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Original Article

Hybrid Renewable Energy System Optimization via Slime Mould Algorithm

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Abstract *- Various techniques have been used in the optimization of hybrid renewable energy systems (HRES). The most effective are metaheuristic algorithms based on artificial intelligence (AI) because of their ability to handle various parameters such as multiple objectives, parallelism features that allow for simultaneous evaluation of multiple schemes, and their ability to obtain optimal results that are systematic and deterministic. However, in the application of optimization algorithms regarding the Non-free lunch theorem, one algorithm performs better than the other in obtaining the best fitness function with convergence time. Therefore, the slime mould algorithm (SMA) prowess was tested in HRES optimization against two conflicting multi-objectives. The best fitness function for the total annual cost (TAC) was obtained with minimum convergence time, while the relationship between TAC and loss of load probability (LOLP) is shown to be proportionate to one another. The SMA provided optimal sizing of solar PV, hydro turbine, and biogas generator to meet the load requirement of the study area. In addition, the result shows that SMA is more promising in terms of convergence time.*

Keywords *- Hybrid Renewable Energy, Lost of load probability, Optimization, Slime mould algorithm, Total annual cost.*

1. Introduction

Global energy demand is significantly increasing over the years due to the increase in population, urbanization, transportation, and industrialization[1]-[4]. Besides, more than 80 per cent of today's world energy supplies are from conventional energy resources (fossil fuel), which lead to serious greenhouse gas emissions/global warming [5], [6] and adversely cause extreme climate change/ weather. To mitigate this climate change and increase energy access to the poor and isolated areas, there is a need to replace conventional energy with clean and affordable RES [7] through optimization. This optimization is a means of getting the best result/solution from the available set of options by changing the parameters through mathematics and science that can be classified into classic and modern optimization. Modern optimization, especially artificial intelligence, involves mimicking nature-inspired behaviours to solve complex problems. Furthermore, nature-inspired algorithms that are metaheuristics are inspired by references to physical laws or biological phenomena and self-organize with a population of agents with multiple solution vectors. These algorithms excel at revolutionizing populations (through mutation, selection, and transition), randomizing to create new vectors, and using local and global search to select the best solution based on survival of the fittest.

Methods of optimization deployed over the year in HRES optima sizing are Probabilistic, Analytical, iterative, application of Commercials Optimization Computation Tools (COCT), and Artificial Intelligence (AI). In addition, AI can be further divided into Fuzzy logic, Expert Systems (Heuristic and Metaheuristic: Evolution Computation), and Artificial Neural Networks (ANN). The Probabilistic Method can obtain the best solution via a constructive random algorithm but cannot adequately represent changes in the dynamic nature of the HRES framework[8]–[10]. Despite the ability of the Analytical optimization method to a long-time climatology data and provides viable information for the selection of the alternative best solution, it lacks the system's related mathematical position equation coefficient under study[7]-[10]. More so, the iterative optimization method can solve the problem through linear methods but cannot invariably determine turbine swept area/height and PV installation area/modules angles[9]. Furthermore, many COCTs, such as Homer Pro, iHOGA, Hybrid, LINDO, and ARENA, among others, are widely used for optimal HRES sizing. Consequently, most COCTs have been proven to be less superior (or less flexible) to Nature-inspired algorithms [10],[13]–[23], which are Heuristic/metaheuristics and embodiment of Artificial Intelligence.

Slime mould is a metaheuristic algorithm developed in the year 2020 based on the No-free-lunch theorem, which encourages the development of new algorithms as a result of forewarning that no single algorithm is capable of analyzing all optimization problems [24], [25]. This algorithm demonstrated excellent exploration capabilities by simulating propagating wave feedback through adaptive weighting and food harvesting in a bio-oscillator. The superiority of SMA has been proved against GWO, MFO, ALO, SSA, MVO, PSO, SCA, m_SCA, IWOA, LWOA, FA, BA, PBIL, AGA, CBA, DE, BLPSO, AGA, CBA, CLPSO, CSSA, CDLOBA, RCBA, and WOA on the twenty-three (23)branch function and 2014 CEC IEEE function respectively by Li et al. [26]. This makes it an algorithm to be sorted after for RE optima sizing. Furthermore, SMA has been used in the energy field for grid optimization to resolve the problems associated with the optimal flow of electricity, photovoltaic modelling, paralleling power design, smart (IoT) electricity distribution, and HRES optimum sizing [60]. However, the literature on HRES optimization using SMA is still limited to three. In the first literature presented by El-Sattar et al. [28], energy cost, LPSP, and power supply to a dummy load to optimal were considered for sizing of HRES comprised of PV/Biomass generator/WT/Battery storage via comparative analysis of SMA, GWO, SOA and SCA. SMA is proven more effective than others regarding the reliability and cost index used. In the second literature by Gupta et al. [29], a Chaotic particle swarm was combined with SMA to form a hybrid algorithm (HCPSOSMA). The said HCPSOSMA, compared with Homer software in optimizing PV/Biomass/FC, proved more effective than Homer Software in terms of cost in optimal sizing of HRES. While in the third literature, a comparative analysis of equilibrium optimizer (EO), three (3) variants of particle swam algorithms, and SMA in terms of cost reduction were presented by Trieu et al. [30]. However, this study failed to present the number of components sized for HRES and the reliability index used for their comparison study that made EO to be superior to others. In place of the above literature, this present work aims to investigate the performance of SMA in optimal sizing of HRES of solar, hydroelectric, and biogas generators to implement cost reduction in clean energy technologies, considering two conflicting objective functions: economic (TAC) and reliability (LOLP) indices.

