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Performance Assessment of Multiple Optimizing Algorithms for Hybrid PV and Diesel Energy System Sizing

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ABSTRACT

This article assesses various optimization algorithms used to find the sizing of standalone hybrid energy system (HES) providing energy to isolated residential area load. The HES comprises three elements: photovoltaic panels (PV), diesel generators (DG). Many optimization algorithms have been assessed in this research to determine the most effective sizing of the HES in order to reduce the PV arrays, DGs number and the overall system cost hence minimizing the cost of energy (COE). The algorithms convergence time and the resulting loss of power supply probability (LPSP) are examined in this comparison. In this article, MATLAB/Simulink is used for its robust capabilities in modeling, simulating, and analyzing dynamic systems. The optimization's constraint is maintaining a reliability of 100%, ensuring uninterrupted energy supply to meet the energy demand. The results of the optimizations demonstrate that some algorithms gave different results of sizing.

1. INTRODUCTION

The rise in demand for electric energy, coupled with increased energy prices and higher reliance on non-renewable energy sources (RESs), has contributed to global warming and environmental concerns, precipitating a significant global political and economic crisis [1].

Thus, RESs hold the promise of enabling sustainable development objectives and access to dependable, clean, and secure energy. However, it faces many limitations such as nature variability, instability, and unpredictability, which degrade the supply reliability [2-5]. Hence, HES offer a promising solution to address these challenges by enhancing reliability [6], efficiency [7], and economics [8], while meeting load demands [9].

As shown in Figure 1, HES is incorporating various sources and storage technologies such as DGs and batteries for improving system stability and mitigating power, frequency, and voltage fluctuations.

Optimal design of HES necessitates appropriately sizing of its components and implementing effective energy management strategies [10-14], which play a pivotal role in continuity of power supply, prioritizing system variables, regulating energy flow [15].

These rules can enhance cost efficiency, reliability, and protection against natural damage. In this paper, MATLAB/Simulink software is utilized to evaluate the sizing optimization using intelligent techniques which require extensive computational resources thus the metaheuristic algorithms for optimization are being used [16].

These stochastic algorithms offer an efficient means of addressing real-world optimization problems by exploring diverse solution spaces. Among these metaheuristic algorithms, Simulated Annealing (SA) [17], Gray Wolf (GW) [18], Genetic Algorithm (GA) [19], Gravity Search Algorithm (GSA) [20], Ant Colony Optimization (ACO) [21], Harmony Search (HS) [22], which proved their effectiveness in optimization objectives. Thus, they are used to minimizing COE and assess how each of them suitable approach for optimizing this case study [23].

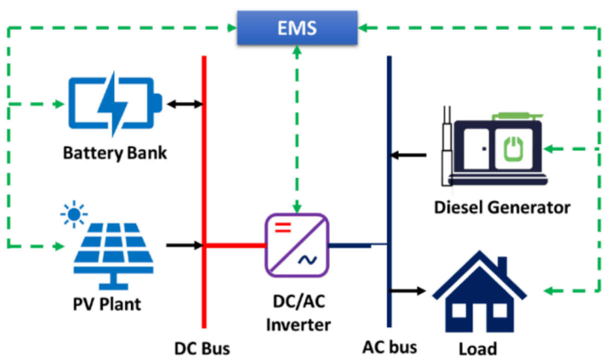

Figure 1. The model HES subjected to sizing optimization

There are many methods to find the proper sizing for HES based on the load and the characteristics of the components.

Table 1 below gives a detailed description of these methods [24].

Table 1. The main sizing methods used in HESs

Software	Computational
HOMER	Analytical
iHOGA	Iterative
HYBRID2	Probabilistic
RETscreen	AI

RESs are hindered by intermittent nature and high costs. New energy systems must integrate numerous resources in a HES with backup storage units to ensure a reliable and efficient power supply to decrease these drawbacks. Much of the world's population lives in remote, grid-less areas. Two billion people lack grid-based power, and 1.2 billion, or 17% of the world's population, lack domestic energy. Due to fuel costs and geographical complexity that makes grid extension unfeasible, conventional energy producers are inadequate in many remote areas [25].

