

Article

Combining Deep Neural Network with Genetic Algorithm for Axial Flow Fan Design and Development

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Abstract: Axial flow fans are commonly used for a system or machinery cooling process. It also used for ventilating warehouses, factories, and garages. In the fan manufacturing industry, the demand for varying fan operating points makes design parameters complicated because many design parameters affect the fan performance. This study combines the deep neural network (DNN) with a genetic algorithm (GA) for axial flow design and development. The characteristic fan curve (P-Q Curve) can be generated when the relevant fan parameters are imported into this system. The system parameters can be adjusted to achieve the required characteristic curve. After the wind tunnel test is performed for verification, the data are integrated and corrected to reduce manufacturing costs and design time. This study discusses a small axial flow fan NACA and analyzes fan features, such as the blade root chord length, blade tip chord length, pitch angle, twist angle, fan diameter, and blade number. Afterwards, the wind tunnel performance test was performed and the fan performance curve obtained. The feature and performance test data were discussed using deep learning. The Python programming language was used for programming and the data were trained repeatedly. The greater the number of parameter data, the more accurate the prediction. Whether the performance condition is met could be learnt from the training result. All parameters were calculated using a genetic algorithm. The optimized fan features and performance were screened out to implement the intelligent fan design. This method can solve many fan suppliers' fan design problems.

Keywords: axial flow fan; deep learning; deep neural network; Python; genetic algorithm; axial fan design



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1. Introduction

Axial flow fans have been used for many decades [1]. This fan forces the air to move parallel to the shaft about which the blades rotate. Axial fans are commonly used for system or machinery cooling processes, such as transferring heat from a condenser and cooling electronic equipment or computer rooms. Axial flow fans are also used for warehouse, factory, and garage ventilation. In the industry sector, the axial fan is often mounted to a motor to cool it.

Axial flow fan designs have been discussed in depth in many industries for fan development. In the fan manufacturing industry, the demand for varying fan operating points makes the design complicated since many design parameters affect the fan performance. There is numerous literature on axial flow fan design. Shahsavari et al. [2] increased the by-pass ratio in a constant diameter turbofan. The design is investigated in detail using a computational fluid dynamics (CFD) tool. The result indicates that the new design strategy

is capable of more efficient performance in turbofan engines. Xu et al. [3] controlled axial-flow aerodynamic noise by designing fans using metal foams. Sarraf et al. [4] studied two blade thicknesses on the performances of an axial-flow fan. The overall performance was measured in a test bench design. Several aspects were discussed, such as the aerodynamic characteristic curve, the efficiency of thick blade fans, the total level of fluctuations, etc. Fan modeling is crucial for performance analysis. Podgaietsky et al. [5] advanced a methodology for axial fan efficiency mapping. The simulation model was built using a mathematical model called “blade element theory”. Different parameters were designed in the past using modeling and meshing simulations. These operations are time-consuming, as finishing a fan design can take as long as half a day.

Zhang et al. [6] improved the volume flowrate for an axial fan through optimizing the blade shape under the demand for a specific static pressure. The optimization was performed using a GA coupled with a NN. Lin et al. [7] combined the CFD and ANN to design a three-dimensional blade for an axial-flow fan. The DNN was used to set up the flow field models and forecast the axial-flow performance. Ding et al. [8] adopted bending and twisting laws for the blade design and optimization of a low-pressure axial flow fan. A multi-objective genetic algorithm was introduced to optimize the fan pressure and efficiency. Hang et al. [9] optimized the structural parameters combination and made an axial fan with the best performance using the back propagation neural network (BPNN) and a GA. The optimized result proved to be received using CFD simulation. The literature indicates that only a few studies adopt AI for axial flow fan design. In addition, there are few AI intelligent fan design predictions, especially for the design of customized small axial fans. Many industries mostly use big data for technical analysis, such as traditional industries, technology industries, etc., or water-cooled chiller equipment. The deep neural network (DNN) is used to predict different models after data collection, select the model with the least error in the test set as the best model, and implement the best predictive model to evaluate system performance and create maintenance plans [10–18].

With advances in science and technology, deep learning and a genetic algorithm (GA) can be used as a rapid and effective method for fan development. There are some important factors in fan design, including noise, manufacturing cost, fan performance, and manufacturing simplicity [1]. In this study, axial flow fan design focuses on fan performance, which is affected by P_{ratio} and Q_{ratio} . The AI optimization design is applied in this study. A fan is designed using data collection, deep learning, and a GA. An artificial intelligence (AI) fan design application system can be conceived to shorten the development schedule. As long as the relevant fan parameters are imported into the system, the characteristic curve (P-Q Curve) for this fan can be generated. The parameters can be adjusted in the system to achieve the required characteristic curve. The fan is drawn using 3D modeling. When the sample is completed and the wind tunnel test verification is performed, the data are integrated and corrected to reduce the design cost and time [19–26].

2. Research Method

This study involves AI applications for small axial flow fans design by combining the DNN and a genetic algorithm. The DNN technique is used to build the fan modeling. The genetic algorithm is then used to find the optimum fan parameters values. This study used the Python programming language using Anaconda distribution. Several libraries also included scikit-learn, Keras, TensorFlow, and DEAP. Figure 1 shows an overview of the proposed approach. There are three main steps: data preprocessing, pressure prediction model, and design parameter optimization.

