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Daily allocation of energy consumption forecasting of a power distribution company using optimized least squares support vector machine

Marzia Ahmed [a,*], Mohd Herwan Sulaiman [b], Md. Maruf Hassan [c], Md. Atikur Rahaman [e], Mohammad Bin Amin [d]

[a] Department of Software Engineering, Daffodil International University, Dhaka, 1341, Bangladesh
[b] Universiti Malaysia Pahang Al-Sultan Abdullah, Pekan, 26600, Pahang, Malaysia
[c] Department of CSE, Southeast University, Dhaka, Bangladesh
[d] Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary
[e] School of Economics and Management, Jiujiang University, 551 Qianjin Donglu, Jiujiang, Jiangxi 332005, PR China

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ABSTRACT

Accurate energy consumption forecasting is critical for efficient power distribution management. This study presents a novel approach for optimal allocation forecasting of energy consumption in a power distribution company, utilizing the Least Squares Support Vector Machine (LSSVM) optimized by novel variants of the Barnacle Mating Optimizer (BMO) such as the new Gooseneck Barnacle Optimizer and Selective Opposition-based constrained BMO. The optimized LSSVM hyper-parameters, specifically the regularization parameter (γ) and the kernel parameter (σ^2), were applied to test data to enhance accuracy guided by the Mean Absolute Prediction Error (MAPE), ensuring precise alignment of forecasted values with actual energy consumption data. The results indicate that the novel gooseneck barnacle base-optimized LSSVM provides a robust and reliable solution with accuracy 99.98% for daily energy consumption for allocation forecasting, making it a valuable tool for power distribution companies aiming to optimize their resource allocation and planning processes.

1. Introduction

Precisely forecasting energy consumption is vital for power distribution companies to manage and plan effectively. This allows them to allocate resources efficiently, ensure grid stability, and meet customer demands more accurately. Forecasting helps in optimizing resource allocation, reducing operational costs, and enhancing the reliability of power supply.

This research [1], addresses the growing need for reliable building energy demand forecasts due to increasing global energy consumption and its economic and environmental impacts. The study presents a CNN–LSTM framework that combines means clustering, Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were utilized to examine energy consumption patterns, capture complex features, and model temporal relationships. Using real-time data from a four-story building at IIT-Bombay, India, the CNN–LSTM model showed higher forecasting accuracy than ARIMA, DBN, MLP, LSTM, and standalone CNN models. Its ability to learn spatio-temporal dependencies led to the lowest values for Mean Squared Error (MSE)

* Corresponding author.
E-mail addresses: ahmed.marzia32@gmail.com (M. Ahmed), herwan@ump.edu.my (M.H. Sulaiman), ancssf@gmail.com (M.M. Hassan), atik@jju.edu.cn (M.A. Rahaman), binaminbd@mailbox.unideb.hu (M.B. Amin).

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at 0.0251, Root Mean Squared Error (RMSE) at 0.1586, Mean Absolute Error (MAE) at 0.1397, and Mean Absolute Percentage Error (MAPE) at 0.1653, proving it to be an exceptionally effective deep learning model for energy consumption prediction. This study [2] introduces an innovative method for short-term consumption of energy forecasting in residential environments, crucial for decentralized power systems. Leveraging Federated Learning and Edge Computing, it allows local training of LSTM, where the users utilize individual data, enhancing privacy and scalability. Simulation results demonstrate comparable forecasting accuracy to centralized solutions, with significantly reduced training time and data exchange. The proposed method achieves an RMSE of 0.1333, highlighting its effectiveness and efficiency in energy forecasting. This study [3] proposes an energy consumption forecasting model combining Empirical Wavelet Transform (EWT) with LSTM. This model emphasizes critical factors and achieves superior accuracy compared to basic LSTM and other models, with MAPE with 4.01%, 5.37%, and 1.60% in three real-life cases. This high-precision method is essential for balancing energy demand and production. This study [4] proposes a hybrid model that combines Singular Spectrum Analysis (SSA) with Parallel Long Short-Term Memory (PLSTM) networks to improve energy consumption forecasting. SSA decomposition enhances the PLSTM's ability to predict sudden changes and capture long-term dependencies in volatile energy data. Experiments show that this model outperforms state-of-the-art models in both prediction accuracy and computational efficiency across different time intervals. This study [5] introduces eDemand, a hybrid forecasting model for energy consumption that combines LSTM with an enhanced Sine Cosine Optimizer (ISCOA) for enhanced accuracy & robustness. The model employs an innovative mutation operator, based on Haar wavelet to improve the effectiveness of optimization algorithm. The LSTM's hyperparameters are optimized using ISCOA. The model proved to be a dependable tool for short-, mid-, and long-term energy consumption forecasting when tested on actual data from an educational institution in IIT Bombay. It outperformed state-of-the-art models in terms of several error metrics. Two deep learning models are proposed in this article [6] to address the problem of energy consumption forecasting in buildings with little historical data: a two-dimensional (2D) convolutional neural network (CNN) with a concentrated attention layer, and a sequence-to-sequence (seq2seq) model. These models improve accuracy for target properties by using a transfer learning approach. The efficacy of the method is shown by a case study involving three commercial structures. The seq2seq model enhances prediction accuracy by 19.69 percent in MAPE and the 2D CNN model by 20.54 percentage points when compared to a simple LSTM model; hence, they are appropriate for sparse data buildings. Traditional forecasting methods often struggle with the complex, nonlinear nature of energy consumption patterns. To address these challenges, machine learning techniques, particularly the LSSVM, have increasingly adopted their robustness and ability to handle nonlinear relationships. However, the execution of LSSVM is highly sensitive to its hyper-parameters. Finding optimal values for these parameters is essential for maximizing prediction accuracy. Recently, nature-inspired metaheuristic optimizers already shown great promise in tuning hyper-parameter for machine learning models [7,8]. Among these, the Barnacle Mating Optimizer (BMO) has emerged as a powerful tool for the optimal performances and. The BMO imitates the reproduction procedures, leveraging exploration and exploitation mechanisms to find optimal solutions. This study proposes a novel approach for the optimal allocation forecasting of energy consumption using variants of the BMO to optimize the hyper-parameters of the LSSVM. By integrating improved BMO with LSSVM, the proposed method aims to enhance the accuracy of energy consumption predictions. The evaluation criteria of this hybrid model is evaluated using real-world energy consumption data, with the objective function guided by the MAPE to ensure precise forecasting.

