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Selective opposition based constrained barnacle mating optimization: Theory and applications

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ABSTRACT

Mathematical models of Barnacle Mating Optimization (BMO) are based on observations of real-world barnacle mating behaviors such as sperm casting and self-fertilization. Nevertheless, BMO considers penis length to produce new offspring through pseudo-copulated mating behavior, with no constraints like strong wave motion, food availability, or wind direction considered. Exploration and exploitation are two crucial optimization stages as we implement the constrained BMO. They are informed by models of navigational sperm casting properties, food availability, food attractiveness, wind direction, and intertidal zone wave movement experienced by barnacles during mating. We will later integrate opposition-based learning (OBL) with constrained BMO (C-BMO) to improve its exploratory behavior while retaining a quick convergence rate. Rather than opposing all barnacle dimensions, we just opposed those that went over the border. In addition to increasing efficiency by cutting down on wasted time spent exploring, this also increases the likelihood of stumbling onto optimal solutions. After that, it is put through its paces in a real-world case study, where it proves to be superior to the most cutting-edge algorithms available.

1. Introduction

In recent years, meta-heuristic optimization approaches have gained popularity due to their ease of use, low computational cost, gradient-free process, and flexibility. However, the No Free Lunch (NFL) theorem in this field posits that no single approach can solve all optimization problems. This implies that while some meta-heuristic algorithms may provide optimal solutions for certain problems, they may offer subpar results for others. This insight motivates further exploration into the field, leading researchers to investigate numerous advancements and enhancements of optimization algorithms based on natural processes, with the genetic algorithm [1–4] being particularly prominent. The primary objective is to identify the globally optimal solution from a population of candidates generated through recombination, mutation, and the inheritance of favorable traits across generations. According to NFL theory, the efficiency of a new algorithm may be improved for diverse applications where problem types vary significantly.

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Despite their advantages, meta-heuristics face challenges such as slow convergence and the risk of becoming trapped in local search regions, which can increase computing costs. To address these limitations and leverage the benefits of meta-heuristics, there has been a significant rise in the development of hybrids, modifications, and improvements [5,6]. Notable examples include hybrid grey wolf [7], hybrid differential evolution [8], hybrid heat transfer and passing vehicle algorithms [9], hybrid harmony search algorithms [10], hybrid ABC [11], hybrid PSO [12], and the hybrid Taguchi salp swarm-Nelder–Mead algorithm [13–15]. Effective meta-heuristics must balance global diversification and local intensification. Achieving an optimal equilibrium between exploration and exploitation is crucial for developing meta-heuristics, as each phase plays a significant role in improving the solution space and reducing overall time. This research utilizes the Gooseneck Barnacle Optimization Algorithm, which has been described in recent work [16]. Additionally, the novel machine learning approach based on this optimizer has been applied in rainfall prediction [17]. Other relevant optimization techniques such as the continuous genetic algorithm have been explored in previous studies [18,19]. Moreover, the hybrid evolutionary algorithm was recently applied for COVID-19 case prediction [20]. Consequently, the quest for more effective approaches remains a pressing issue, leading to an increase in the development of new hybrid meta-heuristics. Over recent decades, researchers have utilized numerous hybrid meta-heuristics to solve engineering design optimization problems, benefiting from enhanced local and global search strategies.

Similarly, the Barnacle Mating Optimizer (BMO) [16,17] derives its name from the mating rituals of barnacles. The algorithm models barnacle reproduction, where barnacles release sperm and eggs into the sea. In BMO, barnacles represent potential optimization targets, and simulated mating sustains and expands barnacle populations. At the start of each mating cycle, the algorithm selects the highest and lowest fitness-rated barnacles and combines their starting points to generate new candidates. The strongest offspring emerge as the most robust barnacles, with the process continuing until a satisfactory solution is found. BMO's simplicity and fewer parameter settings make it user-friendly, and it can address both discrete and continuous optimization problems.

Despite promising results, BMO's stability, scalability, and speed require further investigation, as improvements by various researchers [21–25] have not fully addressed these concerns. The initial BMO implementation, based on pseudo-copulated mating using only penis length as a feature, does not accurately reflect real-world reproductive behaviors. This highlights the need for a more theoretically grounded approach.