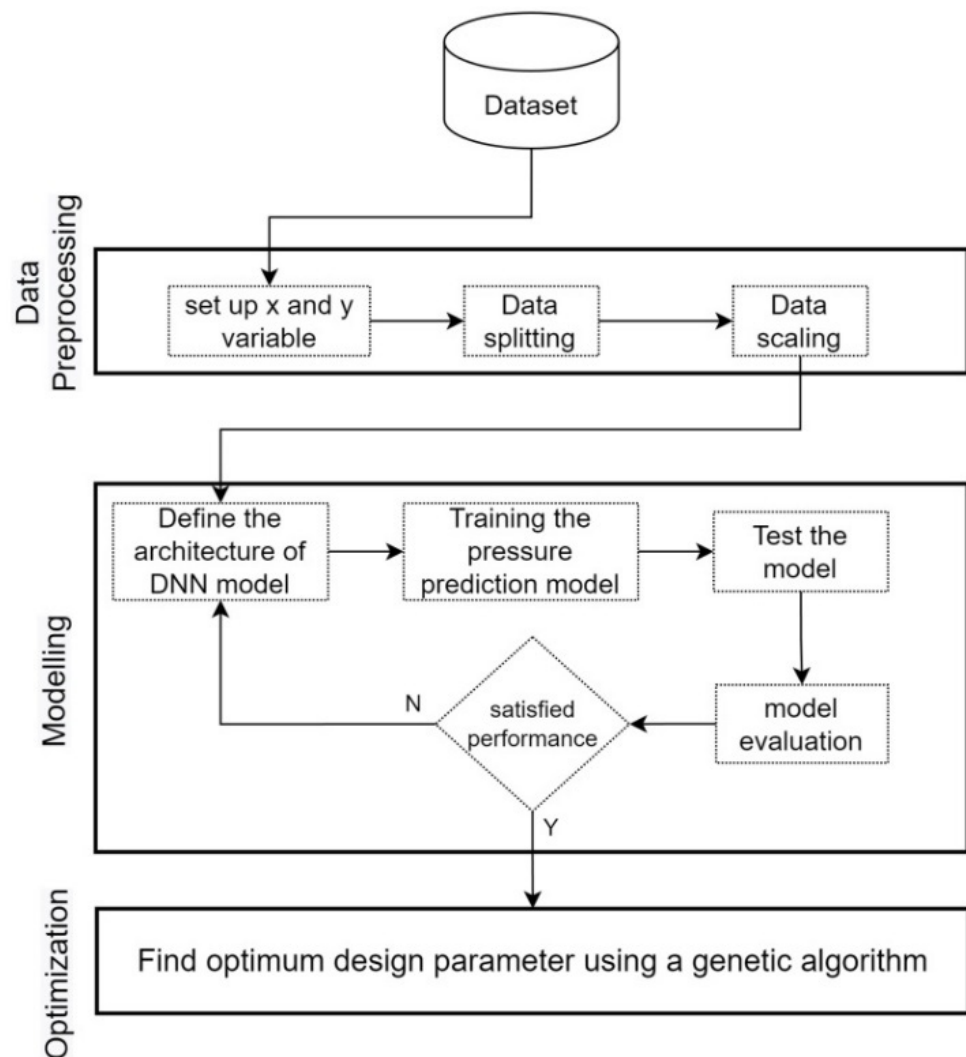


Figure 1. A conceptual framework of the proposed approach.

2.1. Data Preprocessing

The dataset was collected from the axial fan parameters, chord length root, chord length tip, pitch angle, twist angle, impeller diameter, hub outer diameter, blade number, tip clearance, frame thickness, rotating speed, flowrate, and static pressure. The input or independent (x) and output or dependent (y) variables for each model should be determined. The data need to be split randomly into three parts: 70% for training data, 15% for validation data, and 15% for testing data. Data scaling is applied to avoid the models being dominated by large or small data ranges. A standardization technique is used to scale the data where the data values are centered on the mean with the standard deviation as formulated in Equation (1).

$$x_{stand}^i = \frac{x^{(i)} - \bar{x}}{s} \quad (1)$$

where x_{stand}^i , $x^{(i)}$, $\bar{x}$, and s are the standardized data, observed data, sample mean, and sample standard deviation, respectively.

2.2. Modeling Using DNN

A fan design model was built using the DNN technique. DNN is an artificial neural network for executing complex tasks. It has multiple layers and multiple nodes. Figure 2 shows the DNN architecture diagram used in this study. The input layer consists of 11 neurons, which are nine design parameters, rotation speed, and x . The nine design

parameters are chord length root, chord length tip, pitch angle, twist angle, impeller diameter, hub outer diameter, blade number, tip clearance, and frame thickness. There are five hidden layers. Each hidden layer consists of 35 neurons, while the output layer consists of 1 neuron [4–7]. Two DNN models were tested in this study: the flowrate model and the static pressure model. With reference to Figure 2, the flowrate model uses static pressure as x and flowrate as y . In contrast, the static pressure model uses flowrate as x and static pressure as y . One of the two models will be selected for further optimization in the GA based on evaluation assessment. The hyperparameters need to be determined before training the models. Manual hyperparameter tuning is applied to optimize the hyperparameter DNN training [27–30].

