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A hybrid Extreme Learning Machine model with Lévy flight Chaotic Whale Optimization Algorithm for Wind Speed Forecasting

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ABSTRACT

Efficient and accurate prediction of renewable energy sources (RES) is an interminable challenge in efforts to assure the stable and safe operation of any hybrid energy system due to its intermittent nature. High integration of RES especially wind energy into the existing power sector in recent years has made the situation still challenging which draws the attention of many researchers in developing a computationally efficient forecast model for accurately predicting RES. With the advent of Neural network based methods, ELM -Extreme Learning Machine, a typical Single Layer Feedforward Network (SLFFN), has gained a significant attention in recent years in solving various real-time complex problems due to simplified architecture, good generalization capabilities and fast computation. However, since the model parameters are randomly assigned, the conventional ELM is frequently ranked as the second-best model. As a solution, the article attempts to construct a unique optimized Extreme Learning Machine (ELM) based forecast model with improved accuracy for wind speed forecasting. A novel swarm intelligence technique- Lévy flight Chaotic Whale Optimization algorithm (LCWOA) is utilized in the hybrid model to optimize different parameters of ELM. Despite having a appropriate convergence rate, WOA is occasionally unable to discover the global optima due to imbalanced exploration and exploitation when using control parameters with linear variation. An improvement in the convergence rate of WOA can be expected by incorporating chaotic maps in the control parameters of WOA due to their ergodic nature. In addition to this, Lévy flight can significantly improve the intensification and diversification of the Whale Optimization algorithm (WOA) resulting in improvised search ability avoiding local minima. The prediction capability of the suggested hybrid Extreme Learning Machine (ELM) based forecast model is validated with nine other existing models. The experimental study affirms that the suggested model outperform existing forecasting methods in a variety of quantitative metrics.

1. Introduction

1.1. Motivation

Ever since the industrial revolution and urbanization, a steep increase in the energy demand has put the electricity market highly competitive in developing technologies to meet the substantial energy requirement preserving the potential social, economic, and environmental impacts. However conventional fossil fuel-based power generation has led to severe environmental impacts like global warming and subsequent deterioration in biodiversity. In efforts to reduce the greenhouse gas emission and carbon footprint, most countries have taken a worldwide perspective of upgrading their energy sector with potential RES as a sound alternative to the conventional sources. Decarbonizing the energy sector and supporting global initiatives to curtail global warming are highly crucial in the current scenario. Wind energy being a clearly in-exhaustive clean renewable source has drawn an accelerated penetration level in the existing electrical power system in recent years. With 837 GW of global wind power capacity now in 2022, the world will be able to avoid more than 1.2 billion tons of CO_2 every year [1]. But due to the intermittent character of wind speed, the power system has become more unreliable with the increased

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integration of wind power into the existing power system. This crucial problem draws the attention of many researchers in developing a computationally efficient forecast model for accurately predicting wind energy for efficient power system planning, operation management and control [2,3]. Researchers have extensively developed a variety of wind speed prediction systems over the last 20 years to increase the prediction accuracy.

1.2. Literature Review

There are practically two methods to forecast wind energy: (1) direct forecasting of the wind turbine output, and (2) indirect forecasting in which wind turbine output is estimated from the wind speed forecast. Indirect forecasting is more advantageous as the same wind speed forecast model could be utilized to forecast the power output of different turbine models with varying capacity [4]. In the recent few decades, many forecasting models have been suggested that are broadly categorized into mainly two categories: Physical models and Data-driven models. The Physical models are usually established with the aid of Numerical Weather Prediction (NWP) along with terrain details. The accuracy of Physical model in short term forecasting is poor as resolution of NWP is low [5,6]. The Data-driven models utilize historical data in developing the forecast models that make them more effective in short-term forecasting. The Data-driven models are further categorized into two groups: statistical models and artificial intelligence or neural network-based methods. Various statistical models like AR, ARMA, ARIMA, VAR etc. Analyses patterns in the historical dataset to establish a linear model that fail to characterize the nonlinear relationships resulting in high prediction errors [7–10]. With the recent drastic development in information technology, a lot of artificial intelligence-based techniques including ANN [11–14], SVM [15], RNN, LSTM [16–19], GRU [20] are extensively used in wind speed predictions as they accurately map the nonlinearity enabling short-term forecasting.

Conventional ANN models utilize gradient descent learning that requires a lot of computational time due to iterative tuning of the model parameters that sometimes results in the convergence to a local minimum. In 2006, G.B. Hang et al. [21] proposed ELM-Extreme Learning Machine, a fast-computing Single Layer Feedforward Network (SLFFN) that addresses the slow training and local minima convergence of traditional neural networks. Additionally, the computational time requirement of ELM is significantly low when compared to conventional techniques as the hidden layer parameters like biases, input weights are randomly initialized, and the output weights are mathematically determined with a simplified matrix inverse calculation [22,23]. Extensive research is pitching to exploit the applicability of ELM in numerous research fields in classification and regression including wind speed forecasting [24–27]. In the article [24], V. Nikoli et al. used the Extreme Learning Machine (ELM) in developing a wind turbine parameter-based sensor less wind speed estimation model which was robust to air density variations. The article [25] has proved the better computational efficiency of ELM in wind speed forecasting over conventional Backward Propagation Neural Networks (BPNN). In the article [26], a new ELM based hybrid prediction model for wind speed is devised in which ICEEMDAN-ARIMA ensemble method is used for error correction that further improved the prediction accuracy. A novel prediction model based on LSTM, ELM, Singular Spectrum Analysis and Variational Mode Decomposition is evaluated for short-term wind power forecasting in the article [27]. In article [28] a hybrid framework is developed using a probabilistic regularized extreme learning machine (PRELM) and PSO (particle swarm optimization) with improved prediction accuracy for predicting wind speed. The article [29] suggests three effective and precise wind power prediction models namely the ridge ELM (RELM), the online sequential ELM (OSELM), and the hybrid neural network (HNN) that essentially improve the learning speed rate and computational scalability. The article [30] shows that regression problems can be effectively addressed using a unique ELM called residual compensation ELM (RC-ELM), which has a multilayer framework with the baseline layer serving as the foundation for iteratively developing the input-output feature mapping. A unique non-iterative fast multilayer extreme learning machine (ML-ELM) is proposed and evaluated in article [31]. Studies prove the efficacy of ML-ELM over the conventional deep learning models like RNN, LSTM and CNN due to the random feature mapping process. In article [32], a robust ELM (R-ELM) is developed and analyzed to enhance the modelling power and robustness with Gaussian and non-Gaussian noise to model data obtained from uncertain environments that irrelevantly add unknown noise. The mixture of Gaussian (MoG) method is used in R-ELM to create a modified objective function that fits the noise and roughly approximates any continuous distribution. These detailed research studies demonstrate the better modelling capability of ELM over the other alternative forecasting models in terms of forecasting accuracy and computational performance.

Unfortunately, the benefits of ELM are at odds with the time required to study numerous parameter combinations to create an optimal ELM structure. Moreover, research proves that ELM requires a greater number of hidden neurons in many applications. To overcome this drawback of ELM, some researchers have proposed a variant of ELM, evolutionary ELM that exploits the advantage of evolutionary meta-heuristic algorithms in optimizing the different ELM parameters like biases and input weights, number of hidden nodes to get the best prediction model [33]. The swarm intelligence algorithm is an emerging evolutionary algorithm that mimics the group conduct of socially organized animals to accomplish a required task, in the optimization process. Swarm-based algorithms have some advantages when compared to other algorithms like less input parameters and memory requirement that marks its applicability in solving complex problems in various domains. These algorithms begin with a set of random possible solution/outcome and then efforts are made to improve the solution quality using a defined fitness function. According to a defined set of natural laws, the current solutions are continually tweaked to improve the fitness function value. This procedure can efficiently scan the search to converge to an optimal solution. Each metaheuristic algorithm differs primarily in how they hit a balance between global and local search. In the paper [34], an ELM based wind speed prediction model optimized by PSO- Particle Swarm Optimization is analyzed, which shows excellent prediction accuracy. Similar forecasting methodology is shown in Ref. [35], where ELM model is utilized to estimate wind speed first and then an enhanced Bat Algorithm optimized GRNN model is utilized to obtain the anticipated results. In the paper [36], the actual wind speed dataset is first divided into a group of intrinsic mode functions (IMFs) using complete ensemble empirical mode decomposition (CEEMD). IMFs are further modelled by multi-objective grey wolf optimization (MOGWO) optimized extreme learning machine (ELM) and finally the results are combined leading to excellent forecasting performance.

The tedious task in the framework development of any optimization algorithm is to obtain an appropriate balance between local and global search. The major issue in most swarm-based meta-heuristic algorithms is the early convergence into local optima. Popular research topics in algorithm research include methodology to curtail local optima convergence, and exploration-exploitation balance during the optimization phase. In 2016, Australian researcher Seyedali Mirjalili unveiled Whale Optimization Algorithm (WOA), a new swam based bio-inspired algorithm that model the hunting strategy of humpback whales [37]. The benefits of its straightforward structure, limited number of control parameters, and extensive avoidance of local optima made it superior to other swarm based meta-heuristic algorithms. Many stochastic and continuous optimization problems have already been solved using this algorithm, demonstrating its superiority to the most popular meta-heuristics algorithms. In the study [38], WOA is thoroughly discussed in terms of algorithmic background, its traits, constraints, alterations, possible hybrids, and application in various fields. The survey results show that WOA outperforms most popular evolutionary algorithms in convergence speed and the ability to achieve harmony between exploitation and exploration. The article [39] suggests an ultra-short-term forecasting model based on the VMD and Whale Optimized ELM for wind speed forecasting that outperform five conventional models in terms of prediction accuracy. An enhanced WOA is applied to optimize a hybrid wind-solar-hydroelectric system to precisely offer the ideal operation strategy [40]. The photovoltaic model parameters were estimated using the revised WOA method, and the results prove the efficiency of WOA over other optimization algorithms [41,42]. The maximum power point tracking (MPPT) of wind turbines is achieved using the enhanced WOA in the article [43] that shows a superior performance than the existing algorithms. Clearly, studies prove the superiority of WOA in laying the groundwork for the optimization of the ELM parameters.

Despite having an acceptable convergence rate, WOA is unable to identify the global optima that still influences the algorithm's convergence rate. To alleviate this impact and thereby improve the performance efficiency, the Chaotic WOA (CWOA) [44] algorithm was developed by incorporating chaos into primary parameter p, which aids in regulating exploration and exploitation, to boost the WOA performance. Due to its periodicity and non-repetition characteristics, chaotic maps can execute broad searches at faster rates than stochastic searches that largely rely on probability. The chaos approach can enhance the effectiveness of global search. In Ref. [45], the proposed Chaotic WOA algorithm when applied for the array synthesis of MIMO radar gives better solution in lesser number of steps. In Ref. [46], the CWOA is utilized for the evaluation of solar cell parameters. The experimental studies support the suggested method's effectiveness in terms of precision and robustness. A Chaotic WOA is utilized to address the transient stability-constrained optimal power flow problem of the power system accounting for numerous contingencies in Ref. [47]. The findings demonstrate that chaotic WOA enhances the power system's transient performance through a harmonious and balanced interaction between exploration and exploitation phase. The research [48] presents a new chaotic whale optimization algorithm (CWOA), which utilizes chaos parameter into search iteration. Studies on ten relevant datasets reveal that the state-of-the-art CWOA is successful in discovering essential features with good classification performance and few features. A new whale optimization algorithm based on chaos mapping and weight factor (WOACW) is analyzed in the paper [49] that significantly improves the convergence speed. In this work, initialization of the population uses chaos strategy to boost its diversity. The introduction of the weight factor speeds convergence and thereby increases accuracy by regulating influence of the present best solution in the formulation of new individuals. The effectiveness of WOACW is assessed with 13 mathematical functions, and the statistical outcomes are compared with the original WOA, three other WOA variants (IWOA, WOAWC), and two cutting-edge algorithms (SSA, GWO).

Lévy flight is a category of specialized random walk with heavy power law tailed step lengths. Large steps usually aid an algorithm to perform an effective global search. Since Lévy flight trajectory exhibits large steps, a possible improved exploration-exploitation balance can be visualized by incorporating Lévy Flight in WOA. The article [50] suggests a Lévy flight whale optimization algorithm (LWOA) in which Lévy flight aids in minimizing early convergence, enhancing population diversity, and enhancing the local search capability. The paper [51] introduces an enhanced Lévy flight whale optimization algorithm (LWOA) to address various complex optimization problems. The model outcomes show effectiveness of the LWOA method in solving complex constrained real time problems with unexplored search spaces. Using 23 benchmark functions, the LWOA and other nature-inspired algorithms are further compared, and the statistical study reveals that for majority of the benchmark functions, the LWOA outperforms the other algorithms, especially for high dimensional optimization problems.

1.3. Research Contributions

Following are summaries of the in-depth analysis of related literature review considered.

1. Formulation of an efficient forecast model for accurately predicting wind energy is crucial for stable and safe operation of any hybrid energy system.
2. Due to its simplicity in structure and computation, the ELM-based prediction model can be one of the best choices for predicting wind speed.
3. Whale optimization algorithm (WOA) proves to be competent enough to optimize ELM model due to its simple structure, limited number of control parameters, and extensive avoidance of local optima.
4. WOA can be further enhanced by using Lévy flight trajectory and chaotic maps as they avoid early convergence, increase diversity in population and thereby promoting global search.

Considering the aforementioned information, Lévy-flight Chaotic Whale optimized Extreme Learning Machine (LCWOA-ELM) is developed in this article for wind speed forecasting. In LCWOA-ELM, a hybrid variant of WOA-Lévy flight Chaotic Whale Optimization (LCWOA) is used to finetune the parameters of ELM. In the study, one-year hourly average wind speed collected from weather station setup in Kasavanahalli, Bengaluru, India is utilized for modelling and the efficiency of the developed model is evaluated with other existing models. Further, to test the proposed model's robustness and efficacy over unseen data, multi-step ahead forecasting is additionally developed using recursive forecasting mechanism, and one day ahead hourly wind speed is also predicted.

The paper is drafted in a way that section 2 details the principles and methodology used in the proposed hybrid model. Section 3 describes the experimental analysis done while implementing proposed model in wind speed forecasting. Section 4 describes the performance evaluation of the suggested model with other existing models. Section 5 describes the performance of the model in multi-step ahead recursive forecasting mechanism. Section 6 concludes the paper with the research limitation and provides recommendations for future study.

2. Methodology

2.1. Extreme Learning Machine(ELM)

ELM-Extreme Learning Machine is a fast-computing Single Hidden Layer Feedforward Network (SLFFN) formulated by G.B Hang in 2006, which trims down the shortcomings of conventional neural network like local minima and slow training [21]. The model involves random setting of the hidden layer weights and biases and using a simplified Moore Penrose inverse operation to obtain the output. Consequently, computational speed of the algorithm is improved. Fig. 1 shows the typical structure of ELM.

For N different training samples $(x_i, y_i)_{i=1}^{N}$ considered where x_i and y_i are the input and resultant output vector for the ith sample represented by $x_i = [x_{i1}\ x_{i2} \ldots\ldots x_{in}]^T$ and $y_i = [y_{i1}\ y_{i2} \ldots\ldots y_{in}]^T$ for $i = 1, 2, 3, ..$ N respectively, the mathematical model of standard SLFFN is expressed as follows

$$y_j = \mathrm{f}\left(x_j\right) = \sum_{i=1}^{\mathrm{K}} \beta_i \mathrm{h}\left(\omega_i x_j + \mathrm{b}_i\right)\ j = 1, 2, 3 \ldots N$$

b_i and ω_i are the bias and weight parameter values of the ith hidden node respectively.

x_j is a jth sample of input data.

