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ORIGINAL RESEARCH ARTICLE

AN INDEPENDENT FRAMEWORK FOR OFF-GRID HYBRID RENEWABLE ENERGY DESIGN USING OPTIMAL FORAGING ALGORITHM (OFA)

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ABSTRACT

The rapidly increase in electrical energy demand from residential, commercial and industrial sectors is one of the major challenge in power system, especially in the current period of high oil prices, steadily reducing energy sources and increased concerns about environmental pollution. Renewable energy is considered as one of the solution to this increase in power demand. The conventional method of power system cannot meet the power demand for many reasons such as environmental effects, location of the consumer, price of fuel and others. This paper presents the design of an off-grid Hybrid Renewable Energy System (HRES) for electrification of a typical remote area. The designed hybrid system consists of three different configurations of PV/Battery, Wind/Battery and PV/Wind/Battery systems. The system components are modelled and the objective function is designed as a function of total annualized cost of the system subject to some constraints binding the decision variables. The total annual cost is formulated as a function of annual capital cost and annual maintenance cost of the system subject to some operational constraints. In order to determine the optimal number of the decision variables that would satisfy the load demand in the most cost effect manner, Optimal Foraging Optimization (OFA) algorithm was used. Finally, a simulation experiment shows that the total annual cost obtained by each algorithm for the PV/Battery system is $9,340.42 or ₦3,876,274.30, $9,446.77 or ₦3,920,409.55 and $10,076.34 or ₦4,181,681.1 for OFA, GA and PSO respectively. For the Wind/Battery configuration, the total annual cost obtained by OFA, GA and PSO are $17,508.20 or ₦7,265,903, $12,493.27 or ₦ 5,184,707.05 and $16,535.93 or ₦6,862,410.95 respectively. Similarly, the PV/Wind/Battery configuration showed that the OFA, GA and PSO obtained an annualized cost of $15,926.07 or ₦6,609,319.05, $18,167.09 or ₦7,539,342.35 and $16,535.93 or ₦6,862,410,95 respectively. From the results obtained by OFA are compared with that of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) algorithm. Results showed that all the algorithm can efficiently size the hybrid system with OFA obtaining the most economical design. Therefore, for economically and efficiently electrification of a remote area in Abuja using an off-grid hybrid renewable energy system, GA optimization algorithm is recommended for wind/Battery system and OFA optimization algorithm is recommended for PV/Wind/Battery system.

1.0 Introduction

Electricity is requisite for socio-economic development of every society. Unfortunately, sub-Saharan Africa is challenged with different electrification problem. One of the popular technologies which have been widely adopted to improve the electrical energy demand has been based on renewable energy resources especially in remote areas where power generated cannot be supplied to such communities due to difficulties in the transmission and distribution systems (Njoh et al., 2019). Renewable energy generation have identified solution to these problems and as an effective source of energy in such areas. The Off-grid mode of energy generation does not require complex interconnections of power systems generation equipment like the main grid. One of the major challenges which have hinder harnessing renewable energy to full capacity is the weather conditions. The total dependency of wind and solar energy on weather and climatic conditions has been a major drawback in total harvesting their energy to full capacity (Ogunjuyigbe et al., 2016) . The energy generated from the individual sources may not be sufficient for a considerable amount of time. To address these challenges several researches have proposed hybridizing different renewable energy sources to compensate for energy shortage that arise from individual sources. To efficiently and economically utilize the hybrid energy systems, a proper sizing mechanism is important (Ogunjuyigbe et al., 2019). Several studies related to the optimal sizing of stand-alone hybrid energy systems have been conducted in the literature. Dong et al. (2016) reported an improved Ant Colony Optimization (ACO) algorithm for optimizing a multi-objective stand-alone hybrid PV/wind/battery/hydrogen system with major focus on reliability and economy of supply. The loss of power supply and total annual cost were modelled as a dual objective function which the ACO was used to minimize. An optimized hybrid renewable energy system of PV/wind/battery for electrification of a remote area in Iran using particle swarm optimization technique was proposed in (Askarzadeh, 2015).The particles of PSO probe the search space to minimize the life cycle cost (LCC), at the same time maintaining a reliable system. In (Kanase-Patil et al., 2010) LINGO software was used to analyzed integrated renewable energy systems for off-grid rural electrification of remote area in India. The optimal system cost, reliability and cost of energy were evaluated for four different renewable energy technologies which include biomass, micro hydro, solar and wind. In Maleki et al. (2014), a discrete harmony search (DHS) optimization algorithm was used to optimally size an off-grid of PV/wind/diesel system with battery storage. For performance evaluation, the results of DHS are compared with results found by a discrete simulated annealing (DSA) algorithm.

