Chapter

Improved Smell Agent Optimization Sizing Technique Algorithm for a Grid-Independent Hybrid Renewable Energy System

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Abstract

This chapter discuss an improvement on the novel computational intelligent algorithm using the smell phenomenon. In the standard smell agent optimization algorithm, the olfactory capacity is constant thereby assuming that every smell agent has the same sensing capacity. In the improved smell agent optimization algorithm, that is changed to account for the difference in smell agent capacity. The algorithm was run against the standard smell agent optimization on Matlab to find the best HRES design using annual cost, Levelized cost of electricity (LCE), loss of power supply probability (LPSP) and excess energy. It was shown after the comparative analysis that there was a 79%, 99.9% and 53.4% improvement for annual cost, LCE and LPSP respectively. Statistically, results showed that the iSAO obtained the most cost effective HRES design compared to the benchmarked algorithms.

Keywords: smell agent optimization (SAO), improved smell agent optimization (iSAO), hybrid renewable energy system (HRES)

1. Introduction

Technological and societal developments can be observed as the drivers of the changes in interconnected systems like Mini-grids or hybrid renewable energy systems (HRES). HRES consists of two or more renewable sources used to provide system efficiency as well as create better balance in energy tied to the conventional grid or off-grid with battery storage [1, 2] and there are various optimization sizing techniques for such systems namely;

i. Dynamic programming.

ii. Graphical construction technique.

iii. Probabilistic approach.

iv. Multi-objective design.

v. Linear programming.

vi. Iterative technique.

vii. Artificial intelligence.

Over the years, optimization has developed into an established field of computation intelligence (CI) inspired by various natural behavioral rules. Some of these natural behavioral based optimization methods of imitating evolution, ecology, animal activities and apparatus of human culture were established to ease solving several categories of complicated social, economic, scientific and engineering design problems. Such as:

i. Weak problems with little or no area information.

ii. Problems for which a near-ideal solution can be satisfactory.

iii. Non-deterministic Polynomial (NP) complete problems.

iv. Problems with non-smooth and noisy search space.

v. Problems whose environments are uncertain/changes or both [3, 4].

Each branch has a comprehensive theoretical basis and is highlighted by a collection of sophisticated algorithms and software like Genetic Algorithm (GA) which is a heuristic search technique used in artificial intelligence and computing. In this approach, evolution is performed through Elitism, Crossover, Mutation [5].

Artificial intelligence (AI) techniques are suitable as substitute methods to conventional techniques or as mechanisms of integrated systems. These are applied in solving complicated practical problems in various areas and are popular nowadays. AI-techniques have the following features;

i. They learn from previous examples.

ii. They are fault-tolerant and can handle noisy and incomplete data.

iii. They deal with non-linear problems.

iv. Once trained, they can perform forecasts at high speed.

The smell agent optimization technique (SAO) is a newly developed meta-heuristic algorithm using the phenomenon of smell perceptions. The concept of SAO is developed in three distinct modes; sniffing, trailing and random mode [6].

One of the five senses through which the world is perceived is the sense of smell (olfactory). Through the sense of smell, humans and other animals can perceive a large number of chemicals in the external world which enables us to perceive the molecular concentration or smell and intuitively trace this concentration in order the identify the source [7]. In the conventional SAO, the olfaction capacity is set to a constant value which assumes that the smell agent sense of smell cannot change and this assumption comes with certain drawbacks like longer computational time.

2. Case study

This case study proposed an improved SAO technique algorithm that makes the olfaction capacity a dynamic variable thereby improving speed and precision of solving the combinatorial problem of selecting the optimal combination between a hybrid renewable energy system at best annual cost, loss of power supply probability (LPSP) and levelized cost of energy (LCE) (**Figures 1**, **5**, **6**–**10**).

A mathematical model may fail due to any or all of the following reasons:

i. The problem or process may be too complex for mathematical reasoning.

ii. The problem or process may be dynamic and stochastic in nature.

iii. The solution space of the problem may be too large for mathematical computation.

iv. The problem or process may contain some uncertainties.

All these characteristics are exhibited by most real-life problems [8]. To address this challenge, researchers have employed computational intelligence techniques under different environments and promising results have been achieved.

To achieve the stated aim, the following objectives were adopted.

i. Collection of load data and weather data such as solar insolation, solar temperature and wind speed from questionnaires and the NASA website.

ii. To model the hybrid energy system considering PV/Battery, Wind/Battery, PV/Wind/Battery configurations and load.

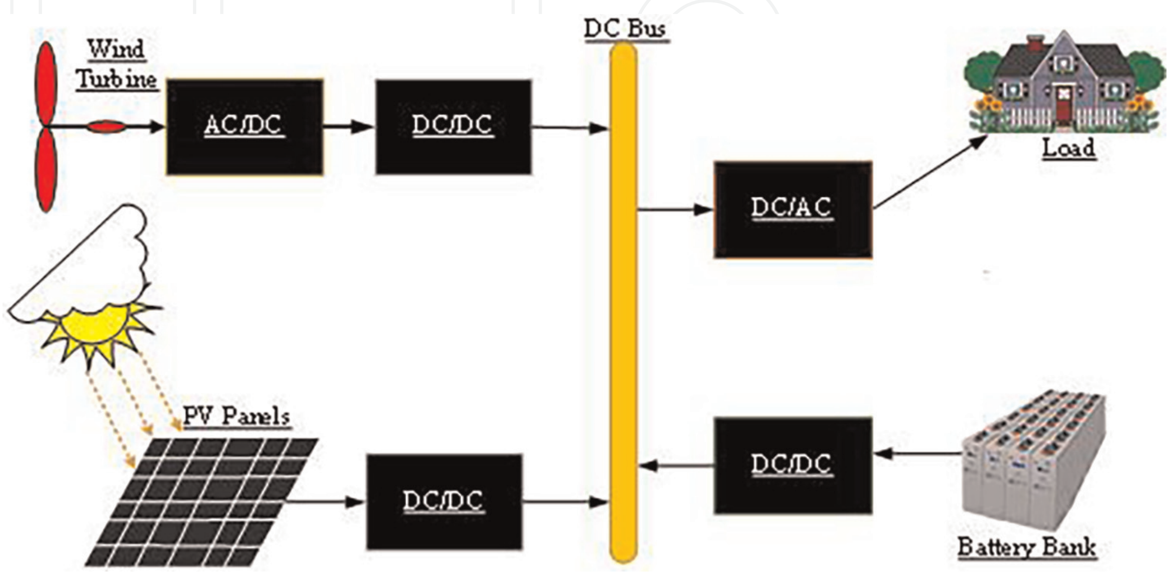

Figure 1.
Illustrates schematic diagram of the proposed hybrid renewable energy system [1].

iii. To develop an improved Smell Agent Optimization iSAO and optimize the developed hybrid model in 2, using the iSAO and the standard SAO.

iv. To validate by comparing the performance of iSAO with SAO on Matlab Simulink.

2.1 Significance of study

A lot of research has been done on efficient sizing utilizing artificial intelligence however, this research proposes an artificial intelligence smell agent optimizing sizing technique for a solar PV, wind turbine and battery storage system. The contributions are as follows;

i. This algorithm is based on the creation of a surface with smell trails and iteration of the agents in finding a path. It can be applied in various computational constraints that use path-based problems and this is useful in solving NP-hard constraints that are related to path discovery [9].

ii. The economic enticement of distribution companies around the world (DISCOs) is to minimize losses in the network. So, when real losses are greater than the standard losses, the DISCOs loses economically or profit when the opposite occurs. This loss minimization in distribution systems is well-suited for researchers [10].

iii. Improving the smell agent optimization sizing technique for a hybrid renewable energy system.

Load data was collected with the help of questionnaires to understand energy demand patterns and from a reputable independent power provider (IPP).

The algorithm was modeled for the following configurations:

i. PV, wind turbines and battery storage configurations.

ii. PV and battery storage configurations.

iii. Wind turbines and battery storage configurations.

In the end, the modified smell agent optimization technique was validated on Matlab Simulink and compared to the standard smell agent optimization technique with annual cost of maintenance, Levelized cost of energy, loss of power supply probability and excess energy as the unit of measure.

