Off-Grid Hybrid Microgrid Sizing Optimization Using The Bezier Curve Optimization Algorithm

Aslı Kurt
Department of Electrical and Electronics Engineering,
Fac. of Engineering and Natutal Sci.,
Karabük University,
Karabük, Türkiye
aslikurt@karabuk.edu.tr

Mehmet Demirtaş
Department of Electrical and Electronics Engineering,
Faculty of Technology,
Gazi University,
Ankara, Türkiye
mehmetd@gazi.edu.tr

İpek Çetinbaş
Department of Electrical and Electronics Engineering,
Fac. of Engineering and Architecture,
Eskisehir Osmangazi University,
Eskişehir, Türkiye
ipekcetinbas@ogu.edu.tr

***Abstract*— This study investigates the problem of optimally sizing a hybrid off-grid microgrid system consisting of photovoltaic (PV), wind turbine (WT), diesel generator (DG), and battery energy storage system (BESS) components for the Gökçeada/Türkiye settlement. This problem was solved using Bezier curve optimization (BCO), glider snake optimization (GSO), and gray langur optimization (GLO) algorithms. These algorithms were evaluated under three different scenarios: economic, balanced, and environmental. Real meteorological data and a synthetic load profile obtained from the NASA POWER database were used in the analyses. The results showed that the BCO algorithm produced more accurate results compared to other algorithms by providing the lowest average objective function and standard deviation values in all scenarios. In the best design results obtained with BCO, the renewable energy ratio ranged from 92.49% to 97.95%, while carbon emissions were reduced from 635383 kg/year to 178506 kg/year. In contrast, energy costs ranged from $0.2700 to $0.3268 per kWh. Based on the results obtained, it was concluded that BCO produces effective, consistent, and reliable solutions in hybrid microgrid sizing optimization and can be used confidently in optimal microgrid design problems.**

Keywords*— hybrid microgrid, optimal sizing, bezier curve optimization, glider snake optimization, gray langur optimization

I. INTRODUCTION

The worldwide transition towards renewable energy systems has become a progressively important solution to meet the growing demand for a sustainable, clean, and reliable energy supply. Accordingly, research efforts are increasingly focused on developing hybrid renewable energy systems to advance energy efficiency, reduce costs, and diminish environmental impact [1]. Although microgrids are an emerging technology that provides several advantages compared with conventional power grids, such as increased reliability, decreased energy costs, improved energy security, environmental benefits, and expanded flexibility, they also face some challenges. These include high capital costs, technical complexity, regulatory challenges, interconnection problems, and operation and maintenance requirements [2]. These problems can be tackled by solving nonlinear optimization problems that require a large search space to identify optimal or near-optimal solutions, and that involve multiple linear or nonlinear constraints and continuous or discrete variables. A review of the recent literature on microgrid applications indicates that metaheuristic optimization algorithms are increasingly being proposed to solve these optimization problems [3].

Demirtaş et al. designed and optimized the sizing of an autonomous AC microgrid consisting of PV, WT, BESS, and DG using the harris hawk algorithm (HHO) on real load and meteorological data. Aiming for an economical and reliable microgrid structure, the study demonstrated that HHO provides higher performance than four meta-heuristic algorithms—particle swarm optimization (PSO), firefly algorithm (FA), grey wolf optimization (GWO), and salp swarm algorithm (SSA)—by achieving savings of between 1.18% and 18.23% in total net present cost [4]. Saleh et al. proposed the multi-objective SSA and the multi-objective whale optimization algorithm (WOA) in a case study covering three load scenarios to minimize the loss of power supply probability (LPSP) and cost of energy (COE) while maximizing the renewable fraction (RF). The comparative evaluation of these algorithms resulted in a COE value of $0.20873 per kWh and an RF value exceeding 88% [5]. Yakout et al. aimed to simultaneously minimize annual cost of the system (ACS), carbon dioxide (CO_2) emissions, and LPSP based on the arctic puffin optimization. The proposed study achieved up to 8% lower ACS, 17% higher renewable penetration, and zero LPSP while maintaining stable convergence behavior [6]. Güven et al. achieved optimal sizing across four different scenarios using genetic algorithm (GA), FA, PSO, and a novel hybrid of the FA and PSO algorithms, reducing total gas emissions and providing uninterrupted annual load coverage with 100% RF [7]. Kharrich et al. studied the optimal sizing of PV panels, wind turbines, diesel generators, and battery storage systems to minimize the net present cost (NPC) design function using the improved Archimedes Optimization Algorithm (AOA). Their work yielded the best possible result with an NPC of $187,181, equivalent to a LCOE of $0.213 per kWh [8]. Bouchekara et al. studied the minimization of the LPSP and the COE objective functions using the improved decomposition multi-objective evolutionary algorithm for different scenarios through a real case study with five and ten houses. The study obtained results of $0.1159 per kWh COE, 63.10% LPSP, and 83.71% RF for the five-house scenario, and $0.0716 per kWh COE, 99.99% LPSP, and 66.12% RF for the ten-house scenario [9]. Fan et al. proposed a study aiming to minimize the total ACS of a residence using the Harmony Search (HS) algorithm. The study showed that the proposed algorithm achieved the best optimum result with a TAC value of 24,259$, 1.12% better than the result given by the HS algorithm, while having a simulation time that was 4.1% shorter [10]. Zhu et al. addressed a multi-objective optimization problem involving the minimization of ACS and LPSP based on the improved multi-objective GWO algorithm, using an island hybrid microgrid composed of photovoltaic, wind, battery, diesel generator, and tidal current components. The study demonstrated that the use of tidal current turbines in regions with high tidal energy potential can contribute to increased system reliability and reduced system investment costs [11]. Samy et al. proposed a study comparing five

XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE

advanced metaheuristic algorithms aimed at minimizing ACS while achieving high renewable energy utilization and system efficiency. Tests conducted using real data from a university campus in Türkiye revealed that the hunger games search algorithm demonstrated the best performance, with an ACS of $603,538.44, a COE of $0.23801 per kWh, and a RF of 80.04% [12]. Çetinbaş et al. proposed a novel hybrid metaheuristic algorithm combining HHO and arithmetic optimization algorithm (AOA) for the design and optimization of a microgrid consisting of PV, WT, BESS, DG, and commercial load components. The study showed that the proposed new hybrid algorithm performed 77.9% better than HHO and 78.6% better than AOA according to the Friedman ranking test. Furthermore, it demonstrated that the optimization performed by the proposed algorithm produced more optimal results than HHO and AOA in LPSP and COE minimization and RF maximization [13]. When the studies conducted in the literature are examined, it is seen that metaheuristic optimization algorithms stand out as a dominant approach in solving hybrid microgrid sizing problems. This situation arises from the nonlinear nature of microgrid design problems, their involvement of numerous decision variables, and the need to simultaneously evaluate multiple objective functions. The abilities of metaheuristic algorithms to perform efficient searches in large solution spaces and generate high-quality solutions have made them important tools in microgrid optimization studies. However, the current literature indicates that no single algorithm consistently demonstrates superior performance in all microgrid optimization problems.

According to the No Free Lunch Theorem, it is not possible for any optimization algorithm to outperform other algorithms in all optimization problems and under all operating conditions. An algorithm that achieves high success rates on some types of problems may not perform the same way on different types and characteristics of problems. Therefore, the effectiveness of an optimization algorithm depends on the structure of the objective function(s), problem constraints, decision variables, problem size, and the characteristics of the problem to be solved [14].

In this study, a hybrid off-grid microgrid design consisting of PV, WT, DG, and BESS was implemented for the Gökçeada settlement, and the optimal sizing of the system was approached as an optimization problem. Metaheuristic optimization algorithms proposed in recent years have been applied to the microgrid sizing problem under three different scenarios: economic, balanced, and environmental, and the results have been examined in detail.

The study consists of five parts. Following the introduction, the load profile of the microgrid system, meteorological data, problem formulation, and scenarios are presented. The next section introduces the optimization algorithms used in the study. Following this, the results and comparative evaluations of microgrid sizing studies conducted under different scenarios are performed. The final section presents the overall results of the study and potential future research directions.

II. Definition of Problem

This study addresses the optimal sizing of an off-grid hybrid microgrid designed for the Gökçeada settlement. Within the scope of the problem formulation, meteorological data, load profile, objective functions, system constraints, and scenario definitions for Gökçeada are presented in three sub-sections.

A. Problem definition: Gökçeada settlement, load, and meteorological data profile

Gökçeada (40°8.1′N, 25°58.6′E), the largest island in Türkiye [15], has an average annual wind speed of 7.25 m/s at a height of 50 m and an average annual daily solar radiation potential of 4.41 kWh/m²/day. The meteorological data used to create the microgrid's production profile was obtained from the NASA POWER database [16]. In contrast, the load profile was synthetically created to represent the consumption characteristics of the region. Typical electricity consumption habits of Türkiye were used as the basis for creating the load profile. In this context, the number of households in Gökçeada was assumed to be 3000 and the daily energy consumption per household was assumed to be 6 kWh/day. It has been noted that daily demand reaches its highest levels especially between 19:00 and 22:00, while seasonal demand increases during the summer months due to the influence of tourism activities [17]. To better represent real-world operating conditions, 8% random noise was added to the generated load profile. Based on this load profile, the microgrid system was sized to provide load demands ranging from 240.47 kW to 2439.44 kW.