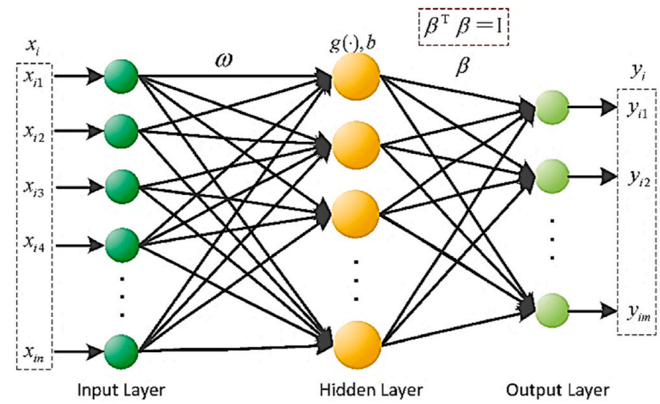

Fig. 1. Extreme learning machine model.

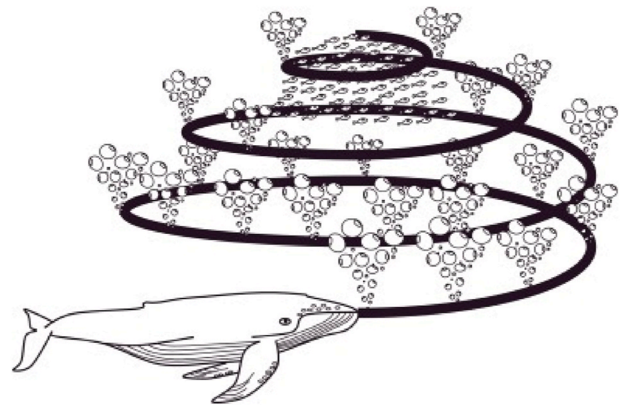

Fig. 2. Hunting strategy of humpback whales [37].

h is the hidden node activation function used like tanh, sigmoid etc.

β_i is the weight parameter between the *i*th hidden node and the output node.

The above formula can be consolidated as in Eqn. 1

$$Y = H\beta \tag{1}$$

Where the output data matrix is Y, the hidden layer matrix is H and output weight matrix is β

$$H = \begin{pmatrix} h(\omega_1 x_1 + b_1) & \cdots & h(\omega_K x_1 + b_K) \\ \vdots & \ddots & \vdots \\ h(\omega_1 x_N + b_1) & \cdots & h(\omega_K x_N + b_K) \end{pmatrix} \tag{2}$$

$$Y = \begin{pmatrix} y_1^T \\ \vdots \\ y_N^T \end{pmatrix} \tag{3}$$

$$\beta = \begin{pmatrix} \beta_1^T \\ \vdots \\ \beta_K^T \end{pmatrix} \tag{4}$$

In ELM, bias and weight a of the ith hidden nodes $\boldsymbol{b_i}$ ***and*** $\boldsymbol{\omega_i}$ are assigned at random without taking into account of the input data. Finally the output weights β are analytically evaluated by a simplified inverse calculation as in Eq. (5), since the matrix H is invertible

$$\beta = \boldsymbol{H}^{\dagger}\, Y \tag{5}$$

where the Moore-Penrose generalised inverse of H is $\boldsymbol{H}^{\dagger}$ $[\boldsymbol{H}^{\dagger} = (\boldsymbol{H}^T\boldsymbol{H})^{-1}\boldsymbol{H}^T]$

Inoder to improve balance between the training accuracy and model complexity, Regularization parameter C is introduced in ELM and optimal problem is now formulated as

$$\min : \frac{\mathbf{1}}{\mathbf{2}}\|\boldsymbol{H\beta} - \boldsymbol{Y}\|^2 + \frac{\boldsymbol{C}}{\mathbf{2}}\|\boldsymbol{\beta}\|^2 \tag{6}$$

Optimal solution β for this function is now evaluated based on Kuhn Tucker conditions as

$$\beta = \left(H^T H + CI\right)^{-1} H^T\, Y \tag{7}$$

2.2. Whale Optimization Algorithm(WOA)

WOA-Whale Optimization Algorithm is an effective swarm-based bio-inspired algorithm developed by Seyedali Mirjalili et al. [37] in 2016. WOA is developed by simulating the typical hunting behavior of humpback whales that mostly prey on a school of small fish or krill. After locating the herd of prey near sea surface, whale dives to the depth of the sea around 12m–15 m from the prey and then upstream to sea surface in shrinking circle/spiral path creating characteristic bubbles along a spiral circular path as depicted in Fig. 2.

The hunting strategy of the whale is mathematically modelled with three stages - prey encircling, bubble-net attacking and prey search as described below [37].

2.2.1. Prey encircling

Initially after locating the prey, humpback whales surround or encircle their prey. In WOA, the best search agent position (best whale location) is optimum prey position or very close to that, as the optimal position is unknown at the outset. The other whales will then update their position close to the best position in every iteration until the maximum number of iterations. Eqns. (8)–(12) describe the mathematical formulation of this prey encircling mechanism.

$$D = |CX^*(t) - X_i(t)| \tag{8}$$

$$X_i(t+1) = X^*(t) - AD \tag{9}$$

$$a = 2 - \frac{2t}{\text{Maxiter}} \tag{10}$$

$$A = 2ar - a \tag{11}$$

$$C = 2r \tag{12}$$

where $X^*(t)$ is the fittest whale position, and $X_i(t)$ is the ith search agent/whale position in the tth iteration. By changing the coefficients, A and C in Eqns. (11) and (12), the present location $X_i(t)$ is updated based on the optimal whale position $X^*(t)$, where r is a random number in the range [0,1] and 'a' is linearly reduced from 2 to 0 throughout the duration of iteration as in Eqn. (10). The whale/the search agent modify its position close to the best solution at any given time as in Eqn. (9) replicating the encircle-prey mechanism. Fig. 3 clearly shows this location update of search agents in a 2-dimensional and 3-dimensional space. By altering the coefficients, A and C, several positions relative to the best search agent can be attained. It is mentionable that by including random parameter 'r' in the equations, any position between the search space's key points is reachable as depicted in Fig. 3. The same idea can be used to an n-dimensional search space, where whale can wander near the best positions in hyperplanes found during that iteration.

2.2.2. Exploitation phase(Bubble-net attack method)

The following two techniques are devised to statistically simulate how humpback whales attack the prey with bubble nets.

2.2.2.1. Shrinking encircling technique. The shrinking encircling action of humpback whales for reaching the prey can be modelled by a linear

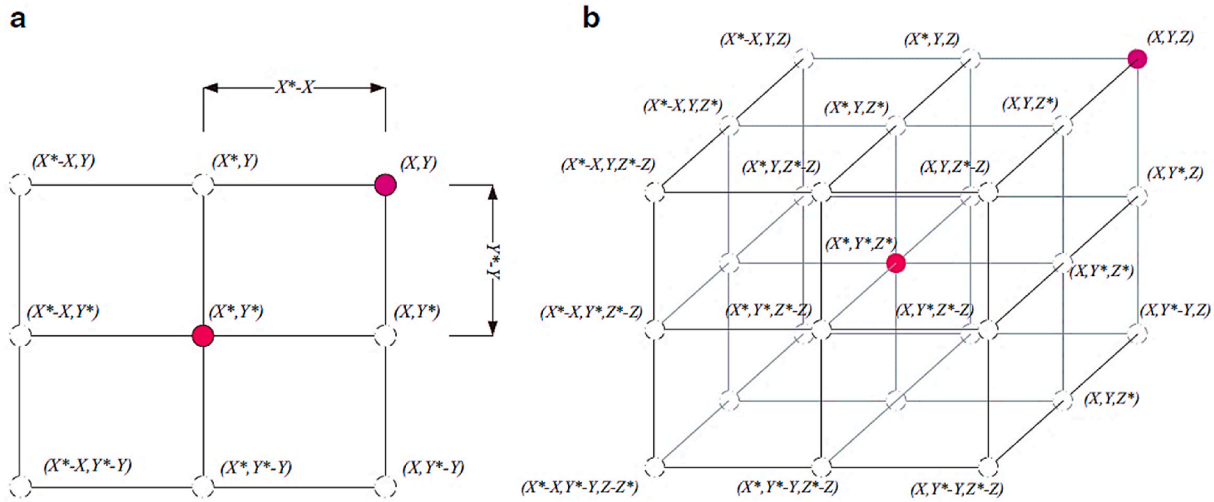

Fig. 3. Possible positions of whales/search agents in a) 2D space b) 3D space [37].

decrease of parameter 'a' from 2 to 0 throughout the duration of iteration as in Eqn. (10). Consequently, coefficient 'A' will be a random number in the range [−1, 1]. The search agent is further repositioned to any position between the present best search agent position and the initial position as shown in Fig. 4 (a). Individual whales reach the current optimal solution when $|A| < 1$.

After detecting the target, whales first determine the distance of prey from them. Following that, they proceed toward the prey in a logarithmic spiral motion, updating its location in accordance with the spiral flight path depicted in Fig. 4 b, that can be mathematically modelled as in Eqn. (12) & (13).

$$L = |X^*(t) - X_i(t)| \tag{12}$$

$$X_i(t+1) = L.e^{b\ell}.\cos(2\pi\ell) + X^*(t) \tag{13}$$

where the spacing between the whale and best whale position is modelled by L, shape parameter of logarithmic spiral is b and ℓ represents a random number in the range [-1, 1].

Naturally, whales are observed to swim simultaneously in a spiraling path and a diminishing circle around their prey in their natural habit. The following mathematical model illustrates this natural behavior by choosing a probability parameter p which clearly indicates 50% chance between the spiral position updating and shrinking encircling mechanisms to update whale in each iteration.

$$X_i(t+1) = X^*(t) - AD \quad \text{if } p < 0.5 \tag{14}$$

$$X_i(t+1) = L.\, e^{b\ell}.\cos(2\pi\ell) + X^*(t) \quad \text{if } p \geq 0.5, \tag{15}$$

where p is a random number in the range [0, 1].

2.2.3. Exploration phase(Prey search)

In the exploration phase, present whale locations are rearranged in accordance with a random whale X_{rand} in place of best whale position in exploitation phase. This method assists the WOA algorithm in carrying out an effective global search, resolving the convergence into local optima. To boost the exploration capability (global search), parameter 'A' can be utilized in the exploration phase with random number greater than 1 or less than −1 to place the search agent farther from randomly chosen reference search agent/whale. The mathematical model for find new whale position is described in Eqns. (16) & (17):

$$D = |C.X_{rand}(t) - X_i(t)| \tag{16}$$

$$X_i\ (t+1) = X_{rand} - AD \tag{17}$$

In conclusion, the algorithm begins with a list of possible positions/solutions. The search agents are then repositioned with respect to either the previously identified best search agent or a random search agent depending on the value of the parameter 'A' at the end of every iteration. The WOA algorithm can smoothly switch between exploration and exploitation phase with adaptive change of the parameter 'A'. The best search agent is picked if $|A| < 1$ and a random search agent if $|A| > 1$ to switch the various search agents' positions. The parameter 'a' is linearly

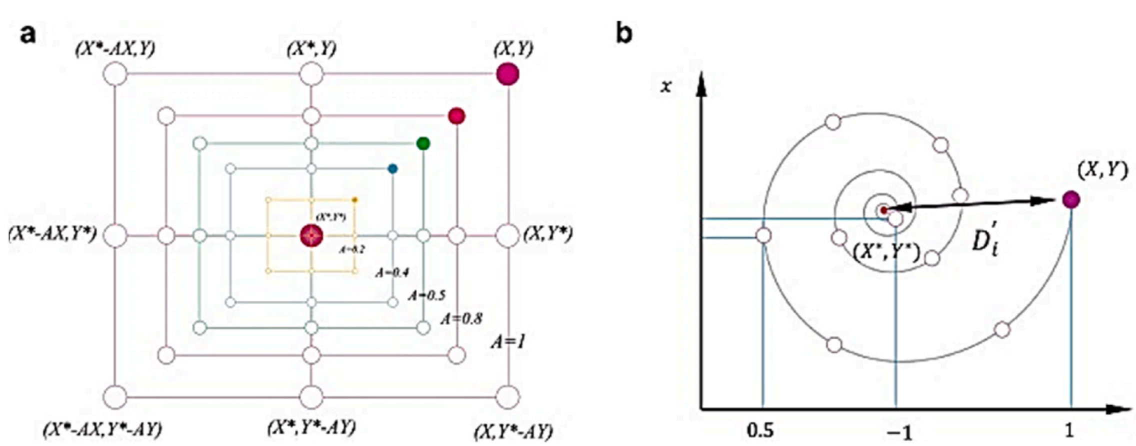

Fig. 4. (a) Shrinking encircling technique (b) spiral updating [37] b) Spiral updating technique.

Table 1
Unidimensional chaotic maps.

Sl. No	Map	Definition
1	Circle Map	$x_{k+1} = \mathrm{mod}\left(\left(x_k + b - \frac{a}{2\pi}\sin(2\pi x_k)\right), 1\right)$ a=0.5, b=0.2
2	Logistic map	$x_{t+1} = 0.5x_k\,(1 - x_k)$
3	Tent map	$xk+1 = \begin{cases} \frac{x_k}{0.7} & x_k < 0.7 \\ \frac{10}{3}(1 - x_k) & x_k \geq 0.7 \end{cases}$
4	Piecewise map	$xk+1 = \begin{cases} \frac{x_k}{K} & 0 \leq x_k < K \quad K = 0.4 \\ \frac{(K - x_k)}{(0.5 - P)} & K \leq x_k < 0.5 \\ \frac{(1 - K - x_k)}{(0.5 - P)} & 0.5 \leq x_k < 1 - K \\ \frac{(1 - x_k)}{K} & 1 - K \leq x_k < 1 \end{cases}$
5	Sinusoidal map	$x_{k+1} = 0.5x_k^2\,t\,\sin(\pi x_k)$
6	Sine map	$x_{k+1} = \frac{b}{4}\sin(\pi x_k)$, $0 < b \leq 4$
7	Mouse/Gauss map	$xk+1 = \begin{cases} 1 & x_k = 0 \\ \frac{1}{\mathrm{mod}(x_k, 1)} & otherwise \end{cases}$
8	Singer Map	x_{k+1}=μ(7.86x_k-23.31x_k^2+28.75 x_k^3-13.302875 x_k^4) where μ=1.07

reduced from 2 to 0 for the smooth conduction of exploration and exploitation phase. In WOA, alternation between spiraling mode and a shrinking circular mode is decided by probability parameter 'p'. The WOA algorithm is finally stopped when a termination requirement is met, and the best search agent ultimately determines the result. In a summary, the parameters A, C, p and ℓ controls the exploitation phase, while the parameters A and C determine the shrinking encircling behavior of whales in the algorithm. The parameter p determines the switching between the Spiral position-updating mode or the shrinking encircling mechanism, whereas the parameter ℓ controls the spiral model. In short the convergence rate of WOA is determined by the four control parameters-A,C,p and ℓ. Algorithm 1 describes the detailed stepwise framework of WOA.