3. Smell agent optimization

The Smell Agent Optimization (SAO) is a recently developed algorithm from the idea of how a smelling agent learns to identify a smell source. The authors of the algorithm argue that, with a well-developed olfaction capacity, an organism (including humans) can perceive smell substance and intuitively follows the smell substance to identify its source [11, 12]. This idea is modeled into three classifiable modes namely; the sniffing, trailing and random modes. These modes interact together to form the smell agent optimization. The detailed information about these modes is discussed as follows:

i. Sniffing Mode

The idea of sniffing mode hinges on the ability of a smell agent (i.e. human) to first perceive the presence of smell molecules around its surrounding while the molecules constantly diffuse from its smell source. This analogy can be further portrayed as, when a smell molecule evaporates from a smell source in the direction of an agent, the agent sniff (sense or perceive) and decide whether it's a pleasant smell or a harmful smell. After this decision is made, the agent either moves towards the direction of the smell molecules or moves away from the smell molecules. Assuming *N* is the total number of smell molecules evaporating from a smell source and *D* is the size of the search spacing where the smell molecules have occupied (dimension). The initial positions of smell molecules can be generated as follows:

$$x_i^t = \left[x_{N,1}^t, x_{N,2}^t, \dots, x_{N,D}^t\right] \tag{1}$$

Meanwhile, the smell molecule's evaporation from the source is in Brownian form, to sustain this Brownian evaporation, each molecule is assigned an initial velocity to aid their movement in the search space. This is achieved using the following equation

$$v_i^t = \left[v_{N,1}^t, v_{N,2}^t, \dots, v_{N,D}^t\right] \tag{2}$$

From Eqs. (1) and (2), the evaporation of smell molecules can therefore be represented as follows:

$$x_i^{t+1} = x_i^t + \left(v_i^{t+1} \times \Delta t\right) \tag{3}$$

where $v_i^{t+1}$is the change in velocity and $\Delta t$is the change in time? Note that for the optimization process, change in time is always 1, i.e., an algorithm moves from one iteration to another with a constant step of 1.

For the molecules to evaporate from one point to another, the velocity of every molecule is updated as follows:

$$v_i^{t+1} = v_i^t + \alpha_1 \times \sqrt{\frac{3kT}{m}} \tag{4}$$

Thus,

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{5}$$

where α_1 is a random number generator, k is Boltzmann's constant given by 1.38 x$10^{-23}JK^{-1}$,T and m are the temperature and mass of smell molecules respectively.

The agent snorts these smell molecules by estimating the fitness of Eq. (5) and decide whether to track the source of the smell molecules or not.

ii. Trailing Mode

From the implementation of the sniffing mode, the fitness of each smell molecule is evaluated, then the position of the agent x^t_{agent} and the position of worst moleculesx^t_{worst} are determined as the positions of molecules with best and worst sniffing fitness respectively. These positions are used to model the trailing behavior of the agent towards the smell source as follows:

$$x_i^{t+1} = x_i^t + \alpha_2 \times \eta \times \left(x_i^t - x^t_{agent}\right) - \alpha_3 \times \eta \times \left(x_i^t - x^t_{worst}\right) \tag{6}$$

where η which is also called *olf* is the olfaction capacity of the agent, α_2 and α_3 are random numbers used to penalize the influence η x^t_{agent} on and x^t_{worst} respectively.

iii. Random Mode

The random mode, which is like a savior strategy the agent employed to avoid getting stuck in local minima. This mode only becomes active when the agent could not obtain the global solution to the optimization problem after implementing the trailing mode. The model is expressed as:

$$x_i^{t+1} = x_i^t + \alpha_4 \times \Phi \tag{7}$$

where Φ a constant step taking by the agent andα_4 is a random number used to penalize the influence ofΦ.

3.1 Objective function formulation

The objective function considered in this work is a tri-objective optimization problem where the aim is to minimize the Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP) and Excess Energy Generated. This is expressed in Eq. (8):

$$\text{minf} = \min\left(\measuredangle\text{LCOE} + \measuredangle\text{LPSP} + \measuredangle\text{EE}\right) \tag{8}$$

Where: $\measuredangle$*is penalty factor*.

These individual objective functions can be expressed as follows:

$$\text{LCOE} = \frac{\text{C}_{\text{A\_total}}}{\text{E}_{\text{total}}} \tag{9}$$

$$\text{LPSP} = \frac{\sum_0^{\text{T}} \text{P}_{\text{Load}} - \text{P}_{\text{pv}} - \text{P}_{\text{wind}} - \text{P}_{\text{SOC}_\text{M}}}{\sum_0^{\text{T}} \text{P}_{\text{Load}}} \tag{10}$$

$$\text{EE} = \sum_0^{\text{T}} \frac{\text{P}_{\text{Load}} - \text{P}_{\text{pv}} - \text{P}_{\text{wind}}}{\text{P}_{\text{pv}} + \text{P}_{\text{wind}}} \tag{11}$$

where; C_{A_total} is the total cost of the hybrid systems, E_{total} is the total cost of energy generation, P_{Load} is the load demand, P_{pv} is the output power from the PV generation units, P_{wind} is the output power from the wind turbine generation unit and T is the total time.

To achieve these tri-objectives, the total annual cost given in equation Eq. (12) must also be minimized.

$$\mathrm{TAC} = \sum_{i=1}^{N} \mathrm{AMC} + \sum_{i=1}^{N} \mathrm{ACC} \tag{12}$$

where N is the total hours considered, TAC is the total annual cost, AMC is the annual maintenance cost and ACC is the annual capital cost. The annual maintenance cost is expressed as:

$$\mathrm{AMC} = n_{pv}P_{pvm} + n_{wt}P_{wtm} \tag{13}$$

Whereas, the total capital cost is calculated as:

$$\mathrm{ACC} = \mathrm{CFR} \times \left[n_{pv}C_{pv} + n_{wt}C_{wt} + n_{Bat}C_{Bat} + n_{Inv}C_{Inv}\right] \tag{14}$$

where n_{pv} is the number of PV panels, C_{pv} is the unit cost of PV panel, n_{wt} is the number of wind turbines, C_{wt} is the unit cost of a wind turbine, n_{Bat} is the number of batteries, C_{Bat} is the present worth of battery, n_{Inv} is the number of converters/ inverters, C_{Inv} is the present worth of converter/inverter and CRF is the Capital Recovery Factor.

The system implemented for hybrid system design consisting of PV/Wind/Battery configuration. The order configurations considered in the study include PV/Battery and Wind/Battery. For PV/Battery systems design, the wind turbine generators shut down and equation Eqs. (15) and (16) is modified as:

$$\mathrm{AMC} = n_{pv}P_{pvm} \tag{15}$$

Whereas, the total capital cost is calculated as:

$$\mathrm{ACC} = \mathrm{CFR} \times \left[n_{pv}C_{pv} + n_{Bat}C_{Bat} + n_{Inv}C_{Inv}\right] \tag{16}$$

Similarly, for the Wind/Battery hybrid system design, the equations are modified as:

$$\mathrm{AMC} = n_{wt}P_{wtm} \tag{17}$$

Whereas, the total capital cost is calculated as:

$$\mathrm{ACC} = \mathrm{CFR} \times [n_{wt}C_{wt} + n_{Bat}C_{Bat} + n_{Inv}C_{Inv}] \tag{18}$$

In all the configurations, the number of each hybrid component is selected as the decision variables using the following boundary constraints:

$$n_{pv-\max} \le n_{pv} \le n_{pv-\min} \tag{19}$$

$$n_{wt-\max} \le n_{wt} \le n_{wt-\min} \tag{20}$$

$$n_{Bat-\max} \le n_{Bat} \le n_{Bat-\min} \tag{21}$$

The number of inverters is selected as 4 and 3 for PV/Wind/Battery and the other two configurations respectively.

3.2 Constrain formulation

The optimization problem of the hybrid renewable system is to determine the right combination of PV panels, wind turbines and batteries which gives the minimum ACC and AMC. The ACC and AMC should, in turn, minimize the TAC given in Eq. (22) while satisfying the following constraints:

$$\begin{aligned} &n_{pv\_\min} \le n_{pv} \le n_{pv\_\max} \quad n_{wt\_\min} \le n_{wt} \le n_{wt\_\max} \quad n_{Bat\_\min} \le n_{Bat} \le n_{Bat\_\max} \\ &\text{and,} \\ &n_{pv}, n_{wt} and\, n_{Bat} = Integer \end{aligned} \tag{22}$$

From Eq. (10), $n_{pv\_\min}$ and $n_{pv\_\max}$ are the lower and upper limit of n_{pv}; $n_{wt\_\min}$ and $n_{wt\_\max}$ are the lower and upper bound of n_{wt} and, $n_{Bat\_\min}$ and $n_{Bat\_\max}$ are the lower and upper bound of n_{Bat}.

The charge quantity of the battery bank at any time should satisfy the following constraints

$$SOC(t_{\min}) \le SOC(t) \le SOC(t_{\max}) \tag{23}$$

The SOC whose maximum and minimum charge quantity is defined by $SOC(t_{\min})$ *and* $SOC(t_{\max})$ and is the battery State of Charge, determined by Eq. (8)

$$SOC(t) = SOC(t-1) \times (1-\omega) + \left[\frac{P_L(t)}{\eta_{Inv}} - (P_{PV}(t) - P_{WT}(t))\right] \times \eta_{BC} \tag{24}$$

where ω is the hourly self-discharge rate of the battery, η_{BC} is the battery bank discharge efficiency, η_{Inv} is the inverter efficiency.