B. Objective function, decision variables, and constraints

The microgrid sizing problem is modeled using three fundamental objective functions: LCOE, CO_2, and LPSP, and the optimization process aims to minimize these three basic objective functions. The decision variables consist of the number of PV panels, the number of WT, the number of DG, and the number of BESS. Furthermore, various constraints have been defined to ensure the solution space meets technical and operational requirements. These include the LPSP value remaining below 2%, RF being above 70%, and the curtailment factor (CF) not exceeding 30%. The proposed optimization model aims to determine the most suitable microgrid configuration under the relevant objective functions and constraints. The objective function is given in Equation (1), and the decision variables and their minimum and maximum number and power values are given in Equation (2).

$$OF(x) = \begin{matrix} f_1(x)\left(\frac{w_1}{0.5}\right) + f_2(x)\left(\frac{w_2}{5E10^6}\right) + f_3(x)\left(\frac{w_3}{0.02}\right) \\ \begin{cases} f_1(x) = LCOE \\ f_2(x) = CO_2 \\ f_3(x) = LPSP \end{cases} \end{matrix} \quad (1)$$

$$x = \begin{bmatrix} n_{PV}(No.) = [0,100] \\ n_{WT}(No.) = [0,20] \\ n_{DG}(No.) = [1,10] \\ n_{BESS}(No.) = [0,500] \end{bmatrix} = \begin{bmatrix} n_{PV}(kW) = [0,10000] \\ n_{WT}(kW) = [0,10000] \\ n_{DG}(kW) = [500,5000] \\ n_{BESS}(kWh) = [0,50000] \end{bmatrix} \quad (2)$$

Where, $OF(x)$ is the overall objective function, $f_1(x)$ is the first objective function/LCOE, $f_2(x)$ is the second objective function/CO_2, $f_3(x)$ is the third objective function/LPSP, w_1, w_2, and w_3 are the weighting coefficients, x is the decision variable vector, n_{PV} is the number of PV panels, n_{WT} is the number of WTs, n_{DG} is the number of DGs, and n_{BESS} is the number of BESSs.

C. Definition of scenarios

The study defines three scenarios: economic, balanced, and environmental. Each scenario was created by transforming the multi-objective optimization problem into a single objective function using a weighted sum approach. The

weighting coefficients used in creating the scenarios are given in Table 1. In the first scenario, the economic scenario, reducing the energy cost of the system is determined as the primary objective, and therefore the highest weight is assigned to the LCOE objective function. In the second scenario, the balanced scenario, the aim is to establish a balance between economic and environmental performance. Accordingly, all objective functions are given similar/equal weighting values. In the third and final scenario, the environmental scenario, reducing carbon emissions is accepted as the main priority, and the highest weighting coefficient is assigned to the CO_2 objective function. These scenarios make it possible to comparatively evaluate microgrid designs obtained under different planning priorities.

TABLE I. WEIGHTING COEFFICIENT PARAMETERS ACCORDING TO SCENARIOS

Scenario/Weighting Coefficient	w_1	w_2	w_3
Economical	0.80	0.10	0.10
Balanced	0.34	0.33	0.33
Environmental	0.10	0.80	0.10

III. OPTIMIZATION ALGORITHMS

Three metaheuristic algorithms, BCO, GSO, and GLO, were used to solve the microgrid sizing problem. The mathematical structure and working mechanism of BCO, the primary comparison algorithm of the study, are presented in detail, while summary information and the control parameters used for the GSO and GLO algorithms are given in the relevant subsection.

A. Bezier curve optimizer (BCO)

BCO was proposed in 2026 by Zhao et al., inspired by Bezier curve theory. The BCO algorithm was developed based on the geometric and mathematical properties of linear, quadratic, and cubic Bezier curves. A relationship was established between these curves, which exhibit different geometric properties, and various search behaviors observed in optimization algorithms. The algorithm consists of the following stages: initialization, exploitation strategy, local avoidance strategy, exploration strategy, and exploration-exploitation balance operator. The linear Bezier curve represents the exploitation process, the quadratic Bezier curve represents the local optima avoidance mechanism, and the cubic Bezier curve represents the exploration process. In addition, the adaptive balance factor ensures a dynamic balance between exploration and exploitation activities. The mathematical basis of the BCO algorithm corresponding to these five processes is given in Equations (3)-(7).

