changes, indoor and outdoor light intensities, ambient temperature, and sound changes. On the consumer situation menu, the membership values obtained according to the sensor data are followed. On the date and time menu, the date is set as day, month, and year. Apart from the date set, the hour and minute settings are made separately.

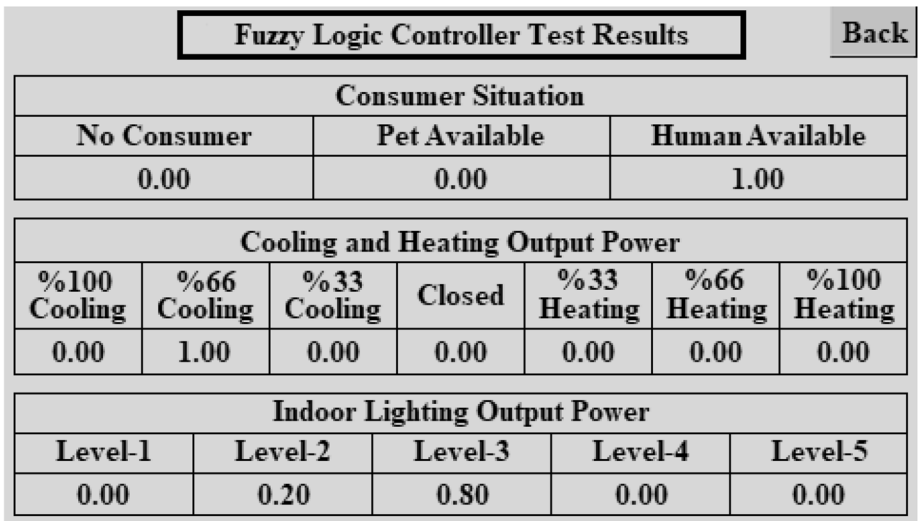


Fig. 14 Fuzzy logic controller test results interface

Experimental results

Light, motion, temperature, and sound sensors are used for system inputs, which are then represented by triangular and trapezoidal membership functions within a fuzzy logic structure. Three fuzzy logic inference engines are constructed using a Mamdani-type inference method and a Centroid defuzzification method. The output power of the lighting, heating, and cooling systems is controlled by the sensor data. Overall management of the system is achieved through a combination of a microcontroller, sensors, and a Nextion HMI display.

The manual trials are conducted on the fuzzy inference mechanism before the system is tested in real time. These trials are performed using the manual test menu on the Nextion LCD screen. The input parameters could be adjusted in three different fuzzy inference engines to test the consumer situation, cooling and heating output

Table 2 Test results for consumer situation

Inputs				Output memberships (μ)			Centroid defuzzification memberships
Indoor light intensity (%)	Sound change frequency	Motion change frequency	Time	No consumer	Pet available	Human available	
51	15	15	12:00	0	0	1	0.9
28	2	7	08:15	0	0.48	0.51	0.8
32	7	12	14:58	0	0	1	0.9
17	12	7	14:58	0	0.79	0.2	0.74
20	22	9	22:39	0	0	1	0.9
40	26	12	00:59	0	0	1	0.9
54	11	15	16:54	0	0	1	0.9
14	0	1	15:15	1	0	0	0.3
14	12	9	21:25	0	0	1	0.9
10	6	15	21:25	0	0	1	0.9
80	19	6	07:25	0	0.39	0.60	0.82

