Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. **70**, *4*, pp. 447–452, Bucarest, 20xx

TECHNO-ECONOMIC BASED OPTIMIZATION OF PHOTOVOLTAIC/BATTERY/DIESEL GENERATOR MICROGRID

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Keywords: Microgrid; Photovoltaic (PV) system; Diesel generator (DG); Battery energy storage system (BESS); Techno-economic study; Wild horse optimizer (WHO).

The global adoption of renewable energy sources (RESs) is rapidly increasing to reduce greenhouse gas emissions. Algeria's abundant solar energy makes it an ideal location for installing photovoltaic (PV) systems. This research examines the techno-economic feasibility of an off-grid microgrid system powered by solar energy, combined with a battery energy storage system (BESS) and a diesel generator (DG), to supply electricity to the rural community of Ghars Boughoufala in Ouargla province, southern Algeria. The proposed system incorporates a PV/BESS/DG configuration with bidirectional DC and AC buses and converters. The study employs a load-following (LF) energy management strategy (EMS) to maintain consistent energy distribution and power supply. Optimization of the proposed configuration was performed using the wild horse optimizer (WHO) metaheuristic. WHO's performance was compared with four cutting-edge algorithms. Results showed that WHO outperforms the other algorithms in terms of convergence speed and in minimizing life cycle cost (LCC) and cost of energy (COE), with the designed microgrid achieving an LCC of 7,229,644 USD and a COE of 0.3845 $/kWh.

1. INTRODUCTION

Utilization of renewable energy sources (RESs) has been increasing to limit greenhouse gas emissions [1]. One of the most important and widely used types of RES is the photovoltaic (PV) system. Over the last decade, the installed PV capacity has increased from 39 GW to 790 GW [2, 3]. Due to its location in the Sunbelt, particularly in southern Algeria, the country offers ideal conditions for PV system installations, with its high levels of solar irradiance making it an excellent location for renewable energy projects [4]. A photovoltaic system converts sunlight directly into electricity using solar cells, making it the simplest and most environmentally friendly way to harness solar energy [5]. However, like any other energy generation system, PV systems also face specific challenges. One of the most significant is their intermittent power output [6]. To address this issue, microgrids are often employed as an effective solution [7]. A microgrid is a decentralized power system that can operate in two modes. It may operate in tandem with the main grid (grid-connected mode) or independently, relying on its own generation resources (islanded mode). A crucial component of microgrids is the energy storage system (ESS), which plays a vital role in maintaining microgrid stability by providing backup power against fluctuations in solar power output during periods of low sunlight or peak demand [8, 9]. Among the different types of ESSs used in microgrids, battery-based energy storage systems (BESS) are the most prevalent [10]. In standalone microgrids, when both the PV system and the BESS are unavailable, the diesel generator (DG) serves as the primary power source, ensuring a continuous supply of electricity to critical loads. DG provides backup power, maintains system stability, and supports load demand, guaranteeing uninterrupted operation during periods of renewable energy unavailability [11].

1.1. LITERATURE REVIEW

Numerous studies have explored the sizing of microgrid systems. These approaches can be classified into distinct groups, with the first group including deterministic techniques such as analytical methods and iterative methods [12]. Despite their simplicity, analytical and iterative methods for microgrid sizing suffer from several limitations, including computational intensity and time-consuming execution, especially for complex systems with numerous variables and constraints. Additionally, analytical methods may rely on simplifying assumptions that do not fully capture the intricacies of real-world microgrid systems. These assumptions can lead to inaccuracies in sizing recommendations, particularly in scenarios with nonlinearities or uncertainties [13]. The second group encompasses software-based methods. Software tools such as HOMER [14], RETScreen [15], TRNSYS, iHOGA [16], and Hybrid2 are commonly utilized in this group [17]. Although easy to use, software-based approaches suffer from several disadvantages. Software tools may not always capture the complexity of the physical environment, resulting in suboptimal sizing recommendations. Additionally, software often relies on input data that may not fully reflect local conditions or be outdated, further impacting the accuracy of the sizing process. Finally, the assumptions and algorithms embedded in software programs may not always align with the specific requirements or constraints of a particular microgrid project, leading to results that are not fully applicable or feasible in practice [18]. The third group consists of approaches based on optimization algorithms. When employing this approach in microgrid sizing, numerous advantages can be observed. Nonlinear and discrete optimization entail solving intricate problems in which variables can assume nonlinear or discrete values. These methods offer significant computational efficiency, providing solutions efficiently. Moreover, they offer a diverse selection of optimization models and optimizers to accommodate various optimization requirements, thereby enhancing system performance and resilience [19].