$$Initialization = \begin{cases} x_i = Low + r \cdot (Up - Low) \\ Low = \left[Low^1, \cdots, Low^j, \cdots, Low^d\right] \quad i = 1, \cdots, N_{BCO} \\ Up = \left[Up^1, \cdots, Up^j, \cdots, Up^d\right] \quad j = 1, \cdots, d \\ x_i = \left[{x_i}^1, \cdots, {x_i}^j, \cdots, {x_i}^d\right] \end{cases} \tag{3}$$

$$Exploitation = \begin{cases} Strategy\ 1 & \begin{cases} P_1 = x_{best} + \left(x_{r_1}(t) + x_i(t)\right)/2 \quad if \quad rand > 0.5 \\ P_1 = x_{best} - \left(x_{r_1}(t) + x_i(t)\right)/2 \quad if \quad rand \le 0.5 \\ a(t) = 1 + ((2r_2 - 1)/(1 + 80t/T_{BCO} + 0.02(10t/T_{BCO})^3)) \end{cases} \\ Strategy\ 2 & \begin{cases} P_1 = x_{mean} + rn_1(x_i(t) - x_{mean}) \quad if \quad rand > 0.5 \\ P_1 = x_{mean} + rn_1 x_{mean} \quad if \quad rand \le 0.5 \end{cases} \\ Strategy\ 3 & \begin{cases} P_1 = x_i^j(t) \quad if \quad rand > 0.5 \\ P_1 = (1-a)x_i^j(t) + a x_k^j(t) \quad if \quad rand \le 0.5 \end{cases} \\ P_0 = x_i(t) \\ x_i(t+1) = (1-a)P_0 + aP_1 \end{cases} \tag{4}$$

$$Local\ Avoidance = \begin{cases} Behavior\ 1 \quad \left\{P_2 = x_i(t) + rn_2\left(x_{best} - x_{r_2}(t)\right) \quad if \quad rand > 0.5 \right. \\ Behavior\ 2 \quad \left\{P_2 = x_i(t) + rn_2\left(x_{mean} - x_{r_2}(t)\right) \quad if \quad rand \le 0.5 \right. \\ P_0 = x_i(t) \\ P_1 = x_{r_2}(t) \\ x_i(t+1) = (1-a)^2 P_0 + 2(1-a)aP_1 + a^2 P_2 \end{cases} \tag{5}$$

$$Exploration = \begin{cases} Behavior\ 1 \quad \left\{P_3 = x_{mean} + 2rn_3\left(x_{r_4}(t) - x_{r_3}(t)\right) \quad if \quad rand < 0.8 \right. \\ Behavior\ 2 \quad \left\{P_3 = x_{r_3}(t) + 2rn_4\left(Low + r_5(Up - Low)\right) \quad if \quad 0.8 \le rand \le 0.9 \right. \\ Behavior\ 3 \quad \left\{P_3 = x_{r_3}(t) + 2rn_4\left({x_{r_4}}^{rd}(t) - x_{r_3}(t)\right) \quad if \quad 0.9 \le rand < 1 \right. \\ P_0 = x_i(t) \\ P_1 = x_{r_3}(t) \\ P_2 = x_{r_4}(t) \\ x_i(t+1) = (1-a)^3 P_0 + 3a(1-a)^2 P_1 + 3a^2(1-a)P_2 + a^3 P_3 \end{cases} \tag{6}$$

$$Exploitation - Exploitation\ Balance = \{A(t) = (a + b\ln(1/r_6))\sin\left((\pi/2)(1 - t/T_{BCO})\right) \tag{7}$$

Where, $x_i(t)$ and $x_i(t+1)$ are the current and updated positions of the ith search agent, ${x_i}^j$ is the position of the ith search agent in the j^{th}dimension. Low and Up are the lower and upper bound vectors, x_{best} is the best position vector obtained so far, x_{mean} is the centroid position of the population, x_{r_1}, x_{r_2}, x_{r_3}, and x_{r_4} are randomly selected search agents from the population, x_k^j is the position of the kth search agent in the jth dimension, ${x_{r_4}}^{rd}$ is the randomly selected dimension rd of the ${r_4}^{th}$ search agent, P_0, P_1, P_2, and P_3 are the control points, r, r_2, r_5, and r_6 are random numbers in the interval (0,1), rn_1, rn_2, and rn_4 are the random numbers, rn_4 is the random vector, N_{BCO} is the population size, d is the problem dimension, t is the current iteration number, T_{BCO} is the maximum number of iterations, $a(t)$ is the time-varying weighting factor, $A(t)$ is the adaptive exploration–exploitation balance factor, and a and b are the baseline and scaling coefficients used in the balance mechanism [18].

