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RESEARCH ARTICLE

Comparative Study of the Performances of Three Metaheuristic Algorithms in Sizing Hybrid-Source Power System

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ABSTRACT

This paper presents compared performances of three metaheuristic algorithms in determining the cost of hybrid renewable energy system. Using genetic algorithm (GA), particle swarm optimization (PSO), and artificial bee colony (ABC), the best affordable sizes of solar photovoltaic array, battery bank, and a minimum-rated diesel generator that could be hybridized to meet the demand of a community in Southwest Nigeria were determined. Load profile, solar radiation, and temperature data were employed as required inputs, and the parameters of the algorithms were properly set to ensure the best result. Bonferroni–Holm method was deployed to ascertain the statistical significance among the algorithms. It was found that ABC produced the best configuration comprising 427 numbers of solar photovoltaic panels, 19 battery units, and 163.2 kW-rated diesel generator. With this, a total annualized cost of \$167 284 and 0.2443 estimated cost of energy were obtained. These were the lowest when compared with PSO and GA. The *t*-test between PSO and ABC are both $5.83 \times 10^{-10} < 0.01666667$, between ABC and GA are $6.09 \times 10^{-6} < 0.01666667$ and $6.09 \times 10^{-6} < 0.025$, while between GA and PSO are $9.13 \times 10^{-1} > 0.01666667$ and $9.13 \times 10^{-1} > 0.05$. PSO/ABC and ABC/GA groups are clarified significant, while GA/PSO group is insignificant; post hoc test reveals that ABC produced the best result. Hence, a reliable and sustainable power supply at a reduced cost is guaranteed for the community.

Index Terms—Artificial bee colony, Bonferroni–Holm method, diesel generator, genetic algorithm, particle swarm optimization

I. INTRODUCTION

In recent years, hybrid renewable energy system (HRES) has been a choice for the electrification of isolated areas where grid extension is difficult and costly or area where there is an epileptic power supply. Hybrid system is the combination of one or more renewable energy sources, such as solar photovoltaic (PV), wind energy, hydro system, and so on, to produce energy [1]. Furthermore, integrating energy storage systems like battery banks or conventional energy sources (such as diesel generators) makes HRESs more cost-effective and reliable [2]. HRES will not only minimize the reliance on the fossil fuels (such as gas, oil, or coal) that produce environmental pollutants but will also allow the use of more natural resources with energy storage system to guarantee stable and reliable energy, which is the major concern of energy users across the world [3, 4].

The development of sustainable power supply is facing two challenges of how to efficiently generate sufficient energy by using sustainable energy resources and generation at a reasonable cost for the users [5]. However, the use of estimated sizing method to determine the appropriate size and selection of HRES components has resulted in either undersized or oversized components. It should be noted that undersizing HRES may result in shortages of energy delivered and operational constraints, while oversizing causes higher initial setup costs and other issues. Part of the solution to these challenges is to employ software tools. In [1, 6], hybrid optimization of multiple energy resources (HOMER) was used in component sizing of HRESs. While [1] deployed HOMER to perform an economic evaluation on PV/distributed generation (DG) with flywheel as a storage system and by which it was shown that integration of HRES greatly reduced the level of diesel fuel consumption, authors in

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[6] presented a HOMER-based optimal configuration and sizing of HRES in supplying reliable energy to a university campus community. However, software tools face the challenges of mono function reduction, more processing time, and frequent stuck in local minima [7]. Therefore, artificial intelligence (AI) technique, such as metaheuristic algorithms, has emerged to develop cost-effective and sustainable HRES [8]. Metaheuristic algorithms solve the problems of HRES in many applications with minimum processing time and achieving optimality [9]. Thus, the use of AI optimization method has become important in order to lower initial costs and increase efficiencies [3], and many studies have been carried out using single or two different algorithms.

Using genetic algorithm (GA), authors in [10] calculated the best cost value from the best configuration of a hybrid energy system; the economic impact of optimal sizing on a rural village microgrid that produces sustainable electricity at a lower cost was analyzed in [11]. Using both GA and traditional system, various components of an HRES system have been analyzed [12], with the results showing that a combination of PV and diesel energy systems yielded the best result at reduced cost. In [13], particle swarm optimization (PSO) was deployed to determine the required components' optimal sizing of a renewable energy-based electric power systems for residential areas, while [14] presented sizing of HRES using PSO algorithms and concluded that the operational cost of fuel usage was greatly minimized using a combination of PV and battery storage. In a study carried out in two different locations, Rabat and Baghdad, the economic cost and size of HRES were determined using PSO techniques [15]. A study intended to achieve the overall minimum system cost of a solar energy system while considering pollution criteria of DG was conducted in [16] using PSO, while a modified heuristic approach based on PSO and GA was deployed in [17] for a study on hybrid system operation using four comparison scenarios, and the result shows that the PSO algorithm is better than the GA. In [18], performances of GA and PSO were evaluated in a study on metaheuristic-based analyses, with comparison of the two algorithms carried out based on iteration convergence time, memory usage time, and solution quality, and the result showed that PSO outperformed GA. In sizing renewable energy and battery storage systems for an HRES, [19] deployed GA, with the use of two cost-effective scenarios of combining PV, wind energy, and battery storage system to determine the cost of energy of the designs.

There are many studies on HRES in the literature, wherein a single algorithm was deployed. Also, in a number of research, two different algorithms have been employed for comparison. In this present study, a comprehensive comparison of the performances of three metaheuristic methods in achieving optimal configuration of HRES is presented. Significances of the algorithms, GA, PSO, and ABC, when applied to an HRES at Ayetoro community in Southwest Nigeria, are also presented.

Main Points

- The proposed hybrid power system is optimized using, comparatively, three metaheuristic algorithms.
- In testing for the statistical significance of the algorithms, Bonferroni–Holm test method is applied.
- Artificial bee colony gives the best result in terms of design, total annualized and estimated energy costs.