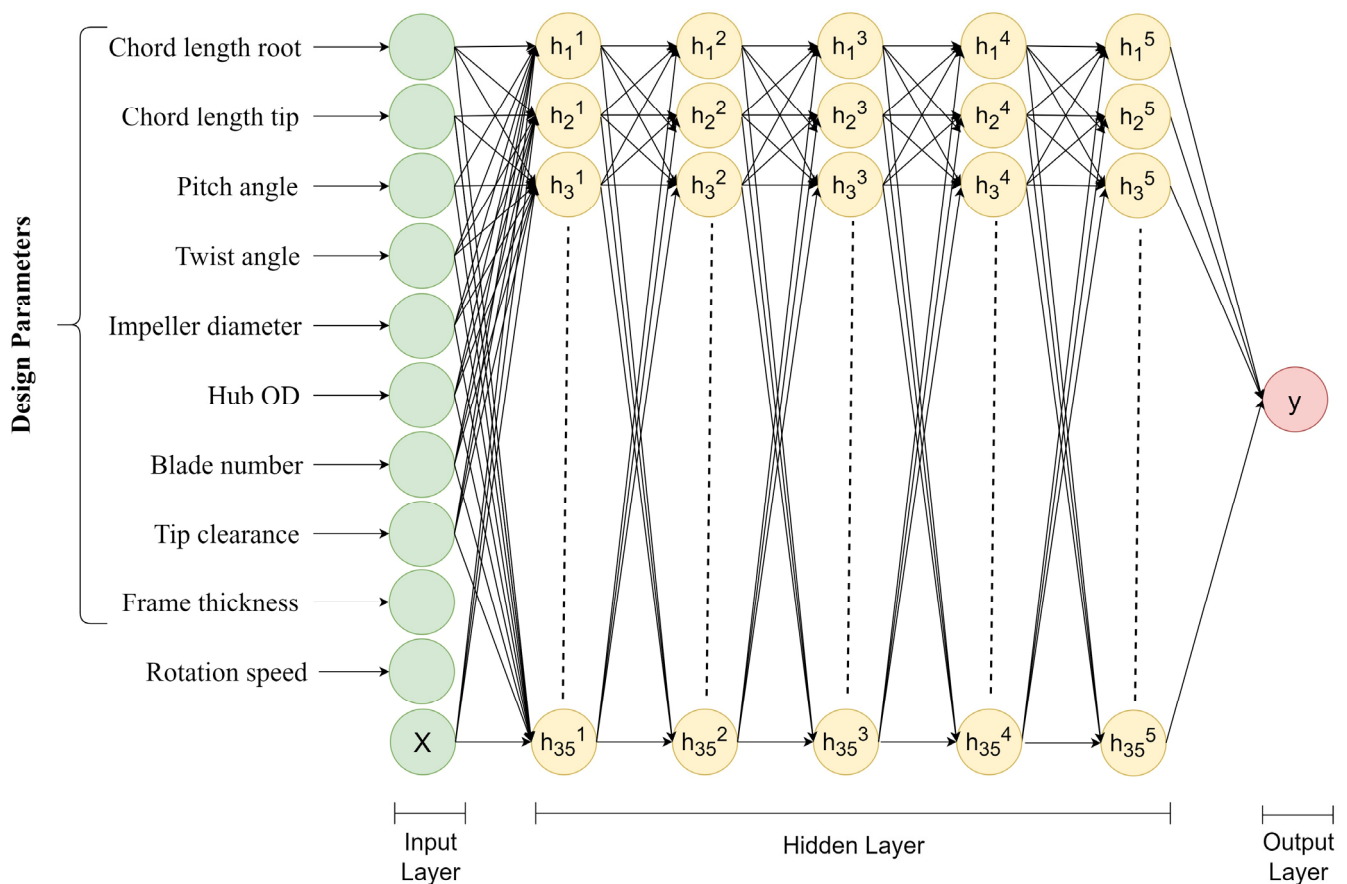


Figure 2. DNN architecture diagram [13].

The neuron output is expressed as Equation (2), where y is the neuron output, f is the activation function, x_i is the input variable, ω_i is the weight, and b is the bias. The weight and bias are learned during the training model. The training objective is to reduce the loss or the error between the algorithm and measured values using mean squared error (MSE) as the loss function, as shown in Equation (3). The activation function used in this study was a ReLU function, expressed as Equation (4), with the function 0 representing negative values and return x representing positive values [31–33].

$$Y = f\left(\sum_i x_i \omega_i + b\right) \quad (2)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (Y_i - P_i)^2 \quad (3)$$

$$f(x) = \max(x, 0) \quad (4)$$

This study used the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) as assessment criteria to evaluate the errors in different models, expressed as Equations (5)–(7). N is the number of samples, Y_i is the measurement value, P_i is the predictive value, and $\bar{Y}$ is the average measurement value. The MAE and RMSE are correlated with the model; R^2 is uncorrelated with the model and hence can be used for studying the performance. The lower the MAE and RMSE values, the better the model performance. The R^2 value usually ranges from 0 to 1, or is negative. It varies with the model.

$$R^2 = 1 - \frac{\sum_{i=1}^N (Y_i - P_i)^2}{\sum_{i=1}^N (Y_i - \bar{Y})^2} \quad (5)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |Y_i - P_i| \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - P_i)^2} \quad (7)$$

2.3. Optimization Using GA

The genetic algorithm (GA) is an evolution method developed from elimination and evolution in nature, and is also known as a hereditary algorithm. It was proposed by Dr. J. Holland in 1975 and evolved from the “survival of the fittest, elimination of the unfit” ethics in the evolutionary process of organisms. The fitness is calculated by random sampling and then the optimum value is calculated by crossover and mutation. This is generally used in the domains of machine learning, optimal combination, and signal processing. The GA is like a natural selection mechanism, where one chromosome imitates biological mating and mutation, and the objective of chromosomes is determined according to their fitness, to achieve optimization, as illustrated by the GA flow chart in Figure 3 [34–37].

The goals of GAs are to find the optimum design parameters based on the operating points. The operating points are static pressure, flowrate, and rotating speed. The selected DNN model is included for fan modeling. Equation (8) shows the fitness function used in this study. The objective function minimizes the y_{error} , where y is the selected model whether pressure or flowrate, y_{op} is the y operating point, and y_{model} is the model output. Several constraints are applied: The P_{ratio} and Q_{ratio} values should be in the 0.5~0.6 range. The chord length root should equal or be less than the chord length tip. A fixed penalty is applied if a constraint is violated. P_{ratio} and Q_{ratio} are calculated using Equations (9) and (10), where P_{op} and Q_{op} are the static pressure and flowrate operating points, respectively. P_{max} is the maximum static pressure, or the static pressure when the flowrate is near 0. Q_{max} is the maximum flowrate, or the flowrate when the static pressure is near 0.