Numerous optimization-based approaches have been employed in the literature to address microgrid sizing problems. Diab et al. [20] proposed a technique based on the equilibrium optimizer (EO) to determine the optimal sizing of a microgrid that includes PV, fuel cells, and batteries in the El Dobaa region of Egypt. They compared the EO with two other algorithms and evaluated performance using the cost of energy (COE) metric. The results revealed that the EO algorithm outperforms the alternatives. Belboul et al. [21] investigated a microgrid configuration consisting of PV, wind turbines, batteries, and diesel generators to meet residential energy demands. The study applied the multi-objective salp swarm algorithm (SSA) as the primary optimizer and compared it with the Dragonfly

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DOI: 10.59277/RRST-EE.2025.70.4.3

algorithm (DA), Grasshopper optimization (GO), and ant lion optimizer (ALO). Performance was evaluated in terms of the cost of energy (COE) and the probability of power supply loss (LPSP). The results showed that SSA outperformed the alternative algorithms in achieving the best COE and LPSP values. A grey wolf optimization-based method for microgrid sizing was proposed by Yadav et al. [22]. The microgrid in India comprised a wind turbine, a photovoltaic system, pumped-hydro storage, and a battery. The optimization task aimed to reduce the levelized cost of energy (LCOE). Parvin et al. [23] investigated the use of a multi-objective particle swarm optimization algorithm to determine the size of a microgrid system in Iran. The setup included a photovoltaic system, a wind turbine, and combined heat and power, forming a microgrid with PV, WT, and CHP components. The suggested approach efficiently reduces both energy costs and power supply losses.

1.2. PAPER CONTRIBUTIONS

This study examined the techno-economic feasibility of providing electricity to a rural community in Ghars Boughoufala, Ouargla province in southern Algeria. To ensure an uninterrupted power supply, the analysis included a pure lead-carbon (PLC) BESS. Additionally, the study considered the operation of a diesel generator (DG) under a load following (LF) energy management strategy. To determine the optimal system size, this work applies a recently developed nature-inspired optimization algorithm, the WHO [24]. In this study, the robustness and efficiency of WHO are benchmarked against four recognized metaheuristic algorithms: SSA, PSO, GWO, and EO.

The core contributions of this study include:

- Introducing the use of the WHO algorithm for optimal sizing of a PV/BESS/DG integrated microgrid.
- Demonstrating the effectiveness of LF-based EMS in managing energy flow between the various microgrid components.

2. **MICROGRID COMPONENTS MODELING**

The standalone microgrid proposed in this study consists of three main components: a SEGS as the renewable source, a BESS, and a DG as the backup source as depicted in Fig. 1. The system adopts a simplified approach to handle excess energy in islanded mode by using a dump load (DL), as the primary objective of the study is to size the microgrid to meet the local energy demand optimally. The DL, DG, and load are linked to the AC bus, whereas the BESS & SEGS are linked to the DC bus via converters (BCC).

2.1 SEGS MODELING

PV power generation is a technology that converts sunlight directly into electricity using PV cells. PV power generation is a clean, renewable, and sustainable energy source that can be used in a variety of applications. Various modeling paradigms have been proposed in previous research to estimate PV system power output. This paper utilized a simple approach to determine the PV panel's output power, considering hourly ambient temperature and hourly solar irradiation specific to the study zone, as shown in eq. (1). This SEGS model aims to provide a straightforward and efficient way to estimate the PV power output [25].

$$P_{PV}(t) = P_R \times \left(\frac{G(t)}{G_R}\right) \times [1 + K_T \times (T_C - T_R)], \tag{1}$$

where P_{PV} is the output power of the PV panel, P_R is the rated power of the PV panel, G is the hourly solar irradiation, G_R is the solar irradiance at reference condition (1000 W/m^2), K_T is temperature coefficient of the maximum power (3.7×10^{-3} 1/°C), T_R is photovoltaic cell temperature at the standard condition (25°C), T_C is PV cell temperature and it is calculated as follows:

$$T_C = \left(0.0256 \times G(t)\right) + T_A(t), \tag{2}$$

where, T_A is the ambient temperature at given hour.

