Using OOA-based proportional-integral-derivative controller to enhance the charging and discharging of battery voltage

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ABSTRACT

Today, hybrid energy harvesters are critical in promoting technological advancement by generating sustainable energy and addressing the financial and environmental concerns around batteries. Because of their unexpected input behavior, hybrid energy harvesters present a challenge in producing the necessary stable energy. Thus, this study provides a power conditioning circuit with an optimal controller. Three proportional-integral-derivative (PID) controllers control the charging and discharging of the battery's bidirectional converter. To improve system performance actively and optimally, optimization algorithms are implemented for the optimization of the PID parameters. Osprey optimization algorithm (OOA)-based PID is used, and its performance is compared with five optimization algorithims (Chimp optimization algorithm (ChOA)-based PID, hony badger algorithm (HBA)-based PID, Zebra optimization algorithm (ZOA)-based PID, and cheetah optimization algorithm (COA)-based PID. The comparison between algorithms was done based on the minimum fitness function value, which shows that the OOA is the best one. All results are implemented in MATLAB/Simulink using the 2021a version as follows: (ChOA 3.061%, CO 4.737%, HBA 3.03%, ZOA 3.058%, and OOA 1.52%).

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1. INTRODUCTION

Since their invention a century ago, proportional-integral-derivative (PID) controllers have been widely applied across diverse control systems. The effectiveness of a PID controller depends largely on its design and tuning methodology [1]. With the increasing complexity of modern industrial processes—characterized by nonlinearity and time-varying uncertainties—obtaining precise mathematical models has become challenging. Consequently, conventional PID controllers are often inadequate for contemporary requirements [2]. PID tuning refers to the adjustment of proportional (K_d), integral (K_i), and derivative (K_d) gains to minimize error and enhance system stability [1], [2]. In renewable energy applications, such as power electronic converters, effective tuning is critical for optimizing performance [3], [4]. Classical methods, such as the Ziegler–Nichols (Z–N) technique, remain widely used. This method applies only to plants with monotonic S-shaped step responses [5]. In Z–N tuning, the integral and derivative gains are initially set to zero. In contrast, the proportional gain is gradually increased until the system output exhibits sustained oscillations with a constant period [6]. The advent of microprocessor-based controllers has enabled the development of more advanced tuning strategies [6]. Artificial neural networks (ANNs), inspired by the functioning of biological neurons, have been employed to tune PID parameters by training on input–output data [7]. Optimization algorithms play a crucial role in this process by automating the search for the optimal PID parameters. These algorithms leverage mathematical techniques to iteratively explore the parameter space and find the values that yield the best control performance [8], [9]. Such approaches have proven effective in enhancing system stability and robustness, making them indispensable tools for control engineers [10]-[12]. In renewable energy systems, unstable charging/discharging can reduce battery lifespan due to stress from oscillations and reduced energy-transfer efficiency. So, the aim is to find the optimal parameter for PIDs that are used in a bi-directional buck-boost DC-DC converter for charging and discharging control, The fitness function (a mathematical function that quantifies the quality of a particular solution or candidate solution within a search space), the proposed error indices is integrate time absolut error (ITAE) stat as fitness function to minimize by optimization algorithm for minimum error and suggestion the magnitude of the PIDs controller that simulated for each run, it calculates the ITAE. In (1) express ITAE [13], [14]:

$$J_{ITAE}(e) = \int_0^t t|e(t)|dt \quad (1)$$

where $(t|e(t)|)$ is the absolute error between the setpoint and the process variable at time t.

