Elitism-crossover barnacle mating optimization and its application to PID controller design for a buck converter

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ABSTRACT

This paper presents an elitism-crossover barnacle mating optimization (ECBMO). It is an improvement of barnacle mating optimization (BMO). The original BMO suffers from local optima problem leading to a low accurate solution. A new method of offspring generation is adopted into the original BMO structure. Some features of the best-so-far solution are incorporated into the generated offspring. The accuracy performance of the proposed algorithm is tested on several IEEE functions. A statistical analysis is conducted to compare its performance over the original BMO. It is also applied to optimize proportional integral derivative (PID) parameters for controlling output voltage of a buck converter. Result of benchmark functions test shows the proposed algorithm has attained higher accuracy for all functions compared to BMO algorithm. Application on the real problem shows both algorithms control the converter voltage satisfactorily. However, the ECBMO has achieved more optimal PID parameters and leading to a better output voltage response.

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1. INTRODUCTION

Barnacle mating optimization (BMO) is a bio-inspired optimization algorithm formulated based on a mating strategy of barnacle population [1]. There are two main phases of the BMO algorithm. The first phase is the mating technique between male and female barnacles. The mating process is possibly occurred on any female barnacle within the range that can be reached by the male barnacle. The range depends on the size of male barnacle penis. This is the unique feature of barnacle mating. If any female barnacle location is beyond the range, self-mating is then occurred. BMO is a promising optimization tool to solve complex real-world problems. In literature, BMO has been applied to solve economic dispatch problem in power system engineering [1], parameter estimation of proton exchange membrane fuel cell [2], microarray cancer classification [3] and control problem for an inverted pendulum system [4], [5]. It also was applied to predict covid-19 cases in China [6], energy optimization in 5G networks [7], and stock price prediction in financial stock market [8].

Buck converter is another real-world problem in power electronics engineering. Buck converter is an important component in many electrical and electronics circuits or devices. It has been used to step-down a voltage to a specified value. However, applying a certain load such as electromechanical devices and DC motor can cause the instability to the output voltage of the converter. The problem leads to unstable performance of the system [9], [10]. Moreover, if a certain set of time-domain performance criteria is needed on the output voltage in the presence of load, a good controller might be required. It may optimally improve the transient response of the output voltage. Some of the possible controllers for the buck converter include fuzzy logic controller [11], sliding mode controller [12], proportional integral derivative (PID) [13] controllers. They are in common such a way that the response of a controlled variable i.e voltage signal is feedback and compared with the desired setting point. Fuzzy logic is more challenging where an expert knowledge is required to design the fuzzy rules, determining the associated antecedents and consequents. Other recent and more advanced control scheme applied on buck converter include adaptive neural network [14], state-space robust control [15], robust μ-synthesis [16], and H-∞ controllers [17]. These control schemes offer a good stability in case of parameter uncertainty and external disturbance are presence in the system. Among these controllers, PID is commonly used in industry due to simplicity of its structure and design [18]. Combination of PID and other controllers are also commonly found in literature [19], [20]. In literature, applications of buck converter are found in solar photovoltaic system [21], electric vehicle and hybrid electric vehicle [22], lead-acis battery charger system [23], and electromagnetic actuator array [24]. As the global trend is moving towards a sustainable future, thus a sustainable technology is demanding and these applications proven the importance of research to tackle the problem arises in DC-DC converter.

This paper proposes an elitism-crossover barnacle mating optimization (ECBMO). Some good features of the best barnacle in the population are crossover and combined with other barnacles. The resultant barnacle is a generated barnacle offspring. It comprises of some good features of parent barnacles and the best barnacle in the population. The proposed algorithm is tested on IEEE competition of evolutionary computation (CEC) 2014 benchmark functions to analyze its accuracy performance in comparison to BMO. It is also applied to optimize PID controller parameters for a buck converter. The controller stabilizes the output voltage of the buck converter. The paper is organized as follows. Section 2 describes the proposed elitism-crossover barnacle mating optimization. Section 3 explains about benchmark functions used to test the performance of the proposed ECBMO, experimental setup and result. Section 4 presents the application of the proposed ECBMO to optimization of PID controller for a buck converter, experimental setup and corresponding result. Section 5 presents conclusion of the paper.