Conventional energy sources emit the most greenhouse gases. Rural areas, especially in developing nations like Iraq and Mauritania, have economic, social, and environmental issues related to electricity supply. Distributed generating appears to be the safest and most feasible solution to these longstanding difficulties. Standalone microgrids using distributed generations are appealing for remote areas where grid connectivity is unavailable or expensive due to declining fossil resources and transmission losses [26]. Increasing DER penetration is expected to increase energy transfer among countries. Moving from centralized to decentralized fossil fuel systems increases complexity without enhancing sustainability.

RESs like wind turbines (WT) and PV provide clean energy in distributed generation systems. There is a global demand for generation models that enhance sustainable energy solutions, system performance, and resource efficiency. Fundamental energy sources such as geothermal, ocean, biomass, and biogas can be combined with other RESs [27]. Biomass and biogas are inappropriate for small household or industrial needs since they require a constant fuel source. Fuel cells complicates system design and demands careful study. Therefore, based on the limitation of each source, the expansion of using these resources are different. In Figure 2, the global consumption of energy in the current century.

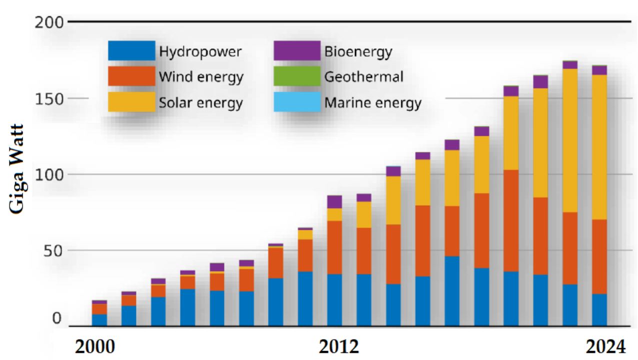

Figure 2. Worldwide renewable energy data [28]

Advanced DGs and DC loads with current power electronics have enabled HES models in DC energy systems. Therefore, HESs can AC and DC grids and a single-stage bidirectional converter to reduce energy conversion. The HES capability is essential for independent operation, especially during main grid outages and powering remote places [29]. Batteries are necessary for controlling the unpredictable nature of RESs for balancing loads while preserving stability and reliability [29]. Short-term, ESS supports the grid by meeting variable power demands and assuring energy supply stability during demand variations. When long-term generation capacity is low, ESS meets load demand. Thus, medium and small HES use batteries for short energy shortages. Power shortages and changing loads are best managed by batteries with high discharge rates and load capacities. For abrupt load shifts or HES dynamics, ESS can be added. Battery energy density is great, but supercapacitors can boost power density [30]. The limited supercapacitors' capacity limits their use. Therefore, batteries are the most used energy storage solution worldwide due to their exceptional performance. Long-term ESS foundation. Non-renewable resources like DGs require expensive upkeep and harm the environment.

This paper describes hybrid PV and DG system sizing design, installation, and operation. Case study investigates a remote northern Iraq. The isolated regions of Northern Iraq encounter a combination of economic difficulties and distinctive climate circumstances. The area experiences a primarily dry environment characterized by elevated temperatures throughout the summer and freezing winters, resulting in notable fluctuations in energy consumption patterns. From an economic standpoint, these regions frequently encounter restricted availability to dependable power networks and heavily depend on independent energy systems. In terms of population distribution, there is a low density, and villages are far dispersed, which adds to the challenges of distributing electricity and connecting to the power grid.

The study provides a comparative analytical view of many optimization algorithms to provide optimum system size details as following: PV panels number, Batteries number, DGs number that give best performance with respect to LPSP, COE, and Convergence time. This depends on system configuration and operational constraints. The design is validated using advanced simulations. This article investigates power constraints, generator prime rating capabilities, and battery bank prices to establish the best PV and BESS scale. The study optimized the grid-connected HES using technoeconomic analysis. Extra goal: improve smart grids energy efficiency. The best power flow study will determine RES locations and ratios to improve system performance.

2. RELATED WORKS

Hybrid PV/DG systems exhibit greater reliability in power generation compared to PV systems operating exclusively on PV, owing to the DG engine generation being independent of atmospheric conditions. The PV/DG combination offers increased adaptability, enhanced productivity, and financial savings without sacrificing energy output. As opposed to a DG system, a PV/DG HES emits less air pollution and has reduced operating expenses.