Table 3 Test results for cooling and heating output power

Inputs			Output memberships (μ)							Centroid defuzzification memberships
Consumer situation memberships (μ)	**Electricity price (%)**	**Ambient temperature (°C)**	**Cooling power 100%**	**Cooling power 66%**	**Cooling power 33%**	**Cooling and heating Off**	**Heating power 33%**	**Heating power 66%**	**Heating power 100%**	
Human available ($\mu = 1$)	29	25	0	1	0	0	0	0	0	0.25
Pet available ($\mu = 0.79$)	46	14	0	0	0	0	0.33	0.66	0	0.708
Human available ($\mu = 1$)	19	34	1	0	0	0	0	0	0	0.125
Human available ($\mu = 1$)	11	20	0	0	0	1	0	0	0	0.5
No Consumer ($\mu = 1$)	91	31	0	0	0	1	0	0	0	0.5
Human Available ($\mu = 1$)	30	8	0	0	0	0	0	0	1	0.875
Human Available ($\mu = 1$)	63	27	0	0.28	0.72	0	0	0	0	0.34
Human Available ($\mu = 0.60$)	15	8	0	0	0	0	0	0	1	0.875
Human available ($\mu = 0.60$)	15	38	1	0	0	0	0	0	0	0.125
Pet available ($\mu = 1$)	83	38	0	0	1	0	0	0	0	0.375
Pet available ($\mu = 1$)	18	38	1	0	0	0	0	0	0	0.125
Pet Available ($\mu = 0.75$)	18	9	0	0	0	0	0	0	1	0.875
Human available ($\mu = 1$)	16	41	1	0	0	0	0	0	0	0.125

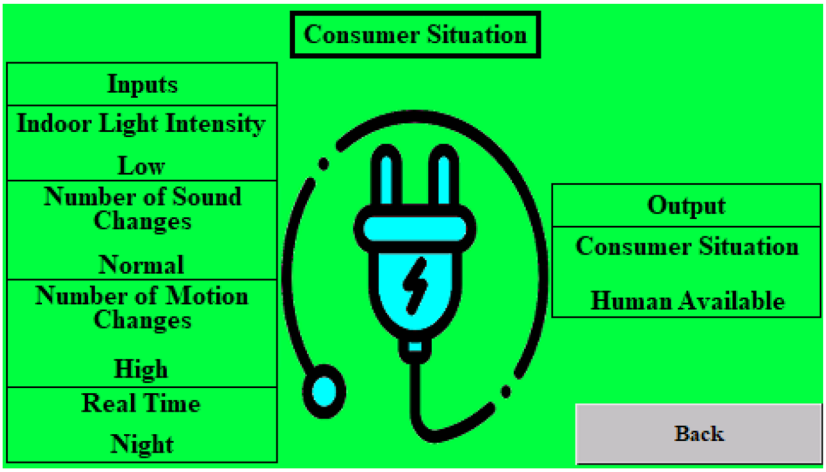
Table 4 Test results for interior lighting output power

Inputs			Light output memberships (μ)					Centroid defuzzification memberships
Electricity price (%)	Outdoor light intensity (%)	Indoor light intensity (%)	Level 1	Level 2	Level 3	Level 4	Level 5	
29	35	51	0	0	0	0.81	0.18	0.81
46	50	17	0	0.8	0.2	0	0	0.44
57	54	6	0.27	0.72	0	0	0	0.34
68	76	20	1	0	0	0	0	0.2
76	90	40	1	0	0	0	0	0.2
11	19	37	0	0	0	0	1	0.9
91	5	14	0	0	1	0	0	0.6
30	76	14	0	1	0	0	0	0.4
63	97	10	1	0	0	0	0	0.2
15	5	80	0	0	0	0	1	0.9
15	68	30	0	0.9	0.1	0	0	0.42

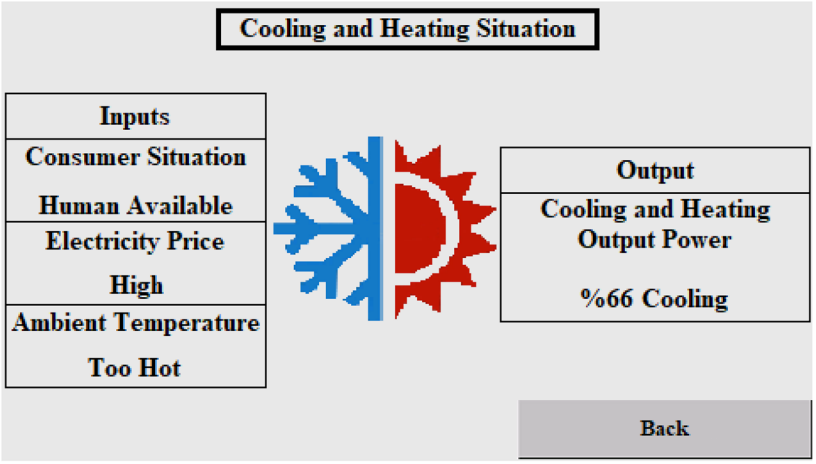
power, and interior lighting output power by varying the parameter values. The input parameters, numerical results of the Centroid defuzzification method, and membership degrees of outputs could be monitored during the trials.