2. ELITISM-CROSSOVER BARNACLE MATING OPTIMIZATION

ECBMO is an improvement of BMO algorithm. The elitism refers to the selection of elite individuals or the best agent from the memory pool [25]. It guides the other agents towards the current best optimal location. The major structure of ECBMO is almost similar to the original BMO. However, in the proposed algorithm, steps 4, 6, and 7 are accordingly modified to suit the new barnacle offspring generation method. The pseudocode of the proposed ECBMO is shown as follows:

Step 0: randomly initialize barnacles position in the population x_i^N on a feasible search space. Set total number of barnacles in the population, $N = 50$. x_i^N is the location of i^{th} barnacle in the N population. Set male barnacle penis as a constant, $b = 7$.

Step 1: calculate fitness value of i^{th} barnacle, f_i. Barnacle with the minimum fitness value is the fittest barnacle, x_{best}.

Step 2: apply a random selection operator for parent barnacle. Define the male and female barnacles as $barn_m$ and $barn_f$ respectively. $x_{barn_m}^N$ =random permutation $(1, N)$. Apply a random number in the range $[1, N]$ to the male barnacles. $x_{barn_f}^N$ =random permutation $(1, N)$. Apply a random number in the range $[1, N]$ to the female barnacles.

Step 3: if selection of parent barnacle $< b$, then, produce first group of barnacle offspring, $x_{i,OS}^N$. $p = rand$, $q = 1 - p. rand$ is a random operator to generate random number in the range $[0, 1]$.

$$x_{i,OS}^N = p. x_{barn_m}{}^N - q. x_{barn_f}^N \tag{1}$$

Step 4: inherit features from the best ancestor to descendants. This produces second group of offspring, $x_{i,Elite}^N$.

$$x_{i,Elite}^N = x_{best}\big(random(2)\big) + x_i^{OS} \tag{2}$$

$x_{best}\big(random(2)\big)$ is used to generate random permutation of features in best-so-far barnacle. The selected features of the best-so-far barnacle are incorporated into the generated offspring.

Step 5: if selection of parent barnacle $> b$, then, produce the third group of barnacle offspring x_i^{SC} through sperm-casting.

$$x_i^{SC} = rand + x_{barn_f}^N \tag{3}$$

Step 6: calculate fitness cost of the newly generated barnacle offspring, $x_{i,OS}^N, x_{i,Elite}^N, x_{i,SC}^N$. The lowest fitness cost is the fittest barnacle, x_{best}.
Step 7: sort the barnacle off-springs $x_{i,OS}^N, x_{i,Elite}^N, x_{i,SC}^N$ and barnacle x_i^N based on their fitness cost. The first 50 barnacles with the lowest cost $f_{i,new}^N$ are considered as the new barnacles $x_{i,new}^N$.
Step 8: repeat step 2 to step 7 until termination condition is satisfied.

3. BENCHMARK FUNCTIONS TEST

Benchmark functions adopted from IEEE CEC 2014 are used as various platforms to test the accuracy performance of the proposed ECBMO algorithm. In the work, 4 functions known as shifted and rotated weierstrass, shifted rastrigin, shifted, and rotated rastrigin and shifted schwefel are considered [26]. Details of the functions, names, features of their landscape and corresponding theoretical optimal solution are presented in Table 1. It is noted from Table 1 that all functions are multimodal types and are upgraded from their basic functions. The number of local optima locations present in their landscape is huge and comprises of combination separable and non-separable features. Theoretically, the optimal solution for functions 1, 2, 3, and 4 is defined as 600, 800, 900, and 1000 respectively.