$$\begin{aligned} \text{Fitness function} &= \text{objectivefunction} + \text{penalty} \\ \text{Objective function} &= \min (y_{error}) \end{aligned} \quad (8)$$

$$y_{error} = \frac{|y_{op} - y_{model}|}{y_{op}}$$

$$P_{ratio} = \frac{P_{op}}{P_{max}} \quad (9)$$

$$Q_{ratio} = \frac{Q_{op}}{Q_{max}} \quad (10)$$

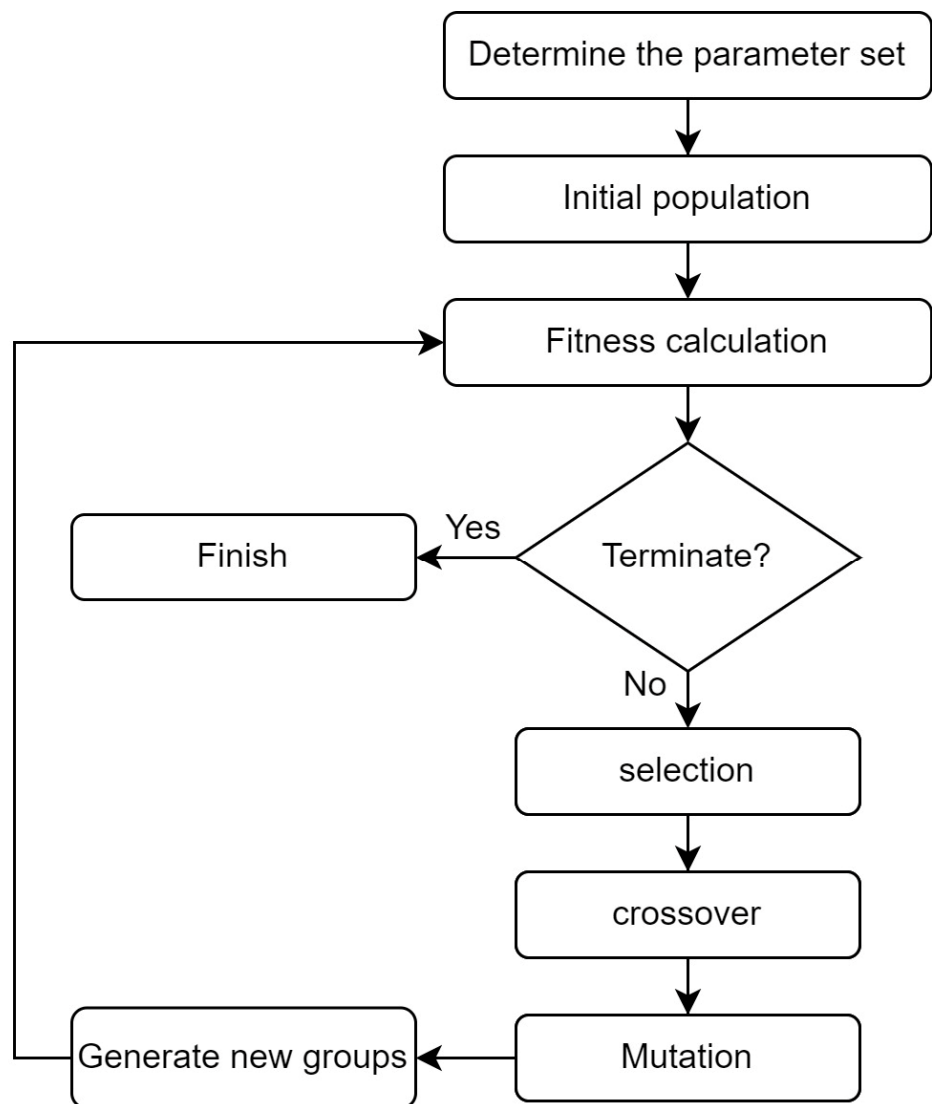


Figure 3. GA flow chart.

3. Results and Discussion

3.1. Axial Flow Fan Erection

Air Movement and Control Association International, Inc. (AMCA) is an international not-for-profit organization dedicated to certifying the performance of fans, louvers, dampers, and other air-handling equipment. Currently, AMCA can provide third-party testing and certification for buyers and sellers for most manufacturers worldwide and has formulated some important industry standards, as shown in Figure 4 [38].

This research used the fan performance measurement system SW-300, as shown in Figure 5, which is a schematic diagram of the wind tunnel equipment. The equipment size is 1.9 m in length $\times$ 1.5 m in width $\times$ 1.4 m in height, and the power supply system is DC 60 V, 10 A 600 W, as shown in Table 1. Wind tunnel equipment is shown in the specification sheet. Fan performance tests were conducted on 19 small axial flow fans, knowing the pressure (P), flowrate (Q), and speed (RPM) of the fan. The characteristic fan parameters were analyzed, including chord length root, chord length blade tip, pitch angle, torsion angle, impeller diameter, outer hub diameter, number of blades, tip clearance, and frame thickness, as shown in Tables 2–5 [38]. The existing 19 fan types were used for data collection. Deep learning training and genetic calculation were performed on the collected data.

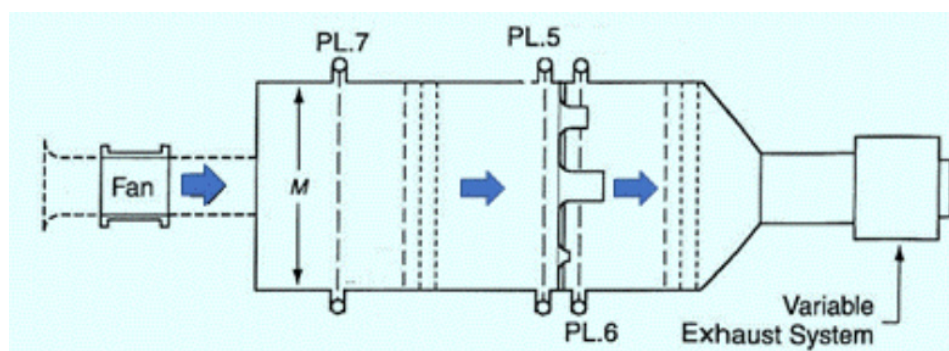


Figure 4. Wind tunnel structure diagram.