The proposed methods minimize the total annual cost (C_T) of the off-grid system effectively. Although various aspects of HRES system have been studied, useful and interesting model and efficient optimization tool for optimal sizing is still a major challenge for researchers. In this regard, this paper presents an efficient sizing technique for optimal sizing of off grid hybrid renewable energy system using Optimal Foraging Algorithm (OFA). The HRES model is designed to incorporate photovoltaic system, wind energy and energy storage. Different configurations including PV/Battery, Wind/Battery and PV/Wind/Battery were considered to analyze the effectiveness of OFA in solving the HRES problem. Each configuration of HRES system is optimization considering total annualize cost as a metric. For performance evaluation the results of OFA are compared with that of found by Particle Swarm Optimization and Genetic Algorithm. The outline of this paper is organized as follows: The modelling of the hybrid energy system is given in section 2. Section 3 presents the hybrid renewable energy optimization problem formulation. Section 4, present the Optimal Foraging Algorithm (OFA). Section 5 gives the simulation results. Finally, a conclusion for this work is stated in section 6.

2. Materials and methods

The hybrid energy system is made up of photovoltaic modules and wind turbines (WTs) as renewable energy sources and battery bank for excessing energy storage. The battery bank helps to maintain constant power supply when the power generated by the renewable energy sources is less than the power demand. If the power generated by the renewable energy sources is higher than the load demand, then excess energy is stored in the battery bank. The schematic representation of the hybrid renewable energy system is shown in Figure 1.

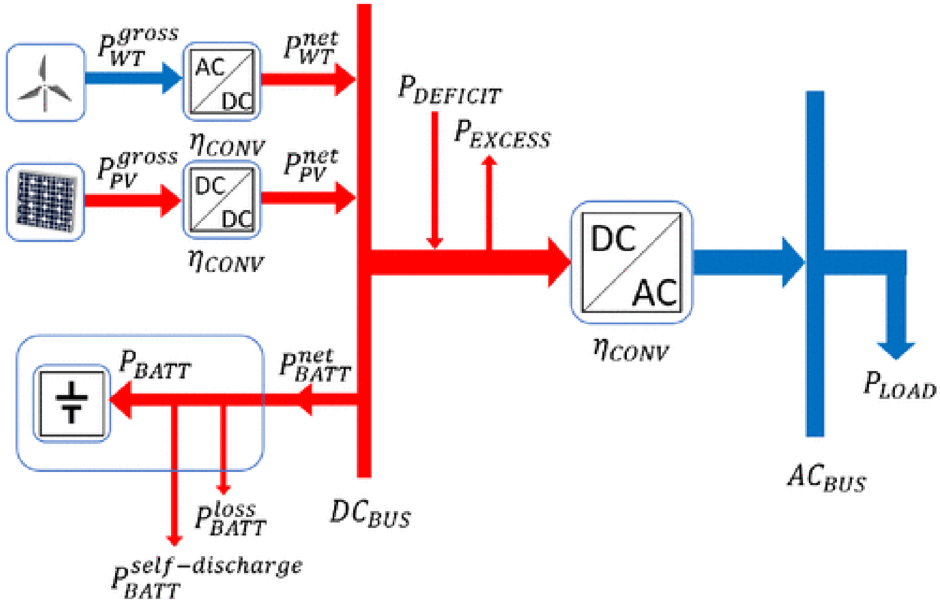

Figure 1. Schematic description of the PV/wind/battery based hybrid system (Gil Mena *et al.*, 2021).

2.1 Modelling

A brief modelling of the hybrid system which consist of PV modules, the wind turbines, the battery storage as being used in the algorithm is as presented.

2.1.1 Photovoltaic System

The output power of every PV system (P_{PV}) at time step t can be calculated from the solar radiation using:

$$P_{pv}(t) = I(t) \times A \times \eta_{pv} \tag{1}$$

Where *I* is the solar radiation (W/m^2), *A* symbolizes the area of PV (m^2) and η_{PV} is the efficiency of the PV's modules. It is assumed that the PV panels is embedded with maximum power point tracking (MPPT) system.

