A Hybrid ANN for Airfoil Self-Noise Prediction using Hyperbolic Secant and Levy Flights based Grey Wolf Optimization

Submitted in partial fulfilment of the requirements

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by

Nithish Krishna Shreenevasan (207151)

Narappa Reddy Yaswanth Reddy (207149)

Rahul Kumar Singh (207158)

Supervisor:

Dr. Sujit Das

Department of Computer Science and Engineering

NIT Warangal

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Nithish Krishna Shreenevasan
Roll No - 207151
Date:

Narappa Reddy Yaswanth Reddy
Roll No - 207149
Date:

Rahul Kumar Singh
Roll No - 207158
Date:

NATIONAL INSTITUTE OF TECHNOLOGY WARANGAL
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APPROVAL SHEET

This Project Work entitled **A Hybrid ANN for Airfoil Self-Noise Prediction using Hyperbolic Secant and Levy Flights based Grey Wolf Optimization**

by

Nithish Krishna Shreenevasan (207151), Narapp Reddy Yaswanth Reddy (207149), Rahul Kumar Singh (207158), is approved for the degree of Bachelor of Technology (B.Tech) in Computer Science and Engineering.

Examiners

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Supervisor

____

Dr. Sujit Das
Assistant Professor, Department of CSE

Chairman

____

Date: __________

Place: NIT Warangal

Declaration

We declare that this written submission represents our ideas, my supervisor's ideas in our own words and where others' ideas or words have been included, and we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Nithish Krishna Shreenevasan
Roll No - 207151
Date:

Narappa Reddy Yaswanth Reddy
Roll No - 207149
Date:

Rahul Kumar Singh
Roll No - 207158
Date:

Certificate

This is to certify that the Dissertation work entitled **A Hybrid ANN for Airfoil Self-Noise Prediction using Hyperbolic Secant and Levy Flights based Grey Wolf Optimization** is a bonafide record of work carried out by **Nithish Krishna Shreenevasan (207151), Narappa Reddy Yaswanth Reddy (207149), Rahul Kumar Singh (207158)**, submitted to the Dr. Sujit Das of Department of Computer Science and Engineering, in partial fulfilment of the requirements for the award of the degree of B.Tech at National Institute of Technology, Warangal during the 2023-2024.

(Signature)
Dr. R Padmavathy
Head of the Department
Department of CSE
NIT Warangal

(Signature)
Dr. Sujit Das
Assistant Professor
Department of CSE
NIT Warangal

Abstract

In sectors like aviation and energy, predicting airfoil noise is essential to minimizing environmental damage and guaranteeing regulatory compliance. This project focuses on developing an accurate predictive model for airfoil self-noise by optimizing an Artificial Neural Network (ANN) model with Hyperbolic Secant and Levy Flights Grey Wolf Optimization (HSLFGWO). Our model seeks to greatly improve forecast accuracy and support the creation of quieter and more ecologically friendly airfoil designs by combining cutting-edge modeling approaches and optimization algorithms. HSLFGWO employs a hyperbolic secant function for the acceleration coefficients and employs levy flights equation for mutation purposes to explore search space and enhance exploration and exploitation capabilities. Subsequently, HSLFGWO is integrated with ANN to optimize weights and minimize training error for accurate prediction. We evaluate the performance of the proposed HLFGWO-ANN model on UCI Airfoil Self-Noise dataset using error measures such as RMSE and MAE, and correlation coefficients such as R^2. The results demonstrate that the HLFGWO-ANN model outperforms existing models, exhibiting lower error rates and stronger correlations, thus offering a more efficient solution for predicting airfoil noise.

Keywords —- Artificial neural networks, Hyperbolic Secant Function, Levy Flights, Grey Wolf Optimization, Airfoil Noise

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Chapter 1

Introduction

1.1 Neural Networks

Inspired by the form and operation of biological neural networks seen in a human brain, a neural network, also known as an artificial neural network, neural net, or simply ANN, is a model. Artificial neurons, which are networked units or nodes that resemble coupled brain neurons, make up an ANN. These are linked together by edges that resemble brain synapses. After processing signals from other connected neurons, each artificial neuron transmits a signal to another connected neuron. Each neuron's output is determined by a non-linear function known as the activation function, which takes the total of its inputs into account [1].

1.1.1 Drawbacks of Gradient Descent

Gradient Descent is the most widely used optimization algorithm for ANNs. However it has its limitations. . Firstly, in high-dimensional or non-convex optimization landscapes, gradient descent may converge slowly or become trapped in local optima. Furthermore, it depends on a set learning rate, which, especially in noisy or dynamic situations, might result in sub-optimal convergence or instability. The selection of initialization and hyper parameters is crucial for gradient descent, necessitating meticulous adjustment to achieve the best results.