Algorithm 1- Framework of WOA
Set the generation counter t to zero, maximum iteration, the number of whales N, and the dimensions determining the position
Initialize randomly the N search agents/whales' position Xj where j = 1, 2 … N in accordance with the dimensions.
while (t < maximum iteration)
  for individual whale/search agent
    Verify and correct any whale/search agents if go outside the search space.
    Determine fitness of whale/search agent by defined function.
    Modify best whale/search agent X* provided a better result is found
    Update the parameters A, C, p and ℓ
    if (p < 0.5) |
      if (|A| < 1)
        Adjust the present whale/search agent position using the encircling mechanism described in Eqn. 14
      else if (|A| ≥ 1)
        Identify a random whale/search agent (X_{rand})
        Adjust the present whale/search agent position using the encircling mechanism as described in Eqn. 17
      end if
        else if (p ≥ 0.5)
          Adjust present whale/search agent position by spiral equation Eqn. 13
      end if
    end for
t = t + 1
end while
return best whale position/search agent X*

2.3. Levy Flight

Lévy Flight is a typical random walk with steps matching the typical Lévy distribution, a probability distribution with heavy tails. Lévy-flight was formulated by Paul Lévy, a French mathematician in 1937 and later modified and described in detail by Benoit Mandelbrot [52]. Various research shows that the flight character of many animals and insects in search of food has typical nature of randomness in choice of direction that can be formulated as Lévy-flight [53–56]. In the article [57], Reynolds et al. explored the behavior of fruit flies searching their area through a set of straight paths disrupted by an abrupt 90° turn, resulting in a scale-free intermittent Lévy-flight search pattern. In the article [58], P Barthelemy and others have demonstrated that Lévy-flight can be used to mimic specific light phenomena. Lévy Flight can be characterized as a random walk process with infinite variance and mean as in Eqn. (18).

$$\mathrm{Levy}(\gamma) \sim u = t^{-1-\gamma},\ (0 < \gamma \leq 2) \tag{18}$$

The Mantegna method [] is a useful algorithm for generating random step lengths with Lévy-flight-like behavior, as follows.

$$s = \frac{\mu}{|\nu|^{\frac{1}{\gamma}}} \tag{19}$$

where μ and ν are stochastic normal distribution with $\mu \sim N(0, \sigma_\mu{}^2)$ and $\nu \sim N(0, \sigma_\nu{}^2)$ and γ=1.5

$\sigma_\nu = 1$

$$\sigma_\mu = \left[\frac{\Gamma(1+\gamma) \times \sin\left(\pi \times \frac{\gamma}{2}\right)}{\left(\Gamma\left[\frac{(1+\gamma)}{2}\right] \times \gamma \times 2^{\frac{(\gamma-1)}{2}}\right)}\right]^{\frac{1}{\beta}} \tag{20}$$

Γ is a gamma function where $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}\,dt$

2.4. Chaotic maps

Chaos is a term used to describe the characteristic unpredictable behavior of a complex system. Chaotic map refers to associating or mapping chaos behavior to some parameter in the algorithm using a mathematical function. Chaotic maps are extensively used in optimization problems due to their ergodic nature. It aids in dynamically exploring the search space with a greater speed than stochastic searches which mainly rely on probability. It can be advantageous if the random components in any meta-heuristic algorithms are replaced by chaotic maps rather than conventional probability distributions. Chaos strategy improves the quality of searching global optimum by avoiding trapping in local optimum values. The eight unidimensional chaotic maps that are comprehensively examined in the paper to innovate the traditional WOA are listed in Table 1.

2.5. Lévy-flight chaotic whale optimization Algorithm(LCWOA)

Despite having an appreciable convergence rate, WOA is still unable to perform to its fullest potential in identifying the global optimal solution, which directly affects its computing efficiency. In the WOA exploration process, each whale location is altered on a small scale with respect to another whale, resulting in a limited search space for the solution. Lévy flight can be added into the exploration process, resulting in frequent smaller movements and occasional huge jumps to boost total exploration capabilities and widen the exploration zone. Lévy flight can considerably improve intensification and diversification of the WOA resulting in an improvised search ability avoiding local minima. In addition to this, using chaotic maps can have a favorable impact on WOA convergence rates because they encourage chaos in the viable region, which is predictable only for very brief initial times and stochastic for longer times. The use of chaotic maps in the WOA control parameters [A,C,p, ℓ] helps to speed up convergence with improved search ability. The different chaotic algorithms analyzed in the article is listed as follows.

2.5.1. Chaotic maps in WOA's shrinking circle technique (CWOA-S)

In this algorithm, the parameters A and C that determine shrinking circle technique is assigned with the chaotic map c(t) rather than the random variable 'r' as shown in Eqns. (21) and (22).

$$A = 2a\,c(t) - a \tag{21}$$

$$C = 2c(t) \tag{22}$$

2.5.2. Chaotic maps in WOA's spiral position updating technique (CWOA-L)

In this algorithm, the parameter ' ℓ' that determines the spiral updating location of the humpback whale are assigned using the chaotic map c(t) updating spiral equation as in Eqn. 23

$$X_i\ (t+1) = L\cdot\, e^{bc(t)}\cos(2\pi c(t)) + X^{*}(t) \tag{23}$$

2.5.3. Chaotic maps in WOA's probability parameter (CWOA-P)

In this work, chaotic map c(t) replaces the probability parameter 'p' of opting either the spiral mode or shrinking circle mode to update whale positions in each iteration.

Numerous studies suggest that including Lévy flight trajectory improves the exploration-exploitation balance in the WOA. In this work, Lévy flight is used to further modify the whale positions as in Eqn. (24).

$$X_i\ (t+1) = X_i(t) + \mu\ \mathrm{sign}\ [r_1 - 1/2].\ \text{Lévy}(\gamma) \tag{24}$$

where X(t) represents ith whale position at tth iteration, r_1 represents a randomly generated number in the range [0,1], μ represents a uniform distributed random number. The stochastic random walk equation, represented by Eq. (24), aids the WOA in ensuring that the search agent will effectively explore the search area, as its step length gets significantly greater in the longer run, removing local minima. In this work, the Lévy flight trajectory is introduced into the above three Chaotic Whale optimization algorithms, leading to the development of three enhanced WOA strategies, LCWOA-S, LCWOA-P, and LCWOA-L.

Algorithm 2 shows the pseudocode for the LCWOA algorithm.

Algorithm 2- Pseudocode for the LCWOA algorithm
LCWOA Algorithm
Set the generation counter t to zero, max iteration, the number of whales N, and the dimensions determining the position
Initialize randomly the positions of the N search agents/whales Xj where j = 1, 2 .... N in accordance with the dimensions.
Update the chaotic type and chaotic number to choose an appropriate chaotic map c (t).
Determine each search agent's fitness by defined function.
while (t < max iteration)
  Verify and correct any search agents if it goes outside the search space.
  Determine fitness of each whale/search agent by defined function.
  Update best whale/search agent X* provided a better result is found
for each whale/search agent X
  Modify parameter 'a' as in conventional WOA
  Update parameter either A&C, p or ℓ according to chaotic type using chosen chaotic map and update the rest of parameter conventionally
  if (p < 0.5) |
    if (|A| < 1)
      Modify the present whale position/search agent by Encircling mechanism as in Eqn. (14) by incorporating values of A &C as in
    else if (|A| ≥ 1)
      Identify a random whale/search agent/(Xrand)
      Adjust the present whale/search agent by Encircling mechanism as Eqn. (17) by incorporating values of A &C as in
    end if
      else if (p ≥ 0.5)
        Adjust the present search agent/whale position by spiral equation as Eqn. 23
    end if
for each whale/search agent
  Adjust the present search agent/whale position using the Lévy flight as in Eqn. 24
End
t = t + 1
end while
return best whale position/search agent X*

Fig. 5 describes the framework of LCWOA that starts with the initialization of the necessary whale population. Then, a suitable chaotic

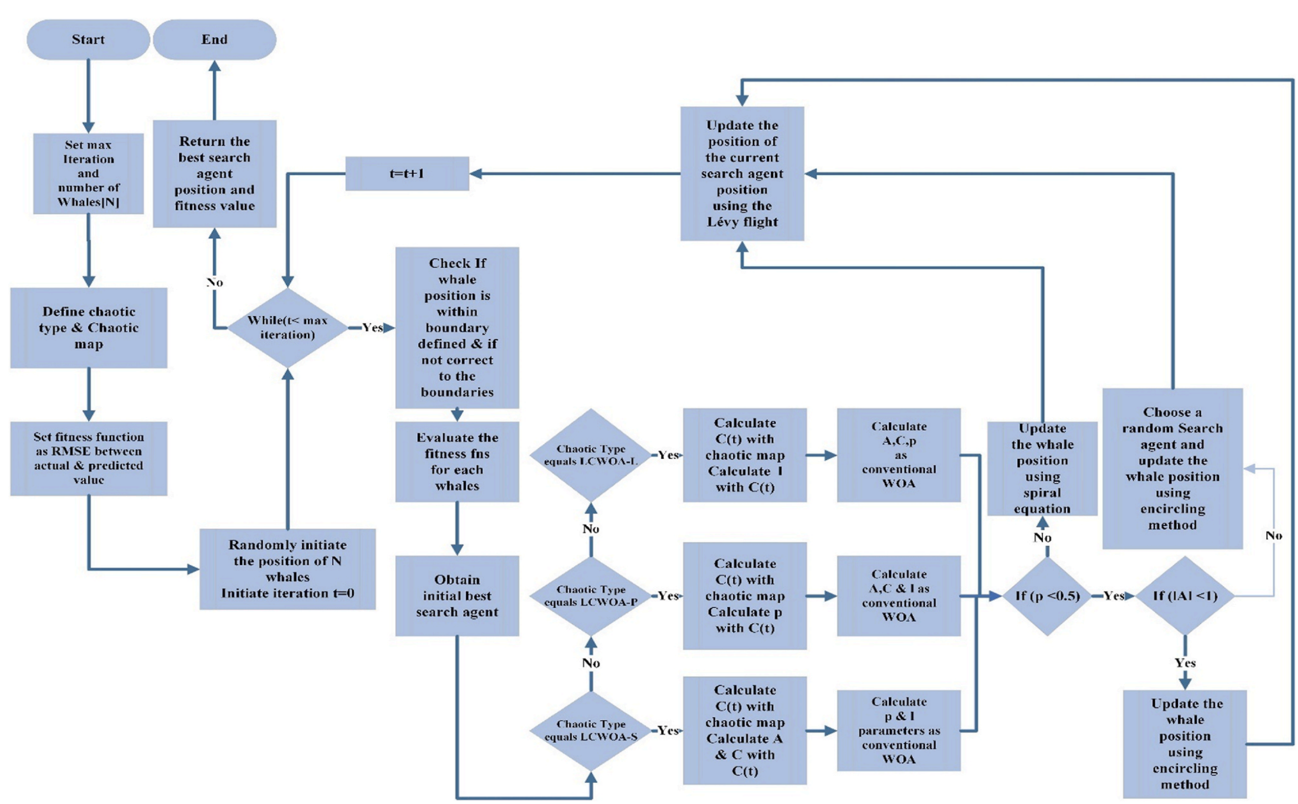

Fig. 5. The framework of the proposed LCWOA.

Table 2
Mathematical functions for testing the proposed algorithm.

Type	Name	Benchmark Function	Dimension (D)	Range	Optimal minimum value
Unimodal functions	Sphere	$f(x)=\sum_{i=1}^{D} x_i^2$	30	[-100,100]	0
	Schwefel 2.21	$f(x)=\mathrm{Max}_i\{\lvert x_i\rvert, 1\le i\le n\}$	30	[-100,100]	0
	RosenBrock	$f(x)=\sum_{i=1}^{D}(x_{i+1}-x_i^2+)+(x_i-1)^2]$	30	[-30, 30]	0
Multimodal functions	Griewank	$f(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\frac{x_i}{\sqrt{i}}+1$	30	[-600, 600]	0
	Pendalized	$f(x)=\sum_{i=1}^{D}u(x_i,10,100,4)+\frac{\pi}{D}\{10\sin^2(3\pi y_i)+\sum_{i=1}^{D-1}(y_i-1)^2[1+\sin^2(3\pi y_{i+1})]+(y_D-1)^2\}$ $y_i=1+\frac{1}{4}(x_i+1)$ $u(x_i,b,p,n)=\begin{cases}p(x_i-1)^n, x_i>b\\ 0, -b\le x_i\le b\\ p(-x_i-1)^n, x_i<-b\end{cases}$	30	[-50, 50]	0

type (LCWOA-S, LCWOA-P or LCWOA-L) is chosen to map the corresponding algorithm parameters with chaotic map chosen as explained above. The fitness of every whale initialized is assessed using the predefined fitness function. The best position/search agent at the end of each iteration is the whale with the highest fitness. When $|A| < 1$ and $p < 0.5$, the present best position/search agent will continue to update its position utilizing the encircling prey mechanism. When $|A| > 1$ and $p < 0.5$, the best position/search agent is updated based on a random whale position using the encircling prey mechanism. If $p \geq 0.5$, the spiral updating position mechanism is used to update the present best search agent position. The present search agent positions will be modified further with Lévy flight at the end of each iteration and the fittest whale position is also updated. The LCWOA algorithm will view the best search agent position as the final optimal solution when the termination condition is reached.

2.5.3.1. Validation of proposed LCWOA algorithm with benchmark functions. To ascertain the performance improvement, each novel optimization technique must be evaluated first with a set of well-defined mathematical functions. In this article, the proposed LCWOA has been evaluated using three unimodal functions- Sphere, Schwefel 2.21 and RosenBrock and two multimodal functions- Griewank and Pendalized. Unimodal benchmark functions are well suited for benchmarking exploitation phase as they have only a single optimum, while the multimodal benchmark functions serve as the testing framework for exploration due to their multiple optimal solutions. The details of unimodal and multimodal mathematical functions used are specified in Table 2.

The proposed three algorithms –LCWOA-P, LCWOA-S and LCWOA-L are compared with conventional WOA, LWOA and the variants of CWOA: CWOA-P, CWOA-S and CWOA-L for the above benchmark functions. The algorithm is run for 10 independent runs with 500 iteration for each of the benchmark function by assuming the whale population as 30. The chaotic map utilized for the experimental analysis is Tent Map. Experimental statistical results like average execution time, average value and the standard deviation are described in Table 3. For the qualitative analysis, the convergence curves of the examined algorithms for various mathematical functions are also shown in Fig. 6. Experimental results prove the following that opens its applicability in various complex real time optimization problems.

1. The performance of proposed three algorithms in unimodal functions proves improved exploitation phase as the convergence to local optimal point is achieved in the early iterations itself as shows in

Table 3
Statistical Results of the performance of different optimization on unimodal and multimodal functions.