2. PROPOSED OPTIMIZATION ALGORITHMS

The osprey optimization algorithm (OOA)-based PID is used, and its performance is compared with chimp optimization algorithm (ChOA)-based PID, honey badger algorithm (HBA)-based PID, zebra optimization algorithm (ZOA)-based PID, and cheetah optimization algorithm (COA)-based PID. All algorithms are discussed as follow:

2.1. Chimp optimization algorithm

ChOA was developed in response to the unique intelligence and sexual motivation of chimpanzees in comparison to other social predators when they hunt in groups. This type of society is one in which members travel across the environment over time, and the colony's composition or size fluctuates. The independent group concept is suggested in considering these problems. In this method, each group of chimps separately uses its strategy to try to discover the search space. Chimpanzees in each group vary in intelligence and skill [15], [16]. The mathematical model of ChOA is defined as the flows driving and chasing the prey (2) and (3) are suggested as a mathematical representation of chasing and driving the prey.

$$d = |cXprey(t) - MXchimp(tc)| \quad (2)$$

$$Xchimp(tc + 1) = Xprey\ (tc) - a.d \quad (3)$$

Where tc is current iteration, $Xprey$ is prey vector, $Xchimp$ is chimp vector, and a and c are coefficient vector.

In (4) and (5) are used to calculate the a and c vectors, respectively.

$$a = 2fr1 - f \quad (4)$$

$$c = 2r2 \quad (5)$$

Through the iteration, f reduces nonlinearly from 2.5 to 0; and $r1$ and $r2$ are random vectors ranging from 0 to 1.

2.2. Honey badger algorithm

The HBA is a new metaheuristic optimization algorithm. This method was created to mathematically develop a search approach that works well for addressing optimization problems. It took inspiration from honey badgers' ingenious foraging techniques. Digging and honey locating techniques are used to develop the exploration and exploitation stages of HBA based on the dynamic search behavior of honey badgers [17]-[20]. Formulation of the suggested HBA mathematically as follows:

The initialization phase, based on (6), starts with setting the honey badgers' placements and population size (N).

$$xi = li + r1x(ui - li) \quad (6)$$

Where xi is ith position, $r1$ is random number from 0 to 1, and li and ui are lower and upper boundaries.

Intensity definition: intensity is correlated with the prey's level of concentration and the distance between it and the honey badger. The prey's smell intensity is (Ii). Updating the density factor to guarantee an uninterrupted transition from exploration to exploitation, the density factor (δ) regulates time-varying randomness. Using (7), modify (δ) that drops over iterations to reduce randomness over time.

$$\delta = C_o \times exp\ (\frac{t_c}{t_{max}}) \quad (7)$$

Where t_c is iteration counter, t_{max} is max. Iteration, and C_o is constant by default siting =2, (≥1).

Agent positions update: the HBA position updating process has two stages: the "digging phase" and the "honey phase" (x_{new}).

2.3. Cheetah optimization algorithm

The algorithm known as the cheetah optimizer is inspired by nature, is inspired by the hunting techniques of cheetahs. Cheetahs typically employ three basic strategies to catch prey: searching, waiting, and attacking. COA uses certain simple techniques, and the hunting methods assist in making the algorithm more efficient, such as sitting and waiting for the prey to become available, returning home if the hunting procedure is unsuccessful, and returning to the last successful hunt if the prey isn't located for a while [21], [22]. Mathematical model of algorithm as follows:

Searching strategy: depending on the hunting environment, a cheetah either scans its surroundings or searches for appropriate prey. The seeking phase is represented by (8):

$$x_{ij}^{t+1} = x_{ij}^{t} + r_{ij}^{-1}.\alpha_{ij}^{t} \quad (8)$$

where, x_{ij}^{t} is indicates the current configuration, x_{ij}^{t+1} is indicates the new configuration, r_{ij}^{-1} is inverse rand parameter, and α_{ij}^{t} is the random length of the step will be calculated by (9) for the leader and (10) for i th cheetah with k cheetahs in the group.

$$\alpha_{ij}^{t} = 0.001 \times \frac{t_o}{T_o} \times (u_i - l_i) \quad (9)$$

$$\alpha_{ij}^{t} = 0.001 \times \frac{t_o}{T_o} \times \left(x_{ij}^{t} - x_{kj}^{t}\right) \quad (10)$$

Where u_i and l_i represent upper and lower boundary, t_o is indicates the current hunting time, and T_o is maximum time of hunting. Sitting-and-waiting strategy, cheetah can hunt quickly. Then they begin their attack.