The maximum charge quantity of the battery bank SOC (t_{max}) takes the value of the nominal capacity of the battery (S_{Bat}) and the minimum charge quantity of the battery bank SOC (t_{min}) is obtained from the maximum Depth of Discharge (DOD) as in Eq. (9).

$$SOC(t_{\min}) = (1 - DOD) \times S_{Bat} \tag{25}$$

4. Modified smell agent optimization

Studies have shown that one of the control parameters which affect the overall performance of smell agent optimization is the olfaction capacity of the agent. Since the ability of the agent to perceive a smell molecule largely depend on the size of the olfactory lobe, proper choice of olfaction capacity will influence the searching ability of Smell Agent Optimization positively. Unlike in the original SAO, where the olfaction capacity is selected arbitrarily, this research developed a model to select the olfaction capacity dynamically. This is to ensure that, the olfaction capacity changes as the algorithm iterate through the optimization process. Assuming the initial olfaction capacity assigned to an agent is given as *olf*, then the dynamic *olf* which is donated as olf_{dyn} can be calculated as

$$olf_{dyn} = olf \times e^{\left(\frac{itr}{itr_{\max}}\right)} \tag{26}$$

The dynamic olfaction capacity given in Eq. (26) is formulated such that, the perception capability of the agent exponentially as the agent approaches the object generating the smell molecules (i.e., optimal solution). The equation is used to modify the trailing mode solution search of SAO. The flow chart for the implementation of the dynamic SAO called the iSAO is given in figure below.

Note: From **Figure 2**, the part highlighted in red shows the improvement added to the standard smell agent optimization.

Step 1: The parameters required to implement the algorithm are initialized. These parameters are the population (positions) of the smell molecules, the initial velocity, search dimension, temperature, Boltzmann constant, random mode step movement and the number of iterations.

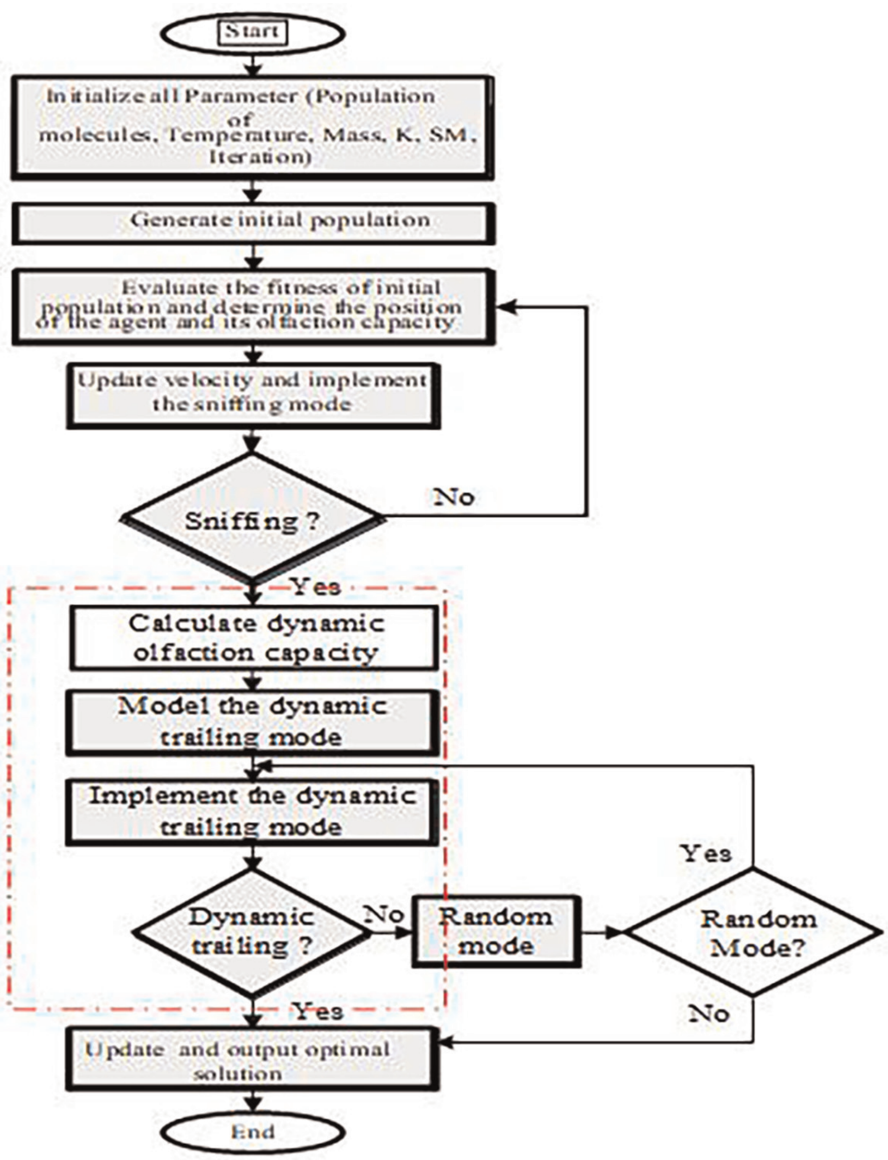

Figure 2.
Illustrates improved smell agent optimization flow chart [1].

Step 2: Randomly generate the initial position of the smell molecules in the search space and assign the velocity of each molecule.

Step 3: The fitness of the generated molecules position and velocity in step 2 are evaluated.

Step 4: The velocity of each molecule is updated.

Step 5: The fitness of the sniffing mode and position of the agent in step 2 with the position of the molecule having the best sniffing fitness are evaluated.

Step 6: The dynamic olfaction capacity is calculated, the position of the molecules with the worst sniffing fitness is determined and the trailing mode behavior is performed.

Step 7: The fitness of the trailing mode is evaluated.

Step 8: The fitness of the trailing mode with the fitness obtained during the fitness mode are compared.

Step 9: If the trailing mode fitness is better than the sniffing mode fitness, step 6 is repeated to step 8 until the smell source is determined. If the sniffing mode fitness is better than the trailing mode fitness, then move to step 10.

Step 10: Random mode behavior is performed.

Step 11: The fitness of the random mode is evaluated.

Step 12: If the fitness of the random mode is better than the fitness of the trailing mode, then determine the new random position of the agent and the worst random position of the molecule and perform the trailing mode again, otherwise repeat step 4 to step 9.

Step 13: Terminate if the stopping condition is satisfied else repeat step 1 to step 12 until the stopping criteria are met.

5. Important assumptions

Highlighted below are some of the important assumptions adopted for the development of the proposed iSAO;

i. The smell molecules evaporate from the smell source constantly in the direction of the agent until the smell object is found.

ii. The velocity of the object evaporating the smell molecules is negligible compared to the velocity of the smell agent. In other words, the object originating the smell is in a fixed position and cannot move.

iii. The smell source could be more than one and each source evaporate the same number of smell molecules with varying concentration [13].

iv. The olfaction capacity is dynamic in nature.

6. Overview of data collection

The data from **Table 1** were compiled from first a questionnaire distributed around Abuja environs to understand the energy behavior of the Nigerian household

Solar (W/m^2)	Wind speed (m/s)	Load (kW)
0	22	6.4
0	23	6.2
0	25	5.8
0	26	5.8
0	26	6
0	26	7.3
198	26	9.1
562	24	12.5
830	22	13.4
800	20	13.4
811	19	13.2
813	17	13.8
403	15	13.2
803	16	13.7
844	16	13.2
678	17	14
322	12	16.3
0	7	18.9
0	3	22.2
0	4	17.9
0	5	12.5
0	6	9.1
0	13	7.5
0	19	6.8

Table 1.
Data collected for the project.

and from data collected by Sunergy, the renewable energy department of Anjeed Innova group.

Table 1 is the data for the daily wind speed, solar insolation and the required daily load. The load peaks at 22.2 kW with a minimum of 5.8 kW.

The graph of **Figure 3** shows a plot of the load required in kW on the y-axis against and the hours of the day. The load steadily climbs from about 6 am at 7.3 kW and maintains by 9 am at about 13 kW then starts to rise again at 5 pm to 16.3 kW then peaks at 22.3 kW by 7 pm then drops till around 6 kW till the next day. This is typical of the average Nigerian family activity.

The graph **Figure 4** below shows a plot of wind speed in m/s and the solar insolation in W/m^2 on the y-axis against the hours of the day on the x-axis. Because of the intermittent nature of solar and wind energy, sunlight is to be expected for about 12 hours and the wind speed rises and falls rapidly throughout the day.