Economic, reliability and environmental criteria are important indicators to optimize energy at minimum cost and determine how visible and reliable a RES project is. Net present cost (NPC), net present value (NPV), levelized cost of electricity (LCOE), total annual cost (TAC), and life cycle cost (LCC) are economic measures available in the literature. Some of the most important reliability indices are Loss of Load Probability (LOLP) and Loss of Power Supply Probability (LPSP). Other reliability studies are also considered: Loss of Load Expectancy (LOLE), Expected Unsupplied Energy (EENS), System Performance Level (SPL), Loss of Load Duration (LOLD), Forced Out Rate (FOR), Power Supply Probability Shortage (DPSP), Loss of Load Frequency (LOLF), Loss of Load Risk (LOLR), and Loss of Load Probability (LOLP), [31]–[37]. However, LOLP was chosen for this study because it has been considered an economic and technical parameter in the most cost-effective design and optimization of power plants [38]. LOLP was used by [22] for comparative analysis of the Evolution algorithm (EA), iterative sizing algorithm (ISA), and Elephant Herding Optimization (EHO) in PV/Battery RES standalone optimal sizing, EHO being metaheuristic algorithm proved to be more efficient than EA and ISA in term of computation time and fitness. However, LOLP was used as a single objective function, while the economic index, one of the major parts of energy sustainability, was left out. In [23], LOLP & LCOE were used as multi-objective functions for optimal sizing/demand side control of Wind/PV/Battery HRES via Fuzzy/modified swarm Cuckoo Search. Application of economic (LCOE) and reliability (LOLP) indices increase the stability of HRES under study. LOLP and NPC were used as multi-objectives for Wind/PV/Battery optimal sizing by [39]. LOLP constraints vary from 1-10% to determine system stability and to select the best economic system relevant to available RE resources via Genetic algorithm, while the trade-off between economics and reliability for discrete optimization problem was presented as inversely but rather this relationship between cost and reliability cannot be substantiated from their results as presented. The authors concluded that as LOLP decreases, the system components' operation simultaneously at that time must increase to meet the required load because of the sporadical nature of RES. Trade-offs between Reliability (Unavailability), economics (NPC), and RE integration were considered for Diesel generator/battery/PV HRES optimal sizing by [40] via Pareto non-dominated-II sorting genetic Algorithm(NSGA-II). The result shows that reliability with long-term impacting cost can be obtained with high RE penetration and oversizing components. This will significantly add to the cost (NPC) and result in high-level reliability with 100% RE integration.

Electricity generation, transmission, and distribution are grossly inadequate in sub-Sahara Africa, putting the populace in untold hardship. This hardship has caused people to rely on self-generated electricity using gasoline generators, which invariably release poisonous gases into the atmosphere. [41]. The Carbon-monoxide and sulfur released from the generator can detach oxygen from oxy-haemoglobin and cause suffocation[42]. Continued erratic electricity supply as experience can also leads to anxiety disorder[43]. Global warming is still a threat to our existence. To avert this ordeal, there is a need to employ clean energy technologies capable of reducing electricity costs and carbon emissions [44] by paralleling/hybridizing two or more RERSs and overcoming the problem that might arise from the intermittent nature of RES. However, this work will significantly advance understanding of HRES optimization by presenting a trade-off between two conflicting criteria (TAC and LOLP) as proportionate to one another and integrating multiple objective criteria (TAC and LOLP) into a bio-inspired algorithm (SMA) to solve complex optimization involving Biomass/Hydropower/Photovoltaic with appropriate energy management scheme.

The remainder of this paper is structured as thus: the second Section (2) covers SMA theory; the third Section (3) deals with system design and modelling; the fourth Section (4) deals with problem formation; the fifth Section (5) covers results & discussion; the sixth Section (6) covers the Conclusion & Recommendations.

2. SMA Theory

The metaheuristic algorithm is based on slime-mode foraging behaviour, where the cytoplasmic flow modifies the wave oscillation to approach, surround, and digest food. Adaptive weights are used to propagate feedback (positive or negative) based on the optimal path to obtain the best solution for obtaining food by relatively superior exploration of the mining and search space[26]. Plasmodium, the active dynamic phase of the SM, is used for algorithm design and implementation due to its unique characteristics, the pattern in which food sources are sought, and the ability to form a network of venous connections between multiple food sources. The vascular structures of the SM develop along the contractile phase difference, so their morphological changes are governed by three (3) correlations, as shown in Figure 1:

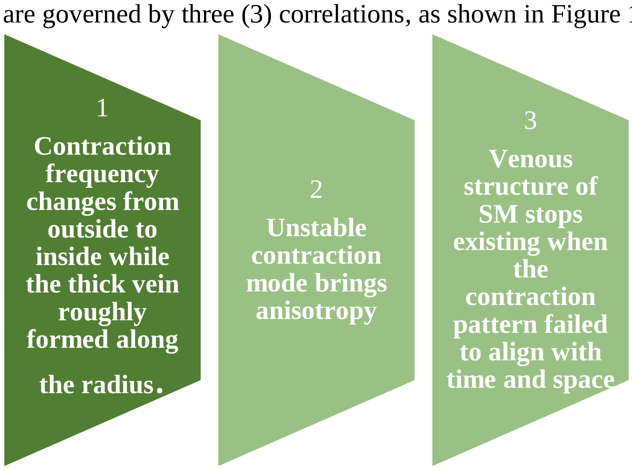

Fig. 1 Correlation of morphological changes

3. System Design and Modelling

The biomimetics method of SMA is implemented for optimum sizing of HRES consisting of solar PV/Hydropower/Bio generators. Solar, hydropower, and bio-generator systems were modelled as shown in Section 3.1, 3.2 and 3.3, respectively, and the capacity was calculated using available resources for 8760Hr at latitude 7.42; longitude 4.144. The proposed configuration is shown in Figure 2, where Solar/Hydro turbine/Biogas generators are connected in parallel to the AC bus while AC transformers are used for load matching and distribution.

Python codes were utilized via Jupiter Notebook on 64-bit operating system Laptop-NODENPOH, Intel ® Pentium ® CPU 44ISU to evaluate- P_{HE}, P_{MAX} , P_{e-bg} and HRES optimum sizing, as shown in Figure 3. The optimization problems are formulated using TAC and LOLP as objective functions, which are minimized in terms of power budget and load constraint, as shown in the previous work. Monte Carlos simulation in Python was used to calculate LOLP while sensitivity analysis was carried out for various values of LOLP ranges from 0%, 1%, 2%, 3%, 4%, 5%, to 10%. The simulation is repeated until all conditions stated as constraints are met.