Table 1. Details of the CEC 2014 benchmark functions

No	Function name	Features	Optimal solution
1	Shifted and rotated weierstrass	Multimodal, separable, continuous, differentiable	600
2	Shifted rastrigin	Multimodal, separable, huge local optima	800
3	Shifted and rotated rastrigin	Multimodal, non-separable, huge local optima	900
4	Shifted schwefel	Multimodal, separable, huge local optima	1000

The benchmark functions test was setup such that an average fitness cost and convergence plot can be recorded for each function. It allows a more accurate analysis can be conducted. In the experimental setup, 25 independent runs were conducted, the population of the barnacle, N was defined as 50 and maximum iteration was set as 1000. Maximum and minimum values of feasible search region were set as [-100, 100] while the dimension of the functions was assigned as 10. Table 2 shows the result of the average value of fitness cost generated from 25 independent runs for each function comparing both ECBMO and BMO algorithms. The result of the best fitness cost between those 2 algorithms is italicized. The smaller value of fitness cost indicates that the algorithm has achieved a better accuracy performance as compared to its counterpart. The table shows ECBMO has achieved cost function 601.9223, 811.3533, 938.0869, 1.2819E+03 while BMO has attained cost function 604.6571, 831.3212, 946.9221, 2.021E+03 for functions 1-4 respectively. Noted from the table that ECBMO has achieved better average fitness cost for all functions.

Table 2. The acquired average fitness cost tested on CEC 2014 functions

No	BMO	ECBMO
1	604.6571	601.9223
2	831.3212	811.3553
3	946.9221	938.0869
4	2.0218E+03	1.2819E+03

Table 3 shows the result of statistical analysis using nonparametric wilcoxon-sign-rank-test. The result is generated based on the fitness cost recorded from 25 independent runs of both ECBMO and BMO. Noted from the table that ECBMO has achieved two-tail, ρ result less than 5% indicating the improvement made by the ECBMO over the BMO is significant [27], [28]. Other parameters associated with the test are also presented in the table. The positive value of zval and larger value of R^+ as compared to R^-indicate that the ECBMO has achieved better result over the BMO [29].

Table 3. Wilcoxon sign rank test result

Function no.	ρ	Zval	R^+	R^-
Function 1	8.0851e-05	3.9419	309	16
Function 2	1.7735e-05	4.2917	322	3
Function 3	0.0016	3.1616	280	45
Function 4	1.2290e-05	4.3724	325	0

The performance difference between those 2 algorithms is clearly portrayed from the convergence plots shown in Figures 1(a)-(d). The convergence plots of the ECBMO are shown as the blue smoothed-line while the convergence plots of the BMO are shown as the red dashed-line. The plots show the result of the cost function versus the number of iterations. The figures show all the plots generated from ECBMO have achieved fitness cost closer to the theoretical value that the BMO. The plots show both ECBMO and BMO have presented almost similar convergence patterns. However, the BMO agents were trapped at the local optima solution and thus resulting in lower accuracy for all functions. On the contrary, the graphs show ECBMO convergence plots have converged sharply in the beginning until a certain iteration and have slowly converged as the iteration moves towards the end. Observation from the naked eye has shown that the searching operation for the ECBMO has settled down at almost 200 iterations for all functions. BMO has shown the slowest convergence for function 1 followed by functions 2, 3, and 4. The BMO graphs failed to converge to the optimal fitness value as shown by the ECBMO cost. The presented graphical results have confirmed the performance of the ECBMO is better than its BMO counterpart.