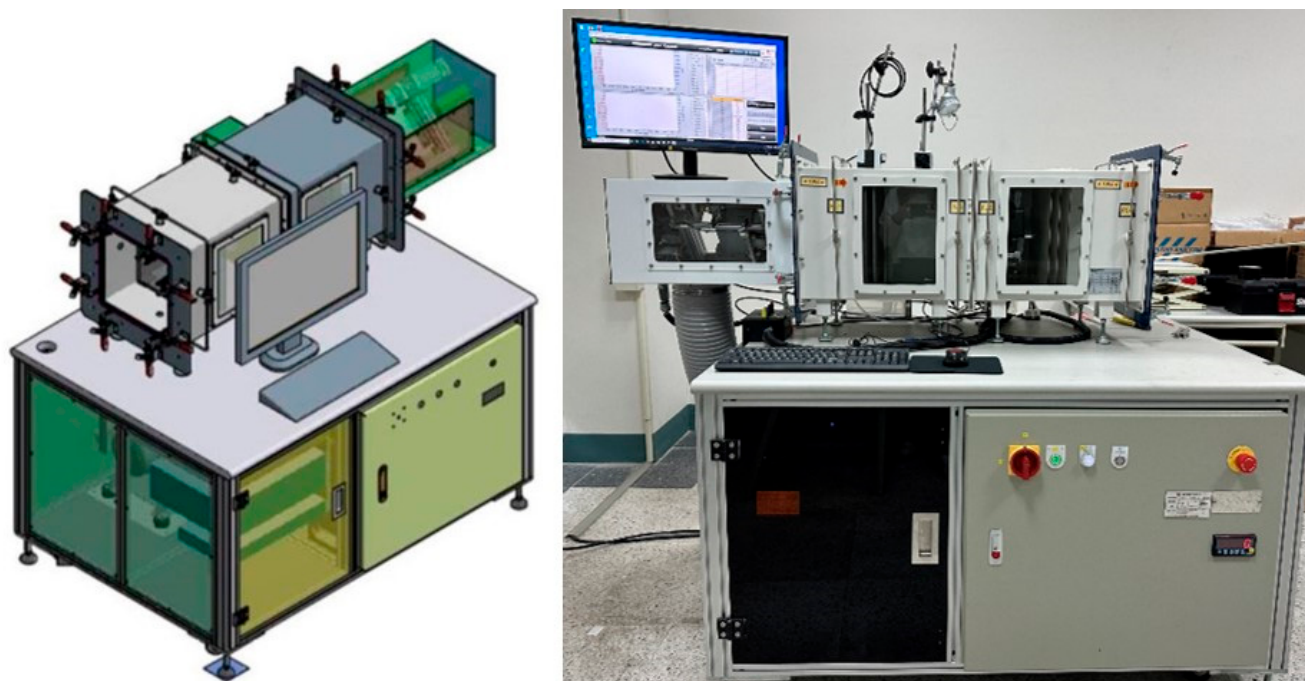


Figure 5. Fan performance measurement system SW-300 [38].

Table 1. Fan performance measurement system specifications.

Product Name		Fan Performance Measurement System
Performance	Airflow Rate	air volume 2.5~300 CFM
	Static Pressure	wind pressure 0~2490 Pa
	Structure	AMCA 210-2016.
	Test Item	System SRC, DC/AC fan P-Q characteristic curve test. Automatic measurement of thermal resistance, TRC curve.
	Static pressure	dp: Static pressure measurement range before and after the nozzle 1277 mmAq PS1: static pressure measurement range 25.4 mmAq PS2: static pressure measuring range 101.6 mmAq PS3: static pressure measuring range 254 mmAq

Table 1. Cont.

	Product Name	Fan Performance Measurement System
Machine size	Weight	200 kg
	Size (W × D × H)	1.9 × 1.5 × 1.4 (m)
Power Systems	DC power supply	DC 60 V, 10 A 600 W
Control System	Control method	PC Base/LONG VICTORY high-precision wind tunnel testing software
	Control program	automatic/manual
Equipment Structure	Cavity material	steel plate painting
	Internal material	steel plate painting

Table 2. Fan characteristics.

Fan Specification	FAN1	FAN2
Chord length root (mm)	20.47	12.17
Chord length tip (mm)	27.61	16
Pitch angle	62.5	39.86
Twist angle	21.32	6.56
Impeller diameter (mm)	75.25	74.3
Hub OD (mm)	32.83	34.24
Blade number	9	11
Tip clearance (mm)	0.9	0.9
Frame thickness (mm)	25.16	15.49
Fan specification	FAN3	FAN4
Chord length root (mm)	17.62	12.17
Chord length tip (mm)	30.5	16
Pitch angle	44.45	39.86
Twist angle	17.66	6.56
Impeller diameter (mm)	74.05	74.3
Hub OD (mm)	32.92	34.24
Blade number	7	11
Tip clearance (mm)	0.8	0.9
Frame thickness (mm)	25.4	15.49
Fan specification	FAN5	FAN6
Chord length root (mm)	18.01	12.17
Chord length tip (mm)	25.97	16
Pitch angle	60.6	39.86
Twist angle	24.6	6.56
Impeller diameter (mm)	72.55	74.3
Hub OD (mm)	32.17	34.24
Blade number	7	11
Tip clearance (mm)	1.3	0.9
Frame thickness (mm)	25.12	15.49

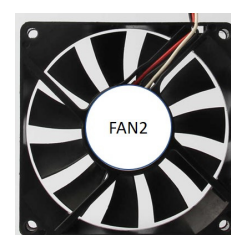


Table 3. Fan characteristics.

Fan Specification		FAN7	FAN8
Chord length root (mm)	7		12.17
Chord length tip (mm)	13		16
Pitch angle	51.7		39.86
Twist angle	16		6.56
Impeller diameter (mm)	47.9		74.3
Hub OD (mm)	25		34.24
Blade number	11		11
Tip clearance (mm)	1.3		0.9
Frame thickness (mm)	15.23		15.49
Fan specification		FAN9	FAN10
Chord length root (mm)	16.9		12.17
Chord length tip (mm)	20.33		16
Pitch angle	60.3		39.86
Twist angle	13.87		6.56
Impeller diameter (mm)	74.21		74.3
Hub OD (mm)	32.26		34.24
Blade number	7		11
Tip clearance (mm)	0.5		0.9
Frame thickness (mm)	25.03		15.49
Fan specification		FAN11	FAN12
Chord length root (mm)	20.63		12.17
Chord length tip (mm)	29.5		16
Pitch angle	45.8		39.86
Twist angle	14		6.56
Impeller diameter (mm)	117		74.3
Hub OD (mm)	40.24		34.24
Blade number	7		11
Tip clearance (mm)	1.5		0.9
Frame thickness (mm)	24.8		15.49

3.2. Fan Installation Process

Before conducting wind tunnel experiments:

- First, confirm that the relevant system connections were completed.
- Turn on the system and host computer power.
- Install the fan to be tested in a suitable location.