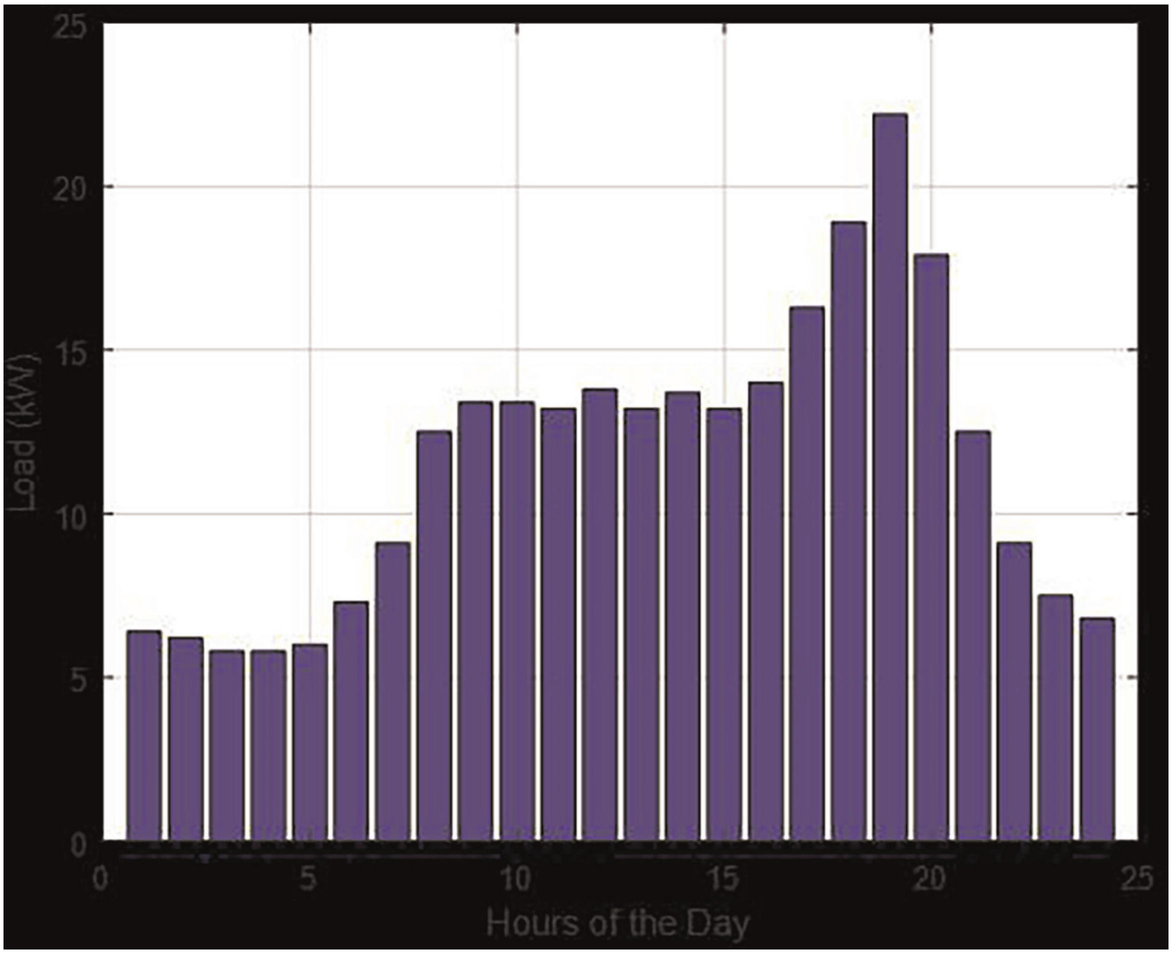

Figure 3.
Illustrating hourly load requirement [1].

7. Results and discussion

The algorithms attempt to find the optimum number of PV panels, wind turbines, and batteries (NBatt) in PV/WT/battery, PV/battery and WT/battery configurations. The minimum and maximum numbers of each component are set to 0 and 100 for the solar PV and wind turbines, respectively the 50 for the battery storage.

Also, the olfaction capacity is dynamic with a total of 100 iterations and to calculate the accuracy of results, 10 independent runs are performed and the results are reported below.

8. Analysis

i. Standard smell agent optimization

Table 2 illustrates the iterations 7for the PV, wind turbine and battery and from the results, the algorithm finds the best and the worst combination economically with optimum reliability.

This program was run on Matlab R2017a and the graph is plotted with the annual cost on the y-axis with the iteration number on the x-axis (**Figure 5**).

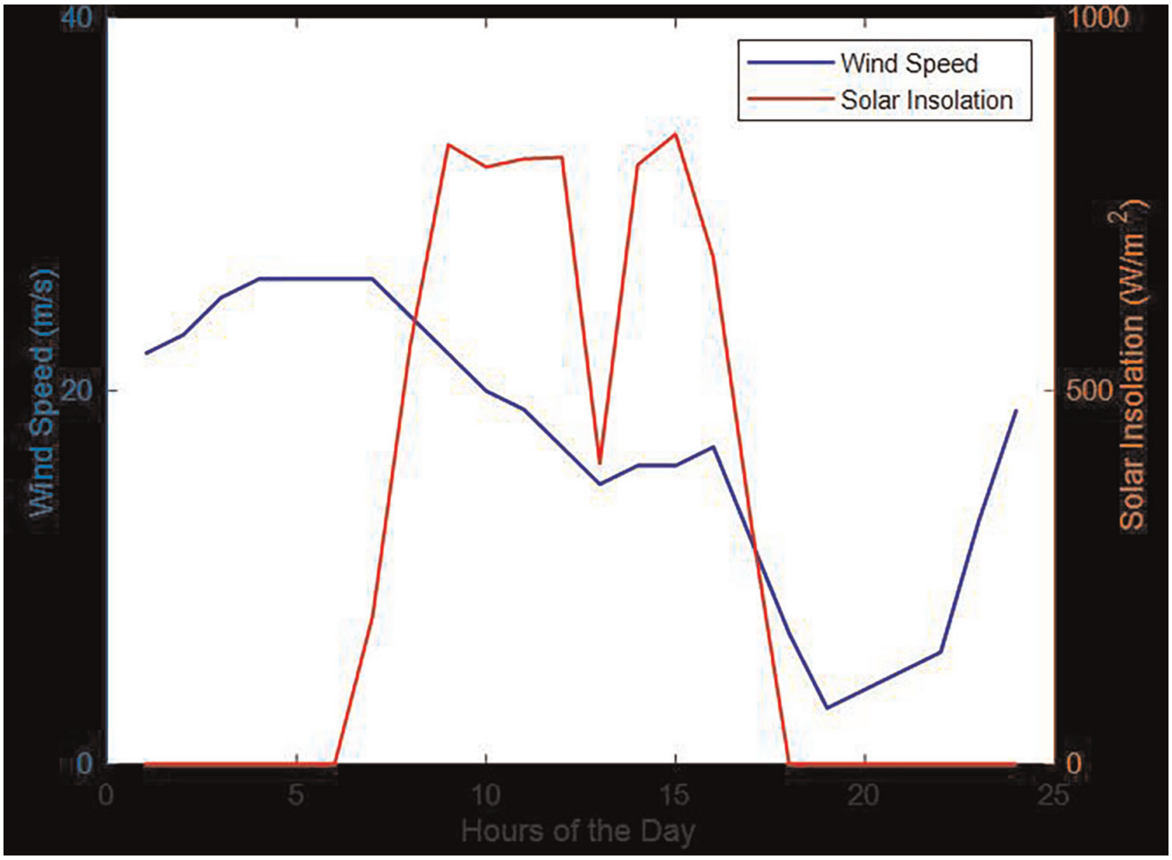

Figure 4.
Illustrating daily wind speed and solar insolation [1].

Table 3 WT and battery using the improved smell agent optimization. and battery. From the results, the algorithm finds the best and the worst combination economically with optimum reliability and the graph is plotted with the annual cost on the y-axis with the iteration number on the x-axis (**Figure 6**).

Table 4 illustrates the iterations for the wind turbine and battery. From the results, the algorithm finds the best and the worst combination economically with optimum reliability and the graph is plotted with the annual cost on the y-axis with the iteration number on the x-axis (**Figure** 7).

ii. Improved smell agent optimization

Table 5 illustrates the iterations for the PV/WT and battery using the improved smell agent optimization. From the results, the algorithm finds the best and the worst combination economically with optimum reliability and the graph is plotted with the annual cost on the y-axis with the iteration number on the x-axis (**Figure 8**).

Table 6 illustrates the iterations for the PV and battery using the improved smell agent optimization. From the results, the algorithm finds the best and the worst combination economically with optimum reliability and the graph is plotted with the annual cost on the y-axis with the iteration number on the x-axis (**Figure 9**).

