Power sharing based on starfish optimization algorithm in DC microgrid

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ABSTRACT

This paper presents a starfish optimization algorithm (SFOA) method for optimizing control parameters in DC microgrids. SFOA is a new metaheuristic inspired by biology to solve optimization problems, which simulates the behavior of starfish, including exploration, preying, and regeneration. SFOA consists of two main phases of exploration and exploitation. This paper evaluates the performance of SFAO on droop control of DC microgrids by comparing with walrus optimizer (WO) and grasshopper optimization algorithm (GOA). From the simulation, SFOA shows superior capability. Validation on DC microgrid control using integral of time-weighted absolute error (ITAE) and integral of time-weighted squared error (ITSE). Simulation results demonstrate that the proposed technique exhibits a superior ITAE relative to WO and GOA, which are 6.88% and 8%, respectively. The performance validation results demonstrate that the SFOA approach exhibits potential and effective performance. The proposed method on DC microgrid control has been successfully applied and shows promising performance. The proposed methodology is particularly suitable for renewable energy integration in isolated or resource-constrained regions.

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1. INTRODUCTION

Microgrids are localised energy systems that can function autonomously or in conjunction with the primary power grid, using diverse distributed energy resources (DERs), storage solutions, and load management to deliver dependable and efficient electricity [1]-[4]. Their significance resides in their capacity to improve energy security, resilience, and sustainability, especially in remote or neglected regions where conventional grid infrastructure is deficient or unreliable. As the global energy landscape shifts towards decentralised and renewable solutions, microgrids emerge as a pivotal innovation in contemporary energy systems, providing the flexibility and adaptability necessary for the effective integration of renewable energy sources (RES) [5]-[8]. RES, such as solar photovoltaics (PV), wind turbines, and biomass, are essential in modern energy systems for diminishing greenhouse gas emissions and dependence on fossil fuels [9]-[12]. The incorporation of RES into microgrids improves sustainability and environmental efficacy, in accordance with global aims to address climate change and facilitate green energy transitions [13]-[17]. The variable and intermittent characteristics of RES provide considerable hurdles in maintaining a continuous and stable power supply, requiring sophisticated tactics to optimise microgrid operations [18]-[20].

The primary control strategy for ensuring microgrid stability is the droop-based method. The droop control technique that integrates output virtual resistance at each source situated farther from the source (current/voltage) is suboptimal. The local DC bus voltage increasingly relies on the loads connected to the system [21]-[23]. The traditional droop method has several disadvantages, including inadequate voltage regulation, imprecision in load power allocation, reliance on line impedance, sluggish dynamic response, and diminished stability margin [24], [25]. While alternative droop approaches purport to address these deficiencies, the stability factor is crucial and often receives insufficient consideration. Traditional droop control approaches cause significant voltage fluctuations, inadequate current distribution, and inadequate regulation of the electric current exchanged between converters. Metaheuristics are high-level computational strategies used to find optimal solutions to complex optimization problems. These methods are not problem-specific and are often inspired by nature, such as animal behavior or evolution [26], [27]. The goal is to find a good enough solution in a short time, especially when manually searching for a perfect solution is impossible due to the sheer number of possibilities [28]-[30]. Many researchers have demonstrated the application of metaheuristic methods to droop control, which produce good simulation results such as particle swarm optimization (PSO) [31], [32], grey wolf algorithm (GWA) [33], [34], artificial rabbits optimization algorithm (ARO) [35], and gravity search algorithm (GSA) [36]. Although several metaheuristic algorithms have been proposed to optimize droop control, significant challenges remain in achieving optimal droop control performance across different problem types. To address these challenges, this work proposes an enhanced and customized droop control technique based on the starfish optimization algorithm (SFOA). This article makes the following contributions.

- Optimizing droop control parameters using SFOA.
- Droop control optimized using the SFOA method is simulated and evaluated using load changes. This study uses comparison algorithms, such as walrus optimizer (WO) and grasshopper optimization algorithm (GOA).