The test results for the first fuzzy inference engine are presented in Table 2. This is a test to determine if the system is functioning correctly. The inputs for interior lighting, sound, and motion changes are adjusted, and the output membership function values are monitored. The second fuzzy inference engine test results are shown in Table 3. This section monitors the value of the heating–cooling output membership functions, which are adjusted based on changes in electricity prices and ambient temperature. The third fuzzy inference engine test results are given in Table 4. Considering the electricity price, indoor lighting and outdoor lighting intensity, the output level of lighting can be determined. These trials are carried out using the interface in Fig. 13. This interface enables manual testing of the system, allowing for verification of whether it produces the correct results.

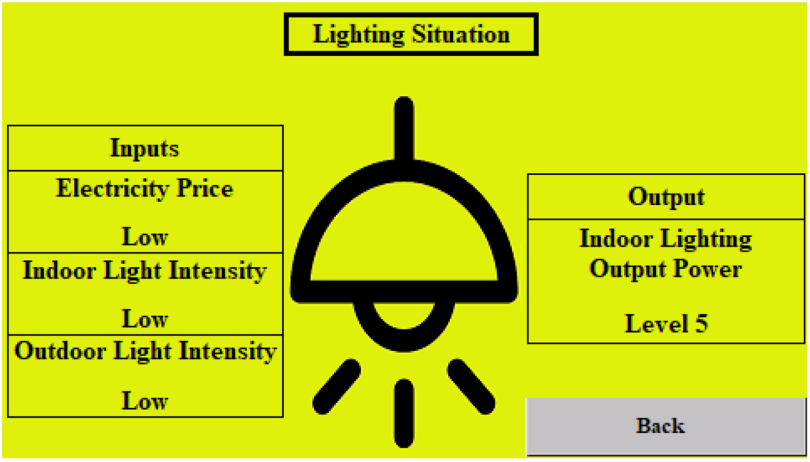
Real-time tests were conducted on the model house, and the obtained results were analyzed. As shown in Fig. 15a, when the system inputs were set to Indoor Light Intensity "LOW," Sound Change "NORMAL," Motion Change "HIGH," and Time "NIGHT," the system output was sensed as Consumer Situation "HUMAN AVAILABLE." In Fig. 15b, when the inputs were set to Consumer Situation "HUMAN AVAILABLE," Electricity Price "HIGH," and Ambient Temperature "TOO HOT," the system output was determined as Cooling and Heating Condition "COOLING POWER 66%." In Fig. 15c, when the inputs were set to Electricity Price "LOW," Indoor Light Intensity "LOW," and Outdoor Light Intensity "LOW," the system output was determined as "LEVEL 5." When the real-time test results were examined, it was observed that all three fuzzy inference engines provided appropriate results by the fuzzy membership values of the input sets.



a



b



c

Fig. 15 **a** Customer situation test result. **b** Cooling and heating output power test result. **c** Indoor light intensity output power test result

Let's examine the operation of the system by considering a typical daily consumer behavior. A person left their house at 07:00 in the morning and returned home at 18:00 in the evening. Upon their return, the outdoor temperature was recorded as 15 °C for a duration of 2 h, followed by 11 °C between 20:00 and 23:00, and 10 °C between 23:00 and 07:00. The consumer turned off the lighting after 23:00 and it was turned back on between 06:00 and 07:00. According to this scenario, in the proposed fuzzy logic-controlled system, the heating operates at 33% power for 1 h, 66% power for 2 h, and 66% power for 4 h and 45 min. The lighting is turned on at 25% power for 2 h and at 50% power for 4 h, and is off for 7 h. In total, the current system consumes 491.1 W-hours for lighting and heating. In the conventional system, under the same conditions, the heating operates at 33% power for 5 h and at 66% power for 5 h. The lighting remains on at 100% power for 6 h and is off for 7 h. Consequently, the conventional system consumes 570.6 W-hours for lighting and heating. Therefore, thanks to the proposed system, instead of consuming 570.6 W-hours per day, only 491.1 W-hours are consumed. The proposed system achieves a daily energy savings of 13.93% in this scenario.