II. METHODS

A. Brief Description of the Study Area and the Data Collection Approach

Ayetoro community is a suburb of Ede in Osun State, Southwest Nigeria. It is on Lat. 7.727637˚S/Long 4.428045˚W coordinate. There are 122 houses in the community, with the inhabitants being farmers, civil servants, or shop owners (petty traders). Electrical loads in the community are majorly domestic and commercial. In profiling the loads, the housing population was grouped into eight sections based on the structures of the buildings and the electrical equipment found the houses. By random approach, eight homes were selected from each section of the community, and a well-structured questionnaire was administered to the stratified sample to obtain information on energy consumption patterns.

Data on the solar radiation and temperature of the location were collected from the National Aeronautics and Space Administration (NASA) surface meteorology and solar energy database online. The solar energy database of NASA has a long-term climatological estimate of meteorological quantities and surface solar energy data majorly needed for the study of environmental process [20].

B. Modeling of the Hybrid System

Presented in Fig. 1 is the block diagram of the proposed HRES. Energy output from the battery source served as input to the inverter, where the DC voltage was converted to AC and fed the electrical load. Components of the system are modeled to determine the numbers of PV panels, battery units required, and the rating of the DG needed to be hybridized to effectively sustain the community load. The modeling was achieved in the MATLAB environment.

1) Solar Panel Modelling

The output power of the panel (P_{pt}) depends on the output voltage (V_{pt}) and the current (I_{pt}) in the panel and is expressed as [21, 22]:

$$P_{pt} = V_{pt} \times I_{pt} \tag{1}$$

While the output voltage is [22]:

$$V_{pt} = V_{\max} + \left(\mu_{voc} \times \Delta T\right), \tag{2}$$

where V_{max} is the maximum value of voltage, μ_{voc} represents the temperature coefficient for open-circuit voltage (V/˚C), and ΔT represents the time step. The corresponding output current (I_{pt}) is obtained as [22]:

$$I_{pt} = I_{sht}\left\{1 - A\left[\exp\left(\frac{V_{\max}}{B \times V}\right) - 1\right]\right\} + \Delta I \tag{3}$$

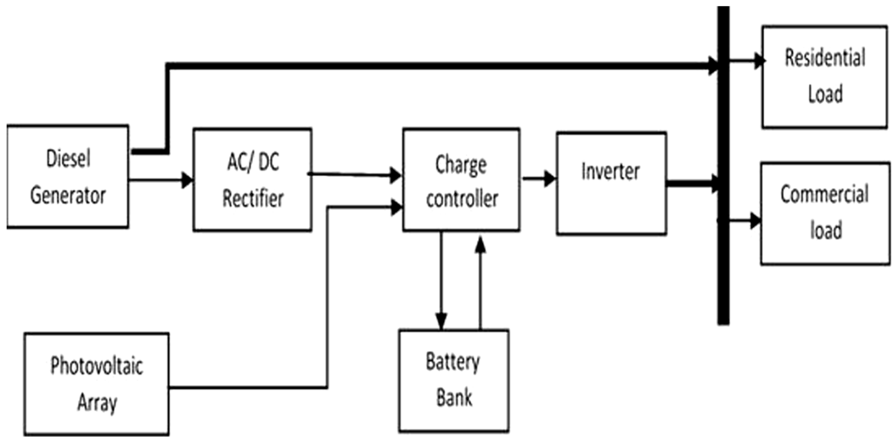

Fig. 1. Block diagram of photovoltaic/distributed generation system.

With the corresponding values of A and B expressed as [21, 22]:

$$A=\left[1-\left(\frac{I_{mx}}{I_{sht}}\right)\right]\exp\left(\frac{-V_{mx}}{B\times V_{oc}}\right) \tag{4}$$

$$B=\left(\frac{V_{mx}}{V_{oc}}\right)-1\times\left[\ln\left(1-\frac{I_{mx}}{I_{sht}}\right)\right]^{-1} \tag{5}$$

where I_{mx} and V_{mx} are the maximum current and voltage, respectively, while I_{sht} is the short circuit current and V_{oc} denotes the open-circuit voltage. The change in the value of the current and temperature over time is [21]:

$$\Delta I=I_{sht}\times\left(\frac{R_T}{R_{fo}-1}\right)+\mu_{sht}\times\Delta K \tag{6}$$

$$\Delta K=K_c-K_{cr} \tag{7}$$

R_T is the hourly irradiation value of the solar panel on a tilted surface, and R_{fo} is the reference point of the radiation energy at 1000 W/m^2. μ_{sht} is the short-circuit temperature coefficient, while K_c and K_{cr} are solar panel specified temperature and reference working point (25˚C), respectively. The value of K_c is further evaluated as [22]:

$$K_c=T_{am}+\left[\left(\frac{NOCT-20}{800}\right)\times G_T\right] \tag{8}$$

where T_{am} is the ambient temperature. Normal operating cell temperature (NOCT) ranges from 42˚C to 46˚C [22].

2) Modeling of Battery Storage

Nominal capacity of a battery storage system is the product of the initial capacity of the battery (B_i) and the ampere-hour (Ah). Therefore, it is important to initially specify the permissible depth of discharge (DOD, %) when determining optimal sizing as [19]:

$$SOC_{\min}=(1-DOD).Bi \tag{9}$$

The stored energy requires accurate estimation of the state of charge (SOC) because the SOC of battery varies with time as [7]:

$$SOC(t+\Delta t)=SOC(t)+\left(P_{bat}(t)B_{Teff}\times\Delta t\right)\left(\frac{1}{V_{dc}}\right) \tag{10}$$

where $P_{bat}(t)$ is the energy of the battery, V_{dc} is the DC voltage of the battery, and t is the step value in 1 hour. The battery charges when $P_{bat}(t)$ is greater than zero and drains when $P_{bat}(t)$ is less than zero. Furthermore, the round-trip efficiency of a battery, B_{Teff}, is defined as [7]

$$B_{Teff}=\left(B_{Teff}^{ch}+B_{Teff}^{d}\right)^{0.5} \tag{11}$$

where B_{Teff}^{ch} and B_{Teff}^{d} denote the charging and discharging round-trip efficiency, the charging and discharging efficiencies vary and are typically around 85% and 100%, respectively. The maximum charge or discharge power at any time is also vital in battery modeling. It is determined by the maximum charge current as [7]

$$I_m=\frac{P_{bat}(t)\times 1000}{N_b\times V_{dc}}. \tag{12}$$

where N_b is the number of batteries connected together. The storage constraints are obtained in [7], where $SOC_{\min}$ and $SOC_{\max}$ are the minimum and maximum SOC of the battery.