Unimodal Function	Algorithm	Avg. Execution Time(s)	Average (m/s)	Standard deviation	Multimodal function	Algorithm	Avg. Execution Time(s)	Average (m/s)	Standard deviation
Sphere	WOA	9.082954931	4.28E-73	1.28E-72	**Griewank**	WOA	9.061406898	**0**	**0**
	LWOA	17.2641742	5.37	1.123209		LWOA	18.03122187	0.289	0.065001
	CWOAL	8.578726602	5.57	0.603143		CWOAL	9.076756787	0.251	0.026822
	LCWOAL	**17.36981592**	**8.01E-75**	**2.40E-74**		**LCWOAL**	**18.21406369**	**0**	**0**
	CWOAP	7.96443398	5.081773	0.938814		CWOAP	8.544021535	0.251274	0.052521
	LCWOAP	**16.10405431**	**8.76E-72**	**2.57E-71**		**LCWOAP**	**16.75213632**	**0**	**0**
	CWOAS	8.363842726	5.341515	0.607898		CWOAS	9.2675318	0.239653	0.062345
	LCWOAS	**17.12451725**	**7.49E-73**	**1.85E-72**		**LCWOAS**	**18.30148549**	**0**	**0**
Schwefel 2.21	WOA	8.384887695	41.8	24.3088	**Pendalized**	WOA	9.671176195	0.0344	0.048625
	LWOA	17.13437178	0.943	0.121311		LWOA	18.47025959	3.62	0.278857
	CWOAL	8.373312116	52	33.06374		CWOAL	9.814686441	3.58	0.208145
	LCWOAL	**17.07849603**	**0.938**	**0.07752**		**LCWOAL**	**18.61118188**	0.0191	**0.015955**
	CWOAP	7.821817636	51.24645	25.86167		CWOAP	9.068264127	3.520512	0.195481
	LCWOAP	**16.13520086**	**0.965593**	**0.03677**		**LCWOAP**	**17.10897572**	**0.0192**	**0.011131**
	CWOAS	8.471002388	44.2305	23.63903		CWOAS	10.02300293	3.469534	0.155106
	LCWOAS	**17.70291631**	**0.925325**	**0.1147**		**LCWOAS**	**18.8127439**	**0.023833**	**0.01361**
RosenBrock	WOA	8.649783301	438	55.03322					
	LWOA	17.27140837	28	0.397501					
	CWOAL	8.770069051	436	77.56729					
	LCWOAL	**17.35701697**	**27.9**	**0.436941**					
	CWOAP	8.158251357	416.5556	170.3582					
	LCWOAP	**16.34800425**	**27.76578**	**0.380215**					
	CWOAS	8.887092781	401.0974	63.03489					
	LCWOAS	**17.65434055**	**27.95003**	**0.415602**					

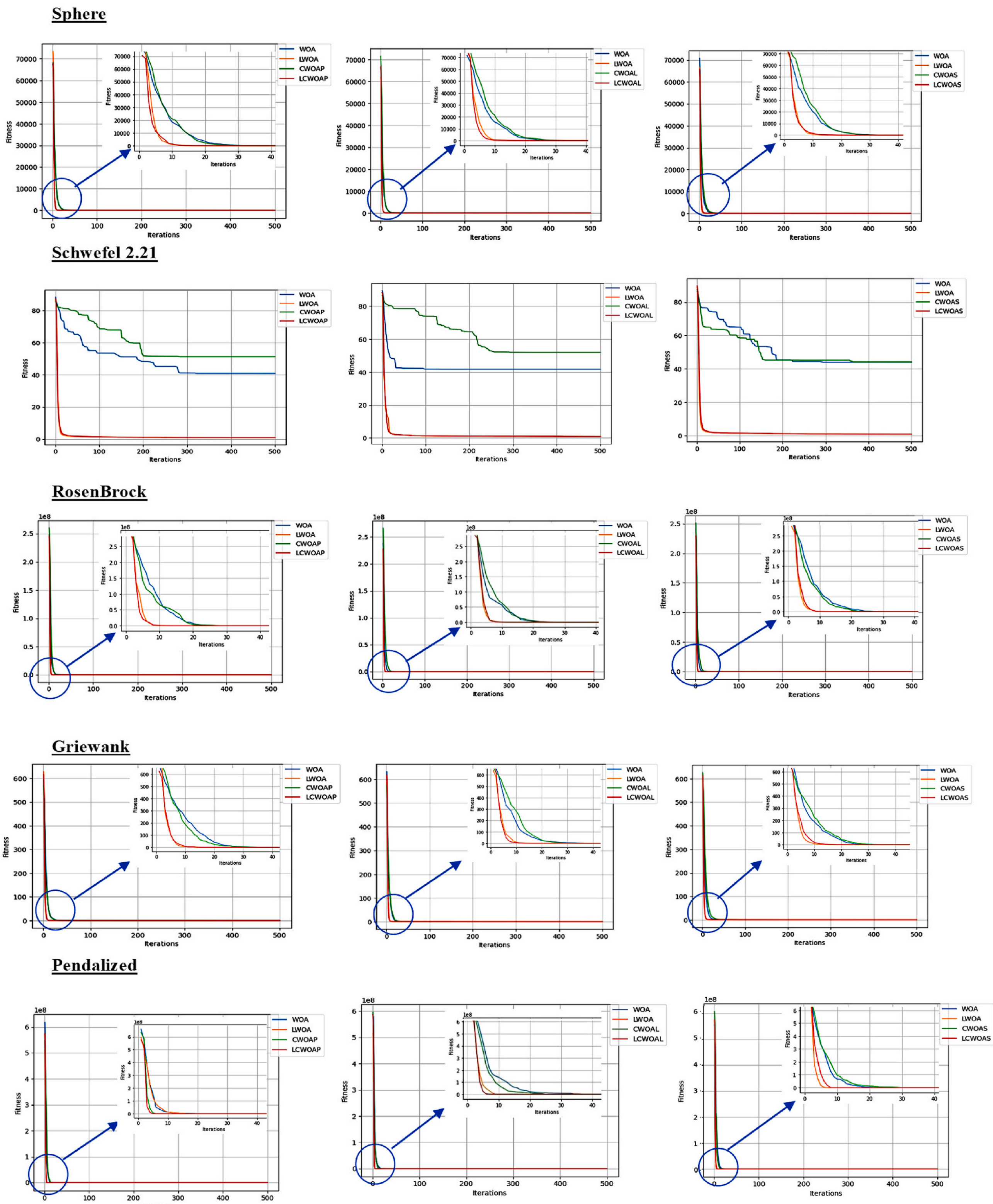

Fig. 6. Comparison of convergence curve of proposed algorithms with WOA, LWOA, CWOA for different mathematical functions.

Fig. 6. For the Schwefel 2.21 function, it is more evident that the proposed three algorithms prove to be the most efficient as it avoids premature convergence.

2. In Multimodal functions, the challenges prone to any algorithm is the increased local optima solution [that increases exponentially with dimensions] which tests the exploration capability of the algorithm. Statistical results and convergence curves prove that the proposed algorithm is either best converging or second-best converging. Results clearly indicate that the integrated mechanism of Lévy flight and chaotic map accelerates the exploration phase by efficiently searching the search space.

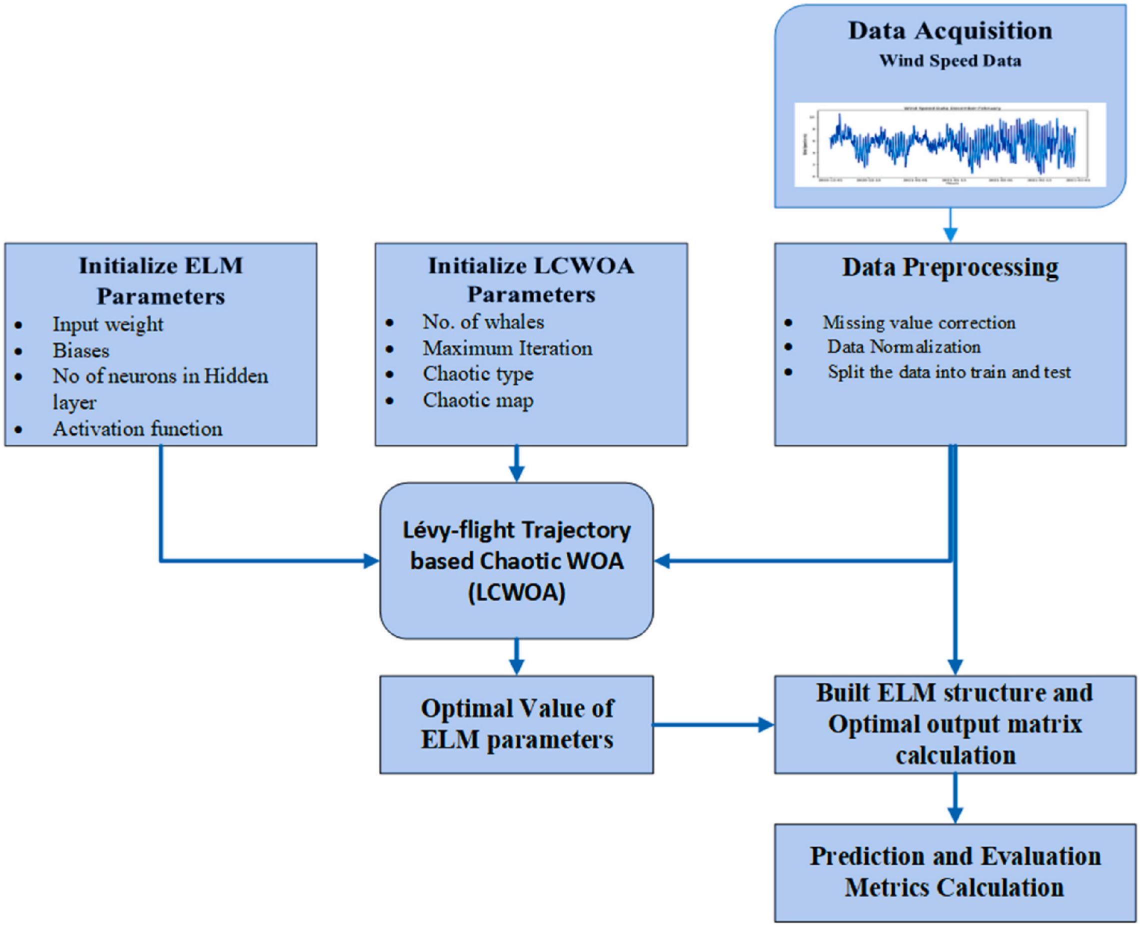

Fig. 7. LCWOA –ELM framework for wind speed forecasting.

3. LCWOA –ELM framework for Wind Speed Forecasting

As discussed, ELM- Extreme Learning Machine is a fast-computing SLFFN used in numerous Engineering applications. However, the most significant flaw of ELM is its lack of generalizability due to the random introduction of initial biases and input weights. Although studies prove that the initial input weights do not adversely affect the efficiency of the ELM model, there is a high possibility that these weights and biases may not converge to best output weights. Moreover, in the conventional ELM, there is no opportunity for the coherent updating of biases and input weights that negatively diminish the computational efficiency of the model.

The ELM model can be paired with an effective optimization technique to fine-tune its model parameters to get around the limitations and increase the effectiveness of ELM. The suggested enhanced Lévy-flight Chaotic Whale optimization algorithm (LCWOA) is used to prune the key ELM parameters, such as input weights, biases, neurons in the hidden layer, activation function and regularization parameter used. In the proposed LCWOA method, the position of whales is defined by above five parameters of ELM. As we are aiming the model performance in time series prediction, the fitness function for choosing best whale position is chosen as the RMSE between actual and predicted value. This method will assess how well the ELM model will perform for various combinations of the parameters. Consequently, each of these parameters can be updated, and finally, the best output weights are chosen leading to a reliable model.

The proposed LCWOA –ELM framework for wind speed forecasting is shown in Fig. 7. The main steps in the framework include data acquisition, data preprocessing, ELM model development and training, prediction, and performance evaluation.

3.1. Data Acquisition

Acquiring real-time weather data is a crucial and difficult stage in developing a reliable forecasting model. The experimental study in the work was conducted in the one-year wind speed dataset acquired from weather station setup in Amrita School of Engineering, Kasavanahalli, Bengaluru, India (12°53′41.6 N 77°40′32.4 E) starting from December 1st, 2020, to November 30th' 2021. An anemometer, mounted at a height of 50 m in the site is used to gather the data as depicted in Fig. 8. The four seasons: December–February, March–May, June–August, and September–November are selected as the forecasting periods from the obtained dataset to analyze the versatility of the proposed forecasting model. The wind speed series for all forecasting periods is depicted in Fig. 9. Table 4 shows the statistical wind speed details for the acquired datasets for different periods.

3.2. Data Preprocessing

Data Preprocessing is an essential step in any forecast model in which collected data is transformed into the desired format for processing without degrading the results. Cleaning and preparing the time series data is crucial because any model's performance is impacted by the quality of the data. Initially the missing values in the dataset are replaced with mean values. Then the data is standardized using the Min-Max scaler to fall within the range (0,1) after missing values are

Fig. 8. Location and Weather station installed in the site.

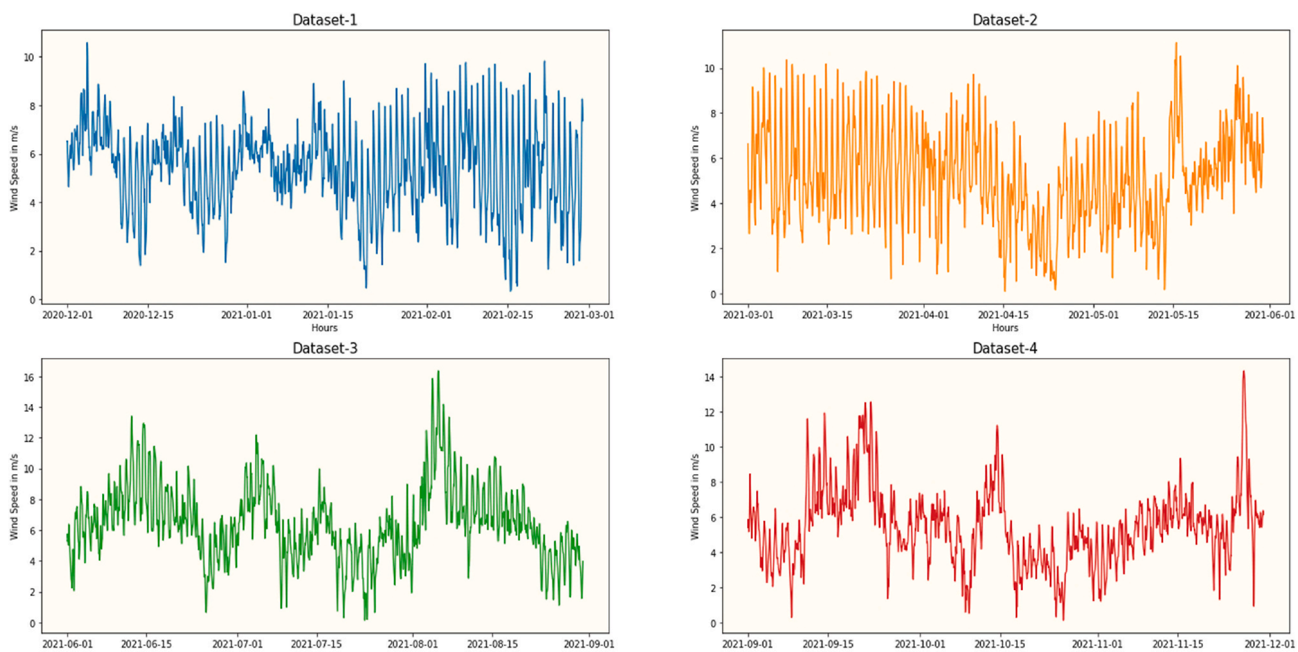

Fig. 9. Wind speed data for all the forecasting period.

Table 4
The statistical wind speed details of the acquired datasets for different periods.

Dataset	Time period	No of samples	Max Value (m/s)	Min Value (m/s)	Std. Dev (m/s)	Mean (m/s)
Dataset1	Dec 1st, 2020–Feb 28th, 2021	2160	10.590	0.330	1.759	5.420
Dataset2	Mar 1st, 2021–May 31st' 2021	2208	11.130	0.100	2.049	5.164
Dataset3	June 1st, 2021–Aug 31st' 2021	2208	14.590	0.210	2.538	6.660
Dataset4	Sep 1st, 2021–Nov 30th' 2021	2184	11.800	0.150	2.042	5.039

imputed.

$$X_{Norm} = \frac{X - X_{Min}}{X_{Max} - X_{Min}} \tag{25}$$

where, the actual data is X, the normalized data of X is X_{Norm}, X_{Min} is the minimum value of X and X_{Max} is the maximum value of X. This normalization on the data can improve the model performance due to the activation function's increased sensitivity to the input variables. So, the input variables must be normalized prior to training as the activation functions are usually in that range of variation. Finally, the normalized data is segregated in such a way that 80% of the data is dedicated to the training phase and the remaining 20% is assigned to the testing phase.

Table 5
ELM model Parameter ranges.