Conclusion

This study proposes a low-budget energy management system for residential homes that uses fuzzy logic control. The system is tested on a model house equipped with two lights, one sound, one temperature, and one motion sensor. The cooling and heating output power of the house is determined based on the current electricity price, the consumer's situation, and the ambient temperature. The indoor lighting output power is adjusted according to the indoor and outdoor light intensity, and the instant electricity price. The lighting system has four different adjustment levels (25%, 50%, 75%, and 100%) in the residence, while the cooling and heating system has three options of 33%, 66%, and 100%, respectively. The natural gas system can be completely closed or opened, depending on the consumer's situation.

The use of fuzzy logic controllers in the design and development of the energy management system provided a cost-effective, efficient, and effective solution for residential homes. The system's performance was observed to depend on the number and sensitivity of sensors used. To increase the system's accuracy, more sensors or wireless sensors could be added after conducting a cost-performance analysis. Additionally, the system can be remotely controlled and monitored through an application by adding a Wi-Fi module. Smart home appliances such as washing machines, dishwashers, dryers, and ovens can also be integrated into the energy management system.

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Author contributions
FA was involved in conceptualization, methodology, software, validation, writing—original draft. MC contributed to formal analysis, investigation, supervision, writing—review and editing.

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Declarations

Competing interests
The authors declare no conflict of interest.