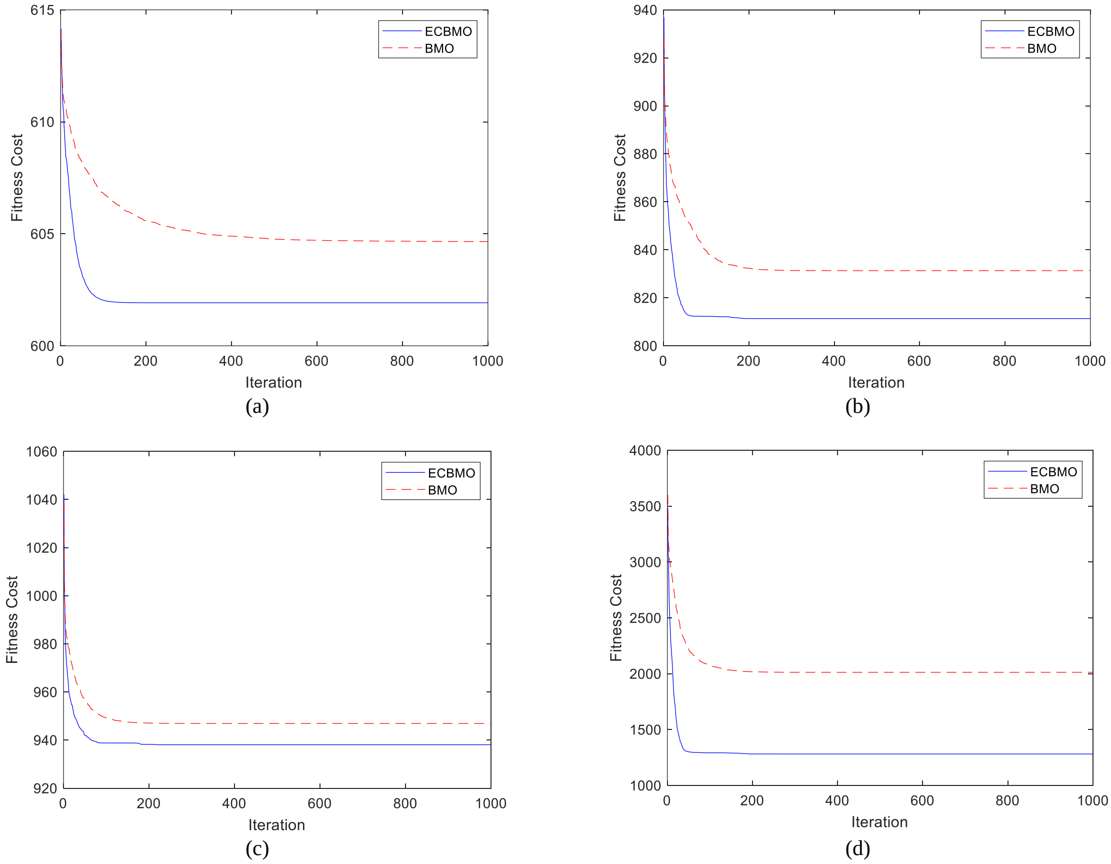

Figure 1. Convergence curve for; (a) shifted and rotated weierstrass, (b) shifted rastrigin, (c) shifted and rotated rastrigin, and (d) shifted schwefel

4. OPTIMIZATION OF PID CONTROLLER FOR A BUCK CONVERTER

The proposed ECBMO is applied as an optimization tool to acquire optimal K_p, K_i, and K_d parameters for a PID controller for a buck converter and compared with the BMO. In the first part of section 4, schematic diagram and derivation of dynamic model of the buck converter are presented. A DC motor is considered as a load connected to the buck converter. Its associated parameters are also presented. The second part of the section presents a closed-loop control strategy for controlling output voltage, U_C of the buck converter. It depicts a schematic diagram of the feedback control strategy showing the structure of PID control scheme and the buck converter. An explanation of application of ECBMO to optimize the PID control parameters and objective function showing the relationship between the ECBMO and PID control scheme are also presented. The section ends with the discussion of the result for both ECBMO, BMO algorithms as well as the PID control performances.

4.1. Buck converter

A schematic diagram of a buck converter is shown in Figure 2. It consists of a voltage source, $V_d = 10\,V,$ a switching device to generate pulse-width-modulator (PWM) in series with a resistor $R_S = 0.025\,\Omega$ and an inductor, $L = 0.0001\,H$ in series with a resistor $R_L = 0.02\,\Omega$ and a capacitor, $C = 0.003\,F$ in series with a resistor $R_C = 0.15\,\Omega$. A DC motor is considered as a load and is arranged in parallel with the capacitor, C and resistor R_C. The DC motor load comprises of armature resistance, $R_a = 3\,\Omega$, armature inductance, $L_a = 0.005\,H$ and back emf, $E_a = 10\,V$. Based on the schematic diagram shown in Figure 2, the differential equations representing the buck converter are derived and stated as (4)-(6) [30]:

$$\frac{du_C}{dt} = \frac{1}{C}(i_L - i_a) \tag{4}$$

$$\frac{di_L}{dt} = \frac{1}{L}(-u_C - (r_L - r_C)i_L + r_C i_a - r_S i_L + V_d) \tag{5}$$

$$\frac{di_a}{dt} = \frac{1}{L_a}(u_C + r_C i_L - (r_a + r_C)i_a - E_a) \tag{6}$$

