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Optimal Selection and Efficient Utilization of Particle Swarm Optimization Methods for Designing Renewable Energy Microgrids

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Abstract:
In recent years, renewable energy sources have gained significant attention. Optimizing small-scale renewable energy systems plays a crucial role in effectively and economically using these resources. Particle Swarm Optimization (PSO) is a popular stochastic optimization method widely applied in various fields. However, standard PSO techniques face challenges, including high computational complexity and rapid convergence rates. This study presents a modified PSO, Comprehensive Learning Particle Swarm Optimization (CLPSO), and Generalized PSO (GEPSO) techniques to optimize the capacity sizing of hybrid power generation systems. These systems include photovoltaic (PV), wind, and battery units to supply power to an Information and Communication Technology (ICT) center. The research evaluates two scenarios: a standalone system with PV, wind, and battery units and a grid-connected system with PV and wind units. Results demonstrate that the CLPSO technique significantly reduces overall investment costs compared to standard PSO, MPSO, and GEPSO algorithms by 53.34% and 27.28% for standalone and grid-connected systems, respectively. Furthermore, CLPSO reduces computation time by 57.9% in grid-connected systems and improves energy procurement efficiency, decreasing the required energy purchased from the grid by up to 11.84%. Ultimately, CLPSO outperforms other PSO techniques in terms of both precision and efficiency, making it the most suitable method for solving optimization problems in renewable microgrid design.

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1. Introduction

The rapid growth in global energy demand, combined with increasing concerns over environmental sustainability and the depletion of fossil fuels, has shifted the focus toward the use of renewable energy sources. Electricity, now essential to daily life, powers homes, industries, and commercial facilities. As traditional power grids expand to meet these growing needs, alternative systems like microgrids have emerged as crucial solutions. A microgrid is a small-scale, localized power system that balances its supply and demand using distributed generation (DG) units and energy storage systems (ESS). These systems can operate autonomously or alongside the central grid, ensuring reliable energy supply even during grid failures. This adaptability and resilience have led to a significant rise in the development of microgrids, driven primarily by the demand for higher reliability, advancements in renewable energy technologies, and concerns about the environmental impacts of fossil fuels [1, 2].

Microgrids, often incorporating renewable energy sources such as photovoltaic and wind turbines, effectively enhance grid stability and promote sustainable energy use. Wind and solar energy are attractive because of their accessibility and decreasing costs due to advancements in technology. However, the variability of renewable energy, caused by factors like wind speed fluctuations and changes in solar radiation, presents a critical challenge for microgrid operators. The balance between energy production and consumption in a microgrid can be difficult to maintain, particularly when these fluctuating renewable sources dominate the energy mix. A common solution is to integrate the microgrid with the central power grid, allowing it to draw on the main grid during periods of low production and export surplus energy when production exceeds local demand. When grid connection is not feasible or desired, energy storage systems, typically composed of batteries, become essential for stabilizing the grid and improving system efficiency by storing excess energy for later use [3-5].

Given the increasing reliance on renewable energy in microgrids, the optimization of these systems has become a focal point of research. Optimizing the design of a

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microgrid involves determining the best combination of DG units and energy storage systems to meet the local demand while minimizing both capital and operational costs. These costs encompass the investment in renewable generation units (such as wind turbines and PV panels) and energy storage systems, as well as the ongoing operational costs related to energy management and grid maintenance. With the increasing complexity of microgrid configurations, traditional mathematical optimization methods have proven insufficient due to their inability to manage the nonlinear and large-scale nature of the optimization problem. Therefore, heuristic approaches such as Particle Swarm Optimization (PSO) have been widely adopted as more efficient solutions [6].

PSO, a popular metaheuristic optimization method, simulates the social behavior of particles moving through a solution space in search of an optimal solution. While PSO has been applied to various problems, including microgrid design, it faces challenges such as premature convergence, high computational costs, and limited performance in large or complex scenarios. To address these shortcomings, several variants of PSO, such as Modified PSO (MPSO), Comprehensive Learning PSO (CLPSO), and Generalized PSO (GEPSO), have been proposed. Despite these advancements, a clear gap remains in the literature concerning their application to the specific challenges posed by microgrid design, particularly in hybrid renewable systems combining wind, solar, and battery storage [7-9].

One of the primary challenges in microgrid design is balancing the fluctuating energy supply from renewable sources with the demands of the grid. Singh et al. [10] addressed the critical role of ESS in stabilizing microgrids, particularly those incorporating wind and solar power. According to Singh's work, ESS is vital in mitigating the inherent variability of these energy sources, allowing for a more consistent power supply. In addition to stabilizing the grid, ESS also contributes to overall system efficiency by storing excess energy during periods of high generation and discharging it during periods of low renewable generation or high demand.

Parhizi et al. [11] and Obarra [12] explored the potential of microgrids to reduce dependence on traditional power grids, particularly in remote or isolated areas where the extension of central grid infrastructure is impractical or cost-prohibitive. These studies highlighted the potential of microgrids to enhance energy reliability and resilience, particularly in areas prone to natural disasters or where the threat of grid disruptions due to geopolitical factors is high.

