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Development of fuzzy logic-based demand-side energy management system for hybrid energy sources

Oladimeji Ibrahim [a], Mutiu Shola Bakare [b], Temitope Ibrahim Amosa [c,*], Abdulrahman Okino Otuoze [a], Waheed Olaide Owonikoko [d], Esraa Mousa Ali [e], Lambe Mutalub Adesina [f], Olalekan Ogunbiyi [f]

[a] Department of Electrical and Electronics Engineering, University of Ilorin, Ilorin 240003, Nigeria
[b] Department of Electrical Engineering, Kampala International University, Ishaka 20000, Uganda
[c] Department of Electrical and Electronic Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, Perak 32610, Malaysia
[d] Department of Electrical and Biomedical Engineering, University of Vermont, Burlington, VT 05405, USA
[e] Department of Aviation Sciences, Amman Arab University, Amman, Jordan
[f] Department of Electrical and Computer Engineering, Kwara State University, Malete, Nigeria

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ABSTRACT

Demand-side energy management techniques, such as load shielding, shifting, and delaying appliance operation during peak periods, are typically used to reduce electricity costs at the expense of users' comfort. To address these challenges, especially where operational delays are unacceptable, distributed generation (DG) is frequently incorporated into the grid system to improve power balance and total energy costs. However, dynamic load demands and varying outputs from renewable DG sources such as solar photovoltaic (PV) systems make energy management in microgrids (MGs) extremely challenging. Moreover, most of the existing studies in this domain focus on objective functions that are geared on optimising the economic balance between cost and value of MG operation over a certain time period. Nevertheless, research that took into consideration the stochastic behaviour of DG's subsystems in addition to cost and benefit of MG operation are still limited. This current study proposed a fuzzy logic control (FLC) integrated energy management system (EMS) for commercial loads with hybrid grid-solar PV/battery energy system. The proposed technique intelligently selects energy sources using the grid energy cost and the state of charge (SoC) of the solar PV/battery at any time of the day. The EMS operate the loads at a reduced cost without any operational delay or shifting. The system was implemented in the MATLAB/Simulink environment, and the techno-economic feasibility of energy cost savings was investigated by comparing the developed scheme with the Homer hybrid energy system model for a hotel building. The developed EMS reduced energy costs by an average of 11.87 % per day and 7.94 % over a 20-year lifetime.

Introduction

The continuous global population growth consequently leads to an increase in global electrical energy demand. Conventional power grids are no longer sufficient in meeting global energy demands, as required by the economic growth witnessed in the manufacturing and telecommunications industries in recent years. The challenge of meeting the electricity demand with available resources often leads to different issues between the users and the utility which includes a hike in electricity charges, different time tariff, maximum demand tariff, and a high peak average ratio (PAR). Energy management is often employed as a way of improving energy efficiency to meet the increasing energy demand at reduced cost through optimal energy utilisation and smart grid. Energy management techniques play a significant role in energy usage thereby positively affecting the efficiency and reliability of the power system. In a broader term, the management of energy in an electrical grid network is broadly classified into two; supply-side management (SSM) and demand-side management (DSM). The SSM generates and efficiently delivers reliable energy to the users. On the other hand, the DSM efficiently manages and reduces energy consumption by continuously monitoring electricity usage and appliance scheduling through advanced communication and control infrastructure [17].

The key element in DSM is demand response (DR) programs that

* Corresponding author.
E-mail address: temitope_21002075@utp.edu.my (T.I. Amosa).

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Nomenclature

Abbreviations

AC	air conditioning
AI	artificial intelligence
BOA	bisector of area
COA	centroid of area
CANREL	Canadian renewable energy laboratory
DG	distributed generation
(DR)	demand response
DSM	demand side management
EV	electric vehicle
EMS	energy management system
FLC	fuzzy logic control
FiT	feed-in tariff
HOMER	hybrid optimization model for electric renewable energy
HVAC	high voltage alternating current
LOM	largest of maximum
LCOE	levelized cost of energy
LV	Low voltage
MAS	multi-agent system
MOM	mean of maximum
MG	microgrid
OBEMS	optimization-based EMS
PAR	peak average ratio
PV	photovoltaic
RBEMS	rule-based EMS
RF	renewable fraction
SSM	supply side management
SOM	small of maximum
SoC	state of charge
SaaS	software-as-service
TOU	time-of-use

Symbols

P_{Bl_j}, P_{Hl_j}	The power rating of basic and heavy operated loads respectively
C_{Bl}, C_{Hl}	The total cost per day of the basic and heavy operated loads
$S(t)$	The state of operation of the appliances at time (t)
$C(t)$	The dynamic Energy tariff at time (t)
E^T_{Bl}, E^T_{Hl}	The Energy consumption of basic and heavy operated loads
E_T	Total Energy consumed by appliances
C_T	Total Energy consumed by appliances
E_{grid}	The total Energy used by grid
$R_p(t)$	Real time price of the grid over a period of time (t)
$E_i(t)$	Hourly Grid Energy used
C_g	The total cost of energy used by grid consumers
A_{PV}	The area of photovoltaic $[m^2]$
σ	The efficiency of solar PV
$\varsigma(t)$	The solar irradiation at time (t) $[kWh/m^2]$
P_F	The packing factor
C_b	The battery capacity
V_b	Battery voltage
DoD	Depth of discharge
l_b	Battery loss
E_t	The Energy demands
D_a	Autonomy days
η^B, η^{inv}	The efficiency of battery and inverter respectively
$E_D(t)$	The Energy demand at time (t)
$C_{op}(t)$	The off-peak cost of Grid at time (t)
$E_b(t)$	The Battery Energy at time (t)
$E_{PV}(t)$	The Solar PV Energy at time (t)
SC_i	Salvage cost
RC_i	Replacement cost
OM_i	Operating and maintenance cost
IC_i	Investment cost
$TNPV_{sys}$	The total net present value of the system
F_t	The fuel expenditures in the year (t)
I_t	The investment expenditures in the year (t)
r	The discount rates
E_1, E_2	The energy used during the peak and off-peak period
P_h, O_h	The peak and off-peak periods in a day
C_1, C_2	The peak cost and off-peak cost of the dynamic pricing
C_{PV}	Total cost of solar panels
C_{b3}	The total cost of battery

encourage the users to actively partake in load shedding strategy as a response to electricity supply or dynamic electricity price timing through demand-supply balancing for improved system reliability. DR is usually defined as changes in electric usage by customers from their normal consumption patterns in response to changes in the price of electricity over time, or incentive payments designed to induce lower electricity use at times of peak demand or when system reliability is threatened [6]. With demand response, the consumers would have the advantage of tariff cost reduction by exercising little waiting time to operate high demand loads during off-peak periods or deciding to pay a higher price during the peak period [25].

The main goal of demand response programs design is to decrease electricity consumption or shift its usage from on-peak to mid or off-peak periods depending on consumers' preferences and lifestyles [39]. In grid system operation with differential Time-of-Use (TOU) rates, consumers pay more during the peak period and energy management approaches are employed to save cost. The demand response schemes are generally implemented within industries, commercial setups as well as residential buildings through the use of dedicated control systems to shed loads in response to a request by a utility or market price conditions. Services such as lights, machines, and air conditioning are reduced according to a pre-planned load prioritization scheme during critical time frames.

The conventional energy management approach for demand response involves load shifting and delays during peak periods to save energy costs when consumers solely depend on utility supply. The technological advancement has introduced new dynamism in achieving the objective of cost savings on the total energy cost without necessarily incurring waiting time on load operations [4,24]. An alternative to load shedding during the peak period for energy cost saving is the on-site generation of electricity to supplement the power grid. With the new distributed generation (DG) and energy control strategies, it's more convenient to switch part of the loads to alternate sources such as on-site solar panels and batteries during the peak period. Under conditions of tight electricity supply, demand response significantly decreases the peak price and improves system reliability.

Recent energy reports have shown that the Levelized Cost of Energy (LCOE) for renewable energy such as solar photovoltaic (PV) is flattering to that of the conventional grid, most especially during peak period charges for commercial and industrial applications [12,31]. The advantage of hybridising DG with the grid system has now been extended to residential demand applications [38,42,44]. A comprehensive survey and analysis on the improvement rates of cost/investment for renewable energy technologies by Benson and Magee established the prospect of solar PV having the highest reduction in cost over time, especially when used at commercial and industrial scales [7].

Investigation of different compositions of hybrid grid/renewable energy systems now shows great promise for meeting increasing energy

demand at low cost. However, given the indeterministic nature and high unpredictability of both renewable resources and load demand, intelligent energy management systems (EMS) capable of controlling power flow among its constituents and ensuring safe, reliable and economic operation of the system are necessary [48,20,15]. Researchers have been interested in these systems for more than a decade, as evidenced by the extensive literature on the subject highlighted in recent review studies [27,45,19]. The large number of EMS designs for microgrid (MG) systems, are mostly non-multi-objective, focusing only on either MG topologies, DG sources controllability, load varieties, or energy storage systems under different settings [2]. Also, from a methodological point of view, the design of the EMS generally entails the definition of objective functions and optimization algorithms to reach the MG desired behaviour by setting the power reference of MG controllable elements according to the available information like energy tariff, previous load consumption data, measured MG variables, weather conditions, etc.

Several possibilities have been reported in this regard over the years. However, a substantial number of these studies are based on objective functions targeted at optimising the economic balance between benefit and cost of MG operation over a certain period. Moreover, these methods are typically not all-encompassing as they do not account for inherent features of DG's nonlinearity, as well as detailed characteristics of energy storage and backup systems, such as the SoC in battery banks or appropriate parameters for configuration and operation of the DG sources [1,2]. Invariably, EMS that does not prioritize the DG status usually incurs high replacement costs, which in the long run does not favour long-term energy cost savings.