2.4. Zebra optimization algorithm

The activity of zebras in nature serves as its fundamental inspiration. ZOA simulates zebras' feeding habits and their defense mechanism against attacks from predators. During the foraging process, a pioneer zebra creates a path for other zebras to approach the food source. Consequently, as the herd moves across the plains, this pioneer zebra leads the others. The first line of defense for zebras against predators is to flee in a zigzag manner [23]. Mathematical modelling as follows:

A matrix can be used to mathematically model the zebra population. The zebras are placed at random in the search space at the beginning. The objective function can be assessed using the suggested values of each zebra for the problem variables. In minimization problems, the optimal candidate solution is the zebra with the lowest objective function value. Two of the zebras' normal natural behaviors—foraging and defense strategies—have been used to let ZOA members. In (11) and (12) allow for the mathematical modeling of updating zebra positions during the foraging period.

$$X_{i,j}^{new,p_1} = X_{i,j} + r.\left(PZ_j - I \times X_{ij}\right) \quad (11)$$

$$X_i = \begin{cases} X_i^{new,p_1} \; F_i^{new,p_1} < F_i \\ \qquad X_i^{else} \end{cases} \quad (12)$$

where X_i^{new,p_1} is i_{th} zebra new status at first phase, $X_{i,j}^{new,p_1}$ is j_{th} dimension value, F_i^{new,p_1} is objective function value, PZ_j is pioneer zebra (best member) jth dimension, r is random number ranging from 0 to 1, $I = round(1 + rand), \in (1,2)$, and rand is random number ranging from 0 to 1.

2.5. Osprey optimization algorithm

It mimics the behavior of ospreys in the wild. An innovative natural behavior that can be the basis for developing a novel optimization algorithm is the osprey's strategy for capturing fish and transporting them to a suitable place for consumption. The two stages of exploration and exploitation that make up OOA's mathematical model are based on a modeling of ospreys' actual hunting behavior [24], [25]. The mathematical modeling as follow:

An underwater fish is an osprey's location in the search space in relation to other ospreys with higher objective function values. Applying (13), a group of fish for each osprey is defined:

$$Fp_i = \{X_k | k \in \{1,2,\dots,N\} \wedge F_k < F_i\} \cup \{X_{best}\} \quad (13)$$

where Fp_i is ith osprey set of fish position and X_{best} is best osprey position.

According to the simulation of the osprey's approach to the fish, the (14) is used to determine a new position for the matching osprey:

$$x_{ij}^{p1} = x_{ij} + r_{ij}.\left(SF_{ij} - I_{ij}.x_{ij}\right)$$

$$x_{ij}^{p1} = \begin{cases} x_{ij}^{p1} lb_j \leq x_{ij}^{p1} \leq ub_j \\ lb_j, x_{ij}^{p1} < lb_j \\ ub_j, x_{ij}^{p1} > ub_j \end{cases} \quad (14)$$

where X_i^{p1} is i_{th} osprey new position on the 1st phase, x_{ij}^{p1} is position in j dimension, F_i^{p1} is value of the objective function, SF_{ij} is selected fish by i_{th} osprey in j_{th} diminution, r_{ij} is random number between 0 and 1, and I_{ij} is random number between 1 and 2.

3. SIMULATION RESULTS

3.1. Classical proportional-integral-derivative

The system connected, as shown in Figure 1, was tested in charging mode and in battery discharging mode, both without and with the use of the results obtained from five optimization algorithms (ChOA, HBA, OOA, CO, and ZOA) for tuning the PID parameters of the bidirectional buck–boost DC–DC converter. The output voltage at the load side, shown in Figure 2, presents the simulation results of the PV system over a 1-second duration. This figure illustrates the transient and steady-state behavior of the PV system outputs (voltage, current, and power), as shown in Figures 2(a)–(c), under specific conditions (constant irradiance and temperature). The corresponding results are listed in Table 1. It can be observed that the output voltage exhibits high oscillations.