Wang investigated various optimization models for microgrids, focusing on the integration of distributed generation units and energy storage systems. The study developed an optimization framework that sought to minimize both capital and operational costs while maximizing the reliability and efficiency of the microgrid [13].

The use of heuristic optimization techniques, particularly PSO, has gained prominence in recent years as an alternative to more traditional methods. PSO, a population-based optimization algorithm inspired by the social behavior of birds and fish, has been applied to various problems in power system optimization. Studies by Obarra [12] and Sheng et al. [14] demonstrated the effectiveness of PSO in solving nonlinear and high-dimensional optimization problems, particularly those involving renewable energy integration in microgrids. However, these studies also noted limitations in the standard PSO algorithm, including its tendency to converge prematurely and high computational complexity.

To address these limitations, several modified versions of PSO have been proposed. One such variant, the MPSO, was explored by Cao et al. [15] in the context of microgrid design. The study found that MPSO offered improved convergence speed and solution accuracy compared to the standard PSO algorithm, particularly in scenarios involving complex microgrid configurations. Another advanced PSO variant, CLPSO, was introduced by Obarra [12] as a solution to the premature convergence problem. CLPSO encourages particles to learn from the best solutions in the entire population rather than being restricted to their local neighbourhoods, which improves global search capability and reduces the risk of being trapped in local optima.

More recently, the GEPSO algorithm has been developed to refine the original PSO technique further. GEPSO incorporates elements of genetic algorithms, such as mutation and crossover, to enhance its exploratory capabilities. Although GEPSO has shown promise in other optimization fields, its application to microgrid design remains relatively unexplored. The study by Cao et al. [15] highlighted the potential of GEPSO in optimizing microgrid configurations but called for more research to compare its performance with other PSO variants in the specific context of renewable energy microgrids.

Finally, the environmental benefits of renewable energy microgrids have also attracted considerable attention in the literature. The work of Zia et al. [16] and Hatzisargyriou [17] emphasized the potential for microgrids to reduce greenhouse gas emissions by replacing fossil-fuel-based power generation with renewable sources. These studies showed that by optimizing the configuration of wind, solar, and storage systems, microgrids could significantly reduce carbon emissions while maintaining a reliable energy supply. However, there remains a lack of comprehensive studies that compare the environmental performance of different microgrid configurations and optimization techniques.

The primary gap in existing research lies in the comparative analysis of different PSO variants in the context of hybrid microgrid optimization. Most studies have applied standard PSO or similar heuristic algorithms without exploring the full potential of advanced PSO techniques, particularly in handling the nonlinear, large-scale optimization problems typical of microgrid design. Furthermore, few studies have considered the broader range of renewable energy sources (i.e., both wind and solar) alongside energy storage systems in standalone and grid-connected configurations. As a result, the specific benefits of using CLPSO and GEPSO for optimizing microgrid design, especially in terms of minimizing investment costs, operational costs, and computation time, remain underexplored.

This study aims to address these gaps by applying advanced PSO techniques—specifically, CLPSO, MPSO, and GEPSO—to optimize the design of a hybrid renewable energy microgrid. The optimization process involves selecting the most efficient combination of wind turbines, PV panels, and energy storage systems to meet the energy demands of an ICT (Information and Communication Technology) center while minimizing both capital and operational costs. A key objective of this research is to determine the most effective configuration of renewable energy units and storage systems under two distinct scenarios: one in which the microgrid operates independently from the central grid and another in which it is connected to the grid. By comparing the performance of CLPSO, MPSO, and GEPSO across these scenarios, this study seeks to identify the most efficient method for hybrid microgrid optimization.

The novelty of this research lies in its application of CLPSO and GEPSO to the problem of hybrid microgrid design. While these techniques have been applied to other optimization problems in power systems, this is the first study to use them for optimizing the capacity and configuration of hybrid renewable energy microgrids. CLPSO has shown promise in other areas of power system optimization but has not yet been applied to microgrids. This research also compares CLPSO, MPSO, and GEPSO, providing insights into their relative performance in terms of cost reduction, computational efficiency, and solution accuracy. Another novel aspect of this study is its focus on both standalone and grid-connected microgrid configurations, enabling a broader understanding of how different optimization techniques perform under varying operational conditions.

In addition to optimizing microgrid performance, this study examines the environmental benefits of integrating renewable energy into microgrids. By reducing the reliance on fossil-fuel-based power generation, renewable energy microgrids can significantly lower carbon emissions and contribute to global sustainability goals. This research evaluates the impact of different microgrid configurations on both energy costs and environmental performance, highlighting the potential for renewable energy to play a key role in future power systems.

Ultimately, this research aims to demonstrate that CLPSO is a more efficient optimization technique than traditional PSO, MPSO, and GEPSO for hybrid microgrid design. Through detailed simulations and a comprehensive comparison of these methods, this study contributes to the growing body of knowledge on renewable energy microgrids and offers practical insights for optimizing their design and operation. The results are expected to have implications not only for the academic community but also for policymakers and engineers seeking to design cost-effective and environmentally sustainable energy systems.