4.2. Optimization of ECBMO-based PID controller

Figure 3 shows the block diagram of a PID controller optimization strategy for a buck converter. It starts with setting up the desired voltage required by the load as 30 volts. The actual output voltage from the buck converter is then feedback and compared with the desired voltage. The difference between the two responses is considered as an error of the system, $e\,(t)$ which is then injected as an input to the ECBMO. The PID parameters which are defined in the ECBMO algorithm are iteratively varied and optimized. The PID parameters are considered as optimal if the error is at the minimum value. Equation of the PID controller is shown as (7) where K_p, K_i, and K_d are the proportional, integral, and derivative constants respectively. The cost function, $f(t)$ of ECBMO algorithm is defined with respect to the error, $e\,(t)$ of the system and it is shown as (8) where N represents total number of sampled data.

$$PD(t) = e(t) \times K_p + K_i \int e(t) + \frac{de(t)}{dt} K_d \tag{7}$$

$$f(t) = \frac{1}{N} \sum_{t=1}^{N} e(t) \tag{8}$$

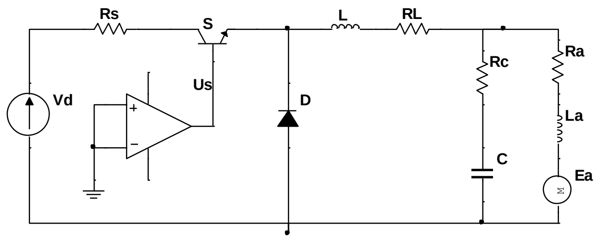

Figure 2. Schematic diagram of a buck converter

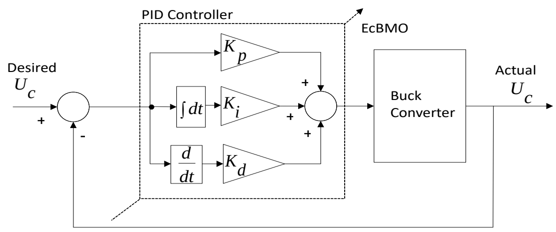

Figure 3. Schematic diagram of closed-loop control scheme for a buck converter

In the experiment, the search agent, iteration, and search range were defined as 10, 50 and [-100, 100] for both algorithms respectively. Figure 4 shows convergence plots of the ECBMO and BMO in obtaining the optimal PID parameters. BMO result is shown as the red-smooth line while the proposed ECBMO result is shown as the blue-dotted line. The plot shows BMO and EBMO graphs have converged to fitness cost 2.5873 and 1.9823 respectively. The ECBMO has attained a significantly better fitness cost. The BMO graph has sharply converged until iteration 5. However, it has hardly converged to a better significant cost beginning from iteration 6 until the end of iteration. The ECBMO graph has slowly converged from the beginning until iteration 22. It has sharply converged to a better significant cost at 2.28 and 1.98 between iterations [22, 28] and [41, 43] respectively. Beginning from iteration 45 until the end of iteration, it unable to converge to a further better cost. The optimized BMO-based PID parameters K_p, K_i and K_d were obtained as [100, 100, 94.0536] respectively while ECBMO-based PID parameters K_p, K_i and K_d were optimized as [0.4449, 3.1167, 0.0389] respectively. Figure 5 shows PID-controlled output voltages of the buck converter optimized by the ECBMO and BMO algorithms. BMO result is shown as the red-smooth line while the proposed ECBMO result is shown as the blue-dotted line. The desired voltage was set as 30 volts as shown by the black-dotted line. Both voltage graphs portray almost the same pattern. However, the output voltage optimized by the ECBMO shows a significantly smaller steady state-error as compared to the BMO output voltage. BMO has acquired steady state error about 1.3869 resulting in error percentage of 4.6%. The ECBMO has attained the steady state error about 0.5258 resulting in error percentage of 1.75%. The ECBMO has achieved 2.85% smaller error percentage than the BMO. On the maximum overshoot result, the BMO graph has reached the maximum voltage at 46.33 volts while the ECBMO graph has reached the maximum voltage at 46.21. It indicates that ECBMO has obtained a better overshoot performance which is 0.26% better than the BMO. On the voltage stability, ECBMO has shown a smaller ripple as compared to the BMO. Considering time for the graph to rise from 10% to 90% of its final value as the rise time performance, both ECBMO and BMO have shown a similar performance at 1.7 msec.