To address these issues, this work aims to develop a fuzzy logic control (FLC) integrated energy management system (EMS) for demand side loads, focusing on the selection of hybrid energy sources using TOU tariffs at various times of the day. The proposed EMS prioritize the characteristic state of the battery charge status for powering classified loads either during peak or off-peak period. The energy system consists of a hybrid grid-solar PV/battery and the proposed EMS that intelligently operates the classified loads at the lowest possible energy cost based on solar PV/battery reserve capacity and the peak load demand hours. The EMS interfaced between the power sources and the loads for effective energy sources selection to operate different classes of loads. The loads were classified based on their power ratings and operated from different power sources to achieve minimum energy cost at different times of the day. The techno-economic analysis was carried out on the daily energy usage while using the EMS and compared with that of the HOMER optimisation model as a baseline to ascertain the effectiveness of the proposed fuzzy logic energy management control in demand response applications.

The unique contributions of this work can be summarised as follows:

1. A novel FLC EMS that utilises a real-time grid cost and solar PV/battery SoC for DSM is presented.
2. The proposed EMS effectively balances power between the grid and the solar PV/battery for operating heavy-duty appliances, thereby improving the overall system reliability.
3. The load classification in this work consequently reduces the DG installation cost over the conventional approaches that often consider the entire load in the MG.
4. The proposed EMS was able to successfully overcome data sparsity concerns in the development of effective DSM schemes.

The remainder of this paper is organised as follows: Section 2 presents a review of related work, detailing various energy management approaches, ranging from simple time-based energy mix switching to an intelligent method that takes into account the state of availability and dynamic cost of various energy sources. In Section 3, the proposed energy management scheme, the modelling of the energy sources, and the classification of various loads are discussed. Furthermore, the implementation of the system in the MATLAB/Simulink environment and the techno-economic analysis were also presented in Section 3. The results of the daily energy mix with the proposed energy management system for commercial loads are investigated in Section 4 together with the cost comparison between the proposed system and Homer hybrid energy model. And finally, the conclusion which identifies the effectiveness of the proposed system in the area of cost-energy saving, grid smoothing, and improved system reliability is presented in Section 5.

Related work

Several investigations have been conducted on the use of different intelligent energy management techniques for integrating DG with the grid to achieve reduced investment cost, operating cost, and improved system reliability. Recently, the use of artificial intelligence (AI) techniques with hybrid energy sources in demand response have significantly addressed the inherent challenge of waiting time usually associated with load shifting or waiting time that characterized conventional demand response energy management techniques. AI-based energy management systems have been designed to handle multiple energy sources or agents such as solar, wind generators, flat-plate collectors, electric and thermal loads, energy storage systems, and fossil fuels with grid system hybridisation [2,10,46]. Artificial intelligence also found its applications in weather forecast, occupancy modelling, usage, and energy price signals to greatly reduce utility bills and improve system reliability [47]. They are employed in monitoring and collecting information about energy consumption in the form of numbers, text, images, and videos for evaluation and optimising energy consumption to reduce its usage during peak hours.

BeeBryte, a France and Singapore-based "software-as-a-service" (SaaS) company reported to have built a cloud-based intelligence software that monitors real-time load in large commercial and industrial facilities. The software automatically switches specific loads such as high voltage alternating current (HVAC) systems to battery storage based on TOU charges and the system has delivered up to 40 % savings in utility bills [23]. Also, Fikru investigated electricity bill savings and the role of energy efficiency improvements on residential solar adopters in the USA. The residential solar adopters reduce summer electricity bills by 61 % on average [16]. The work shows that solar adopters with an efficient heating/cooling system and lighting have higher savings in electricity bills than those without. The output of the investigation encouraged households to first consider performing efficiency upgrades when installing solar panels for demand response applications.

On utility bill savings in demand response, Tatiani et al., examine the cost-effectiveness of residential PV systems in the UK by considering the changes that occur in the supporting mechanism and the Feed-in Tariff (FiT) [18]. The analysis stresses the importance of the FiT scheme and determines the lowest cost of produced energy that domestic PV systems can achieve with the current policies in the UK. The study revealed that domestic PV systems can reach grid parity for certain scenarios and in certain UK cities within a short-term period. A study on cost-effective energy billing mechanisms for small-scale industrial customers in Uganda was presented in [36]. The case study involves the designing of a solar hybrid system for a coffee processing industry in Uganda. Three energy systems Grid/Solar PV/Diesel with net metering and without net metering were analysed using multiple sources of data from the questionnaire, literature, and site data. The system is compared with the existing grid backed up with a generator and the grid-alone systems. The result of the analysis shows that the coffee factory had huge savings within one year by reducing the simple payback period by 5 years. The findings further suggested that DG systems with net metering mechanisms are the most economical energy supply systems in Uganda for small and medium-scale enterprises.

At the large-scale industrial level, renewable DGs are employed against maximum demand penalty and to bridge the gap of waiting time that might arise from load shifting during peak demand hours when conventional energy management techniques are employed [11].

Demand charge savings from solar PV and energy storage was investigated for a variety of scenarios by Darghouth et al. [13]. The study explores how demand charge savings vary with demand charge designs and customer load profiles. The system was modelled for a variety of residential and commercial customers. The findings show that demand charge savings are lowest under a basic, non-coincident demand charge design where the demand charge is based on the maximum demand level over the month, regardless of timing. The investigated scenarios also show that PV provides greater demand charge savings, for both commercial and residential customers, when demand charge designs are based on predefined, daytime peak periods or longer averaging intervals. Demand charge savings from solar PV combined with storage were found to be greater than the sum of the savings attained through either technology separately.

Recent literature has shown that different energy management systems have been proposed for hybrid energy mix and load management with the targeted objective of saving the initial investment and operating cost on energy. Some of the techniques range from a simple approach of operating different renewable energy resources at different times of the day without necessarily considering the state of the energy source to computational intelligence methods that accounted for the state of the system units for improved energy cost savings and smooth system operation. Renewable energy resource outputs are generally not constant due to their intermittent nature, and this makes their integration and management a little bit complex in grid and MG applications. The complexity of renewable energy resources in hybrid energy systems is best managed with the incorporation of different artificial intelligence techniques to efficiently manage the system more reliably and cost-effectively without necessarily reducing power supply reliability.

Methodologically, designing an EMS involves defining objective functions and optimization algorithms to achieve the desired behaviour of the MG by adjusting the power reference of MG controllable elements based on the available data (like measured MG variables, energy tariff forecasted data, weather conditions, etc.). In recent years, several approaches have been suggested in the literature about how to do this. But in most of these existing works, the goal is to find the best balance between the cost and benefit of running a MG over a certain period. This is in addition to taking into account different energy scenarios. As a result, the formulation of objective functions based on these economic goals includes, among other things, grid tariff policies and user comfort requirements.

A design and performance analysis of a multi-agent system (MAS) was proposed and applied to the decentralized energy management problem of autonomous polygeneration MG [28]. The proposed strategy for managing energy makes use of game theory. The simulation-based system's results showed effective energy handling and successful MG management for all five of its participating agents. In order to achieve optimal energy management and control for the functioning of the MG, the created MAS has five agents, some of which either compete or collaborate, depending on the level of the energy produced by the RES and the energy stored in the battery bank. When comparing the result to a previously implemented MAS that uses computational intelligence algorithms (fuzzy cognitive maps), the proposed MAS energy management system performs better in terms of improved efficiency, reduced power losses, and a lower cost for a 20-year investment period.

An optimization rule-based energy management system was proposed for the Canadian Renewable Energy Laboratory (CANREL) MG facility by [37]. The EMSs were developed and implemented for the MG testbed located in Guelph, ON, Canada, for the existing hardware, software, and communication infrastructure. A rule-based EMS (RBEMS), which is commonly found in MG controllers nowadays, and an Optimization-based EMS (OBEMS), which is not yet popular in today's controllers, was tested and demonstrated in the MG testbed. The RBEMS is made up of a state machine that symbolizes the system commitment of various Genset units as well as the reduction of load and renewable generation. The OBEMS is based on a MG unit commitment model that reduces the cost of generation and curtailment while running the MG's hardware within technical bounds. The successful implementation and performance of the EMS demonstrate that the MG's components comply with dispatch orders. The OBEMS, uses the already-existing communications links to produce better overall results than the RBEMS while preserving the stability of the MG.

A decentralized energy management system, based on multi-agent systems, was developed for the efficient charging of electric vehicles, by expanding a state-of-the-art fuzzy logic controller-based energy management strategy, in combination with a charging power controller, based on fuzzy cognitive maps. The performance of the proposed multi-agent decentralized energy management system achieved a significant reduction in the investment costs of the MG, as compared with the use of a sole fuzzy logic controller-based energy management strategy [9]. Also, in [8], charging in a low voltage (LV) network and a fuzzy energy management strategy for the coordination of electric vehicle (EV) charging was investigated. The distance of the EVs from the transformers was considered in the proposed fuzzy management systems because one of the investigated cases on the maximum number of chargeable EVs in the study shows that the distance of the EVs from the network's substation affects the maximum number of chargeable EVs significantly. The proposed fuzzy logic EV charging management takes into consideration the SoC of the charging EVs, their distance from the grid's substation, and the charging delay time. The outcomes of the scenarios considered indicate that using distance in the proposed fuzzy management system may cut the charging time for EVs by up to 14.7 %.

The fuzzy logic approach is considered to be very robust for hybrid energy management systems due to its ability to accept multiple input data types or agent parameters as may be necessary for taking effective decisions [3,14]. A new multimodal fuzzy EMS was presented for implementing smart residential prosumers. The proposed EMS is equipped with multiple modes to satisfy different objectives throughout the year, thus allowing the utilization of prosumers with various lifestyles driven by current needs. The study uses weather and price data from three different U.S. locations over three years and residential buildings are modelled using the simulation program GridLAB-D. The proposed multimodal system was evaluated and compared with a single-mode EMS with the sole goal of lowering electricity bills. Criteria including electricity bill and average state of charge (SoC) were used for the multi-objectives of the proposed EMS. The findings of the analysis show that, while maintaining the desired lifestyle, the average annual power cost was reduced by roughly 1.8 dollars ($) in two of the three locations and the average SoC increased by at least 10 %.