Fig. 1 represents a general flow of the study. Here, in objective (1), the barnacle hybridized with LSSVM. Each barnacle's position serves as a multidimensional vector encoding hyper-parameter values for the LSSVM model. As barnacle optimizer iteratively explore and exploit the search space, barnacle positions are continuously adjusted. The fitness of each barnacle is determined by evaluating the corresponding LSSVM model's performance with the encoded hyper-parameters.

Through this iterative refinement, barnacles converge to optimal hyperparameter values, representing a highly optimized configuration for the LSSVM model. The final hybrid model utilizes these optimized hyperparameters, providing an enhanced and effective solution for the overall optimization task to evaluate the prediction error that used as the fitness function. Later, in objective (2), when expected accuracy does not meet, this study implemented some conventional approaches to improve the BMO [9,10] for better optimization. After evaluating the accuracy of prediction again, the study found significant flaws in original BMO [11] that affect the accuracy enhancement. Finally, in objective (3), this research proposes a new bio-inspired gooseneck barnacle optimizer (GBO) [12], that meets all the requirements from every aspect.

Following is the arrangement of the remaining sections: The data description, Proposed Variants for daily forecasted energy consumption, the gaps in BMO described, after that the study provides a clear explanation of the new Gooseneck Barnacle Optimizers. Then it offers a full comparative analysis on an actual case study to verify and evaluate the performance of GBO. Lastly, the paper closes by making some recommendations for further research.

2. Data description

Data has been collected from 2015–2018 from the link in Kaggle Hourly Energy Consumption Data of Power Distribution Company. Table 1 provides a graphical representation of the dataset for easier comprehension. We obtained a dataset for four years from the source, then processed it to assess and forecast the daily average usage of an energy distribution company.

3. Proposed system with BMO variants for daily energy consumption of a power distribution company

The methodology for the research is meticulously structured to create a robust predictive model for forecasting daily average energy consumption of a power distribution company. The process begins with the original Barnacle Mating Optimizer (BMO),

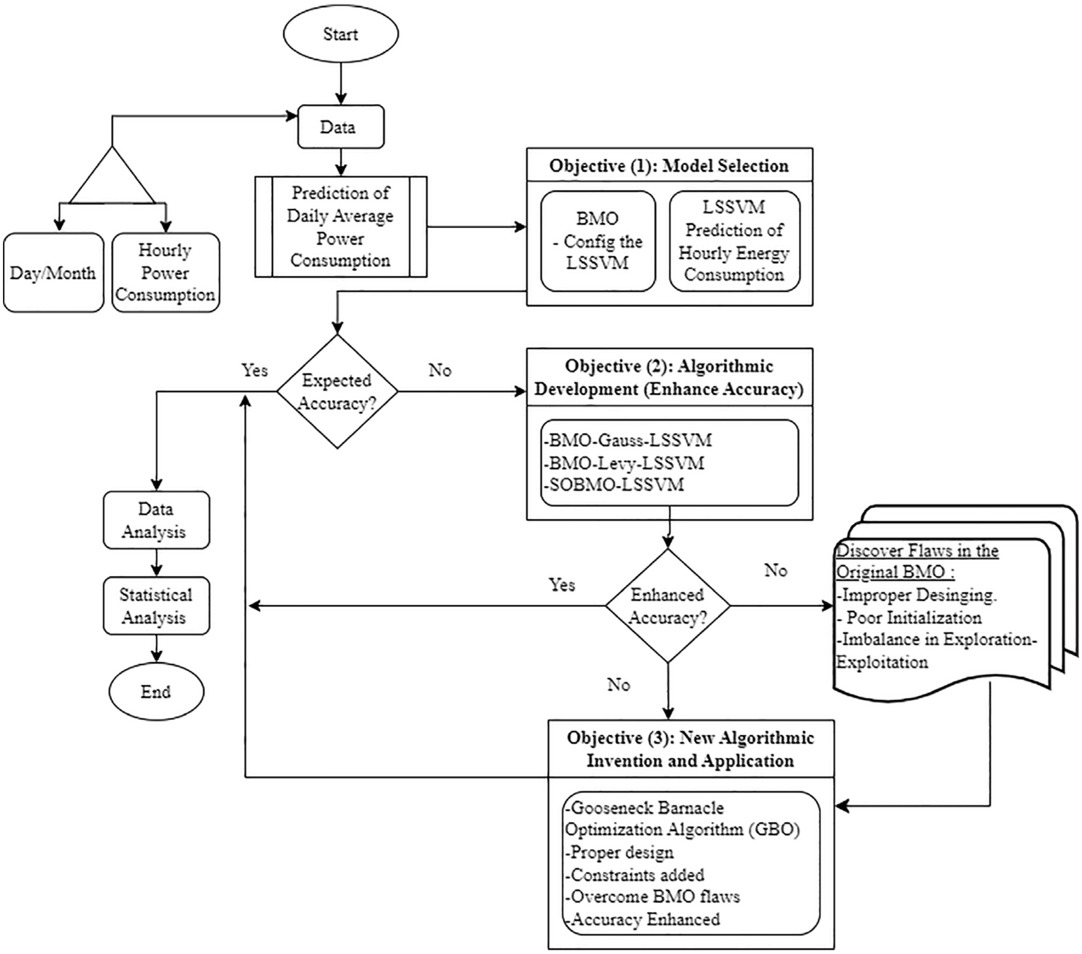

Fig. 1. General flow chart.

Table 1
Schematic diagram of dataset.

