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A novel approach for noise prediction using Neural network trained with an efficient optimization technique

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Abstract. Aerofoil noise as self-noise is detrimental to system performance, in this paper NACA 0012 optimization parameters are presented for reduction in noise. Designing an aerofoil with little noise is a fundamental objective of designing an aircraft that physically and functionally meets the requirements. Aerofoil self-noise is the noise created by aerofoils interacting with their boundary layers. Using neural networks, the suggested method predicts aerofoil self-noise. For parameter optimization, the quasi-Newtonian method is utilised. The input variables, such as angle of attack and chord length, are used as training parameters for neural networks. The output of a neural network is the sound pressure level, and the Quasi Newton method further optimises these parameters. When compared to the results of regression analysis, the values produced after training a neural network are enhanced.

Keywords: Aerofoil self-noise / noise prediction / neural network training / optimization / quasi Newton method

1 Introduction

In aerodynamics, the cross-sectional shape of an airplane blade, wing, or sail is referred to as an aerofoil. The flow of fluid across an aerofoil shape creates an aerodynamic force. This force is characterised by two components. Lift is the section that is not in the same direction as the movement. The drag component runs in the same direction as the motion. An aerofoil, which is both a wing and a propeller blade, propels an aircraft forward. The first thing that needs to be designed for an aeroplane or even a car is its wings or propeller blades [1,2]. A number of parameters must be considered for their design. The prominent parameters that are considered while designing the wings are D ("Drag"), L ("lift"), AoA ("angle of attack"), Mach number, CL ("Coefficient of lift") and so forth. The parameters considered in the design of the blade are L ("lift"), D ("drag"), flow rate, pressure difference, p ("power generated"), efficiency, AoA ("angle of attack"), etc. Once the design parameters for an efficient geometry is are chosen, a suitable aerofoil to fulfil all requirements must be determined [3,4]. The body of an aerofoil generates self-noise on its own. A motor plane's self-noise is generated when the trailing edge of the blades interacts with turbulence in its boundary layer. The noise generated by the aerofoil affects blade performance and increases flutter in a wing, affecting the integrity of the system. Aerofoil self-noise has to be predicted prior to designing a blade or wing to avoid performance affecting behavior of the design [5]. As there are no standard methods to predict the input and output parameter related to the noise, the prediction of the same needs a learning method [6]. Learning methods based on the neural network are used in the present experiment to model input parameters and output. An aerofoil self-noise was predicted using neural network model and optimised using the Quasi Newton method [6,7]. Using experimental data, a neural network forecasting tool was created. This method predicts airfoil self-noise. Machine learning is rarely used in airfoil design due to the small airfoil database and lack of open-source access. This mathematical interconnection underlies AI airfoil optimization. By evaluating the information, it may anticipate an airfoil's performance. The optimised airfoil can yet be improved upon. Artificial neural networks help speed up the first step of airfoil optimization.

2 Literature review

Zhang et al. studied aerodynamics using different CNN architectures. Using them, it was possible to predict lift coefficients based on an aerofoil's shape and a given flow

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condition. Comparisons were made between the traditional MLP technique and the CNN technique for generating predictions. Many convolution schemes were used to build two types of CNN architectures. Aero-CNN-II uses the idea of "artificial images" to incorporate aerodynamic problems into a single framework of the CNN. For aerodynamic meta-modeling of CNN, it has been successfully applied to synthesise geometric boundary conditions (e.g., aerofoil shape). The result gives a useful approach for harnessing deep learning techniques for engineering meta-modeling tasks using well-developed image recognition techniques [8].

Rabii El Maani et al. use backtracking for multi-objective optimization (BSAMO). BSA uses the quick non-dominated sorting method and the crowding distance to handle design problems with multiple goals better. When compared to the NSGA-II algorithm, the results show that BSAMO is better at dealing with complicated and multi-physics systems and is more competitive in this area. However, it is limited to only using parametric optimization neural network combination to get noise level integration [9].

Oh et al. compared the predictions made by surrogate models using RSMs and ANNs to a variety of data sets. Through the construction of surrogate models, the comparison of wind turbine aerofoils' aerodynamic performance is explored. According to the current paper, the ANN model predicts better than that computed by the RSM, but vice versa when the data are low in complexity. The model with high precision produces the optimal design, improving the performance of an aerofoil when it is used to amplify the efficiency of the surrogate models. The results of optimization indicate that constructing an accurate surrogate model leads to a better optimal design [10].

