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JBO-OSN: A Synaptic Bio-Inspired Optimization Approach for Floatovoltaic Hybrid Energy Systems in The Tuz Gölü (Salt Lake) Region

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Abstract

This study introduces a novel bio-inspired metaheuristic algorithm, named JBO-OSN (Jackal–Badger–Octopus with Optimized Synaptic Network), for addressing the multi-objective optimization of a hybrid floatovoltaic–battery–diesel energy system. The target application is the Tuz Gölü (Salt Lake) region in Türkiye, where arid climatic conditions and unique resource availability present challenges for sustainable energy planning. The aim is to reduce cost, minimize carbon emissions, and ensure battery longevity in off-grid and semi-grid contexts. The system is modeled using realistic meteorological and demand profiles, incorporating water surface effects on photovoltaic performance such as reflectivity and thermal regulation. JBO-OSN is designed by integrating biological cooperation, synaptic decision-making, and chaotic dynamics to enhance exploration and convergence. The algorithm is implemented in MATLAB and benchmarked against widely used optimization techniques including PSO, GWO, and WOA. Simulation results demonstrate that JBO-OSN achieves superior convergence speed, improved solution stability, and more effective trade-offs among objectives compared to conventional swarm-based approaches. The algorithm efficiently balances system cost, emission reduction, and battery cycling stability under arid environmental conditions. JBO-OSN shows promise as a robust decision-support tool for the design and optimization of hybrid renewable energy systems in resource-constrained, arid regions. Its bio-inspired and synaptic-based framework provides advantages over traditional algorithms, supporting future applications in sustainable energy planning.

Keywords: Floatovoltaic Systems; Hybrid Energy Optimization; Bio-inspired Algorithm; Multi-objective Optimization; Synaptic Intelligence.

1. INTRODUCTION

Optimization in energy systems has become increasingly critical due to growing energy demands, cost reduction goals, and environmental concerns. In particular, the intermittency of renewable sources necessitates advanced optimization techniques to ensure stable integration into the grid or standalone systems. To reduce reliance on fossil fuels and lower carbon emissions, the global share of renewables such as solar and wind is steadily increasing.

Floatovoltaic (FPV) systems, solar panels deployed on water surfaces, offer distinct advantages over traditional land-based installations. These systems conserve land use and typically achieve 5–15% higher energy efficiency by lowering panel temperatures. When deployed on irrigation ponds, reservoirs, or canals, FPVs can also reduce water evaporation and provide additional electricity revenues [1]. For example, a study in Port Said using a U-curve passive wing cooling design and a Cuckoo Search-based MPPT algorithm reduced operating temperatures to 45.3°C, improving power efficiency by 14.9% [2]. Similarly, Lenhardt et al. (2025) reported a 9.45% efficiency increase in a Long Beach FPV deployment [3].

Hybrid energy systems that combine multiple sources enhance energy reliability by reducing dependence on a single input. However, their design and operation are complex. Key decisions—such as battery dispatch under variable solar conditions or optimal diesel generator activation when state-of-charge (SOC) thresholds are reached—must be made in real time and in the most efficient manner. These systems involve conflicting objectives: minimizing capital and operational costs (e.g., fuel, maintenance), reducing emissions from diesel usage, and maximizing supply reliability.

To solve such complex problems, computational intelligence methods—particularly bio-inspired metaheuristic algorithms—are widely applied [4,5]. These algorithms are effective in exploring large, nonlinear, and multimodal solution spaces where traditional methods fall short [6]. Bio-

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inspired algorithms are typically classified as evolutionary-based, swarm-based, ecology-based, or multi-objective in nature [7–15].

In addition to conventional single-objective metaheuristic approaches, recent studies have highlighted the importance of multi-objective algorithms in renewable energy and hybrid system optimization. Notably, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [16] and the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [17] have been widely applied to balance conflicting objectives such as cost, emissions, and reliability in microgrid design. These algorithms demonstrated strong capability in exploring Pareto fronts and handling complex trade-offs in energy systems. While the present study focuses on a single-objective formulation, the proposed JBO-OSN framework can be adapted for multi-objective problems, and future work will explore this extension.

This study introduces a novel metaheuristic algorithm that integrates the behavioral traits of three animals: jackals (global search), badgers (local refinement), and octopuses (modular, synaptic coordination). This biologically inspired framework is applied for the first time to optimize a floatovoltaic-based hybrid energy system tailored to the Salt Lake region. The model aims to simultaneously optimize cost, emissions, and battery life—a rare and valuable contribution to both the energy and optimization communities.