Table 7 illustrates the iterations for the WT and battery using the improved smell agent optimization. From the results, the algorithm finds the best and the

S/no	Npv	Nwt	Nbat	pvCost	CwtCost	Bat_Cost	Conv_Cost	Total_Cost	LCE	LpSP	E_Ex
1	16	34	50	1.28E+04	5.59E+03	3.23E+02	1.07E+02	2.04E+04	0.039754	0.173659	93.64366
2	80	61	8	6.42E+04	1.00E+04	51.62501	1.07E+02	7.59E+04	0.02212	0.173659	1.68E+02
3	0	0	3	0	0	19.35938	1.07E+02	1.63E+03	Inf	0.187702	-0.01159
4	92	100	12	7.38E+04	1.65E+04	77.43751	1.07E+02	9.19E+04	0.013504	0.173659	2.76E+02
5	25	71	50	2.01E+04	1.17E+04	3.23E+02	1.07E+02	3.37E+04	0.019042	0.173659	1.96E+02
6	47	100	38	3.77E+04	1.65E+04	2.45E+02	1.07E+02	5.60E+04	0.013517	0.173659	2.75E+02
7	61	82	26	4.89E+04	1.35E+04	1.68E+02	1.07E+02	6.42E+04	0.016474	0.173659	2.26E+02
8	48	75	17	3.85E+04	1.23E+04	1.10E+02	1.07E+02	5.26E+04	0.018016	0.173659	2.07E+02
9	95	68	50	7.62E+04	1.12E+04	3.23E+02	1.07E+02	8.93E+04	0.019839	0.173659	1.88E+02
10	55	100	11	4.41E+04	1.65E+04	70.98439	1.07E+02	6.23E+04	0.013514	0.173659	2.75E+02

Table 2.
Summary of the results for the hybrid systems obtained by SAO algorithm for 10 runs of the PV/WT/BAT configurations.

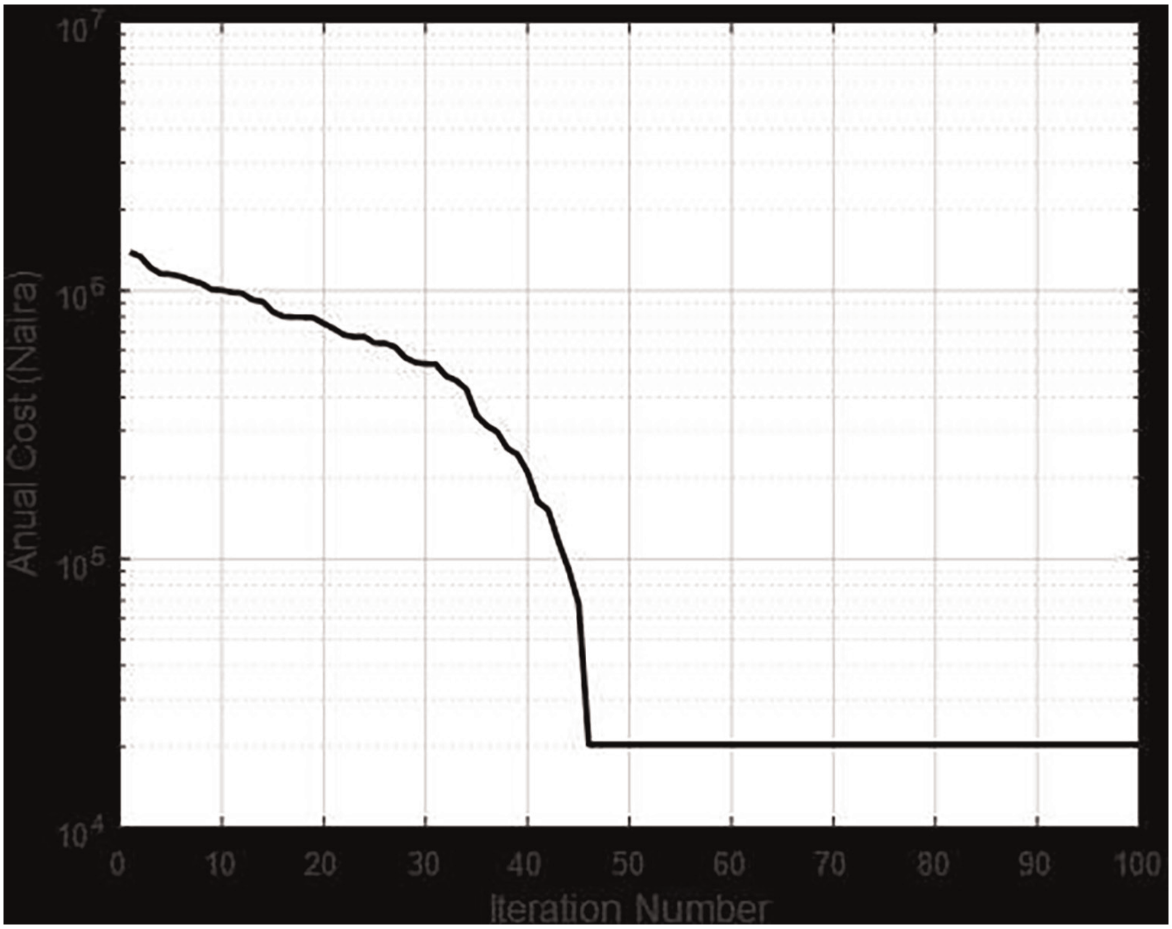

Figure 5.
Illustration of annual cost against iteration number for PV/wt/battery configurations [1].

S/no	Npv	Nbat	pvCost	Bat_Cost	Conv_Cost	Total_Cost	LCE	LpSP	E_Ex
1	95	18	7.62E+04	1.16E+02	8.00E+01	7.75E+04	6.851904	0.173659	0.531792
2	67	18	5.37E+04	1.16E+02	8.00E+01	5.51E+04	9.715386	0.173659	0.371637
3	45	35	3.61E+04	2.26E+02	8.00E+01	3.75E+04	14.46513	0.173659	0.2458
4	57	50	4.57E+04	3.23E+02	8.00E+01	4.73E+04	11.41984	0.173659	0.314438
5	90	16	7.22E+04	1.03E+02	8.00E+01	7.35E+04	7.232565	0.173659	0.503192
6	99	33	7.94E+04	2.13E+02	8.00E+01	8.08E+04	6.575059	0.173659	0.554671
7	88	0	7.06E+04	0	8.00E+01	7.18E+04	7.396941	0.173659	0.491753
8	43	50	3.45E+04	3.23E+02	8.00E+01	3.60E+04	15.13793	0.173659	0.234361
9	78	0	6.26E+04	0	8.00E+01	6.38E+04	8.345267	0.173659	0.434555
10	84	0	6.74E+04	0.00E+00	8.00E+01	6.86E+04	7.749177	0.173659	0.468874

Table 3.
Summary of the results for the hybrid systems obtained by SAO algorithm for 10 runs of the PV/BAT configurations.

worst combination economically with optimum reliability and the graph is plotted with the annual cost on the y-axis with the iteration number on the x-axis (**Figure 10**).