1.2 Meta Heuristic

A meta heuristic is a higher-level procedure used in machine learning or optimisation that is meant to find, generate, modify, or select a heuristic that might provide a feasible solution, especially in scenarios with limited computing power or incomplete or imperfect information. Since meta heuristics tend to make few assumptions about the optimisation problem that needs to be solved, they can be used in a variety of scenarios.

1.2.1 Grey Wolves Optimization

The Grey Wolf Optimizer (GWO) emulates the natural hunting strategy and leadership structure of grey wolves. Alpha, beta and delta are the three varieties of grey wolves that are used to model the leadership hierarchy. Furthermore, to carry out optimization, three primary phases are used: hunting, encircling prey, and attacking prey.

1.2.2 Hyperbolic and Levy Flights in GWO

GWO employs an acceleration coefficient a which is modelled using a linear equation. This limits the exploration capability of GWO. To improve GWO, the *sech* function is used to model a [2, 3]. Additionally, the solutions often get stuck in a local optima, hence levy flights technique is used to mutate the solutions which may produce better results [4].

1.3 Objectives

- Introducing HSLFGWO as an extension of GWO for the better searching capabilities.
- Hybridizing HSLFGWO with ANN, we propose an ANN-HSLFGWO model tailored for predicting airfoil self-noise characteristics and optimizing airfoil designs, particularly in high-risk operating conditions.
- This model aims to enhance the efficiency and accuracy of airfoil self-noise prediction and optimization, contributing to the development of quieter and more efficient airfoil systems across various industries.
- Demonstrate the consistency and robustness of the proposed model on NASA dataset.
- Comparative analysis of the proposed model with the existing models on various error measures such as RMSE, MSE, MAE, and correlation coefficients such as R^2

Chapter 2

Background

2.1 Overview

This section covers some basic ideas and their descriptions relevant with the proposed model such as ANN and Grey Wolf Optimization algorithm.

2.2 ANN

Artificial neural networks were initially conceptualized as mathematical models mirroring the information processing of biological nerve cells. Although ANN belong to a statistical framework, their structural elements are similar to those found in neuroscience. An artificial neural network (ANN) consists of one or more hidden layers [5], wherein neurons are linked together as units that process information. Adjustable weights connect these neurons, allowing signals to flow across the network both sequentially and parallelly [6]. Three layers typically make up an ANN: the input layer, which receives data; the hidden layer, which processes information internally and looks for patterns; and the output layer, which generates the network's final outputs. A representation of the ANN structure may be found in Fig. 2.1.

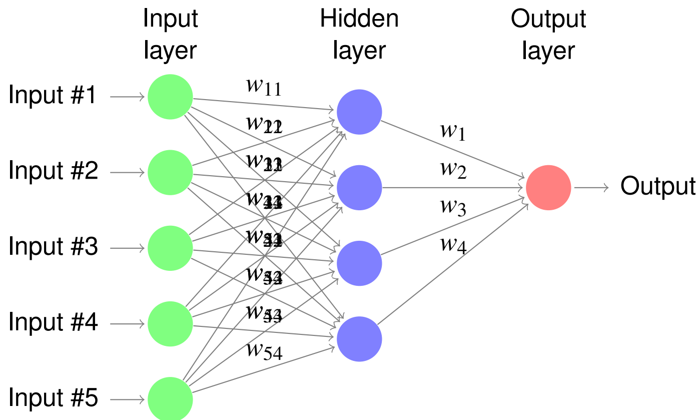

Figure 2.1: Structure of ANN

Kustrin [5] illustrated that ANN acquires knowledge by identifying patterns and relationships within data and refining their understanding through experience. They stress that in order to reduce prediction mistakes and reach an appropriate level of accuracy, ANNs learn by modifying the connections between their internal units. An ANN can include new data into its model after it has been trained and tested. The generalised delta rule, often known as backpropagation, is the training method that an artificial neural network uses to learn from data. An ANN is trained by a number of iterative steps in the process. Single-case data is initially supplied into the input layer, which multiplies the output by the original set of connection weights before forwarding it to the hidden layer. The input signals are then combined and processed to create outputs, which are sent to the second connection weight matrix. The network output is ultimately produced by further aggregating, transforming, and processing the incoming data. At this point, the error term is propagated backwards through the network by computing the difference between the output value and the known value for each occurrence. Performance optimisation of the network is ensured by adjusting connection weights based on their contribution to the error. The following iteration's updated connection weights are then saved, and the case input set is queued up for processing.