2. Methodology

This study focuses on the integration of renewable energy sources like wind and PV systems with energy storage (battery) systems. The primary objective is to minimize the total investment and operational costs while ensuring that energy demand is reliably met through the hybrid system. PSO, including its variants such as CLPSO, MPSO, and GEPSO, is employed to solve this optimization problem.

An optimal renewable microgrid design has been proposed for powering the Information and Communication Technology Center at Mansoura University in Egypt [18]. This design incorporates wind turbines and PV units as renewable energy sources, coupled with batteries for energy storage. To ensure accurate modeling, the design also considers the costs associated with power inverters connecting the wind and PV units to the microgrid, as well as PV controllers.

The microgrid operates in two distinct modes: grid-connected and off-grid. In the off-grid mode, the battery storage system becomes active, storing excess energy during periods of surplus and supplying energy during periods of deficit. Conversely, in the grid-connected mode, the battery is inactive, allowing the microgrid to sell excess energy to the main grid or purchase energy when needed.

A schematic representation of the proposed microgrid system is shown in Figure 1.

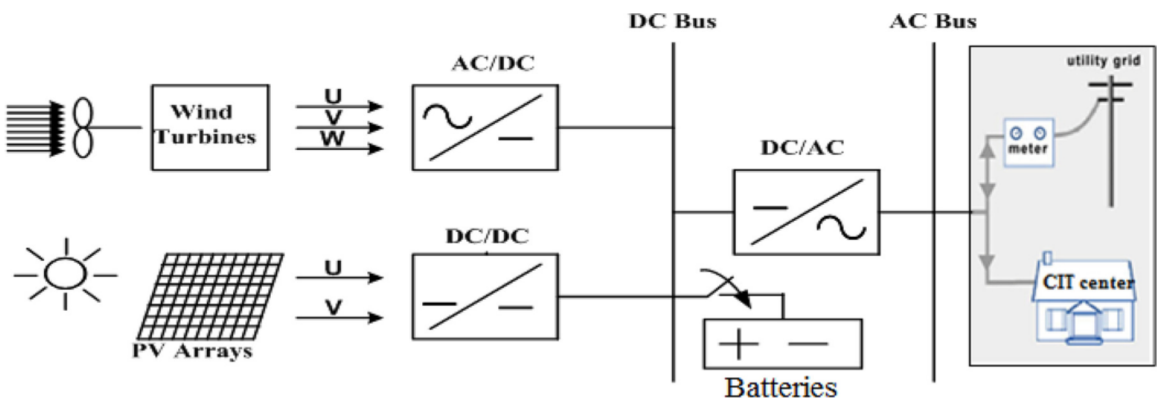

Figure 1. Schematic of the proposed microgrid design

2.1. Objective Function

The primary goal of this study is to minimize the total cost of the hybrid renewable energy system over its lifetime. The total cost includes the initial capital investment, operational and maintenance costs, and, in the case of grid-connected systems, the cost of purchasing energy from the grid. The objective function can be formulated as:

$$\text{Minimize TC} = \sum(C_{\text{inv}} + C_{\text{oper}} + C_{\text{maint}} + C_{\text{grid}} - C_{\text{sell}}) \quad (1)$$

where T_C is the total system cost, C_{inv} represents the capital investment cost for wind turbines, PV panels, and battery systems, C_{oper} is the operational cost of the system, which includes fuel costs for backup power generation if required, C_{maint} refers to maintenance costs for the system components, C_{grid} denotes the cost of energy purchased from the grid (applicable in grid-connected scenarios), and C_{sell} represents revenue generated from selling excess energy to the grid.

2.2. Constraints

Various operational and physical constraints must be incorporated into the model to ensure that the solution is feasible. The first constraint ensures that the total energy generated meets or exceeds the energy demand:

$$\sum(E_{PV}N_{PV} + E_{WT}N_{WT} + E_{grid}) \geq E_{load} \quad (2)$$

where E_{PVE} is the energy output from PV panels and wind turbines, N_{PVN} is the number of PV panels and wind turbines, E_{grid} represents the energy purchased from the grid, and E_{load} is the annual energy demand.

Other constraints include limitations on the capacity of inverters and controllers, as well as restrictions on the battery depth of discharge to ensure efficient storage operation.

2.3. Modeling Components of the Microgrid

The components of the hybrid renewable energy system are modeled mathematically to simulate their performance. These components include wind turbines, photovoltaic panels, battery storage systems, inverters, and controllers.

2.3.1. Wind Turbine Model

The output power of a wind turbine is a function of wind speed, which can be modeled using a Weibull distribution for wind speed data at the turbine's hub height. The probability density function (PDF) for the Weibull distribution is [19]:

$$f(x) = \frac{\beta}{\eta}.\left(\frac{x}{\eta}\right)^{\beta-1}.e^{-\left(\frac{x}{\eta}\right)^{\beta}} \quad (3)$$

where v is the wind speed, η is the scale parameter, β is the shape parameter. The total energy output from the wind turbine over a specific period can be calculated as:

$$E_{WT} = T_{hr}.\sum_{v_{min}}^{v_{max}} P_c\, f(v,\beta,\eta) \quad (4)$$

where T_{hr} is the total operational hours, and P_c is the power output from the turbine at a given wind speed.