To avoid air leakage, seal the test unit tightly with tape, as shown in Figure 6. After the installation, open the test software, set the test parameters, and confirm whether the parameter values are correct, as shown in Figure 7. After the test is completed, the software will automatically output an Excel report. The P-Q Curve of each fan will be obtained based on an Excel report. The outputs are used for the subsequent study of deep learning and genetic algorithms.

Table 4. Fan characteristics.

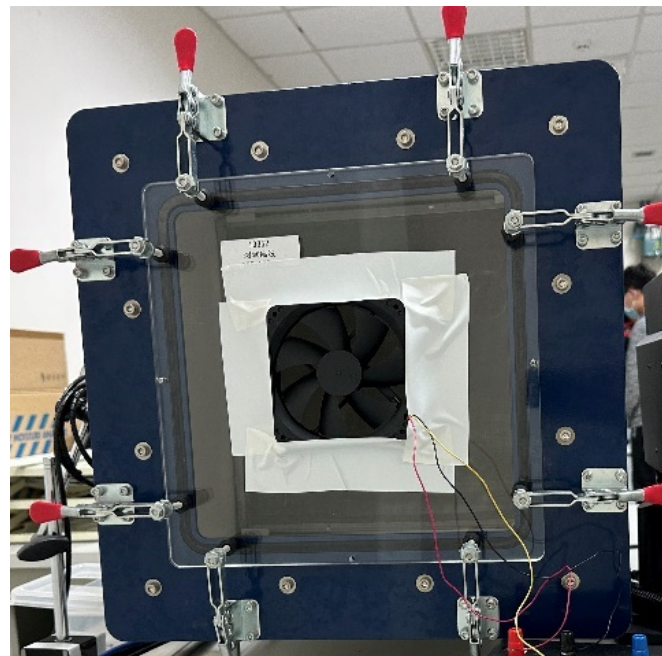
Fan Specification		FAN13	FAN14
Chord length root (mm)	11.5		12.17
Chord length tip (mm)	16.5		16
Pitch angle	60.4		39.86
Twist angle	18.6		6.56
Impeller diameter (mm)	65		74.3
Hub OD (mm)	31.5		34.24
Blade number	9		11
Tip clearance (mm)	1.5		0.9
Frame thickness (mm)	15.2		15.49
Fan specification		FAN15	FAN16
Chord length root (mm)	13.5		12.17
Chord length tip (mm)	18.5		16
Pitch angle	40		39.86
Twist angle	12.5		6.56
Impeller diameter (mm)	55		74.3
Hub OD (mm)	54.6		34.24
Blade number	7		11
Tip clearance (mm)	1		0.9
Frame thickness (mm)	15.2		15.49
Fan specification		FAN17	FAN18
Chord length root (mm)	22		15
Chord length tip (mm)	25		18.5
Pitch angle	43		68.9
Twist angle	6.13		11
Impeller diameter (mm)	75.3		74.5
Hub OD (mm)	37.5		32.24
Blade number	7		7
Tip clearance (mm)	2		1.5
Frame thickness (mm)	25.3		24.95
			

3.3. Modeling

Two prediction models were built with the DNN model architecture: the flowrate model and the static pressure model. The dropout rate 0.01 is added to avoid overfitting after the first, second, third, and fourth hidden layers. The ReLU was selected as the activation function. The epochs were set as 1000, the batch was set as 32, the optimizer was *adam*, and the loss function was MSE. Figure 8 shows a scatterplot between the actual flowrate and the flowrate model output using (a) training data and (b) testing data. Figure 9 shows a scatterplot between the actual static pressure and the static pressure model output using (a) training data and (b) testing data. From Figures 8 and 9, both flowrate and static pressure can be successfully predicted. Both models are evaluated using R^2 , MAE, and RMSE, as shown in Table 6.

Table 5. Fan characteristics.

Fan Specification	FAN19
Chord length root (mm)	19
Chord length tip (mm)	30
Pitch angle	46
Twist angle	15
Impeller diameter (mm)	110
Hub OD (mm)	39.6
Blade number	7
Tip clearance (mm)	2.3
Frame thickness (mm)	25

**Figure 6.** Schematic diagram of fan installation.

The table above indicates that the R^2 of the static pressure model is higher than that of the flowrate model for both training and testing. The MAE and RMSE of the static pressure model is lower than that of the flowrate model for both training and testing. Therefore, the static pressure model is selected for further optimization.

3.4. Optimization

The fan parameter range was given, with the minimum and maximum values for each parameter determined for the individual. The individual values will be converted into integers, as described in Table 7. The GA parameters used in this study are the population size is set to 300, the generation number is set to 300, the crossover probability is set to 0.8, the mutation is set to 0.1, the hall of fame is set to 30, the crowding factor is set to 20, and the penalty value is set to 10. The operating points are determined in advance, namely, 50 Pa of static pressure, 0.01 m³/s of flowrate, and 6000 RPM of rotating speed. From those operating points, the optimum fan parameters can then be obtained using a GA based on a static pressure DNN model. Table 8 shows the operating point, optimum design parameter, and assessment result. Using the optimum design parameter, flowrate, and rotating speed, the static pressure can be predicted, which is 49.96 Pa. It is similar to

our design with 0.1% error. Q_{max} and P_{max} can also be obtained, while Q_{ratio} and P_{ratio} are still in our design range.