Input		Output
Days (Month)	Hourly power consumption	Daily average consumption
PC-Day1	D1H1, D1H2, …, D1H23, D1H24	D1AC
PC-Day2	D2H1, D2H2, …, D2H23, D2H24	D2AC
PC-Day3	D3H1, D3H2, …, D3H23, D3H24	D3AC
PC-Day4	D4H1, D4H2, …, D4H23, D4H24	D4AC
PC-Day5	D5H1, D5H2, …, D5H23, D5H24	D5AC
PC-Day6	D6H1, D6H2, …, D6H23, D6H24	D6AC
PC-Day7	D7H1, D7H2, …, D7H23, D7H24	D7AC
…	…	…
PC-Day30	D30H1, D30H2, …, D30H23, D30H24	D30AC

which initiates by generating a population represented as X based on Eq. (1). The subsequent steps involve producing new offspring using Eqs. (2) and (3). These offspring undergo a thorough examination process before being merged with their parent solutions. A sorting method is applied to rank the solutions, ensuring that the most effective ones occupy the top positions in the population. In preparation for the following iteration, the lower half of the population is assumed to be removed, and only the upper half of the population, comprising a mix of parents and offspring, is retained. The formula used to mimic the nature:

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

$$UB = [ub_1, \dots, ub_i] \tag{2}$$

$$LB = [lb_1, \dots, lb_i] \tag{3}$$

Exploitation Process:

$$x_i^{N\_new} = px_{dad\_barnacle}^N + qx_{mom\_barnacle}^N \tag{4}$$

Exploration Process:

$$x_i^{barnacle\_new} = rand() * x_{mom\_barnacle}^N \tag{5}$$

The heart of this methodology lies in the integration of Least Square Support Vector Machines (LSSVM) to create a predictive model capable of forecasting daily average energy consumption on an hourly basis. Enhanced barnacle mating, known as variants of BMO or Improved Barnacle Mating Optimization (IBMO), is introduced to fine-tune the LSSVM model, enhancing its predictive capabilities. The methodology uses a range of statistical measures such as Mean Squared Error, Mean Absolute Prediction Error, and Theil's U to validate the reliability of the model. This validation process is carried out on data that was not used during the model training phase.

The final stage involves deploying the model, which can then be used to predict the daily consumed energy of a power distribution company for optimal energy allocation. The remaining dataset is employed to validate the model and evaluate its predictions against actual values. A user-friendly flowchart Fig. 2 provides a clear visual representation of the entire approach, from data collection Table 1 to model deployment. This comprehensive and systematic methodology underpins the development of a predictive model with the potential to revolutionize energy consumption forecasting and optimal allocation. The variants of BMO and LSSVM, validated by rigorous evaluation, form the core of this research's contributions. The variants will be discussed in detail in the following subsection respectively.

3.1. BMO variant 1: Exploration enhanced using Gauss distribution

The value of p_l is essential to BMO's definition of the exploration and exploitation processes. It is clear from Eq. (5) that the generation of new offspring, which is regarded as the exploration process, uses simple random integers. The exploration procedure is improved in this study by changing Eq. (5) to the following expression:

$$x_i^{(N_{\text{new}})} = x_{\text{barnacle}_m}^n + \text{Gauss}(N) \tag{6}$$

where

$$\text{Gauss}(N) = 0.01 \times \text{Step Size} = 0.01 \times \frac{r_1 \times \sigma_s}{|r_2|^{1/\beta}} \tag{7}$$

The Gauss distribution is performed using the following equations:

$$\sigma_s = \sigma_0 \exp(-\mu n) \tag{8}$$

where σ_0 and μ are constants valued at $\frac{1}{2}$ and -0.0001, respectively. β is a constant set to $\frac{3}{2}$, r_1 and r_2 are random numbers in the range [0,1], and i is the current generation. A proper step size is crucial for the search space: if the step size is too large, the new selection will be too far from the old one, and if it is too small, the change in position will be too minimal.

3.2. BMO variant 2: Exploration enhanced using levy flight

After implementing BMO-LSSVM and BMO-Gauss-LSSVM and scrutinizing the results, there is a necessity to validate them. Therefore, Levy flights are used to generate another variant from the original BMO for validation purposes. The execution follows the same steps as previous implementations due to the same problem definition and dataset.

Similar to previous variants, the value of p_l is crucial in defining the exploration and exploitation processes. From Eq. (5), it can be noted that simple random numbers to generate new offspring are treated as an exploration process. In this variant of BMO, the improvement to the exploration process is made where Eq. (5) is changed to the following expression:

$$x_i^{(N_{\text{new}})} = x_{\text{barnacle}_m}^n + \text{Levy}(N) \tag{9}$$

where Levy flight is determined as follows:

$$\text{Levy}(N) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{1/\beta}} \tag{10}$$

and

$$\sigma = \left(\frac{\tau(1+\beta) \times \sin(\pi\beta/2)}{\tau\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{1/\beta} \tag{11}$$

where $\tau(y) = (y-1)!$, β is a constant set to 1.5, and r_1 and r_2 are random numbers in the range [0,1].