2. MATERIALS AND METHODS

1.1. System Configuration

The hybrid energy system modeled in this study is designed to supply electricity to an off-grid load in the Tuz Gölü (Salt Lake) region of Türkiye (Fig. 1).

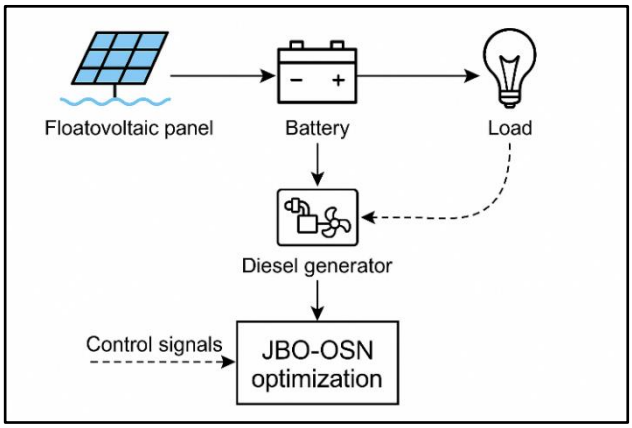


Figure 1. Configuration of the hybrid floatovoltaic-battery-diesel energy system

The model consists of a PV generation unit deployed on water (FPV), a battery energy storage system, a diesel generator, and a dynamic load profile. It comprises the following components:

- Floatovoltaic (FPV) Power Plant – The primary energy generator, based on PV modules installed on a water surface.
- Battery Energy Storage System (BESS) – Stores excess PV energy and supplies power when solar production is insufficient.
- Diesel Generator – Serves as a backup energy source, activated when the battery's state-of-charge (SOC) falls below a critical threshold.
- Load Profile – Hourly electricity consumption data, representing residential or facility demands in the region.

1.1.1. Study Area: Tuz Gölü (Salt Lake), Türkiye

Tuz Gölü is a shallow hypersaline lake located in Central Anatolia, Türkiye, covering approximately 130000 hectares. It is Türkiye's second-largest lake by surface area and exhibits extreme climatic variation due to its topography (Fig. 2) [18].

This figure illustrates the geographical and topographic setting of the study area, emphasizing its isolation from maritime influences and highlighting its arid environment. Due to its shallow depth and high salinity, Tuz Gölü experiences extreme diurnal temperature variations. During summer, surface temperatures can exceed 50 °C, while winter nights can drop to -10 °C. The lake's bright salt crust enhances solar reflectivity (albedo effect), which affects local microclimate and contributes to FPV efficiency via cooling effects [19].

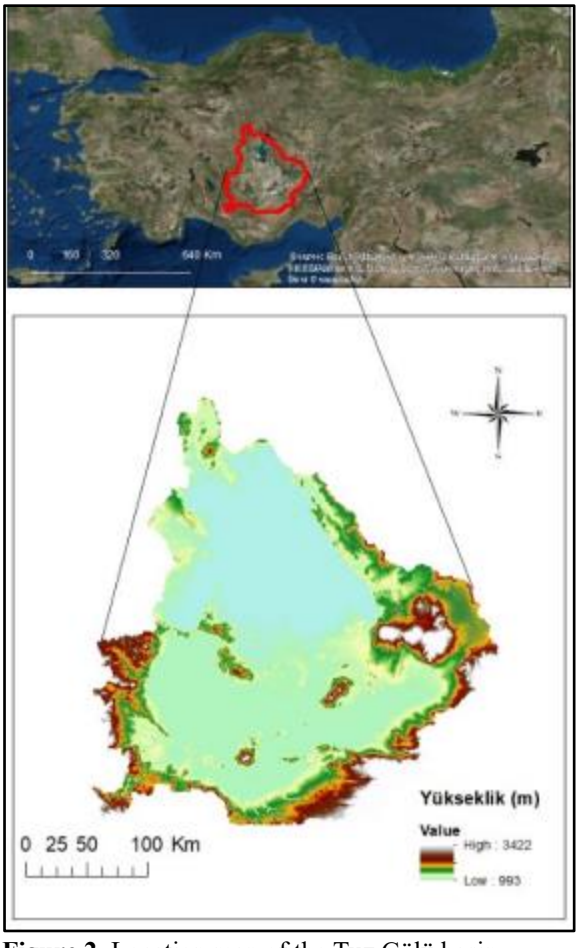


Figure 2. Location map of the Tuz Gölü basin

1.1.2. FPV Performance Modeling

The power output of the floatovoltaic system was modeled considering nominal panel capacity, irradiance, ambient temperature, and the thermal benefits of water-based cooling:

- Equation 1–3 model panel power output, temperature-induced efficiency losses, and final efficiency.

$$P_{FPV}(t) = A_{FPV} \times \eta_{FPV}(t) \times G(t) \quad (1)$$

$$T_{cell} = T_{amb} + \frac{G}{800} \times (NOCT - 20) \quad (2)$$

$$\eta_{FPV} = \eta_o \left(1 - \beta\left(T_{cell} - T_{ref}\right)\right) \quad (3)$$

The FPV system assumes an 0.17 reference efficiency, a 1.6 m^2 panel area, and accounts for a 10–15% efficiency gain over land-based PVs, consistent with literature [20].