One of the main goals of EMS design is cost reduction, but this also resulted in reduced energy usage which could translate to lowered CO_2 emissions, while considering extensive energy usage. A centralized integrated model of water and energy consumption optimization in the building was proposed by [26]. In this study, the authors implemented 12 machine learning prediction algorithms to accurately forecast the ideal condition for an integrated model of water and energy consumption optimization in buildings. The findings of this research demonstrate that, prior to creating a model for maximizing water and energy use in buildings in any area, it is possible to utilize prediction algorithms to accurately forecast the objective functions of both cost and CO_2 emission reductions. The decision-maker can use this work to identify the state of any energy management model under various economic and carbon emission reduction scenarios throughout the planning stage.

From the surveyed literature, existing hybrid EMS are majorly centred around cost saving, in which the DG penetration level to the grid is not controlled. The inherent challenge from this design focus usually resulted in grid instability as a result of frequency excursion arising from DG source supply variation and load changes. Most DG sources employed power electronics inverter interface for integration into the grid system, which lacks inherent inertial associated with power plant synchronous generators. This is a major problem that has been limiting the integration of large-scale penetration of renewable DGs into grid

systems. It is now paramount that the design of EMS for hybrid grid/renewal DG systems must consider the total healthy system operation. To sum up, the following gaps are also identified from the reviewed studies:

- Limited studies on the commercial setting, as most research efforts are focused on residential and industrial setups.
- Only a few studies, majorly from developing countries considered FiT, which has been proven to deliver more energy cost savings.
- Limited studies considered safe operation of various components of the MG (like batteries, load etc.)
- Most studies focus on total load against classifying load, which lowers the installation and replacement cost as well as assists in grid smoothening.
- EM design in most studies only focused on cost reduction, majorly in demand-supply price, with very few considerations for operation and maintenance cost.

Proposed energy management system

The main power source supplying a building is usually the conventional grid system, however, the alternative power sources are now been integrated for an improved energy mix to save energy costs. The cost of energy during peak periods when loads needed to be operated, possible power failure, and the issue of maximum demand penalty now make the application of hybrid energy systems more popular in energy management systems. However, most of the existing hybrid EMS suffers among other challenges, the issue of uncontrolled renewable DG sources incorporation into hybrid energy systems for cost saving. Moreover, this long-standing practice threatens the stability and reliability of the grid system. This work proposed an EMS comprising hybrid sources of the grid and solar PV/Battery power sources addressing the above-mentioned problem. The system is, however, employed to manage different sources and various categories of commercial building loads. As presented in Fig. 1, the energy management scheme comprises the EMS which plays a vital role in selecting the cheapest energy source available at a specific period and controls the load being operated. The loads are classified into basic and heavy operated loads and the selection of power source and load control are implemented using a Fuzzy logic controller which was evaluated in MATLAB/Simulink environment.

The EMS senses the peak and off-peak periods to determine the right power sources to operate the loads, hence satisfying user comfort without any waiting time. The decision-making of EMS is implemented using a fuzzy logic controller that manages the hybrid energy resources by continuously monitoring the load demand and the charging and discharging state of the battery in such a way as to manage the system power without interrupting the supply to the load. The grid is the primary source of energy which is assumed to be available at all times of the day, the fuzzy controller decides the type of loads to be operated by the grid or solar PV/battery depending on the time, cost, and the battery state of charge. The energy management and dispatch controller operate most loads with the grid during off-peak periods and only the basic loads during the peak period. Nevertheless, once the battery is charged to a certain threshold, the controller increases the number of heavy loads on the solar PV/battery irrespective of the time of the day.

Fig. 2 provides the flowchart that indicates the proposed methodology used in this study. The study begins with the collection of necessary data such as solar irradiance, grid tariff, battery parameters and PV parameters. Also, loads within the building were surveyed and classified at this stage. After collecting all necessary data and component parameters, the system design and component modelling were carried out. Furthermore, the proposed EMS was designed, and the load energy demand in the system as well as the energy sources were all modelled. MATLAB/Simulink implementation of the modelled system was developed, and then the evaluation of the built system was carried out using HOMER. Moreover, at the evaluation stage, a techno-economical evaluation was also performed.

Load profile

The load profile of the targeted commercial building of the demand side energy consumer where an energy management scheme with

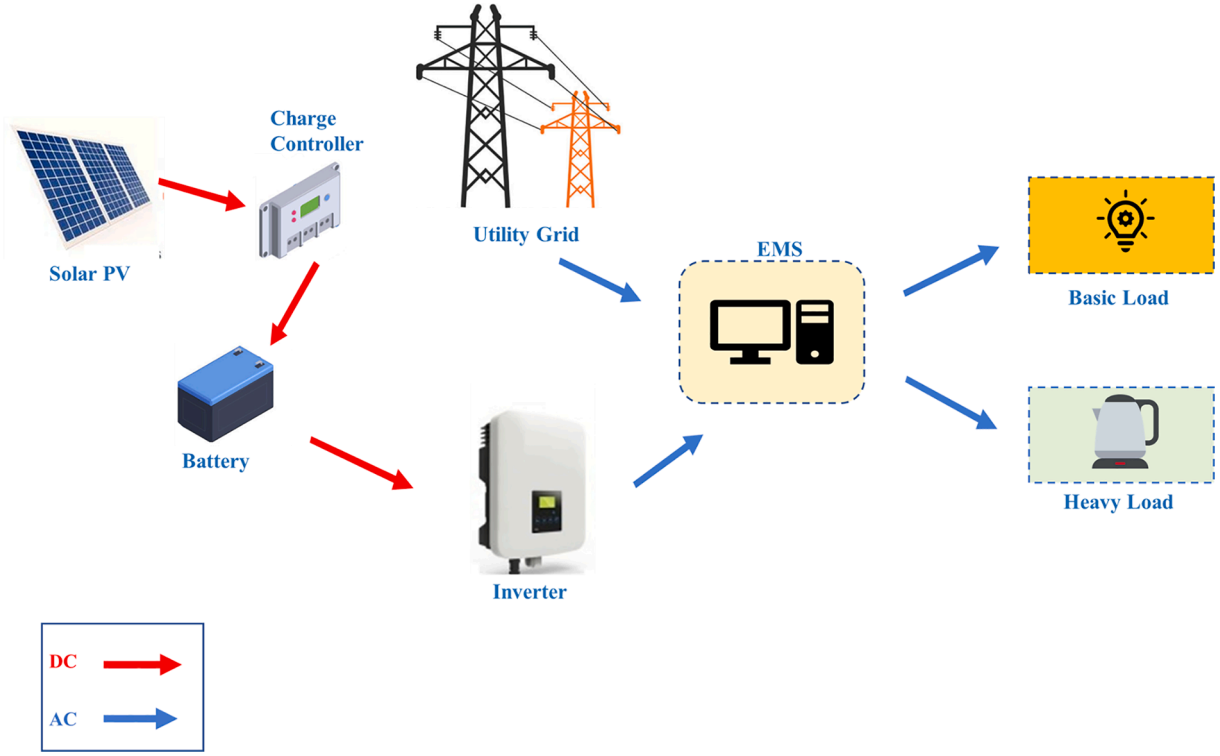


Fig. 1. EMS with Grid and Solar PV/battery sources.

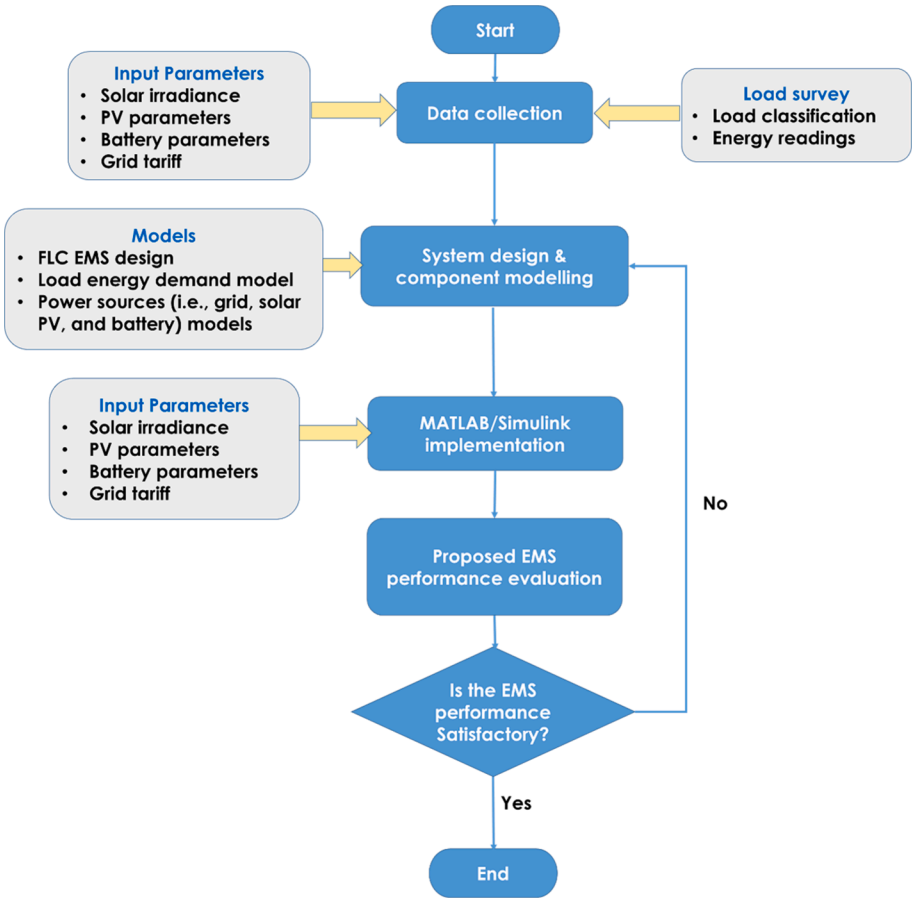


Fig. 2. Proposed FLC EMS flowchart.

hybrid power sources is to be implemented was classified based on the power ratings or operating hours. These loads are then operated from different power sources for minimum energy cost in a day. In this study, the appliances whose power rating is less than 300 W such as the television, decoder, bulbs, home theatre, phones, and laptops are classified as basic operated appliances (Bl). The appliances with power ratings above 300 W including the washing machine, pumping machine, electric kettle, freezer, oven, air conditioner, and heater are classified as heavy-operated appliances (Hl) in the building. A manual survey and observation approach was used to obtain the number of appliances within the building during the summer period of the year and their ratings are presented in Table 1. The summer period was considered because it is during this period that most of the heavy loads are put to use for a longer period and time and as such more energy is consumed at that time.