Finally, the total energy generated by the SEGS can be calculated as follows:

$$E_{SEGS}(t) = P_{PV}(t) \times N_{SEGS}. \tag{3}$$

where, N_{SEGS} is the total number of needed project PV panels.

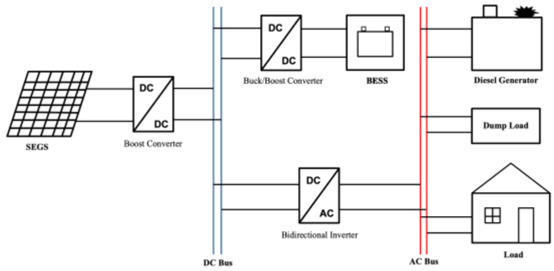

Fig. 1 – Proposed microgrid system diagram.

2.2 BESS MODELING

BESS stores electricity generated from SEGS during low-demand periods for later use, providing both backup power and grid stabilization. A BESS is a group of rechargeable batteries that store energy efficiently and can be deployed at various scales, from residential to utility-level installations. These systems fulfill a vital function in integrating renewable energy into the grid and enhancing energy reliability and flexibility. The charging process of BESS involves storing surplus energy generated by SEGS in batteries. This stored energy can then be used when the primary power source is not available or during periods of high demand. In the discharge phase, the electricity produced by SEGS falls short of the load demand. As a result, the BESS balances this power difference. The process of BESS charging and discharging is described as follows [26]:

$$\begin{aligned} E_{BESS}(t) &= (1-\sigma) \times E_{BESS}(t-1) + \\ &+ \left(E_G(t) - \frac{E_L(t)}{\eta_C}\right) \times \eta_{EC} \times \eta_{RB}, \end{aligned} \tag{4}$$

$$\begin{aligned} E_{BESS}(t) &= (1-\sigma) \times E_{BESS}(t-1) - \\ &- \left(\frac{E_L(t)}{\eta_C} - E_G(t)\right) / \eta_{RB}, \end{aligned} \tag{5}$$

where, $E_{BESS}(t)$ and $E_{BESS}(t-1)$ represents the levels of energy of BESS at two different time, E_G represents entire produced energy, E_L is the energy demand, σ is the specific BESS self-discharge rate, η_C represents bi-directional converter efficiency coefficient, η_{RB} represents BESS round trip efficiency and η_{EC} is controller efficiency coefficient.

The generated energy can be calculated as:

$$E_G(t) = E_{SEGS}(t) \times \eta_C. \tag{6}$$

2.3 DG MODELING

DG has an important role in standalone microgrids by providing energy in situations where BESS cannot meet load demand, or when SEGS face prolonged uncertainties due to persistent cloudy weather or during nighttime. Therefore, integrating DGs into the microgrid enhances its power reliability by offering a dependable energy source in emergencies and helping to meet peak load demands when BESS falls short. The instantaneous fuel consumption of the diesel generator can be computed applying a simple equation that depends on the demanded load, as expressed by [27]:

$$F_{DG}(t) = (\alpha_{DG} \times P_{DG}(t) + \beta_{DG} \times P_{DGR}), \qquad (7)$$

where, F_{DG} is the DG hourly fuel consumption, α_{DG} and β_{DG} map the DG curve of consumption, with respective values being: α_{DG}=0.246 (l/kWh), β_{DG}=0.08145 (l/kWh). P_{DG} and P_{DGR} are, respectively, the DG's generated power and its rated power.