With the ANSYS software, a parameterized finite element model of the blade's aerodynamically optimised shape was made. Full-field turbulence is applied to the wind turbine to create a time series of accelerations, moments, and aerodynamic forces acting on the blade segments. Then, the maximum values of the forces and moments were taken and put into the blade finite element model at the same time to make a copy. ANSYS software is used to make a parameterized finite element model of the aerodynamically optimised blade. This model is loaded with the maximum forces and moments taken from the simulated time series [11].

Luo et al. proposed two optimization techniques for finlet optimization: RANS-CFD ("Reynolds-averaged Navier-Stokes computational fluid dynamics") and artificial neural networks (ANN). For trailing edge noise, a numerical method consisting of a RANS CFD model, an experimental model for wall pressure spectrum, and Howe's diffraction coefficients has been formulated. The first step is to build a parametric model of finlets in 3-D and then optimise the model using ANNs, which are forged from 100 samples generated through the design of experiments. Whether an aerofoil has fins or not, the aim is to minimise OASPLs, lift coefficients, and drag coefficients. This paper seeks to reduce the trailing edge noise of aerofoils without degrading aerodynamic performance by finding the optimal finlet configuration for each fin type. Based on the findings of Shi et al. [12], trailing edge noise reduction with finlets is attributed to a reduction of streamwise velocity and turbulence kinetic energy near the wall.

Martins et al. proposed that an aerodynamic optimization of an aerofoil can be completed within a few seconds with this fast, interactive design framework. An efficient way to model shape parameters using this framework to reduce a design space is GAN ("generative adversarial network") model, which eliminates unrealistic aerofoils to contain all relevant shapes. A mixed model of perceptrons, RNNs ("recurrent neural networks"), and mixed expert models is applied to predict response parameters for a large assortment of Mach and Reynolds numbers. We compare the results of direct CFD-based optimization with those captured by the proposed optimization framework in order to validate our proposed optimization framework. According to the results, the optimal designs computed by this framework (lift, drag, and pressure distribution) are comparable to those computed directly by CFDA-based optimization and evaluation. Users can predict parameters like drag, lift, etc., and it is possible to integrate the framework into Webfoil by achieving high accuracy and speed and optimising aerofoil aerodynamics using any modern computing device with this framework [13].

Wen et al. proposed an artificial neural network based on GABP to optimise aerofoil design. An aerofoil curve can be summed up into eight pairs of coordinates by implementing the Bessel polynomial. The study used training sets consisting of 1446 arrays and test sets consisting of 50 datasets. This method trained the GABP for predictions of CL ("lift coefficient") and L/D ("maximum lift-drag ratio") and for optimising an aerofoil using the characteristics of Bessel curves. The optimization target has been achieved after taking 168 seconds and being adjusted 529 times. The proposed method for optimising aerofoils significantly reduces time spent on optimization. Additionally, the study can help predict and optimise other aerofoil characteristics with sufficient data input. In this research, a neural network was used to predict the aerofoil curve, and the aircraft produced matched the method of calculation presented here well. As a result of artificial neural networks, new methods of aerofoil optimization can be used, which accelerate the optimization process [6,14].

3 Proposed method

The proposed method uses a neural network for training the self-noise dataset, which is later optimised by the quasi-Newton method. The considered dataset has 1503 samples with different variables. For various AoA outcomes, Figure 1 describes the aerodynamic parameters used in the proposed method.