$$SOC_{\min}\le SOC(t)\le SOC_{\max} \tag{13}$$

3) Inverter System Modeling

The inverter rating capacity is designed with an increase of 20% to compensate for losses and enable the system to meet the maximum load demand [22], with P_{inv}, $P_{loadmax}$, and eff_{inv} given as [22, 23]:

$$P_{inv}=120\%p_{load\max} \tag{14}$$

$$eff_{inv} = \frac{P_{out}(t)}{P_{in}} \tag{15}$$

where P_{inv} is the nominal rating of the inverter, $P_{loadmax}$ is the maximum required load energy demanded, eff_{inv} is the efficiency, and P_{out} is the output power of the inverter.

4) Diesel Generator Modeling
The DG operational cost for the design was obtained as [22]:

$$C_{DF}(t) = P_F(t) \times \left[AP_D(t) + BP_{DE}(t) \right] \tag{16}$$

where A and B are fuel curve coefficients, $P_F(t)$ is the fuel price, $P_D(t)$ and $P_{DE}(t)$ are the output power (W) and rated power (W) of the DG, respectively.

The operational strategy was formulated such that when the renewable resource was insufficient to satisfy the load demand, the battery bank provided the necessary power as given in Fig. 2 [24]. $\Delta P(t)$ denotes the change in power value, either excess or deficit, after the design utilizes the solar source. The following scenarios are considered regarding the value of $\Delta P(t)$ given in (6):

$$\Delta P(t) = P_{load}(t) - \left(P_{pt}(t) + P_{bat}\right) \tag{17}$$

Scenario I: If the energy supplied by the solar source is insufficient to meet up the load demand, then more energy is needed from the battery bank (i.e., $\Delta P_{(t)} > 0$), and SOC of the battery bank is then fully monitored. The DG system is utilized if SOC drops within the minimum preset value of 20%.

Scenario II: If the energy supplied by the PV source is in excess compared to the load demand (i.e., $\Delta P_{(t)} < 0$), then excess energy is diverted to the battery bank for the charging process. When maximum SOC is met, excess energy is dumped for future usage. The DG system is switched off.

Scenario III: If the energy supplied by the solar source meets the load demand (i.e., $\Delta P_{(t)} = 0$), then the battery bank is placed on standby for an emergency, and the DG system is switched off.

C. Formulation of Objective Function
As one of the important economic measures used for system cost analysis, the cost of energy (COE) is the total cost of the HRES multiplied by the amount of electrical energy generated annually within the system. COE is given as [25]:

$$COE(\$/\text{kWh}) = \text{TASC} \times \frac{C_{capRef}(j,z)}{\sum_{t=1}^{8760} P_g(t)} \tag{18}$$

where the total annualize system cost (TASC) is achieved by identifying the various decision parameters and their corresponding variables. Formulating the objective function is subject to constraints to make the sizing optimal. TASC is obtained as [22]:

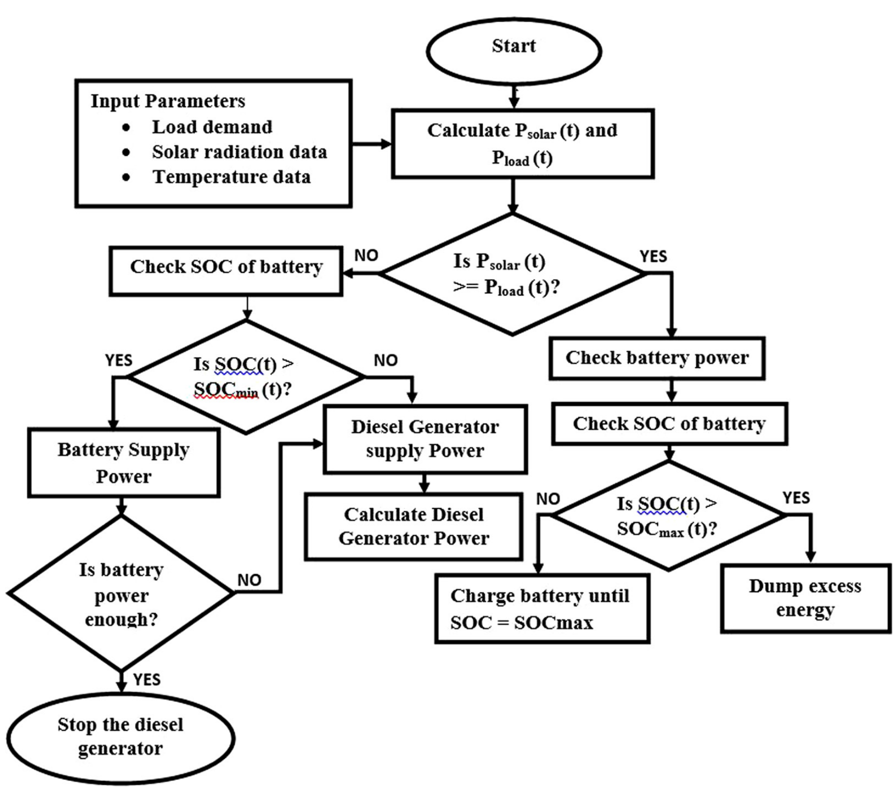

Fig. 2. Flowchart of system operation strategies.