This article is structured as follows. Section 2 elucidates the Starfish optimisation technique and droop control. Section 3 presents the proposed approach SFOA for the regulation of DC microgrids. Section 4 contains discussions and simulations. The conclusion is located in the section 5.

2. METHOD

2.1. Starfish optimization algorithm

A novel swarm intelligence algorithm, termed the SFOA, is based on starfish behavior to address global optimization and engineering challenges. Starfish are predominantly found in oceanic environments, particularly in deep-sea regions, and are rarely located in freshwater areas due to their lack of an osmoregulatory system [37].

The exploratory, predatory, and regenerative behaviors of starfish can inspire the development of a stochastic optimization algorithm, termed the SFOA. Similar to other prominent metaheuristic algorithms, SFOA incorporates both exploration and exploitation phases; the exploration phase emulates the foraging behavior of starfish, while the exploitation phase is formulated based on predation and regeneration strategies. It should be noted that most existing metaheuristic algorithms employ a vectorial search pattern during their exploration phases, which can yield effective performance when addressing separable functions across all dimensions. During the initialization step of SFOA, the positions of starfish are randomly generated within the limits of design variables, represented as a matrix:

$$X = \begin{bmatrix} X_{1,1} & \cdots & X_{1,2} & \cdots X_{1,m} \\ \vdots & \ddots & \vdots & \iddots \ \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots X_{i,m} \\ \vdots & \iddots & \vdots & \ddots \ \vdots \\ X_{N,1} & \cdots & X_{N,j} & \cdots \ X_{N,m} \end{bmatrix}_{Nxm} \tag{1}$$

$$X_{i,j} = lb_j + r_{i,j} \cdot (ub_j - lb_j) \tag{2}$$

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{Nxm} \tag{3}$$

where X is the starfish location population matrix, $X_{1,1}$ is the i th starfish (candidate solution), $X_{i,j}$ is the jth dimension (problem variables), N is the number of starfishs, m is the number of problem variables, $r_{i,j}$) is a random number in the interval [0, 1], lb_j and ub_j are the lower and upper bounds of the j th problem variable, respectively. Since each starfish is a candidate solution to the problem, corresponding to each starfish, the objective function can be evaluated. The evaluated values for the objective function of the problem can be represented using a vector according to (3). F is a vector of objective function values and F_1 is the obtained objective function value for the i th starfish. The evaluated value for the objective function is the main criterion for evaluating the quality of candidate solutions. Therefore, the best value obtained for the objective function corresponds to the best candidate solution (i.e., the best member), and the worst value obtained for the objective function corresponds to the worst candidate solution (i.e., the worst member). Given that the positions of the starfishs in the search space are updated at each iteration, the candidate best solutions should also be updated at each iteration.

2.1.1. Exploration phase

To mimic the exploratory behavior of starfish, we define the exploration phase within the SFOA algorithm, modeling the search capabilities of the five arms of a starfish, with eyes positioned at the tips of the arms. During the investigation phase of SFOA, an innovative search pattern is introduced, integrating the five-dimensional search pattern for $D > 5$ and the unidimensional search pattern for $D \leq 5$ across many optimization issues. The dimensional threshold is determined by the five arms (or rays) of the starfish. If the size of the optimization issue exceeds $5(D > 5)$ the search space becomes extensive, necessitating the starfish to maneuver all five arms to investigate the surrounding environment. Furthermore, the appendages of starfish necessitate an understanding of the optimal positioning among search agents to direct their locomotion. Consequently, we formulate the mathematical model for this phase.