2.3.2. PV Panel Model

The power output of a photovoltaic panel depends on solar irradiance and panel temperature. The output is modeled using the following equations [20]:

$$P_{PV} = V.I(V) \quad (5)$$

$$I(V) = \frac{I_x}{1-e^{\left(\frac{1}{b}\right)}}.[1-e^{A}] \quad (6)$$

$$A = \left(\frac{V}{b.V_x} - \frac{1}{b}\right) \quad (7)$$

where P_{PV} is the power output of the PV panel, V is the output voltage, I(V) is the current at a specific voltage, and I_x is the function of solar irradiance and temperature. The total energy produced by the PV array over a year is given by:

$$E_{PV} = P(SR_x).(SW).(365) \quad (8)$$

where SW is the total sunlight hours, and SR_x is the average solar irradiance.

2.3.3. Battery Storage Model

The battery system is modeled to ensure a reliable energy supply during periods of low renewable generation. The total capacity required for the battery system can be calculated using [21]:

$$B_R = \frac{L_{Ah/Day}.N_C}{M_{DD}.D_F} \quad (9)$$

where B_R is the required battery capacity, $L_{Ah/Day}$ is the daily energy demand in ampere-hours, N_C is the number of autonomous days, M_{DD} is the maximum depth of discharge, and D_F is the discharge factor.

2.4. Optimization Algorithm: PSO Variants

To optimize the microgrid system, the study uses PSO and its advanced variants CLPSO, MPSO, and GEPSO.

2.4.1. PSO Algorithm

PSO is a population-based optimization algorithm where particles (solutions) explore the search space by adjusting their positions and velocities. The velocity of each particle is updated based on its previous velocity, its best-known position (p_{best}), and the global best-known position (g_{best}) of the swarm.

The velocity update formula is [22]:

$$v_i(t+1) = wv_i(t) + c_1r_1(p_i(t) - x_i(t)) + c_2r_2(g(t) - x_i(t)) \quad (10)$$

where w is the inertia weight, c_1 and c_2 are cognitive and social acceleration constants, and r_1 and r_2 are random numbers between 0 and 1.

Particles update their positions as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (11)$$

The iterations continue until convergence is achieved or a predefined termination criterion is met.

2.4.2. GEPSO Variant

GEPSO further improves the standard PSO by introducing dynamic inertia weights and incorporating random velocities to increase diversity. This approach enhances the algorithm's ability to escape local optima and converge on a global solution [8].

2.5. Economic and Environmental Analysis

The economic analysis is conducted using a Net Present Value (NPV) approach to assess the profitability of the microgrid investment. The environmental analysis evaluates the reduction in greenhouse gas (GHG) emissions by comparing the proposed renewable energy microgrid to conventional fossil-fuel-based energy systems.

The NPV is calculated as [23]:

$$NPV = \sum_{y=1}^{n} \frac{C_{cash}}{(i+1)^{y}} \quad (12)$$

where C_{cash} is the net cash flow for each year, i is the discount rate, and n is the number of years in the project's lifetime.

The environmental analysis focuses on the reduction of CO_2 emissions by replacing fossil-fuel-generated electricity with renewable energy sources. This reduction is calculated based on the difference in emissions between the grid and the renewable system.

2.6. Simulation Setup

Simulations were performed using MATLAB. The test microgrid consisted of wind turbines, PV arrays, and battery storage, with data for wind speed, solar irradiance, and demand based on actual measurements from a case study site. Simulations were run for both grid-connected and off-grid scenarios, with different optimization techniques applied to each scenario.

The PSO-based approach is applied using real data to identify the optimal configuration and sizing of a hybrid photovoltaic/wind system capable of meeting the energy demands of the CIT centre with minimal investment cost.

Table 1 shows the monthly energy demand of the CIT center, with the peak load recorded at 68 kW. The average monthly wind speed and solar radiation are obtained from NASA meteorological data [18]. Table 2 displays the average monthly solar radiation received on a horizontal surface, while Table 3 shows the average monthly wind speeds at 50 meters above ground level. As explained in previous sections, if wind speeds are measured at a height other than the turbine hub height, adjustments must be made. In this study, wind towers with a hub height of 20 meters are considered, requiring the measured wind speeds to be corrected.

Simulation code was developed for different commercial models of wind turbines, photovoltaic cells, batteries, controllers, and inverters. Based on the characteristics of each product, the model selects the most optimal configuration for the microgrid. Tables 4 to 8 provide technical-economic data on wind turbines, photovoltaic cells, batteries, inverters, and controllers, respectively.