3.1 Dataset of Self-noise

In this study, the self-noise of an aerofoil was calculated by using a five-input, open-source dataset with a decibel output. There are a lot of different designs that can be made from them. The goal of this research is to find the aerofoil design that is the quietest, most efficient, and most

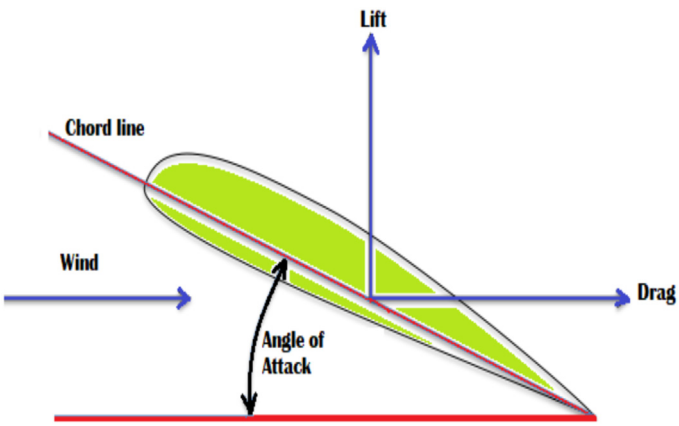

Fig. 1. Two-dimensional section of wing with Angle of Attack and other Aerodynamic forces representation.

effective at the moment (scaled sound pressure level). It is not possible to figure out the noise level of an aerofoil based on its known parameters. A neural network was used to make this possible. The network is given the input parameters so that it can be fine-tuned and work at its best. Once a certain point is reached, scalable vector graphics (SVBs) no longer respond as appealing as they did before. As the number of decimal places gets smaller, an SVG can get messed up in a different way, just like a pixel. In out task is to determine the best balance between the number of characters and how well individuals look in terms of size and decimal precision. Inputs are shown in Table 1.

3.2 Neural network

Neural networks are used when the relationship between inputs and outputs is nonlinear and random. The proposed work utilises the neural network for the training of different input parameters, as between input and output there is a nonlinear relationship as presented in Table 2. A feed-forward, backward-propagation network was used to accomplish the task. An NN can be constructed with five input parameters f, AoA, c, V_∞ and δ.

3.3 Mathematical modelling

The mathematical modelling of the neural network takes the inputs tabulated in Table 1 to produce the output "scaled sound pressure level." The data is fed forward into the neural network layers. The layers are shown in Figure 2.

The following subsections illustrate the mathematical modeling of neural network with input parameters

(–) Scaling layer

scaled_f = (f − 800)/3151.530029;

scaled_AoA = (AoA − 8.4)/5.916160107;

scaled_c = (c − 0.0508)/0.09350989759;

scaled_ V_∞ = (u − 71.3)/15.56760025;

scaled_δ = (δ − 0.00529514)/0.01314590033

(–) Perceptron layer

["perceptron_layer_1_output_0 = tanh(–0.146704 + (scaled_f* − 0.149792) + (scaled_AoA*0.0295288) + (scaled_c*-0.0133423) + (scaled_ V_∞ *0.0868042) + (scaled_δ *0.10127));

perceptron_layer_1_output_1 = tanh(0.0787598 + (scaled_f*-0.175305) + (scaled_AoA*-0.180554) + (scaled_c*-0.0561645) + (scaled_ V∞ *-0.166431) + (scaled_δ *-0.190979));

perceptron_layer_1_output_2 = tanh(−0.0773438 + (scaled_f*-0.151392) + (scaled_AoA*0.132581) + (scaled_c*0.170642) + (scaled_ V∞*0.0917359) + (scaled_V∞*-0.0932007));

perceptron_layer_2_output_0 = (0.0740478 + (perceptron_layer_1_output_0*-0.107361) + (perceptron_layer_1_output_1*-0.197021) + (perceptron_layer_1_output_2*-0.00783691))"]

(c) Un-scaling layer

unscaling_layer_output_0=3.3799973+0.5(perceptron_layer_2_output_0+1)*(140.9869995-103.3799973);*

Table 1. Parameters of optimization.

S. No	Input parameters
1	f- Frequency in "Hertz"
2	AoA − Angle of attack in "degree"
3	$V\infty$ − Free stream velocity "m/s"
4	c − Chord length in meter in "m"
5	δ − Suction side displacement thickness in "m"

Table 2. Directional output.