At present, investigations are being conducted to optimize HES through the determination of optimal storage battery capacity, DG capacity, and PV module quantity. Literature-based research focuses on identifying the optimal dimensions for hybrid PV/DG systems. Reference [31] presented a sophisticated approach to enhancing hybrid PV/DG systems.

By implementing the GA, HES generation is improved. The quantity and variety of batteries, the power of the DG, the power of the inverter, and the dispatch mechanisms are five variables that necessitate optimization. HES modeling is accomplished through the utilization of hourly PV radiation data and hourly load demand. The hourly generated current by the PV array, the intended load current, and the battery's charge level will be determined by this model. Two sections comprise the generated genetic algorithm.

The first segment aims to determine the most efficient system configuration to satisfy the load demand, considering variables including the type and quantity of parallel batteries, as well as the number and type of parallel PV panels. The objective of the second phase is to optimize, from an operational strategy standpoint, each configuration generated by the initial section. In order to determine the optimal configuration, the total cost of the system is computed with an emphasis on reducing energy expenditures. However, this study does not address certain unresolved issues, including the optimization of inverter size, the verification of hourly PV radiation data accuracy, and the assessment of the system design's dependability.

In order to ascertain the optimal system design, reference [32] optimized the control strategy of HES using GA. A vector representing the system's control is constructed, comprising five decision variables corresponding to each hour of the year. The physical implementation of the optimal vector in this optimized system and the potential impact of meteorological variables on its operation remain uncertain.

The optimal construction of a PV/DG system is illustrated in reference [33], which commences with the development of a DG model and continues with the determination of the utmost dimensions for the PV array and batteries. This is accomplished by utilizing a specific weather profile to compute the storage days and the smallest area necessary for the PV array. Developed dispatch strategies for DG operating IN HES site. The objective of this research endeavor is to determine the most cost-effective set points for starting and halting the DG. In order to forecast the long-term system cost and energy efficiency, an optimization is executed for a customary dispatch plan.

The study [34] utilized simulated WT/DG, and battery HESs to provide electricity to typical rural loads in Cameroon. For WT/DG HES, a 5 kW single-phase DG operating at a 70% load fraction is coupled with two 290W WT. A DG must be operational for 106 hours per year in order to supply this system with a 7 kWh/day burden. The proportion of RESs in the overall energy generated by the HES is computed as RESs percentage [35].

This percentage is incorporated into the design of WT/DG/ battery HES. The use of PV/DG/battery HES to power rural loads in remote regions of the far north province of Cameroon was the subject of one study. The hourly PV energy obtained by south-facing PV panels that are tilted at latitude is calculated. A 5 kW single-phase generator operating at a 70% load factor and a 1440 Wp PV array comprise HES. The configuration necessitates the operation of a DG for 136 hours per year to supply 7 kWh of power per day.

A study [36] was conducted on a battery backup DG/PV that was deployed for the benefit of a Saudi Arabian community. For system optimization, hourly PV energy data and the HOMER software are utilized. To ascertain the most advantageous configuration for the PV/DG combination, an assortment of system setups is examined, comprising four generators that vary in rated power, fuel expenses, battery capacity, and converter dimensions.

The ideal configuration comprises a 2000 kWp PV array complemented by four generators of 1250 kW, 750 kW, 2250 kW, and 250 kW, in that order. The annual operating time of the generators is 3,317, 4,242, 2,820, and 3,150 hours, respectively. By employing a DG price of 0.2$/L for size considerations, the energy unit costs for exclusive DG and PV/DG/battery systems with 21% PV penetration are calculated to be 0.190$/kWh and 0.219$/kWh, respectively. In reference [37], the HES was considered to be more economically viable in comparison to the DG system. For remote electrification, a PV/DG system is under consideration, according to research concentrating on rural and remote areas. Moreover, it is asserted that integrating DGs with RESs like PV or WT can increase system reliability and decrease initial costs.