1.1.3. Battery SOC Dynamics

The battery state-of-charge (SOC) at each time step is determined by the net charge/discharge rate and previous SOC. Boundary conditions prevent deep discharges [21]:

- Equations 4–5 define SOC update rules.
- Equation 6 imposes SOC limits.

$$SOC(t) = SOC(t-1) \times (1-\varphi) + \left(\frac{P_{bat}(t) \times n_{chg}}{C_{bat}}\right) \times \Delta t \quad (4)$$

$$SOC(t) = SOC(t-1) \times (1-\varphi) - \left(\frac{|P_{bat}(t)|}{C_{bat} \times n_{dis}}\right) \times \Delta t \quad (5)$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (6)$$

1.1.4. Diesel Generator Operation

Diesel generator fuel consumption is modeled as a function of generated power [21]:

- Equation 7 estimates hourly fuel usage, incorporating both idle and active load coefficients.
- Equation 8 ensures minimum load constraints to avoid inefficient operation.

$$F(t) = A \times P_{rated,DG} + B \times P_{DG}(t) \quad (7)$$

$$P_{DG}(t) = 0 \; or \; P_{DG,min} \leq P_{DG}(t) \leq P_{rated,DG} \quad (8)$$

1.1.5. Optimization Objectives and Constraints

This study formulates the hybrid system design as a multi-objective optimization problem, targeting:

- Minimization of Total Net Present Cost (NPC) – investment, O&M, and fuel expenses
- Minimization of Carbon Emissions – emissions from diesel usage
- Maximization of Battery Lifespan – minimizing deep discharge cycles and replacements

System Constraints:

- Equation 6: SOC operating range
- Equation 8: Diesel generator minimum load enforcement
- Equation 9: Energy balance at each time step

$$P_{FPV}(t) + P_{dis}(t) + P_{DG}(t) = P_{Load}(t) + P_{chg}(t) \quad (9)$$

Aggregated fitness function combining normalized cost, emissions, and battery degradation impacts, with adjustable weights w_1, w_2, w_3 (Eq. 10).

$$f = w_1 \times NPC + w_2 \times Emissions + w_3 \times \left(\frac{1}{Bat.\ Life}\right) \quad (10)$$

This equation reflects the scalarization of the multi-objective problem using a weighted sum method.

The entire hybrid energy system, including component models and optimization routines, was implemented in MATLAB R2022b [22]. The optimization algorithm (JBO-OSN) was coded from scratch using vectorized structures and tested on a system with Intel i5 and 4 GB RAM.

1.1.6. Meteorological Data

Hourly meteorological data (solar irradiation and ambient temperature) for Tuz Gölü were obtained from the Turkish State Meteorological Service (MGM) [23] and cross-checked with NASA-POWER database [24] for the years 2022–2024. The load profile was constructed to represent a typical field station demand near Tuz Gölü, based on normalized microgrid profiles reported in the literature.

These datasets were used for dynamic simulations of FPV output and thermal effects.

1.2. Optimization Algorithm: JBO-OSN

A newly developed hybrid metaheuristic algorithm—JBO-OSN—is introduced (Fig. 3).