S. No	Input name	Value
1	Frequency	800
2	Angle of attack	8.4
3	Chord length	0.0508
4	Free stream velocity	71.3
5	Suction side displacement thickness	0.00529514
6	Scaled sound pressure level	127.556

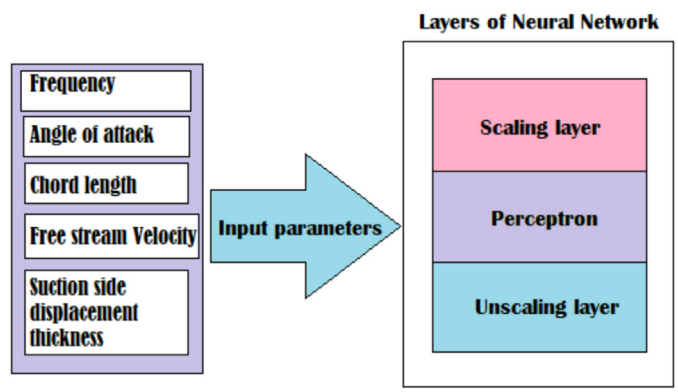

Fig. 2. Layers of neural network.

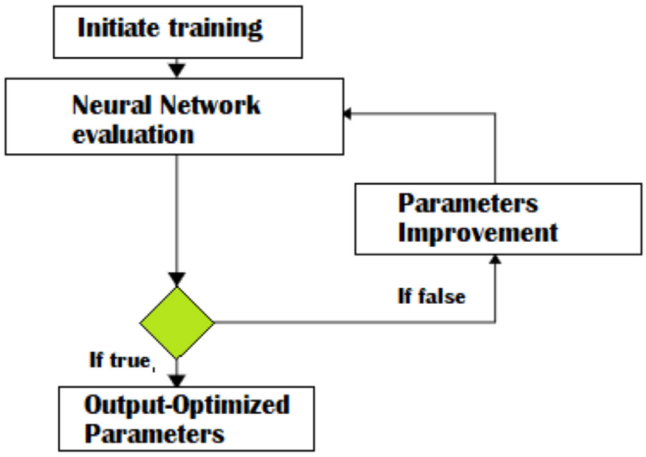

Fig. 3. Neural network Training: State diagram.

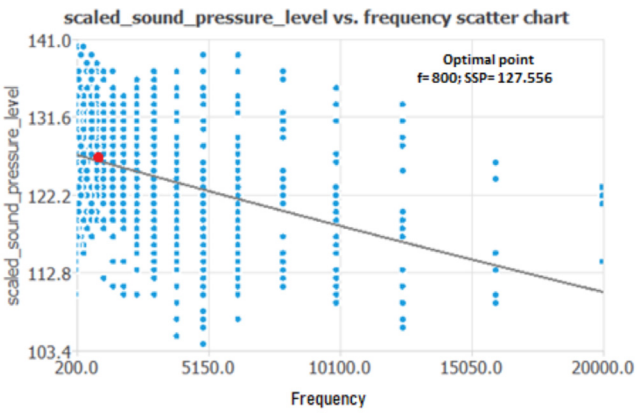

Fig. 4. Scatter plot frequency and sound pressure level.

3.4 Optimization of parameters using Quasi-Newton method (QNM)

Training neural networks involves finding parameters with a minimum loss index, and the considered parameters also function in a nonlinear way. An epoch is involved in the search for parameters with a minimum loss index. By adjusting the parameters of a neural network, the loss can be decreased at each epoch. Therefore, a parameter increment refers to the apparent change in the parameters. To train the neural network, random parameter vectors are used. The reduction loss index is calculated by generating parameter vectors at the end of every iteration.

The proposed method employs the quasi-Newton method for the calculation of the learning direction using a matrix of second derivatives and a Hessian of the loss function. The selected method provides the learning direction points with minimum loss and high accuracy as it uses higher order information [9]. At each iteration, using gradient information, the quasi-Newton method computes an inverse Hessian approximation. Using line minimization, the learning rate is adjusted at each epoch as shown in Figure 3.