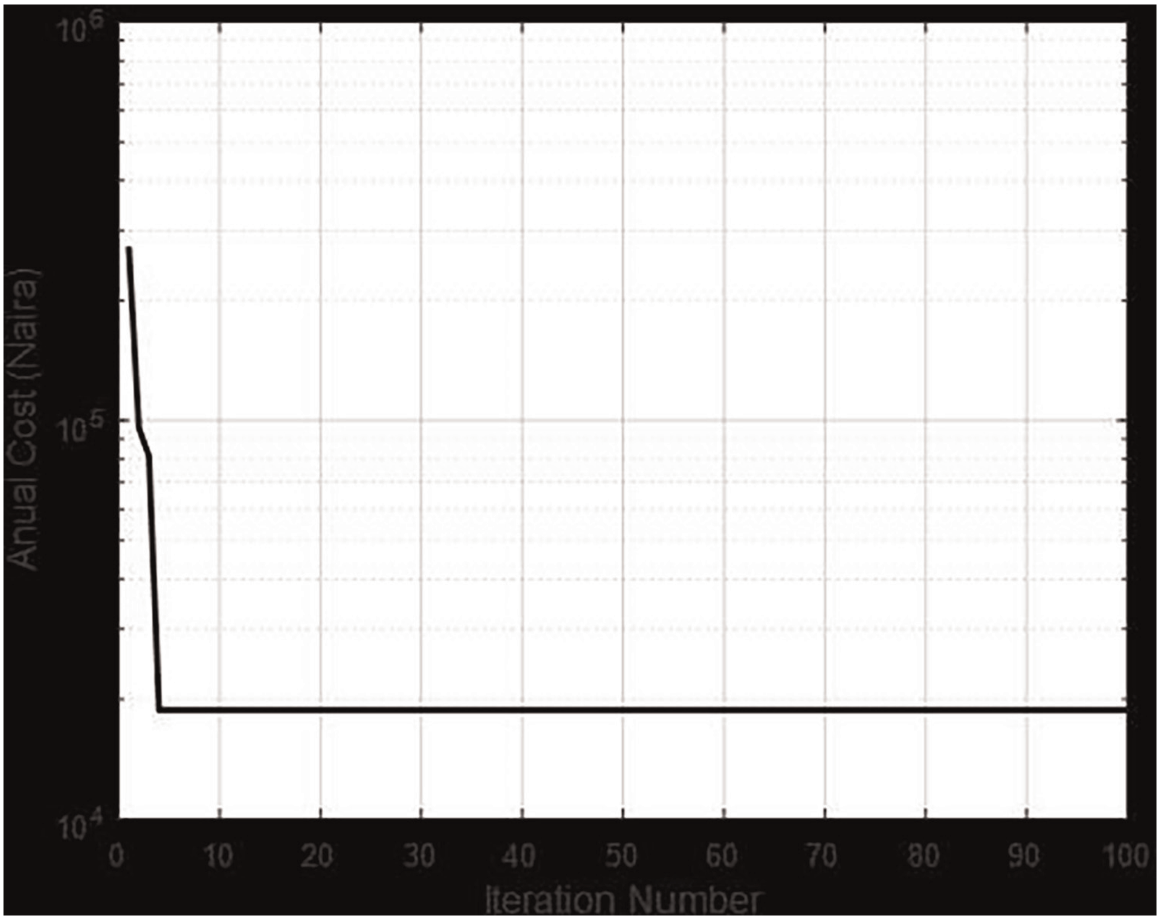

Figure 6.
Illustration of annual cost against iteration number for PV/battery configurations [1].

S/no	Nwt	Nbat	CwtCost	Bat_Cost	Conv_Cost	Total_Cost	LCE	LpSP	E_Ex
1	29	17	4.77E+03	1.10E+02	8.00E+01	6.09E+03	0.046654	0.093959	7.98E+01
2	61	28	1.00E+04	1.81E+02	8.00E+01	1.14E+04	0.02218	0.093959	1.68E+02
3	100	30	1.65E+04	1.94E+02	8.00E+01	1.79E+04	0.01353	0.093959	2.75E+02
4	16	22	2.63E+03	1.42E+02	8.00E+01	3.98E+03	0.084561	0.093959	4.40E+01
5	30	28	4.94E+03	1.81E+02	8.00E+01	6.32E+03	0.045099	0.093959	8.25E+01
6	94	32	1.55E+04	2.07E+02	8.00E+01	1.69E+04	0.014393	0.093959	2.59E+02
7	100	50	1.65E+04	3.23E+02	8.00E+01	1.80E+04	0.01353	0.093959	2.75E+02
8	17	50	2.80E+03	3.23E+02	8.00E+01	4.33E+03	0.079587	0.093959	4.68E+01
9	53	29	8.72E+03	1.87E+02	8.00E+01	1.01E+04	0.025528	0.093959	1.46E+02
10	33	16	5.43E+03	1.03E+02	8.00E+01	6.74E+03	0.040999	0.093959	9.08E+01

Table 4.
Summary of the results for the hybrid systems obtained by SAO algorithm for 10 runs of the WT/BAT configurations.

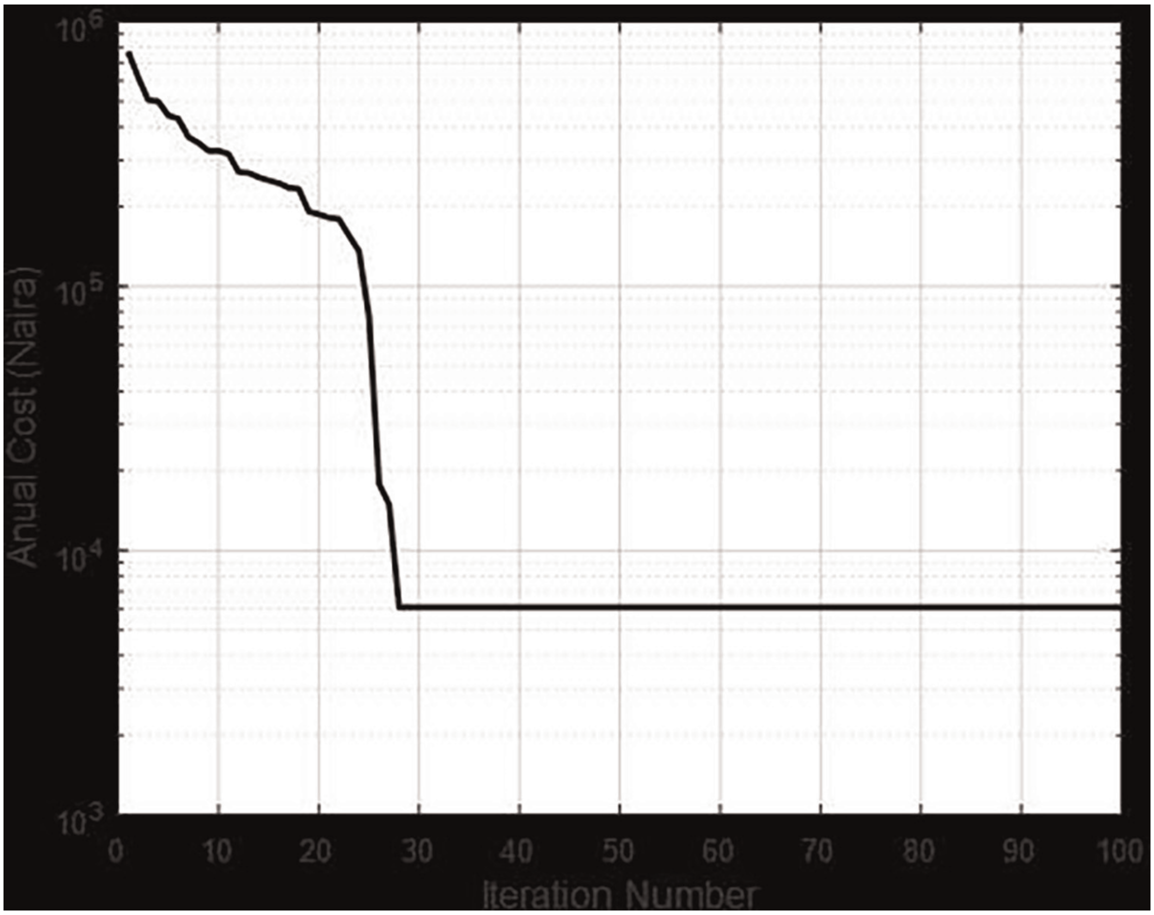

Figure 7.
Illustration of annual cost against iteration number for wt/battery configurations [1].

9. Comparative analysis

It should be noted from the table that only the best results obtained by each algorithm are used as a metric for comparing the performance of the algorithm. The algorithm is developed by the phenomenon of smell and the trailing behavior of agents in identifying smell sources. The results showed that the improved SAO is efficient and can compete with other computational intelligent algorithms.

Table 8 illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the standard SAO PV/WT/batt configurations.

Table 9 illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the standard SAO PV/batt configurations.

Table 10 illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the standard SAO WT/batt configurations.

Table 11 illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the improved SAO PV/WT/batt configuration.

S/no	Npv	Nwt	Nbat	pvCost	CwtCost	Bat_Cost	Conv_Cost	Total_Cost	LCE	LpSP	E_Ex
1	0	45	41	0	7.40E+03	2.65E+02	1.07E+02	9.28E+03	0.030066	0.093959	1.24E+02
2	63	100	28	5.05E+04	1.65E+04	1.81E+02	1.07E+02	6.88E+04	0.013512	0.173659	2.76E+02
3	92	36	48	7.38E+04	5.92E+03	3.10E+02	1.07E+02	8.16E+04	0.037384	0.173659	99.58211
4	95	100	22	7.62E+04	1.65E+04	1.42E+02	1.07E+02	9.44E+04	0.013503	0.173659	2.76E+02
5	72	100	41	5.78E+04	1.65E+04	2.65E+02	1.07E+02	7.61E+04	0.01351	0.173659	2.76E+02
6	36	64	50	2.89E+04	1.05E+04	3.23E+02	1.07E+02	4.13E+04	0.021116	0.173659	1.76E+02
7	14	0	15	1.12E+04	0	96.79689	1.07E+02	1.29E+04	46.49506	0.173659	0.068486
8	31	92	50	2.49E+04	1.51E+04	3.23E+02	1.07E+02	4.19E+04	0.014696	0.173659	2.53E+02
9	17	88	22	1.36E+04	1.45E+04	1.42E+02	1.07E+02	2.99E+04	0.015369	0.173659	2.42E+02
10	100	3	50	8.02E+04	4.94E+02	3.23E+02	1.07E+02	8.26E+04	0.421769	0.173659	8.816014

Table 5.
Summary of the results for the hybrid systems obtained by improved smell agent algorithm for 10 runs of the PV/WT/BAT configurations.