Table 1
Appliances classification.

Basic appliances	Power rating (W)	Quantity	Heavy appliances	Power rating (W)	Quantity
Television	85	30	Washing machine	500	2
Decoder	25	10	Pumping machine	1500	1
Home theatre	95	2	Electric kettle	1200	1
Bulbs	15	79	Air conditioner	1500	31
Fan	100	30	Freezer	500	4
Laptop	50	5	Microwave	750	1
			Oven	2250	1
			Heater	1000	2

System component modelling

The components of the energy management scheme are modelled in this section. The system units are basically classified as the loads and the power sources unit which briefly presented in the following subsections.

Load energy demand

The load is an important part of the energy management system, the loads are classified into basic loads (Bl) and heavy loads (Hl) in such a way that EMS will be able to distinguish between the kinds of loads to be operated with the particular power source in a particular period. Assuming a set of electrical appliances $K = [K_1, K_2, K_3, \cdots K_N]$ such that $K_1, K_2, K_3, \cdots K_N$ represents each appliance over the time horizon $t \in T = [1, 2, 3 \cdots 24]$. $K_N = [Bl \cup Hl]$ represents a set of appliances, where Bl is basic operated loads and Hl is heavy operated loads.

The energy consumption by (Bl) is represented as:

$$E_{Bl}^{T} = \sum_{t=1}^{T} \left(\sum_{j=1}^{Bl} P_{Bl_j} \times S(t) \right) \tag{1}$$

Also, the total energy cost per day for the (Bl) is given by:

$$C_{Bl} = \sum_{t=1}^{T} \left(\sum_{j=1}^{Bl} P_{Bl_j} \times S(t) \times C(t) \right) \tag{2}$$

Where P_{Bl} and P_{Hl} are the power rating of basic and heavy operated loads respectively, $S(t)$ is the state of operation of the appliances and $C(t)$ is the dynamic energy tariff.

Similarly, the energy consumption of heavy load (Hl) is represented as:

$$E_{Hl}^{T} = \sum_{t=1}^{T}\left(\sum_{j=1}^{Hl} P_{Hl_j} \times S(t)\right) \tag{3}$$

The total cost for (Hl) in a day is computed from:

$$C_{Hl} = \sum_{t=1}^{T}\left(\sum_{j=1}^{Hl} P_{Hl_j} \times S(t) \times C(t)\right) \tag{4}$$

If the total energy consumed by the appliances in the total time interval is E_T, then

$$E_T = E_{Bl}^{T} + E_{Hl}^{T} \tag{5}$$

Similarly, the total cost per day of appliances is calculated:

$$C_T = C_{Bl} + C_{Hl} \tag{6}$$

Power sources

In this part, the model of the power sources including the conventional grid system, photovoltaic system, and battery storage are presented. The conventional grid system is the main power source to the building since it is expected to always be available at all times. The grid hourly energy demand is considered with a range between the minimum and maximum hourly demand, and the threshold is set to be between 1 kWh and 7 kWh in this project based on the sample building's daily demand. The total grid energy used per day is calculated from (7) [33]:

$$E_{grid} = \sum_{i=1}^{24} E_i(t) \tag{7}$$

In estimating the cost of used energy, the hourly grid energy is multiplied by the dynamic energy pricing of both off-peak to peak periods and the total cost is computed as:

$$C_g = \sum_{i=24}^{24} E_i(t) \times R_p(t) \tag{8}$$

where: $R_p(t)$ is the real-time dynamic energy price of the grid over a period and $E_i(t)$ is the hourly energy used

The photovoltaic system is another power source incorporated as part of the hybrid source to serve the loads. To install solar PV, some factors must be considered for an efficient operation, and these include energy produced by PV, the cost of PV, and solar PV sizing. The output energy generated by a solar PV system is given by [21]:

$$E_{pv}(t) = A_{pv} \times \rho \times \varsigma(t) \times P_F \tag{9}$$

where: A_{pv} is the area of photovoltaic (m^2),ρ is the efficiency of solar PV taken, ς is the solar irradiation at time t (kWh/m^2), and P_F is the packing factor taken as 0.9.

The excess generated energy from the photovoltaic system is stored in the battery to make it readily available throughout the day. The battery should be large enough to store sufficient energy to operate heavy appliances during peak periods. The battery capacity (C_b) is represented as:

$$C_b = \frac{E_t \times D_a}{l_b \times DoD \times V_b} \tag{10}$$

In order to improve the battery lifespan, the charging and discharging state were given adequate consideration. The charging and discharging states of the battery $(E_b(t))$ were obtained from Eqs. (11) and (12) respectively [5]:

$$E_b(t) = E_b(t-1) \times (1 - DoD) + \left[E_R(t) - \frac{E_D(t)}{\eta^{inv}}\right] \times \tag{11}$$

$$E_b(t) = E_b(t-1) \times (1 - DoD) + \left[\frac{E_D(t)}{\eta^{inv}} - E_R(t)\right] \tag{12}$$

where: D_a is autonomy days, DoD is the depth of discharge, l_b is battery loss, V_b is battery voltage, B_s is battery size, N_r is the number of batteries replaced in a lifetime, $E_D(t)$ is the energy demand, η^B and η^{inv} are the efficiency of battery and inverter respectively.

Energy management scheme

The purpose of the energy management controller based on fuzzy logic is to intelligently control the engagement of the power sources and ensure smooth operation between the power sources and the load to minimize the operating cost. The control strategy uses the grid cost, solar irradiation level, battery parameter, and other constants for the best power source matching the load demand at a particular time of the day. The energy from the grid is readily available to operate the basic load and heavy load throughout the day, however, once the battery is charged to a certain threshold then heavy loads are shielded from the grid and supplied with solar PV/battery energy most especially during the peak hours. The power sources selection for operating the loads is done by a fuzzy logic load controller as presented in Fig. 3 flowchart where the $E_g(t), E_{pv}(t)$, and $E_b(t)$ are the grid, solar PV, and battery energy respectively. The fuzzy logic EMS aims to achieve the specified objectives of fulfilling load demand at any particular time of the day, managing the power sources based on energy cost, and also maintaining the battery SoC within the set threshold.

The Fuzzy Logic model was used to implement the energy management operation to achieve the best hybrid energy mix for a reduced cost. The Fuzzy Logic system intelligently takes control decisions using language variables at the inference engine based on the provided set rules. The implementation stages start with input data which are fuzzified to the membership function, then the inference engine with the rules, and lastly the defuzzification stage [8,22]. The Fuzzy Logic operation uses four input parameters including the time of the day, the daily dynamic energy cost, the Solar PV/battery status, and the grid power as the input for decision making. The minimum and maximum range of these sample input data are fuzzified by mapping the crisp values into fuzzy sets of membership functions (MF). The triangular membership function was used due to its high level of precision and good computation accuracy and all the input data used has two membership functions as presented in Table 2:

The Fuzzy Logic inference engine interacts between the inputs and output using the IF-THEN statement rules as the detail of the rules is presented in Table 3. The accuracy of the system depends on the number of prepared rules constructed for the energy management system considering different operational conditions based on the time of the day (day and night), the solar PV/battery state of charge (low, high), the load demand type (basic, heavy) and grid energy cost (peak and off-peak).

The last stage of the Fuzzy Logic system is the defuzzification stage, where all processed fuzzified data are converted back to values and viewed in the output graph displayed by the system as energy mix consumed from different sources with the different types of the load based on time of the and cost of energy. The details on some commonly used defuzzification methods such as mean of maximum (MOM), the centroid of area (COA), the bisector of area (BOA), smallest of maximum (SOM), and largest of maximum (LOM) are presented in [43]. The centroid of area (COA) is used in this work because of its simplicity, which takes the output of the distribution found in the previous stage and finds the centre of the area to obtain one crisp number.

Energy management system implementation

The hybrid power sources, energy management controller, and loads were all modelled in the MATLAB/Simulink environment to evaluate the overall system performance. A hotel suite situated in a high-density residential area of Ilorin (latitude 8.481573 and longitude 4.575896) Nigeria is used as a case study. The hotel features 2-star accommodation with 26 single rooms and 2 suites, an executive bar, and a bar. Among