3. HES MODELLING

The power output of PV array depends on the temperature and PV radiation levels [38]. When there is a shortfall in the energy output from the PV system, DGs operate to compensate for the deficit. However, the DG operation depends on upon the fuels availability and cost, the rate of fuel consumption over time. The PV output power is calculated in Eq. (1):

$$P^{PV}(t) = P_r \times D_r \times \left(\frac{S_{rad} \times (1 + F(T^C - T^{STC})}{S_{rad-STC}} \right) \quad (1)$$

where, $P^{PV}(t)$ is PV output power, P_r is PV rated power, D_r is derating factor of PV, S_{rad} is radiation (W/m^2), $S_{rad\text{-}STC}$ PV radiation in standard test condition (W/m^2), T^C is PV cell temperature, F is the reduction factor of $P^{PV}(t)$ due to the increase 1 Celsius of the T^C, T^{STC} is standard test temperature. DGs operate when the is extra demand that PV cannot fulfill, and Battery state of charge (SoC) is below minimum level of operation. DGs operation costs depend on fuel cost, the consumption of fuel over time (t) is calculated by Eq. (2):

$$F^C(t) = (0.25 \times P^{adg}) + (0.084 \times P^{rdg}) \quad (2)$$

where, $F^C(T)$ is fuel consumption over time, P^{adg} average output power of DG, P^{rdg} is DG rated power. The coefficients 0.25 and 0.084 in the fuel consumption formula are determined using empirical data analysis, which considers the performance characteristics of the diesel generators utilized in the study.

The coefficients indicate the rate at which fuel is consumed under specific load situations. These coefficients have been verified using data from the manufacturer and previous research. Total consumption of the fuel calculated by Eq. (3):

$$F_T^C = \sum_{t=1}^{N} F^C(t) \quad (3)$$

where, N is the HES project life span which is proposed to be 219000 hours.

The above calculation will lead to finding LPSP and COE. In Tables 2-4, parameters of units used in this HES are depicted.

Table 2. The parameters of PV penal

Type	Monocrystalline
Power (W)	300
Radiation (W/m^2)	1000
Maintenance costs ($)	10/Month
Life (Years)	20
Cost ($)	200/Panel

Table 3. Monoblock-Tubular batteries specifications

Voltage Type (V)	12
Efficiency (%)	90
Capacity (Wh)	2400
Maintenance costs ($)	0
Life (Years)	5
Cost ($)	250

Table 4. Perkins generator (DG) specificazione

Apparent Power Generation (KVA)	250
Real Apparent Power Generation (kW)	200
Frequency (Hz)	50
Maintenance costs ($)	400/month
Life (Years)	4
Cost ($)	10000/Penal

4. METHODOLOGY

In this paper, six metaheuristic algorithms are used to optimize the sizing of HES, then this method will be compared to observe the outcome of each one with respect to minimum required panels, minimum number of DGs, and minimum energy cost.

As shown in Figure 3, the sizing method use a sequence of steps to calculate the best sizing that cope with Fluctuation in the power supplied to HES. The power fluctuation rate and the standard deviation are used to describe the energy delivered fluctuation in HES.

Simulated Annealing (SA), Gray Wolf (GW), Genetic Algorithm (GA), Gravity Search Algorithm (GSA), Ant Colony Optimization (ACO) Harmony Search (HS) stand out for their effectiveness in optimization objectives. In Tables 5 to 10, the parameters of each algorithm are stated.

Table 5. Simulated annealing optimization parameters

Parameter	Value
Initial temperature (T)	100
Cooling schedule	Geometric cooling with a cooling rate 0.95
Acceptance criterion	Metropolis criterion
Convergence criteria	Maximum number of iterations 100

Table 6. Gray wolf optimization parameters

Neighbourhood Structure	Value
Population size	50
Exploration rate	0.2
Exploitation rate	0.2
Convergence criteria	Maximum number of iterations 100

Table 7. Genetic algorithm optimization parameters

Convergence Criteria	Value
Population size	50
Crossover probability	0.6
Mutation probability	0.05
Selection method	Tournament selection with tournament size is 3
Convergence criteria	Maximum number of iterations 100

Table 8. Gravity search algorithm optimization parameters

Termination Criteria	Value
Number of agents	50
Gravitational constant	0.1
Mass calculation	Proportional to fitness
Attraction coefficient	1
Convergence criteria	Maximum number of iterations 100

Table 9. Ant colony optimization parameters

Parameters	Value
Number of ants	100
Pheromone evaporation rate	0.1
Heuristic information	Inverse of distance between nodes
Convergence criteria	Maximum number of iterations 100

Table 10. Harmony search algorithm optimization parameters

Convergence Criteria	Value
Harmony memory size	50
Harmony memory consideration rate	0.9
Pitch adjustment rate	0.5
Convergence criteria	Maximum number of iterations 100