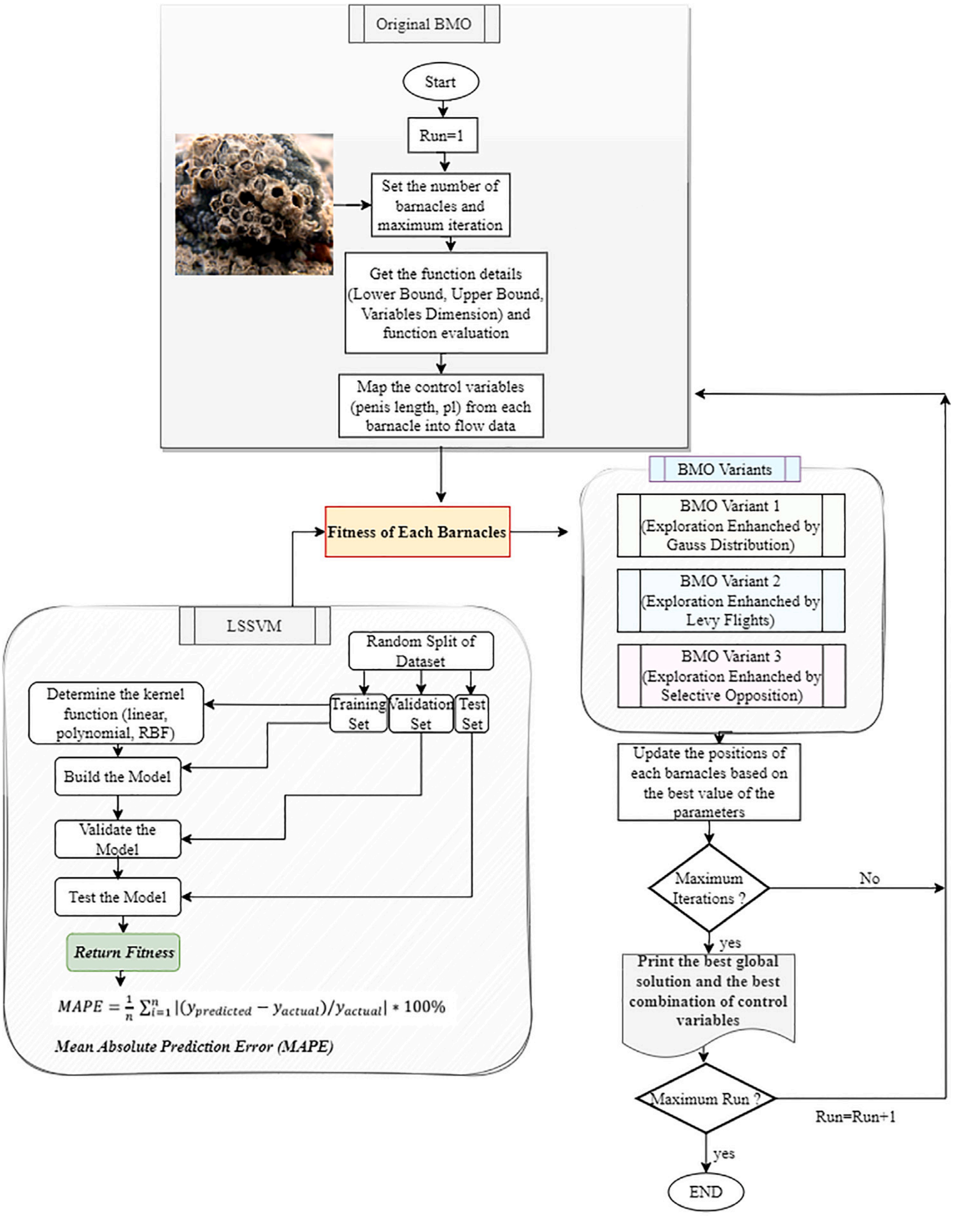

Fig. 2. Block diagram of the proposed time-series prediction system using BMO-variants.

3.3. BMO variant 3: Enhanced using selective opposition based learning

There are several methods offered to enhance metaheuristics, such as OBL, chaos, hybridization, and others. One such method that has proven to be successful is Opposition-Based Learning (OBL) [13,14]. Many computer scientists have shown interest in OBL algorithms, and applying OBL [15] has improved various algorithms, including GSA, SA, GA, PSO, ACO, ABC, DE, etc.

Selective opposition-based learning involves creating two sets of solutions: one set representing the current population and the other representing the opposition population. The opposition population is created by applying a set of opposition-based rules to the current population to improve exploration and exploitation capabilities. Selective Opposition-Based Gray Wolf Optimization (SOGWO) integrates OBL with GWO to increase diversity and exploration without reducing convergence speed [16], while also reducing exploitation. In summary, it works by creating opposition pairs from a population of solutions and performing a competition between these pairs to determine the most optimal solution. This article [17] optimizes LSSVM hyperparameters using SOGWO, decreasing LSSVM's inappropriate-for-specific-tasks constraints and increasing the program's generalization capabilities.

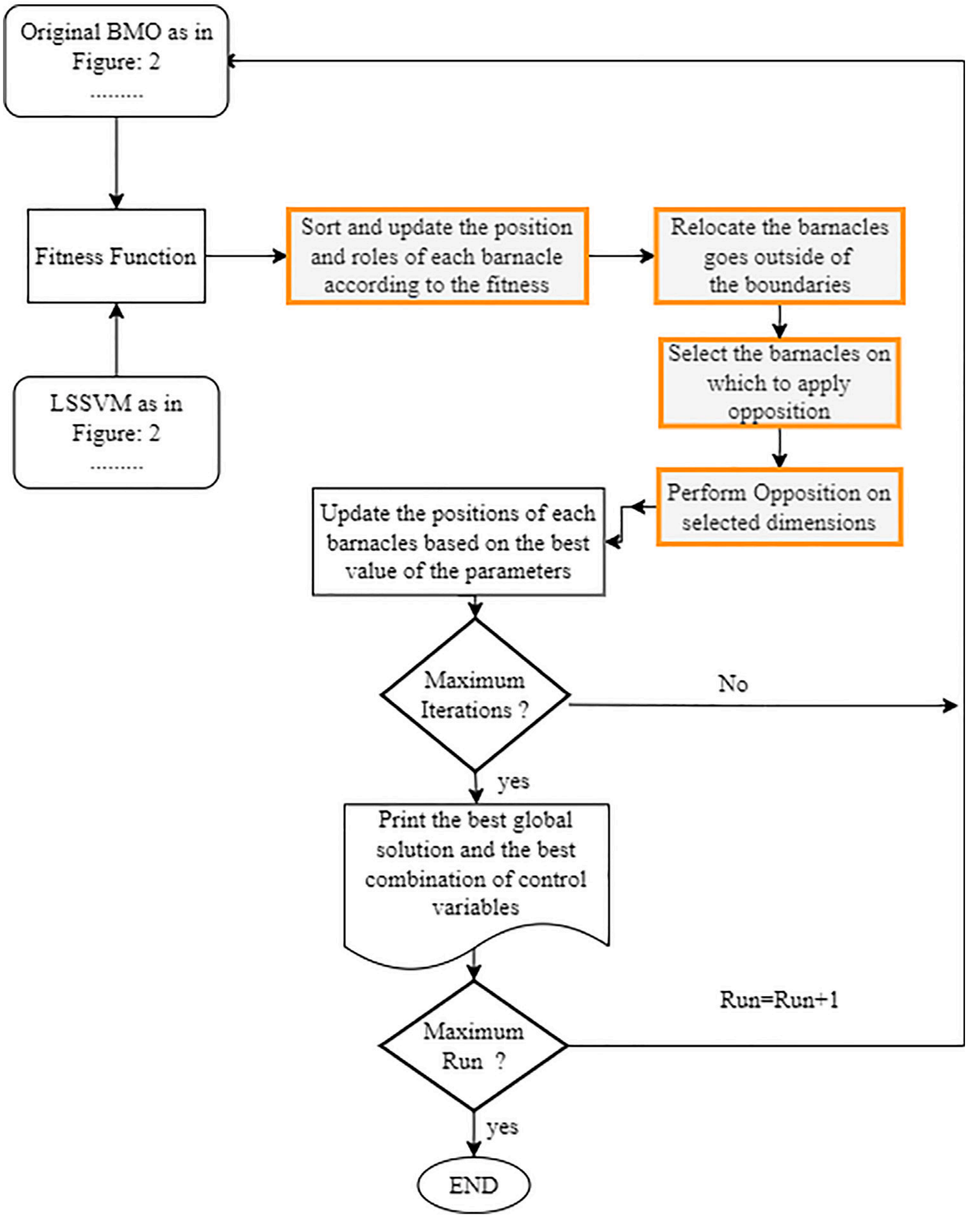

Fig. 3. Flow diagram for SO-BMO-LSSVM.