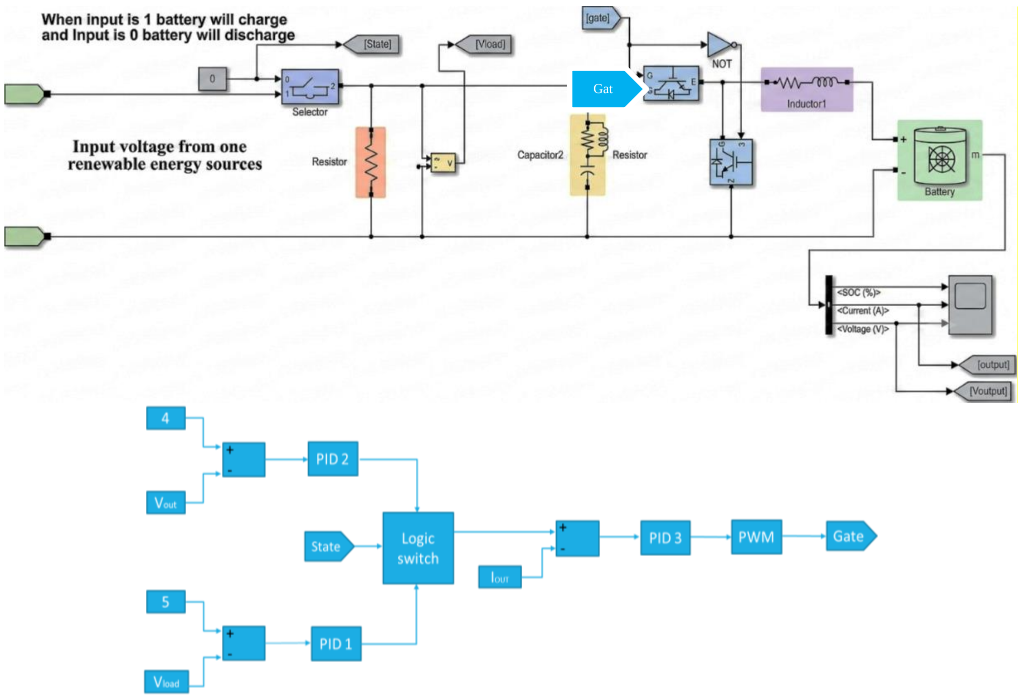

Figure 1. System connection

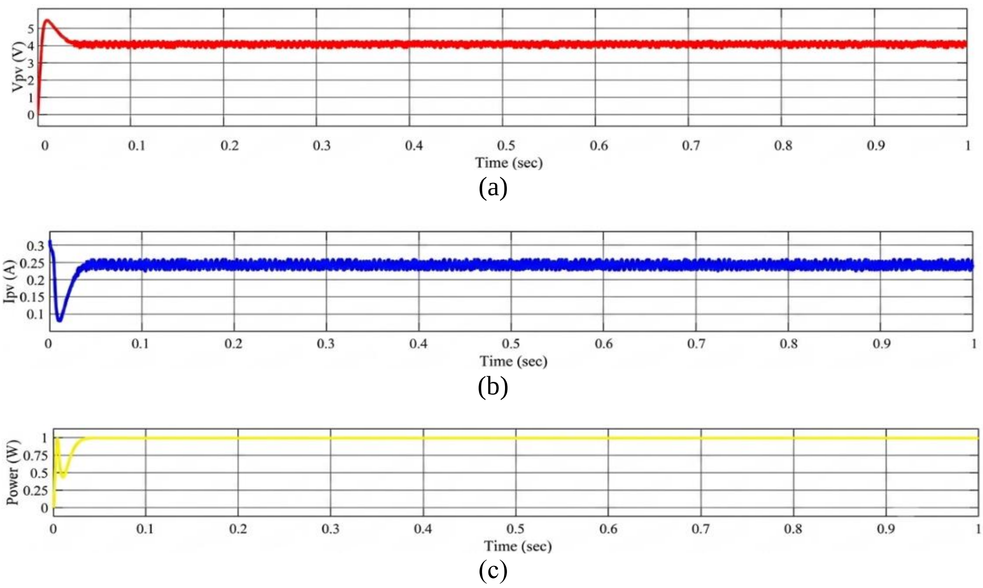

Figure 2. PV output; (a) voltage, (b) current, and (c) power

Table 1. PV system results

Quantity	Value
PV voltage (VPV)	4.2 V
PV current (IPV)	0.231 A
Battery voltage	3.98 V
Load voltage	5.287 V
Load current	0.243 A
Overshoot (load voltage)	29.439%

3.2. Optimized proportional-integral-derivative

Two cases are applied, the first one is a population size of 10 and 10 iterations, and the second one is a population size of 25 and 20 iterations. The proposed optimization algorithms' parameters are listed in Table 2 and the simulation results are listed in Tables 3 and 4.