The training procedure of an ANN with backpropagation for minimizing the RMSE typically involves several key steps.

Initialization of weights: Initially, the network's weights and biases are randomly initialized. Let w_{ij} denote the weight connecting the i_{th} input node to the j_{th} hidden layer node.

Calculation of Weighted Sum with Bias: For each hidden layer node j, the weighted sum of inputs is computed by multiplying each input node value x_i by its corresponding weight w_{ij}, and then adding a bias term b_j. This can be expressed mathematically as shown in Eq. 2.1:

$$Z_j = \sum_{1=1}^{N} (x_i * w_{ij}) + b_j \tag{2.1}$$

where N is the number of input nodes.

Rectified Linear Unit (ReLU) activation function: The ReLU activation function is applied to the weighted sum z_j to introduce non-linearity into the network and allow the model to learn complex patterns. It replaces all negative values of z with zero and keeps positive values unchanged. The ReLU function is defined as shown in Eq. 2.2:

$$f(z) = max(0, z) \tag{2.2}$$

Passing to Hidden Layer: Upon determining the ReLU activation for every node in the hidden layer, the obtained values are supplied as inputs to the subsequent layer, which could be either the output layer or another hidden layer. Until the output layer is reached, the procedure is repeated.

Prediction: In the output layer, the same process of weighted sum calculation, activation function application, and passing to the next layer is repeated. Finally, the output layer produces the predicted values based on the learned weights and activation functions.

Error Calculation: The predicted output is compared to the actual target values to compute the error. This error is typically measured using a loss or cost function such as RMSE or Cross-Entropy Loss.

$$RMSE \ = \ \sqrt{\frac{1}{n}\sum_{1=1}^{n}(o_i - o_i')^2} \tag{2.3}$$

where n is the number of samples in the dataset, o_i is the actual value and o_i' is the predicted value.

Back Propagation: It is the procedure for adjusting the network's weights to reduce error. This entails calculating the loss function's gradients about each weight and modifying the weights to reduce error.

Iterative Training: The entire process of forward propagation, error calculation, and backpropagation is repeated iteratively over multiple epochs until the network converges to a set of weights that minimize the error on the training data.

By iteratively adjusting the weights based on the observed errors, the neural network learns to make more accurate predictions over time, which can effectively capture the underlying patterns and relationships in the data. Lastly, a different test set is used to gauge how well the trained model generalizes. A study discussing the use of ANNs in decision support systems emphasizes the crucial role of data structure, quality, and quantity in the learning process. The attributes chosen for training must be comprehensive, relevant, measurable, and independent. In ANN, weight optimization plays a critical role in ensuring effective decision-making. The weights assigned to connections between neurons determine how input data is processed throughout the network. Optimizing these weights is essential for enhancing the network's ability to capture relationships in the data, ultimately leading to more accurate predictions and decisions. By adjusting the weights based on training data, the ANN can learn to generalize from the provided examples and make informed decisions, which can significantly influence the network's decision-making capabilities and predictive accuracy.

2.3 Grey Wolf Optimization

The hierarchical organisation of GWO [7] is categorized with three distinct groups such as alpha (α), beta (β), and delta (δ). The α wolf is responsible for pivotal decision-making within the group whereas the β wolf aids the α wolf in informed choices such as hunting strategies or selecting habitats. The δ wolf is tasked with surveillance, protection, and provisioning, and omega wolves are guided by the three leader wolves to seek global optima.

The collaborative hunting behaviour of grey wolves typically unfolds in three stages: tracking and reaching the target prey, surrounding it, and initiating an attack [8]. Following a thorough examination of grey wolf group dynamics, it is concluded that within a given swarm, the top three solutions with the best fitness values are designated as the leader wolves, while the remaining individuals function as omega wolves, which gradually refine their positions under the guidance of the top three individuals.

The GWO algorithm focuses on three behaviours: encirclement behaviour, hunting behaviour, and attack behaviour.
Below are the steps of the GWO algorithm:

1. Initialize the population and parameters such as maximum iterations T, population size N, population dimension dim, convergence factor a, and the coefficient vectors A and C.
2. Determine each wolf's fitness by computing the optimization problem's fitness function using Eqn (2.3).
3. Find the three wolves X_α, X_β, X_δ with best fitness values.
4. The next position of grey wolf i is denoted as X_{i+1}. The distance between grey wolf α and prey is D_α. The positions of the individual populations are updated according to Eqns. (2.4) – (2.6).