The Barnacle Mating Optimizer (BMO) algorithm, though widely cited with over 300 references, lacks critical analysis of its theoretical and structural foundations. The algorithm's simplicity raises questions about its efficacy due to the absence of specialization in theoretical, structural, or natural mimicry. For example, the Hardy-Weinberg principle is unsuitable for modeling biological processes in hermaphroditic species like barnacles. The BMO method, which considers the relative contributions of parents' qualities to their offspring, may not be necessary for optimizing the search space.

In particular, BMO's exploration equation for sperm-cast mating is flawed. While BMO aims to maximize global search sites, it lacks the limits and validation needed to support its exploration–exploitation balance. This issue underscores the need for a robust theoretical basis in any effective optimization method.

To address these limitations, the Improved Barnacle Mating Optimization (IBMO) algorithm incorporates gooseneck barnacle behavior into the exploration and exploitation phases, enhancing the algorithm. IBMO's random variable helps avoid local optima, although its theoretical foundation is not yet fully established.

The incorporation of Opposition-Based Learning (OBL) offers a potential solution to these issues. OBL enhances the algorithm's search space exploration by considering both candidate solutions and their inverses, increasing the likelihood of finding the global optimum. OBL improves performance by avoiding early convergence and ensuring a better balance between exploration and exploitation, and has been successfully applied to various optimization techniques.

Integrating OBL [26,27] within the BMO framework significantly strengthens the algorithm. The enhanced BMO, supported by OBL, navigates complex datasets more effectively, avoids local optima, and provides more reliable results. This approach addresses the limitations of the original BMO and aligns the optimization process with natural constraints.

The study's key contributions are:

- Enhancing the original BMO by introducing constraints such as wave action and wind direction, and integrating Opposition-Based Learning (OBL). This combination improves the algorithm's exploration–exploitation balance and enables a more efficient search of the solution space.
- Developing a hybrid model that combines the Selective Opposition-Based Constrained BMO (SO-C-BMO) with LSSVM. This hybrid model optimizes hyperparameters, avoids premature convergence, and effectively addresses time series prediction challenges.
- Comparing SO-C-BMO with leading metaheuristic algorithms, demonstrating its superior performance in terms of statistical significance, convergence speed, exploration–exploitation ratio, and diversity.

The structure of the paper is organized as follows: Section 2 presents the study's rationale and biological basis. Section 3 describes the methodology in detail. Section 4 offers a comprehensive comparison of various advanced technologies and a real-life case study to validate and confirm the effectiveness of SO-C-BMO. Finally, Section 5 concludes the study and provides suggestions for future research.

2. Basic theory and notations

2.1. Barnacle Mating Optimizer (BMO)

The Barnacle Mating Optimizer (BMO) is a biologically inspired algorithm introduced in [28,29]. It mimics barnacle mating habits, which involve both traditional copulation and sperm-casting techniques. The initial barnacle population X, representing solution candidates, is given by:

$$X = \begin{bmatrix} x_1^1 & \cdots & x_1^N \\ \vdots & \ddots & \vdots \\ x_n^1 & \cdots & x_n^N \end{bmatrix} \tag{1}$$

Here, n denotes the total population size, and N is the number of control variables to be optimized. After evaluating the population, the best solution is identified, sorted, and placed at the top of the list.

The reproduction process in BMO is described by the following equations:

$$x_i^{(N_{\text{new}})} = p \times x_{\text{barnacle\_dad}}^N + q \times x_{\text{barnacle\_mum}}^N \tag{2}$$

$$x_i^{(N_{\text{new}})} = \text{rand}() \times x_{\text{barnacle\_mum}}^n \tag{3}$$

In these equations, $x_{\text{barnacle\_dad}}^N$ and $x_{\text{barnacle\_mum}}^N$ are the control variables of the parent barnacles. p represents normally distributed random numbers, and q is calculated as $q = 1 - p$.

2.2. Limitations of BMO

- **Lack of Theoretical and Structural Foundation:** The BMO algorithm lacks a well-defined theoretical basis and structural specialization. Despite its widespread citation, its foundational principles have not been critically examined, raising concerns about its validity.
- **Inaccurate Biological Mimicry:** The algorithm oversimplifies biological processes, such as applying the Hardy-Weinberg principle to barnacle offspring generation. This approach does not align with natural barnacle behavior, leading to questionable relevance in optimization tasks.
- **Unjustified Exploration and Exploitation:** BMO struggles with balancing exploration and exploitation, crucial for effective optimization. Its exploration equation, inspired by sperm-cast mating, lacks clear validation and constraints, making its optimization process difficult to justify.
- **Dependence on Ineffective Metrics:** BMO relies on metrics, such as penis length in pseudo-copulated mating, that do not significantly contribute to the optimization process, limiting its effectiveness.
- **Susceptibility to Local Optima:** BMO's performance is influenced by its initialization strategy and may struggle to escape local optima, resulting in unreliable outcomes, especially with complex datasets.
- **Insufficient Real-World Application:** BMO has not been thoroughly applied to real-world scenarios, with its development focusing narrowly on barnacle behavior, limiting its usability for complex optimization problems.