3.1. Solar PV Modelling

Single-diode PV was used to model the PV system as proposed by [45]–[47]. The current (I) supplied in the single diode model is expressed as the function output voltage(V) as shown in equations 1-3

$$I(V) = I_{PH} - I_O\left[exp\left(\frac{V+IR_S}{d} - 1\right)\right] - \frac{V+IR_S}{R_P} \tag{1}$$

$$P_{PH} = \frac{G}{G_0}\left[I_{PH-STC} + C_T(T - 298)\right] \tag{2}$$

$$I_0 = I_{0-STC}\left(\frac{T}{298}\right)^3\left[\exp\frac{qE_g}{dK}\left(\frac{1}{298} - \frac{1}{T}\right)\right] \tag{3}$$

Where,

V- PV Voltage, I- Current of the PV modules, I_0 is diode reverse saturated current, I_{0-STC} is nominal saturated voltage, G- Available solar irradiation, G_O-Nominal solar radiation (1000W/m^2), P_{PH}-Photocurrent, d-ideality factor, C_T-Cell circuit current temperature coefficient, R_S- series resistor, K-Boltzman constant. (1.38 x 10-23 J/K), R_P-parallel resistor, q-Electron charge (1.602 x 10-19 C), and E_g-Energy gap of a semiconductor.

3.2. Hydropower Modelling

Linear and nonlinear hydraulic turbine models with elastic and inelastic column effects have been defined. Considering the river head and flow velocity, the theoretical power (P) of the turbine is given in Equations 4 and 5. The flow rate of a hydroelectric drainage system of a particular catchment with rainfall (hourly, daily, and monthly) [48], [49] is given as follows

$$Q_{SITE} = K\left[\frac{A_{SITE}}{A_{GAUGE}}\right]Q_{GAUGE} \tag{4}$$

Hydroelectric power (P_{HE}) generated by the turbine [49] is given as

$$P_{HE} = \eta_{Tt} * \rho * gQH \tag{5}$$

$$\eta_{Tt}(\lambda, Q) = \left[\frac{1}{2}\left(\frac{90}{\lambda_i} + Q + 0.78\right) exp\left(\frac{-50}{\lambda_i}\right)\right] * (3.33Q) \tag{6}$$

$$\lambda_i = \left[\frac{1}{\lambda+0.089} - 0.0035\right]^{-1} \quad (7)$$

$$\lambda = \frac{RA\omega}{Q} \quad (8)$$

Where- Q_{SITE}, K, A_{GAUGE} , Q_{GAUGE}, ρ, η_{Tt}, g, Q, H, R, A, and ω is discharged at the site(m^3/s), scaling function, gauge catchment area (m^2), discharge at the gauge, power plant catchment area (m^2), water density(1000kg/m^3), turbine hydraulic efficiency, acceleration due to gravity (10m/s^2), flow rate, head, the radius of the hydraulic turbine blade (m), swept area of the rotor(m^2) and angular speed of rotor respectively

3.3. Bio-Generator Modelling

Biomass gasification performance depends on the low calorific value of biofuel, and its gasification efficiency is determined as shown in equation 9. [50]

$$\eta_{gasification} = \frac{M_g LHV_g}{M_b LHV_{bg}} \quad (9)$$

The output power of biomass generators (P_{e-bg})results from Equation 10

$$P_{e-bg}(t) = \eta_{gasification} * Q_{bg} * LHV_{bg} \quad (10)$$

$$LHV_{bg} = \frac{P_{methane}}{100} * LHV_{methane} \quad (11)$$

The hourly energy production of the biomass gasifier is as follows[51].

$$Q_{bg} = \frac{P_{W-bg}(t)}{\eta_{gasification} LHV_{bg}} \quad (12)$$

In addition, the $P_{E-Annual}$annual electricity production from biomass gasification is given as the capacity utilization factor (CF).

$$P_{E-Annual} = P_{BMG-R} * (8760 * CF) \quad (13)$$

Energy production per hour is also given as the utilization factor.

$$P_{E-HR} = P_{BMG-R} * \eta_{gasification} \quad (14)$$

Where

$\eta_{gasification}$ is electrical conversion efficiency (25 - 40%), Q_{bg}- flow consumption of biogas (m^3/h), LHV_{bg}- a measure of the volume of methane fraction in organic matter (36.3MJ/m^3 or 10kEh/m^3), $P_{methane}$- the percentage of methane in the biomass and P_{BMG-R}- The rated power output of a biogas electricity generator.