The implementation of SOGWO [16] in hyperparameter optimization served as the foundation for creating a novel optimization variant, SO-BMO-LSSVM. This novel variant adopted the same theoretical principles as SOGWO but applied them within the framework of the Barnacle Mating Optimizer (BMO), tailored specifically for LSSVM hyperparameter optimization. The population starts with the number of search agents, the upper bound, the lower bound, and the dimension of the search agents. The population vectors are chosen randomly while considering the provided limitations. Fewer parameter settings make BMO user-friendly. Similar to SOGWO, SO-BMO combined with LSSVM is detailed in Fig. 3.

By generating a new candidate solution via opposition, this study seeks the opposite location in the search space (relative to the candidate whose opposition is produced). Keeping this in mind, the location of the best solution is considered optimal in the search space. Barnacles may be positioned both close to and distant from this optimal point. OBL is applied to the barnacles that are far from the optimal solution to improve the fitness of the least fit barnacles.

By employing a chosen OBL technique in BMO, both the convergence speed and the likelihood of reaching the global optimum are enhanced. After each cycle, a new set of potential solutions, including new barnacles, is generated. Consequently, there is a possibility that the least fit barnacles may be located far from the optimal point or its vicinity within the search space. Therefore,

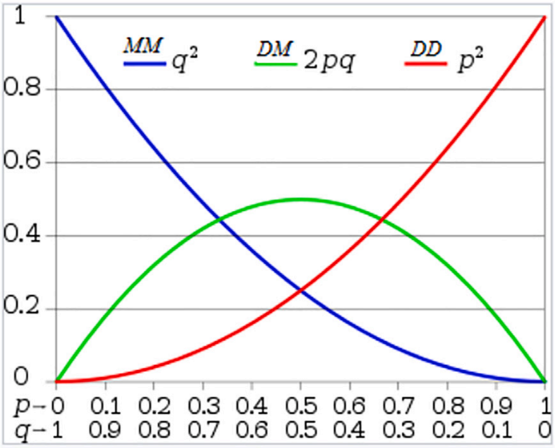

Fig. 4. Hardy–Weinberg principles.

after each iteration, the ranking correlation coefficient of each possible solution relative to the best solution is computed. If the correlation coefficient is negative, the search agent's viewpoint is considered opposing. The Spearman coefficient helps to select opposing barnacles and dimensions, thus focusing and refining the search to make it more efficient.

Initialized as d, a threshold variable is linearly reduced in every iteration. This number decides whether the dimension of the least fit barnacles is close to or distant from the optimal point. The difference, diff(j), between the provided vector $X(j)$ and the vector $X_i(j)$ is determined for each dimension j.

3.4. Gaps in original barnacle mating optimization algorithm and its variants

Upon careful examination, this thesis discovered that the Barnacle Mating Optimizer (BMO) lacks specialization in theoretical, structural, or natural imitation aspects that simplify the algorithm. Despite over 300 citations of this method according to Google Scholar, no research has critically examined the fundamental basis of the algorithm.

Firstly, it is claimed that barnacles have both sexes. Since barnacles are hermaphrodites in nature, they possess both reproductive organs. However, during BMO offspring generation, the Hardy–Weinberg principle was applied merely to represent the parents with frequencies for the newly created features, i.e., the proportion of each parent involved. It is questioned why this concept or equation is necessary. Furthermore, this bio-inspired algorithm is designed to find the optimal global location in the search space. The primary issue should be the location of the new offspring, rather than whether it is 66% from the father or mother. Consequently, the initial equation of barnacle exploitation holds no special significance (see Fig. 4).

Other concerns with the exploration equation are discussed in the article by the inventor: "Sperm-cast mating, on the other hand, is the mating process in which the eggs are fertilized by sperms released into the water". These behaviors serve as motivation in the creation of BMO to address optimization difficulties. However, a rigorous analysis of the equation reveals that there are no limits or explanations, indicating that sperm casting mating occurred in water. Thus, the most important aspect of an optimization algorithm is to provide justified validity for exploration and exploitation, which this method [11] lacks.

The Improved Barnacle Mating Optimization (IBMO) Algorithm, introduced in research [18], is an enhancement and combination of the Barnacle Mating Optimization (BMO) algorithm that helps to overcome the limitations seen in traditional optimization methods. For issues where classical algorithms fail, this study aims to create sophisticated stochastic optimization algorithms that can efficiently estimate optimal solutions with constrained computer resources. When developing an algorithm, it is crucial to incorporate findings from natural behavior modeling to traverse complex search spaces, which are a challenge for conventional optimization techniques. The IBMO algorithm improves the exploration and exploitation stages of optimization by integrating the movement and mating habits of Gooseneck Barnacles into BMO. This random variable k helps avoid becoming trapped in local optima, improves exploration and exploitation, and finds a better balance between these two phases. In contrast, the research offers a theoretical explanation for gooseneck mobility and lifetime that is not supported by random multiplication. The role of this variable in confirming efficiency remains vague.

This upgrade should be characterized by stability, scalability, and performance optimizations. More in-depth theoretical research is needed to better understand BMO's actions and outcomes. The original BMO is used to illustrate pseudo-copulation mating traits due to its deviation from the true mating behavior of BMO. The real-world events behind the original BMO have not received sufficient attention. The method was developed by focusing on a single BMO characteristic—penis length—using constraint-free pseudo-copulated mating.