ELM parameter	Range/value
Weights between input layer and hidden layer (w)	[-1,1]
Hidden layer Bias (b)	[0,1]
Neurons/nodes in the hidden layer(n)	[10,200]
Activation Function	['sigmoid', 'relu', 'sin', 'tanh', 'leaky relu']
Regularization parameter (C)	[0.1,1]

Table 6
Parameter setting of LCWOA algorithm.

LCWOA parameter	Value
Maximum number of iterations	200
Whale population	[10,20,30,40,50,60,70,80,90,100]
Chaotic type	LCWOA-S, LCWOA-P, and LCWOA-L
Chaotic map	[Circle map, Logistic map, Tent map, Piecewise map, Sinusoidal map, Sine map, Gauss/mouse map, Singer Map]

3.3. LCWOA-ELM model Development

In this work, the Lévy-flight Chaotic Whale optimization algorithm (LCWOA) is utilized to prune the relevant parameters of ELM like input weights, biases, the activation function used, neurons in the hidden layer and regularization parameter. In the LCWOA algorithm, the position of whales is determined by the mentioned five parameters of ELM. This process will analyze the performance of the ELM model for a set of possible values of the above-mentioned parameters. As a result, all these parameter values are updated effectively, and final output weights are determined in a way leading to a robust model. The mentionable advantage of the LCWOA algorithm is that it is dependent on only a few parameters like maximum number of iterations, whale population, chaotic type and chaotic map chosen as described in the algorithm. The relevant ELM parameter ranges initialized in the algorithm are specified in Table 5. The parameter setting of LCWOA algorithm is described in Table 6.

Table 7
Optimal Whale population for LCWOA-ELM.

Forecasting period	Whale population
Dec 1st, 2020–Feb 28th' 2021	80
Mar 1st, 2021–May 31st' 2021	90
June 1st, 2021–Aug 31st' 2021	90
Sep 1st, 2021–Nov 30th' 2021	100

For finding the optimal whale population, the algorithm is run for different whale population for 200 iterations. The RMSE variation for different whale populations is illustrated in Fig. 10. Table 7 shows the optimal whale population chosen for LCWOA with minimum RMSE for further tuning of ELM model.

Generally, any forecast model is designed for one-step ahead prediction with the aid of a set of N input variables/lag value that must be properly chosen. Lag values are the observation at earlier time steps that are utilized as a key input feature for time series forecasting which predominantly determine the model accuracy. In this work, the proposed method is first evaluated for one-step ahead wind speed prediction that aims to predict the next time step values (x_{t+1}) by considering historical time series with t lag observations (x_1, x_2, x_3. ., x_t) as the input features. For finding an optimal lag value, LCWOA-ELM algorithm is run for different time lags ranging from 1 to 30 and corresponding RMSE errors are noted against each time step. Fig. 11 shows the impact of time lag on the different wind speed series chosen. The time lag with minimum RMSE is chosen as optimal lag value for modelling the corresponding forecasting periods. The experimental results for determining optimum lag values are consolidated in Table 8.

The performance of the ELM is checked for all three Lévy flight chaotic algorithms (LCWOA-S, LCWOA-P, and LCWOA-L) by properly choosing the chaotic type and position updating using Lévy-flight Trajectory in each case. Eight most significant unidimensional chaotic maps (as discussed in Table .1) have been analyzed for each algorithm to come up with a most efficient robust model. As we are aiming the model

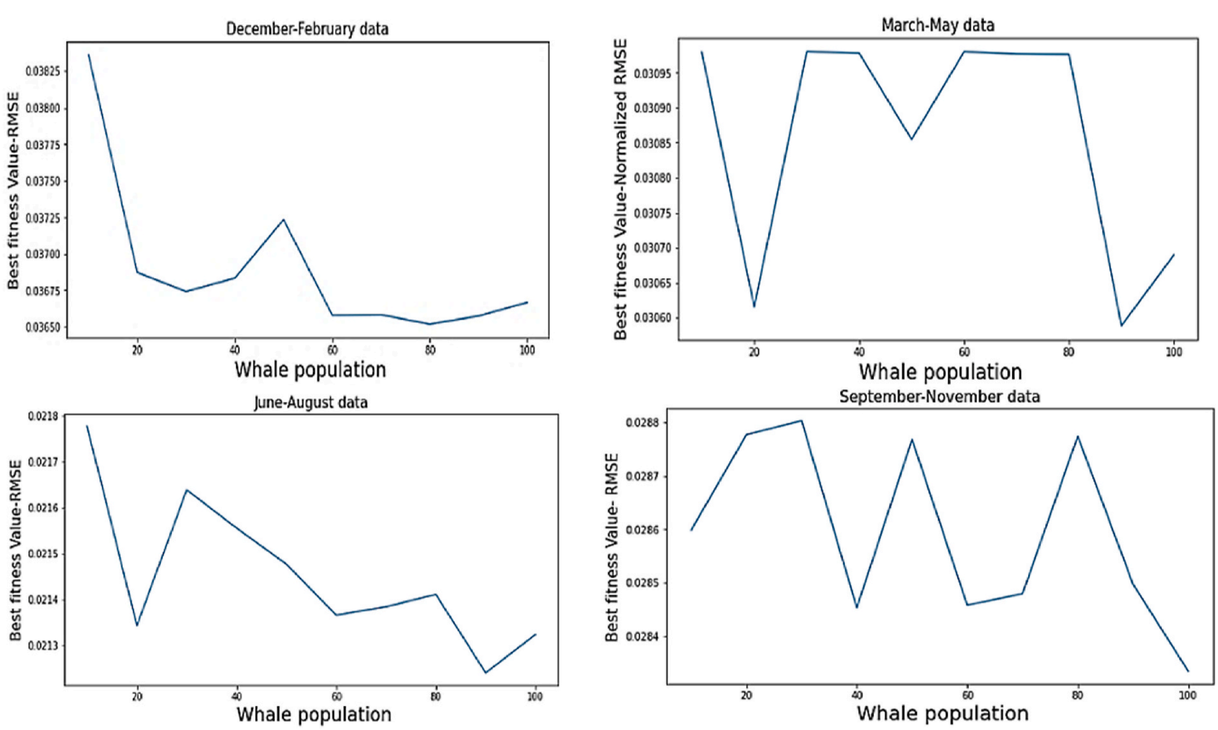

Fig. 10. Effect of whale population on the fitness value.

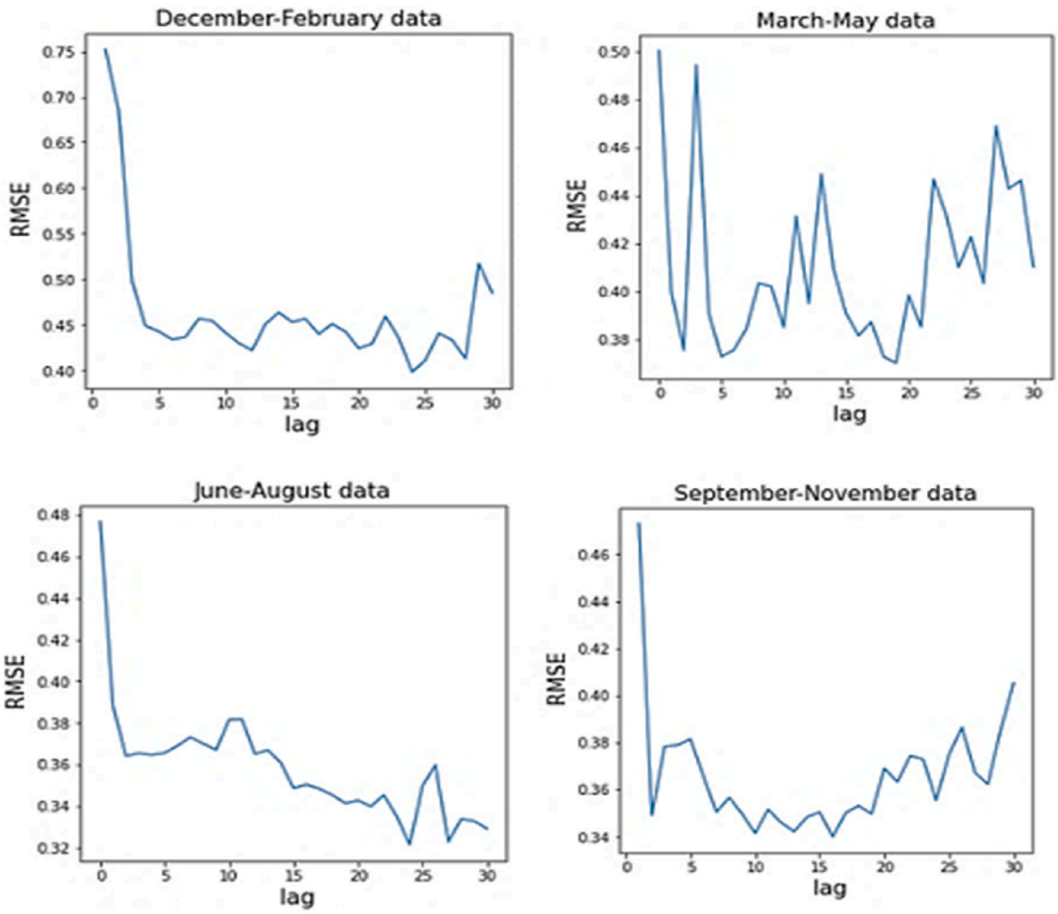

Fig. 11. Plot of RMSE against lag values for different dataset.

Table 8
Optimal lag value for ELM modelling different forecasting period.

Forecasting period	Time lag
Dataset −1	24
Dataset −2	19
Dataset −3	24
Dataset −4	16

Table 9
Evaluation metrics.

Evaluation metrics	Description	Equation
MSE	Mean Square Error	$\frac{\sum_i (x_t - \widehat{x}_t)^2}{n}$
R^2-score	Coefficient of Determination	$1 - \frac{(x_t - \widehat{x}_t)^2}{(x_t - \overline{x})^2}$
RMSE	Root Mean Square Error	$\sqrt{\frac{\sum_i (x_t - \widehat{x}_t)^2}{n}}$
MAE	Mean Absolute Error	$\frac{\lvert(x_t - \widehat{x}_t)\rvert}{n}$
MAPE	Mean Absolute Percentage Error	$\frac{1}{n}\sum_t \frac{(x_t - \widehat{x}_t)}{x_t}$

performance in time series prediction, the fitness function for choosing best whale position is the RMSE between predicted and actual value. As depicted in the flowchart shown in Fig. 5, each whale's fitness value is determined for each iteration up to the maximum iteration. The whales reposition themselves based on the control parameters A, C, p, and ℓ that are chaotically determined. The best whale position is also updated based upon fitness value evaluation that corresponds to minimum RMSE. At the end of each iteration new whale positions are further modified by Lévy-flight that improves population diversity. When the termination condition reaches, the best search agent position corresponds to the optimal parameters of ELM.

3.4. Performance Evaluation

Performance evaluation is the most crucial step in validating any model. Five performance assessment indices: MSE R2-score, MAE, MAPE and RMSE are utilized to model evaluation. The evaluation indices as indicated in Table 9 are computed for all the models in which x_t is the actual value and $\widehat{x}_t$ is the predicted value at time t. $\overline{x}$ is mean of all actual values considered for study.

Additionally, the robustness of the proposed model with other ELM based models is evaluated with the Percentage Reduction in RMSE (P_{RMSE}) as defined in Eqn. (26).

$$P_{RMSE} = \frac{RMSE_1 - RMSE_2}{RMSE_1} \times 100 \tag{26}$$

3.5. Forecasting Results and Analysis

The prediction capability and performance of the suggested model is validated with nine other existing models like WOA-SVR(whale optimized Support Vector Regression), WOA-LSTM(whale optimized Long short term Memory),WOA-GRU(whale optimized Gated Recurrent Unit),ELM(Extreme learning Machine),WOA-ELM (Whale Optimized ELM), CWOA-S-ELM(Whale Optimized ELM with Chaotic Maps for

Table 10
Configuration Parameters of models used for comparison.

Forecasting models	WOA Parameters		Model Parameters	
	Parameter	Value	Parameter	Value
WOA-SVR	random vector (r)	[0,1]	Kernel function	Radial basis function (RBF)
			Cost	[0.001,10]
	a	linearly decreased from 2 to 0 over the iterations	Gamma	[0.001,10]
	Maximum number of iterations	200	Hidden layers Number	[1,4]
WOA-LSTM			Cells in hidden layer	[10,200]
WOA-GRU			Batch Size	[10,200]
WOA-ELM, LWOA-ELM	random vector (r)	[0,1]	Weights between input and hidden layer (w)	[-1,1]
	a	linearly decreased from 2 to 0 over the iterations	Biases between input and hidden layer(b)	[0,1]
	Maximum iteration	200	Neurons/nodes in the hidden layer(n)	[10,200]
			Activation Function	['sigmoid', 'relu', 'sin', 'tanh', 'leaky relu']
			Regularization parameter C	[0.1,1]
CWOA-P-ELM, CWOA-L-ELM, CWOA-S-ELM	random vector (r)	[0,1]	Weights between input and hidden layer (w)	[-1,1]
	A	linearly decreased from 2 to 0 over the iterations	Biases between input and hidden layer(b)	[0,1]
	Maximum iteration	200	Neurons/nodes in the hidden layer(n)	[10,200]
	Chaotic map	[Circle map, Tent map, Piecewise map, Logistic map, Sine map, Gauss/mouse map, Sinusoidal map, Singer Map]	Activation Function	['sigmoid', 'relu', 'sin', 'tanh', 'leaky relu']
			Regularization parameter C	[0.1,1]

Table 11
The statistical results analysis of the performance of eight chaotic maps in improvising the conventional WOA–ELM model.

Dataset-1(December–February)

Chaotic map	CWOA-P-ELM	CWOA-L-ELM	CWOA-S-ELM	LCWOA-P-ELM	LCWOA-L-ELM	LCWOA-S-ELM
Circle Map	0.037355	0.037463	0.038521	**0.03654**	0.03759	**0.0368**
Logistics Map	0.037196	0.03702	0.037112	0.037404	**0.03677**	0.03852
Tent Map	**0.037111**	0.038361	0.038431	0.037125	0.037071	0.038517
Piecewise Map	0.038521	**0.036972**	0.03852	0.0372	0.038481	0.037274
Sinusoidal Map	0.037367	0.037366	0.037011	0.036655	0.038172	0.037459
Sine Map	0.037692	0.037334	0.038419	0.037221	0.036937	0.037052
Gauss/mouse Map	0.037158	0.037128	0.037559	0.037231	0.038295	0.038002
Singer Map	0.038134	0.037607	**0.03701**	0.037118	0.038166	0.037133

Dataset −2(March–May)

Chaotic map	CWOA-P-ELM	CWOA-L-ELM	CWOA-S-ELM	LCWOA-P-ELM	LCWOA-L-ELM	LCWOA-S-ELM
Circle Map	0.030827	0.030785	0.030981	0.030729	0.030989	**0.030697**
Logistics Map	**0.030443**	**0.030743**	0.030989	0.030731	0.030762	0.030989
Tent Map	0.030989	0.030818	0.030981	0.030847	**0.030664**	0.030989
Piecewise Map	0.030989	0.030789	0.030989	**0.030587**	0.030989	0.030989
Sinusoidal Map	0.030989	0.03098	0.03098	0.03059	0.030989	0.030989
Sine Map	0.030698	0.030989	0.030989	0.030773	0.030837	0.030859
Gauss/mouse Map	0.030989	0.030893	0.030981	0.030989	0.030989	0.030989
Singer Map	0.030603	0.03098	**0.030761**	0.030691	0.030989	0.030891

Dataset-3(June–August)

Chaotic map	CWOA-P-ELM	CWOA-L-ELM	CWOA-S-ELM	LCWOA-P-ELM	LCWOA-L-ELM	LCWOA-S-ELM
Circle Map	0.0186	0.018679	0.018723	0.01874	0.018749	0.018636
Logistics Map	**0.0185**	0.018788	**0.01867**	0.018708	0.018772	0.018663
Tent Map	0.018735	0.018737	0.018742	0.018878	0.018789	**0.0186**
Piecewise Map	0.018585	0.018774	0.018684	0.01874	0.01871	0.018705
Sinusoidal Map	0.018676	0.018728	0.018856	0.01876	**0.01858**	0.018773
Sine Map	0.018633	0.018774	0.018766	**0.01871**	0.018642	0.018875
Gauss/mouse Map	0.0187	0.018808	0.018758	0.018786	0.018852	0.018773
Singer Map	0.018771	**0.018621**	0.018886	0.018796	0.018797	0.01875

Dataset-4(September–November)

Chaotic map	CWOA-P-ELM	CWOA-L-ELM	CWOA-S-ELM	LCWOA-P-ELM	LCWOA-L-ELM	LCWOA-S-ELM
Circle Map	0.02465	0.024635	0.024648	0.02465	0.024301	**0.024298**
Logistics Map	0.02465	**0.024609**	0.024655	0.02465	0.02465	0.02465
Tent Map	0.024632	0.024634	0.024648	0.024105	0.02427	0.02465
Piecewise Map	0.024653	0.02462	0.024708	0.02465	0.02465	0.02465
Sinusoidal Map	0.024654	0.024635	**0.024619**	0.02437	0.02465	0.02465
Sine Map	**0.024659**	0.024632	0.02466	**0.02432**	0.024268	0.02465
Gauss/mouse Map	0.024621	0.024646	0.024637	0.024405	0.02465	0.02465
Singer Map	0.024667	0.02466	0.024655	0.024356	**0.024099**	0.024504

Table 12
Statistical error indices for one-step ahead wind speed prediction for different datasets.