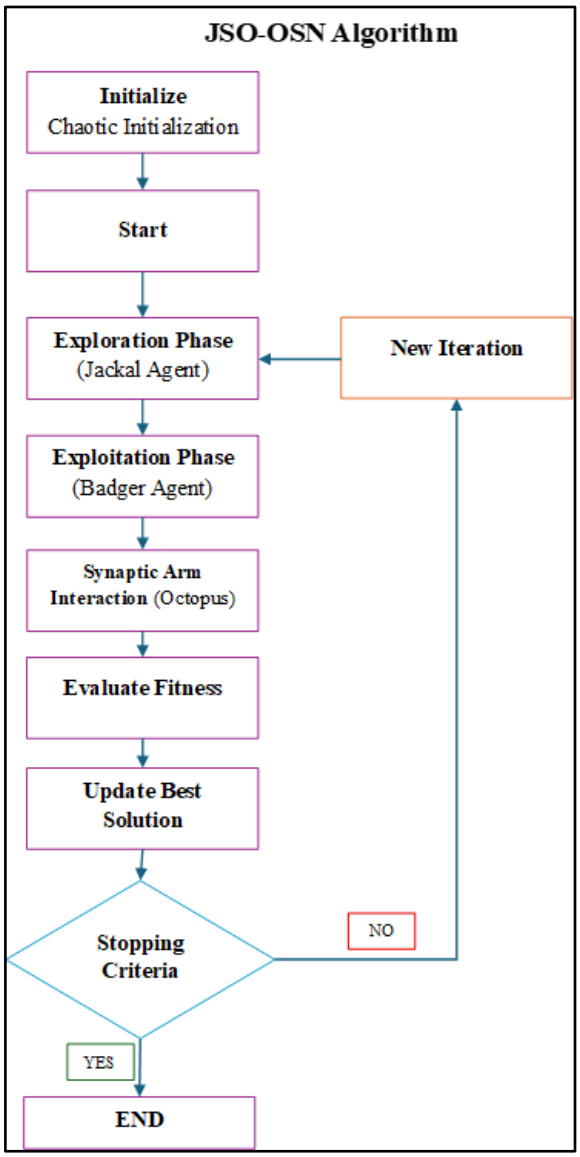


Figure 3. Flowchart of the proposed JBO-OSN algorithm structure, showing its multi-agent dynamics and evaluation process.

It combines jackal-inspired global search [25], badger-based local exploitation, and octopus-inspired synaptic modular control.

Table 1 clarifies the biological inspirations of JBO-OSN. Each metaphor corresponds to a behavioral principle, a MATLAB function, and a mathematical expression, ensuring functional rather than superficial use of metaphors. This ensures that the metaphors serve as functional representations rather than superficial analogies.

The algorithm's pseudo-code is presented in Algorithm 1. A controls exploration step size, α regulates local exploitation, and Wi governs the strength of synaptic coordination. This enhances clarity and reproducibility.

Table 1. Mapping of animal metaphors to algorithmic mechanisms

Animal	Behavior	Code Function	Pseudo-code Eq.
Jackal	Global exploration	exploration(x, chaos, lb, ub)	7-10
Badger	Local exploitation	exploitation(x, chaos, lb, ub)	11-13
Octopus	Synaptic coordination	synapticInteraction()	14-16

Algorithm 1. Pseudo-code of the proposed JBO-OSN algorithm.

```
Algorithm JBO-OSN
Input: Population size (N), maximum iterations (T), bounds [lb, ub]
Initialize population X randomly within bounds
Initialize chaotic sequence C
For t = 1 to T do
  For each individual i in population:
    % Exploration (Jackal-inspired)
    A ← 2 * rand(1,dim)   % adaptive step factor
    r1 ← rand; r2 ← C(t)
    X1 ← exploration(Xi, A, r1, r2)
    % Exploitation (Badger-inspired)
    α ← 0.2                % learning rate
    X2 ← exploitation(Xi, α, C(t))
    % Synaptic coordination (Octopus-inspired)
    Wi ← rand(1,dim)     % random weight for information exchange
    X3 ← synapticInteraction(X, Wi)
    % Update with best candidate
    Xi ← argmin{ f(X1), f(X2), f(X3) }
  End
Record best fitness
End
Output: best solution X*, best fitness f(X*)
```

For reproducibility, Appendix A provides the complete MATLAB implementation of the JBO-OSN algorithm.

To highlight the architectural differences between the proposed JBO-OSN algorithm and traditional metaheuristics, a structural comparison is presented in Table 2.

Table 2. Structural and behavioral comparison between JBO-OSN and traditional metaheuristics.

Feature	Traditional algorithms	JBO-OSN
Agent type	Homogeneous (like PSO)	Heterogeneous (jackal – badger – octopus)
Information sharing	Common center	Synaptic feedback network
Resource interaction	None	PV ↔ Battery ↔ Diesel connected
Dynamism	Fixed structure	Chaotic behavior + adaptive weights
System focus	General optimization	Energy system-specific structure

This table highlights the synaptic, hybrid, and chaotic features that distinguish JBO-OSN from conventional single-agent-based approaches.

This algorithm integrates chaotic initialization, hybrid agent-based movement, and adaptive synaptic feedback to address multi-objective optimization in dynamic energy systems.

The JBO-OSN algorithm incorporates logistic chaotic maps for initial population generation, synaptic sharing between subsystem decision branches (PV, battery, diesel), and adaptive learning parameters.