Furthermore, it is possible that the intricate dataset produced better outcomes for BMO. Among the species that have been discovered are Gooseneck Barnacles, which reproduce through sperm casting or self-fertilization. It is essential that the BMO

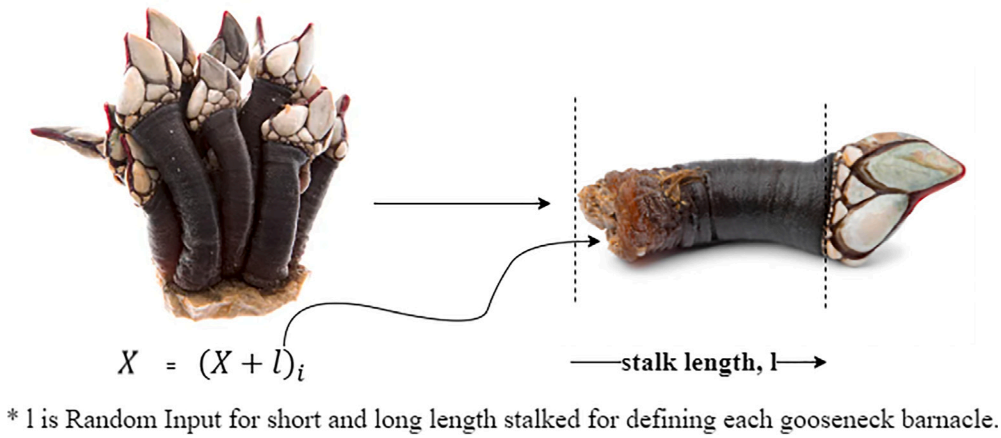

Fig. 5. Hardy–Weinberg principles.

algorithm takes these constraints into account. The initialization strategy of BMO has a significant impact on its performance. If it becomes stuck in the local search space, it could struggle to locate the global optimum and generate reliable results. By using penis length, an ineffectual metric, the program aims to find a compromise between the BMO stages of exploration and exploitation. Numerous authors have recently released papers on this topic, and this field of study is being applied to other animals with distinctive natural characteristics.

4. Gooseneck Barnacle Optimizer (GBO)

The Gooseneck Barnacle Optimizer (GBO) is a novel nature-inspired metaheuristic algorithm that mimics the biological mating behavior of barnacles [19]. The mating behavior of goosenecks, determined by sperm dispersion and the influence of wind and wave action on reproduction, is its most significant characteristic. An algorithm can be developed if it becomes possible to mathematically represent these attributes.

The mathematical model can be stated as follows:

$$X_{i+1} = X_i + WD_i + T_{\text{dim}} + S(X_i, \text{Sp\_water}_j) + H_s \cdot X_i \tag{12}$$

In this context, $X = (x + l)$ denotes the gooseneck or stalked barnacles in the ith iteration, WD represents the wind direction within the degree range [0, 359] during that iteration, T_{dim} signifies the target dimension to progress towards the optimal solution or target, $S(X_i, \text{Sp\_water}_j)$ denotes the logarithmic spiral in water connecting the jth mating region and the ith X_i. Significant wave height is represented by H_s.

A depiction of the gooseneck barnacle population, namely the gooseneck barnacle population, is shown below. This population serves as the potential starting point for solution X in the population-based algorithm GBO:

$$X = \begin{bmatrix} (x+l)_{1,1} & (x+l)_{1,2} & \cdots & (x+l)_{1,d} \\ \vdots & \vdots & \ddots & \vdots \\ (x+l)_{n,1} & (x+l)_{n,2} & \cdots & (x+l)_{n,d} \end{bmatrix} \tag{13}$$

where n represents the overall population size and d denotes the number of variables for optimization. The length l of each gooseneck will be chosen randomly. This choice is motivated by the fact that, as depicted in Fig. 5, goosenecks exhibit an edible and variable structure for individuals.

Each gooseneck will have an associated region in the water where sperm is located for mating purposes. This aspect is integral to the proposed algorithm, referred to as 'Mating_Region,' which shares a similar matrix structure with X, outlined as follows:

$$\text{Mating\_Region} = \begin{bmatrix} (mr)_{1,1} & (mr)_{1,2} & \cdots & (mr)_{1,d} \\ \vdots & \vdots & \ddots & \vdots \\ (mr)_{n,1} & (mr)_{n,2} & \cdots & (mr)_{n,d} \end{bmatrix} \tag{14}$$

In the intertidal zones, H_s is identified to range between 0.8 to 1.5–3 m, which is the tolerance range for barnacles to mate and reproduce [20,21]. Conventionally, different researchers denote H_s as $4\sqrt{H^2T}$ [22–25]. In GBO, we calculate:

$$H_s = 1.5 - \left(\frac{\text{Iteration} \cdot (1.5 - 0.2)}{\text{Maximum Iteration}}\right) \tag{15}$$