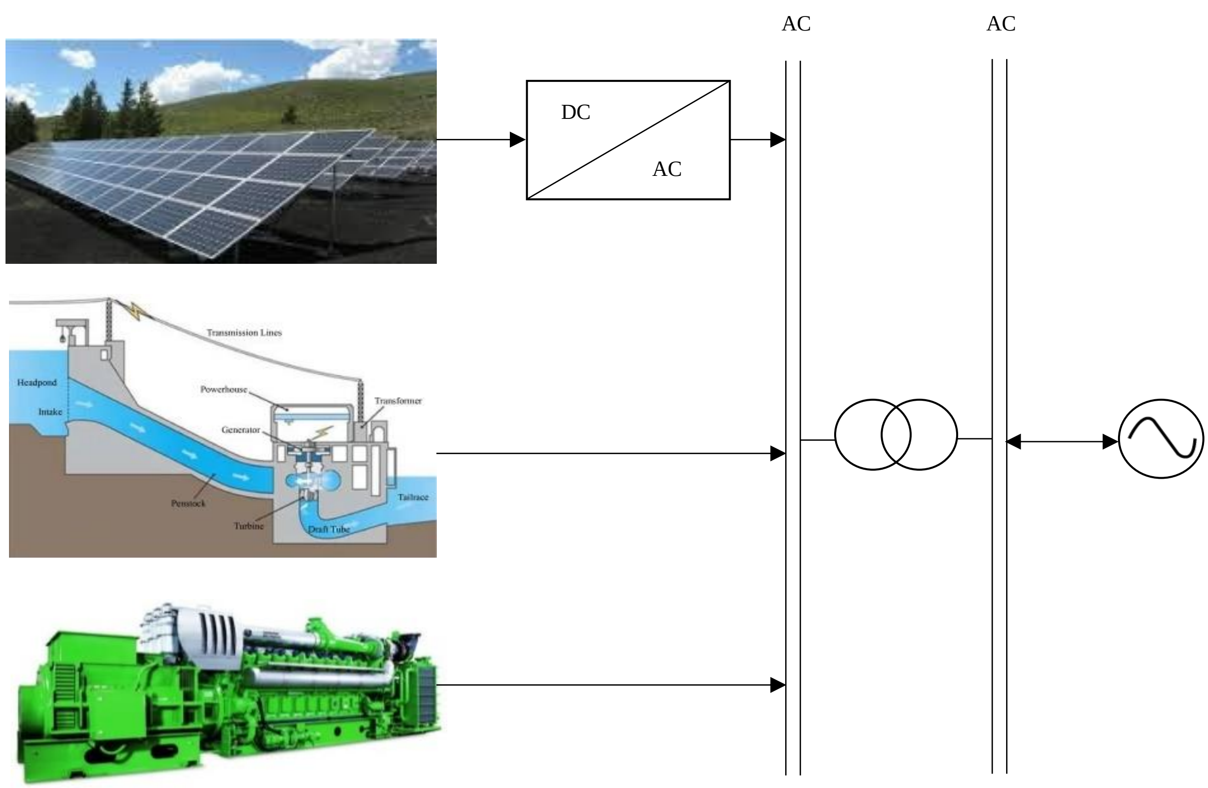

Fig. 2 Proposed HRES

Table 1. Techno-economic characteristics of HRES components

Components	PV	BG	hydro Turbine	Converter
The principal cost of Installation ($/kW)	883	2,543	1870	625
O&M cost (% of the principal cost)	2	2	2	2
Replacement Cost (% of Principal Cost)	80	80	80	80
Lifetime	25	25	50	15
Efficiency	16.8	η_{gas}=40	90	98.8
Project lifetime	25	25	25	25
Interest rate	5	5	5	5

Source: [52], [57]-[59]

3.4. Reliability and Economic Modeling

A reliability index study is carried out using LOLP. The calculation is obtained via Monte Carlos simulation in a Python programming environment for optimum sizing of PV/Hydro-turbine/Bio-generator HRES while a sensitivity.

The analysis is introduced at the step of 0% to 5% LOLP. LOLP have expressed mathematically, as shown below, considering the power supply (E_t), capacity duration loss (t_i), and loss of capacity probability (ρ_i)[35], [61]

$$E_t = \rho_i t_i \tag{15}$$

$$LOLP = \sum_{i=1}^{n} \rho_i t_i \tag{16}$$

$$LOLP = \frac{LOLH}{8760} \tag{17}$$

TAC is considered an economic index for this design, and it comprises Annual Capital Cost (ACC), Annual Operation& Maintenance Cost (AOMC), and Amortization factor (AF), as shown in equations 18-24.

$$TAC = ACC + AOMC + AR \tag{18}$$

$$ACC = TCC * A\mathrm{F} \tag{19}$$

$$TCC = CC_K * n_K \tag{20}$$

$$AOMC = C_{o\&m} * ACC \tag{21}$$

$$ARC = C_r\left(\frac{LC}{LT} - 1\right) * AF \tag{22}$$

$$AF = \frac{i_r * (1+ i_r)^{LC}}{(1+i_r)^{LC}-1} \tag{23}$$

Finally,$TAC_{TOTAL} = TAC_{hYDRO} + TAC_{PV} + TAC_{CONV} + TAC_{BIO}$(24

4. Problem Formation

4.1. Objective Function

To reduce cost and minimize loss of load risk by the System, multiple objective functions of LOLP and TAC are considered for optimum HRES sizing, as shown in equations 25 and 26.

$$f(X) = \propto_1 f_1(TAC) + \propto_2 f_2(LOLP) \tag{25}$$

$$F^{obj} = mim\,\{\textstyle\sum_n (TAC) + (LOLP)\} \tag{26}$$

Where $n = Hydro, PV, Biogas$

4.2. Power Balance Constraint

This is used to show the relationship between the RE-generating plants (PG_{RE}) to the desired/ or expected load demand (LP_{Di}). This relationship ensures that power generated from all RE plant meet the load demands at all time, preventing system failure and attaining reliability of LOLP < 1. Equation 27 shows the power balance between the generating plant the load, and as guided by load constraint and energy management.

$$\sum_{i=1}^{n}[PG_{RE}(t)] = \sum_{i=1}^{n} LP_{Di} \tag{27}$$

4.3. Load Constraint

Load Constraint is a yardstick to attain system reliability in HRES optimum sizing. It depicts (lower and upper) band limits for each generating plant which invariable aid in obtaining HRES capacity with respect to Table 1. Equation 28 shows the RE system combination, and equations 29-31 show the bands limit assigned for optimum sizing of PV/Hydro/Biogas HRES under study.

$$P_H(t) + P_{PV}(t) \pm P_{BG} = PG_{RE} \tag{28}$$

$$0 \le P_{PV(i)} \le P_{PV}^{MAX} \tag{29}$$

$$P_{H(i)}^{MIN} \leq P_H^{MAX} \quad (30)$$

$$0 \leq P_{BG(i)} \leq P_{BG}^{MAX} \quad (31)$$

4.4. Energy Management

Three scenarios were presented for solar/hybrid/biomass energy management. The scenario I considered is a situation shown in equation 32, where power generation from hydropower (P_H) and Photovoltaic is less than load demand (LP), and the preferred expected solution to prevent system collapse is shown in equation 33.