Dataset-1(December–January)						Dataset-2(March–May)					
MODEL	**MSE**	**R2**	**RMSE**	**MAE**	**MAPE**	**MODEL**	**MSE**	**R2**	**RMSE**	**MAE**	**MAPE**
WOA-SVR	0.186584	0.961784	0.431953	0.310532	0.112808	WOA-SVM	0.134445	0.947855	0.366667	0.258738	0.041601
WOA-LSTM	0.183556	0.962404	0.428434	0.315414	0.093001	WOA-LSTM	0.138213	0.946394	0.37177	0.258835	0.040836
WOA-GRU	0.186876	0.961724	0.432291	0.327964	0.098309	WOA-GRU	0.153162	0.940595	0.39136	0.329789	0.057452
ELM	0.180332	0.963064	0.424655	0.294012	0.097823	ELM	0.132277	0.948696	0.363698	0.26352	0.042779
WOA-ELM	0.173319	0.964501	0.416316	0.292733	0.085484	WOA-ELM	0.12632	0.951006	0.355415	0.254975	0.041213
LWOA-ELM	0.162509	0.966715	0.403123	0.282517	0.081237	LWOA-ELM	0.139844	0.945761	0.373957	0.277427	0.044942
CWOA-P-ELM	0.160067	0.967215	0.400084	0.27266	0.077652	CWOA-P-ELM	0.119639	0.953597	0.345889	0.249846	0.040283
CWOA-L-ELM	0.162726	0.96667	0.403393	0.278922	0.079075	CWOA-L-ELM	0.121919	0.952713	0.349168	0.252799	0.040817
CWOA-S-ELM	0.160978	0.967028	0.401221	0.288824	0.087447	CWOA-S-ELM	0.117039	0.954606	0.34211	0.246527	0.039822
LCWOA-P-ELM	**0.15174**	**0.968921**	**0.389538**	**0.270316**	**0.078902**	**LCWOA-P-ELM**	**0.116792**	**0.954702**	**0.341748**	**0.244956**	**0.039558**
LCWOA-L-ELM	**0.15226**	**0.968813**	**0.390210**	**0.263165**	**0.073983**	**LCWOA-L-ELM**	**0.116975**	**0.954631**	**0.342016**	**0.246911**	**0.039881**
LCWOA-S-ELM	**0.154685**	**0.968317**	**0.3933**	**0.273218**	**0.076265**	**LCWOA-S-ELM**	**0.116796**	**0.9547**	**0.341755**	**0.246424**	**0.039792**
Dataset 3(June–August)						**Dataset-4(September–November)**					
MODEL	**MSE**	**R2**	**RMSE**	**MAE**	**MAPE**	**MODEL**	**MSE**	**R2**	**RMSE**	**MAE**	**MAPE**
WOA-SVR	0.1279	0.968576	0.357631	0.274307	0.057471	WOA-SVR	0.139775	0.966497	0.373865	0.255214	0.047093
WOA-LSTM	0.127384	0.968702	0.356908	0.253628	0.053641	WOA-LSTM	0.137461	0.967051	0.370757	0.249566	0.047437
WOA-GRU	0.16118	0.960399	0.401473	0.299839	0.055767	WOA-GRU	0.13731	0.967088	0.370554	0.248601	0.047761
ELM	0.12331	0.969703	0.351155	0.264015	0.053081	ELM	0.166839	0.96001	0.408459	0.275484	0.050277
WOA-ELM	0.100126	0.975399	0.316427	0.225703	0.044878	WOA-ELM	0.129899	0.968864	0.360416	0.244223	0.045391
LWOA-ELM	0.1049	0.974227	0.323882	0.233626	0.04638	LWOA-ELM	0.124487	0.970161	0.352826	0.239089	0.044607
CWOA-P-ELM	0.100782	0.975238	0.317462	0.231717	0.04615	CWOA-P-ELM	0.120141	0.971203	0.346614	0.235312	0.043945
CWOA-L-ELM	0.101318	0.975107	0.318304	0.227721	0.045232	CWOA-L-ELM	0.121432	0.970894	0.348471	0.236065	0.0441
CWOA-S-ELM	0.101037	0.975176	0.317863	0.226537	0.044986	CWOA-S-ELM	0.121636	0.970845	0.348764	0.236463	0.04415
LCWOA-P-ELM	**0.094158**	**0.976866**	**0.306852**	**0.220444**	**0.044059**	**LCWOA-P-ELM**	**0.118808**	**0.971523**	**0.344685**	**0.23632**	**0.044276**
LCWOA-L-ELM	**0.095594**	**0.976513**	**0.309182**	**0.221821**	**0.043918**	**LCWOA-L-ELM**	**0.117566**	**0.97182**	**0.342879**	**0.238393**	**0.044703**
LCWOA-S-ELM	**0.093745**	**0.976967**	**0.306178**	**0.22188**	**0.044566**	**LCWOA-S-ELM**	**0.121659**	**0.970839**	**0.348796**	**0.247**	**0.046157**

Shrinking Circle Mechanism),CWOA-P-ELM(Whale Optimized ELM with Chaotic Maps for Probability Parameter) and CWOA-L-ELM(Whale Optimized ELM with Chaotic Maps for Spiral Shaped Mechanism). The configuration parameters of benchmark models are specified in Table 10.

The performance analysis of eight chaotic maps in improvising the conventional WOA –ELM model is done by comparing the normalized RMSE while incorporating different chaotic Map in the specific WOA parameter. Detailed result analysis is shown in Table 11 in which the value in bold represents best chaotic map for the specific algorithm for a particular dataset. The forecasting accuracy of various models for one-step forward wind speed prediction based on various statistical error indices is shown in Table 12. The numbers in bold type represent the minimum error attained. Fig. 12 shows the performance comparison of different models based on RMSE.

Summary of the experimental findings are listed as follows.

1. Among the twelve-forecasting model considered, the prediction accuracies of the proposed three models LCWOA-P-ELM, LCWOA-L-ELM and LCWOA-S-ELM are higher for all the four datasets considered as the error metrics have the least value as indicated in Table 12. It clearly shows that Lévy-flight Trajectory based Chaotic WOA (LCWOA) has better performance in optimizing the parameters of ELM model when compared to the conventional model for wind speed prediction.
   a. For dataset 1, circle map and logistic map give a better performance in improvising the conventional WOA algorithm for tuning the parameters of ELM as shown in Table 11. Among all the hybrid models, LCWOA-P-ELM outperforms the other counterparts in prediction accuracy with least RMSE and MAE of **0.389538** and **0.270316** respectively.
   b. For the dataset 2, circle map, tent map and piecewise map give a significant contribution in improvising LCWOA algorithms for ELM modelling. Among all the hybrid models, LCWOA-P-ELM gives a remarkable prediction accuracy with the least RMSE and MAE of 0.341748 and **0.244956** respectively.
   c. For the dataset 3, Sine map, sinusoidal map and tent map clearly improvise the LCWOA-ELM model as shown in Table 11. Among the hybrid model, LCWOA-S-ELM outperforms its counterpart in prediction accuracy with the least RMSE and MAE of **0.306178 and 0.22188** respectively.
   d. For the dataset 4, sine map, sinusoidal map and tent map give a better performance in improvising the LCWOA-ELM model. Among all the hybrid models, LCWOA-L-ELM outperforms its counterpart in prediction accuracy with the least RMSE and MAE of **0.348796 and 0.247** respectively.
2. The prediction models for dataset-3 have reported low error levels based on MAE and RMSE in contrast to the other datasets which emphasis on the fact that prediction accuracy depends on the datasets and algorithms employed

Figss. 13–16 show the one-step-ahead wind speed prediction curves obtained by the different models for different datasets considered for study.

The computational improvement of the suggested LCWOA-ELM model in comparison to the traditional ELM model in terms of the percentage reduction in RMSE (P_{RMSE}) is shown in Table 13 and Fig. 17. Summary of the experimental findings are listed as follows .

1. The suggested three LCWOA-ELM models significantly outperform other models due to their higher prediction accuracy in all the four scenarios.
2. Incorporating chaotic maps in WOA for optimizing ELM has significantly shown an improvement of 3–4% for most of the cases, which clearly shows improvement due to local minima avoidance.
3. Incorporating Lévy fight in WOA (LWOA) clearly shows an improvement in dataset −1 and dataset-4, which justifies the idea of combining Lévy-flight and Chaotic maps in improvising WOA.

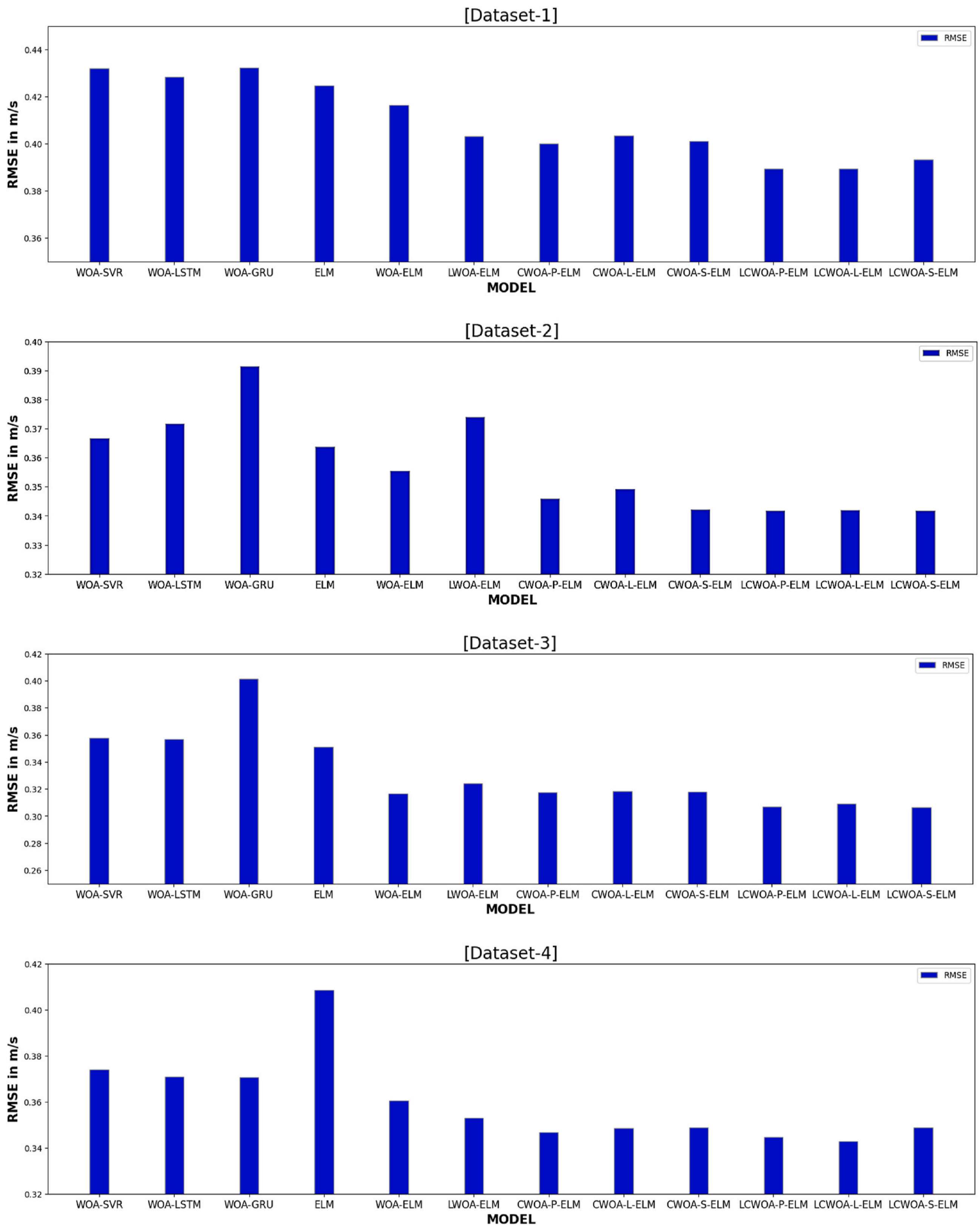

Fig. 12. Comparison of different models based on RMSE.

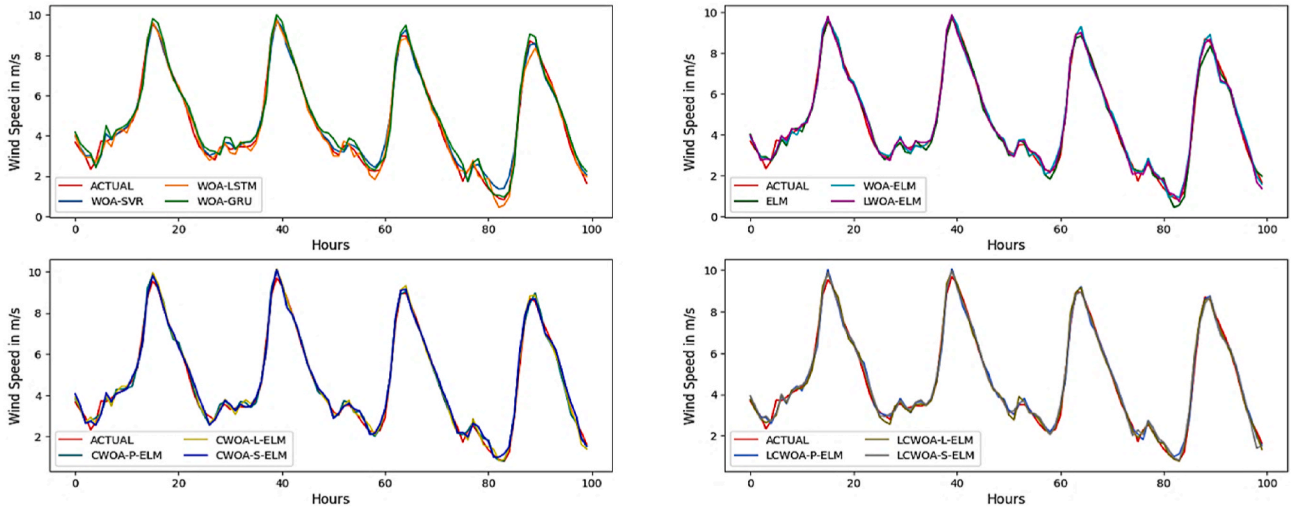

Fig. 13. Wind speed prediction curves obtained by the different models for Dataset-1[first 100 points].