Table 1. Monthly Electrical Load Required by the CIT Centre

Usage Type	Required Load (kWh/month)
Servers	190
Computers	145
Lighting	100
Central HVAC	80
Other Usage	35
Total	550

Table 2. Average Monthly Solar Radiation Received During the Day (kWh/m²/day)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Solar Radiation (kWh/m²/day)	3.04	3.84	5.14	6.49	7.44	8.10	7.78	7.19	6.19	4.66	3.42	2.74

Table 3. Average Monthly Wind Speeds at 50m and corrected at 20m (m/s)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Wind Speed at 50m (m/s)	5.61	5.94	5.72	5.19	5.04	4.90	5.01	5.09	5.17	5.18	5.00	5.49
Corrected Wind Speed at 20m (m/s)	4.92	5.21	5.02	4.56	4.42	4.30	4.39	4.46	4.53	4.54	4.39	4.81

Table 4. Technical-Economic Information on Different Wind Turbines

Model	Rated Output (W)	Investment Cost ($)	Installation Cost ($)	Maintenance Cost ($)	Energy Produced (kWh/year)
SouthWest (Air X)	400	1248.985	74.6955	24.8985	506.27
SouthWest (Whisper 100)	900	844.985	253.4955	84.4985	1411.16

SouthWest (Whisper 200)	1000	1000.00	300.00	100.00	2952.03
SouthWest (Whisper 500)	3000	3076.391	922.9173	307.6391	8852.62
Bornay (Inclin 6000)	6000	6783.701	2035.11	678.3701	21250.96

Table 5. Technical-Economic Information of Different Solar Cells

Model	Characteristic Constant	Output at 1000 W/m² (W)	Investment Cost ($)	Installation Cost ($)	Maintenance Cost ($)	Energy Produced (kWh/year)
Sharp ND-250QCS	0.153	250	240.00	108.00	6.00	489.31
Hyundai HiS-255MG	0.160	255	229.50	103.275	5.7375	483.22
Canadian Solar CS6X-300P	0.156	300	249.00	112.05	6.225	602.10

Table 6. Technical-Economic Information of Different Batteries

Model	Capacity (Ah)	Investment Cost ($)	Installation Cost ($)	Replacement Cost ($)
MK 8L16	370	1749.03	35.7	1749.03
Surrette 12-Cs-11Ps	375	6851.425	139.825	6851.425
Trojan T-105	225	991.27	20.23	991.27

Table 7. Technical-Economic Information of Different Inverters

Manufacturer	Model	Output Power (W)	Investment Cost ($)	Installation Cost ($)	Maintenance Cost ($)	Replacement Cost ($)
Schneider Electric	DR1524E	1500	350.00	7.15	1.95	350.00
Schneider Electric	XW6048	6000	1518.00	30.375	4.60	1518.00

Table 8. Technical-Economic Information of Different Controllers

Manufacturer	Model	Output Power (W)	Investment Cost ($)	Installation Cost ($)	Maintenance Cost ($)	Replacement Cost ($)
Schneider Electric	XW-MPPT-60	1500	284.00	4.96	0.7453	248.00
Outback	FM 80	2000	335.00	6.70	1.005	335.00

Efficiency and Economic Assumptions:
- Inverter Efficiency: 97%
- Controller Efficiency: 97%
- Wire and Cable Efficiency: 96%
- Battery Efficiency: 90%

3. Results and Discussion

This section compares the performance of the algorithms used in this study. The comparison is based on key factors: total investment cost, convergence speed, and the computation time required by each algorithm. Another factor examined is the amount of greenhouse gas emissions, which occur when the microgrid is connected to the main power grid and purchases electricity from it, thereby contributing to emissions.

Figure 2 shows the variations in total investment cost for the off-grid scenario across the four algorithms—PSO, MPSO, CLPSO, and GEPSO. As can be seen, with its high convergence speed, the PSO algorithm quickly reaches a solution but suffers from premature convergence. As previously mentioned, PSO often gets trapped in local optima, resulting in unreliable outcomes. This issue is somewhat mitigated in the MPSO algorithm, where the optimal solution is reached after more iterations, albeit with a slight delay compared to PSO. The optimal solution in MPSO is found after more iterations than in the PSO algorithm.

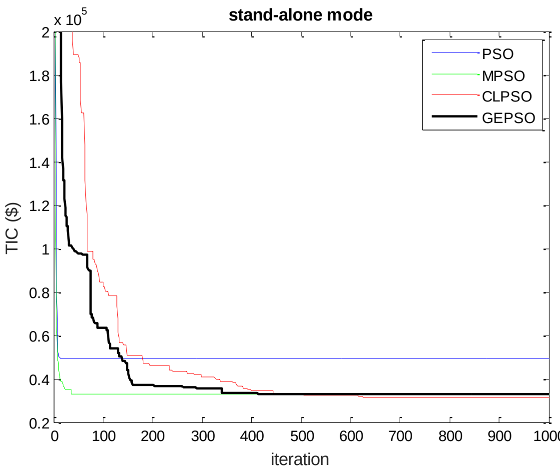

Figure 2. Comparison of convergence speed of algorithms in the off-grid scenario

The GEPSO algorithm performs slightly better, identifying a more refined optimal solution after evaluating more iterations and solutions. However, the CLPSO algorithm shows significant improvement, as seen in Figure 2, where convergence occurs much later—towards the final quarter of iterations—providing greater confidence in finding the global optimal solution.