In scenario II, as shown in equation 34 and 35, equation 34 shows a situation when power generated from the Hydro turbine and Photovoltaic is greater/or equal to load demands, while equation 35 present a preferred solution to equation 34 as utilized in the design and simulation.

Likewise, in scenario III, equation 36 shows the expected situation where power from Photovoltaic is zero, while equation 37 presents an expected solution, and this particular situation is expected every night. This work considers all these scenarios in design and optimization, as shown in Figure 1.

Scenario I

$$\text{When } P_H + P_{PV} < LP \quad (32)$$

Then,

$$LP = P_H + P_{PV} + P_{BG} \quad (33)$$

Scenario II

$$\text{When } P_H + P_{PV} \geq LP \quad (34)$$

Then,

$$LP = P_H + P_{PV} - P_{BG} \quad (35)$$

Scenario III

$$\text{When } P_{PV} = 0 \quad (36)$$

Then,

$$P_H + P_{BG} = LP \quad (37)$$

4.5. Formation of SMA

The formation of SMA is based on three(3) morphology behaviours [26], [54] as shown mathematically below-

4.5.1. Approach Food

SM is attracted to food odour available in the air. This approach can be mathematically expressed as

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{Vb}.\left(\overrightarrow{W}.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), r < p \\ \overrightarrow{Vc}.\overrightarrow{X(t)}, \quad r \geq p \end{cases} \quad (38)$$

Where $\overrightarrow{Vb}$ − parameter with a range of $[-a, a]$

$\overrightarrow{Vc} - decrease\ linearity\ from\ 1\ to\ 0$

$t - curent\ iteration$

$\overrightarrow{X_b} - individual\ locatioin\ with\ a\ highest\ odour\ concerbtrtation\ currently\ found$

$X_A\ \&\ X_B$ $- two\ individual\ randomly\ selected\ from\ SM$

$\overrightarrow{W} - the\ weight\ of\ SM$

Where,

$$P = tanh / s(i)\text{-}DF \quad (39)$$

$i \in 1, 2, 3, 4 \dots\dots\dots\dots n,$

$s(i) - fitness\ of\ \overrightarrow{X},$

$DF - best\ fitness\ attained\ in\ the\ iteration,$

$$\overrightarrow{Vb} = [-a, a] \quad (40)$$

$$a = \operatorname{arctanh}\left(-\left(\frac{t}{\max\_t}\right) + 1\right) \quad (41)$$

$$\overrightarrow{W\left(Smell\ index\ (i)\right)} = \begin{cases} 1 + r.\log\left(\frac{bF - s_i}{bF - wF} + 1\right) condition \\ 1 - r.\log\left(\frac{bF - s_i}{bF - wF} + 1\right) others \end{cases} \quad (42)$$

$$Smell\ index = Sort(S) \quad (43)$$

Where

$s(i) - ranks\ first\ half\ of\ the\ population$

4.5.2. Wrap Food

This shows the structure of the contractile mode of SM vascular tissue during feeding. The flow rate of the cytoplasm generates bio-oscillators, and the thickness of the SM vessel is proportional to the nutrient concentration in contact, providing negative or positive feedback between vessel wildness and nutrient concentration. The mathematical relationship of SM in food packages and location updates is as follows.

$$\vec{X} = \begin{cases} rand.(UB - LB) + LB, rand < Z \\ \overrightarrow{X_b(t)} + \overrightarrow{Vb}.\left(W.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), r < p \\ \overrightarrow{Vc}.\overrightarrow{X(t)}, r \geq p \end{cases} \quad (44)$$

Where,

$UB\ \&\ LB - denote\ Upper\ \&\ Lower\ bpoundaries\ of\ the\ searchrand\ \&\ r - random\ value\ in\ [0, 1]$

4.5.3. Grabble Food/Oscillation

SM moves towards better food preservation as it oscillates to alter cytoplasmic venous flow by propagating waves. Instead of relying on local search for support, venous diameter is simulated to determine $\overrightarrow{\mathrm{Vb}}$ and $\overrightarrow{\mathrm{Vc}}$, SM efficiency when approaching food slowly or quickly depending on food concentration/quality to obtain the optimal solution (food source).$\overrightarrow{\mathrm{W}}$