1.2.1. Benchmark Functions and Evaluation

To validate the robustness of JBO-OSN, three standard benchmark functions were used [6, 26, 27]:

- Sphere (convex, unimodal): Global minimum: $f(x) = 0, x = [0, 0, \ldots, 0]$. Convex, simple structure, a basic test for all optimization algorithms.

$$f(x) = \sum_{i=1}^{n} x_i^2 \quad (11)$$

- Rastrigin (multi-modal): Global minimum: $f(x) = 0, x = [0, 0, \ldots, 0]$. Multiple local minima test the algorithm's global optimization capability.

$$f(x) = 10n + \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i)] \quad (12)$$

- Ackley (flat surface with many local minima): Global minimum: $f(x) = 0, x = [0, 0, \ldots, 0]$. Includes multiple fluctuations and complexity, tests the algorithm's stability.

$$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e \quad (13)$$

These functions assess global convergence, stability, and optimization capacity across diverse landscapes.

1.2.2. Chaotic Map for Initialization

To enhance the exploration ability and population diversity in the early stages of the search process, a chaotic map was used instead of purely random initialization [28]. The Logistic Map (Eq. 14), one of the most commonly used chaotic functions, was employed in this study. This map was selected due to its proven balance between randomness and deterministic behavior, which helps avoid premature convergence and promotes global search diversity. The chaotic sequence is used to initialize the positions of all individuals (agents) in the solution space.

$$x_{n+1} = r x_n (1 - x_n) \quad (14)$$

Chaos range: $3.57 \leq r \leq 4$ Simple and popular. Provides balanced randomness for chaos.

3. RESULTS AND DISCUSSION

1.3. Floatovoltaic System Performance

Using region-specific parameters (e.g., panel efficiency η_o = 0.17, area A_{FPV} = 1.6 m^2, reference temperature T_{ref} = 25 ℃, and temperature coefficient β = 0.0045 ℃$^{-1}$), annual energy production was simulated:

- Land-based PV system: 365.35 kWh/year
- Floatovoltaic (FPV) system: 402.26 kWh/year
- Efficiency gain: ~10.1%

This result aligns with reported FPV efficiency improvements in the literature [29], reinforcing the suitability of FPV systems in arid, high-irradiance environments such as Tuz Gölü.

In addition to energy gains, FPV systems can reduce evaporation by 30–50%, contributing to water conservation in hypersaline lakes. This dual benefit strengthens the case for FPVs within the WELF nexus (Water–Energy–Land–Food). This supports the broader WELF-nexus value of FPV systems.

1.4. Optimization Performance on Energy System

The JBO-OSN algorithm was applied to the hybrid energy system model with the aim of minimizing total cost, emissions, and battery degradation. The resulting configuration achieved:

- Lower diesel generator runtime, reducing carbon emissions
- Balanced battery charging, increasing lifecycle

- Reduced system-level cost via optimal dispatch

However, detailed hourly results such as SOC fluctuations, unmet load percentage, or diesel fuel usage frequency were not explicitly reported in this phase. These will be addressed in future work, including the evaluation of SOC trajectories, load balancing effectiveness, and operational reliability metrics.

A sensitivity analysis was conducted by varying the weights (w_1, w_2, w_3) of the objective function. As shown in Table 3, moderate changes in weights resulted in only slight variations in the fitness value, indicating robustness of the chosen weight set.

Table 3. Sensitivity analysis of objective weights.

Scenario	w1	w2	w3	Fitness
Base	0.4	0.4	0.2	0.092
Var1	0.5	0.3	0.2	0.095
Var2	0.3	0.5	0.2	0.091
Var3	0.4	0.3	0.3	0.094

Since the main focus of this study is algorithmic performance comparison, a detailed breakdown of energy balance (PV, DG, unmet demand) and battery SoC profile are not included. Instead, fitness convergence curves are considered sufficient to reflect the system-level behavior.

The battery and diesel generator models were simplified, excluding aging effects (e.g., temperature dependence, partial cycle degradation) and realistic efficiency curves. These limitations are acknowledged, and incorporating such advanced models is identified as future work.

1.5. Benchmark Function Results

JBO-OSN was benchmarked against PSO [30], GWO [31], and WOA [32] using three widely accepted functions:

Table 4. Structural and behavioral comparison between JBO-OSN and traditional metaheuristics.