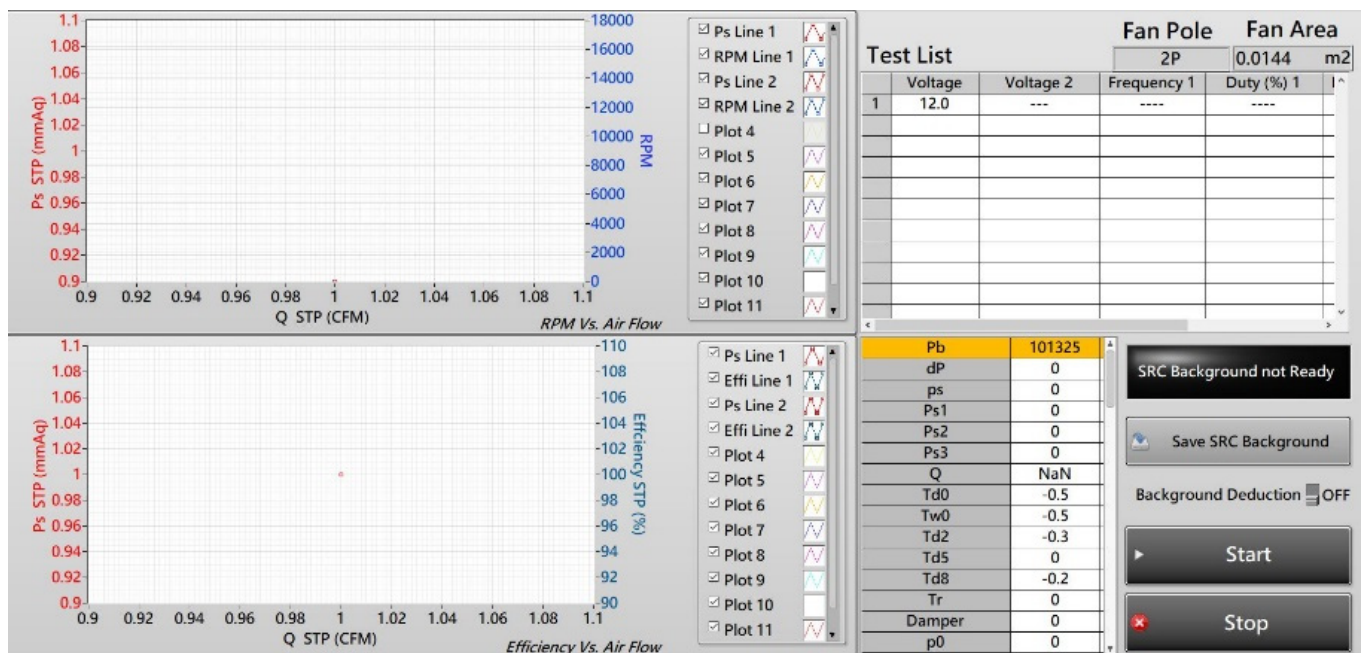


Figure 7. Data collection interface.

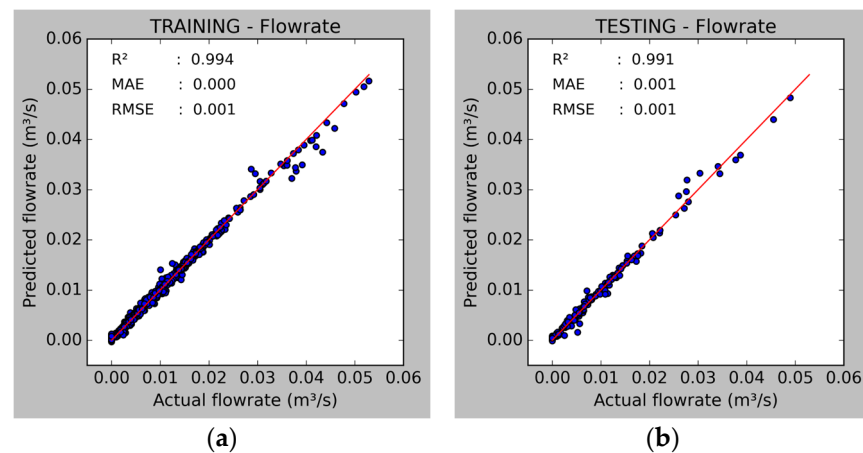


Figure 8. Scatterplot of the flowrate prediction model using (a) training data and (b) testing data.

Figure 10 shows the P-Q Curve using the optimum design parameter. The red dot indicates the operating point and the blue dots indicate the static pressure values using flowrate variation. In Figure 10, the red point is on the P-Q Curve, meaning that the specified parameter conformed to the design range. P_{ratio} and Q_{ratio} are 0.5, which is within the design range. Therefore, the red dot point is almost in the center of the blue line.

3.5. Discussion

The DNN is able to predict fan static pressure successfully, where the R^2 is higher than 0.99. A GA is also then able to find the optimal design parameters with the specified operating point, P_{ratio} and Q_{ratio} . Therefore, this technique will be implemented in the fan manufacture. Over time, a new fan design will be produced and tested using test measurements. The data will be collected as in the previous work. The fan dataset will be

updated and will continue to be huge. The minimum and maximum operating parameters will be wider. Therefore, the AI fan design application will continue to perform better.