Additionally, the chart depicts the total investment cost for the CIT microgrid in the off-grid scenario for all four algorithms. As the graph illustrates, the CLPSO algorithm achieves the lowest investment cost compared to the other algorithms. GEPSO ranks second, followed by MPSO in third, and the standard PSO algorithm at the bottom.

These trends are consistent in the grid-connected scenario as well. In this case, the CLPSO algorithm once again outperforms the others, both in avoiding premature convergence and in its superior ability to minimize total investment costs. This is clearly illustrated in Figure 3.

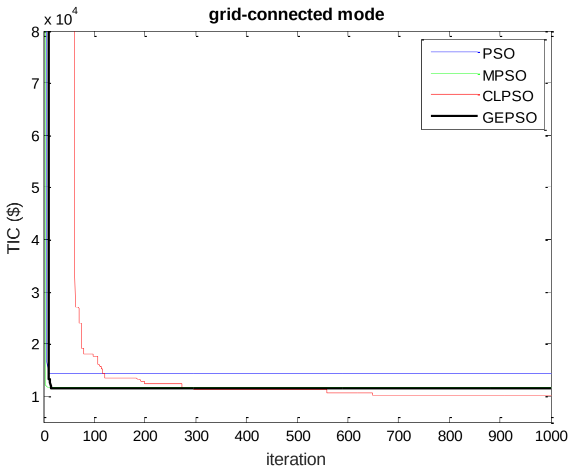

Figure 3. Comparison of algorithm convergence speed in grid-connected mode

The data in Table 9 indicates that the CLPSO algorithm achieves the lowest total investment cost in off-grid and grid-connected scenarios compared to the other three algorithms; specifically, in the off-grid scenario, CLPSO reduces the cost by 34.53%, 2.38%, and 2.30% compared to the PSO, MPSO, and GEPSO algorithms, respectively. In the grid-connected scenario, these reductions are 28.27%, 12.07%, and 11.15%, respectively.

For a clearer understanding of the data in Table 9, Figure 4 provides a useful visual tool. As shown, the lowest investment cost across all three microgrid scenarios is achieved by the CLPSO algorithm. Additionally, it is evident that the total investment cost in the grid-connected scenario is significantly lower—approximately one-third—compared to the off-grid scenario. This is primarily due to the absence of battery systems in the grid-connected microgrid. Batteries not only have a high initial purchase price but also incur substantial replacement costs throughout the microgrid's operational lifetime, which contributes to the higher overall investment costs in the off-grid scenario.

The duration of optimization computations performed by each of the four algorithms for the microgrid of the Communication and Information Technology Center, in both off-grid and grid-connected modes, is summarized in Table 10. By comparing these results, it was found that among the four algorithms, the CLPSO algorithm completed the computations in a shorter time than the others. Furthermore, while the general PSO algorithm does not achieve the lowest overall investment cost, it ranks second in computation time, followed by the GEPSO algorithm. The MPSO algorithm ranks fourth in both grid-connected and off-grid modes. Figure 5 complements Table 10 and is designed to enhance understanding. A quick glance at the figure clearly shows that the MPSO algorithm has the longest computation time, while the CLPSO algorithm, having completed the computations in the shortest time, stands out as the most efficient among the four.

The next factor compared to the performance of the algorithms for microgrid optimization is their estimation of energy purchased from the main power grid. Electricity is only purchased when the microgrid is connected to the grid. As shown in Table 11, the PSO algorithm results in the highest amount of energy purchased from the grid, followed by the MPSO algorithm in second place and GEPSO in third. However, the CLPSO algorithm was able to reduce these values by 11.84%, 10.4%, and 6.91%, respectively, resulting in a microgrid design that purchases the least amount of energy from the main power grid.

Figure 6 illustrates the amount of energy purchased from the main power grid by the four algorithms. This becomes particularly significant when considering greenhouse gas emissions and environmental pollutants. The more energy a renewable microgrid purchases from the main grid, the more it relies on thermal power plants, which are major contributors to environmental pollution. Therefore, this study estimated the amount of greenhouse gas emissions based on the energy purchased from the grid, using this information to help select the optimal algorithm. According to these calculations, the CLPSO algorithm, which purchases significantly less energy compared to the other algorithms, results in fewer pollutants being released into the atmosphere, making it the preferred algorithm from an environmental standpoint.