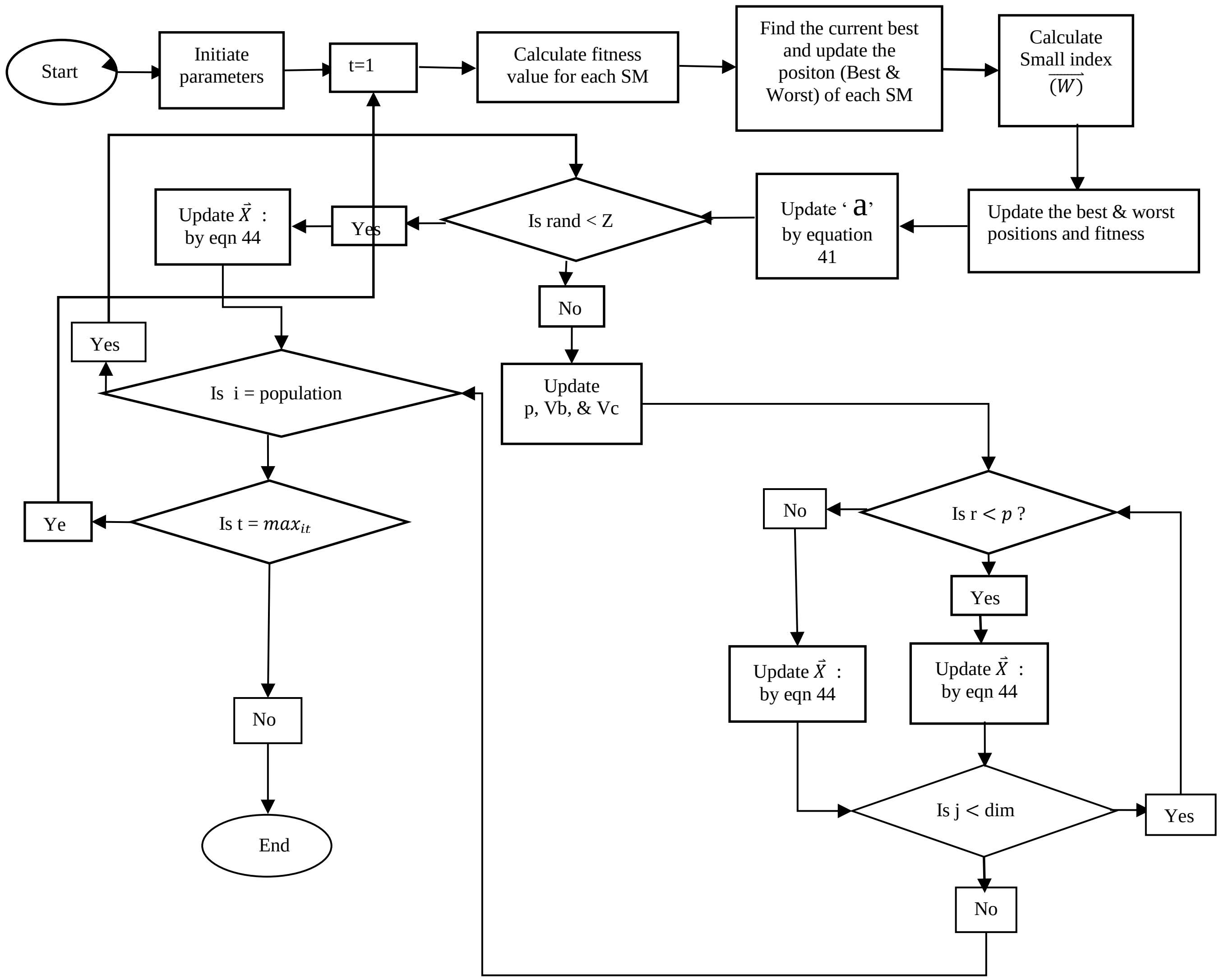

Fig. 3 SMA flow chart

Based on the rule above, Pseudocode is generated as shown below

*Enable pop size parameters and Max iteration*s setting

Initialize & set slime mould position Xi (i = 1, 2,······n);
Run the remaining variable parameters setting;
While ($t \leq$ *Max iteration*)
Calculating the suitability/fitness functions for each slime mould population and ranking each population in increasing order of importance;
Update the *best Fitness functions*, *Xb*;
Calculate the $\overrightarrow{W}$ of each slime mould by Eq.(42);
Update $\overrightarrow{Vc}$, p, & $\overrightarrow{Vb}$ for each quest agent;
update $\vec{X}$ using Equation (44);
Finalize if
t = t + 1;
Discontinue While
Returning optimal *best Fitness function*, *Xb*

5. Result and Discussion

The following results presented below were obtained through modelling, simulation, and optimization of solar, hydro, and biomass energy for HRES in Osun State, Nigeria, using nature-inspired code in a Python environment. Data such as Load demand, Solar radiation, and Hydrology were collected from the Distribution Company, NASA website, and Osun River basin, respectively. The hourly load data profile, hydroelectric power, solar photovoltaic output, and bio-generator simulation result are shown in Figures 4, 5, 6, and 7. The minimum and maximum loads for the year are 69600kWh and 211800kWh respectfully, there was a significant load concentrated between 12000kWh and 16000kWh, as shown in Figure 4. The PV output for a year, for solar panel power per hour in the consideration area in the hybrid renewable energy optimization study using the slime mould algorithm, are presented in Figure 5; the minimum and maximum value ranges between 0 and 204.80743420002682 W peak, respectively. The outcome simulation of hydropower generator power is illustrated in Figure 6; the simulation hydraulic turbine results range between 353.16 kW and 15539.04 kW to display the novel of our study. Figure 7 shows the simulation result of biomass-generated resources using a Bio generator, and biomass can easily be transported around the surrounding areas of the generating resources. The simulation outcome from the Biogas generator ranges between 328.6161919 kW and 328.61619195 kW. TAC includes annual capital costs, annual operation, and annual maintenance, and annual replacement costs are minimized with respect to LOLP<1. The results in Figure 8 show the best score of TAC versus iteration, while Table 2 shows TAC results for twenty (20) numbers of iterations. The best result is obtained at $ 49656401.85 at zero seconds, which proved that SMA converges faster than any other studied algorithm.