$$\begin{aligned} D_\alpha &= |C_1 * X_\alpha - X| \\ D_\beta &= |C_2 * X_\beta - X| \\ D_\delta &= |C_3 * X_\delta - X| \end{aligned} \tag{2.4}$$

$$\begin{aligned} X_1 &= X_\alpha - A * D_\alpha \\ X_2 &= X_\beta - A * D_\beta \\ X_3 &= X_\delta - A * D_\delta \end{aligned} \tag{2.5}$$

$$X(t+1) = \frac{(X_1 + X_2 + X_3)}{3} \tag{2.6}$$

5. Compute a, A, and C parameters using Eq. (2.7).

$$\begin{aligned} A &= 2a * r_1 - a \\ C &= 2 * r_2 \\ a &= 2 * (1 - t/T) \end{aligned} \tag{2.7}$$

6. Here, t is the current iteration, X is the wolf's current location, D is the distance between the wolves and the prey, r_1 and r_2 are random values between [0, 1], and a $\in$ [0, 2].

7. Determine each grey wolf's fitness and update the positions of the α, δ and δ wolves.

8. Repeat steps 3-7 till the terminal conditions are met. Then, output the α wolf and its fitness as the result.

.

Chapter 3

Related Work

3.1 Predicting airfoil self-noise with DNN

This work mainly investigates the relationship between prediction accuracy and error rates and neural network architecture. Stephane et al. [1] extensively employed the NASA dataset, which consists of 1503 entries with 5 independent characteristics and 1 dependent feature, to investigate various neural network architecture configurations. They systematically change the number of units in each layer and the depth of the network in an attempt to determine the relationship between architecture complexity and prediction performance. Amazingly, their results show a strong trend: the prediction error decreases with increasing neural network units and layers. This realization emphasizes how crucial network width and depth are to identifying the complex relationships present in the dataset and enhancing prediction accuracy.

3.2 Enhanced GWO algorithm for best truss structure design

This paper [3] proposed using exponentially decreasing functions to represent parameters a_α, a_β and a_δ, each of which are acceleration coefficients. a_α and a_δ are computed for each iteration using the exponentially decreasing equation. The equation uses parameters a_{max} and a_{min} which are dynamically assigned based on the problem statement that the algorithm is trying to optimize. a_β is simply taken as the average of previously computed a_α and a_δ values. This scheme significantly enhances the exploration and exploitation capabilities of classic GWO and the proposed model proves the same by outperforming other GWO variants in commonly used benchmark functions.

3.3 Mutation driven Grey Wolf Optimizer

This paper proposed a model for combining levy flights with the search mechanism of GWO and was tested on 23 well-known benchmark functions [4]. The proposed model additionally used a randomized equation for aggregating the intermediate values obtained in classic GWO i.e., X_1, X_2 and X_3. Levy flights enable the population to mutate themselves and free themselves from the local optima trap thus delivering better results. The proposed model surpassed all other GWO variants in terms of performance and error values.

3.4 Electrical power prediction using hybrid ANN models optimized by WCA, SBO and ALO

This paper performed a comparative analysis of predicting the electrical power generated using models such as ANN-WCA, ANN-SBO and ANN-ALO [9]. ALO performs lesser computations and hence can be used with ANN if time efficiency is required. In terms of prediction capabilities, WCA worked better with ANN than SBO and ALO. The tests were conducted on the Combined Cycle Power Plant dataset with 9568 instances, with 4 independent features and 1 dependent variable.

Chapter 4

Proposed Solution

4.1 Overview

For improved decision-making abilities in practical applications, we suggest a decision-making model in this part that is based on HSLFGWO and ANN. The HSLFGWO operating principle is explained in Subsection 4.2, and the suggested HSLFGWO-based ANN model is shown in Subsection 4.3.

4.2 Hyperbolic Secant and Levy Flights based Grey wolf optimization (HSLFGWO)

In the proposed HSLFGWO framework, we introduce a refined method for determining the convergence factor and acceleration coefficients within the GWO algorithm. To get the ideal parameter sets, these parameters are crucial in improving the search space's capacity for exploration and exploitation. To enhance the adaptability and effectiveness of GWO, we advocate for the integration of hyperbolic equations in the parameters. Traditionally, these parameters control the rate at which wolves update their positions in the search space during optimization. By utilizing the hyperbolic secant function, we introduce a hybrid mechanism that enhances the exploration and exploitation based on the evolving dynamics of the optimization landscape. This approach allows the algorithm to adapt its behaviour to the changing features of the problem space, ultimately improving convergence speed and solution quality. Specifically, we define the convergence rates a_α, a_β, and a_δ using hyperbolic equations as shown in Eq.(3.1), which capture the intricate relationships inherently in optimization landscapes. The acceleration coefficients A_α, A_β, A_δ, and C_α, C_β, C_δ are shown in Eqns. (4.2) - (4.3).