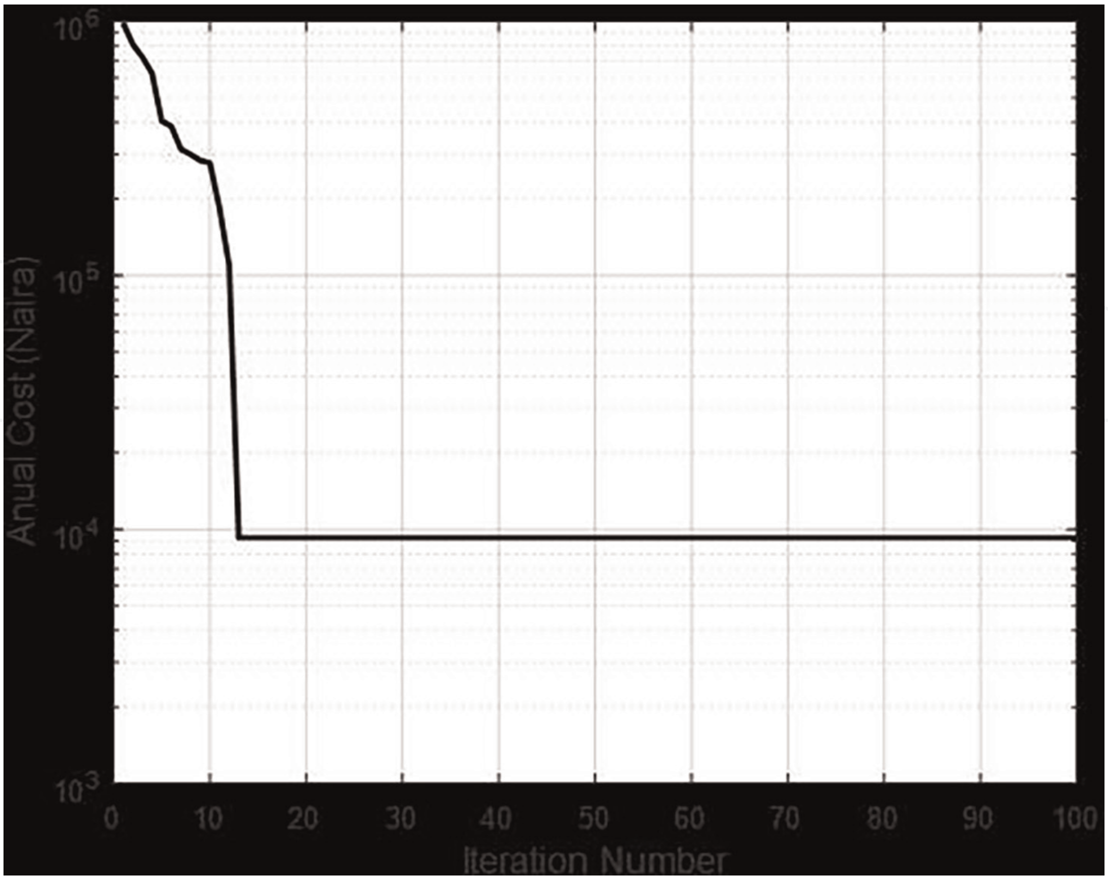

Figure 8.
Illustration of annual cost against iteration number for PV/wt/battery configurations using the improved smell agent optimization [1].

S/no	Npv	Nbat	pvCost	Bat_Cost	Conv_Cost	Total_Cost	LCE	LpSP	E_Ex
1	19	17	1.52E+04	1.10E+02	1.07E+02	1.70E+04	34.25952	34.25952	0.097085
2	78	35	6.26E+04	2.26E+02	1.07E+02	6.44E+04	8.345267	0.173659	0.434555
3	32	46	2.57E+04	2.97E+02	1.07E+02	2.76E+04	20.34159	0.173659	0.171443
4	19	33	1.52E+04	2.13E+02	1.07E+02	1.71E+04	34.25952	0.173659	0.097085
5	36	30	2.89E+04	1.94E+02	1.07E+02	3.07E+04	18.08141	0.173659	0.194322
6	33	40	2.65E+04	2.58E+02	1.07E+02	2.83E+04	19.72518	0.173659	0.177163
7	100	47	8.02E+04	3.03E+02	1.07E+02	8.21E+04	6.509308	0.173659	0.560391
8	100	46	8.02E+04	2.97E+02	1.07E+02	8.21E+04	6.509308	0.173659	0.560391
9	100	29	8.02E+04	1.87E+02	1.07E+02	8.20E+04	6.509308	0.173659	0.560391
10	34	13	2.73E+04	83.89064	1.07E+02	2.90E+04	19.14502	0.173659	0.182882

Table 6.
Summary of the results for the hybrid systems obtained by improved smell agent algorithm for 10 runs of the PVBAT configurations.

Table 12 illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the improved SAO PV/batt configurations.

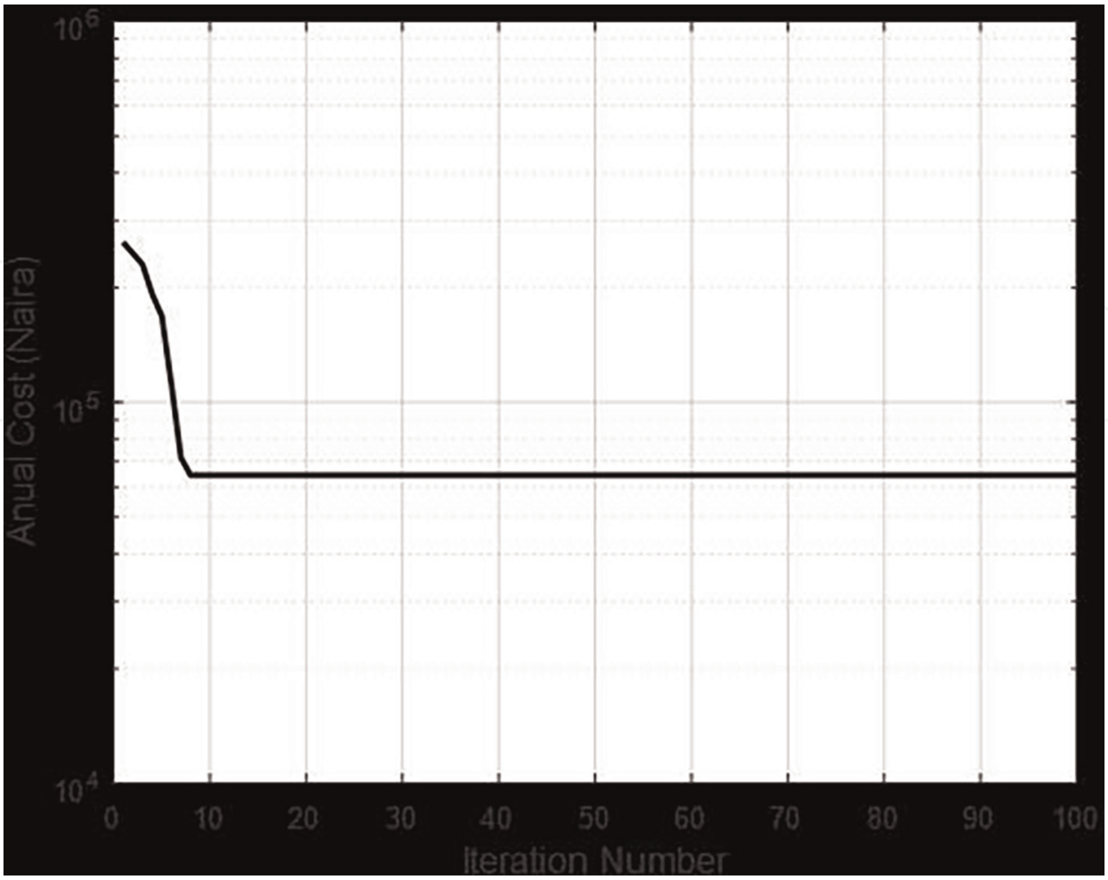

Figure 9.
Illustration of annual cost against iteration number for PV/battery configurations using the improved smell agent optimization [1].