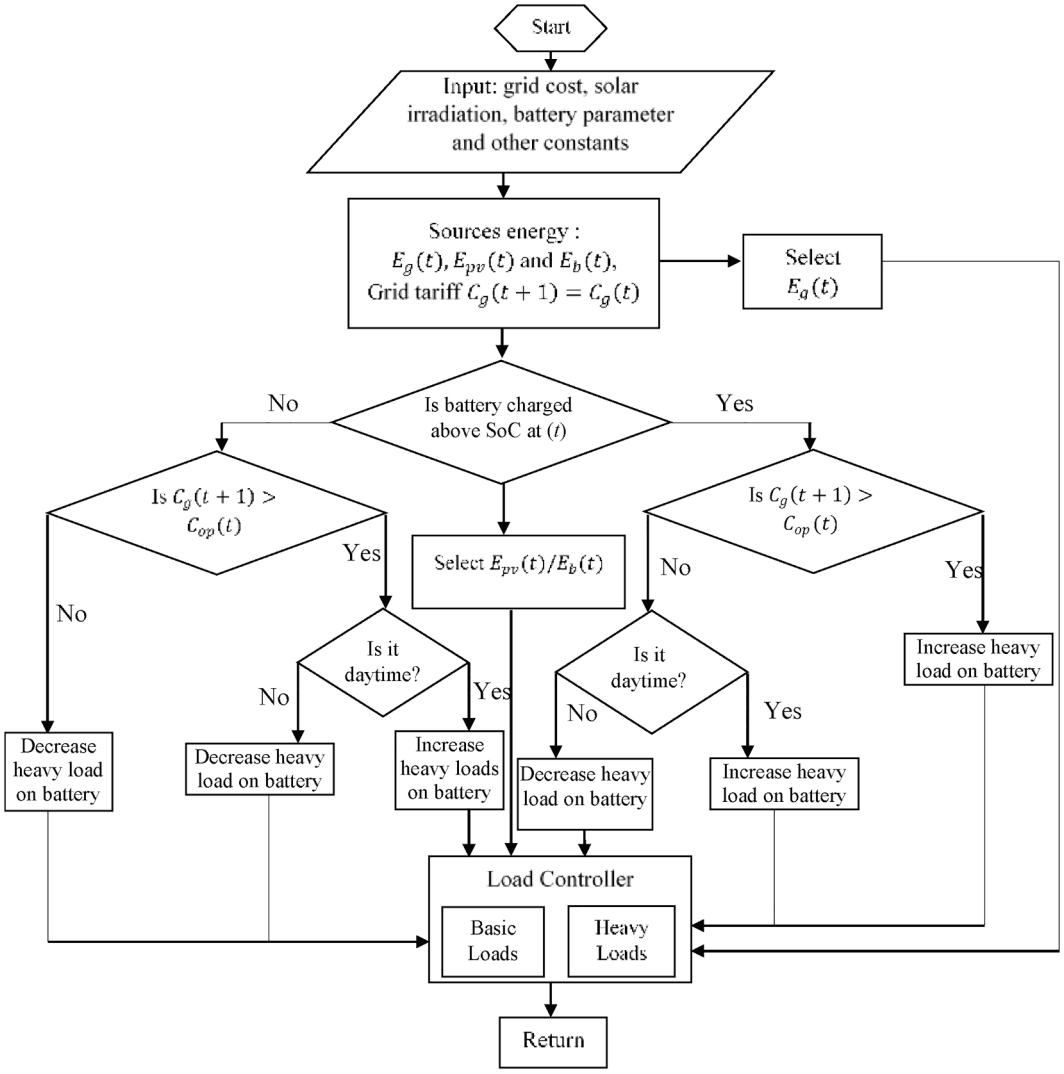


Fig. 3. Energy management scheme.

Table 2
Input data fuzzy sets.

Input data	Membership No.	Fuzzy set	Value range
Time of the day (hours)	1	Day time	6:00–18:00
	2	Night-time	18:00–06:00
Grid Energy cost (₦)	1	Off-peak	0–43
	2	Peak	43–58.5
Solar PV/Battery SoC (%)	1	Low battery SoC	0–35
	2	High battery SoC	35–100
Grid power (kW)	1	Grid off	0–1
	2	Grid on	1–7

the facilities of the hotel are the reception hall, kitchen, and laundry services. The main power source to the building is the conventional three-phase grid system and the energy consumed in all parts of the hotel building is obtained for one week as recorded in the prepaid meter readings. This serves as the basis for sizing the proposed distributed generation of solar PV/battery alternative power source for the building.

The conventional grid system is modelled in such a way that the hourly energy produced is equal to the hourly energy demand with a set peak threshold of 7.5 kWh based on the sample building's daily load demand. The grid system has the capacity to supply total load demand as presented in Fig. 3 consisting of three-phase programmable voltage sources, three-phase instantaneous power measurement, and the gain.

Table 3
Fuzzy Rule Base for Load/Power Sources Management.

Day time	Grid	PV/Battery charged to threshold	Energy tariff	Load type	Fuzzy output
Day	YES	No	Peak	Basic	Connect to grid
				Heavy	Connect to PV/ Battery
			Off-peak	Basic	Connect to grid
				Heavy	Connect to grid
	YES	Yes	Peak	Basic	Connect to grid
				Heavy	Connect to PV/ Battery
			Off-peak	Basic	Connect to grid
				Heavy	Connect to PV/ Battery
Night	YES	No	Peak	Basic	Connect to grid
				Heavy	Connect to grid
			Off-peak	Basic	Connect to grid
				Heavy	Connect to grid
	YES	Yes	Peak	Basic	Connect to grid
				Heavy	Connect to PV/ Battery
			Off-peak	Basic	Connect to grid
				Heavy	Connect to PV/ Battery

The building load demands are modelled as basic loads with less than 300 W power ratings and heavy loads with power ratings above 300 W. The Solar PV as the complementary power source to the energy management controller was implemented based on the load demand using the solar panel data specification [40]. The daily total obtainable energy from the solar PV was dictated by the solar irradiation of the study location and the irradiance data were obtained from the NASA daily solar irradiance data (NASA)[34]. The maximum possible energy demand from solar PV based on the specified capacity was sufficient to cater for the daily maximum heavy load demand (*Hl*).

The battery is modelled in such a way that its capacity can meet the heavy load demand for at least a day which can be extended to any number of autonomous days by increasing the battery capacity. The battery rating was chosen as 40 kWh amounting to 60 % of daily energy demand using a 30 % minimum SoC. Also, the system assumes a maximum power point (MPP) operation of the PV source ensuring that the load demands are fulfilled based on the time of the day or the SoC condition. The design settings provide sufficient energy for the total daily heavy loads demand. This was evident in the result section as the minimum average SoC at the end of the test period was 40 % which is more than the considered 30 % minimum used for the design stage. Literature has shown that lead battery is more economical, and the Shenzhen polinovel battery (Lithium Battery System) was selected for implementation due to the high depth of discharge and longer life span [32]. The depth of discharge of the battery was set at 70 % which is a 30 % state of charge, which implies that the battery will halt at that predefined value. The complete system model presented in Fig. 4 shows the power sources, dynamic grid energy cost, and time of the day as input to the energy management controller. The fuzzy logic-based EMS takes decisions to control the load operation and manage the power sources by continuously monitoring the load profile and state of the battery charge without interrupting the load operations.

In order to establish the effectiveness of the developed fuzzy-based energy management controller, an equivalent Homer model was built using the same hybrid power input specification to serve as a baseline for the developed energy management comparison. The Hybrid Optimization Model for Electric Renewable Energy (HOMER) is software used to design and analyse financial and technical options of off and on-grid power systems for remote, stand-alone, and distributed generation applications. This software puts huge consideration into factors such as technological, financial, and resource availability. In this work, a grid-connected hybrid system consisting of Grid and Solar PV/Battery energy configurations was considered to have the same parameters as the implemented fuzzy-based controlled energy system.

The performance analysis and selection criteria for most hybrid energy systems are commonly based on component sizes, total net present value (TNPV), LCOE, a renewable fraction (RF), and annual carbon emission. The two economical parameters considered in this work are the LCOE and TNPV. The system capacity, capital cost, distributed renewable energy sources, grid, hourly load demand, and hourly solar irradiation are fed into the system as shown in Fig. 5. The simulation process was implemented based on criteria assumption which includes zero operational and maintenance cost, 95 % converter efficiency, and 30 % battery state of charge.

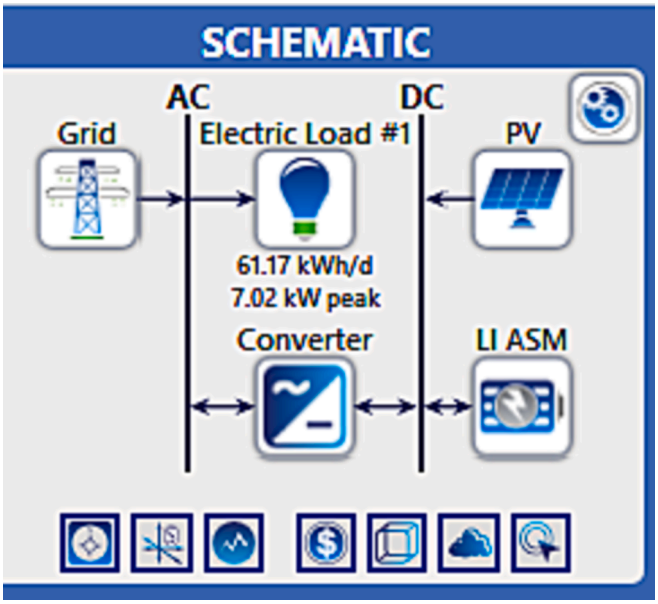


Fig. 5. Homer model of hybrid grid-connected solar PV/battery system.

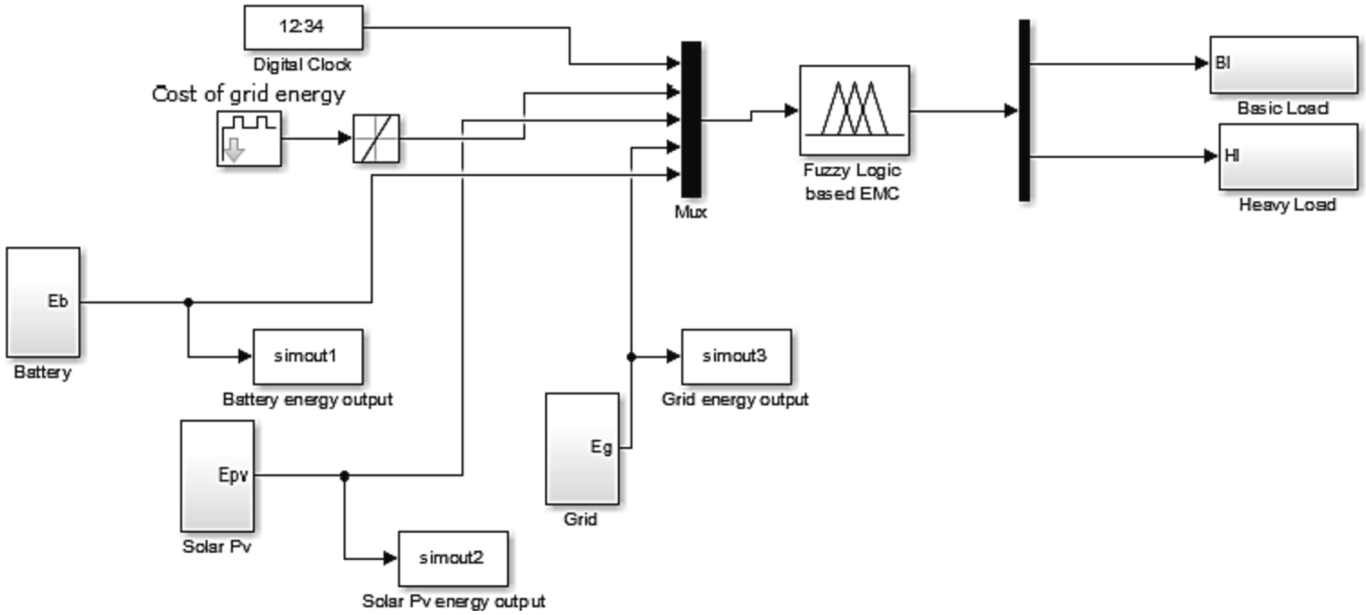


Fig. 4. Energy management Simulink model.