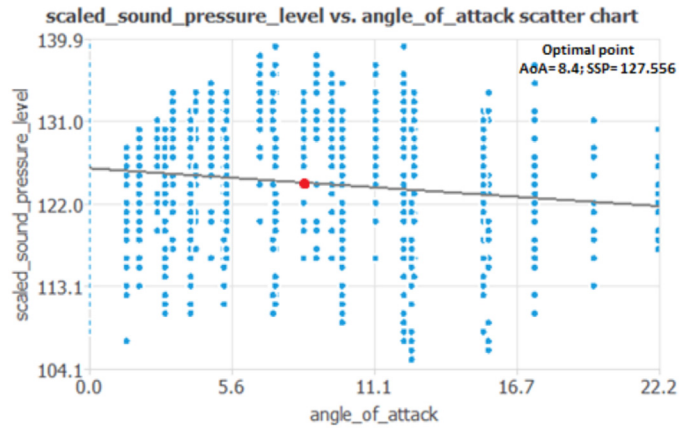

Fig. 5. Scatter chart of Angle of attack and sound pressure level.

4 Results

Figure 4 represents the scatter plot for the input frequency and scaled sound pressure level. It also shows the regression line between both variables, of type exponential, whose correlation value is −0.396778. The optimal point is at $f = 800$ and SSP = 127.556.

Figure 5 represents the plot for the AoA and scaled sound pressure level. It also shows the regression line between both variables, of type exponential, whose correlation value is −0.158097. The optimal point is between an *8* and 8.4 degree angle of attack and SSP 127.556.

Figure 6 represents the scatter plot for the chord length and scaled sound pressure level. It also shows the regression line between both variables, of type linear, whose correlation value is −0.236162. The optimal point occurs at 0.05 chord length and 127.556 sound pressure levels.

Figure 7 illustrates the scaled sound pressure and free-stream velocity. Additionally, a linear regression line with a correlation of 0.125103 is displayed between the two variables. The optimal value at 127.556 dB is 71.3 m/s. The study is supported by the fact that the noise data gathered using the current methodology corresponds pretty well to the literature used for validation purposes. There are potential applications for this technology in mind [15].

Figure 8 shows the scatter plot for "scaled sound pressure level" and "suction side displacement thickness." It also shows the regression line between both variables, of type power, whose correlation value is −0.320744. The optimal point is found at and SSP = 127.556.

4.1 Aerofoil geometry post optimization

Figure 9 demonstrates the aerofoil geometry pre and post-optimization, where the geometry changes at the optimal point (0.05, 0.5).

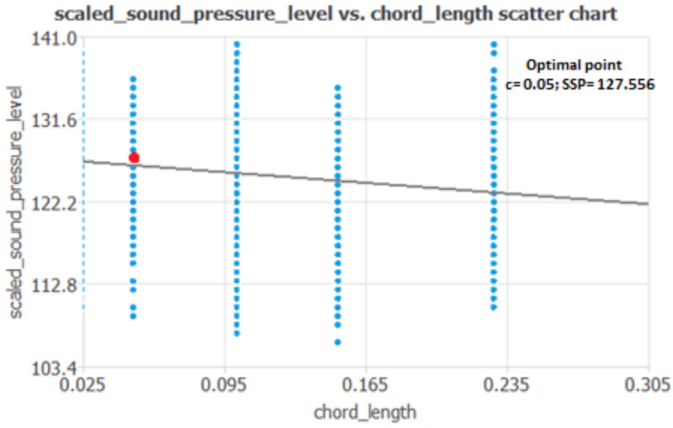

Fig. 6. Scatter plot of sound pressure level and chord length.

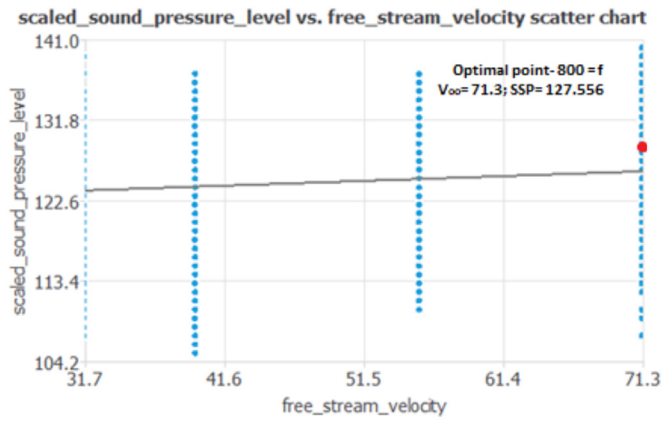

Fig. 7. Scatter chart sound pressure level and free stream velocity.