$$\min TASC = \min\left(N_{PV}TC_{PV} + N_B TC_B + P_D TC_D + P_{inv}TC_{inv}\right) \quad (19)$$

where TC_{PV} is the PV panel cost, TC_B is the battery storage cost, TC_D is the DG cost, and TC_{inv} is the inverter cost. Also N_{pv} and N_B are the number of panels and batteries required while P_D and P_{inv} are the power ratings of the generator and inverter system needed to achieve minimum cost. The total costs of TC_{PV}, TC_B, and TC_D can be further calculated using [22]:

$$TC_{PV} = C_{PVC} + C_{PVI} + C_{PVM} \quad (20)$$

$$TC_B = C_{BC} + C_{BI} + C_{BM} + C_{BO} \quad (21)$$

$$TC_D = C_{DC} + C_{DI} + C_{DM} + C_{DO} \quad (22)$$

where C_{BC} is the battery capital cost, C_{BI} is the battery installation cost, C_{BM} is battery maintenance cost, and C_{BO} is the battery operational cost. Table I presents the cost and life expectancies of the components. The capital recovery factor is a ratio to determine the present worth of the annuity using the real interest rate and the project's lifetime as given in [26]:

$$C_{capRef}\left(j,z\right) = \frac{j\left(1+j\right)^z}{\left(1+j\right)^z - 1} \quad (23)$$

where j denotes the annualized interest rate and z represents the useful lifetime in years. The interest rate is given as [26]:

$$j = \frac{\left(i_n - a_f\right)}{\left(1+a_f\right)} \quad (24)$$

where i_n denotes the nominal interest rate and a_f represents the inflation rate. The objective function was minimized by deploying the following sets of constraints:

$$1 \le N_{PV} \le N_{PV\max} \quad (25)$$

TABLE I.
ANALYSIS OF COMPONENT PARAMETERS [7]

S/N	Item	Component	Parameter	Value
1.	Solar panel	Capital cost	250	$ each
		Replacement cost	150	$
		Maintenance and operation cost	10	$/year
		Solar panel life	20	Years
2.	Inverter	Capital cost	1250	$ each
		Replacement cost	750	$
		Maintenance and operation cost	50	$/year
		Inverter life	20	Years
		Inverter efficiency	90	%
3.	Battery bank	Capital cost	750	$ each
		Replacement cost	250	$
		Maintenance and operation cost	10	$/year
		Battery life	7	Years
		Inverter efficiency	90	%
		Minimum state of charge	20	%
		Maximum state of charge	100	%
4.	Diesel generator	Capital cost	520	$ each
		Replacement cost	350	$
		Maintenance and operation cost	80	$/year
		Diesel generator life	25	Years
		Diesel generator efficiency	80	%
		Fuel cost	0.38	$/L

$$1 \le P_D \le P_{D\max} \tag{26}$$

where $N_{PV\max}$ and $P_{D\max}$ are the maximum numbers of solar panels and maximum power demand from DG.

D. Brief Descriptions of the Algorithms

1) PSO Algorithm

PSO was first described in 1995 by Kennedy and Eberhart, and has been successfully applied in many scientific domains [27]. The PSO technique influenced the combined intelligence of a group of animals, such as a flock of birds, animals travelling in herds, or schools of fish moving together. Each particle utilized the distance between the current position and the new position. A change in the velocity and position of each particle is performed using [28]:

$$V_{pw}(t+1) = \alpha\left[\left(V_{pw}(t) + C_a U_a\right)\left(p_{bestpw}(t) - X_{pw}(t)\right) + \left(C_b U_b\right)\left(g_{bestpw}(t) - X_{pw}(t)\right)\right] \tag{27}$$

$$X_{pw}(t+1) = X_{pw}(t) + X_{pw}(t+1) \tag{28}$$

where $\propto$ is the factor of the inertial component that affects the algorithm, $V_{pw}(t)$ is particle velocity in the algorithm. C_a and C_b represent parameters of the metacognitive components, U_a and U_b represent two random variables in the range of 0 and 1 employed to keep the population diverse, and $X_{pw}(t)$ is the change of position toward the particle best positions. The PSO algorithm offers a certain appealing feature of good memory where the particles retain the knowledge of good solutions compared to the GA approach [29].

2) Genetic Algorithm

It is a search algorithm that is based on the natural selection process. It is based on one of the most significant survivals of the fittest values. The best person represents the optimal solution after a few generations until the population can no longer endure. GA simulates the evolutionary mechanism by which inherited traits are passed on from one generation to the next. A gene is the most fundamental unit of inheritance [11]. Chromosome exchange and reordering are known as crossover. The steps taken for the technique are as follows: It starts with the initialization of the algorithm's process and checks for the condition for process continuation, as shown in Fig. 3. The fitness function examines and evaluates the result generated to determine the best outcome to be retained for the process. Population diversity is achieved through mutation. It produces new results in the system; the procedure is repeated on several occasions until it converges, indicating the optimum solution [30].

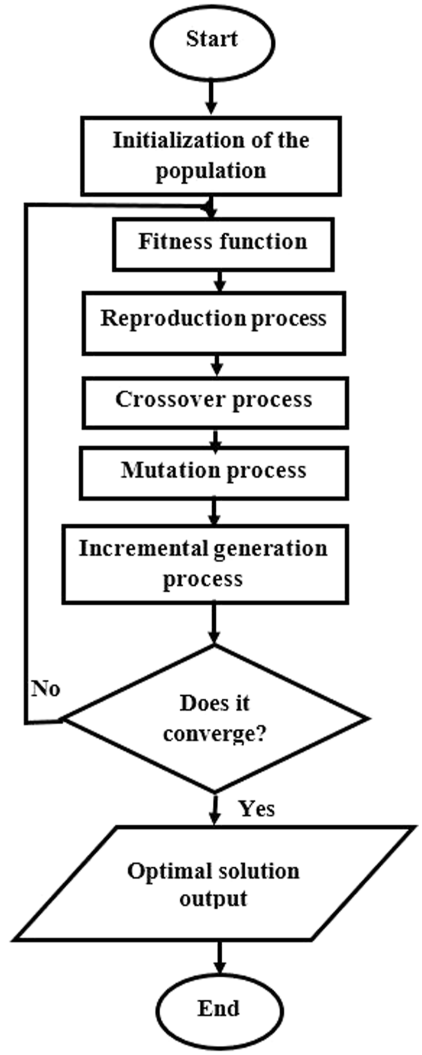

Fig. 3. Flow chart of genetic algorithm.