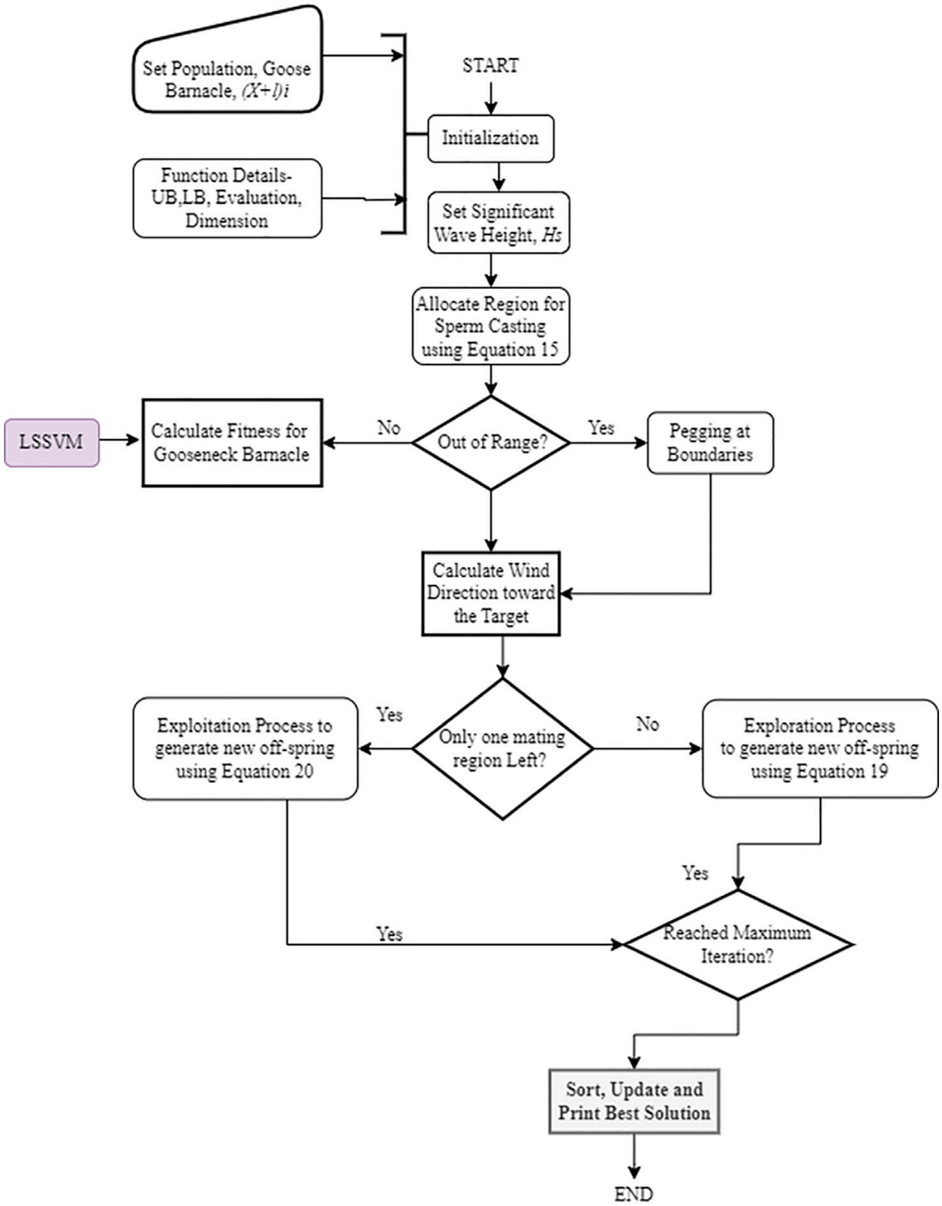

Fig. 6. Hardy–Weinberg principles.

For pseudo-copulation, it is defined as follows:

$$S((X+l)_{i,}(Sp\_water)_j) = D_i \cdot e^{bt} \cdot \cos(2\pi t + (Sp\_water)_j) \tag{16}$$

$$D_i = (X+l)_{i,} - (Sp\_water)_j \tag{17}$$

where $(X+l)_{i,}$ denotes the ith barnacle, $(Sp\_water)_j$ represents the jth sperm casting region, and D_i calculates the distance between the barnacle and sperm in the mating region inside the logarithmic spiral. In this context, b denotes the growth factor of the logarithmic spiral [26–28] inside the inter-tidal zones. Here, t is a random generator in the range $[-1, 1]$.

Table 2
Parameter setting during experiment.

Parameter	Value
Size of the population	30
Number of Iterations (Lower–Upper Bound)	500
Lower Bound	1
Upper Bound	1000

4.1. Off-spring generation

After generating new offspring in the search space, their location is updated using a movement vector denoted by $\Delta(X+l)_i$ as follows:

$$\Delta(X+l)_{i+1} = W D_i + T_{\text{dim}} + H_s \cdot \Delta(X+l)_i \tag{18}$$

$$(X+l)_{i+1} = (X+l)_i + \Delta(X+l)_{i+1} \tag{19}$$

$$(X+l)_{i+1} = (X+l)_i + \text{Levy} \cdot (X+l)_i \tag{20}$$

where Levy flight is determined as follows:

$$\text{Levy}(N) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{1/\beta}} \tag{21}$$

In this context, the constant β is set to 1.5, and r_1 and r_2 are random numbers in the range [0, 1]. The value of σ is given by:

$$\sigma = \left(\frac{\tau(1+\beta) \cdot \sin(\pi\beta/2)}{\tau((1+\beta)/2) \cdot \beta \cdot 2^{(\beta-1)/2}} \right)^{1/\beta} \tag{22}$$

where $\tau(y) = (y-1)!$.

5. Optimizing LSSVM for energy prediction with GBO

The Gooseneck Barnacle Optimizer (GBO) is employed in this study to optimize the hyper-parameters (regularization γ and kernel σ^2) of the Least Squares Support Vector Machine (LSSVM) for energy prediction. Daily average energy consumption of a power distribution company is predicted by LSSVM using these optimized values. It is imperative for GBO to identify optimal values for these hyper-parameters, as the accuracy of LSSVM predictions is significantly influenced by them. To evaluate the accuracy of forecasting, the optimization procedure employs the objective function where the Mean Absolute Percentage Error (MAPE) is considered. The objective is to minimize prediction error by obtaining the most optimal hyper-parameter values. The LSSVM's fitness function evaluation in the hybrid GBO-LSSVM algorithm, which is illustrated in Fig. 6. This evaluation is based on the results of the training and validation processes.

6. Optimization setting of all the proposed algorithms

Population Size represents the number of candidate solutions in the population considered during each iteration of the optimization algorithm. The Lower Bound property denotes the lower limit of the hyper-parameter values that the optimization algorithm is allowed to explore. In this context, the lower bound is set to 1 for all algorithms. The Upper Bound represents the upper limit of the hyper-parameter values that the optimization algorithm can explore, which is consistently set at 1000 for all four algorithms (see Table 2).

7. Evaluation criteria

This section demonstrates the agreement amongst the measurements used for assessing time series forecasting models. The performance metrics for regression used in this study are Mean Absolute Percentage Error (MAPE), Theil's U, and Accuracy. Their definitions are as follows:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_{\text{predicted},i} - y_{\text{actual},i}}{y_{\text{actual},i}} \right| \times 100\% \tag{23}$$

$$\text{Theil's U} = \sqrt{ \frac{\frac{1}{N}\sum_{i=1}^{N} (y_{\text{actual},i} - y_{\text{predicted},i})^2}{\frac{1}{N}\sum_{i=1}^{N} y_{\text{actual},i}^2} + \frac{\frac{1}{N}\sum_{i=1}^{N} y_{\text{predicted},i}^2}{\frac{1}{N}\sum_{i=1}^{N} y_{\text{actual},i}^2} } \tag{24}$$

$$\text{Accuracy} = 1 - \text{MAPE} \tag{25}$$

Table 3
Comparison of performances.

Optimizers + LSSVM	MAPE	Accuracy	Theil's U
BMO	0.037	96.30%	0.07911
BMO-Gauss	0.0202	97.98%	0.0178
BMO-Levy	0.0198	98.02%	0.0214
SO-BMO	0.0155	98.45%	0.0278
GBO	0.00022	99.98%	0.01414
HBA	0.01312	98.68%	0.042426
PSO	0.003	99.7%	0.054772
DA	0.00072	99.92%	0.026457

Table 4
Forecasting value for daily energy consumption of power distribution company.