2.1.2 Wind Turbine

Low speed winds usually don't have sufficient power to subdue friction of the wind turbine. Therefore, at wind speed less than the cut-in wind speed (V_{ci}) no power is generated. With increase in velocity greater than the cut-in wind speed, the power generated by the wind turbine generator rises as the cube of wind speed. As the wind speed increase continuously, up to the rated value say (V_r), the generator produces as much power it is designed for say (P_r) in kW. At a certain level, when the wind speed is so high it becomes a threat to the wind turbine. At this wind speed, named the cut-out wind speed (V_{co}), the wind turbine needs to be shut down to prevent it from damaging (Maleki et al., 2016). Hence, the output power is zero. Mathematically, this behavior can be expressed as follows:

$$P_{WT}(t) = \begin{cases} 0 & v(t) \leq V_{ci} \text{ or } v(t) \geq V_{co} \\ P_r \frac{v^3(t) - V_{ci}^3}{V_r^3 - V_{ci}^3} & V_{ci} < v(t) < V_r \\ P_r & V_r < v(t) < V_{co} \end{cases} \tag{2}$$

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Where $v(t)$ is the wind speed in m/s at time t.

The rated power of the wind turbine generator (P_r) is defined as a function of the air density (ρ_a), the swept rotor area occupied by the rotating wind turbine blades (A_w), the power coefficient (C_p) and the wind turbine generator efficiency (η_g) as follows:

$$P_r = \frac{1}{2} \times \rho_a \times A_w \times C_p \times \eta_g \times V_r^3 \quad (3)$$

2.1.4 Battery

The battery is used to store the excess generated power by the renewable resources and also cut power mismatch between generation and load demand. State of Charge (SOC) of battery in accordance with productivity and consumption period can be obtained when the total output power of the hybrid system is greater than the load demand, $ePV(t) + eWT(t) > E_{Load}(t)$, The charge quantity of the battery at time t can be written as (Maleki et al., 2014):

$$eBat(t) = eBat(t-1) \times (1-\sigma) + [ePV(t) + ewT(t)) - \frac{E_{Load}(t)}{\eta_{inv}}] \times \eta_{BC} \quad (4)$$

Where $eBat(t)$ and $eBat(t-1)$ are the charge quantities of the battery bank at time t and $t-1$, σ is the hourly self-discharge rate, η_{Inv} is the inverter efficiency, $E_{Load}(t)$ is the load demand for a particular hour and η_{BC} is the charge efficiency of the battery bank.

When the total output power of hybrid system is less than the load demand, $ePV(t) + eWT(t) < E_{Load}(t)$, the battery bank is in discharging state. The charge quantity of the battery at time t can be obtained as:

$$eBat(t) = eBat(t-1) \times (1-\sigma) - \left[\frac{E_{Load}(t)}{\eta_{Inv}} - ePV(t) + eWT(t)) \right] \quad (5)$$

Where η_{BD} is the discharging efficiency of the battery bank which ranges from 0-100%. In this research, the value is assumed to be 100%.

2.1.5 Load Profile

The load profile defines the requirements of power supply from the off-grid PV/wind hybrid energy system. The hourly load profile for a residential building collected through questioner (Figure 2). The study of the load profile reveal that the households wake up in the morning to prepare for business, work and school (more electricity is needed to prepare for hot showers and breakfast). People then leave for business, work and school typically at 7:00hr and close by 18:00hr on weekdays. At around this time, most households switch on lighting points, fans, prepare for dinner and watch TV up to around 22:00hr before bed time.