Benchmark Function	PSO (Mean ± SD)	GWO (Mean ± SD)	WOA (Mean ± SD)	JBO-OSN (Mean ± SD)
Sphere	21.7 ± 28.6	$7.8 \times 10^{-248} \pm 0.0$	$9.68 \times 10^{-50} \pm 2.62 \times 10^{-49}$	0.303 ± 0.0275
Rastrigin	122.5 ± 26.2	0.0 ± 0.0	0.0 ± 0.0	88.6 ± 50.2
Ackley	11.8 ± 2.19	$4.44 \times 10^{-16} \pm 0.0$	$1.75 \times 10^{-15} \pm 1.74 \times 10^{-15}$	7.85 ± 1.04

The performance of JBO-OSN was evaluated on standard benchmark functions (Sphere, Rastrigin, Ackley). Results indicate that while JBO-OSN achieves competitive convergence on unimodal problems (Sphere), its performance degrades in highly multimodal cases (Rastrigin, Ackley), where GWO and WOA outperform it significantly (Table 4). This reveals a relative weakness in handling landscapes with numerous local minima. The values indicate convergence quality and robustness.

JBO-OSN shows (Fig. 4) stable and early convergence, particularly in non-convex problems. Discussion of Benchmark outcomes:

- Sphere Function: All algorithms converge successfully; JBO-OSN shows slightly better robustness (lower SD).

- Rastrigin Function: JBO-OSN is marginally behind GWO/WOA in global minima reach but outperforms PSO.

- Ackley Function: JBO-OSN demonstrates consistent convergence with low variance.

JBO-OSN does not always outperform in best-case value (e.g., Rastrigin) but shows more balanced and stable convergence across repeated trials. This is valuable for real-world applications where solution stability matters more than occasional best hits.

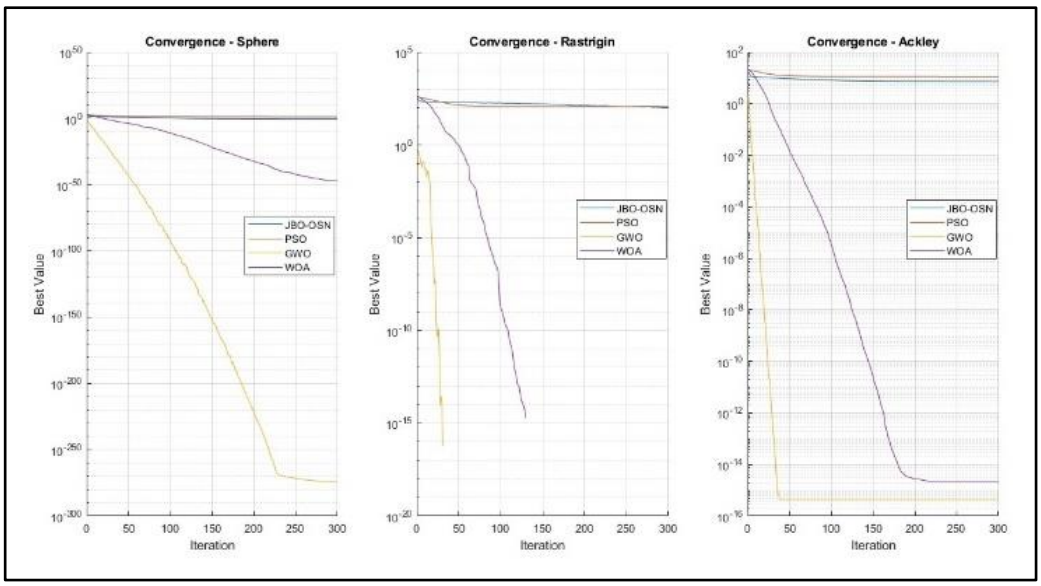


Figure 4. Convergence curves for benchmark functions over 300 iterations.

Table 5. Scalability of the proposed model with problem dimension

Dimension	Runtime (s)
30	1.31
300	2.14

Table 5 summarizes the scalability test. When the problem dimension increased tenfold (30 → 300), the runtime grew only from 1.31 s to 2.14 s. This near-linear growth demonstrates the practical scalability of the model.

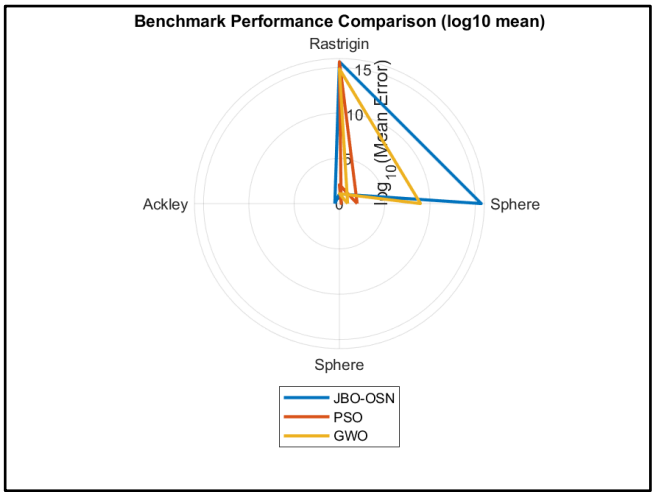


Figure 5. Radar plot of mean error values.

