Airport Aviation Noise Prediction Based on an Optimized Neural Network

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Abstract: In order to alleviate noise pollution and improve the sustainability of airport operation, it is of great significance to develop an effective method to predict airport aviation noise. A three-layer neural network is constructed to gain computational simplicity and execution economy. With the preferred node number and transfer functions obtained in comparative tests, the constructed network is further optimized through the genetic algorithm for performance improvements in prediction. Results show that the proposed model in this paper is superior in accuracy and stability for airport aviation noise prediction, contributing to the assessment of future environmental impact and further improvement of operational sustainability for civil airports.

Key words: noise prediction; neural network; genetic algorithm; sustainable air transport

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0 Introduction

Aviation noise is inevitable as one of the negative externalities of air operation, and impacts residents especially in the area near busy airports. Since the 1950s, the number and scale of civil airports have been continuously expanding due to the vigorous development of the air transport industry[1], and the improvements in speed and load of aircraft have made the issue of aviation noise pollution increasingly prominent. Therefore, effective assessment and prediction of airport aviation noise is indispensable for preventing and mitigating noise pollution, improving the sustainability of airport operation, so as to ensure the coordinated development of the airport and the city.

Airport aviation noise considers all operating aircraft within the airport area including those are taxiing, taking off, and landing[2]. Currently, laudable achievements have been made in the research on airport aviation noise. In terms of noise assessment, a non-uniform poisson model was established and employed by Guarnaccia et al.[3] to effectively evaluate the aviation noise in Nice International Airport; Li[4] explored and verified the highly linear relationship between the aviation noise contour area and the noise level at the noise observation point, which contributed a lot to quntification of the noise pollution in airport neighborhood. In the studies of Gasco et al.[5], the most common noise indicators used in airports from Europe, Australia, and the United States of America were reviewed and different visualizations that airports used to communicate noise information were also described.

To make reasonable operational decisions that help control airport aviation noise, a new model for predicting airport overall noise based on the differential evolution algorithm (DEA) was developed by Xu et al.[6], and supported the development of future noise reduction plans. Yang[7] compared the par-

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allel runway with the single one and summarized the influencing factors in multi-runway airports concerning aviation noise, followed by which several methods for reducing noise in multi-runway airports were proposed. Taken both noise pollution and CO_2 emissions into account, Postorino and Mantecchini[8] explored the relationship between the connectivity (measured by air links and the number of flights) and environmental impacts of airport operation, also proposed a viable connectivity index (VCI), which could be used as a preliminary test for airport operators to identify suitable policies addressed to reduce their noise and carbon amount and keep good connectivity levels at the same time.

Although many excellent studies on the airport aviation noise have been conducted, there are still deficiencies in terms of the research dimension and solution approach. On the one hand, accurate prediction is essential for effective targeted decision-making to reduce airport aviation noise so as to improve the sustainability of airport operation. However, the existing research on airport noise is mostly carried out from the perspective of noise assessment while less involves noise prediction. On the other hand, the methods widely employed in predicting are usually computationally complex and economically inefficient, resulting in poor feasibility in practical application. It is practical and far-reaching to develop an effective method of airport aviation noise prediction. In this regard, this paper contributes to airport aviation noise prediction from three aspects:

(1) The supervised learning method is employed to model the airport aviation noise, ensuring a significantly simplified obtainment for prediction results;

(2) The constructed network is further optimized through the genetic algorithm for performance improvements in prediction;

(3) An application example using the data of Nanjing Lukou International Airport is given, indicating the feasibility and reliability of the proposed method.

1 Neural Network Model for Airport Aviation Noise Prediction

1.1 Noise evaluation index

Airport aviation noise has a wide range of influence as well as a long duration[9]. With its intermittent exposure and cumulative effect, the level of airport aviation noise is disorderly unsteady. In terms of the evaluation metric of airport aviation noise, there is no absolute uniform standard can be found in the literature. The sound exposure level (SEL), the day-night average sound level (L_{dn}) and the weighted effective continuous perceived sound level (L_{WECPN}) are the three mostly used ones in current studies.