3) Artificial Bee Colony

In 2005, Karaboga devised the ABC method [31] that mimics the well-organized social structure and division of labor in honeybee colonies. There are three major bee colony classifications: employed, onlooker, and scout bees. At first, employed bees will randomly select a set of food source locations. The amount of nectar they generate will be measured, and they returned with specialized dances to communicate with the other bees about that food source. Onlooker bees are another type of bee that waits on the dance floor to select which food sources to pursue after collecting information about it from employed bees [32]. Scout bees go on a random quest for new food sources. The quality of the fitness is related to the solution achieved, which indicates the quantity of available food that corresponds to it in this method. The position of the available food reflects the possible point of solution to the problem. Compared to other algorithms, it has fewer control parameters and convergence speed increased due to its direct operation. The probability P_x of selecting a food source x is determined as given in:

$$P_x = \frac{fit_x}{\sum_{q=1}^{N_f} fit_q} \tag{29}$$

where fit_x represents the fitness value of the amount of food source at x position and N_f is the number of food sources.

E. Statistical Analysis

One of the most used statistical tools in research is the analysis of variance (ANOVA) approach [33], which focuses on analyzing the differences in group means by comparing between- and within-group variance differences. The dependent and independent variables are utilized in the test. When comparing the means of three groups, the null hypothesis is identified if the population means of the three groups are all the same. However, the alternative hypothesis is identified when at least one of the population means of the three groups is different, rather than the population means of the three groups are all the same. The null hypothesis (H_0) and alternative hypothesis (H_1) are given as [34]:

$$H_0\colon \mu_1 = \mu_2 = \mu_3 \tag{30}$$

$$H_1\colon \mu_1 \neq \mu_2 \text{ or } \mu_1 \neq \mu_3 \text{ or } \mu_2 \neq \mu_3 \tag{31}$$

As a result, if the means of any two of the three groups differ, the null hypothesis can be rejected.

The Bonferroni-Holm technique is a statistical procedure used to compare two groups of a data set and solve the problem of multiple comparisons by modifying the rejection parameters for each assumption the most generally suggested method to examine the significant effects [35].

III. RESULTS AND DISCUSSION

The load profile of the community, as obtained during raining season (June–November) and the dry season (December–May), is presented in Fig. 4. The profile shows there was low demand between 21:00 h and 2:00 h and between 7:00 h and 15:00 h, while the demand slightly rise from 4:00 h to 6:00 h when people are preparing for their various places of work. The peak load of the community exists between the period of 16:00 h and 20:00 h when most of the people arrive from work. It can also be noted that peak load is higher during the dry season than in the rainy season. The peak and the minimum demand during the rainy season are 148.28 kW and 45.03 kW, respectively, while 163.29 kW peak demand with corresponding 45.04 kW minimum demand was obtained during the dry season. Daily and yearly load demands are 2089.48 kWh and 680 850 kWh, respectively.

As shown in Fig. 5, the irradiation level in the community, which is 1561.99 kWh/m^2/day during the dry season, is high enough to produce reliable solar energy. Likewise, the locality has a good temperature gradient with the maximum recorded being 38.44˚C in the dry season and the minimum being 17.447˚C in the rainy season as presented in Fig. 6.

Fig. 7 shows the plot of numbers of solar panels, battery units, and the system cost of the 50 runs.

Table II shows the results obtained for the total number of solar panels, the battery unit, minimum DG required, and component cost analysis of the components. The results are 423, 38, and 163.2 kW for GA; 426, 27, and 163.2 kW for PSO; 430, 20, and 163.2 kW for ABC, respectively. The result indicates that ABC shows the lowest total annualized cost (TAC) of $167 284 compared to PSO and GA with TAC of $167,693 and $168 566, respectively. The COE of the optimal sizing for GA, PSO, and ABC are 0.2476, 0.2463, and 0.2457, respectively, indicating that ABC has the lowest COE. Table III presents the results of optimal sizing when based on PV solar system only and battery storage system only respectively. Fig. 8 presents the comparison of the cost analysis of three scenarios used for different component configurations.

ANOVA test for the three algorithms was conducted using data analysis available in Microsoft Excel. Table IV shows the algorithms' sum, average, and variance of the total cost of energy, while Table V

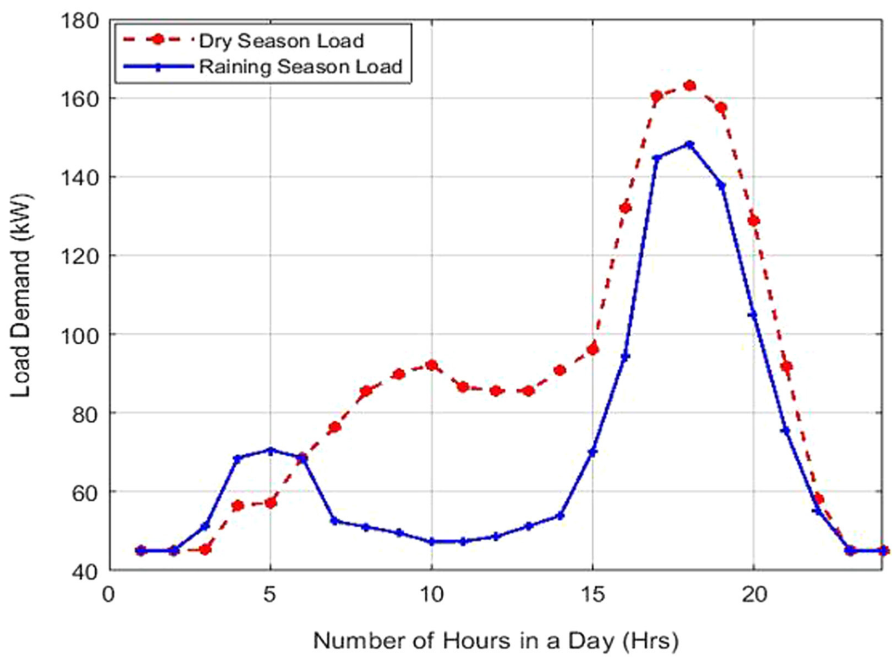

Fig. 4. Raining season and dry season load demand profile of the community.