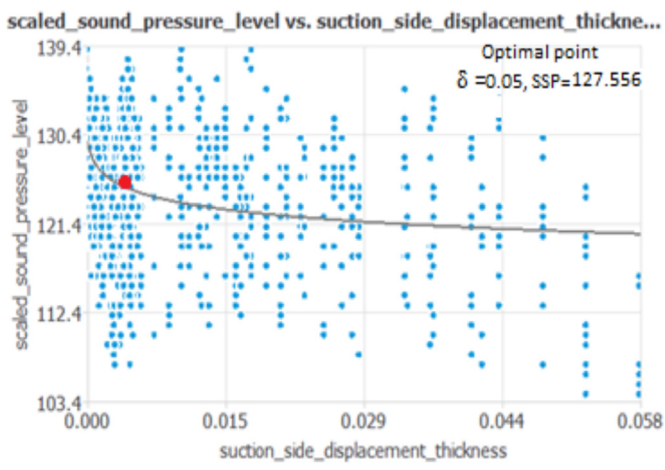

Fig. 8. Scatter plot of suction side displacement thickness vs sound pressure level.

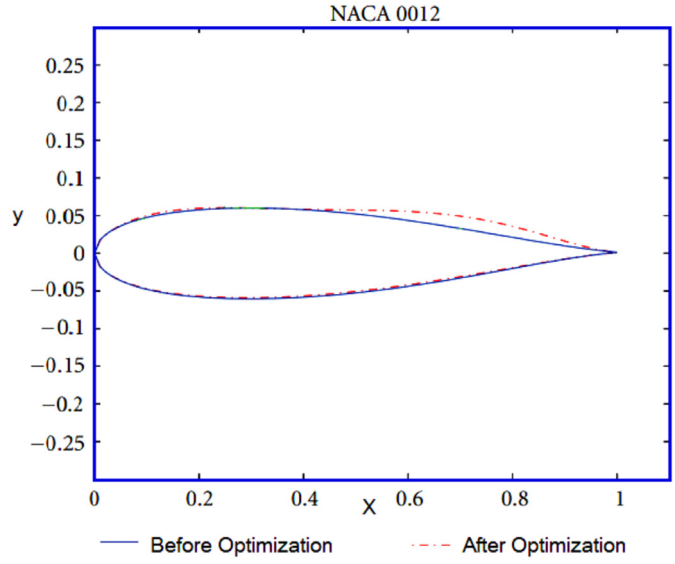

Fig. 9. Optimized aerofoil geometry vs original aerofoil geometry.

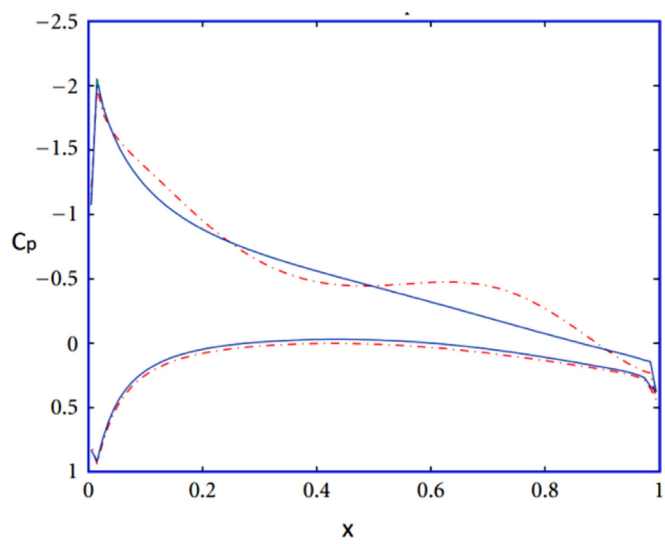

Fig. 10. NACA0012 vs optimized pressure distribution.