Fuel consumption in a DG refers to the amount of diesel fuel the generator burns to produce electrical energy. It is typically measured in liters and depends on factors such as the generator's load, efficiency, and size. The DG cumulative yearly fuel usage (TAFC) can be calculated as follows:

$$\mathrm{TAFC} = \sum_{t=1}^{8784} F_{DG}(t). \qquad (8)$$

2.4 ENERGY MANAGEMENT STRATEGY

In this paper, the LF method is employed as the EMS. This strategy involves adjusting power generation in real time to match fluctuations in energy demand. The fundamental principle behind the LF strategy is that DG steps in to cover any shortfall in energy demand when the BESS and SEGS cannot meet it. It primarily focuses on supplying power to cover the deficit demand without diverting energy towards charging BESS [28]. In terms of performance, LF outperforms other EMS options such as cycle charging and combined dispatch [29]. The comprehensive operation of the load following EMS is detailed throughout the subsequent operation states:

- State 1: The operational sequence involves the SEGS initially attaining the load demand, followed by the storage of any surplus energy generated in BESS, ensuring that the energy demand is met.
- State 2: In this state, the SEGS first handles the load demand. Subsequently, if the BESS reaches its maximum capacity, any surplus energy is to be linked to the shunt load.
- State 3: The scenario involves this state of operation, where the SEGS-generated energy falls short of meeting the load demand. Consequently, the BESS will compensate for the deficit load. Figure 2 represents the proposed EMS flowchart used in this study.

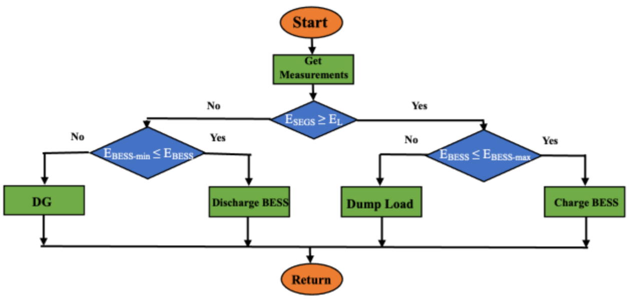

Fig. 2 – The proposed LF-based energy management strategy.

2.5. CHARACTERISTICS OF THE STUDY AREA

The proposed standalone microgrid is intended to be situated in Ghars Boughoufala, Ouargla province, in the south of Algeria (32.1249° N, 5.3701° E). The studied village is a rural community comprised of 108 households and 44 farms. The load demand of the study area is estimated based on the needs of the local population. This estimated load takes into account various power needs of the local population, including domestic, community (community Hall, streetlights, primary school, hospital, and mosque), agricultural (water pumps), and commercial (shops). To simplify load demand estimation in the study area, the year has been divided into two distinct seasons: the summer season (May-October) & the winter season (November-April). Figure 3 represents the estimated hourly energy demand (E_L) of the studied area. The high energy demand observed during the summer season is mainly due to the extreme heat in Algeria's southern region, which drives extensive air conditioner use. Another contributing factor is the operation of water pumping motors to extract groundwater for crop irrigation. The utilized solar irradiance is shown in Fig. 4, and the temperature variations are shown in Fig. 5. In this study, the meteorological data were collected in 2020, which was a leap year (8,784 hours).

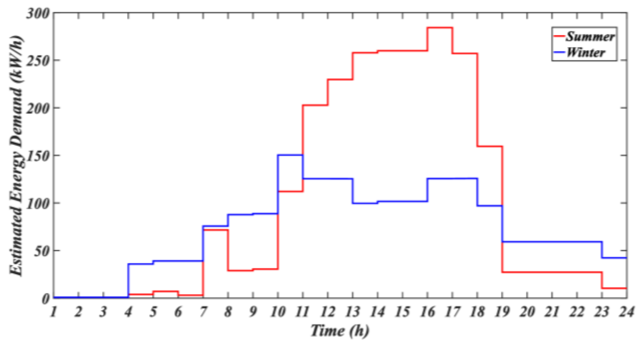

Fig. 3 – Estimated energy demand of summer - winter day.