2.3. Variants and hybridization of BMO

The Barnacle Mating Optimizer (BMO), inspired by barnacle mating, has been used to solve various optimization challenges, including technical and economic problems. However, it faces drawbacks such as delayed and premature convergence. Hybridization, which involves combining BMO with other optimization methods, has been explored to improve convergence speed, exploration, and exploitation. Adjustments to the fundamental algorithm or parameters, such as adaptive mutation rates or varied population sizes, have been suggested to enhance BMO's performance.

The following table summarizes some enhancements and hybridization of BMO (see Table 1).

In conclusion, hybridization and enhancement of BMO can improve its performance and resilience, making it more effective for solving optimization problems. Future studies may further explore these methods.

2.4. Constrained Barnacle Mating Optimizer (C-BMO)

Nature-inspired optimization methods should ideally replicate natural constraints to minimize computational complexity, as constraints shape natural system behaviors and interactions. Ignoring these constraints can lead to suboptimal solutions. For example, genetic algorithms often include task constraints in the fitness function to ensure viable solutions are evaluated. This approach can improve search effectiveness and convergence speed. However, incorporating all constraints may increase computational complexity, so balancing constraint integration with computational feasibility is essential.

The initial BMO design did not incorporate constraints. This study introduces three factors to improve BMO's exploration and exploitation processes: wave action in intertidal zones, surrounding wind activity, and wave and wind direction towards targets.

Table 1
BMO enhancements and hybridizations in other fields of study.

Sl#	Improvements of BMO	Applications	Ref
1	BMO-LSSVM	COVID-19 confirmed cases prediction	[30]
2	BMO based Support Vector Machine	Selection of genes for microarray-based cancer classification	[31]
3	BMO based transfer learning model	Detection and classification of malaria parasites in biomedical contexts	[32]
4	BMO-NN	Stock price predictive analysis	[33]
5	BMO-Levy	Forecasting COVID-19 confirmed cases using time-series analysis while accounting for total vaccination	[34]
6	BMO-Gauss	Forecasting COVID-19 confirmed cases using time-series analysis while accounting for total vaccination	[35]
7	Conventional mathematical formula used to Improve the exploration and then BMO hybridize with SVM	Estimating the state of charge for lithium-ion batteries	[36]
8	BMO-Levy Flight	The objective is to find the unknown parameters for fuel cells by minimizing the sum of squared differences between the experimentally observed and anticipated output voltage	[37]

Barnacles typically inhabit the higher and intermediate intertidal zones, with significant wave heights between 0.8 and 1.5 to 3 meters above mean low water. Traditionally, the significant wave height H_s is given by $H_s = 4(H_{2T})$. This study uses the following modified formula for H_s:

$$H_s = 1.5 - \frac{(\text{Iteration} \times (1.5 - 0.2))}{\text{Maximum Iteration}} \tag{4}$$

Equations for the updated BMO are:

$$x_{(i+1)}^{(N_{\text{new}})} = p \times x_{\text{barnacle\_dad}}^{N} + q \times x_{\text{barnacle\_mum}}^{N} + \text{WD}_i + \text{T}_{\text{dim}} + H_s \times x_i^{(N_{\text{new}})} \tag{5}$$

$$x_{(i+1)}^{(N_{\text{new}})} = \text{rand}() \times x_{\text{barnacle\_mum}}^{n} + \text{WD}_i + \text{T}_{\text{dim}} + H_s \times x_i^{(N_{\text{new}})} \tag{6}$$

$$\text{WD}_i = \text{randi}[0, 359] \tag{7}$$

The wind direction WD_i adjusts the search space using cosine and sine functions. Integrating this with target dimensions T_{dim}, and assuming a constant wind direction towards the target, enhances Eq. (6). This enhancement through selective opposition improves exploration, leading to better convergence and avoidance of local optima compared to BMO or C-BMO.