$$
\begin{aligned}
a_\alpha &= sech\left(3 * \frac{t}{Maxiter}\right)^2 \\
a_\delta &= sech\left(2 * \frac{t}{Maxiter}\right)^2 \\
a_\beta &= (a_\alpha + a_\delta) * (0.5)
\end{aligned}
\tag{4.1}
$$

$$
\begin{aligned}
A_\alpha &= 2 * a_\alpha * r_1 - a_\alpha \\
A_\beta &= 2 * a_\beta * r_1 - a_\beta \\
A_\delta &= 2 * a_\delta * r_1 - a_\delta
\end{aligned}
\tag{4.2}
$$

$$
\begin{aligned}
C_\alpha &= 2 * r_2 \\
C_\beta &= 2 * r_2 \\
C_\delta &= 2 * r_2
\end{aligned}
\tag{4.3}
$$

where t represents the current iteration number and $Maxiter$ is the total number of iterations. The hyperbolic function $sech\,(x)$ is defined as

$$
sech\,(x) = \frac{2}{e^x + e^{-x}}
$$

Additionally, Levy Flights technique is integrated into GWO which is distinguished by long, irregular jumps, providing a stochastic mechanism for exploration that supplements GWO's exploitation capabilities. GWO's capacity to escape local optima and explore attractive portions of the search space is improved by including Levy flights. Because of its integration, the algorithm is more resilient and flexible, which makes it appropriate for a variety of optimization problems. Levy flights' intrinsic randomness adds diversity to the search by encouraging the investigation of unexplored territory and averting early convergence. Specifically, we define the mutation operation using the following equations,

$$
\begin{aligned}
X_{new} &= X_{best} + N(0, 1, dim) * (X_{best} - X) \\
X_{new} &= X_{best} + 0.05 * Levy(\theta, dim) * (X_{best} - X)
\end{aligned}
$$

where $Levy(\theta, dim)$ is the function that generates Levy flight distributed random numbers. Mathematically it can written as,

$$Levy(\theta, dim) = \frac{u}{|v|^{\frac{1}{\theta}}}$$

The parameters u and v are determined as follows, and they have normal distributions. $u = N(0, \sigma u^2), v = N(0, \sigma v^2)$. The following equations describe. σ_u and σ_v.,

$$\sigma_u = \left(\frac{\Gamma(1+\theta) * \sin(\pi\theta/2)}{\Gamma[(1+\theta)/2] * \theta * 2^(\theta-1)/2} \right)$$

$$\sigma_v = 1$$

By incorporating hyperbolic secant functions into the determination of acceleration coefficients and by incorporating levy flights equations for mutating the population we aim to provide an enhanced GWO with a more adaptive and efficient mechanism for exploring and exploiting the search space. This adaptive strategy enables the algorithm to dynamically adjust its behaviour, leading to improved convergence and solution quality across a wide range of optimization tasks.

Following are the steps that make up the HSLFGWO algorithm:

1. Initialization of parameters: maximum number of iterations $Maxiter$, population size N, population dimension dim, randomly initialize r_1 and r_2.
2. Determine each wolf's fitness by computing the optimization problem's fitness function.
3. Find the three wolves $X_\alpha, X_\beta, X_\delta$ with best fitness values using Eqn (2.3).
4. Compute the convergence factor a_α, a_β, and a_δ according to Eqn. (4.1).
5. Compute coefficient vectors A and C as A_α, A_β, A_δ, and C_α, C_β, C_δ as shown in Eqns. (4.2)-(4.3)
6. Calculate the Distance ($D_{\alpha,\beta,\delta}$) between wolf and prey using Eqn (4.4).

$$\begin{aligned} D_\alpha &= |C_\alpha * X_\alpha - X| \\ D_\beta &= |C_\beta * X_\beta - X| \\ D_\delta &= |C_\delta * X_\delta - X| \end{aligned} \tag{4.4}$$