3. MICROGRID ECONOMIC ANALYSIS

To determine the financial soundness of microgrid designs, many approaches have been investigated in the literature [30]. In this paper, we have utilized the life cycle cost (LCC) objective function. LCC method is a comprehensive accounting technique that considers all costs associated with the designed system over its entire lifespan, including initial costs of components, operational costs like maintenance, and fuel consumption, microgrid components replacements costs, for that the LCC method allows for informed decision-making by providing a complete picture of the total cost of ownership, enabling organizations to make more strategic investments and reduce overall costs over the long term [31]. The LCC is calculated by summing the total initial capital cost (TICC), the total installation cost (TIC), the total actual of annual operation & maintenance (O&M) cost value ($TAV_{O\&M}$), the total actual of the annual fuel cost value (TAV_F), the value of total actual annual replacement cost (TAV_R) as given by the following equation:

$$\mathrm{LCC} = \mathrm{TICC} + \mathrm{TIC} + \mathrm{TAV}_{O\&M} + \mathrm{TAV}_{F} + \mathrm{TAV}_{R}. \qquad (9)$$

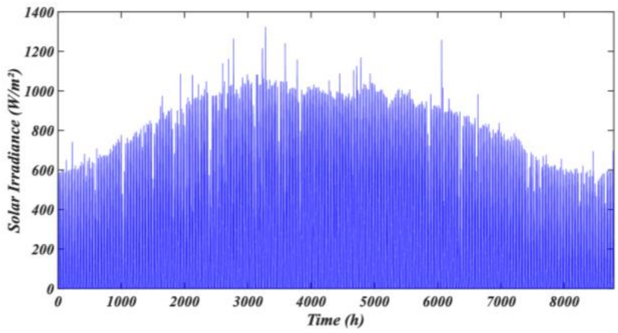

Fig. 4 – Annual solar irradiance of Ghars Boughoufala.

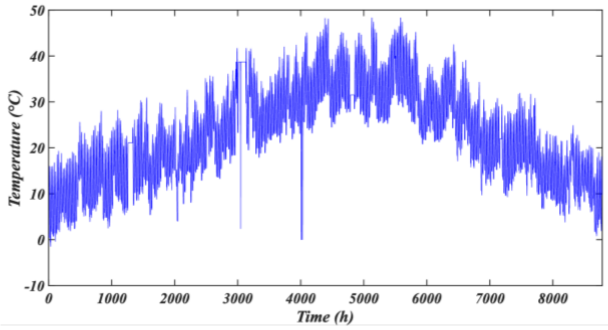

Fig. 5 – Annual temperature of Ghars Boughoufala.

4. **PROBLEM FORMULATION**

The following discussion addresses objective functions, including LCC and COE, alongside boundaries associated with the DG, SEGS and BESS.

4.1 LCC OBJECTIVE FUNCTION

Objective function presented in eq. (10) is aiming to minimize the designed microgrid LCC while adhering to imposed limiting factors. LCC primarily relies on two selection variables: the solar panels number that constitutes the SEGS (N_{SEGS}) and the batteries number that constitutes BESS (N_{BESS}).

$$\min \mathrm{LCC}(\mathrm{N_{SEGS}}, \mathrm{N_{BESS}}) = \sum_{\mathrm{C=SEGS,BESS,BCC,DG}}^{\min} (\mathrm{LCC})_{\mathrm{C}}. \quad (10)$$

4.2 COST OF ENERGY

The cost of energy (COE) stands as a paramount parameter extensively deployed in evaluating the economic viability of the microgrid [32]. Calculated as follows:

$$\mathrm{COE}\ (\$/\mathrm{kWh}) = \frac{\mathrm{LCC}}{\sum_{t=1}^{8784} \mathrm{E_L(t)}} \times \mathrm{CRF}, \quad (11)$$

where, CRF represents the capital recovery factor [33] and it is calculated as follows:

$$\mathrm{CRF} = \frac{\mathrm{z} \times (1+\mathrm{I_N})^{\mathrm{N}}}{(1+\mathrm{I_N})^{\mathrm{N}} - 1}, \quad (12)$$

where, N is the life span of the project and I_N is the nominal interest rate.

4.3 SEGS BOUNDS

Additionally, the SEGS is subjected to the following constraints.

$$0 \le \mathrm{N_{SEGS}} \le \mathrm{N_{SEGS-max}}, \quad (13)$$

where N_{SEGS} is SEGS PV panels count.