Table 2. Algorithms' parameters

Algorithm	Parameter value
ChOA	α=(1), m=(1.1), c=(1.1), and f=(2.5)
CO	m=2
HBA	C=2, β=6
ZOA	R=0.01, I ∈(1.2)
OOA	I_{ij} ∈ (1.2), r_{ij} ∈ (0.1)

Table 3. Algorithm simulation results (population=10, iterations=10)

PID parameters	ChOA	CO	HBA	ZOA	OOA
		PID1			
k_p	-16.0813	75.379	97.3516	-9.3427	9.421
k_i	64.2801	2.4637	96.6568	-34.213	8.74313
k_d	14.001	-52.4781	2.21138	7.41931	0.72268
FIT	0.15236	0.041145	0.040599	0.040617	0.039224
		PID2			
k_p	85.256	86.2125	45.0175	43.05541	61.73571
k_i	100	-26.1147	14.6712	11.25629	58.50137
k_d	-41.7539	-9.5828	-0.43245	-0.40442	3.273507
FIT	0.077569	0.063527	0.05646	0.05644	0.05625
		PID 3			
k_p	30.6249	100	67.5991	38.8187	2.21296
k_i	-72.1697	-100	74.25	-5.88312	1.39715
k_d	-0.5718	-1.07376	-3.08227	-0.4283	-0.02627
FIT	0.04104	0.042584	0.042215	0.04081	0.040742

Table 4. Algorithms simulation results (population=25, iteration=20)

PID parameters	ChOA	CO	HBA	ZOA	OOA
PID1					
k_p	69.5443	94.7643	49.6201	51.2507	60.8779
k_i	-100	52.9297	-62.399	45.38441	25.44
k_d	-0.5699	43.6560	0.08519	0.50757	0.5233
FIT	0.035408	0.036714	0.035142	0.038547	0.033956
PID2					
k_p	100	55.989	73.0909	73.4899	40.1417
k_i	-9.9507	40.2790	55.9928	37.9038	38.1730
k_d	-0.8929	-1.4976	-0.8304	-0.7881	-0.4029
FIT	0.016612	0.01712	0.016238	0.016234	0.01622
PID 3					
k_p	100	58.8012	100	33.6719	20.7074
k_i	100	31.3583	100	63.4071	33.0858
k_d	-0.7801	-7.4800	-0.9984	-0.2850	-0.20519
FIT	0.041266	0.041293	0.0412742	0.041246	0.040266

The output voltage, power, current for the testing parameter of OOA algorithm using the second case result separately are shown in Figure 3 shows the simulation result for the system over 2 second duration, these figure illustrate the transient and steady -state behavior of the system out put (voltage, current, and power) shows in Figures 3(a)-(c) simultaneously for optimizing PID parameters.