2.5. Selective opposition-based C-BMO (SO-C-BMO)

Selective Opposition improves metaheuristic optimization algorithms by reversing the exploration orientation of solutions that outperform the current optimum, helping escape local optima and explore the solution space more effectively. This technique accelerates convergence to the global optimum, especially for non-convex objective functions with multiple local optima.

Selective Opposition (SO) has been applied in various algorithms, including evolutionary algorithms, particle swarm optimization, and gradient-based methods [38–41]. The methodology enhances algorithm effectiveness with minimal processing requirements, preventing local optima and improving exploration.

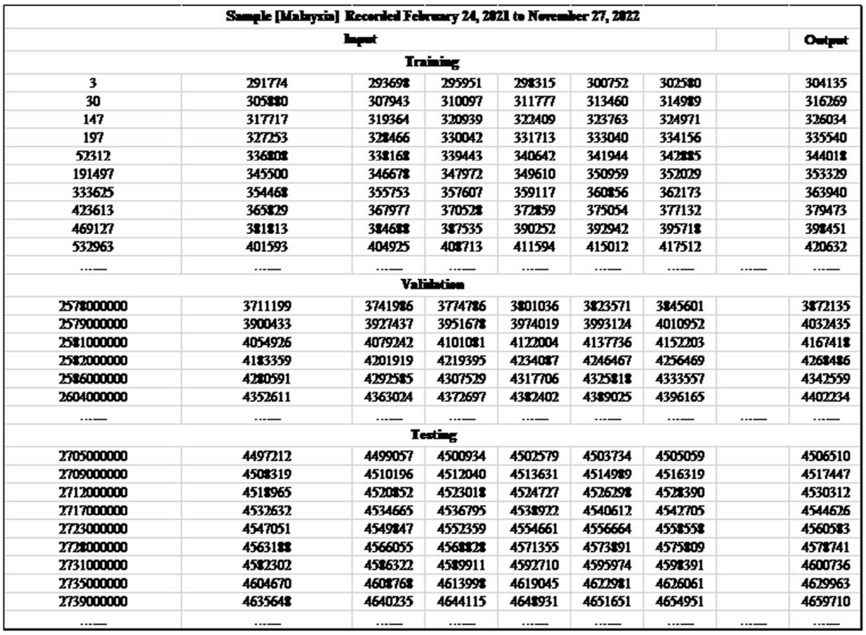
We have hybridized the constrained BMO with Selective Opposition and LSSVM to form SO-C-BMO-LSSVM. This combined approach uses C-BMO to find optimal LSSVM hyperparameters for time series prediction. Selective Opposition improves C-BMO-LSSVM's performance in handling non-convex functions by exploring solution space more effectively and avoiding local optima.

Recent studies have explored applications of machine learning beyond time series prediction. For instance, [42] used Recurrent Neural Networks (RNNs) for solving the persistent defensive location problem (CDLP), reducing computing costs and optimizing defensive facility placement. Other studies have utilized RNNs in IoT settings [43] and developed a personalized healthcare recommender system using community detection algorithms [44]. Further research [45] suggests Hybrid Ant-Bee Colony Optimization (HABCO) for feature selection issues. These applications and methods will be evaluated for their performance and potential internal modifications.

3. Methodology

3.1. Data description

Data was collected daily from February 24, 2021, to November 27, 2022, as described in [46]. The dataset was segmented into training, validation, and test sets. Each day's vaccination case [47] from the exact date was combined with previous days' data to