4.4 BESS BOUNDS

The modeling of BESS amount of energy that can be at specified time (h) is restricted utilizing [34]:

$$\mathrm{N_{BESS-min}} \le \mathrm{N_{BESS}(t)} \le \mathrm{N_{BESS-max}}. \quad (14)$$

The allowable BESS working limits of energy are calculated as:

$$\mathrm{E_{BESS-max}} = \left(\frac{\mathrm{N_{BESS}} \times \mathrm{V_{BESS}} \times \mathrm{C_{BESS}}}{1000}\right) \times \times \mathrm{SoC_{BESS-max}}. \quad (15)$$

$$\mathrm{E_{BESS-min}} = \left(\frac{\mathrm{N_{BESS}} \times \mathrm{V_{BESS}} \times \mathrm{C_{BESS}}}{1000}\right) \times \times \mathrm{SoC_{BESS-min}}. \quad (16)$$

where, C_{BESS} and V_{BESS} are BESS rated capacity and BESS voltage.

The allowable BESS working limits of SoCs are calculated as outlined below:

$$\mathrm{SoC_{BESS-min}} = 1 - \mathrm{DoD}. \quad (17)$$

$$\mathrm{SoC_{BESS-max}} = \mathrm{SoC_{BESS-min}} + \mathrm{DoD}, \quad (18)$$

where DoD is BESS depth of discharge.

4.5 DG BOUNDS

The diesel generator demonstrates greater efficiency when operating at elevated loads. This condition prevents DG operation at very low loads, which are inefficient and result in excessive fuel consumption. The constraint thus guarantees that the generator contributes power only in its efficient range. DG will engage in simulation only after adhering to this prescribed limitation [35]:

$$\frac{E_L(t)}{\eta_{\mathrm{C}}} \ge \mathrm{P_{DGR}}. \quad (19)$$

5. **RESULTS AND DISCUSSION**

This research paper explores the optimal sizing of a standalone microgrid system. The setup incorporates PV renewable energy resource (SEGS) and PLC-based BESS alongside a DG. Table 1 presents the cost and characteristics of the utilized BESS technology, and Table 2 presents the cost and characteristics of SEGS/Converter/DG, along with the economic characteristics of the project. The configuration is examined using the LF dispatch strategy and subjected to analysis through five metaheuristic algorithms: SSA, PSO, GWO, EO, and WHO. The algorithms are executed with default parameters. For the PSO and GWO algorithms, the population limit is 100, and for SSA, EO, and WHO, the population limit is 30, with 100 maximum of iterations.

Table 1

Cost and characteristics of PLC BESS.

BESS type	Pure Lead Carbon (PLC)
Manufacturer	Leoch Battery
Model	PLH100FT 12V/100Ah
Nominal voltage	12 V
Nominal capacity	100 Ah
Round trip efficiency	85%
Lifespan (year)	3 at DOD = 70%
Self-discharge rate	0.3%
Capital cost ($)	410
Annual O&M cost ($)	2.5 of capital cost
Operating temperature	Discharge: −40 °C to +65 °C Charge: 0 °C to +54 °C

Life cycle	800 cycles at DOD = 70%

Table 2

Cost and characteristics of SEGS/Converter/DG and economic characteristics of project.

SEGS		DC/AC Converter	
Manufacturer	SpolarPV	Rated power	60 kW
Model of PV Panel	SPV420-PM10-108	Lifetime	10 Year
Rated power of PV Panel	410 W	Capital cost	6875 $
Panel Lifetime	20 Year	O&M	15 $
Capital cost	266 $	Efficiency	95%
PV O&M	3.2 $	DG	
PV Mechanical structure cost	41 $	Manufacturer of DG	Volvo
Life time of mechanical structure	25 Year	Model of DG	DB-68GF-85KVA
PV panel AO&M	3.2 $	Capital cost of DG	6550 $
Economic characteristics			
Project lifetime	20 Year	Inflation rate	0.048
Nominal interest rat	0.03	Diesel price	0.34 $

5.1. CONVERGENCE EFFICIENCY OF WHO

The convergence curves of the five utilized algorithms for the microgrid are presented Fig. 6, the proposed setup achieved the minimum LCC (7,229,644 USD) with PSO, EO, SSA and **WHO** algorithms, reaching the highest optimal value at 55th, 82nd, 69th and **38th** iterations successively, while GWO reached another higher value (7,231,979 USD) at the 90th iteration.

Based on the preceding analysis, it is evident that the proposed WHO algorithm exhibits rapid convergence rates, outperforming other algorithms' rates and outperforming other algorithms in swiftly identifying the optimal solution, as stated for addressing microgrid size challenges due to its high convergence speed and its efficient capability in locating the optimal LCC.