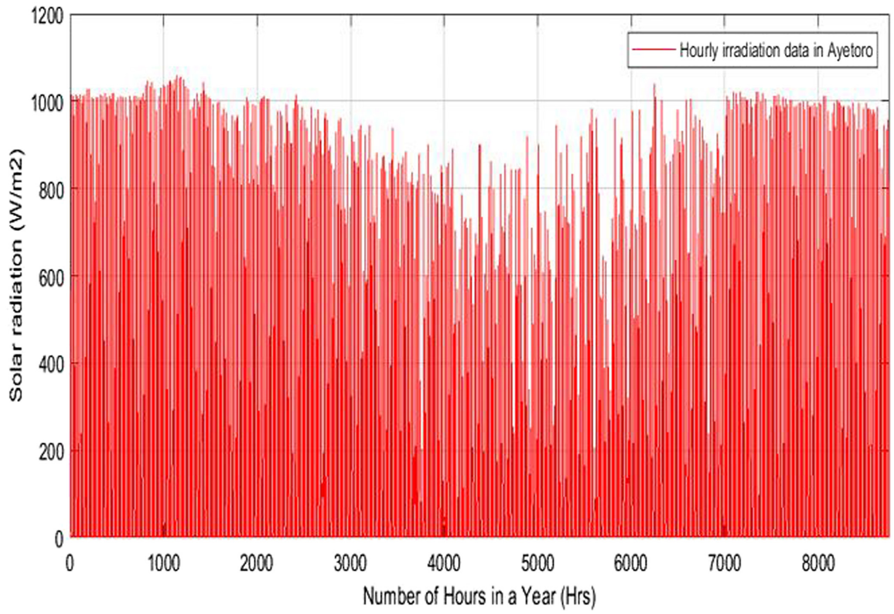

Fig. 5. Solar radiation plot of the community.

shows the sources of variance between groups and within groups with their sum of squares, degree of freedom, and the mean square. The *F*-statistic of one-way ANOVA has a *P* value of 1.822×10^{-7} which is less than the alpha value of 0.05. The results show that statistical differences exist in the data group. The null hypothesis is therefore rejected, and the result is statistically significant. The results obtained from using the Bonferroni-Holm method of multiple comparison tests indicate that the *t*-test between PSO and ABC are both $5.83 \times 10^{-10} < 0.01666667$, between ABC and GA are $6.09 \times 10^{-6} < 0.01666667$ and $6.09 \times 10^{-6} < 0.025$ while between GA and PSO are $9.13 \times 10^{-1} > 0.01666667$ and $9.13 \times 10^{-1} > 0.05$ as shown in Table VI. This further clarifies that PSO/ABC group and ABC/GA are significant while GA/PSO group is insignificant. These post hoc tests reveal that two treatment pairs are statistically different and ABC produces the best result. The convergence plot of the three algorithms is presented in Fig. 9.

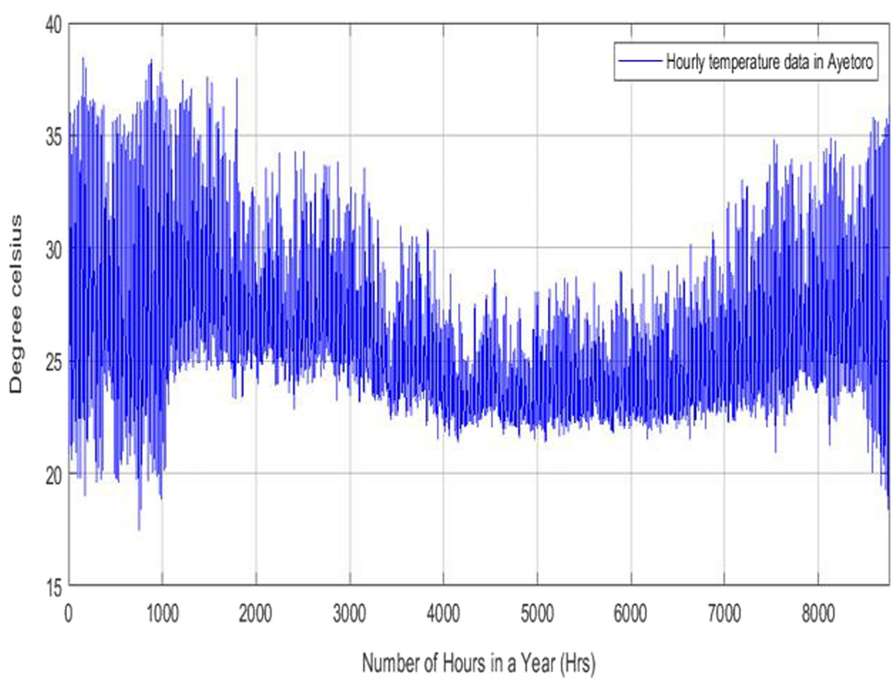

Fig. 6. Hourly temperature plot of Ayetoro community.