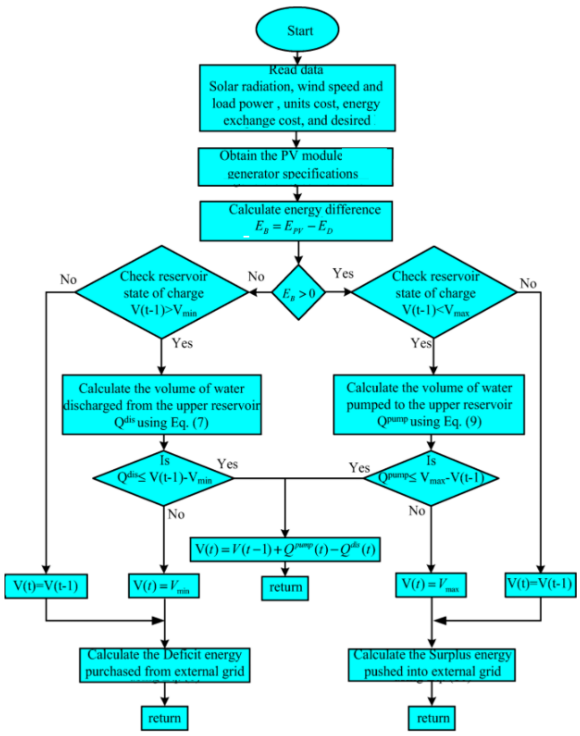

Figure 3. Flowchart describing the operation of HES

5. RESULTS AND DISCUSSIONS

Using the modelling and operation parameters the results that is required to calculate is minimum number of generation units such as PV panels and DGs. It is easy to operate the load on 2 DGs but the cost of energy will be high since the operational and maintenance costs are high.

Also, depending on PV panels only would increase the energy cost due to its high installation costs. Thus, the computing complexity and efficiency of metaheuristics algorithms will help to find the best sizing and hence the cost of energy.

The first algorithm to be assessed in HES sizing optimization is Simulated Annealing (SA). The results of SA optimized HES sizing to provide optimum system size details as following:

(1) PV panels number = 199
(2) Batteries number = 1
(3) DGs number = 1
(4) LPSP = 1.001%
(5) COE = $6.03
(6) Convergence time is 0.34 s

Figure 4 below shows the loss probability load after each iteration of SA sizing optimization.

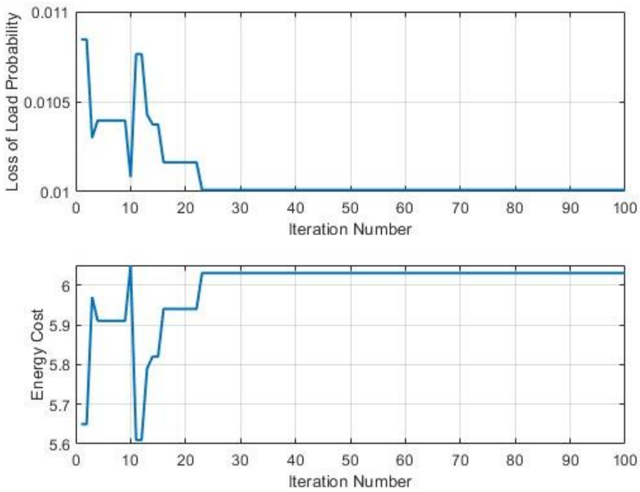

Figure 4. SA optimized HES sizing results

The second algorithm to be assessed in HES sizing optimization is Gray Wolf (GW). The results of GW optimized HES Sizing to provide optimum system size details as following:

(1) PV panels number = 198
(2) Batteries number = 1
(3) DGs number = 1
(4) LPSP = 1.006%
(5) COE = $6.00
(6) Convergence time is 0.34 s

Figure 5 below shows the loss probability load after each iteration of GW sizing optimization.

The third algorithm to be assessed in HES sizing optimization is Genetic Algorithm (GA). The results of GA optimized HES Sizing to provide optimum system size details as following:

(1) PV panels number = 199
(2) Batteries number = 1
(3) DGs number = 1
(4) LPSP = 1.001%
(5) COE = $6.03
(6) Convergence time is 0.27 s

Figure 6 below shows the loss probability load after each iteration of GA sizing optimization.