$$\begin{cases} Y_{i.p}^T = X_{i.p}^T + \alpha_{i,j} \cdot \left(X_{best.p}^T - X_{i.p}^T\right) \cos\theta & r \leq 0.5 \\ Y_{i.p}^T = X_{i.p}^T - \alpha_{i,j} \cdot \left(X_{best.p}^T - X_{i.p}^T\right) \sin\theta & r > 0.5 \end{cases} \tag{4}$$

$$\alpha_1 = (2r - 1)\pi \tag{5}$$

$$\theta = \frac{\pi}{2} . \frac{T}{T_{max}} \tag{6}$$

where $Y_{i.p}^T$ and $X_{i.p}^T$ represent the acquired and present positions of a starfish, respectively. $X_{best.p}^T$; p is the p-dimensional representation of the current optimal position, where p consists of five randomly selected dimensions from a total of D dimensions, and r is a value within the interval (0,1). T denotes the current iteration, whereas T_{max} signifies the maximum iteration. Sine and cosine functions indicate that the limbs of starfish can rotate left or right to access food with equal likelihood. During the exploration phase, α_1 is randomly generated for the updating position in each candidate and iteration, while h varies with the number of iterations, $r \in (0.1)$ where two parameters assess the impact of distance between the optimal position and the current position in the designated updating dimension. In the case of $D > 5$ in an optimization problem, a dimensional search pattern is employed in (4) to update solely five dimensions of the positions, thereby enhancing search capacity and improving search efficiency relative to the vectorial search pattern. Subsequently, when the revised position lies beyond the confines of the design variables, the arms tend to persist in their prior position instead of transitioning to the updated location. This can be expressed mathematically as (7)-(9):

$$X_{i.p}^{T+1} = \begin{cases} Y_{i.p}^T & I_{l.p} \leq Y_{i.p}^T \leq U_{b.p} \\ X_{i.p}^T & I_{i.p} \leq Y_{i.p}^T \leq U_{b.p} \; Otherwise \end{cases} \tag{7}$$

$$Y_{i.p}^T = E_t X_{i.p}^T + A_1 \cdot \left(X_{k_1.p}^T - X_{i.p}^T\right) + A_1 \cdot \left(X_{k_2.p}^T - X_{i.p}^T\right) \tag{8}$$

$$E_t = \frac{T_{max} - T}{T_{max}} \cos\theta \tag{9}$$

where $X_{k_1.p}^T$ and $X_{k_2.p}^T$ are the p-dimensional coordinates of two randomly chosen starfish, A_1 and A_2 represent two random numbers within the interval (-1, 1), and p is the randomly picked integer in the D dimensions. Et represents the energy of the starfish. p signifies the revised dimension, while $I_{l.p}$ and $U_{b.p}$ reflect the lower and upper limits of the design variables, respectively. θ is determined by (6). Consistent with the prior updating rule, if a starfish's calculated location exceeds the boundary, it is inclined to remain in its former position rather than transition to the updated one.

2.1.2. Exploitation phase

In SFOA, predation and regeneration behaviours are incorporated into the exploitation phase to seek global solutions, resulting in two distinct updating strategies within this phase. To simulate the predatory behaviour of starfish, SFOA employs a parallel bidirectional search approach that requires information from neighbouring starfish and the global optimal position of the population. The algorithm initially calculates the distances between each starfish and the optimal position, then randomly selects two distances to guide the position adjustment of each individual using the concurrent bidirectional search mechanism.

$$d_m = \left(X_{best}^T - X_{mp}^T\right), m = 1, \dots ,5 \tag{10}$$

$$Y_i^T = X_i^T + r_1 \cdot d_{m1} + r_2 \cdot d_{m2} \tag{11}$$

where d_m is five obtained distances between the global best and other starfish, while mp are five randomly selected starfish. where r_1 and r_2 are random numbers between (0,1), and d_{m1} and d_{m2} are randomly selected in d_m. Based on the parallel two directional search strategy, the candidates of starfish are moving toward the better guiding solution, while other candidates are moving backward in the same iteration. Thus, the candidates have the same capacity to overcome the local optima. Moreover, starfish are susceptible to other predators due to their sluggish locomotion. When a predator seizes a starfish, the starfish may sever and relinquish an arm to escape capture. Consequently, the regeneration phase of SFOA is executed solely in the last starfish of the population ($i = N$). The regeneration step necessitates several months, resulting in a notably slow movement speed for the starfish.