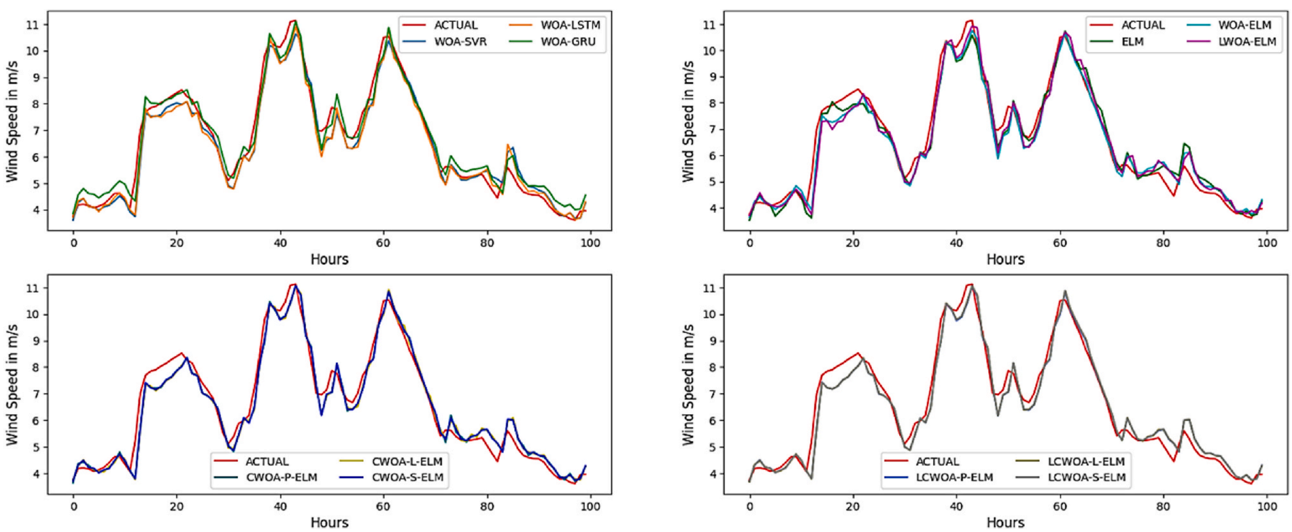

Fig. 14. Wind speed prediction curves obtained by the different models for Dataset-2[first 100 points].

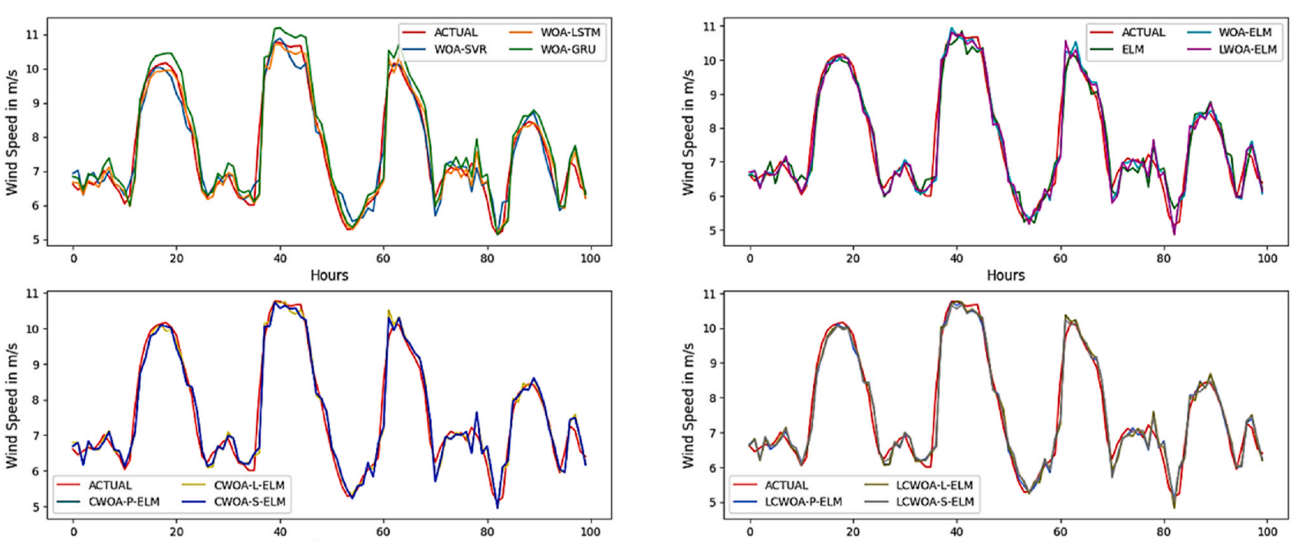

Fig. 15. Wind speed prediction curves obtained by the different models for Dataset-3[first 100 points].

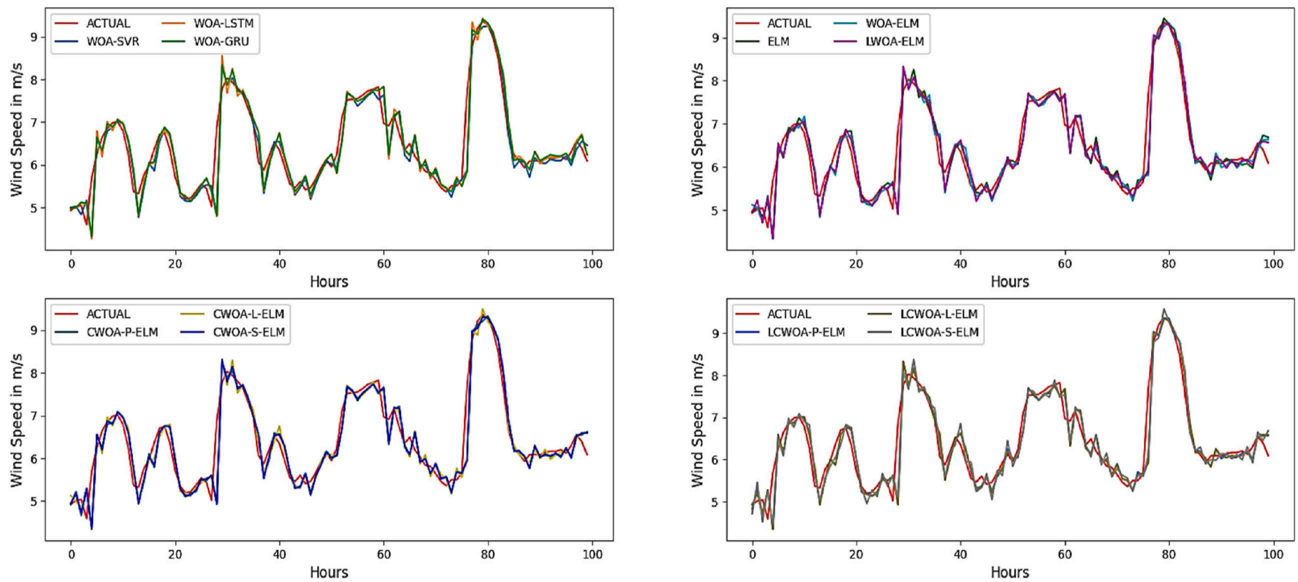

Fig. 16. Wind speed prediction curves obtained by the different models for Dataset-4[first 100 points].

Table 13
Percentage reduction in RMSE(P_{RMSE}) for different models.

	P_{RMSE} (%)			
Model	Dataset-1	Dataset-2	Dataset-3	Dataset-4
WOA-ELM	1.963648	4.958268	9.889595	11.76211
LWOA-ELM	5.070337	2.743155	7.766606	13.62013
CWOA-P-ELM	5.786041	7.505512	9.594844	15.14103
CWOA-L-ELM	5.006776	6.628624	9.35506	14.68656
CWOA-S-ELM	5.518271	8.516155	9.480623	14.6148
LCWOA-P-ELM	**8.269581**	**8.612887**	12.61647	15.61338
LCWOA-L-ELM	8.111216	8.541232	11.95271	**16.05542**
LCWOA-S-ELM	7.383627	8.611159	**12.80829**	14.60692

4. For the dataset-1 and 2, the forecasting accuracy LCWOA-P-ELM is better when compared to other models as the RMSE reduces to 8.269% and 8.612% respectively. Similarly, for dataset-3, LCWOA-S-ELM proves to better with 12.208% reduction in RMSE, while LCWOA-L-ELM turns up to be best for dataset-4 with 16.055% reduction in RMSE.
5. Clearly results prove that performance of WOA can be improved by incorporating Chaotic maps and Lévy flight together in the algorithm.

4. Multistep ahead forecasting

To access the effectiveness of the model over unseen data, multistep ahead forecasting is evaluated for the proposed model, by recursive forecasting mechanism. The recursive forecasting mechanism involve the usage of previous time step prediction result in the prediction of next time step value as depicted in Fig. 18. The computational efficiency of proposed model for one day ahead [24-h ahead] forecast scenarios are evaluated and compared with benchmark models. The performance comparison in terms of RMSE(m/s) for different models in 24-h ahead wind speed prediction is indicated in Table 14.The one day ahead forecast plot of wind speed for all models using recursive prediction analyzed is depicted in Fig. 19.

The experimental analysis of multistep ahead prediction by different models for different dataset proves the following.

1. In one day ahead hourly wind speed prediction by recursive forecasting, the proposed three models of LCWOA-ELM outperform the other models for all the four datasets as the RMSE is the least.
2. LCWOA-P-ELM model provides greater prediction accuracy for datasets 1 and 2, whereas LCWOA-L-ELM and LCWOA-S-ELM, respectively, provide superior results for datasets 3 and 4.
3. Experimental results affirm the fact that incorporating improved versions of WOA in optimizing ELM modelling clearly improves the prediction capability of model in recursive forecasting.

5. Conclusion

In this paper, a hybrid Lévy Flight Chaotic Whale Optimized ELM is suggested for wind speed forecasting. The suggested hybrid model employs Lévy flight Chaotic Whale Optimization algorithm (LCWOA) to prune the ELM model parameters. The performance of the proposed model is thoroughly assessed using various statistical error metrics. The prediction capability of the proposed model is validated with nine other existing benchmark models and results prove the efficacy of the suggested model and affirms the fact that performance of WOA can be improved by incorporating Chaotic maps and Lévy flight in the algorithm. To check the robustness of the proposed model over unseen data, recursive multi-step ahead forecasting is also analyzed, and results clearly prove its efficiency.

The following are the drawbacks of the suggested model for predicting the wind speed that can be thought as potential future research paths.

1. The proposed work concentrates on univariate wind speed forecasting model. In the future, correlated features like pressure, temperature, humidity, wind direction etc. Can also be incorporated as the input features to develop and evaluate multivariate ELM models.
2. It is also recommended that usage of hybrid data decomposition techniques can significantly improve the accuracy of the proposed model. In the future, the effectiveness of such models can also be investigated.
3. To further improve the prediction accuracy, a suitable error correction algorithm can be devised to post process the errors and the efficacy of the proposed model with error correction can be analyzed in future.

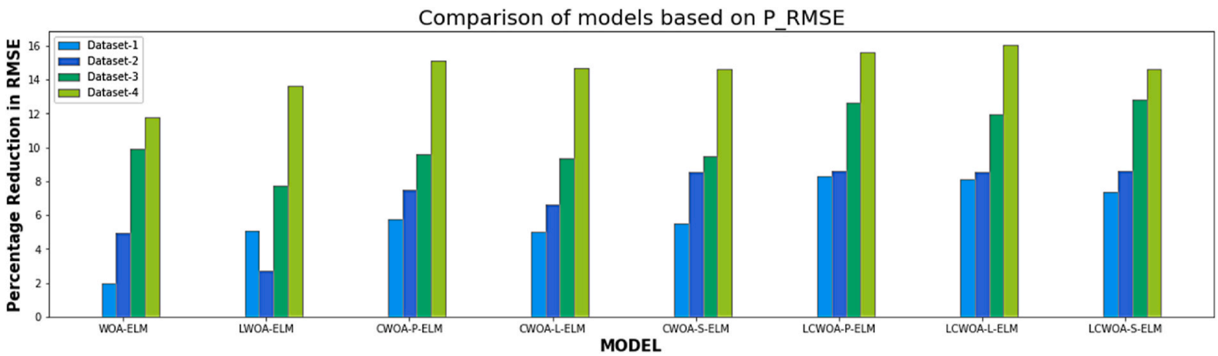

Fig. 17. Comparison of models based on P_RMSE

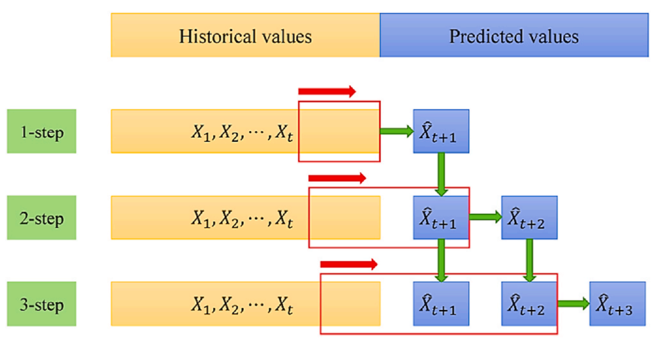

Fig. 18. Recursive forecasting mechanism.

Table 14
RMSE(m/s) of 24-h ahead wind speed prediction by recursive Forecasting for different models.