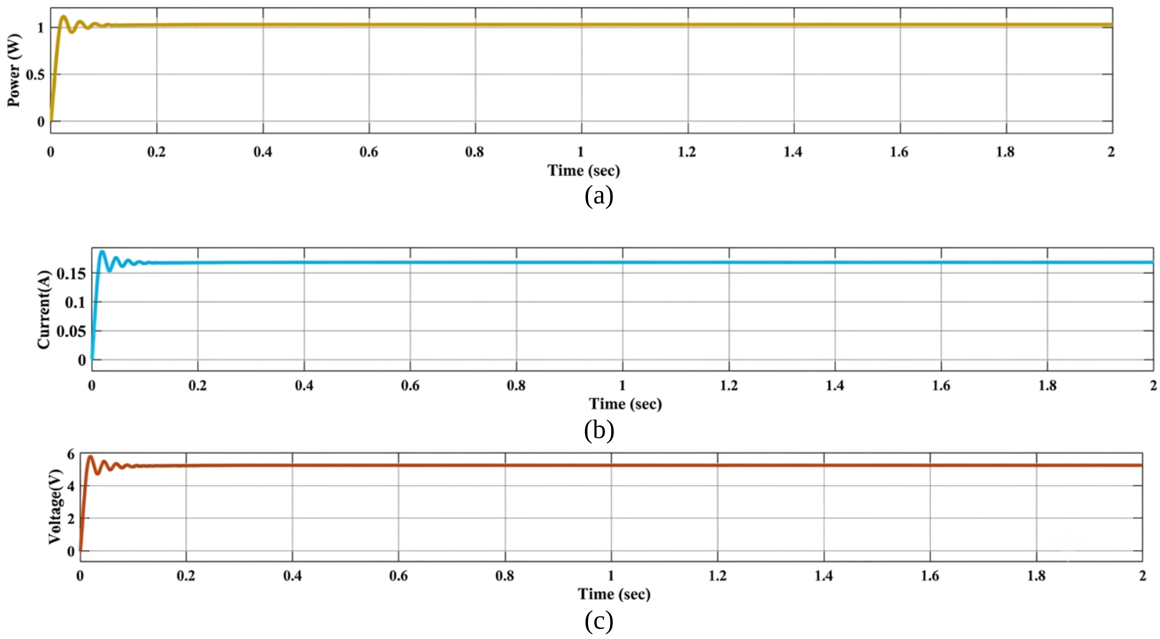

Figure 3. System output using OOA parameters; (a) power, (b) current, and (c) voltage

Five optimization algorithms are applied to three PIDs at the first population size, and iterations are set to 10. Convergence curves illustrate how an optimization algorithm progressively improves its solution, step by step and iteration by iteration. The goal is to minimize the error (fitness value) as fast and efficiently as possible. Figure 4 shows convergence curves; as we can see, the OOA algorithm drops quickly, potentially indicating fast initial convergence. In contrast, ChOA gets the worst convergence for PID1.

Convergence curves of optimization for the second case, with an algorithm population size of 25 and 20 iterations, were set. Figure 5 shows convergence curves; as we can see, the OOA algorithm drops quickly, potentially indicating fast initial convergence. In contrast, CO gets the worst convergence for PID1. The result of implementing OOA to obtain the PIDs parameter is successful in minimizing errors and achieving stability for the overall system, which is listed in Table 5.