Techno-economic analysis

Techno-economic analysis plays an important role in determining the lifetime cost of power sources. It allowed the evaluation of the cost, emission, and performance of a power source before it is attempted [21]. Among the available tools for techno-economic analysis is the Levelized Cost of Energy (LCOE) which is a measure of the lifetime cost of a power source that allows for comparison with other methods of power generation consistently. The LCOE is computed from the total cost of energy generation divided by the total energy produced during its useful lifetime. The LCOE is represented by the relation [29]:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{13}$$

Where I_t is the investment expenditures in the year t, M_t is the operations and maintenance expenditures in the year t, F_t is the fuel expenditures in the year t, E_t is the electrical energy generated in the year t , r is the discount rate and n is the expected lifetime of the system or power station.

The life cycle cost (*LCC*) of a hybrid power system is commonly assessed using the Net Present Value (*NPV*) method. The total net present value (*TNPV*) of a system is the sum of investment cost (*IC*), salvage cost (*SC*), Replacement cost (*RC*), operating and maintenance cost (*OM*) as expressed in (14) [41].

$$TNPV_{sys} = \sum_{i=1}^{n} (IC_i + OM_i + RC_i - SC_i) \tag{14}$$

To minimise the total cost of energy, the objective cost function is based on the net present value presented in Eq. (15), and the total *TNPV* values should be minimum for the total usage period for all the power sources.

$$minTNPV(E_{grid}, E_{pv}, E_b) = NPV_{PV} + NPV_b + NPV_{grid} \tag{15}$$

The *LCOE* of the grid is computed based on the dynamic pricing of the day for both peak and off-peak periods to give an estimated cost of the grid at a particular period of the day as shown in the relationship of (16):

$$LCOE_g = \frac{[C_1 \times P_h \times E_1] + [C_2 \times O_h \times E_2] \times d \times y}{[E_1 \times P_h + E_2 \times O_h] \times d \times y} \tag{16}$$

where d is the number of days in a year,C_1 and C_2 is the peak cost and off-peak cost of the dynamic pricing, E_1 and E_2 is the energy used during the peak and off-peak period, P_h and O_h is the peak and off-peak period in a day.

The LCOE of the solar PV unit is computed to know the lifetime cost for a specified unitization period, and this is represented by:

$$LCOE_{pv} = \frac{C_{pv}}{E_t \times d \times y} \tag{17}$$

where C_{pv} is the total cost of solar panels estimated by multiplying the number of solar PV with the cost of each solar panel and E_t is the average energy consumed per day.

The battery LCOE is the lifetime cost of the battery for years is represented as:

$$LCOE_b = \frac{C_{b3}}{E_t \times d \times y} \tag{18}$$

where: C_{b3} is the total cost of battery estimated by multiplying the number of batteries used with the cost of each battery and the number of times batteries are replaced during the lifetime of the project.

A Solar PV system comprises other installation components such as the charge controller, inverter, cables, and electrical accessory. In most settings, the cost of the other installation components is usually assumed to be 10 % of the total cost of the main component, and the LCOE is estimated as follows [30].

$$LCOE_i = \frac{10\%(C_{b3} + C_{pv})}{E_t \times d \times y} \tag{19}$$

Result and discussions

Energy management controller performance

This work investigates the impact of the proposed EMS on a hybrid grid-solar PV/battery system for commercial buildings' energy cost saving and improved power balance. The common EMS design practice at the DSM ends usually focused on load shielding or shifting at the expense of user comfort. However, recent analysis of RES shows flattening cost as compared to grid energy cost. This competitive advantage was explored in this study to ensure that the load operation pattern is not distorted, as desired in commercial buildings such as the hotel building adopted as a case study. The performance of a Fuzzy Logic rule-based EMS was investigated for a period of one week in the MATLAB/SIMULINK environment. The performance was evaluated using a typical load demand of a hotel building with daily average energy consumption of 65 kWh per day. EMS manages the hybrid energy system comprising the grid system, solar PV/battery power sources, and the loads classified into basic and heavy load types. In the system operation, the grid is readily available to operate both the basic and heavy loads throughout the day. However, the heavy loads are shielded from the grid and served by solar PV/battery systems by the energy management control action most especially during the peak sunshine hours when the battery SoC level is above the 30 % minimum threshold. This state is maintained until the battery state of charge is reduced to below 30 % or when the grid energy cost becomes lower during the off-peak period.

The daily energy demand from solar PV/battery was specified as 40 kWh which is sufficient to operate all the heavy loads and amounts to 60 % of the daily energy needed for operating all the loads.

In order to ascertain that the generated energy from the solar PV/battery system is sufficient to supply the heavy loads during peak hours, an investigation was conducted on the solar PV system's ability to charge the battery to the required SoC of 30 % and above during the system operation. The solar irradiance of Ilorin (latitude 8.481573 and longitude 4.575896) in Nigeria which is the location of the site under consideration was obtained from the NASA website (NASA) and modelled together with the battery in MATLAB/Simulink. The hourly solar irradiation was fed into the model to estimate the energy produced at each hour of the day. The result of the weekly daily average solar irradiance with the battery SoC when the energy management control system was tested is presented in Fig. 6. The output power generation from the solar PV was sufficient to charge the battery to supply the total daily energy demand by the heavy loads. As observed in Fig. 6, the minimum average SoC recorded during the system operation is 40 %, which is more than the 30 % SoC required for the system operation.

The daily energy mix of the hybrid sources was investigated for a period of one week to study the EMS control action performance for different days' energy demands. Presented in Fig. 7(a – d) is the building energy demand with the EMS for the first four weekdays i.e., Monday, Tuesday, Wednesday, and Thursday are considered as weekdays. The Figures show the hourly daily energy demands of the combined basic and heavy loads over 24 h period with the EMS. The dotted (starred marked) line shows the daily hourly energy demand been supplied from the hybrid power sources operation while the remaining two energy curves show the grid (diamond-marked line) and Solar PV/battery (cross-marked line) contributions to total load energy demand when the energy management controller is in operation. The grid power source contribution to total energy demand in the building can be seen to have been reduced throughout the day and the remaining load energy demand has been supplied by the solar PV/battery system depending on the battery SoC dictated by the solar irradiance when the EMS is in operation.

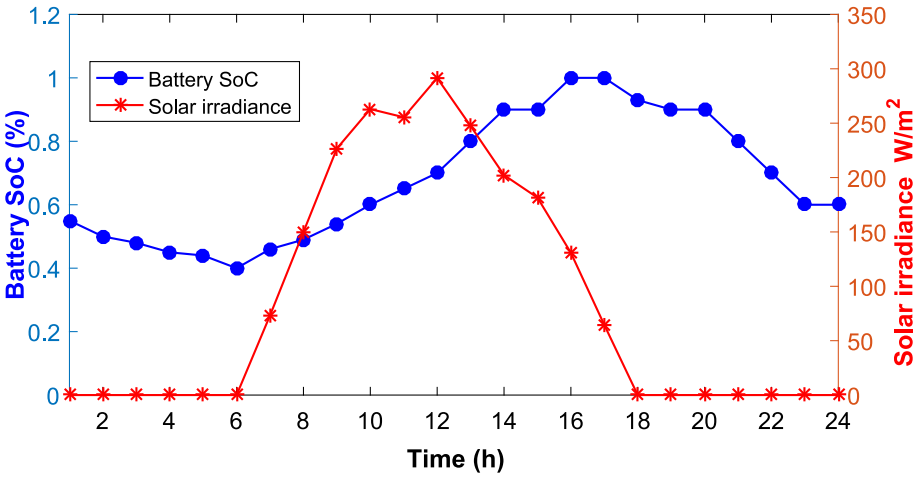


Fig. 6. Weekly daily average of SoC and Irradiance.

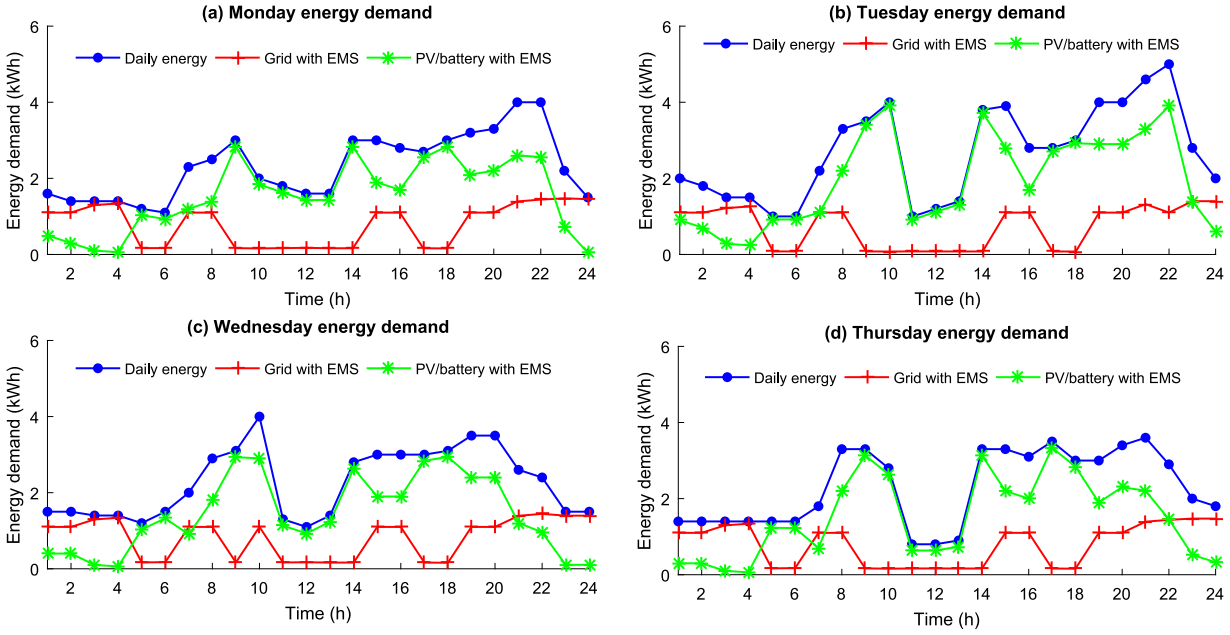


Fig. 7. Weekday energy demand with EMS.