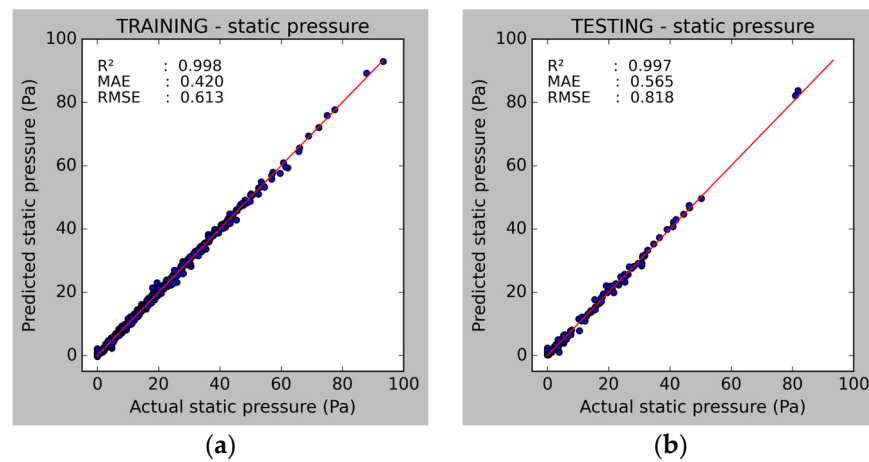


Figure 9. Scatterplot of the static pressure prediction model using (a) training data and (b) testing data.

Table 6. Performance evaluation of flowrate and static pressure models.

Performance Evaluation	Flowrate Model		Static Pressure Model	
	Training	Testing	Training	Testing
R^2	0.994	0.991	0.998	0.997
MAE	0.000	0.001	0.420	0.565
RMSE	0.001	0.001	0.613	0.818

Table 7. Design parameters range.

Parameters	Range
Chord length root	20~50 mm (interval 1 mm)
Chord length tip	25~60 mm (interval 1 mm)
Pitch angle	35~50° (interval 1°)
Twist angle	0~20° (interval 1°)
Impeller diameter	40/50/60/70/80/92/120/140 mm
Hub OD	25~60 mm (interval 5 mm)
Blade number	3/5/7/9/11
Tip clearance	1~2.5 mm (interval 0.5 mm)
Frame thickness	15/20/25/38 (mm)

Table 8. Operating point, optimum design parameter, and assessment result.

Operating point	Static pressure (Pa)	50
	Flowrate (m ³ /s)	0.01
	Rotating speed (RPM)	6000
Optimum design parameter	Chord length root (mm)	22
	Chord length tip (mm)	40
	Pitch angle (°)	42
	Twist angle (°)	7
	Impeller diameter (mm)	80
	Hub OD (mm)	30
	Blade number	5
	Tip clearance (mm)	2
	Frame thickness (mm)	38

Table 8. Cont.

Assessment	Predicted static pressure (Pa)	49.96
	Static pressure error (%)	0.1
	P_{ratio}	0.50
	Q_{ratio}	0.50

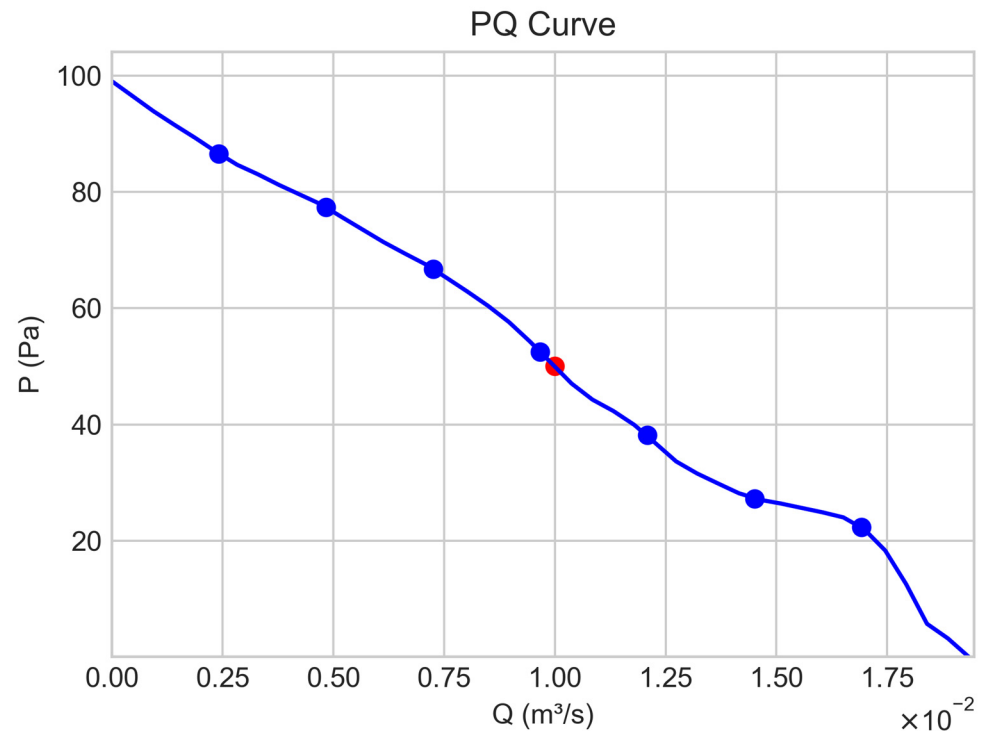


Figure 10. P-Q Curve using optimum design parameter.

4. Conclusions

This study used a deep neural network to build two prediction models: the static pressure model and the flowrate model. The static pressure prediction model was selected for further optimization using GA. The performance model using testing data had $R^2 = 0.997$, MAE = 0.565, and RMSE = 0.818. The inputs are nine design parameters, rotating speed, and flowrate. The nine design parameters are chord length root, chord length tip, pitch angle, twist angle, impeller diameter, hub outer diameter, blade number, tip clearance, and frame thickness. The goals of the GA were to find the optimum design parameters based on the operating points. The operating points are static pressure, flowrate, and rotating speed. Several constraints are applied: The GA will search for the design parameters that have P_{ratio} and Q_{ratio} in the 0.5~0.6 range. The chord length root should equal or be less than the chord length tip. The operating points are determined in advance, namely, 50 Pa of static pressure, 0.01 m³/s of flowrate, and 6000 RPM of rotating speed. The results show that the GA is able to find the optimal design parameters with the specified operating points and constraints, with only 0.01% of static pressure error. The results can be used as a reference for engineers to evaluate whether the fan met requirements. This approach can reduce the design time and material. Various design parameters can be obtained from numerous data. Therefore, a new small axial flow fan was developed.

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