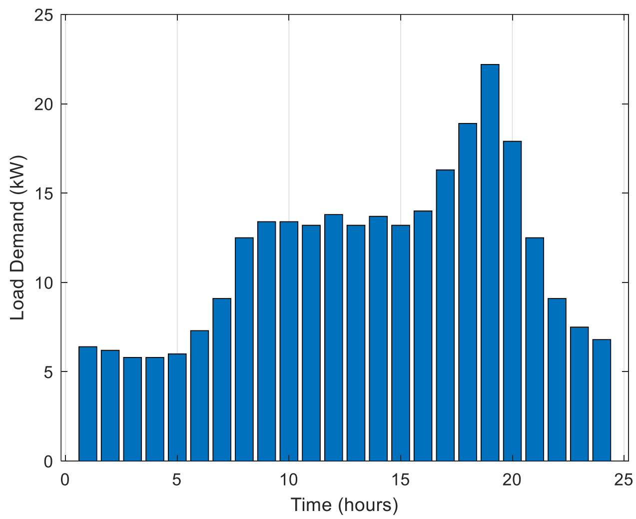

Figure 2. Hourly load profile

3. Problem formulation

3.1 Objective function

The optimization problem is to minimize the total annual cost (TAC) of system. The TAC consists of annual capital cost (C_{AC}) and annual maintenance cost (C_{AM}). To optimally size the stand-alone hybrid energy system, the following cost function is minimized using Optimal Foraging Algorithm (OFA). (Kellogg et al., 1998).

$$TAC = C_{AC} + C_{AM} \tag{6}$$

Capital cost take place at the starting of a project while maintenance cost take place during project life.

To transform the initial capital cost to the annual capital cost, the capital recovery factor (CRF) is expressed by equation (7). (Belfkira et al., 2014).

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{7}$$

Where, n denotes the life span of the system and i is the interest rate.

The duration of the proposed hybrid energy system is assigned to be 20 years. Some of the hybrid system components is expected to be changed during the project's lifetime. The lifetime of a battery is assumed to be 5 years. Using single payment present worth factor, we have (Eltamaly et al., 2016):

$$C_{Bat} = P_{Bat} \times \sum_{k=0,5,10,15} \frac{1}{(1+i)^k} \tag{8}$$

Where C_{Bat} is the present worth of battery and P_{Bat} is the battery price.

Similarly, the duration of converters is assumed to be 10 years. We can calculate the converter cost as

$$C_{conv} = P_{conv} \times \sum_{k=0,10} \frac{1}{(1+i)^k} \tag{9}$$

Where $C_{Conv/Inv}$ is the present worth of converter/inverter components and $P_{Conv/Inv}$ is converter/inverter price.

Thus, the total annual capital and maintenance cost are obtained by equations (10) and (11) relatively.

$$C_{AC} = CRF \times \left[nPV \times C_{pv} + nWT \times C_{WT} + nBat \times C_{Bat} + nConv \times C_{conv} \right] \quad (10)$$

Where nPV is the number of PV panels, C_{PV} is unit cost of PV panel, nWT is the number of wind turbines, C_{WT} is the unit cost of wind turbine, $nBat$ is the number of batteries and $nConv$ is the number of converter/inverter systems.

$$C_{AM} = C_{pv-Mtn} \times N_{pv} + C_{WT-Mtn} \times N_{WT} \quad (11)$$

Where C_{PV-Mtn} and C_{WT-Mtn} are the annual maintenance cost of PV panel and wind turbine respectively. The maintenance costs of battery and converter/inverter systems are ignored.

3.2 Constraints

For the stand-alone PV/wind/Storage energy system, the following decision variable constraints should be satisfied:

$$nPV_{\min} \le nPV \le nPV_{\max},\ nPV = Integer \quad (12)$$

$$nWT_{\min} \le nWT \le nWT_{\max},\ nWT = Integer \quad (13)$$

$$nBat_{\min} \le nBat \le nBat_{\max},\ nBat = Integer \quad (14)$$

Where nPV_{max}, nWT_{max} and $nBat_{max}$ are the upper bound of the PV panels, Wind turbines and Batteries respectively. Then, nPV_{min}, nWT_{min} and $nBat_{min}$ are the lower bound of PV panels, Wind turbines and Batteries respectively.

Moreover, at any time, the quantity of charge in the battery bank should satisfy:

$$eBat_{\min}(t) \le eBat(t) \le eBat_{\max}(t)$$

The maximum charge quantity of the battery bank $eBat_{max}$ takes the value of nominal capacity of battery bank (S_{Batt}) and the minimum charge quantity of the battery bank E_{min} is obtained by maximum depth of discharge (DOD).

$$eBat_{\min} = (1 - DOD) \times S_{Batt} \quad (15)$$

4. Optimal Foraging Algorithm (OFA)

The OFA is a metaheuristic algorithm developed from the idea of Optimal Foraging Theory (OFT). Optimal foraging theory is a concept that described the dietary patterns of biology organisms towards food (Salawudeen et al., 2018, Mu'azu et al., 2018) . When a biological organism searches for food, three important questions must be considered. These questions are: i. where is best suitable to search for food? ii. At what point/time should a new source of food be searched? and iii. what kind of food sources should be exploited? Organisms employ these three rules to maximize the net energy acquired during foraging process. This concept was used to develop the OFA by Zhu and Zhang. (Ahmed T S et al., 2020) and (Zhu et al., 2017).