Day	Target	GBO	BMO	BMO-Levy	BMO-Gauss	SO-BMO	HBA	PSO	DA
20	376 209	376 133.7582	362 289.267	368 760.0618	368 609.58	370 377.7605	371 243.041	375 080.373	375 908.03
21	384 045	383 968.191	369 835.335	376 440.909	376 287.29	378 092.3025	378 975.606	382 892.865	383 737.76
22	390 612	390 533.8776	376 159.356	382 877.8824	382 721.64	384 557.514	385 455.922	389 440.164	390 299.51
23	365 916	365 842.8168	352 377.108	358 670.8632	358 524.5	360 244.302	361 085.909	364 818.252	365 623.27
24	310 545	310 482.891	299 054.835	304 396.209	304 271.99	305 731.5525	306 445.806	309 613.365	310 296.56
25	332 289	332 222.5422	319 994.307	325 709.6778	325 576.76	327 138.5205	327 902.785	331 292.133	332 023.17
26	358 516	358 444.2968	345 250.908	351 417.3832	351 273.98	352 959.002	353 783.589	357 440.452	358 229.19

In these equations, n denotes the number of test instances. $y_{\text{predicted},i}$ refers to the predicted values at the ith time point, while $y_{\text{actual},i}$ signifies the actual values at the ith time point. The standard metrics for assessing regression prediction model errors are provided in Eqs. (23) to (25) and should ideally be minimized. Theil's U, also known as Theil's inequality coefficient or Theil's entropy, is a statistical measure used to compare the performance of different algorithms. Higher values of Theil's U indicate significant performance differences, providing insights into the effectiveness and efficiency of the methods in solving optimization problems.

8. Result analysis

The simulations for this study were performed in a uniform environment with iterations capped at 100 and the population size set at 30. It has been demonstrated that GBO-LSSVM surpasses all other algorithms in Table 3, which compares the performance of various optimization algorithms in estimating a power distribution company's daily energy usage.

The projected and actual values computed by each of the comparison methods using LSSVM are displayed in Table 4. According to our research, GBO-LSSVM has the fewest variations with target or actual values.

A power distribution company's daily energy usage is graphically represented in Fig. 7, which clearly demonstrates that GBO-LSSVM is nearest to the target compared to the Barnacle Mating Optimizer (BMO), its variants, Honey Badger Algorithm (HBA), Particle Swarm Optimization (PSO), and Dragonfly Algorithm (DA).

9. Conclusion

Among all the variants of Barnacle Optimizers, the gooseneck optimizers present significant advancement in population-based optimization methods, drawing inspiration from the intricate mating behaviors of gooseneck or stalked barnacles. Unlike its predecessor, the Barnacle Mating Optimizer (BMO), which relied primarily on penis length for offspring generation, GBO incorporates a more comprehensive model that includes sperm casting dynamics, wind direction, and wave movement influences. This sophisticated approach improves the algorithm's capacity to handle diversification and intensification, which is essential for solving complex optimization problems.

The practical application of GBO in forecasting the daily average energy consumption of a power distribution company underscores its potential and adaptability in real-world scenarios. The algorithm's performance can be further improved through refined settings and hybridization with other optimization techniques. Future empirical validations and case studies across diverse sectors will be essential in establishing GBO as a reliable and versatile optimization paradigm.

CRediT authorship contribution statement

Marzia Ahmed: Plan, Conduct and evaluate the experiments and create figures and/or tables. examine the present strategy, Present a unique strategy and write the draft and submission. **Mohd Herwan Sulaiman:** Supervised the experiments, Assessed the data, Finalized the revised version. **Md. Maruf Hassan:** Supervised and finalized the revised version. **Md. Atikur Rahaman:** Supervised and finalized the revised version. **Mohammad Bin Amin:** Supervised and Funded.

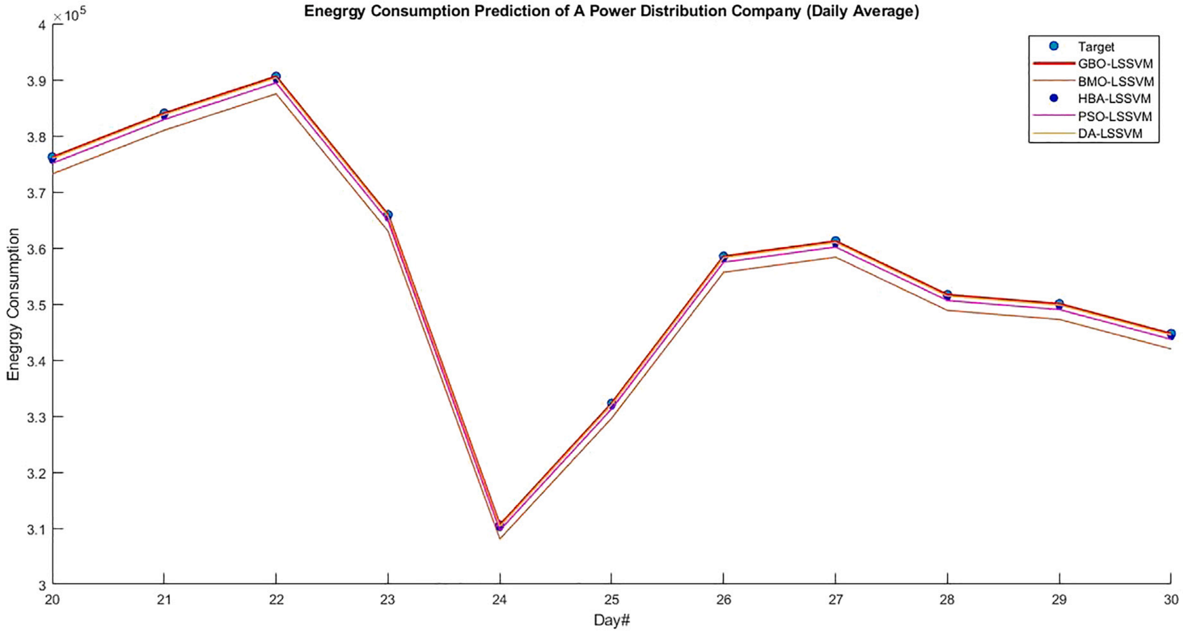

Fig. 7. Comparison of daily energy consumption forecasting using different algorithms.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marzia Ahmed reports was provided by Daffodil International University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

I have shared the link.

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