	WOA-SVR	WOA-LSTM	WOA-GRU	ELM	WOA-ELM	LWOA-ELM	CWOA-P-ELM	CWOA-L-ELM	CWOA-S-ELM	LCWOA-P-ELM	LCWOA-L-ELM	LCWOA-S-ELM
	RMSE(m/s)											
Dataset-1	1.03701	1.02671	1.04197	1.25259	1.19064	0.90626	1.16274	1.05818	0.92100	**0.71065**	0.84482	0.91487
Dataset-2	0.47470	0.94374	2.15489	0.51993	0.41966	0.42869	0.43034	0.42951	0.42494	**0.42766**	0.42912	0.42868
Dataset-3	1.84138	1.63572	2.01947	0.92431	0.78222	0.67898	0.84186	0.65008	0.84186	0.66941	**0.56994**	0.71951
Dataset-4	0.52564	1.26887	1.36137	0.57181	0.87579	0.83984	0.91073	0.88845	0.87443	0.8738	0.85427	**0.71078**

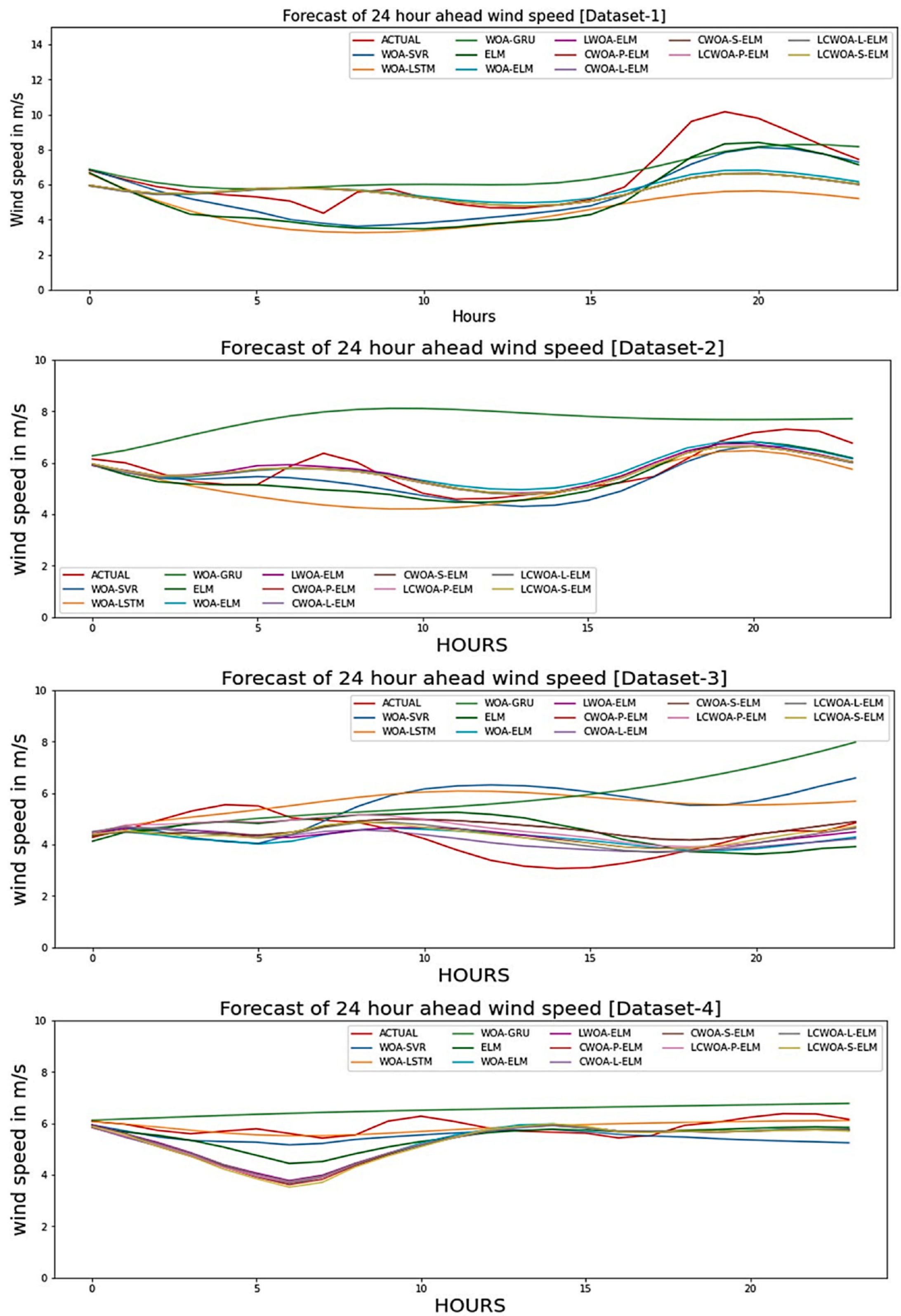

Fig. 19. One-day ahead hourly average wind speed forecast by Recursive Forecasting.

Credit author statement

Syama S- Conceptualization, Visualization, Methodology, Data curation, Software, Investigation, Validation, Writing – original draft. J Ramprabhakar: Conceptualization, Supervision, Writing – review & editing. Anand R: Supervision, Writing – review & editing. Josep M. Guerrero: Supervision, Writing – review & editing.

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

Data will be made available on request.

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References

[1] GWEC, Global Wind Report, 2022. April 4th.
[2] Z. Gao, et al., An overview on development of wind power generation, in: 2016 Chinese Control and Decision Conference (CCDC), 2016, pp. 435–439.
[3] Y. Zuo, H. Liu, Evaluation on comprehensive benefit of wind power generation and utilization of wind energy, in: 2012 IEEE International Conference on Computer Science and Automation Engineering, 2012, pp. 635–638.
[4] C.A. Nicksson, de Freitas wind speed forecasting: a review, Int. J. Eng. Res. Afr. 8 (1) (2017) 4–8.
[5] E. Pelikan, K. Eben, J. Resler, P. Juruš, P. Krč, M. Brabec, T. Brabec, P. May, Wind power forecasting by an empirical model using NWP outputs, in: Environment and Electrical Engineering (EEEIC), 2010, 9th International Conference on, 2010, pp. 45–48.
[6] K. Eben Pelikan, J. Resler, P. Juruš, P. Krč, M. Brabec, T. Brabec, P. May, Wind power forecasting by an empirical model using NWP outputs, in: 2010, 9th International Conference on Environment and Electrical Engineering (EEEIC, 2010, pp. 45–48.
[7] E. Erdem, J. Shi, ARMA based approaches for forecasting the tuple of wind speed and direction, Appl. Energy 88 (4) (2011) 1405–1414.
[8] U. Schlink, G. Tetzlaff, Wind speed forecasting from 1 to 30 minutes, Theor. Appl. Climatol. 60 (1–4) (1998) 191–198.
[9] M. Lydia, S.S. Kumar, A.I. Selvakumar, G.E.P. Kumar, Linear and non-linear autoregressive models for short-term wind speed forecasting, Energy Convers. Manag. 112 (2016) 115–124.
[10] P. Gomes, R. Castro, Wind speed and wind power forecasting using statistical models: autoregressive moving average (ARMA) and artificial neural networks (ANN), International Journal of Sustainable Energy Development 1 (2012).
[11] K.R. Nair, V. Vanitha, M. Jisma, Forecasting of wind speed using ANN, ARIMA and Hybrid models, in: 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), 2017, pp. 170–175.
[12] K. Sireesha Kiranvishnu, J. Ramprabhakar, in: Comparative Study of Wind Speed Forecasting Techniques, 2016 Biennial International Conference on Power and Energy Systems: towards Sustainable Energy (PESTSE), 2016, pp. 1–6.
[13] G.H. Guo, J. Wu, H.Y. Lu, J.Z. Wang, A case study on a hybrid wind speed forecasting method using BP neural network, Knowl. Base Syst. 24 (7) (2011) 1048–1056.
[14] G. Li, J. Shi, On comparing three artificial neural networks for wind speed forecasting, Appl. Energy 87 (7) (2010) 2313–2320.
[15] G. Santamaría-Bonfil, A. Reyes-Ballesteros, Gershenson C Wind speed forecasting for wind farms: a method based on support vector regression, Renew. Energy 85 (2016) 790–809.
[16] Y. Fu, W. Hu, M. Tang, R. Yu, B. Liu, Multi-step ahead wind power forecasting based on recurrent neural networks, in: 2018 IEEE PES AsiaPacific Power and Energy Engineering Conference (APPEEC), 2018, pp. 217–222.
[17] T.G. Barbounis, J.B. Theocharis, M.C. Alexiadis, P.S. Dokopoulos, Long-term wind speed and power forecasting using local recurrent neural network models, IEEE Trans. Energy Convers. 21 (1) (2006) 273–284.
[18] M.A. Ehsan, A. Shahirinia, N. Zhang, T. Oladunni, in: Wind Speed Prediction and Visualization Using Long Short-Term Memory Networks (LSTM), 2020 10th International Conference on Information Science and Technology (ICIST), 2020, pp. 234–240. Bath, London, and Plymouth, UK.
[19] S. Syama, J. Ramprabhakar, in: Multistep Ahead Solar Irradiance and Wind Speed Forecasting Using Bayesian Optimized Long ShortTerm Memory," 7th International Conference on Communication and Electronics Systems, 2022, pp. 164–171, https://doi.org/10.1109/ICCES54183.2022.9835840. ICCES 2022 - Proc., no. Icces.
[20] V.B. Kumar, V.M. Nookesh, B.S. Saketh, S. Syama, J. Ramprabhakar, Wind speed prediction using deep learning-LSTM and GRU, in: 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), 2021, pp. 602–607, https://doi.org/10.1109/ICOSEC51865.2021.9591886. Trichy, India.
[21] G.B. Huang, Q.Y. Zhu, C.K. Siew, Extreme learning machine: a new learning scheme of feedforward neural networks, in: Proceedings of International Joint Conference on Neural Networks (IJCNN2004), 2004, pp. 985–990, vol 2, no 25–29.
[22] S. Ding, X. Xu, R. Nie, Extreme learning machine and its applications, Neural Comput. Appl. 25 (3–4) (2014) 549–556.
[23] Y. Wang, R. Zou, F. Liu, et al., A review of wind speed and wind power forecasting with deep neural networks, Appl. Energy 304 (2021), 117766.
[24] V. Nikolić, S. Motamedi, S. Shamshirband, D. Petković, S. Ch, M. Arif, Extreme learning machine approach for sensorless wind speed estimation, Mechatronics 34 (2016) 78–83.
[25] Y. Ren, Short-term wind power prediction based on extreme learning machine, in: 2021 International Conference on Digital Society and Intelligent Systems (DSInS), 2021, pp. 188–192.
[26] L. Wang, X. Li, Y. Bai, Short-term wind speed prediction using an extreme learning machine model with error correction, Energy Convers. Manag. 162 (2018) 239–250.
[27] Hui Liu, Xiwei Mi, Yanfei Li, Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM, Energy Convers. Manag. 159 (2018) 54–64. ISSN 0196-8904.
[28] M. Qi, H. Gao, L. Wang, Y. Xiang, L. Lv, J. Liu, Wind power interval forecasting based on adaptive decomposition and probabilistic regularized extreme learning machine, IET Renew. Power Gener. 14 (2020) 3181–3191.
[29] S.P. Mishra, Short-term forecasting of wind power generation using extreme learning machine and its variants, Int. J. Power Energy Convers. 8 (2017) 68–89.
[30] Jie Zhang, Wendong Xiao, Yanjiao Li, Sen Zhang, Residual compensation extreme learning machine for regression, Neurocomputing 311 (2018), https://doi.org/10.1016/j.neucom.2018.05.057.
[31] Non-iterative and fast deep learning: multilayer extreme learning machines, in: Jie Zhang, Yanjiao Li, Wendong Xiao, Zhiqiang Zhang, Zhang (Eds.), J. Franklin Inst. 357 (2020), https://doi.org/10.1016/j.jfranklin.2020.04.033.
[32] Jie Zhang, Yanjiao Li, Wendong Xiao, Zhiqiang Zhang, Robust extreme learning machine for modeling with unknown noise, J. Franklin Inst. 357 (14) (2020) 9885–9908, https://doi.org/10.1016/j.jfranklin.2020.06.027. ISSN 0016-0032.
[33] Qin-Yu Zhu, A.K. Qin, P.N. Suganthan, Guang-Bin Huang, Evolutionary extreme learning machine, Pattern Recogn. 38 (10) (2005) 1759–1763. ISSN 0031-3203.
[34] A. Li, X. Wei, Short-term wind speed forecasting based on PSO-ELM, in: C.T. Yang, Y. Pei, J.W. Chang (Eds.), Innovative Computing, Lecture Notes in Electrical Engineering, vol. 675, Springer, Singapore, 2020.
[35] Liye Xiao, Feng Qian, Wei Shao, Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm, Energy Convers. Manag. 143 (2017) 410–430. ISSN 0196-8904.
[36] Chunying Wu, Jianzhou Wang, Xuejun Chen, Pei Du, Wendong Yang, A novel hybrid system based on multi-objective optimization for wind speed forecasting, Renew. Energy 146 (2020) 149–165. ISSN 0960-1481.
[37] Seyedali Mirjalili, Andrew Lewis, The whale optimization algorithm, Adv. Eng. Software 95 (2016) 51–67, https://doi.org/10.1016/j.advengsoft.2016.01.008. ISSN 0965-9978.
[38] Hardi M. Mohammed, Shahla U. Umar, Tarik A. Rashid, A systematic and meta-analysis survey of whale optimization algorithm, Comput. Intell. Neurosci. 2019 (2019). Article ID 8718571, 25 pages.
[39] L. Lian, K. He, Ultra-short-term wind speed prediction based on variational mode decomposition and optimized extreme learning machine, Wind Eng. 46 (2) (2022) 556–571, https://doi.org/10.1177/0309524X211038547.
[40] X.L. Yin, L. Cheng, X. Wang, et al., Optimization for hydro-photovoltaic-wind power generation system based on modified version of multi-objective whale optimization algorithm, Energy Proc. 158 (2019) 6208–6216.
[41] W. Long, T.B. Wu, J.J. Jiao, et al., Refraction-learning-based whale optimization algorithm for high dimensional problems and parameter estimation of PV model, Eng. Appl. Artif. Intell. 89 (2020), 103457.
[42] G.J. Xiong, J. Zhang, D.Y. Shi, et al., Parameter extraction of solar photovoltaic models using an improved whale optimization algorithm, Energy Convers. Manag. 174 (2018) 388–405.
[43] M.H. Qais, H.M. Hasanien, S. Alghuwainem, Enhanced whale optimization algorithm for maximum power point tracking of variable-speed wind generators, Appl. Soft Comput. 86 (2020), 105937.
[44] G. Kaur, S. Arora, Chaotic whale optimization algorithm, Journal of Computational Design and Engineering 5 (3) (2018) 275–284.
[45] P. Yuan, C. Guo, Q. Zheng, J. Ding, Side lobe suppression with constraint for MIMO radar via chaotic whale optimization, Electron. Lett. 54 (5) (2018) 311–313.
[46] D. Oliva, M.A.E. Aziz, A.E. Hassanien, Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm, Appl. Energy 200 (2017) 141–154.
[47] D. Prasad, A. Mukherjee, V. Mukherjee, Transient Stability Constrained Optimal Power Flow Using Chaotic Whale Optimization Algorithm, Handbook of Neural Computation, 2017, pp. 311–332.

[48] G.I. Sayed, A. Darwish, A.E. Hassanien, A new chaotic whale optimization algorithm for features selection, J. Classif. 35 (2018) 300–344.
[49] Yintong Li, Tong Han, Bangjie Han, Hui Zhao, Zhenglei Wei, Whale optimization algorithm with chaos strategy and weight factor, J. Phys. Conf. 1213 (2019), 032004, https://doi.org/10.1088/1742-6596/1213/3/032004.
[50] Y. Ling, Y. Zhou, Q. Luo, Levy flight trajectory-based whale optimization algorithm for global optimization, IEEE Access 5 (2017) 6168–6186.
[51] Y. Sun, X. Wang, Y. Chen, Z. Liu, A modified whale optimization algorithm for large-scale global optimization problems, Expert Syst. Appl. 114 (December 2018) 563–577.
[52] X.S. Yang, D. Suash, Cuckoo search via Lévy flights, in: World Congress Nature Biologically Inspired Computer (NaBIC), IEEE Publication, New York, NY, USA, 2009, pp. 210–214.
[53] Anis Farhan Kamaruzaman, Azlan Mohd Zain, Suhaila Mohamed Yusuf, Amirmudin Udin, Lévy flight algorithm for optimization problems - a literature review, Appl. Mech. Mater. 421 (September 2013) 496–501.
[54] C.T. Brown, L.S. Liebovitch, R. Glendon, Lévy flights in Dobe Ju/'hoansi Foraging patterns, Hum. Ecol. 35 (1) (Dec. 2007) 129–138.
[55] I. Pavlyukevich, Lévy flights, non-local search and simulated annealing, J. Comput. Phys. 226 (2) (Oct. 2007) 1830–1844.
[56] I. Pavlyukevich, Cooling down Lévy flights, J. Phys. Math. Theor. 40 (41) (Sep. 2007), 12299.
[57] A.M. Reynolds, M.A. Frye, Free-flight odor tracking in Drosophila is consistent with an optimal intermittent scale-free search, PLoS One 2 (4) (Apr. 2007) e354.
[58] P. Barthelemy, J. Bertolotti, D.S. Wiersma, A Lévy flight for light, Nature 453 (7194) (May 2008) 495–498.