In OFA, individual foragers select areas to forage using a certain rule. After foraging a new search space, the individual foragers decide whether the food energy in this area is beneficial or not. Other foragers are attracted to the new area if the food energy is valuable thus increasing the diversification of the algorithm. Now, assume there are N individual foragers in a group foraging in D-dimensional search space. The initial positions of the foragers $x_i^t = [x_{i,1}^t, x_{i,2}^t, ..., x_{N,D}^t]$ can be generated as (Zhang et al., 2017, Zhu et al., 2017 and Salawudeen et al., 2021):

$$x_i^t = x_i^L + r_1 \times \left(x_i^U - x_i^L\right) \tag{16}$$

The objective function of this initial position is computed as

$$f(x_i^t) = \min_{x \in R} f(x), R = \left\{x_i^L \le x_i^t \le x_i^U, i = 1, 2, 3, ..., D\right\} \tag{17}$$

where R is the constrain space, x_i^L and x_i^U are the lower and upper bound values, r_1 is a random number generated within the range of 0 and 1.

As the foragers in OFA iterate during the optimization process, the best foragers in the group forage using

$$x_i^{t+1} = x_i^t - k \times r_2 \times (x_i^t - x_{worst}^t) + k \times r_3 \times (x_i^t - x_{worst}^t) \tag{18}$$

The remaining individual in the foraging group forage using

$$x_i^{t+1} = x_i^t - k \times r_3 \times (x_{random}^t - x_i^t) + k \times r_5 \times (x_{random}^t - x_i^t) \tag{19}$$

where k is defined as $k = t / t_{\max}$, t is the current iterations, t_{max} is the maximum iteration number, r_2, r_3, r_4 and r_5 are all randomly generated number.
In OFA, the position of foragers obtained after t iterations is regarded as unprofitable position, and the corresponding fitness is regarded as unprofitable fitness (F_j^t). Similarly, the positions of foragers after iteration t+1 is regarded profitable prey location and the corresponding fitness can be represented as F_j^{t+1}. Based on this information, the positions of current foragers are updated if the following equation is satisfied (Eltamaly et al., 2016) and (Zhang et al., 2017).

$$\frac{\lambda_i^{t+1} \times F_j^{t+1}}{1 + \lambda_i^{t+1} \times (t+1)} < \frac{F_j^t}{t} \tag{20}$$

where λ is a random number.
If the above equation (22) is not satisfied the previous position of the foragers are retained

5. Results and discussion

This section discourses the results of the hybrid renewable energy system obtained by the optimal foraging algorithm in comparison with genetic algorithm and particle swarm optimization. The hybrid system design was implemented in MATLAB R2020b simulation platform. As input, the model employed data of wind speed and solar irradiance measured in in Abuja, Nigeria (latitude: 9.0820^0 N, Longitude: 8.6753^0 E). The hybrid resources component parameters have been given in Table 1. The parameter settings of the OFA, GA and PSO are as follows. OFA: $k = iter/iter_{max}$ $N = 50$, $iter_{max} = 30{,}000$, PSO: $N = 50$, $c_1 = 2$, $c_2 = 2$, $\omega = 1$, $iter_{max} = 300{,}000$; GA: $N = 50$, $iter_{max} = 300{,}00$. The lower and upper bounds of the decision variables were set to 0 and 300 respectively. At the initial stage, it is assumed that the battery is charged at 30% of its nominal capacity. The average (Avg), best (Best) and standard deviation (Std) performed over 30 independent runs are summarized in Table 2.