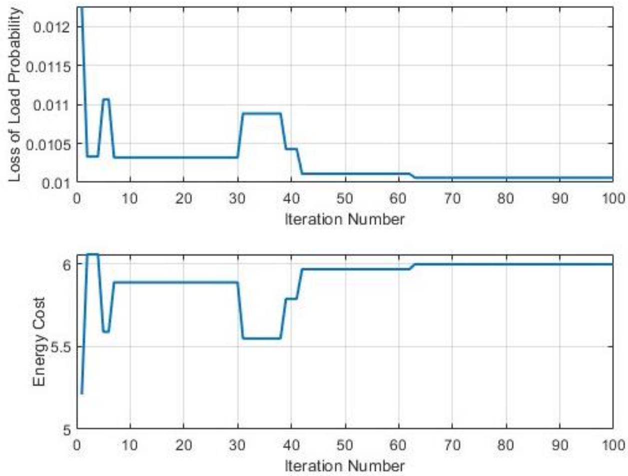

Figure 5. GW optimized HES sizing results

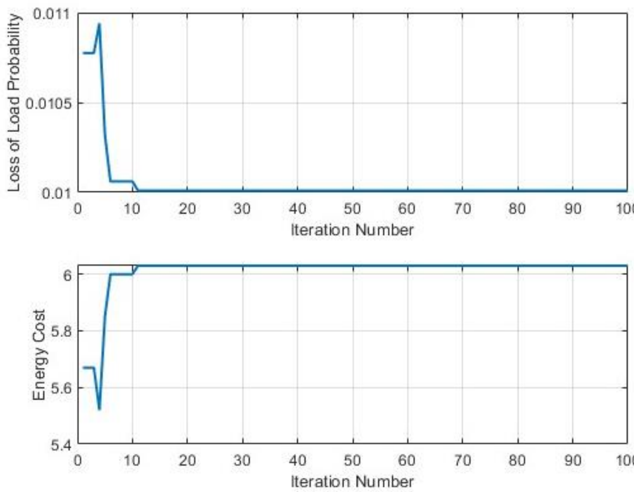

Figure 6. GA optimized HES sizing results

The fourth algorithm to be assessed in HES sizing optimization is Gravity Search Algorithm (GSA). The results of GSA optimized HES Sizing to provide optimum system size details as following:

(1) PV panels number = 198
(2) Batteries number = 1
(3) DGs number = 1
(4) LPSP = 1.006%
(5) COE = $6.00
(6) Convergence time is 0.27 s

Figure 7 below shows the loss probability load after each iteration of GSA sizing optimization.

The fifth algorithm to be assessed in HES sizing optimization is Ant Colony Optimization (ACO). The results of ACO optimized HES Sizing to provide optimum system size details as following:

The optimum system size is:

(1) PV panels number = 198
(2) Batteries number = 1
(3) DGs number = 1
(4) LPSP = 1.006%

(5) COE = \$6.00
(6) Convergence time is 0.29 s

Figure 8 below shows the loss probability load after each iteration of ACO sizing optimization.