B. Brief summary of BCO, GSO, and GLO algorithms

Basic information, inspiration sources, and control parameters of the BCO, GSO, and GLO algorithms used in this study are summarized in Table 2. Since the detailed mathematical background of these algorithms is presented in the relevant sources, only their basic characteristics and the control parameters used are given in this study. Except for the population size and the number of iterations, the control parameters used in the algorithm analysis were obtained from the original articles of the algorithms and the algorithms were run with these control parameters.

TABLE II. INSPIRATION SOURCES AND CONTROL PARAMETERS OF BCO, GSO, AND GLO ALGORITHMS

Algorithm	Inspiration	Control Parameter	Values
BCO [18]	Bezier curve theory	Number of populations	N_{BCO}=30
		Maximum number of iterations	T_{BCO}=5000
GSO [19]	Arboreal snake gliding behavior	Adaptive coefficient	A_{GSO}=(0,1)
		Number of populations	N_{GSO}=30
		Maximum number of iterations	T_{GSO}=5000
GLO [20]	Gray langur group behavior	Migration rate	ω=0.05
		Lévy distribution parameter	β=1.5
		Number of populations	N_{GLO}=30
		Maximum number of iterations	T_{GLO}=5000

IV. RESULTS AND DISCUSSION

This section comparatively evaluates the performance of the BCO, GSO, and GLO algorithms under three different scenarios. All analyses were performed using 30 individual population size, 5000 maximum iterations, and 30 independent runs. The population size, iteration number, and run number used in these analyses are commonly preferred and accepted values in literature and were therefore used in this study as well. They were chosen equally to provide a fair comparison environment in the algorithms. The performance of the algorithms was primarily compared using computational accuracy and computational time metrics. Subsequently, the microgrid sizing results obtained for the algorithm showing the best performance are presented in detail.

A. Evaluation metrics results for computational accuracy

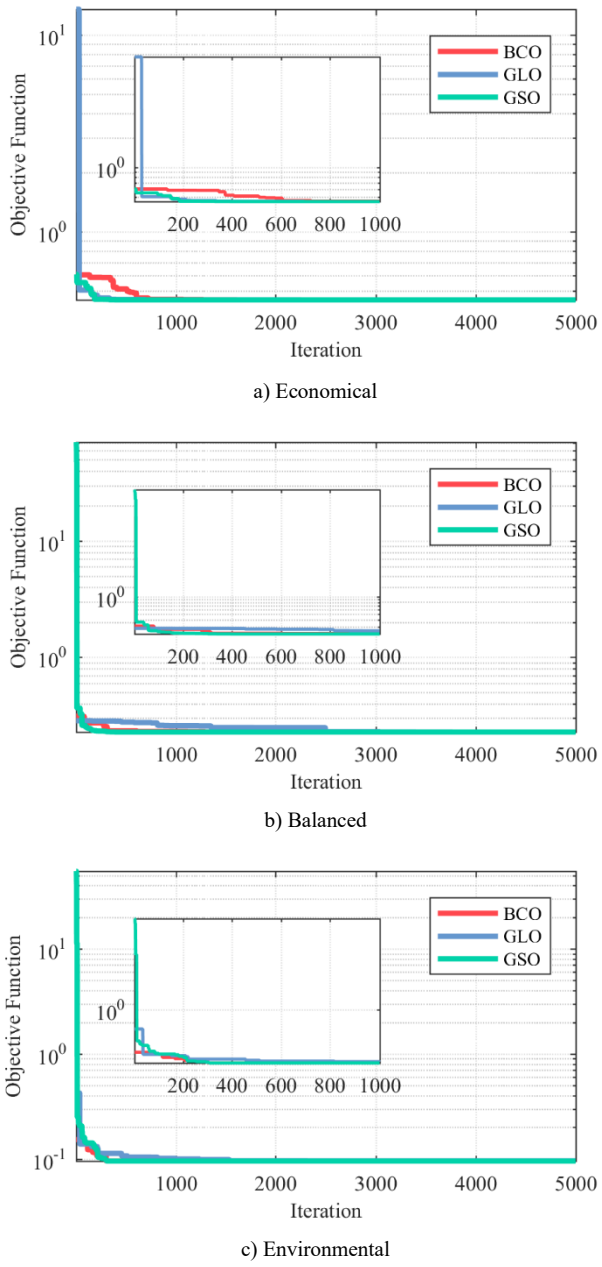
The results of the computational accuracy evaluation metrics, consisting of average, maximum, minimum, and standard deviation, are given in Table 3. Examination of the table shows that the BCO algorithm exhibits the best performance in terms of average objective function value and standard deviation in all economic, balanced, and environmental scenarios. In particular, the significantly lower standard deviation values compared to other algorithms indicate that BCO can produce more stable and repeatable results in different runs. Examining the maximum and minimum objective function values also shows that the BCO algorithm maintains its solution quality more consistently. To illustrate the convergence behavior of the algorithms, the convergence curves for the 30th independent run are given in Figure 1. Examination of Figure 1 shows that the BCO algorithm exhibits more stable convergence behavior in all three scenarios, which supports the computational accuracy results obtained in Table 3.