7. The updated position of the wolves are computed using Eqn. (4.5 - 4.6)

$$\begin{aligned} X_1 &= X_\alpha - A_\alpha * D_\alpha \\ X_2 &= X_\beta - A_\beta * D_\beta \\ X_3 &= X_\delta - A_\delta * D_\delta \end{aligned} \tag{4.5}$$

$$X(t+1) = \frac{(X_1 + X_2 + X_3)}{3} \tag{4.6}$$

8. Find the fitness of the updated wolves and replace if it is better.
9. Generate a random number r. If r is less than 0.5, then get the mutated solution using Eqn. (4.6)

$$X_{new} = X_{best} + N(0,1,dim) * (X_{best} - X) \tag{4.7}$$

10. Else, get the mutated solution using Eqn. (4.7)

$$X_{new} = X_{best} + 0.05 * Levy(\theta, dim) * (X_{best} - X) \tag{4.8}$$

11. Find the fitness of the mutated wolves and replace if it is better.

12. Repeat steps 3-11 till the terminal conditions are met. Then, output the α wolf and its fitness as the result.

4.3 Proposed HSLFGWO based ANN model

This section describes the working principle of the proposed HSLFGWO-ANN, which follows a structured approach to optimize the coefficient parameters of the ANN model based on HSLFGWO [10, 11]. It allows the proposed model to capture complex patterns and relationships within the data, which enhances the predictive capabilities. Initially, the input data is preprocessed and divided into training and testing data with a split of 70% and 30% respectively.The training dataset consisting of input variables is fed into the ANN model. Each input variable is processed through the ANN layers, which include input, hidden, and output layers.

Initially, the first layer receives single-case data as input. The outputs of this layer are then sent to the hidden layer and multiplied by the initial connection weights. Subsequently, the incoming signals undergo transformation, summing, and passing before reaching the second connection weight matrix. After that, the network uses these altered signals to generate an output. This error is then propagated backward through the network using HSLFGWO based on the RMSE cost function. Next, the predicted value is compared to the actual value for error evaluation. To improve the performance of the model, the connection weights are changed in proportion to how much of an error they cause. In order to ensure that the learning process is continuously improved, the next set of input data is queued and the adjusted connection weights are preserved for the subsequent cycle. Since we are tackling a regression problem, the number of nodes in the output layer corresponds to the number of variables to be predicted, which in our instance is 1.

The process of optimization starts after the ANN model is initialized. To optimize the weights and biases of the ANN model in this hybrid approach, the HSLFGWO algorithm is utilized. Utilizing the hyperbolic secant function in conjunction with the hierarchical leadership and hunting behavior of grey wolves, the HSLFGWO algorithm effectively explores and exploits the search space. The HSLFGWO algorithm seeks to determine the ideal weights of the ANN model that minimize the error between the predicted and actual values by iteratively changing the positions of search agents (wolves). Until the termination criteria—typically defined by convergence or a maximum number of iterations—are satisfied, the optimization process iterates. The ANN model is then run on the testing dataset to produce predictions after the ideal weights have been determined.

To assess the model's accuracy and predictive power, some error metrics are used, including mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). In addition, correlation coefficients like R^2 are calculated to evaluate the associations between variables. The suggested HSLFGWO-based ANN model provides a thorough framework for airfoil self-noise prediction.

4.3.1 Pseudo Code

Algorithm 1 : The proposed HSLFGWO-based ANN model

Input: *Population* (N)*, random parameters* (r_1, r_2)*, Maximum iterations* $(maxiter)$*, Population dimension* (dim)

Output: *Optimal parameters* $(weights)$

Begin
Divide the dataset into training and testing subsets after pre- processing
Training phase
Generate initial population with a size of dim and find fitness function (RMSE)
Compute the fitness values of the initial individuals using Eqn. (1)
    For $k = 1 \rightarrow maxiter$ do
        Identify the leader wolves (X_α, X_β, and X_δ) based on the top three fitness values
        Compute the convergence factors a_α, a_β, and a_δ using Eqn. (8)
        For $i = 1 \rightarrow N$ do
            Compute coefficient vectors (A_α, A_β, A_δ), and (C_α, C_β, C_δ) using Eqns.(9)-(10)
            Calculate the distances (D_α, D_β, D_δ) using Eqn.(11)
            Update the positions of the wolves using Eqn. (12)
            Find the fitness of the updated wolves and replace if RMSE is better
            Generate a random number r.
            If r is less than 0.5, then calculate the mutated wolf using Eqn. (13)
            Else calculate the mutated wolf using Eqn. (14)
            Compare and pick the wolf with better fitness.
        End For
    End For
Returns optimal weights as the global optimal parameter set.
Testing phase:
Compute the predicted values of testing data using obtained optimal weights
Evaluate the performance measures
End

Chapter 5

Experimentation and Discussion

5.1 Comparative Analysis

This section presents a real-life case study focusing on airfoil self-noise prediction using the proposed HSLFGWO-ANN model. The model's applicability and performance are evaluated using a comprehensive dataset of airfoil flow simulations, and its effectiveness in accurately predicting airfoil self-noise characteristics is assessed. To confirm the HSLFGWO-ANN model's accuracy and resilience in forecasting the scaled sound pressure level, its performance is also contrasted with that of other ML models.