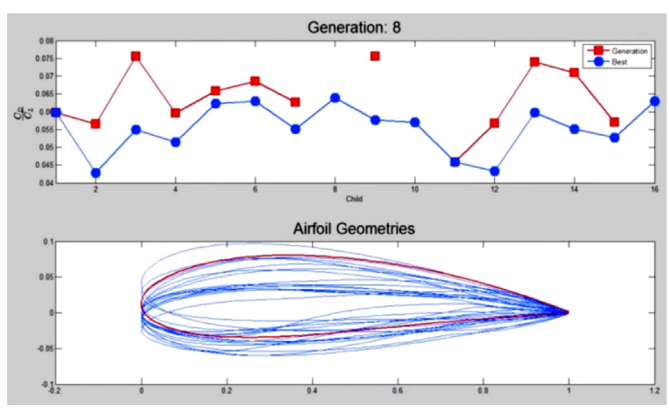

Fig. 11. Optimized aerofoil at 8th generation.

Table 3. Errors after Neural network training.

	Training	Selection	Testing
SSE	210.84	119.83	118.337
MSE	0.233489	0.399433	0.394456
RSE	0.483207	0.632007	0.628057
NSE	1.01803	1.02532	1.01936
Minkowski error	600.318	281.351	281.448

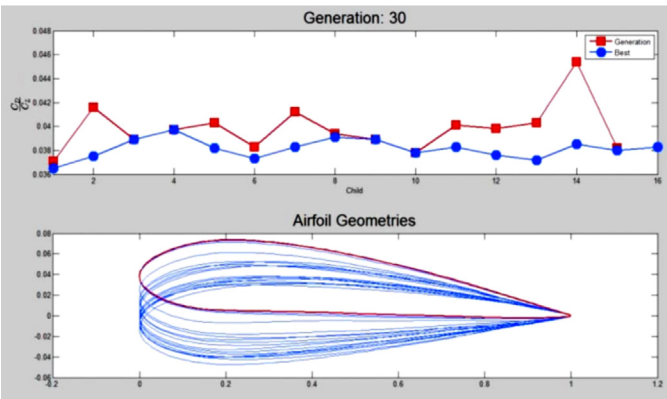

Fig. 12. Optimized aerofoil at 30th generation.

Figure 10 demonstrates the pressure distribution of NACA 0012 with the optimised geometry. The Cp gradually increases at 0.5 and declines at 0.7. Figures 11 to 14 represent the optimised geometry at different generations of iterations in the parametric training.

Figure 11 shows the optimised geometry of the selected aerofoil at 8 degrees of the pitch angle. The performance of the aerofoil is better at the selected angle.

Table 3 represents the errors after training in neural network with sum squared errors of 210.84, 119.83, and 118.337 for training, selection, and testing, respectively. MSE 0.233489, 0.399433, and 0.394456. RMSE 0.483207, 0.632007, and 0.628057. NSE of 1.01803, 1.02532, and 1.01936. Minkowski error of 600.318, 281.351, and 281.448.

5 Conclusion

It is possible for the wings or blades of an aerofoil to collapse due to the vibrations caused by the aerofoil's own noise. In addition, the effectiveness of the fan blades is severely diminished because of the resulting aerodynamic noise. Predicting aerofoil self-noise is crucial in systems where blades or wings are utilised because of the impact it has on system performance. This research makes use of a number of machine learning methods. Based on investigation, a neural network is clearly superior to a regression model. When applied to the problem of predicting aerofoil self-noise, the existing analysis for deleting superfluous components improves the execution of the upgraded neural network. Predictions of aerofoil self-noise using the present method were quite accurate. The method's versatility means it can be used for the construction of any aerofoil, be it a blade or a wing, giving it a massive advantage over more traditional prediction techniques.