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References
1. Energy efficiency: The clean facts. https://www.nrdc.org/stories/energy-efficiency-clean-facts. Accessed 10 Dec 2022.
2. Rajesh P, Shajin FH, Kannayeram G (2022) A novel intelligent technique for energy management in smart home using internet of things. Appl Soft Comput 128:109442
3. Yousefi M, Hajizadeh A, Soltani MN (2019) A comparison study on stochastic modeling methods for home energy management systems. IEEE Trans Industr Inf 15(8):4799–4808
4. Zupančič J, Filipič B, Gams M (2020) Genetic-programming-based multi-objective optimization of strategies for home energy-management systems. Energy 203:117769
5. Kwon K, Lee S, Kim S (2021) AI-based home energy management system considering energy efficiency and resident satisfaction. IEEE Internet Things J 9(2):1608–1621
6. Han J, Choi CS, Park WK, Lee I (2011) Green home energy management system through comparison of energy usage between the same kinds of home appliances. In: 2011 IEEE 15th ınternational symposium on consumer electronics (ISCE): 14–17 June; Singapore. IEEE: 1–4
7. Ahmed MS, Mohamed A, Homod RZ, Shareef H (2016) Hybrid LSA-ANN based home energy management scheduling controller for residential demand response strategy. Energies 9(9):716
8. Mahapatra C, Moharana AK, Leung VC (2017) Energy management in smart cities based on internet of things: peak demand reduction and energy savings. Sensors 17(12):2812
9. Lissa P, Deane C, Schukat M, Seri F, Keane M, Barrett E (2021) Deep reinforcement learning for home energy management system control. Energy AI 3:100043
10. Kontogiannis D, Bargiotas D, Daskalopulu A (2021) Fuzzy control system for smart energy management in residential buildings based on environmental data. Energies 14(3):752
11. Arabul FK, Arabul AY, Kumru CF, Boynuegri AR (2017) Providing energy management of a fuel cell–battery–wind turbine–solar panel hybrid off grid smart home system. Int J Hydrog Energy 42(43):26906–26913
12. Atef S, Ismail N, Eltawil AB (2022) A new fuzzy logic based approach for optimal household appliance scheduling based on electricity price and load consumption prediction. Adv Build Energy Res 16(2):262–280
13. Baniyounes A (2019) Energy performance of fuzzy logic controllers in smart buildings. Int J Energy Econ Policy 9(1):41–47
14. Christopoulos K, Raptis A, Antonopoulos C, Orfanoudakis T, Voros NS (2018) A scalable approach to efficient house power consumption and CO 2 management through fuzzy logic. In: 2018 IEEE ınternational conference on ındustrial technology (ICIT): 20–22 February ; Lyon, France. IEEE: 1132–1137
15. Garrab A, Bouallegue A, Bouallegue R (2017) An agent based fuzzy control for smart home energy management in smart grid environment. Int J Renew Energy Res 7(2):599–612
16. Collotta M, Pau G (2015) A solution based on bluetooth low energy for smart home energy management. Energies 8(10):11916–11938
17. Behrooz F, Ramli A, Samsudin K (2009) A new fuzzy logic approach to building automation from safety and health perspective. In: International Advanced Technology Congress (ATCi): November 3–5; Malaysia
18. Fayaz M, Kim D (2018) Energy consumption optimization and user comfort management in residential buildings using a bat algorithm and fuzzy logic. Energies 11(1):161
19. Khalid R, Javaid N, Rahim MH, Aslam S, Sher A (2019) Fuzzy energy management controller and scheduler for smart homes. Sustain Comput Inform Syst 21:103–118
20. Jarndal A (2016) Smart home system for energy saving using genetic-fuzzy-neural networks approach. Int J Sustain Water Environ Syst 8(1):27–31
21. Iqbal MM, Kumar S, Lal C, Kumar C (2022) Energy management system for a small-scale microgrid. J Electr Syst Inf Technol 9(1):5
22. Otuoze AO, Mustafa MW, Larik RM (2018) Smart grids security challenges: classification by sources of threats. J Electr Syst Inf Technol 5(3):468–483
23. Han J, Choi C-S, Park W-K, Lee I, Kim S-H (2014) Smart home energy management system including renewable energy based on ZigBee and PLC. IEEE Trans Consum Electron 60(2):198–202
24. Anvari-Moghaddam A, Monsef H, Rahimi-Kian A (2014) Optimal smart home energy management considering energy saving and a comfortable lifestyle. IEEE Trans Smart Grid 6(1):324–332
25. Erol-Kantarci M, Mouftah HT (2011) Wireless sensor networks for cost-efficient residential energy management in the smart grid. IEEE Trans Smart Grid 2(2):314–325
26. Bolurian A, Akbari H, Daemi T, Mirjalily S, Mousavi S (2022) Energy management in a smart grid including demand response programs considering internet of things. Renew Energy Res Appl 3(1):131–141
27. Zunnurain I, Maruf MNI, Rahman MM, Shafiullah G (2018) Implementation of advanced demand side management for microgrid incorporating demand response and home energy management system. Infrastructures 3(4):50

28. Krigger J, Dorsi C (2004) Residential energy: cost savings and comfort for existing buildings. Saturn Resource Management
29. Bazila S, Kalinga E, Ibwe K, Abdalla AT (2022) Electrical power behavioral usage in public institutions and its intervention: a case of tanzania higher learning institutions. J Electr Syst Inf Technol 9(1):1–14
30. Knypiński Ł (2022) Performance analysis of selected metaheuristic optimization algorithms applied in the solution of an unconstrained task. COMPEL Int J Comput Math Electr Electron Eng 41(5):1271–1284
31. Deniz V, Çunkaş M (2019) Real time fuzzy logic controlled fire detection system for home applications. Int J Intell Eng Inform 7(5):441–456
32. Rai N, Rai B (2018) Control of fuzzy logic based PV-battery hybrid system for stand-alone DC applications. J Electr Syst Inf Technol 5(2):135–143
33. Acun F, Çunkaş M (2022) Low-cost energy management system in homes. In: International conference on engineering technologies (ICENTE'22): 17–19 November ; Konya, Turkey. 421–427

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