TABLE III. EVALUATION METRICS FOR COMPUTATIONAL ACCURACY BASED ON 30 INDEPENDENT RUNS

Scenario	Algorithm	Average	Rank	Maximum	Rank	Minimum	Rank	Standard Deviation	Rank
Economical	BCO	4.5099412E-01	1	4.5099412E-01	1	4.5099412E-01	1	2.2584051E-16	1
	GSO	4.5101079E-01	2	4.5149413E-01	2	4.5099412E-01	1	9.1288814E-05	2
	GLO	4.5214875E-01	3	4.6831353E-01	3	4.5099412E-01	1	4.3940743E-03	3
Balanced	BCO	2.2791453E-01	1	2.2791453E-01	1	2.2791453E-01	1	1.1292026E-16	1
	GSO	2.2829178E-01	2	2.2993409E-01	2	2.2791453E-01	1	7.6264871E-04	2
	GLO	2.2903302E-01	3	2.3932922E-01	3	2.2791453E-01	1	2.3719329E-03	3
Environmental	BCO	9.5751202E-02	1	9.6070375E-02	1	9.5471926E-02	1	3.0366310E-04	1
	GSO	9.7108475E-02	2	1.2400404E-01	3	9.5471926E-02	1	5.4546559E-03	3
	GLO	9.7110941E-02	3	1.0719218E-01	2	9.5471926E-02	1	2.6000311E-03	2

TABLE IV. EVALUATION METRICS FOR COMPUTATIONAL TIME BASED ON 30 INDEPENDENT RUNS

Scenario	Algorithm	Average	Rank	Maximum	Rank	Minimum	Rank	Standard Deviation	Rank
Economical	BCO	5.3519518E+00	3	7.0227057E+00	3	5.2385170E+00	3	3.1889322E-01	3
	GSO	5.1896563E+00	2	5.2271345E+00	2	5.1583577E+00	2	1.7939217E-02	1
	GLO	4.2267153E+00	1	4.2896576E+00	1	4.1607412E+00	1	2.6029055E-02	2
Balanced	BCO	5.2691110E+00	3	5.3070340E+00	3	5.2446997E+00	3	1.2565463E-02	2
	GSO	5.1967740E+00	2	5.2208554E+00	2	5.1749883E+00	2	1.0343634E-02	1
	GLO	4.2541095E+00	1	4.3228340E+00	1	4.1945240E+00	1	2.5207077E-02	3
Environmental	BCO	5.2879602E+00	3	5.3167081E+00	3	5.2695619E+00	3	1.2420370E-02	1
	GSO	5.2147910E+00	2	5.2493279E+00	2	5.1927364E+00	2	1.3807402E-02	2
	GLO	4.3065176E+00	1	4.3719828E+00	1	4.2522045E+00	1	3.0483893E-02	3



a) Economical

b) Balanced

c) Environmental

Fig. 1. Convergence curves

B. *Evaluation metrics results for computational time*

The evaluation metrics for computation time (s), consisting of average, maximum, minimum, and standard deviation, are presented in Table 4. When the results are examined, GLO has the lowest average computation time in all scenarios. BCO, on the other hand, requires the highest computation time among the evaluated algorithms. Microgrid systems are generally designed considering a project lifespan of 20-25 years. Sizing optimization, the most important step in the design, is performed only once during the design phase. Therefore, while computation time is an important performance indicator, the reliability of the final design and its ability to produce similar results in different runs are considered a more critical evaluation criterion in most cases. From this perspective, despite having a longer computation time, the high computational consistency provided by BCO can be considered a significant advantage for microgrid sizing problems. Considering the computational consistency results, it is seen that the BCO algorithm can produce more stable and repeatable solutions.