$$Y_i^T = \exp\left(-T \times \frac{N}{T_{max}}\right) X_i^T \tag{12}$$

$$X_{i.p}^{T+1} = \begin{cases} Y_i^T I_b & \le Y_i^T \le U_b \\ I_b & Y_i^T < I_b \\ u_b & Y_i^T > u_b \end{cases} \tag{13}$$

where T represents the current iteration, T_{max} denotes the maximum number of iterations, and N signifies the population size. If the position derived from (11) or (12) exceeds the limits of the design variables, we can designate the position as (13).

2.2. Hierarchical microgrid control

Hierarchical control strategies are quite common in DC microgrids, and are organized into three levels, an illustration of this concept is shown in Figure 1. The primary control layer deals with voltage regulation and load sharing among units, by controlling the power converters directly. In some studies, microgrid protection, namely overcurrent, is also implemented in the primary layer. The secondary control copes with voltage fluctuations by tightening the regulation to a reference value and improving the load sharing accuracy. And in most cases, the secondary controller requires a communication link [38]. The tertiary control layer, or supervisory control, incorporates an energy management system.

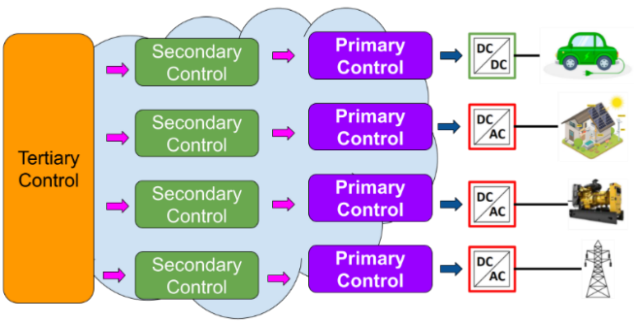


Figure 1. DC microgrid hierarchical control

To reduce the current flowing, we can use primary control. Primary control is the initial control consisting of droop control and control loop. This control is responsible for regulating the system voltage and current by adjusting the current supplied to the DC bus. At this level, the load power can be shared among the

DC generators with communication links using distributed control techniques. Figure 2 illustrates primary control. This control level adjusts the voltage reference supplied to the internal current and voltage control loops [39]. The output voltage can be expressed as (14):

$$V^*{}_o = \mathrm{V}_{ref} - (\mathrm{R}_d \cdot i_0) \quad (14)$$

where V_{ref} is the DC bus voltage reference point; R_d is the virtual output impedance; and i_0 is the output current. In recent years, various centralized, decentralized, and distributed techniques have emerged within the hierarchical control framework to improve the reliability of DC microgrids, adjust voltage shifts, and improve power distribution accuracy. Voltage shifts are handled using secondary control. To determine the output voltage, the voltage level in the microgrid V_{MG} is detected, compared with the reference voltage V_{ref}, and the error processed through the compensator is sent to all dv_o units Figure 2. The following is the control (15) and (16):

$$\mathrm{dv}_o = \mathrm{k}_p(\mathrm{V}_{ref} - \mathrm{V}_{MG}) + \mathrm{k}_i \int(\mathrm{V}_{ref} - \mathrm{V}_{MG})dt \quad (15)$$

$$V^*{}_o = V_{ref} - R_d \cdot I_o + dv_o \quad (16)$$

where k_p and k_i are secondary control parameters. Note that dv_o needs to be limited to stay below the maximum voltage deviation.