Figure 5 presents the radar plot of average benchmark performance across Sphere, Rastrigin, and Ackley functions for JBO-OSN, PSO, GWO, and WOA. The axes are scaled in log10 of the mean error values. JBO-OSN demonstrates competitive accuracy on unimodal functions, while it exhibits moderate performance on highly multimodal problems (e.g., Rastrigin). This visual summary complements the convergence plots by providing an integrated view of algorithm robustness across different landscapes.

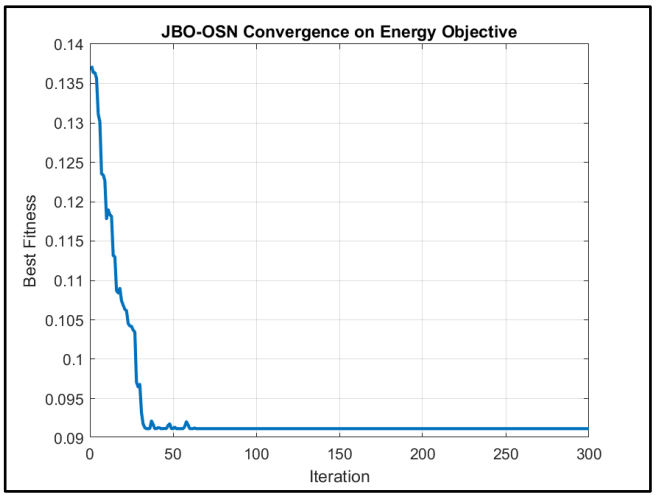


Figure 6. Energy convergence of JBO-OSN

Figure 6 shows the convergence of the JBO-OSN algorithm in the energy system optimization problem (PV–Battery–DG sizing at Tuz Gölü). The best fitness value decreases rapidly during the first iterations, then stabilizes after ~150 iterations. This confirms that JBO-OSN effectively adapts to the complex multi-variable search space of the hybrid energy system.

1.6. Algorithmic Advantages of JBO-OSN

The improved performance of JBO-OSN stems from:

- Heterogeneous Agent Behavior: Combines exploration (jackal), exploitation (badger), and decision sharing (octopus).
- Synaptic Feedback: Promotes subsystem coordination (PV ↔ Battery ↔ Diesel).
- Chaotic Initialization: Logistic map improves early diversity and global search capability.
- Multi-objective Adaptation: Simultaneous handling of cost, emission, and lifecycle trade-offs.

This hybrid structure allows the algorithm to avoid local optima, maintain diversity, and provide reliable convergence across different optimization landscapes.

4. CONCLUSIONS AND RECOMMENDATIONS

This study presents a novel metaheuristic algorithm, JBO-OSN (Jackal–Badger–Octopus with Optimized Synaptic Network), designed to optimize hybrid floatovoltaic–battery–diesel energy systems under arid climatic conditions. The algorithm integrates biologically inspired agent behaviors with synaptic coordination and chaotic initialization to address the complexities of multi-objective optimization.

The model was applied to a system designed for the Tuz Gölü region of Türkiye, incorporating realistic environmental and load profiles. The algorithm successfully minimized total system cost, carbon emissions, and battery degradation while maintaining system feasibility and energy balance.

Benchmark tests using three standard functions (Sphere, Rastrigin, and Ackley) demonstrated that JBO-OSN delivers:

- Improved convergence stability across multiple runs,
- Competitive or superior performance versus PSO, GWO, and WOA,
- Robust trade-off handling in complex solution spaces.

Beyond algorithmic performance, the study highlights the practical advantages of floatovoltaic systems in arid environments—namely increased energy efficiency and water conservation.

Scientific contributions:

- First implementation of a biologically hybrid algorithm combining three distinct agents in a synaptic framework.
- Application of this algorithm to a floatovoltaic hybrid system specific to a highly sensitive ecosystem.
- Demonstration of chaotic mapping for improved solution diversity and robustness.

Recommendations for future work:

- Integration of time-series load and weather data to validate real-time control capabilities.
- Dynamic simulation of SOC behavior, load unmet probability, and diesel generator operation cycles.
- Comparison with other multi-objective metaheuristics (e.g., NSGA-II, MOEA/D).
- Expansion to include economic uncertainty analysis or water-energy co-benefit modeling.