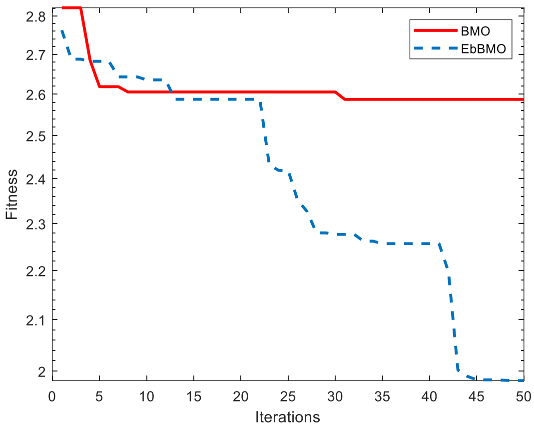

Figure 4. ECBMO and BMO convergence plots comparison

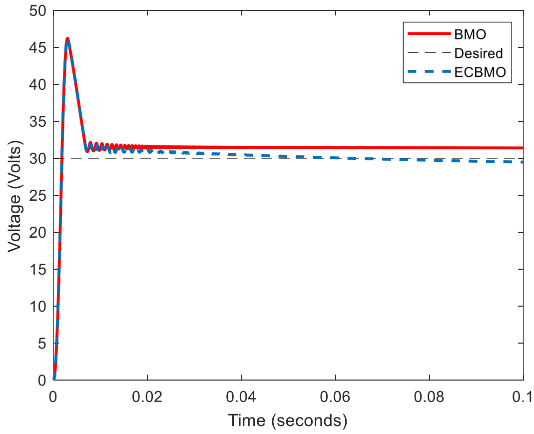

Figure 5. Comparison of output voltage of buck converter

Table 4 shows a summary of time-domain performance for both ECBMO-based PID and BMO-based PID. Three performance criteria are evaluated which include steady-state error (e_{ss}) percentage overshoot ($\% \, os$) and rise time (t_r). The result of the best performance between those two algorithms is italicized. The table shows that ECBMO-based PID dominates the time-domain performance and thus outperforms the BMO-based PID.

Table 4. Time domain performance of the ECBMO-based PID and BMO-based PID

Criteria	BMO	ECBMO
Steady-state error (e_{ss})	1.3869	0.5258
Percentage overshoot ($\% \, os$)	46.33	46.21
Rise time (t_r) (msec)	1.7	1.7

5. CONCLUSION

ECBMO has been presented in the paper. It is an improved version of original BMO algorithm. An elitism-crossover strategy has been incorporated into the mating strategy of BMO. Some good features of the best-so-far agent are inherited into new offspring of the barnacle. It also has improved communication between the best-so-far agent and all other agents. The proposed algorithm has been tested on four CEC 2014 benchmark functions. Its accuracy performance in obtaining theoretical optima solution of the benchmark function is compared with BMO. Moreover, the algorithm has been applied to optimize the parameters of PID for the buck converter system. Both numerical and graphical results have been included comparing the performance of ECBMO and BMO. The result of the experiment has shown that ECBMO has attained better accuracy when tested on benchmark functions. On the PID control design problem, both algorithms have satisfactorily optimized the PID parameters. However, the response of output voltage of the buck converter optimized by ECBMO has shown a smaller steady-state error and overshoot than the BMO. The proposed algorithm will be further tested on more challenging platforms such as nonlinear fuzzy logic and neural network models in the future.

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