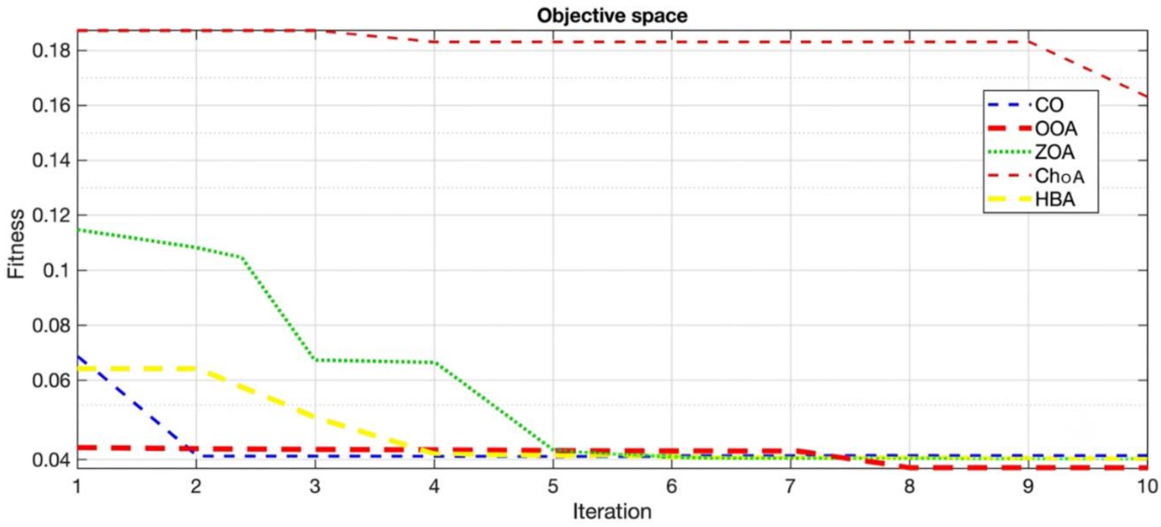

Figure 4. Convergence curves for PID1 (population=10, iterations=10)

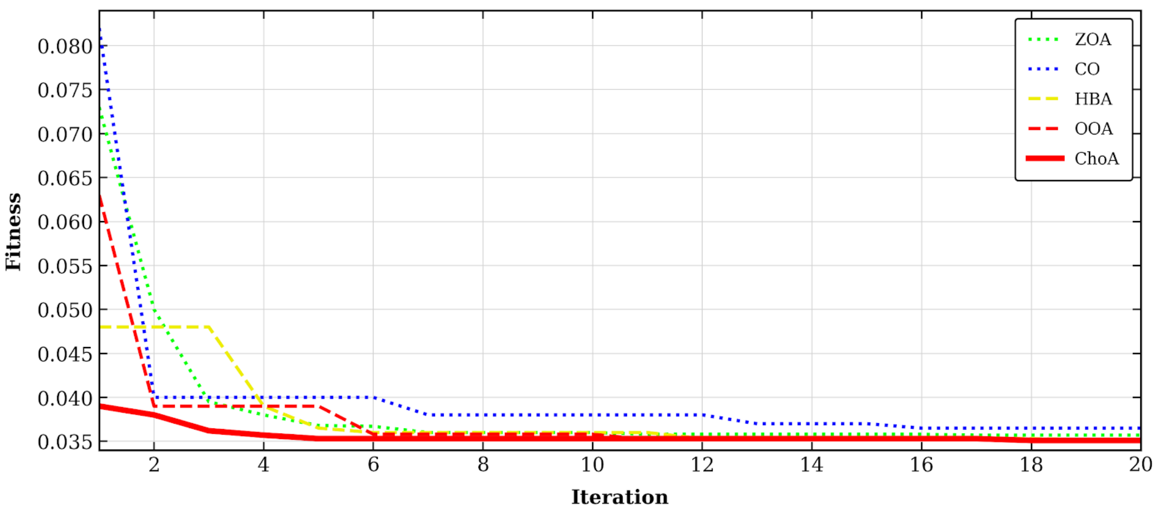

Figure 5. Convergence curves for PID1 (population=25, iterations=20)

Table 5. System output result

Parameter	ChOA	CO	HBA	ZOA	OOA
Load voltage (V)	4.984	4.936	4.947	4.928	5.092
Load current (A)	0.158	0.1582	0.1585	0.1579	0.1819
Power (W)	0.7872	0.7811	0.7842	0.7782	0.919
Overshoot (voltage)	3.061%	4.737%	3.030%	3.058%	1.52%
Settling time(ms)	1.008	1.9911	1.058	1.007	1.006
Rise time (µs)	307.658	402.194	300.141	307.661	454.589

4. CONCLUSION

The optimization algorithms ChOA, CO, ZOA, HBA, and OOA are implemented to get the optimal parameter gain for three PID controllers of a bi-directional DC-DC buck–boost converter. The three control parameters are set to achieve the desired system performance. Smooth control of the power flow, the simulation system has provided valuable insights into its performance and potential. The optimizationprocess successfully set the control parameter leading to the desired performance and ensures smooth control of power flow. The result provides valuable insights into the system's potential and is intended to serve as a foundation for practical implementation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hassanin Falah Abdul Hassan	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Issa Ahmed Abed		✓				✓		✓	✓	✓	✓	✓	✓	

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

Upon reasonable request, the corresponding author [Issa Ahmed Abed] may disclose the data supporting the study's conclusions.

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