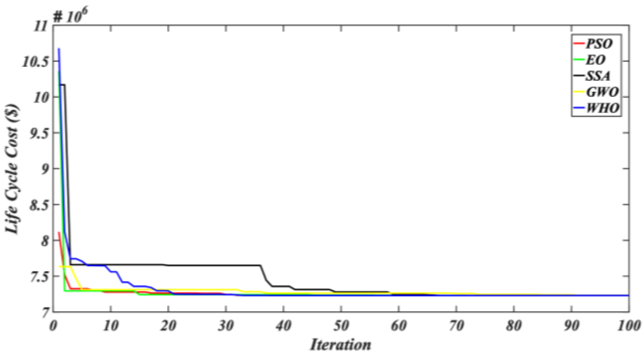

Fig. 6 – Convergence curves of the PLC-BESS-based microgrid.

5.2 MICROGRID CONFIGURATION EVALUATION

Table 3 describes the optimization results of PLC-BESS based microgrid configuration along with the mean elapsed time of one iteration (METI) of each optimization algorithm, according to the table it is observed that, the four-optimization methods converge to minimum LCC of (7,229,644 USD) except for GWO that converge to LCC of value 7,231,979 USD with difference of 0.03%, and for the COE the algorithms converge to value of 0.3845, the optimal setup composed of 4,379 N_{SEGS} and 554 N_{BESS} and consumes 11,659 l of fuel in the year. It is also observed that the EO algorithm exhibits the lowest METI, with differences of 108%, 0.45%, 107%, and 5.14% compared to the PSO, SSA, GWO, and WHO optimization algorithms, respectively.

Table 3

Optimization results of the PLC-BESS based microgrid

	N_{SEGS}	N_{BESS}	TAFC	LCC ($)	COE ($/kWh)	METI (s)
PSO [23]	4,379	554	11,659	7,229,644	0.3845	29.8040
EO [20]	4,379	554	11,659	7,229,644	0.3845	8.9093
SSA [21]	4,379	554	11,659	7,229,644	0.3845	8.9496
GWO [22]	4,383	554	11,658	7,231,979	0.3846	29.5891
WHO	4,379	554	11,659	7,229,644	0.3845	9.3798

6. **CONCLUSION**

This research paper proposes a method for optimally sizing a stand-alone microgrid system energized by a solar energy generation source (SEGS), combined with a diesel generator (DG) and battery energy storage system (BESS), composing hybrid microgrid configuration, referred to as SEGS/BESS/DG, the microgrid includes two buses a direct current (DC) bus as well as another alternating current (AC) bus which are bi-directionally linked through a converter. The key objective of the designed standalone microgrid is to meet the energy demands of a rural community in Ghars Boughoufala, Ouargla province, in southern Algeria. To achieve this, the paper proposes an optimization design using the wild horse optimizer (WHO), a nature-inspired metaheuristic, to minimize the life-cycle cost (LCC) and the cost of energy (COE). In order to get the best configuration in terms of cost and guarantee a steady power supply, the study examines Pure Lead Carbon (PLC) as BESS and based on a load following (LF) energy management strategy (EMS). To demonstrate the robustness and efficiency of the Wild Horse Optimizer (WHO) algorithm, it is matched with four other verified methods in the MATLAB environment. The results indicate that the proposed WHO algorithm consistently finds the best optimal solutions for both LCC and COE, outperforming other algorithms. Moreover, the WHO algorithm's fast convergence efficiency property proves its capability in getting a favorable optimal solution quickly. The results reveal that the microgrid powered by PLC batteries achieves the lowest LCC and COE of 7,229,644 USD and 0.3845 $/kWh, respectively. This study aims to offer support on electricity supply to alike off-grid microgrid projects, in order to contribute to the economic growth, creating job opportunities for locals and reducing polluted emissions.

CREDIT AUTHORSHIP CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: A. F, M. B, A, D; draft manuscript preparation: A. F, M. B, A, D; software: A. F, M. B, A, D; analysis and interpretation of results: A. F, M. B, A, D. All authors reviewed the results and approved the final version of the manuscript.

Received on 6 November 2024

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