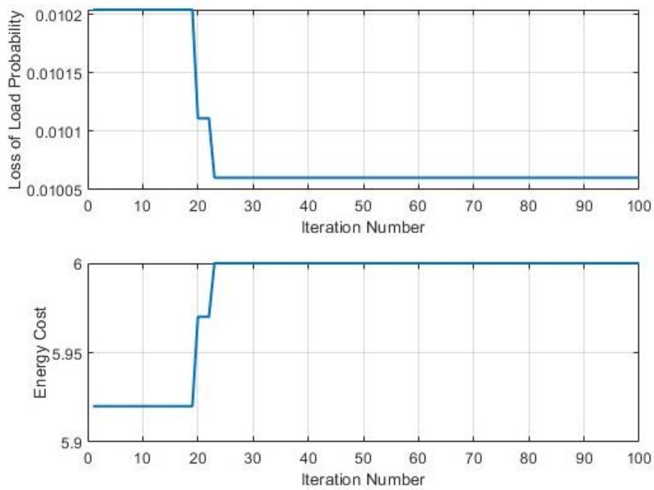

Figure 7. GSA optimized HES sizing results

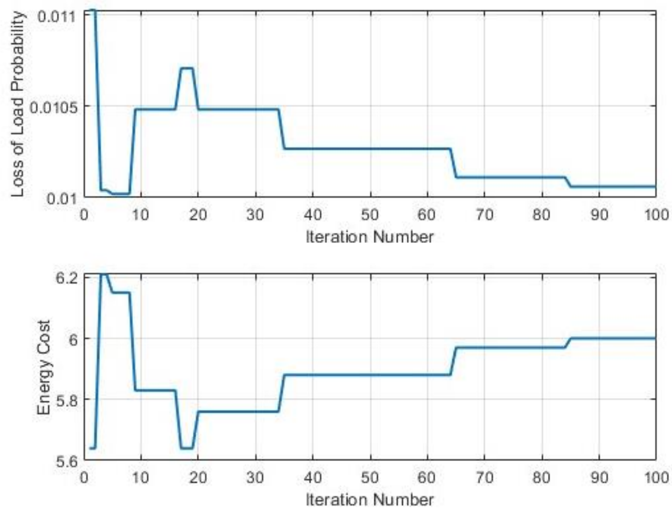

Figure 8. ACO optimized HES sizing results

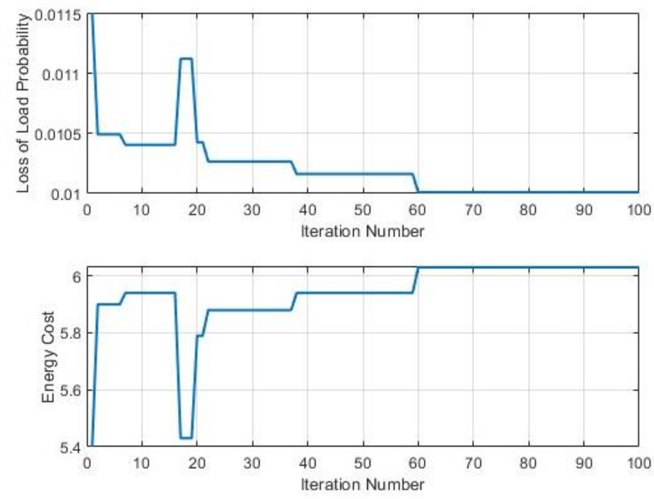

Figure 9. HS optimized HES sizing results

The last algorithm to be assessed in HES sizing optimization is Harmony Search (HS). The results of HS optimized HES Sizing to provide optimum system size details as following:

The optimum system size is:
(1) Batteries number = 1
(2) DGs number = 1
(3) LPSP = 1.001%
(4) COE = \$6.03
(5) Convergence time is 0.28 s

Figure 9 above shows the loss probability load after each iteration of HS sizing optimization.

The results show that there is algorithm optimization with superior performance with respect to LPSP such as Simulated Annealing and Genetic Algorithm. The optimization algorithms with superior performance in COE are Gray Wolf, Gravity Search Algorithm, Ant Colony Optimization, and Harmony Search. The optimization algorithms with less convergence time are Genetic Algorithm and Gravity Search Algorithm. The algorithm with the best overall sizing performance is Harmony Search which find the best LPSP with less COE and computing time. The subpar convergence of GSA and ACO algorithms is ascribed to its intrinsic tendency for thorough solution search, which is more comprehensive but slower in comparison to alternative algorithms.

6. CONCLUSION

This study extensively tested several optimization strategies for sizing standalone HES for isolated load demands. The research sought to reduce the number of PV and DGs while assuring 100% energy supply reliability and lowering COE. The study tested several metaheuristic algorithms such as Simulated Annealing, Gray Wolf, Genetic Algorithm, Gravity Search Algorithm, Ant Colony Optimization, and Harmony Search to optimize HES sizing. These algorithms produced different sizing results. Simulated Annealing and Genetic Algorithm produces a reduced LPSP, while Gray Wolf, Gravity Search Algorithm, Ant Colony Optimization, and Harmony Search produces a reduced COE. However, Genetic and Gravity Search Algorithms also converged faster. Harmony Search has the best balance, attaining optimal LPSP with low COE and convergence time. These findings emphasize the importance of choosing the right optimization algorithm for unique HES to improve RESs dependability, efficiency, and cost-effectiveness.

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