Sample [Malaysia] Recorded February 24, 2021 to November 27, 2022								
Input								Output
Training								
3	291774	293698	295951	298315	300752	302580		304135
30	305880	307943	310097	311777	313460	314989		316269
147	317717	319364	320939	322409	323763	324971		326034
197	327253	328466	330042	331713	333040	334156		335540
52312	336808	338168	339443	340642	341944	342885		344018
191497	345500	346678	347972	349610	350959	352029		353329
333625	354468	355753	357607	359117	360856	362173		363940
423613	365829	367977	370528	372859	375054	377132		379473
469127	381813	384688	387535	390252	392942	395718		398451
532963	401593	404925	408713	411594	415012	417512		420632
......	......	......	......	......	......	......	......	......
Validation								
2578000000	3711199	3741986	3774786	3801036	3823571	3845601		3872135
2579000000	3900433	3927437	3951678	3974019	3993124	4010952		4032435
2581000000	4054926	4079242	4101081	4122004	4137736	4152203		4167418
2582000000	4183359	4201919	4219395	4234087	4246467	4256469		4268486
2586000000	4280591	4292585	4307529	4317706	4325818	4333557		4342559
2604000000	4352611	4363024	4372697	4382402	4389025	4396165		4402234
......	......	......	......	......	......	......	......	......
Testing								
2705000000	4497212	4499057	4500934	4502579	4503734	4505059		4506510
2709000000	4508319	4510196	4512040	4513631	4514989	4516319		4517447
2712000000	4518965	4520852	4523018	4524727	4526298	4528390		4530312
2717000000	4532632	4534665	4536795	4538922	4540612	4542705		4544626
2723000000	4547051	4549847	4552359	4554661	4556664	4558558		4560583
2728000000	4563188	4566055	4568828	4571355	4573891	4575809		4578741
2731000000	4582302	4586322	4589911	4592710	4595974	4598391		4600736
2735000000	4604670	4608768	4613998	4619045	4622981	4626061		4629963
2739000000	4635648	4640235	4644115	4648931	4651651	4654951		4659710
......	......	......	......	......	......	......	......	......

Fig. 1. Sample dataset.

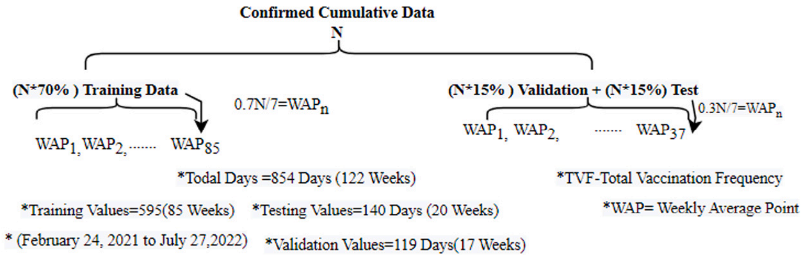


Fig. 2. Schematic diagram of dataset after segmentation.

produce a cumulative verified COVID-19 dataset—Malaysia's total number of vaccinations since the start of daily collection. Figs. 1 and 2 illustrate the dataset sample after segmentation (70-15-15) and the schematic diagram for better understanding, respectively.

Fig. 2 the schematic diagram illustrates the segmentation of cumulative confirmed COVID-19 cases and vaccination frequency data into three parts: 70% for training, 15% for validation, and 15% for testing, covering 854 days (122 weeks) from February 24, 2021, to July 27, 2022. The data is divided into Weekly Average Points (WAP) calculated by averaging the confirmed cases and vaccination frequency over a 7-day period. Each week is denoted as $W_1D_1, W_1D_2, \ldots, W_1D_7$, where $D_1, D_2, \ldots, D_7$ represent daily confirmed cases.

In this setup, the seventh day of the first week (W_1D_7) might fall on a specific day, such as Friday. The number of confirmed and vaccination cases for the preceding six days ($W_1D_1, W_1D_2, \ldots, W_1D_6$) influences the weekly average. This means that weekly trends are shaped not just by the end-of-week data point but also by daily fluctuations throughout the week. For example, if there is a spike or drop in confirmed cases or vaccination frequency on specific weekdays, it will significantly affect the overall WAP for that week.

The cumulative confirmed cases and vaccination data are averaged to form a WAP, calculated as:

$$WAP_n = \frac{N_{week}}{7}$$

where N_{week} is the total number of confirmed cases or vaccinations in a week.

This approach helps capture weekly trends in a balanced way, smoothing out daily variances while still reflecting important fluctuations throughout the week, which might be influenced by factors such as weekday vaccination drives or spikes in confirmed cases.

For training, 85 weeks (595 days) of data are used, while 17 weeks (119 days) are used for validation and 20 weeks (140 days) for testing. This distribution ensures a balanced representation of the dataset, allowing for efficient model training and testing on unseen data, preserving the trends seen in both confirmed cases and vaccination efforts.

Table 2
Performance evaluation of different algorithms.