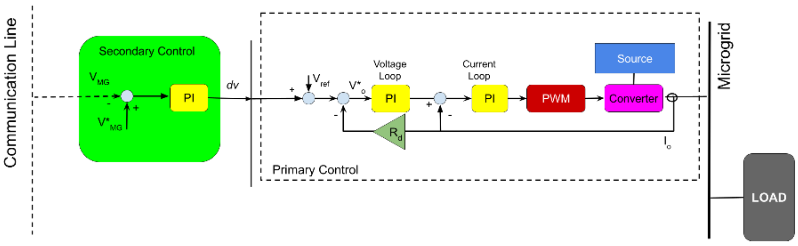


Figure 2. DC microgrid control structure

3. PROPOSED METHOD

To evaluate the performance of the proposed control strategy. Simulink is used to model and simulate the system according to the basic idea, with the dc bus voltage set at 100 V and having 2 DC sources. Figure 3 is an illustration of the control using SFOA with 2 sources in a DC microgrid. The values of microgrid voltage overshooting/undershooting, power sharing, and system responsiveness are used to evaluate the robustness of the proposed technique.

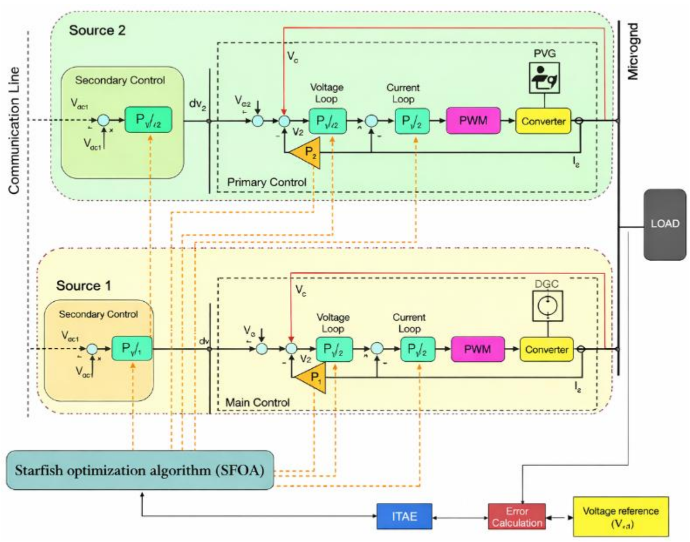


Figure 3. Control optimization using SFOA in DC microgrid

4. RESULTS AND DISCUSSION

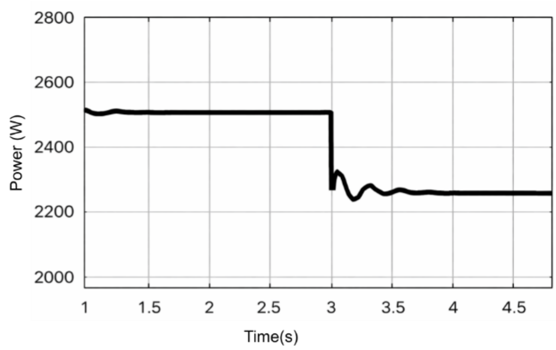
The performance testing of DC microgrid system also compares the traditional droop control using fixed droop resistance ($Rd_0 = 0.632\ \Omega$) with droop control regulated using SFOA. Several test scenarios are conducted to test the capability of the proposed method. The system has an initial load power of 2500 W, then the load power decreases by 250 W in the fourth second. The power source must be able to share the load proportionally. This study compares the proposed method with WO and GOA. Details of the control parameters of each algorithm can be seen in Tables 1 and 2. The output of power on the Bus and the current distribution between the 2 sources can be seen in Figures 4(a) and (b).