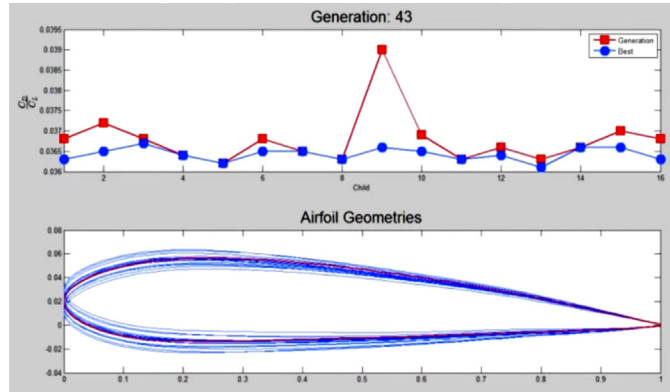

Fig. 13. Optimized aerofoil at 43rd generation. gr

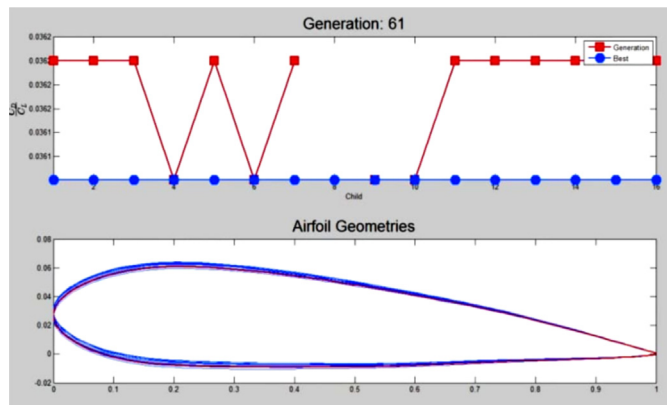

Fig. 14. Optimized aerofoil at 61st generation.

References

1. Z. Sun, Z. Li, M. Fan, Airfoil shape optimization based on Non Uniform Rational Bspline and optimization algorithm, IOP Conf. Ser.: Earth Environ. Sci. **474**, 052075 (2020)
2. A. Agriss M. Agouzoul, A. Ettaouil, A. Mehdari Numerical study of new techniques drag reduction: application to aerodynamic devices, Int. J. Simul. Multidisci. Des. Optim. **12**, 16 (2021)
3. H. Wen, S. Sang, C. Qiu, X. Du, X. Zhu, Q. Shi, A new optimization method of wind turbine aerofoil performance based on Bessel equation and GABP artificial neural network, Energy **187**, 116106 (2019)
4. P. Pal, R. Datta, D. Rajbansi, A. Segev, A neural net based prediction of sound pressure level for the design of the aerofoil, in *Swarm, Evolutionary, and Memetic Computing and Fuzzy and Neural Computing* (Springer, Cham, 2019), pp. 105–112

5. D.K. Choi, Multilevel-modeling interpretation of trailing-edge noise models for wind turbines with NACA 0012 airfoil, Int. J. Precis. Eng. Manufactur. Green Technol. **8**, 1501–1514 (2021)
6. K. Yang, T. Fan, T. Chen, Y. Shi, Q. Yang, A quasi-Newton method based vertical federated learning framework for logistic regression, ArXiv preprint arXiv:1912.00513 (2019)
7. B. Yu, L. Xie, F. Wang, An improved deep convolutional neural network to predict airfoil lift coefficient, in *International Conference on Aerospace System Science and Engineering*. (Springer, Singapore, 2019, July), pp. 275–286
8. Y. Zhang, W.J. Sung, D.N. Mavris, Application of convolutional neural network to predict airfoil lift coefficient, in *2018 AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference* (2018), p. 1903
9. R. El Maani, S. Elouardi, B. Radi, A. El Hami, Multiobjective aerodynamic shape optimization of NACA0012 airfoil based mesh morphing, Int. J. Simul. Multidisci. Des. Optim. **11**, 11 (2020)
10. S. Oh, Comparison of a response surface method and artificial neural network in predicting the aerodynamic performance of a wind turbine airfoil and its optimization, Appl. Sci. **10**, 6277 (2020)
11. K.-N. Chen, P.-Y. Chen, Structural optimization of 3 MW wind turbine blades using a two-step procedure, Int. J. Simul. Multidiscipl. Des. Optim. **4**, 159–165 (2012)
12. J. Luo, Y. Shi, W. Song, Finlet optimization for airfoil trailing edge noise minimization using ANN, in *AIAA AVIATION 2020 FORUM* (2020), p. 2537
13. X. Du, P. He, J.R. Martins, Rapid airfoil design optimization via neural networks-based parameterization and surrogate modeling, Aerospace Sci. Technol. **113**, 106701 (2021)
14. X. Fang, Q. Ni, M. Zeng, A modified quasi-Newton method for nonlinear equations, J. Comput. Appl. Math. **328**, 44–58 (2018)
15. T. Brooks, D. Stuart Pope, Michael A. Marcolini, Airfoils self-noise and predictions, NASA Reference Publication **1218** (1989)

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