Table 1: Component Parameters

Parameters	Value	Parameters	Value	Parameters	Value
I	5%	**Diesel generator**		**Battery**	
n	20years	P_{DR}	1.9 kW	Voltage	12 V
PV panel		C_{Diesel}	1713.15$	S_{Batt}	2.4kWh
rated power	260 W	$C_{Diesel\text{-}Mtn}$	0.2 $/h	η_{BC}	85%
A	1.656m^2	Life span	8760 h	η_{BD}	100%
η_{PV}	15.7%	P_{Fuel}	1.24 $/l	P_{Batt}	170 $
C_{PV}	585 $			DOD	0.8
$C_{PV\text{-}Mtn}$	21 $	**Wind turbine**		σ	0.0002
Life span	20 years	rated power (P_r)	1 kW	Life span	5 years
Power Conv/Inv		V_{ci}	$2.5\,m/s$		
Rated power	3 kW	V_{co}	$13\,m/s$		
η_{inv}	95%	V_r	$11\,m/s$		
$P_{conv/inv}$	2000 $	C_{WT}	2313$		
Life span	10years	$C_{WT\text{-}Mtn}$	40$		
		Life span	20 years		

Table 2. The mean, standard deviation, best and worst performances of the algorithms

HRES	Index	Algorithms		
		OFA	GA	PSO
PV/wind/battery	Mean	17,957.19	18,720.07	17,549.15
	Std	2,601.833	543.67	1,066.27
	Best	15,926.07	18,167.09	16,535.93
	Worst	21,765.71	19,331.17	18,948.22
	Rank	1	3	2
PV/battery	Mean	10,601.46	10,601.46	10,178.25
	Std	1,274.94	1224.256	102.47
	Best	9,340,42.00	9,446.77	10,076.34
	Worst	11,223.17	10,601.46	10,319.43
	Rank	1	2	3
Wind/battery	Mean	18,527.51	13,527.51	17,745.15
	Std	1,492.00	705.512	933.5633
	Best	17,508.20	12,493.27	16,535.93
	Worst	19,759.55	13,527.51	18,075.15
	Rank	3	1	2
Average rank		2.5	3	3.5
Final rank		1	2	3

The breakdown of the statistical results obtained by the algorithms on each sizing component is presented in Table 2. From this table, the algorithms are ranked based on the best results obtained for each configuration. It can be observed that the OFA obtained the best final rank with a rank of 1. Whereas the GA and PSO obtained a rank of 2 and 3 respectively. This shows that, for the hybrid system design in this paper, the OFA appears to be the suitable algorithm for obtaining the most economical system. This further justifies the acceptability of the algorithms in solving the HRES problem, the characteristics of the algorithms were generated. The superimposed convergence graph of the algorithms on each hybrid system configuration is given in Figure 3, Figure 4 and Figure 5 for PV/Battery, Wind/Battery and PV/Wind/Battery, respectively.

It is seen from Tables 3-5, that economically the PV/battery configuration obtained the best annualized cost for supplying the load demand. The total annual cost obtained by each algorithm for the PV/Battery system is $9,340,42, $9,446.77 and $10,076.34 for OFA, GA and PSO respectively. For the Wind/Battery configuration, the total annual cost obtained by OFA, GA and PSO are $17,508.20, $12,493.27 and $16,535.93 respectively. Similarly, the PV/Wind/Battery configuration showed that the OFA, GA and PSO obtained an annualized cost of $15,926.07, $18,167.09 and $16,535.93 respectively. The optimal size of the hybrid resources obtained by the OFA are as follows. PV/Batter: nPV = 102, nBat = 35, Wind/Battery: nWT = 101, nBat = 99 and PV/Wind/Battery: nPV = 125, nWT = 18, nBat = 115. The cost of other components has also been given in the table.

Table 3. Summary of the best results obtained for PV/Battery System

HRES	OFA	GA	PSO
N_{PV}	102	66	77
N_{WT}	--	--	--
N_{Batt}	35	100	97
$N_{Conv/Inv}$	4	4	4
PV cost ($)	6,930.07	4,484.17	5,231.52
WT cost ($)	--	--	--
Battery cost ($)	1,374.00	3,926.57	3,808.78
Conv/Inv cost ($)	1,036.04	1,036.04	1,036.04
Total annual cost ($)	9,340,42	9,446.77	10,076.34

Table 4. Summary of the best results obtained for Wind/Battery System

HRES	OFA	GA	PSO
N_{PV}	--	--	--
N_{WT}	101	77	75
N_{Batt}	99	115	102
$N_{Conv/Inv}$	3	3	3
PV cost ($)	--	--	--
WT cost ($)	11,988.00	6,941.67	6,761.37
Battery cost ($)	4,673.20	4,515.56	4,005.10
Conv/Inv cost ($)	847.51	1,036.04	1,036.04
Total annual cost ($)	17,508.20	12,493.27	11,802.51