As observed in Fig. 7(a and b), the EMS ensures that the solar PV/battery system supplies more of the load demand, especially the heavy loads during the daytime when the solar irradiance is high to charge the battery over the minimum threshold. The light-operated load gets their supply from the grid during the day and night, but a significant percentage of the heavy operated loads were supplied by the Solar PV/battery at night-time and early morning between 18:00 hr up till 00:06 hr most especially during the peak period. The total energy demand when the EMS is in operation were shared between the two power sources throughout the day with the grid constantly operating the light load while the heavy load is being shielded from the grid depending on the state of charge of the solar PV/battery system and the grid peak period.

As shown by the Monday load demand (refer to Fig. 7(a)), the total appliance energy usage for the day was 55.60 kWh. Given a 100 % supply from the grid system, the cost of electricity for the day would be ₦2780.00 at ₦50/kWh on average of peak and off-peak prices in Nigeria at the time of the study. The EMS operation was able to share the loads among the two sources with the grid supplying 18.85 kWh which is 33.90 % and the remaining 66.1 % of 36.75 kWh from the solar PV/battery. The LCOE with EMS shows that the grid cost ₦942.5 and solar PV/battery cost ₦1180.38 summing to ₦ 2122.88 for the same day. Aside from the fact that the LCOE for the day shows that energy cost was reduced, there was also less stress on the grid during the peak period. In a temperate region like Nigeria, operating a hotel requires lots of heavy equipment like several units of air conditioning (AC) system, and water heaters etc. During peak periods, these heavy load operations impose higher burdens on the grid system, thereby leading to load grid imbalance between supply and demand. The overall effect of these on the central grid system resulted in poor reliability, consequently leading to frequent grid collapse from high frequency excursion.

Similarly, Fig. 7(c and d) show the building's total daily energy demand and each power source's contribution with the EMS for the next two weekdays i.e., Wednesday and Thursday respectively. The dotted (starred marked) line shows the daily hourly energy demand from the hybrid power sources and the remaining two energy curves shows the contribution from the grid (diamond-marked line) and solar PV/battery (cross-marked line) to the total load energy demand when the energy management controller is in operation. As observed in Fig. 7, the EMS controller was able to balance the supply of the heavy loads from the

solar PV/battery sources during the daytime and during the peak hours at night and morning. The heavy load gets much of their supply from the solar PV/battery system during the peak hours of 00:05hr to 00:09hr morning hours and 00:16hr to 00:21hr night-time after which some of the heavy loads are transferred to the grid supply during the off-peak period. The total energy cost for Tuesday and Wednesday with the EMS were ₦2368.05 and ₦2092.38 respectively as against ₦3205 and ₦2710 if all appliances were to be operated from the grid supply.

The weekend day's energy demand of the hotel building is presented in Fig. 8(a – c) for the total daily hourly energy demand and that of energy contribution from each source when operated with EMS. The Fig. 8(d) presented one week's daily average energy contribution from each source. Fig. 8(a and b) show the energy demand for Friday and Saturday respectively. The energy demand on these two-weekend days shows a significant increase in daily energy demand as the hotel room occupancy during the period usually increases coupled with increased social activities that demand more energy. With the EMS action on the energy supply mix, it was observed that the solar PV/battery correspondingly contributes to daily energy demand during the peak hours and during the daytime when there is much irradiance to charge the battery for later usage was higher. The battery charge capacity was sufficient to serve the heavy loads during the day and retained sufficient charges for the peak period during the evening time and early next day morning.

Presented in Fig. 8(c) is the Sunday energy demand with the EMS, the energy demand is minimum for the day as most people stay indoors preparing for the new week's workdays. The EMS performance for this day is also satisfactory and follows the same pattern of energy mix between the grid and solar PV/battery system for the heavy and light loads and during off-peak periods. The solar PV/battery system supplied the heaviest load during the daytime and also at night hours when the grid is in peak tariff until 21:00 h. After this time as observed in Fig. 8(c), much supply now comes from the grid because the grid tariff is now in the off-peak period and the battery state of charge too would have reduced since no irradiance to charge the battery at night-time. The total energy cost for Sunday and daily average demand with the EMS were ₦ 1752.53 and ₦ 2317.04 against ₦ 2205 and ₦ 3081.61 if all appliances were to be operated from the grid supply respectively.

The FLC EMS plays an important role in intelligent decision-making for ensuring the best energy mix that guarantees minimum energy cost at the best system performance. The results of the investigation of the FLC EMS on the overall daily energy usage, cost and wellbeing of the grid system underline the importance of EMS in electricity management. The incorporation of the EMS does not only offer energy cost reduction, but it also improves grid reliability and more importantly ensures that the comfort of the users is not in any way trampled since load usual practise of shifting or shielding in most EMS cannot be perfectly fit in some important commercial settings like in the hotels, banks and other places that render essential services.

Levelized cost of energy (LCOE)

The energy management controller is primarily employed to save the cost of electricity during peak hours and for eliminating the possibility of the maximum demand charge. The economic benefit can be established by evaluating the levelized cost of energy from the available power sources for a specific period. The levelized cost of energy (LCOE) allowed the estimation of cost, emission, and performance of power sources to reveal their economic viability. In this work, the levelized cost of energy was computed for both the grid and the solar PV/battery system considering the hotel's total energy demand with the EMS. The current dynamic grid kWh energy cost of ₦43 ($0.11) off-peak and ₦58 ($0.15) peak period in Nigeria for the daily load demand was used to compute the LCOE kWh unit cost for 20 years life span period (NERC) [35]. Similarly, the solar PV, battery and inverter LCOE were also computed for 20 years life span period.

The summary of the cost for the grid and solar PV system comprising of solar panel module, batteries, inverter, installation components, and the maintenance estimated for 20 years period is presented in Table 4. The LCOE of the grid considering the daily off-peak and on-peak hourly

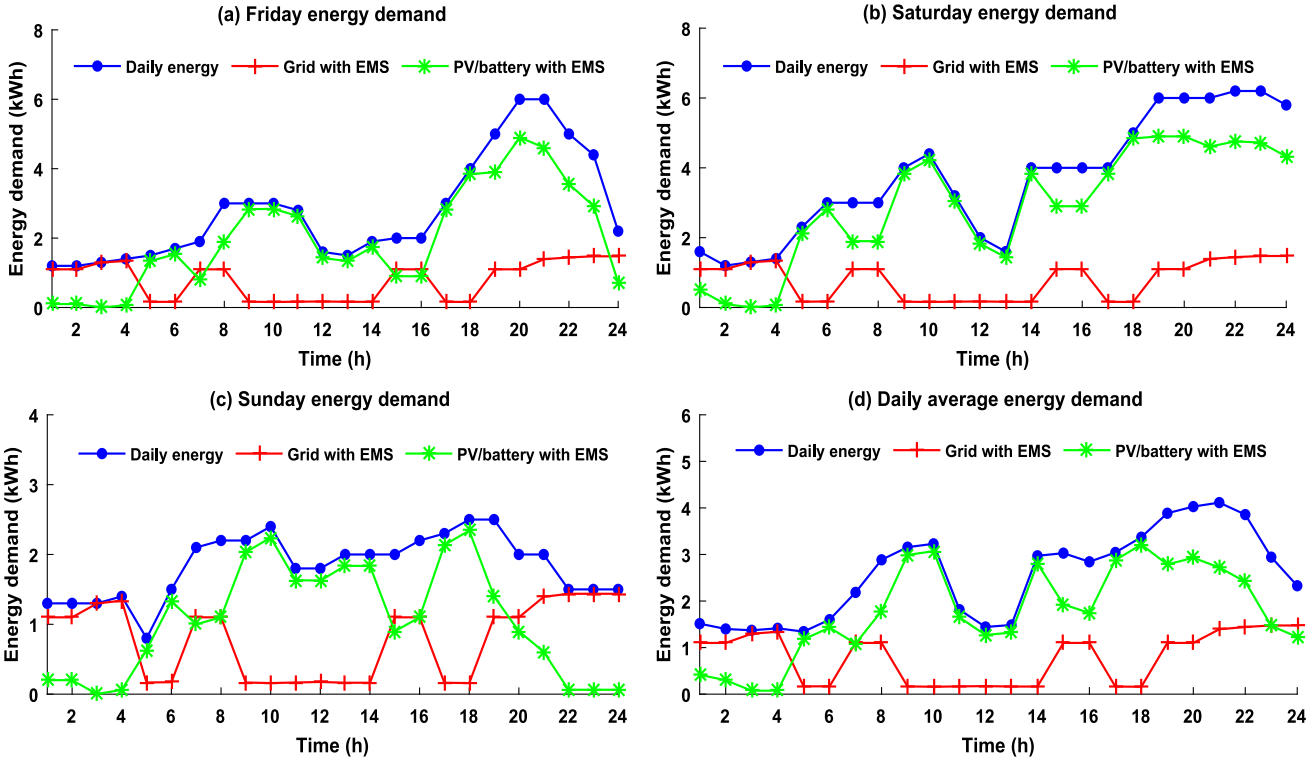


Fig. 8. Weekend (a-c) and (d) average daily energy demand with EMS.