Optimizers with LSSVM	MAPE	Accuracy	Theil's U
SO-C-BMO	0.002211	0.99649	0.047
HBA	0.0036	0.9901	0.061
PSO	0.004	0.992	0.069
DA	0.006	0.991	0.083
BMO	0.0118	0.9813	0.119
SSA	0.02	0.97	0.159
MVO	0.025	0.97	0.1603

3.2. Hybrid selective opposition-based constrained Barnacle Mating Optimizer (SO-C-BMO)

This research introduces a novel hybrid approach to assessing COVID-19 individuals with complete vaccination. It integrates Selective Opposition into the Constrained Barnacle Mating Optimizer (C-BMO) to enhance both exploration and exploitation capabilities. The Least Squares Support Vector Machine (LSSVM) approach is combined with Selective Opposition-Based Constrained BMO to optimize hyperparameters for predictive tasks. This results in the Selective Opposition-Based Constrained Barnacle Mating Least Squares Support Vector Machine (SO-C-BMO-LSSVM), which improves C-BMO's efficacy through Opposition-Based Learning (OBL).

Figs. 3 and below pseudo code show the proposed developments of the original BMO. The technique involves establishing initial population characteristics and boundaries, computing wave height and wind direction, and randomly selecting vectors within specified limitations. The algorithm enhances search space exploration by creating potential solutions through opposition, using OBL to improve less efficient barnacles and accelerate convergence to the global optimum.

4. Pseudo code

Each iteration generates a new batch of options, with the best option determined by ranking the newly formed offspring based on their adaptation to wave and wind conditions. The optimal solution and its vicinity may be located at opposite ends of the search space from the least well-fit barnacles. The ranking correlation coefficient between each solution and the optimal solution is calculated after each iteration. If the coefficient is negative, the search perspective is misaligned with the data, leading to a narrowed search by selecting opposing dimensions and barnacles using the Spearman coefficient.

4.1. Evaluation criteria

Traditional metrics for evaluating time series forecasting models include accuracy, Mean Absolute Percentage Error (MAPE), and Theil's U. The definitions for these performance measures in regression models are provided below:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{\text{predicted}} - y_{\text{actual}}}{y_{\text{actual}}}\right| \times 100\% \tag{8}$$

$$\text{Theil's U} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{\text{actual}} - y_{\text{predicted}})^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{\text{actual}})^2 + \frac{1}{N}\sum_{i=1}^{N}(y_{\text{predicted}})^2}} \tag{9}$$

$$\text{Accuracy} = 1 - \text{MAPE} \tag{10}$$

In these equations, n represents the number of test instances, $y_{\text{predicted}}$ denotes the predicted values at the ith time, and y_{actual} refers to the actual values at the ith time. These metrics quantify the error rate of the prediction model in regression, with the goal of minimizing their values.

5. Results and discussion

The SO-C-BMO-LSSVM approach effectively addresses real-world, context-specific problems, similar to other metaheuristic algorithms. This subsection presents the results of using the SO-C-BMO and LSSVM methods to forecast the time series of confirmed COVID-19 cases. Table 2 summarizes the performance of various hybrid algorithms used in this study for predicting verified cases while considering the total vaccination rate.

Table 3 compares actual confirmed case values with target values for all hybrid algorithms considered in this study, factoring in total vaccination.

Fig. 4 illustrates a comparison between actual and predicted values. It demonstrates that the SO-C-BMO-LSSVM method outperforms other approaches—BMO-LSSVM, HBA-LSSVM, DA-LSSVM, MVO-LSSVM, PSO-LSSVM, and SSA-LSSVM—in predicting confirmed COVID-19 cases in Malaysia, factoring in total vaccination.