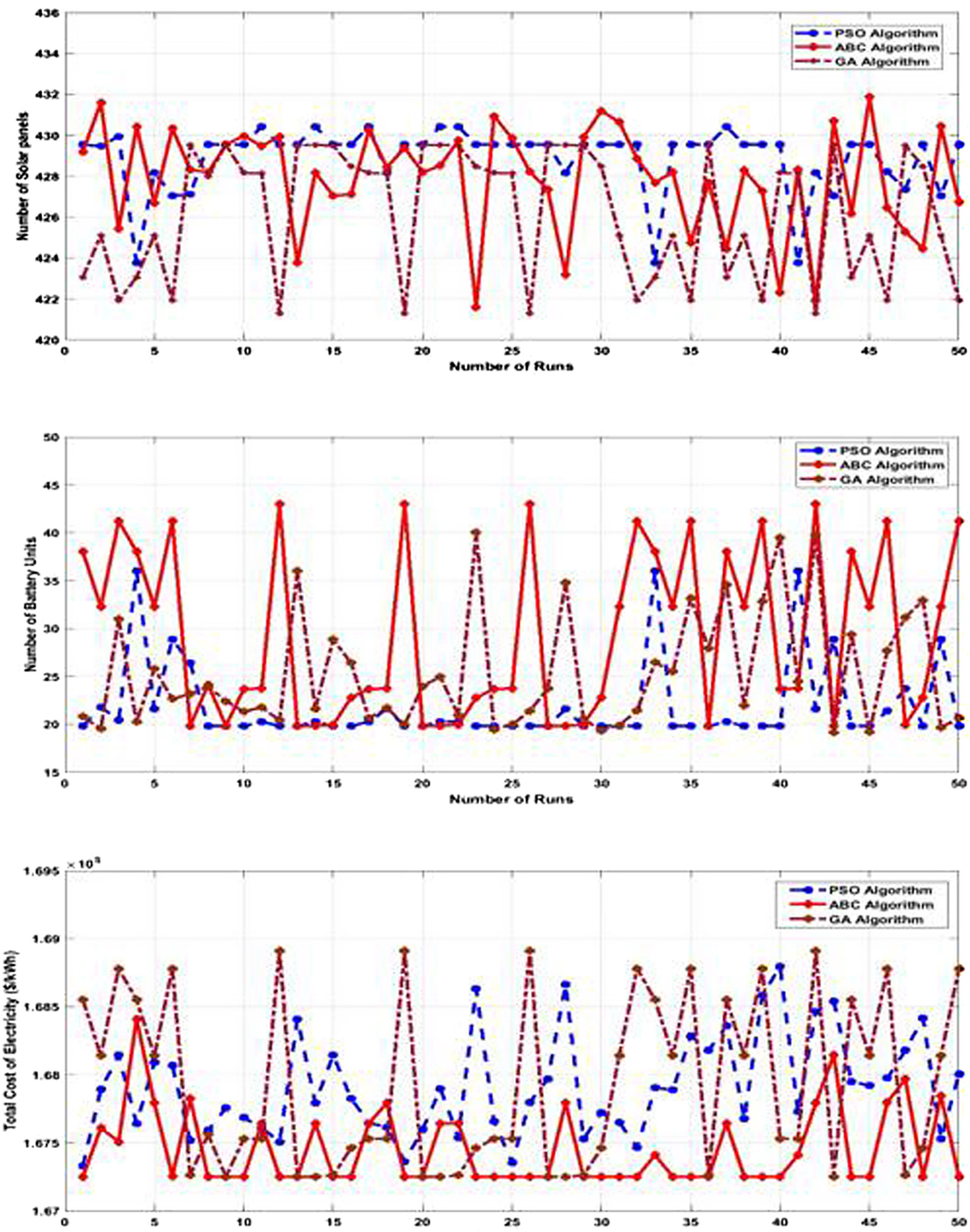

Fig. 7. Plot for the three algorithms showing the solar photovoltaic required, battery units, and total cost of electricity.

TABLE II.
COMPARATIVE RESULTS OF THE OPTIMAL SIZING AND COST ANALYSIS

Parameter	GA	PSO	ABC
Number of solar panels required (kW)	423	426	430
Number of battery units	38	27	20
Total load of community (kW)	680 850	680 850	680 850
Total solar cost ($)	143 260	144 368	145 450
Diesel generator cost ($)	735.69	735.69	735.69
Total battery cost ($)	7308.30	5327.31	3836.29
Power inverter cost ($)	17 262	17 262	17 262
Total annualized cost ($/year)	168 566	167 693	167 284
Cost of energy ($)	0.2476	0.2457	0.2443

ABC, artificial bee colony; GA, genetic algorithm; PSO, particle swarm optimization.

TABLE III.
OPTIMAL SIZING OF SOLAR PV PANEL-ONLY AND BATTERY-ONLY POWER SOURCE

	PV Solar Panel-Only Power Source			Battery-Only Power Source		
Algorithms	**GA**	**PSO**	**ABC**	**GA**	**PSO**	**ABC**
Number of solar panels	175	175	175	0	0	0
Number of battery units	0	0	0	10	37	49
DG energy generation (kW)	4.537×10^5	4.537×10^5	4.537×10^5	6.749×10^5	6.594×10^5	6.516×10^5
Total annualized cost ($/year)	3.5469×10^5	3.5469×10^5	3.5463×10^5	3.9356×10^5	3.9055×10^5	3.8917×10^5
Cost of energy ($)	0.5210	0.5210	0.5209	1.4687×10^4	1.4687×10^4	1.4687×10^4

ABC, artificial bee colony; DG, distributed generation; GA, genetic algorithm PSO, particle swarm optimization; PV, photovoltaic.