5.1.1 Error values and graphs

This case study focuses on the selection of optimal airfoil designs for noise reduction in high-risk operating conditions, aiming to identify airfoil configurations with the most effective noise mitigation capabilities among a set of 1503 candidate designs. The objective is to minimize airfoil self-noise in critical operating scenarios, thereby enhancing safety and performance in aerospace applications.

The evaluation takes into account the following input variables: chord length, free stream velocity, frequency, angle of attack, and suction side displacement thickness. The output variable is the scaled sound pressure level. The objective is to predict the scaled sound pressure level for various airfoil designs effectively to minimize noise pollution in various applications.

Table 5.1: Description of variables in airfoil dataset

Variables	**Description**
Frequency	Measured in Hertz
Angle of Attack	Measured in degrees.
Chord Length	Measured in meters
Free Stream Velocity	Measured in meters per second
Suction side displacement thickness	Measured in meters
Scaled Sound Pressure	Measured in decibels

Table 5.1 describes the input and output variables concerned with the airfoil dataset. We aim to mitigate the risk of noise-related issues and enhance operational efficiency in airfoil systems, contributing to safer and more sustainable technological advancements. We update the parameters based on a combination of the a_α, a_β and a_δ until we obtain the optimal weights. The graphical representation of acceleration coefficients A_α, A_β and A_δ with the declination of functional values with the number of iterations are shown in Fig. 5.1.