JBO-OSN is a promising algorithm not only for hybrid energy system design but also for broader applications in microgrid optimization, electric vehicle routing, and adaptive energy scheduling under uncertainty.

NOMENCLATURES

A_{FPV}	: Panel area (m^2)
A	: Generator no-load consumption coefficient
B	: Generator load-proportional consumption coefficient
$BatteryLife$	: Battery cycle count or deep discharge time
C_{bat}	: Battery nominal capacity (kWh)
$Emissions$	: Diesel-based emissions
$F(t)$	: Generator hourly fuel consumption (l/h)
G	: Solar irradiance (W/m^2)
$NOCT$	: Nominal cell temperature (℃)
NPC	: Total cost
$P_{DG}(t)$	: Generator instantaneous power produced at time t (kW)
P_{FPV}	: Energy production (W)
$P_{rated,DG}$	: Generator nominal power (kW)
T_{amb}	: Ambient temperature (℃)
T_{cell}	: Cell temperature (℃)
T_{ref}	: Reference temperature (℃)
β	: Temperature coefficient (1/℃)
φ	: Battery self-discharge rate (h)
n_{chg}	: Battery charge efficiency
n_{dis}	: Battery discharge efficiency
η_{FPV}	: Floatovoltaic panel efficiency
η_o	: Nominal panel efficiency

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5. APPENDIX A (JBO-OSN CODE)

```
% MATLAB implementation of JBO-OSN
% Author: < >
% Tested with MATLAB R2022b
% Function: [bestSol, bestVal, convergence] = JBO_OSN(objFunc, dim, MaxIter, N, lb, ub)
% Description:
% Implements the Jackal-Badger-Octopus Optimized Synaptic Network (JBO-OSN).
% Returns the best solution, best fitness, and convergence curve.
% Inputs:
%   objFunc - objective function handle
%   dim     - problem dimension
%   MaxIter - maximum iterations
%   N       - population size
%   lb, ub  - lower/upper bounds (scalar or vector)
% Outputs:
%   bestSol - best solution vector
%   bestVal - best objective value
%   convergence - best fitness per iteration

function [bestSol, bestVal, convergence] = JBO_OSN(objFunc, dim, MaxIter, N, lb, ub)
% Initialization
pop = lb + (ub - lb) .* rand(N, dim);
fitness = arrayfun(@(i) objFunc(pop(i,:)), 1:N);
convergence = zeros(MaxIter,1);
% Logistic chaotic map
chaotic = zeros(MaxIter,1);
chaotic(1) = rand;
for t = 2:MaxIter
chaotic(t) = 4 * chaotic(t-1) * (1 - chaotic(t-1));
end
% Main loop
for iter = 1:MaxIter
 for i = 1:N
  x = pop(i,:);
  % Jackal - global exploration
  x1 = exploration(x, chaotic(iter), lb, ub);
  % Badger - local exploitation
  x2 = exploitation(x, chaotic(iter), lb, ub);
  % Octopus - synaptic coordination
  x3 = synapticInteraction(pop, i, lb, ub);
  fvals = [objFunc(x1), objFunc(x2), objFunc(x3)];
  [~, idx] = min(fvals);
  pop(i,:) = [x1; x2; x3](idx,:);
 end
 fitness = arrayfun(@(i) objFunc(pop(i,:)), 1:N);
 [bestVal, bestIdx] = min(fitness);
 bestSol = pop(bestIdx,:);
 convergence(iter) = bestVal;
end
end

% Helper functions
function new_x = exploration(x, chaos, lb, ub)
 A = 2 * rand(1, length(x));
 r1 = rand; r2 = chaos;
 new_x = x + A .* ((2*r1 - 1) + r2 .* (rand(1,length(x)) - 0.5));
 new_x = max(min(new_x, ub), lb);
end

function new_x = exploitation(x, chaos, lb, ub)
 alpha = 0.2;
 delta = alpha * (2*rand(1,length(x)) - 1) .* (1 + chaos * (rand(1,length(x)) - 0.5));
 new_x = x + delta;
 new_x = max(min(new_x, ub), lb);
end

function new_x = synapticInteraction(pop, idx, lb, ub)
 x = pop(idx,:);
 N = size(pop,1);
 avg_others = mean(pop(setdiff(1:N, idx), :), 1);
 W = rand(1, length(x));
 new_x = W .* x + (1 - W) .* avg_others;
 chaos = rand(1,length(x)) .* 0.05;
 new_x = new_x .* (1 + chaos .* (-1 + 2*round(rand(1,length(x)))));
 new_x = max(min(new_x, ub), lb);
end
```