Table 1. Control values of each algorithm from Source 1

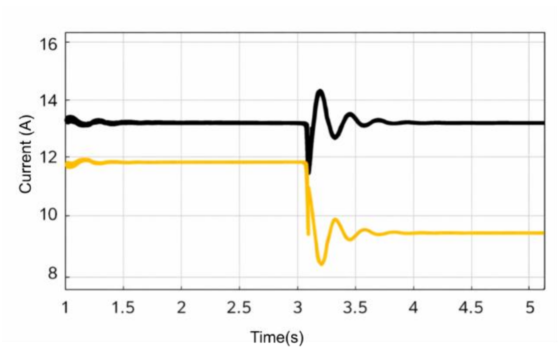
Methods	P_{vl}	I_{vl}	P_{cl}	I_{cl}	P_{sc}	I_{sc}	R_{d1}
SFOA	4.9210	2.2479	3.1206	1.9164	4.9481	3.3638	3.5738
WO	2.486	4.7302	4.2349	0.6729	2.2309	2.3705	1.6797
GOA	4.6957	2.1235	4.8793	0.5929	3.4855	1.5158	4.5113

Table 2. Control values of each algorithm from Source 2

Methods	P_{vl}	I_{vl}	P_{cl}	I_{cl}	P_{sc}	I_{sc}	R_{d1}
SFOA	1.8212	3.9113	1.9877	4.7953	1.4062	1.1948	1.9190
WO	4.1631	4.1849	4.001	4.3227	2.3292	4.4417	4.7023
GOA	3.4159	4.2489	2.7746	3.0952	4.2921	2.9380	4.9408



(a)



(b)

Figure 4. Result of; (a) power and (b) current

The voltage comparison can be seen in Table 3. From the simulation, it was found that the proposed method has the best integral of time weighted absolute error (ITAE) and integral of time-weighted squared error (ITSE) values of bus voltage compared to the GOA and WO methods. It can be seen in Table 4. The ITAE value of SFOA is 6.88% better than WO and 8% better than GOA. Meanwhile, the ITSE value of the SFOA method is 13.4% better than GOA and 10.63% better than WO. Figure 5 is the output of the bus voltage.

Table 3. Voltage comparison results when the load changes

Time (s)	SFOA		WO		GOA	
	Volt (V)	Error	Volt (V)	Error	Volt (V)	Error
0-3	100.033	0.033	100.0343	0.0343	100.0334	0.0334
3-6	100.0643	0.643	100.0643	0.643	100.0643	0.643

Table 4. Comparison results of bus voltage transient conditions

Methods	ITAE	ITSE
SFOA	0.023	0.0252
WO	0.0247	0.0282
GOA	0.025	0.0291

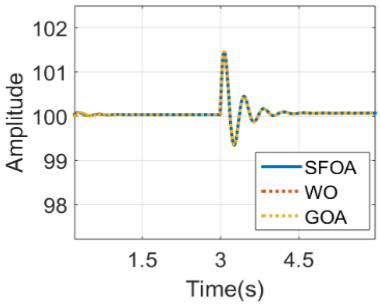


Figure 5. DC bus voltage results of each algorithm

5. CONCLUSION

This paper introduces a SFOA for optimizing control parameters in DC microgrid systems. SFOA is an innovative metaheuristic algorithm inspired by biological principles to address optimization challenges, specifically emulating the behaviors of starfish, including exploration, predation, and regeneration. The algorithm comprises two primary phases: exploration and exploitation. The main contribution of this study is the application of SFOA as an optimizer for control parameters in DC microgrids. The performance of the proposed method is evaluated through simulation of a DC microgrid system under various load conditions. For comparative analysis, this study employs the WO and GOA as benchmark methods. Simulation results demonstrate that the proposed SFOA method achieves superior performance in terms of ITAE, showing improvements of 6.88% and 8% compared to WO and GOA, respectively. The performance validation results confirm that the SFOA technique exhibits promising and effective performance for DC microgrid control parameter optimization. Several avenues for future research emerge from this work. First, the application of SFOA could be extended to AC microgrid systems and hybrid AC/DC microgrids to evaluate its versatility across different grid configurations. Second, the algorithm's performance should be validated under more complex scenarios, including grid-connected and islanded modes with RES uncertainties. Finally, investigating the algorithm's scalability for larger microgrid networks and its integration with energy storage systems would further enhance its practical applicability.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [initials: WA].

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