Table 5. Summary of the best results obtained for PV/Wind/Battery System

HRES	OFA	GA	PSO
N_{PV}	125	25	39
N_{WT}	18	140	107
N_{Batt}	115	65	75
$N_{Conv/Inv}$	5	5	5
PV cost ($)	8,492.74	1,698.55	2,649.73
WT cost ($)	1,622.73	12,621.23	9,646.22
Battery cost ($)	4,515.56	2,552.27	2,944.93
Conv/Inv cost ($)	1,295.05	1,295.05	1,295.05
Total annual cost ($)	15,926.07	18,167.09	16,535.93

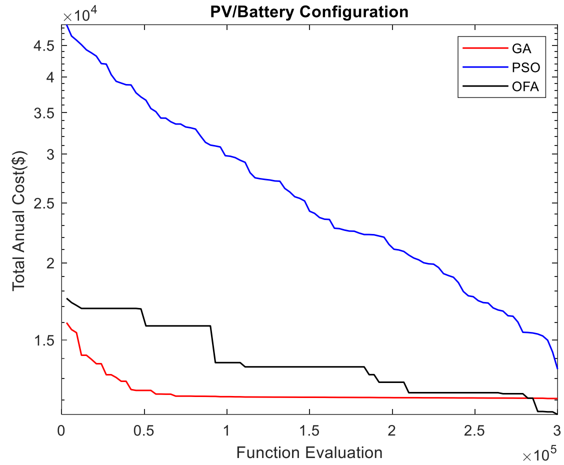

Figure 3: Convergence on PV/Battery Configuration

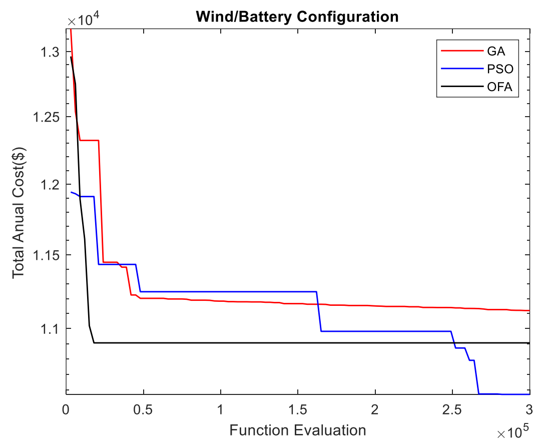

Figure 4: Convergence on Wind/Battery Configuration

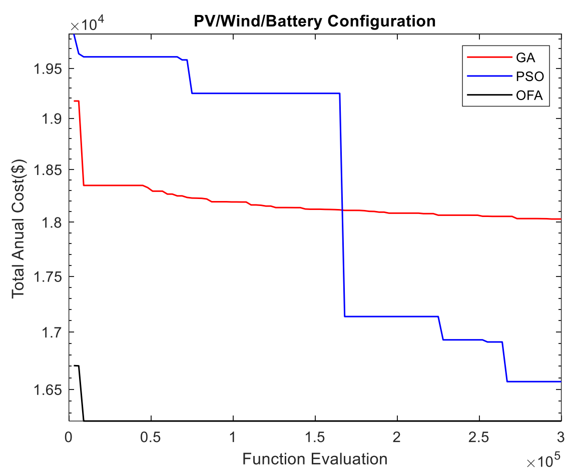

Figure 5: Convergence on PV/Wind/Battery Configuration

From the convergence plots given in Figures 3 to 5, it can be observed that the OFA converges faster in Wind/Battery and PV/Wind Battery configurations. For the PV/Battery Configuration, only GA has a better convergence over OFA.

6. Conclusion

This paper presents an off-grid hybrid renewable energy system for electrification of a remote area in Abuja, Nigeria. The hybrid system was formulated into an optimization problem where the annualized cost serves as the objective function to be minimized. The optimization problem was solved using optimal foraging optimization algorithm and results was compared with genetic algorithm and particle swarm optimization. Results analysis showed that the optimal foraging algorithm obtain the best result in terms of the objective function cost and convergence analysis.

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