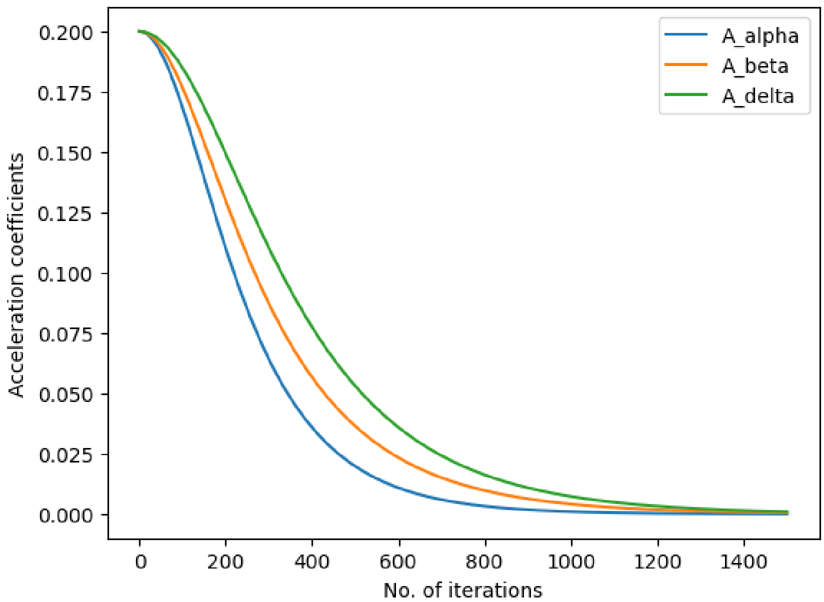

Figure 5.1: Behaviour of acceleration coefficients of HSLFGWO

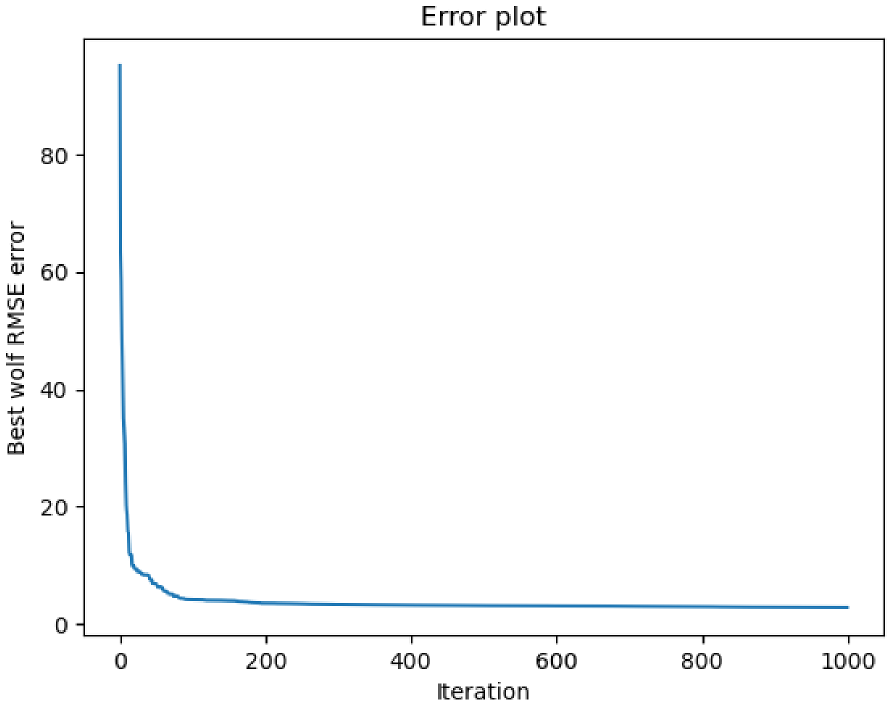

Figure 5.2: Convergence curve of RMSE

Subsequently, the ANN-HSLFGWO model gives the optimal RMSE values over the number of iterations as graphically shown in Fig. 5.2. The HSLFGWO exhibits its performance in minimizing the RMSE and MAE due to the progressive decreasing values of the hyperbolic secant functional values observed in the convergence factor and acceleration coefficients to obtain the optimal weights in the training phase.

The test data takes the optimal parameters returned by the HSLFGWO-based ANN model, i.e., the α wolf from the training phase and tests the model to obtain the predicted values for test data. The form of the α wolf solution is converted back to the shape of the neural network architecture and all the metrics are computed.

The full dataset is split into training and testing sets, with 70% and 30% of the dataset going to each set. According to the results, the proposed HSLFGWO-ANN model outperformed the other comparable models consistently when it came to correlation coefficients like R^2 and error measures like RMSE, MSE, and MAE.

Table 5.2: Comparison of HSLFGWO-ANN model with existing models

Model	**RMSE**		**MSE**		**MAE**		R^2 **coefficient**	
	Tr_data	Te_data	Tr_data	Te_data	Tr_data	Te_data	Tr_data	Te_data
ANN [1]	2.64	2.73	6.99	7.50	2	2.07	0.85	0.84
ANN-SBO [12]	6.26	6.97	39.27	48.61	4.92	5.53	0.17	-0.02
ANN-GWO [13]	5.25	5.53	27.68	30.62	4.22	4.28	0.42	0.32
ANN-HSGWO	4.06	4.11	16.56	16.93	3.06	3.028	0.648	0.65
Proposed ANN-HSLFGWO model	**2.83**	**2.71**	**8.01**	**7.37**	**2.22**	**2.165**	**0.826**	**0.8603**

The proposed HSLFGWO-ANN model achieved significantly lower error values with 2.83 and 2.71 for the training and testing data for RMSE, which is a low error compared to the existing models as shown in Table 5.2. In the same way, MAE errors for the training and testing data were 2.22 and 2.165, respectively, lower than that of the current models. The proposed model has shown its consistent performance in achieving low error rates and effectively predicting the target variables compared to the existing baseline models.

Chapter 6

Conclusion

In summary, this research has investigated the issue of airfoil self-noise prediction and has developed a novel hybrid artificial neural network (ANN) model that is augmented by Levy Flights-based Grey Wolf Optimization (HSLFGWO) method and Hyperbolic Secant (HS) activation functions. The impact of airfoil self-noise on environmental sustainability, operational efficiency, and regulatory compliance was emphasized, along with its significance in a number of industries, including aviation, energy, and civil engineering. We have shown through thorough testing and analysis that our suggested method is successful in precisely forecasting the characteristics of airfoil self-noise.

Through the application of sophisticated machine learning algorithms and meta-heuristic optimization methods, our hybrid model outperformed conventional approaches in terms of prediction accuracy, efficiency, and robustness. We were able to better capture complicated nonlinear interactions in the data by integrating improved GWO with the ANN model, which improved the representational power and generalization performance of the model. Furthermore, effective search space exploration was made possible by the inclusion of Levy Flights-based Grey Wolf Optimization, which made it easier to find ideal solutions and go past local optima.

Our findings provide a promising way to create more ecologically friendly and quieter airfoil designs, and they have important implications for the design and optimization of airfoil systems. Our suggested model helps minimize noise pollution in a variety of applications, such as wind turbines, hydrodynamic structures, and aeroplanes, by precisely forecasting the self-noise characteristics of airfoils. It can also help with design choices and performance parameter optimization.

Future research directions could involve validating the model's performance across a range of airfoil geometries and operating conditions, investigating other machine learning methods and optimization methodologies, and further optimizing and refining the suggested model.

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