Table 9. Comparison of Total Investment Costs in Off-Grid and Grid-Connected Scenarios Among the Algorithms Used

Algorithm	Off-Grid Scenario	Grid-Connected Scenario
PSO	49,038.92	14,259.62
MPSO	32,885.40	11,631.50
CLPSO	32,103.77	10,227.86
GEPSO	32,859.31	11,511.54

Improvement of CLPSO compared to PSO (%)	-34.53%	-28.27%
Improvement of CLPSO compared to MPSO (%)	-2.38%	-12.07%
Improvement of CLPSO compared to GEPSO (%)	-2.30%	-11.15%

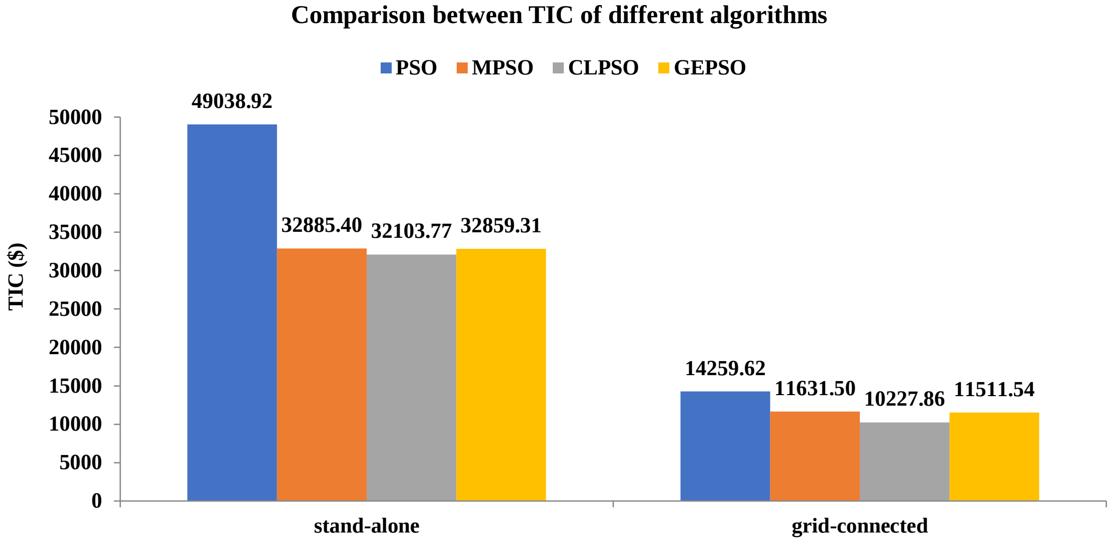

Figure 4. **Total investment cost chart in both off-grid and grid-connected scenarios for the algorithms used**

Table 10. **Comparison of computation time in off-grid and grid-connected scenarios among the algorithms used**

Algorithm	Off-Grid Scenario	Grid-Connected Scenario
PSO	94.50	93.78
MPSO	196.89	340.37
CLPSO	89.49	84.80
GEPSO	115.53	108.61
Improvement of CLPSO compared to PSO (%)	-5.30%	-9.57%
Improvement of CLPSO compared to MPSO (%)	-54.55%	-75.08%
Improvement of CLPSO compared to GEPSO (%)	-22.53%	-21.92%

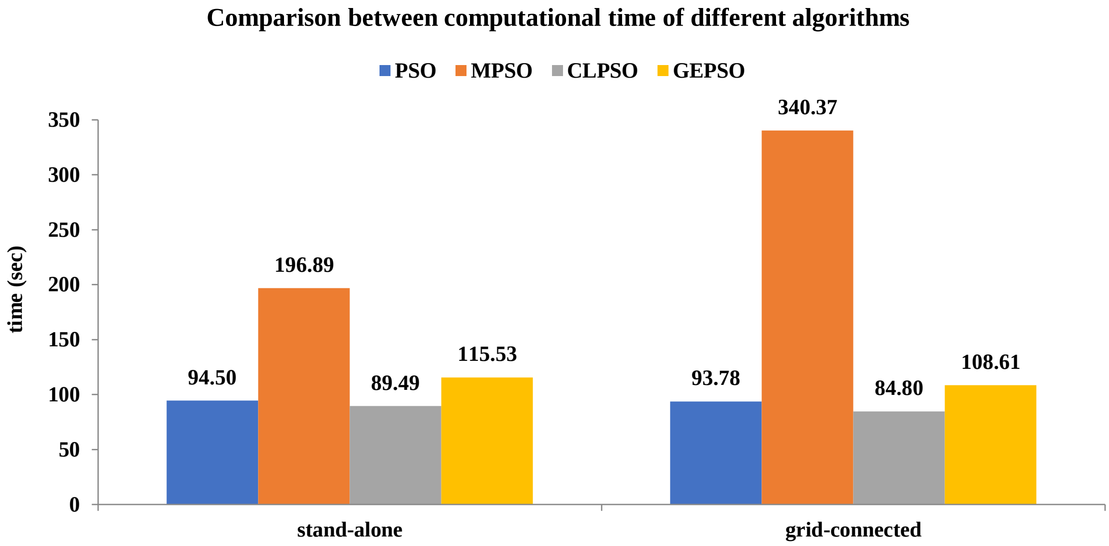

Figure 5. **Computation time comparison in off-grid and grid-connected scenarios for the algorithms used**