C. *Sizing optimization results of BCO algorithm*

The sizing results of the BCO algorithm, which showed the most successful performance in terms of calculation accuracy and consistency, are presented in Table 5, while the best design results are presented in Table 6. When Tables 5 and 6 are examined together, it is seen that the most significant change between the scenarios occurs in the PV panel and BESS capacity. In scenarios where environmental priorities increased, the increase in the number of PV panels from 52 to 56 and the number of BESSs from 133 to 220 can be considered a natural consequence of the system's tendency to increase the use of renewable energy and reduce carbon emissions. In contrast, the WT and DG numbers remained constant in all scenarios. When Table 6 is examined, it is seen that as the scenario shifts from the economic to the environmental scenario, the LCOE value increases from 0.2700 $/kWh to 0.3268 $/kWh, while carbon emissions decrease from approximately 635383 kg/year to 178506 kg/year. Similarly, as the renewable energy ratio increases from 92.49% to 97.95%, the LPSP value decreases. These results demonstrate a natural trade-off between cost and environmental performance. Overall, the BCO algorithm is able to produce consistent designs that satisfy technical and operational constraints under different scenarios. Due to its high computational accuracy, it can be considered a suitable alternative for applications such as microgrid sizing optimization.

TABLE V. BCO'S SIZING RESULTS ON 30 INDEPENDENT RUNS

Scenario	PV (No.)	PV (kW)	WT (No.)	WT (kW)	BESS (No.)	BESS (kW)	DG (No.)	DG (kW)
Economical	52	5200	2	1000	133	13300	2	1000
Balanced	55	5500	2	1000	175	17500	2	1000
Environmental	56	5600	2	1000	220	22000	2	1000

TABLE VI. BCO'S BEST-RUN DESIGN RESULTS ON 30 INDEPENDENT RUNS

Scenario	LCOE ($/kWh)	Emission (kg/year)	LPSP (%)	RF (%)	CF (%)	OF
Economical	0.27001271	6.3538356E+05	0.12532236	92.493277	29.885486	0.45099412E-01
Balanced	0.29224390	3.0957598E+05	0.05307067	96.417221	29.968925	0.22791453E-01
Environmental	0.32676608	1.7850574E+05	0.03115583	97.949156	29.831100	0.95471926E-02

V. CONCLUSION

This study addresses the hybrid off-grid microgrid sizing problem consisting of PV, WT, BESS, and DG for the Gökçeada settlement, and uses BCO, GSO, and GLO algorithms for its solution. The algorithms were compared in three different scenarios: economic, balanced, and environmental. The results show that BCO provides more accurate results compared to other algorithms by achieving the lowest average objective function and standard deviation values in all scenarios. When examining the best design results obtained with BCO, it was observed that in scenarios where environmental priorities increased, the RF ratio increased from 92.49% to 97.95%, and carbon emissions decreased from approximately 635383 kg/year to 178506 kg/year. In contrast, the LCOE value increased from $0.2700 to $0.3268 per kWh. In conclusion, the BCO algorithm was found to be an effective and reliable alternative for hybrid microgrid sizing optimization.

REFERENCES

[1] N. Oubouch, A. Redouane, A. Makhoukh, and A. El Hasnaoui, 'Techno-economic optimization of hybrid renewable energy systems for green hydrogen production and rural electrification', Energy, vol. 12, p. 100625, Jul. 2026, doi: 10.1016/j.nxener.2026.100625.

[2] S. Shahzad, M. A. Abbasi, H. Ali, M. Iqbal, R. Munir, and H. Kilic, 'Possibilities, Challenges, and Future Opportunities of Microgrids: A Review', Sustainability, vol. 15, no. 8, p. 6366, Apr. 2023, doi: 10.3390/su15086366.

[3] H. Rezk, A. G. Olabi, E. T. Sayed, and T. Wilberforce, 'Role of Metaheuristics in Optimizing Microgrids Operating and Management Issues: A Comprehensive Review', Sustainability, vol. 15, no. 6, p. 4982, Mar. 2023, doi: 10.3390/su15064982.

[4] İ. Çetinbaş, B. Tamyürek, and M. Demirtaş, 'Sizing optimization and design of an autonomous AC microgrid for commercial loads using Harris Hawks Optimization algorithm', *Energy Conversion and Management*, vol. 245, p. 114562, Oct. 2021, doi: 10.1016/j.enconman.2021.114562.

[5] A. A. Saleh and G. Magdy, 'Multi-objective sizing and performance optimization of islanded hybrid renewable microgrids: a case study in yanbu, Saudi Arabia', Sci. Rep., vol. 16, no. 1, p. 12743, Apr. 2026, doi: 10.1038/s41598-026-47028-1.