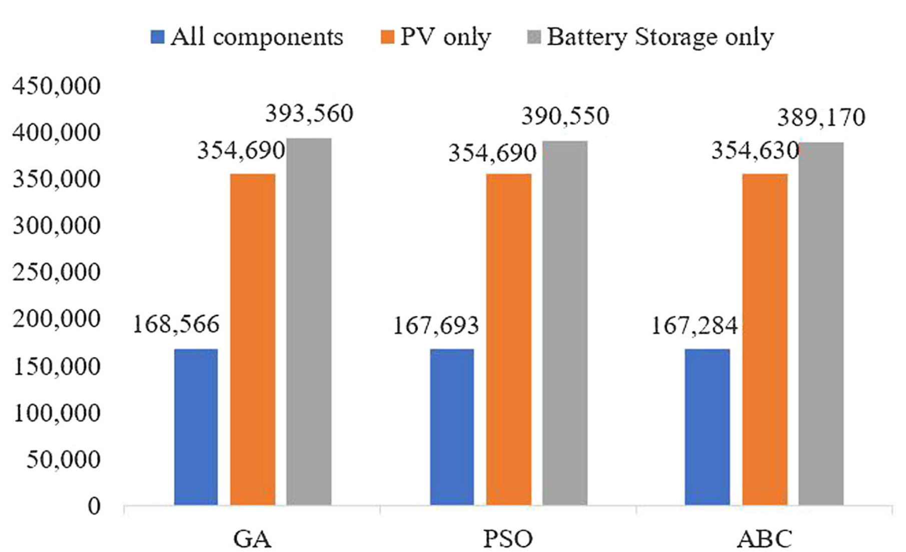

Fig. 8. Cost analysis of three different scenarios used in sizing.

TABLE IV.
ONE-WAY ANOVA RESULT FOR ALGORITHMS

Groups	Count	Sum	Average	Variance
PSO	50	8 395 454.816	167 909.0963	142 282.2543
ABC	50	8 372 446.689	167 448.9338	81 742.71787
GA	50	8 396 030	167 920.6	404 458.8163

ABC, artificial bee colony; GA, genetic algorithm PSO, particle swarm optimization.

TABLE V.
SHOWS THE VALUE OF ***P*** VALUES AND F CRITICAL VALUES WHERE ($\propto = 0.05$)

Source of Variation	Sum of Squares	Degree of Freedom	Mean Square	F-Stat	*P*-Value	*F* Critical
Between groups	7 239 182.17	2	3 619 591.085	17.27773008	1.822E-07	3.057620
Within groups	30 795 705.64	147	209 494.5962			
Total	38 034 887.81	149				

TABLE VI.
BONFERRONI AND HOLM POST HOC TEST

Algorithms	*P* Value (*t*-test)	Bonferroni	Rank	Holm	Significant
PSO vs. ABC	5.83E-10	0.01666667	1	0.0166667	Yes
ABC vs. GA	6.09E-06	0.01666667	2	0.025	Yes
PSO vs. GA	9.13E-01	0.01666667	3	0.05	No

ABC, artificial bee colony; GA, genetic algorithm PSO, particle swarm optimization.

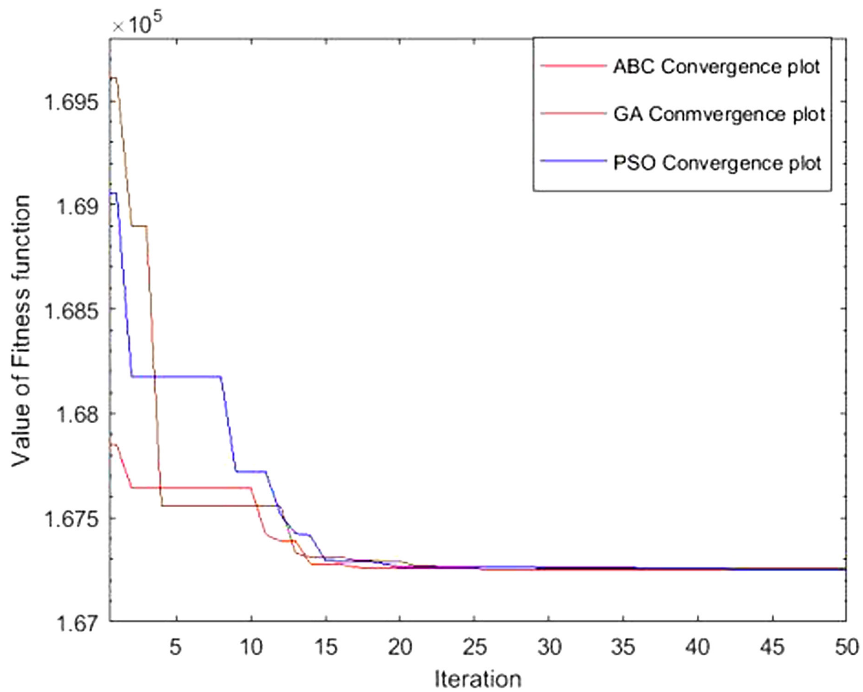

Fig. 9. Convergence plot of particle swarm optimization, artificial bee colony, and genetic algorithm.

IV. CONCLUSION

A hybrid energy system that consists of PV panels and battery storage units has been designed to provide sustainable and reliable electrical energy to a community in Nigeria. This paper uses a mathematical model of the components to determine the optimal size and ensure that the design's constraints are not violated. Results obtained from the three metaheuristic algorithms (GA/PSO/ABC) show that ABC produces the best configurations with 427 numbers of solar PV panels, 19 battery units, and 163.2 kW diesel generator ratings with the lowest TAC of \$167 284 as compared to PSO and GA with \$167 693 and \$168 566, respectively. The COE estimate is 0.2443 for ABC, 0.2476 for GA, and 0.2457 for PSO. The results obtained from Bonferroni-Holm multiple comparison tests indicate that the *t*-test between PSO and ABC are both $5.83 \times 10^{-10} < 0.01666667$, between ABC and GA are $6.09 \times 10^{-6} < 0.01666667$ and $6.09 \times 10^{-6} < 0.025$ while between GA and PSO are $9.13 \times 10^{-1} > 0.01666667$ and $9.13 \times 10^{-1} > 0.05$. This further clarifies that PSO/ABC and ABC/GA groups are significant while GA/PSO group is insignificant. These post hoc tests reveal that two treatment pairs are statistically different and ABC produces the best result. It is concluded that the hybrid system completely satisfied the load demand of the community.

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