S/no	Nwt	Nbat	CwtCost	Bat_Cost	Conv_Cost	Total_Cost	LCE	LpSP	E_Ex
1	56	29	9.21E+03	1.87E+02	1.07E+02	1.10E+04	0.02416	0.093959	1.54E+02
2	44	3	7.24E+03	19.35938	1.07E+02	8.87E+03	8.87E+03	0.093959	1.21E+02
3	1	14	1.65E+02	90.34376	1.07E+02	1.86E+03	1.352972	0.093959	2.740283
4	0	16	0	1.03E+02	1.07E+02	1.71E+03	Inf	0.187702	-0.01159
5	12	3.10E+01	1.97E+03	2.00E+02	1.07E+02	3.78E+03	0.112748	0.093959	33.0109
6	8	50	1.32E+03	3.23E+02	1.07E+02	3.25E+03	0.169122	0.093959	22.0034
7	99	28	1.63E+04	1.81E+02	1.07E+02	1.81E+04	0.013666	0.093959	2.72E+02
8	14	26	2.30E+03	1.68E+02	1.07E+02	4.08E+03	0.096641	0.093959	38.51465
9	100	15	1.65E+04	96.79689	1.07E+02	1.82E+04	0.01353	0.093959	2.75E+02
10	100	50	1.65E+04	3.23E+02	1.07E+02	1.84E+04	0.01353	0.093959	2.75E+02

Table 7.
Summary of the results for the hybrid systems obtained by improved smell agent algorithm for 10 runs of the WT/BAT configurations.

Table 13 illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the improved SAO WT/batt configurations.

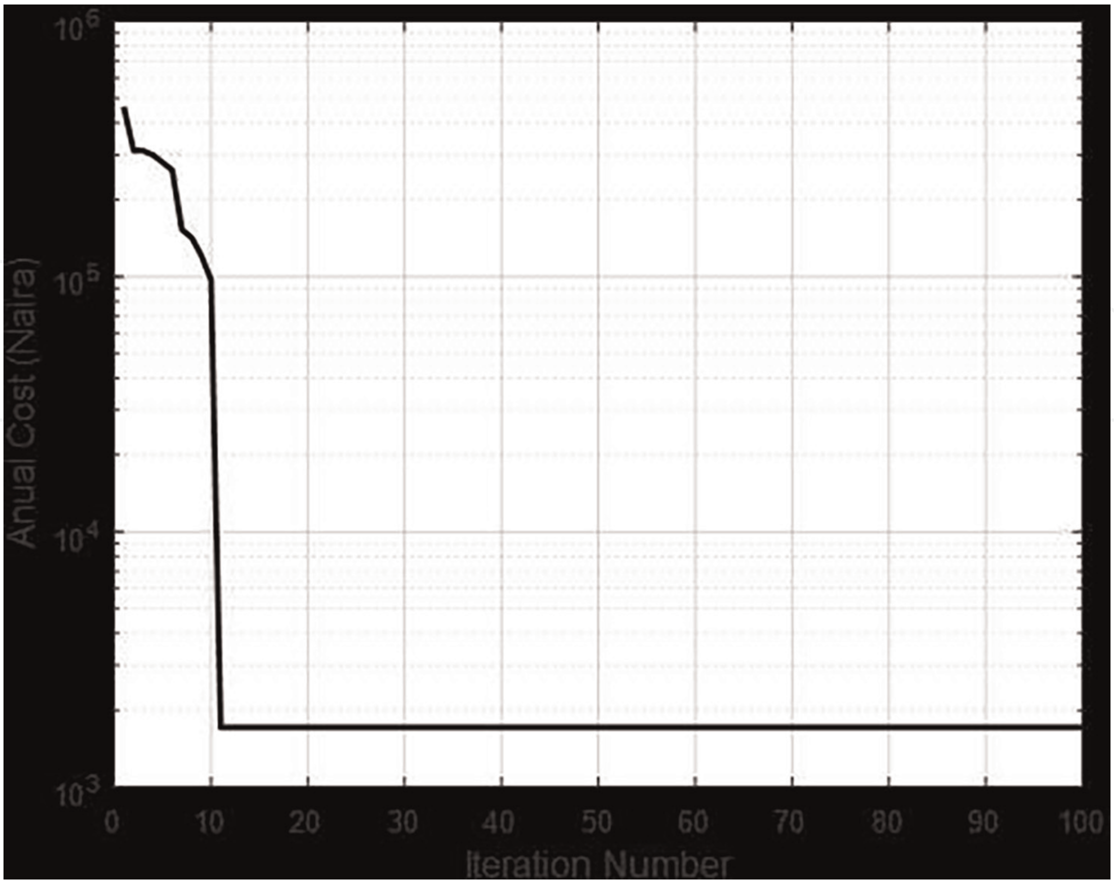

Figure 10.
Illustration of annual cost against iteration number for wt/battery configurations using the improved smell agent optimization [1].

	Total annual cost	LCE	LPSP	Ex.Energy
Best	1.63E+03	0.013504	0.175063	−0.01159
Avg	5.48E+04	0.017578	0.175063	190.4398
SD	2.91E+04	0.009886	0.004441	87.82577

Table 8.
Illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the standard SAO PV/WT/batt configurations.

	Total annual cost	LCE	LPSP	Ex.Energy
Best	3.75E+04	6.575059	0.173659	0.234361
Avg	6.12E+04	9.488919	0.173659	0.415107
SD	1.63E+04	3.157008	2.92569E-17	0.117073

Table 9.
Illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the standard SAO PV/batt configurations.

	Total annual cost	LCE	LPSP	Ex.Energy
Best	1.01E+04	0.01353	0.093959	1.46E+02
Avg	1.02E+04	0.038606	0.093959	1.47E+02
SD	5.60E+03	0.026223	0	9.32E+01

Table 10.
Illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the standard SAO WT/batt configurations.

	Total annual cost	LCE	LPSP	Ex.Energy
Best	1.29E+04	0.013503	0.093959	0.068486
Avg	5.39E+04	4.707598	0.165689	1.73E+02
SD	3.07E+04	14.68316	0.025204	1.09E+02

Table 11.
Illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the improved SAO PV/WT/batt configuration.

	Total annual cost	LCE	LPSP	Ex.Energy
Best	1.70E+04	6.509308	0.173659	0.171443
Avg	4.60E+04	17.36854	3.582245	0.303571
SD	2.81E+04	10.66591	10.77889	0.200066

Table 12.
Illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the improved SAO PV/batt configurations.

	Total annual cost	LCE	LPSP	Ex.Energy
Best	1.10E+04	0.01353	0.1877	−0.1159
Avg	8.92E+03	886.9933	0.103333	1.19E+02
SD	7.05E+03	2804.288	0.029644	1.18E+02

Table 13.
Illustrating the best, average and the standard deviation values for the total annual cost, Levelized cost of energy, loss of power supply probability and excess energy of the improved SAO WT/batt configurations.

10. Findings of the study

The findings of this study are as follows:

i. The percentage of improvement for the total annual cost and loss of power supply probability between the standard smell agent optimization and the improved smell agent optimization is 79% and 53.4% respectively.

ii. The sizing technique is suitable for off-grid and grid configurations.

iii. The technique can be used for various component configurations.

iv. The improved SAO is better at detecting and discriminating scent agents in the environment due to varying olfactory capacity.

v. The improved SAO has a better capacity to follow a scent or odor plum.

11. Conclusions

Unlike in the original SAO, where the olfaction capacity is selected arbitrarily, this research developed a model to select the olfaction capacity dynamically. This is to ensure that, the olfaction capacity changes as the algorithm iterate through the optimization process.

This simple modification improved the trailing and tracking to obtain the cost effective HRES design.

12. Recommendations

The improved SAO has both constant and dynamic variables which play a significant role in the general performance of the algorithm. For this reason, the following areas are highlighted for consideration.

i. Practically, an increase in the temperature of gas molecules increases its evaporation and the velocity of the gas. In this study, these values are constant and since smell molecules in SAO are considered as gas molecules, a method to adaptively select temperature can be considered that the temperature has a decreasing value as the algorithm moves towards the optimum solution. This will enable the algorithm to converge faster and eventually terminate the process when the minimum value of the temperature is attained.

ii. In this work, all gas molecules are assumed a fixed mass. That is not always the case so making the mass of the gas molecules adaptive can be considered. E.g., larger values of mass favor the exploitation capability of the agent while the smaller value will favor exploration capability.

iii. This suggests the possibility of developing a novel algorithm using other sensory systems such as sense of taste, sense of feel and sense of hearing. It is logical to suggest that an algorithm can be developed using other senses like the use of the senses of smell and taste coordinated through the chemosensation process.

iv. The improved SAO can be hybridized or cascaded with similar computational intelligent algorithms for improved performance.

v. The improved SAO can be applied to problems related to other fields like image and signal processing, power systems and sensor networks etc.

13. Limitations

The aim of the research is the development of an improved smell agent optimization sizing technique algorithm for a hybrid renewable energy system for off-grid use to obtain the most cost effective HRES design. This was achieved by modifying the smell agent optimization technique and this has been successfully achieved. However, it could not establish that all the molecules evaporating from a smell source are accounted for by the agent. It is assumed that the agent only makes its decision on the smell molecules it perceived.

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