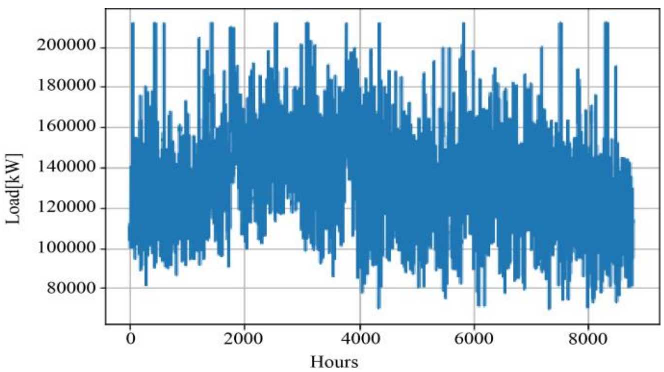

Fig. 4 Hourly load data for a year

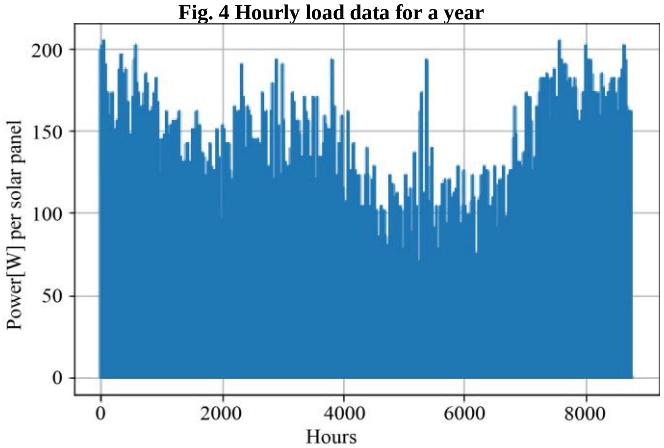

Fig. 5 PV output for a year

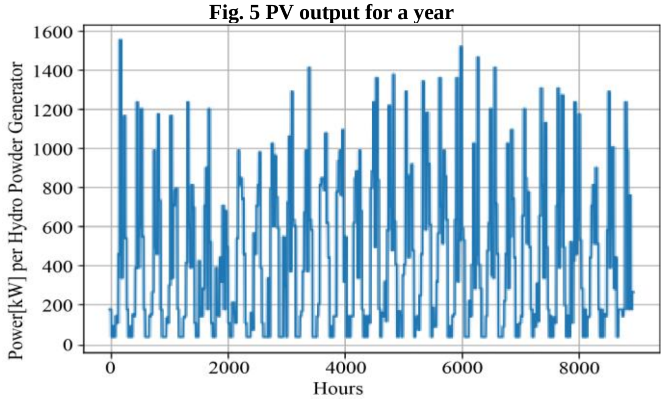

Fig. 6 Hydropower simulation for a years

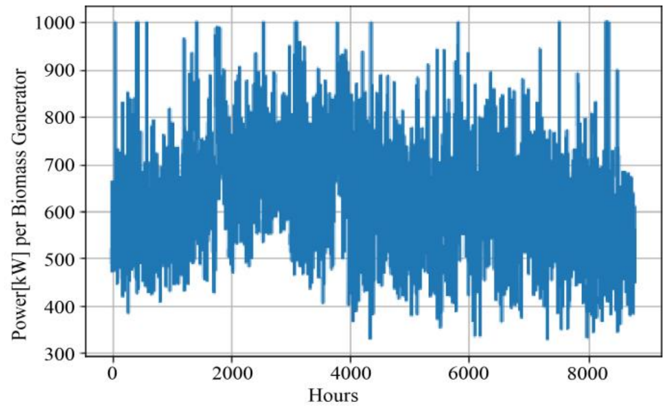

Fig. 7 Power-generated Bio-generator

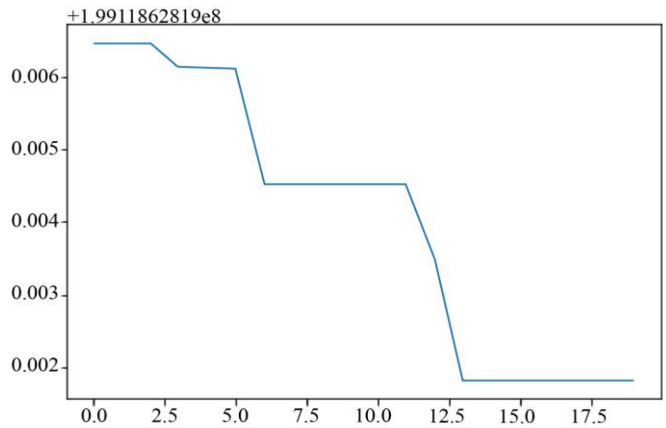

Fig. 8 Convergences curve of TAC Vs iteration

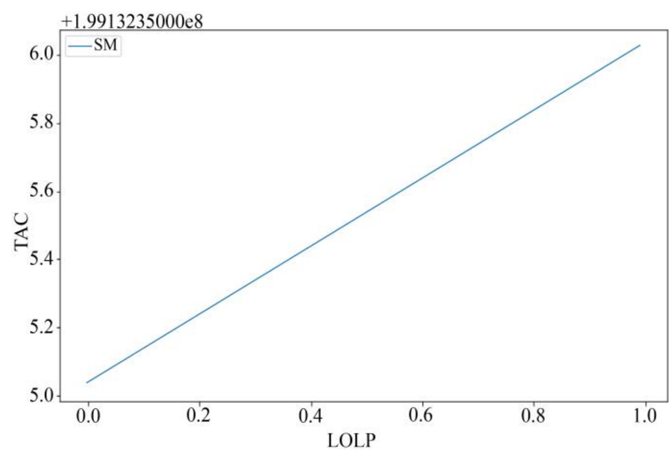

Fig. 9 TAC Vs LOLP

The optimum result obtained from HRES sizing is presented in Table 3 with respect to the Techno-economic characteristics of the HRES component in Table 1. The optimum sizing result obtained using SMA is shown in Table 3, in which 193200 units of Solar panels, 4 units of hydro-turbines, 460 units of converters, and 46 units of bio-generators were proposed to meet the load deficit of the state. The capacity of each component was also shown to be 80,000 kW, 53,130 kW and 46,000 kW for Hydropower, Solar PV, and Bio-generator, respectively, as shown in Table 3.

Table 2. Iteration Vs TAC ($)

No of iteration	TAC ($)	No of iteration	TAC ($)
0	308522.180	10	71650369.657
1	4499967.233	11	20690241.494
2	9384316.670	12	23100075.843
3	1048530.093	13	66636247.273
4	63927827.312	14	14033781.251
5	27115788.201	15	27115788.201
6	47187261.704	16	57267492.879
7	70484206.989	17	54769208.000
8	52382009.064	18	5827685.202
9	61059914.975	19	10913302.675

The relationship between TAC (Cost) and LOLP (Reliability) at different percentages is shown in Figure 9, the result shows that cost is proportionate to the reliability, contrary to what was early presented by [55] and [39] that shows that reliability(LOLP) and TNPC (TAC) are inversely proportionate to each other in their work. [55] used single objective problem formulation contrarily to multi-objective problem formulation recommended by [56] for solving complex multi-modal problems and to reduce challenges associated with optimization techniques in HRES optimal sizing. Furthermore, [39] conclusion regarding the relationship between cost and reliability cannot be substantiated by the results presented by the author. From a controversial point of view, it is inevitable to know that from the point of argument, as shown in Figure 9, TAC (Cost) should be proportionate to the reliability because as much complex (sophisticated) the system, the higher the cost (Installation, O&M and Replacement cost). Finally, the worst and best values of TAC are $49658842.88 and $49656401.85, respectively, with a proven convergence time of less than 1 second. While TAC mean value equals $49657622.57.