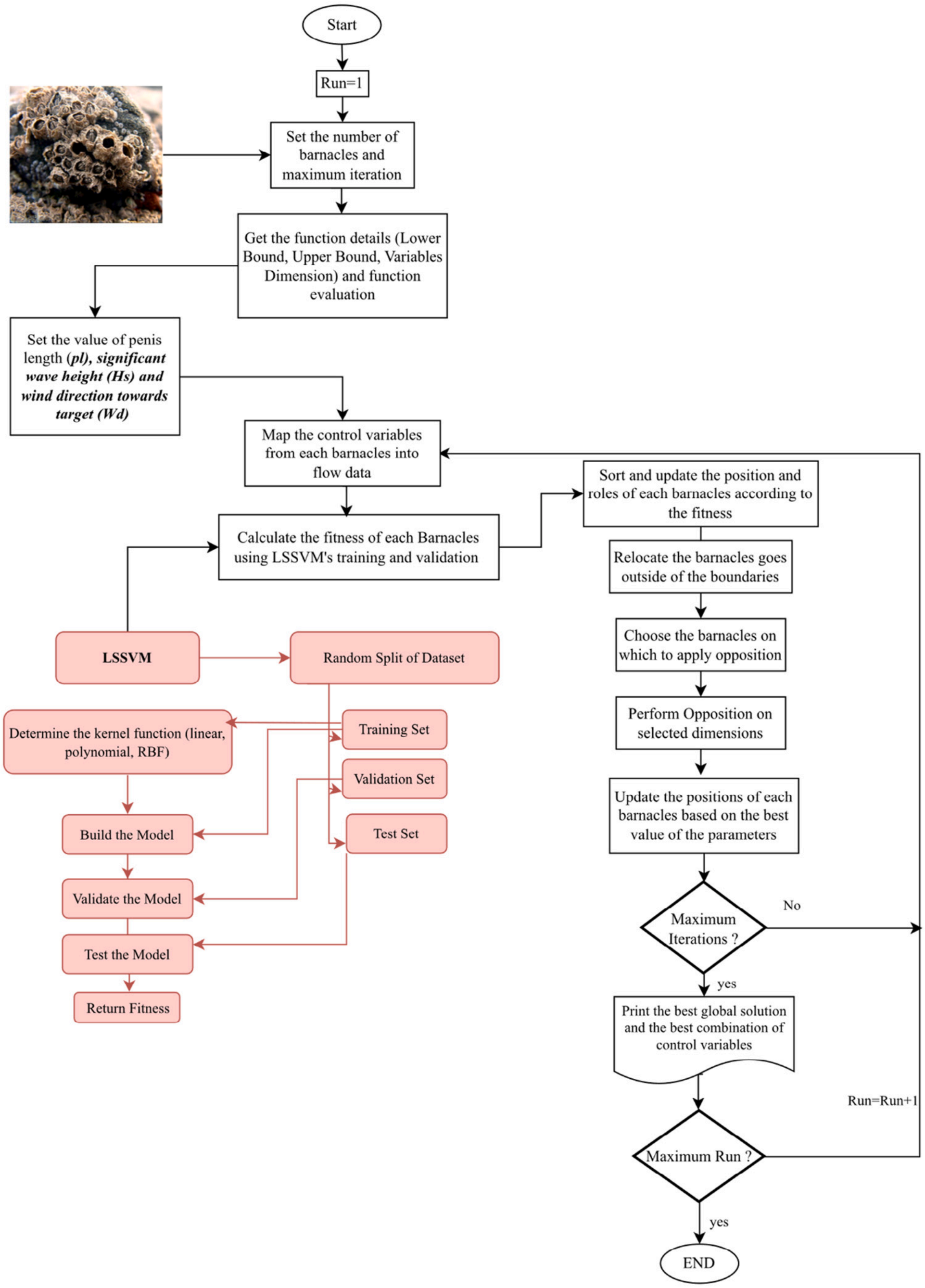


Fig. 3. Workflow diagram of SO-C-BMO-LSSVM.

6. Conclusion

In this study, we introduce a novel enhancement to the BMO algorithm, termed SO-C-BMO, which is designed to strike a more effective balance between exploration and exploitation. By efficiently navigating the search space and avoiding suboptimal regions, SO-C-BMO shows improved performance in solving complex optimization tasks. The algorithm's effectiveness was rigorously evaluated in real-world scenarios, highlighting superior statistical outcomes, an optimized exploration–exploitation trade-off, and more rapid convergence. The integration of SO-C-BMO with the LSSVM model, termed SO-C-BMO-LSSVM, demonstrated significant

Algorithm 1 Barnacle Optimization Algorithm with LSSVM and SOBL.

Initialize population X_i (each barnacle)
Determine fitness of X_i based on LSSVM (training + validation)
Sort and update the position of X_i
while $I < Max\_Iterations$ **do**
  Set pl value
  Calculate Significant Wave Height, H_s using Eq. (4)
  Calculate Wind Direction towards target, WD using Eq. (7)
  Selection of parents
  if selection of parents == pl **then**
    for each barnacle **do**
      // Exploitation Process
      Generate offspring using Eq. (5)
    end for
  else if selection of parents > pl **then**
    for each barnacle **do**
      // Exploration Process Improved by SOBL
      Generate offspring using Eq. (6)
      Relocate barnacles that go outside the search space
      Arrange the search agents in ascending order based on their fitness values
      $limit = 2 - \left(\frac{I \times 2}{Max\_Iterations}\right)$
      $boundary = limit$
      for $r = 1$ to number of relocated barnacles **do**
        for $d = 1$ to total dimensions **do**
          $diff(d) = |X(d) - X_i(d)|$
          if $diff(d) > boundary$ **then**
            $Albarnacle\_no = Albarnacle\_no + 1$
          end if
        end for
        Calculate SRCE using:

$$SRCE = 1 - \frac{6 \sum_j diff(j)^2}{dim(dim^2 - 1)}$$

        if $SRCE \leq 0$ **then**
          if $(dim - Albarnacle\_no) < Albarnacle\_no$ **then**
            for each $p \in \{d : diff(j) > boundary\}$ **do**
              $X(p) = ub(p) + lb(p) - X(p)$
            end for
          end if
        end if
      end for
    end for
  end if
  Determine fitness for the new X_i using LSSVM (training + validation)
  Sort and update the position of better solutions
  $I = I + 1$
end while
return position

success in time series prediction. The algorithm efficiently identifies optimal hyperparameters for LSSVM, resulting in highly accurate forecasts. By leveraging selective opposition, SO-C-BMO is adept at handling non-convex objective functions with multiple local optima, thus improving its ability to locate global optima and deliver precise predictions.

A comparative analysis with other optimization techniques, such as PSO, DA, HBA, BMO, MVO, and SSA, further underscores the advantages of SO-C-BMO-LSSVM in addressing complex search spaces. It excels in both convergence speed and maintaining an effective exploration–exploitation balance. Future research will explore enhancements to the C-BMO algorithm by incorporating features like chaotic maps, binary objectives, and multi-objective frameworks, aimed at addressing large-scale optimization problems more effectively.

Table 3
Weekly Prediction comparison performances.

Week	Target	SO-C-BMO-LSSVM	BMO-LSSVM	HBA-LSSVM	MVO-LSSVM	PSO-LSSVM	SSA-LSSVM	DA-LSSVM
67	4 506 510	4490286.564	4452941.116	4490255.018	4390692.693	4485329.403	4405564.176	4375165.783
68	4 517 447	4501184.191	4463748.108	4501152.569	4401348.612	4496214.999	4416256.187	4385784.02
69	4 530 312	4514002.877	4476460.181	4513971.165	4413882.982	4509019.534	4428833.011	4398274.063
70	4 544 626	4528265.346	4490604.031	4528233.534	4427829.112	4523266.258	4442826.378	4412170.876
71	4 560 583	4544164.901	4506371.35	4544132.977	4443376.017	4539148.26	4458425.941	4427662.802
72	4 578 741	4562257.532	4524313.506	4562225.481	4461067.356	4557220.917	4476177.202	4445291.579
73	4 600 736	4584173.35	4546047.051	4584141.145	4482497.085	4579112.541	4497679.514	4466645.525
74	4 629 963	4613295.133	4574926.63	4613262.723	4510972.951	4608202.174	4526251.829	4495020.691
75	4 659 710	4642935.044	4604320.027	4642902.426	4539955.453	4637809.363	4555332.496	4523900.702

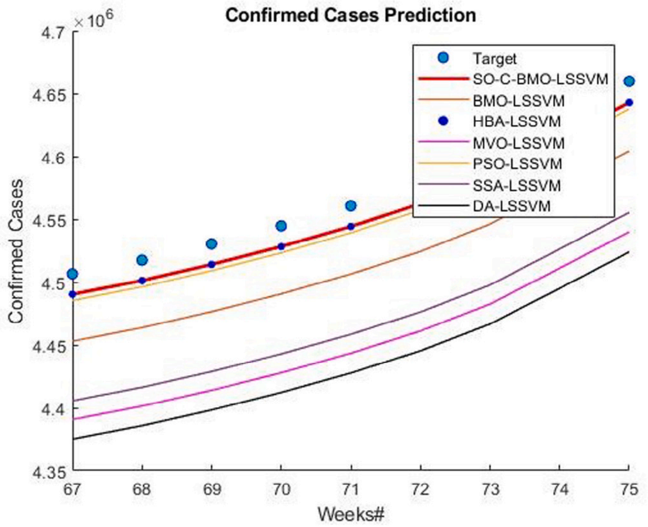


Fig. 4. Prediction comparison between algorithms.

Ethical approval

None sought.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link.

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