Table 4
The 20 years power sources component cost.

S/N	LCOE component	Value (₦)	Value ($)
1	Total cost of battery	1,758,403	4,538.44
2	Total cost of battery for lifetime	8,792,015	22,692.19
3	Total cost of solar panel	2,066,667	5,334.07
4	Inverter and other components	1,085,868.3	2,802.28
5	Total grid cost for lifetime	21,926,623	56,592.61

demand and solar PV system components for the 20 years using the typical load demand of the hotel is presented in Fig. 9. The obtained LCOE for a kWh of the grid is ₦49.02 ($0.127) and that of the solar PV system including solar PV, batteries, and inverters totals at ₦32.12 ($0.083) after considering other installation and maintenance components. It was assumed that the battery has zero maintenance cost, and they are to be replaced every-Five (5) years which is 4 times during the project 20 years lifetime.

Daily and long-term energy cost savings

This section presents the short and long-term energy cost savings with the operation of the energy management controller when compared with the Homer energy optimization model for the hybrid grid and Solar PV/battery system in meeting the load energy demand. The total daily energy cost for the hybrid power sources of the grid and solar PV/battery on each day of the week with the EMS and that of the Homer is presented in Fig. 10. As shown in Fig. 10, there is a difference between the daily cost of the energy mix by the developed EMS and that of the Homer hybrid grid-solar PV/battery system. The presented 7 days' daily energy cost and the daily average in Fig. 10 shows that the developed energy management controller has reduced cost compared to that of the Homer model.

The Table 5 presents the daily energy cost savings of the EMS compared to the Homer model. On Monday, the cost of the total energy supplied from the hybrid energy mix by the Homer model is ₦2475.30 ($6.40) while that of the developed EMS was reduced to ₦2265.44 ($5.85) and thereby saving about 8.48 % on the day energy cost. Similarly, there was a reduction in the cost of daily energy with the developed EMS for all other days of the week from Tuesday up to Sunday with daily cost savings of 12.72 %, 7.40 %, 6.95 %, 12.15 %, 10.43 %, and 23.83 % respectively. The cost reduction is highest on Sunday due to low energy demand by heavy loads, which is associated with a low turnout of customers and fewer activities in the considered hotel building. Also, presented in Table 5 is the daily average energy cost computed from the weekly daily average energy cost. The Homer hybrid energy system model has an average daily energy cost of ₦2773.64 ($7.17) and the developed EMS is ₦2444.41 ($6.32) amounting to 11.87 % daily energy cost savings.

The computed average daily energy demand and cost were the benchmarks used for estimating the long-term cost of energy. The daily average energy cost when supplying all loads from hybrid grid-solar PV/battery with the HOMER model and EMS developed were used as a multiplying factor for 20 years. The long-term cost of energy with the Homer and cost of energy using the EMS for 20 years period is estimated as ₦13,829,920 ($35,736.23) and ₦12,731,696 ($32,898.44) respectively. This consequently translates to an amount of ₦1,098,224 ($2,837.79) which is 7.94 % cost savings over 20 years as represented in Fig. 11.

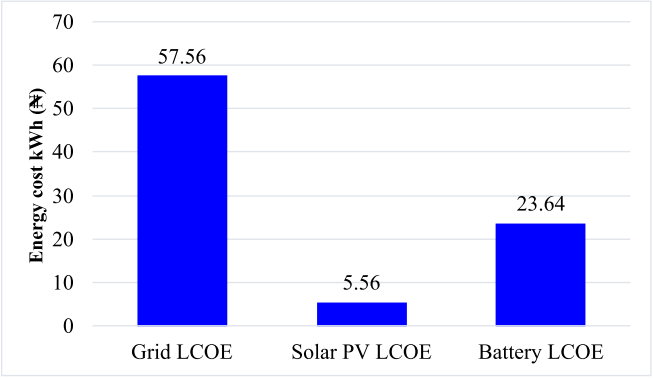


Fig. 9. 20 years LCOE of power sources.

Conclusion

In this study, an integrated FLC EMS was developed for demand-side load management with a focus on eliminating the need for load shifting that distorts processes in commercial infrastructure settings. The system intelligently and efficiently selected different energy sources to optimally operate the demand side basic and heavy loads at a reduced cost while ensuring smoothened operation of energy resources. The performance evaluation of the developed EMS for hybrid grid-solar PV/battery sources with limited fuzzy rules on hotel buildings achieved a reduced daily electricity cost by an average of 11.87 % per day when compared with the HOMER model. For 20 years, the anticipated long-term energy costs for the Homer and the EMS are 13,829,920 (or $35,736.23) and 12,731,696 (or 32,898.44), respectively. As a result, this amounts to a saving of 1,098,224 (or $2,836.79) for 20 years representing a 7.94 % cost reduction. In addition to energy cost savings, more importantly, the EMS ensures continuous load operation by eliminating any form of grid instability that might arise while restoring heavy shielded loads and also helps the grid reliability during the peak load demand when heavy loads get their supply from RES. The proper consideration given to the state of energy resources guaranteed their optimal operation with less stress like the case of batteries maintained beyond SoC that increased the lifespan, reduce replacement time and consequently reduce the lifetime LCOE.

While several studies, majorly from the affluence world have stressed the importance of feed-in tariffs, the adoption of such schemes in developing countries (like Nigeria) remained low. In future works, the investigation into the depth and acceptance level of FiT and its significance on energy cost saving should be considered. Also, the use of AI-based prediction models trained on historic data (such as load demand pattern, renewable DG output, climate data etc.) brings about informed efficient EMS decision making, thereby improving overall energy system performance. Thus, future work should focus more on the contribution of reliable and well distributed data of that kind, as well as do more on improving the accuracy of such models using sophisticated machine- and deep-learning algorithms.

CRediT authorship contribution statement

Oladimeji Ibrahim: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Mutiu Shola Bakare:** Software, Data curation, Writing – original draft, Investigation. **Temitope Ibrahim Amosa:** Conceptualization, Visualization, Writing – original draft, Investigation. **Abdulrahman Okino Otuoze:** Data curation, Supervision. **Waheed Olaide Owonikoko:** Software, Validation. **Esraa Mousa Ali:** Writing – review & editing. **Lambe Mutalub Adesina:** Data curation, Writing – review & editing. **Olalekan Ogunbiyi:** Data curation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

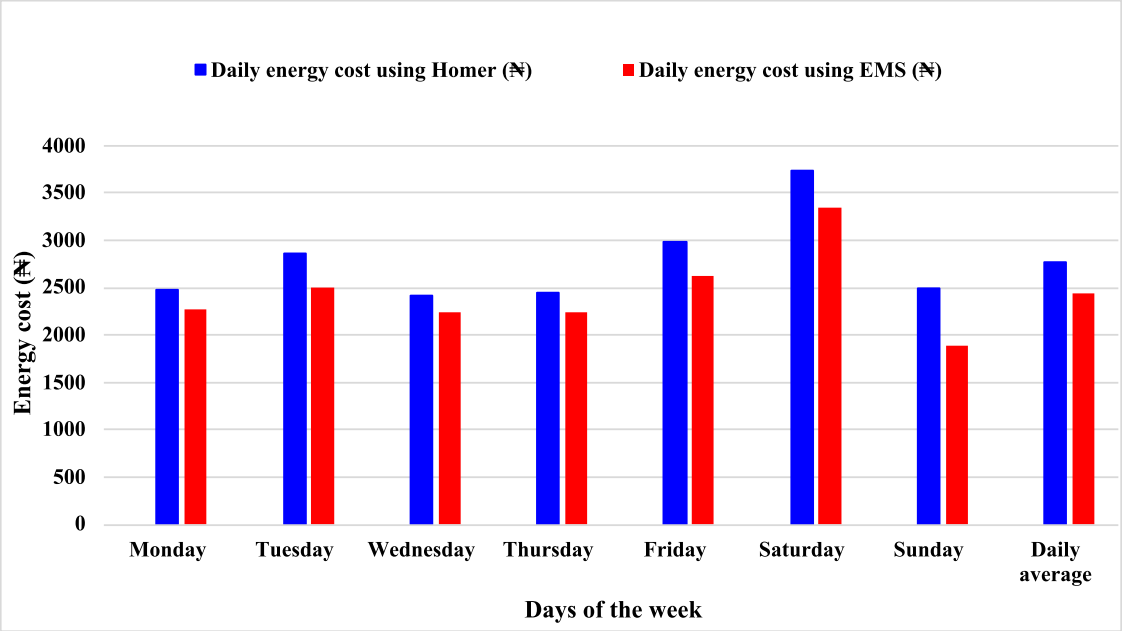


Fig. 10. Daily and averaged daily cost of energy.

Table 5
Daily energy cost savings of the EMS compared with the Homer model.

Days	Daily energy cost saving (₦)	Percentage cost reduction (%)
Monday	209.86	8.48
Tuesday	364.05	12.72
Wednesday	179.1	7.40
Thursday	207.08	6.95
Friday	362.27	12.15
Saturday	389.42	10.43
Sunday	592.81	23.83
Average	329.23	11.87

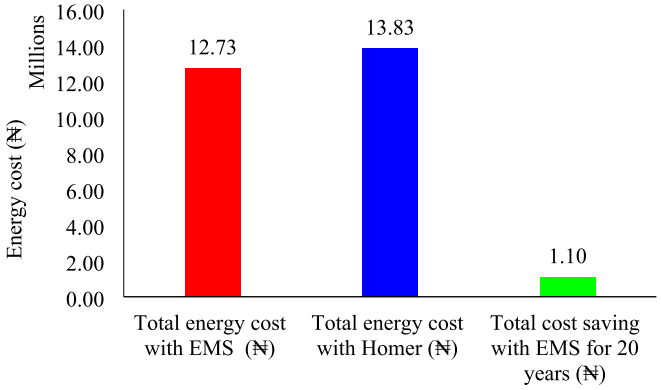


Fig. 11. Long-term energy cost.

Data availability

No data was used for the research described in the article.

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