Table 11. **Comparison of the amount of energy purchased from the main power grid among the algorithms used**

Algorithm	Grid-Connected Scenario

PSO	207.58
MPSO	204.23
CLPSO	183.00
GEPSO	196.59
Improvement of CLPSO compared to PSO (%)	-11.84%
Improvement of CLPSO compared to MPSO (%)	-10.40%
Improvement of CLPSO compared to GEPSO (%)	-6.91%

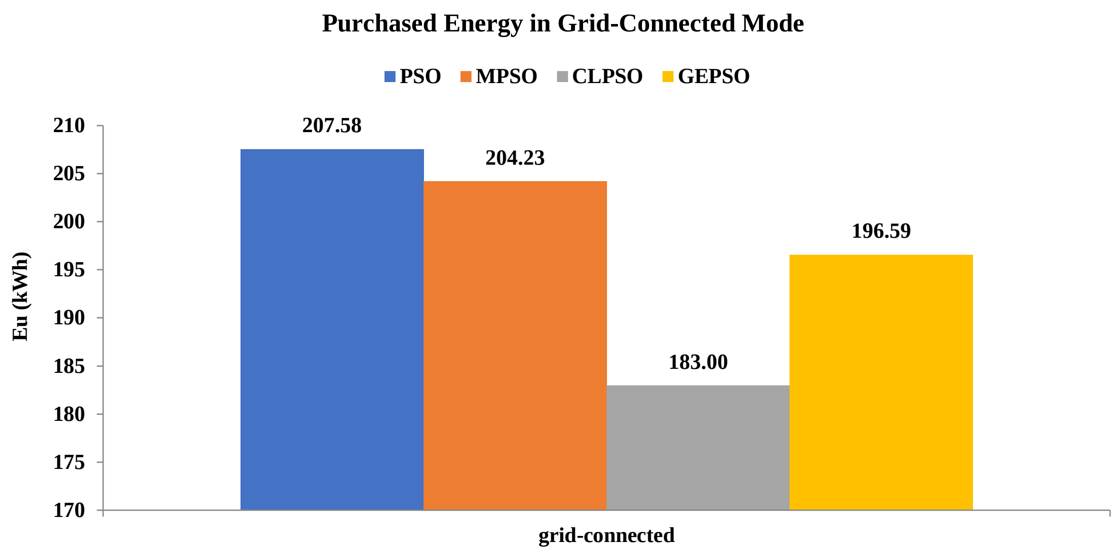

Figure 6. **The amount of energy purchased from the main power grid in the algorithms used**

4. Conclusion

In this study, the optimization of a hybrid microgrid consisting of photovoltaic units, wind turbines, and batteries for the Communication and Information Technology Center at Mansoura University in Egypt was conducted. The introduction and the need for the research were outlined in the first chapter. The second chapter provided a review of the theoretical foundations related to microgrids and renewable energy units, as well as an analysis of relevant studies. Chapter three introduced and discussed the PSO algorithm along with its variants, such as MPSO, CLPSO, and GEPSO. The mathematical modeling of the microgrid problem was also presented, followed by the formulation of objective functions and the simulation approach. In the fourth chapter, the results from the simulations using the four algorithms were analyzed and compared.

The main findings of the project are summarized as follows:

PSO and MPSO algorithms showed premature convergence when optimizing the CIT microgrid, resulting in suboptimal and less reliable solutions compared to those generated by the CLPSO and GEPSO algorithms. Notably, the hybrid microgrid's total investment cost significantly decreased when it was connected to the main power grid. This result was consistent across all four algorithms. However, CLPSO demonstrated superior performance in reducing total investment costs in both grid-connected and off-grid scenarios, achieving a cost reduction of 34.53% and 28.27% compared to PSO in off-grid and grid-connected modes, respectively.

GEPSO provided better results than PSO and MPSO in minimizing total investment costs for both scenarios, although it lagged behind PSO in terms of computation time. CLPSO also outperformed all other algorithms by completing the optimization process in the shortest time, reducing computational time by 5.3% to 75% compared to the other algorithms.

Additionally, CLPSO resulted in a significantly lower purchase of energy from the main power grid, cutting energy consumption by 11.84% compared to PSO. This reduced reliance on grid electricity led to fewer greenhouse gas emissions, making CLPSO the environmentally preferable option.

In conclusion, CLPSO emerged as the most efficient optimization algorithm in terms of convergence speed, minimizing total investment costs and computation time, and reducing environmental pollutants. It outperformed PSO, MPSO, and GEPSO in all key metrics. Therefore, CLPSO is recommended as the optimal algorithm for solving microgrid optimization problems.

5. Statements & Declarations

5.1. Acknowledgments

Acknowledgments of people, grants, funds, etc., should be placed at the end of the paper, before the references section. The names of funding organizations should be written in full.

5.2. Funding

Please describe any sources of funding that have supported the work. The statement should include details of any grants received (please give the name of the funding agency and grant number).

5.3. Author Contributions

Authors are encouraged to include a statement that specifies the contribution of every author to the research and preparation of the manuscript.

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