Table 3. Component optimum sizing and capacity

Variables	Units	Unit Rating (kW)	Capacity (kW)
N_{KH}	4	20,000	80,000
N_{KPV}	193200	0.275	53,130
N_{KCONV}	460	100	46,000
N_{KBG}	46	1000	46,000

6. Conclusion

Real-time problems are multi-facet and complex, which required the usage of multi-objective functions solutions. Solving such problems through optimization involves formulation of the problem into objective functions and setting criteria to obtain the best fitness function. These optimization techniques are inherent with demerits, such as long convergence time and premature convergence, which can be resolved using SMA.

In this work, optimum sizing of HRES consisting of Solar PV/Hydropower/Biogas generator was carried out using novel SMA in a Python environment considering multiple objectives. The best fitness function was obtained at microsecond, which confirmed SMA to be a promising algorithm in terms of speed. The analysis further shows that the reliability and cost of HRES in optimal sizing are proportionate to one another.

Finally, the prowess of SMA is presented, and SMA is recommended for further development for HRES optimization.

Author Contributions

Conceptualization: E.A.O, S.G, and O.K.A.; Assessment and Methodology; E.A.O., S.G, and Research: O.K.A.; Preparation of original draft: O.K.A.; Editing, proofreading, and coding O.O. and O.K.A.; Supervision: S.G and E.A.O. There are no conflicts of interest among the writers, who have all seen and approved the text before it was published.

Abbreviation

SMA	Slime Mould Algorithm
IoT	Internet of things
GWO	Grey Wolf Optimization
SOA	Seagull optimization algorithm
SCA	Sine Cosine Algorithm
MFO	Moth Flame Algorithm
ALO	Anti Lion Optimizers
SSA	Salp Swarm Algorithm
MVO	Multi-Verse Optimizer
PSO	Particle Swarm Optimization
mSCA	Modified Sine Cosine Algorithm
IWOA	Improved whale optimization algorithm
LWOA	Levy flight Whale Optimization Algorithm
FA	Firefly Algorithm
K	scaling function
A_{GAUGE}	gauge catchment area (m^2)
A_{SITE},	dis power plant catchment area (m^2)
ρ	water density
η_{Tt}	turbine hydraulic efficiency
g	acceleration due to gravity
Q	flow rate
H	Head
R	turbine radius
A	rotor swept area
ω	angular speed of rotor
LOLF	Loss of Load Frequency
LOLD	Loss of Load Duration
LOLH	Loss of Load Hour

BA	Bat Algorithm	P_{HE}	Hydroelectric power
WOA	Whale Optimization Algorithm	Q_{bg}	Flow consumption of biogas (m^3/h)
PBIL	Population-Based Incremental Learning	$P_{e\text{-}bg}$	Power output of Biomass generator
BLPSO	Biogeography-based learning particle swarm optimization	M_g	Masses of gas generated by gasification
CLPSO	Comprehensive Learning Particle Swarm Optimization Algorithm	LHV_g	Lower heating value of gas generated by gasifier
AGA	Adaptive Genetic Algorithm	E_t	Power supply
CBA	Chaotic Bat Algorithm	t_i	Capacity duration
DE	Differential Evolution	ACC	Annual Capital Cost
LOLP	Loss of load probability	AOMC	Annual Operation& Maintenance Cost`
COCT	Commercials Optimization computation tools	LC	Lifetime of the whole system
TAC	Total annual cost	LT	lifetime of an individual
AI	Artificial Intelligence	LP_{Di}	Expected load demand
AC	Alternative Current	$\overrightarrow{Vc}$	Decrease linearity
LOLE	Loss of Load Expectancy	$\overrightarrow{X_b}$	Individual location
LCOE	Levelized Cost of Electricity	$\overrightarrow{W}$	SM weight
NPC	Net Present Cost	$s(i)$	Fitness of $\vec{X}$
DPSP	Power Supply Probability Shortage	UB	Upper boundary
FOR	Forced out Rate	RCBA	Recursive coordinate bisection algorithm
EA	Evolution algorithm	CDLOBA	Ccollaborative and dynamic learning of opposite population
EHO	Elephant Herding Optimization	N_{RCON}	No of converter
ISA	iterative sizing algorithm	N_{KH}	Number of hydro-turbine
V	PV Voltage	RES	Renewable Energy Source
I	Current of the PV modules	$\eta_{gasification}$	Gasification electrical conversion efficiency
I_0	diode reverse saturated current	LHV_{bg}	volume of methane fraction in organic matter
I_{0-STC}	nominal saturated voltage	$P_{methane}$	% of methane in the biomass
G	Solar irradiation	M_b	masses of biomass
G_O	Nominal solar radiation	LHV_{bg}	lower heating value of biomass
P_{PH}	Photocurrent	P_{BMG-R}	Rated power output of a biogas generator
d	ideality factor	ρ_i	Capacity probability
C_T	Cell current temperature coefficient	AF	Amortization factor
R_S	series resistor	TCC	Total capital cost
K	Boltzman constant	i_r	Interest rate
R_P	Parallel resistor	PG_{RE}	RE generating plants
Q	Electron charge	$\overrightarrow{Vb}$	parameter with a rang [-a, a)
E_g	Semiconductor Energy gap	t	current iteration
Q_{SITE}	discharged at the site (m^3/s)	$\vec{X}$	Location of SM
LB	lower boundary	X_A & X_B	randomly selected two individual SM
CSSA	Charged System Search (CSS) algorithm	DF	best fitness attained in the iteration
N_{KGB}	No of Bio-generator	N_{KPV}	Number of Photovoltaic

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