[6] A. H. Yakout et al., 'Sustainable sizing, dispatch, and resilience planning of hybrid microgrids using Arctic Puffin Optimization', Sci. Rep., vol. 16, no. 1, p. 7494, Feb. 2026, doi: 10.1038/s41598-026-37727-0.

[7] A. F. Güven, N. Yörükeren, E. Tag-Eldin, and M. M. Samy, 'Multi-Objective Optimization of an Islanded Green Energy System Utilizing Sophisticated Hybrid Metaheuristic Approach', IEEE Access, vol. 11, pp. 103044–103068, 2023, doi: 10.1109/ACCESS.2023.3296589.

[8] M. Kharrich, A. Selim, S. Kamel, and J. Kim, 'An effective design of hybrid renewable energy system using an improved Archimedes Optimization Algorithm: A case study of Farafra, Egypt', Energy Convers. Manag., vol. 283, p. 116907, May 2023, doi: 10.1016/j.enconman.2023.116907.

[9] H. R. E. H. Bouchekara, Y. A. Sha'aban, M. S. Shahriar, S. M. Abdullah, and M. A. Ramli, 'Sizing of Hybrid PV/Battery/Wind/Diesel Microgrid System Using an Improved Decomposition Multi-Objective Evolutionary Algorithm Considering Uncertainties and Battery Degradation', Sustainability, vol. 15, no. 14, p. 11073, Jul. 2023, doi: 10.3390/su151411073.

[10] J. Fan and X. Zhou, 'Optimization of a hybrid solar/wind/storage system with bio-generator for a household by emerging metaheuristic optimization algorithm', J. Energy Storage, vol. 73, p. 108967, Dec. 2023, doi: 10.1016/j.est.2023.108967.

[11] W. Zhu, J. Guo, G. Zhao, and B. Zeng, 'Optimal Sizing of an Island Hybrid Microgrid Based on Improved Multi-Objective Grey Wolf Optimizer', Processes, vol. 8, no. 12, p. 1581, Nov. 2020, doi: 10.3390/pr8121581.

[12] M. M. Samy and A. F. Güven, 'Optimal dimensioning of grid-connected PV/wind hybrid renewable energy systems with battery and supercapacitor storage a statistical validation of meta-heuristic algorithm performance', Sci. Rep., vol. 15, no. 1, p. 45658, Dec. 2025, doi: 10.1038/s41598-025-28234-9.

[13] İ. Çetinbaş, B. Tamyürek, and M. Demirtaş, 'The Hybrid Harris Hawks Optimizer-Arithmetic Optimization Algorithm: A New Hybrid Algorithm for Sizing Optimization and Design of Microgrids', *IEEE Access*, vol. 10, pp. 19254–19283, 2022, doi: 10.1109/ACCESS.2022.3151119.

[14] D. H. Wolpert and W. G. Macready, 'No free lunch theorems for optimization', IEEE Trans. Evol. Comput., vol. 1, no. 1, pp. 67–82, Apr. 1997, doi: 10.1109/4235.585893.

[15] M. Gökçek and C. Kale, 'Optimal design of a Hydrogen Refuelling Station (HRFS) powered by Hybrid Power System', Energy Convers. Manag., vol. 161, pp. 215–224, Apr. 2018, doi: 10.1016/j.enconman.2018.02.007.

[16] NASA POWER | Data Access Viewer" NASA. https://power.larc.nasa.gov/data-access-viewer/ (accessed Apr.21, 2026)

[17] A. Demiroren and U. Yilmaz, 'Analysis of change in electric energy cost with using renewable energy sources in Gökceada, Turkey: An island example', Renew. Sustain. Energy Rev., vol. 14, no. 1, pp. 323–333, Jan. 2010, doi: 10.1016/j.rser.2009.06.030.

[18] W. Zhao, Y. Xie, L. Wang, Z. Zhang, N. Khodadadi, and S. Mirjalili, 'An effective Bezier curve-based optimization (BCO) for large-scale numerical problems and 3D unmanned aerial vehicle path planning with efficient multiple threats evasion', Adv. Eng. Inform., vol. 73, p. 104524, Jul. 2026, doi: 10.1016/j.aei.2026.104524.

[19] E.-S. M. El-kenawy et al., 'Glider snake optimizer (GSO): a nature-inspired metaheuristic algorithm for global and engineering optimization problems', Artif. Intell. Rev., vol. 59, no. 3, p. 91, Feb. 2026, doi: 10.1007/s10462-026-11504-x.

[20] S. Barshandeh et al., 'Gray langurs optimizer: a multi-group bio-inspired optimization algorithm', Artif. Intell. Rev., vol. 59, no. 7, p. 166, Apr. 2026, doi: 10.1007/s10462-026-11529-2.