L_{WECPN} takes the spectral characteristics and duration of noise into consideration[10]. Besides calculating the basic physical parameters, it uses the psychological impact on humans to quantify the degree of aviation noise. Additionally, compared with the consideration about two periods of 07:00—22:00 and 22:00—07:00 for L_{dn}, one day is divided into three durations including 07:00—19:00 (daytime), 19:00—22:00 (evening) and 22:00—07:00 (night) for L_{WECPN}, which contributes to the assessment results with higher rationality and accuracy[11]. Therefore, the indicator L_{WECPN} is taken as the evaluation index of airport aviation noise

$$L_{WECPN} = \overline{L_{EPN}} + 10\lg(N_1 + 3N_2 + 10N_3) - 39.4 \tag{1}$$

where N_1, N_2, N_3 are the daily numbers of flight takeoff and landing during 07:00—19:00, 19:00—22:00, and 22:00—07:00 respectively; $\overline{L_{EPN}}$ is the average effective perceived noise level of multiple flights, which can be expressed as

$$\overline{L_{EPN}} = 10\lg\left(\frac{1}{N_1 + N_2 + N_3}\sum_i\sum_j 10^{L_{EPN}^{ij}/10}\right) \tag{2}$$

where L_{EPN}^{ij} is the effective perceived noise level at a certain observation point on route j caused by aircraft i.

1.2 Influencing factors of airport aviation noise

The level of airport aviation noise is affected by many factors. For a single aircraft before cumulation, the aircraft performance, the location of monitoring points and atmospheric condition are the three primary influencing factors of perceived noise:

(1) Aircraft performance

The theoretical noise value is a function of the distance and the engine thrust. When an aircraft needs a certain lift during operation, the required specific value of thrust greatly depends on the engine performance[12]. Shortly speaking, the generated noise differs with the selection of aircraft type.

(2) Observation location

There is continuous energy loss in the process of noise propagation. The farther noise propagates, the more attenuation generates and the less noise will be perceived. Therefore, various noise evaluation results will be obtained at various observation points for the same aircraft at the same time. This is also the reason why noise impacts more on those people nearby the airport.

(3) Atmospheric condition

It has been suggested that a medium is required in the sound transmission, and the airport aviation noise that people perceive can spread through the air. That means the effect of the atmospheric condition on aviation noise. For example, the factor of wind may change the direction and speed of noise propagation, and the atmospheric temperature affects the propagation speed by changing the velocity of gas molecules.

Consequently, the noise caused by a single aircraft needs to be modified

$$L_{\mathrm{EPN}}=L_{\mathrm{EPN}}(P,d)+\Delta v-\Lambda(\beta,L)+\Delta L \tag{3}$$

where $L_{\mathrm{EPN}}(P,d)$ is the sound level obtained by interpolation using the basic data of aviation noise according to the engine thrust P and the shortest distance d between the observation point and the flight track.

1.3 Three-layer neural network model for airport aviation noise

Artificial neural network is an effective technology of supervised learning. It is an information or signal processing system composed of a large number of nodes called neurons and weighted connections, which jointly complete parallel distributed processing and computing tasks[13]. By simulating the structure and functions of the biological brain and nervous system, it has advantages in self-learning ability, problem-solving efficiency as well as application operability.

In this paper, a three-layer neural network for airport aviation noise prediction is constructed. Considering the diversity and uncertainty of the aircraft type in the airport area, the factor of aircraft performance is not taken into consideration. As can be seen in Fig.1, the location information of the observation point, including its longitude, latitude and altitude, along with the speed of atmospheric wind are set as the parameters (namely the nodes of x_1, x_2, x_3, and x_4) in the input layer X. The preferred evaluation indicator of airport aviation noise, L_{WECPN} is selected as the parameter (namely the node of z) in the output layer Z. Additionally, the nodes of y_1, y_2, y_3, $\cdots$, y_{n-2}, y_{n-1} and y_n in the hidden layer Y work to transfer the information between X and Y.

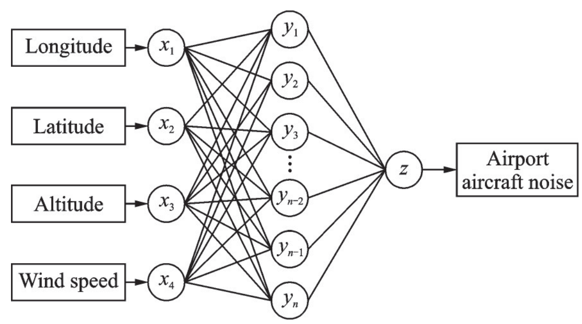

Fig.1 Topology of the three-layer neural network of airport aviation noise

2 Optimized Solution of the Neural Network Using the Genetic Algorithm

2.1 Back propagation to learn from errors

The main procedure of the neural network includes two parts: Forward output calculation and backward error propagation[14]. With randomly initializing connection weights and biases between layers at the beginning, once the normalized four input parameters are given, the output value of node y_j in the hidden layer, $y(j)$ can be obtained by

$$y(j)=f_y\left(\sum_{i=1}^{4} w_{ij}x(i)+b_y\right) \quad j=1,2,\cdots,J \tag{4}$$

where f_y is the transfer function for layer Y; w_{ij} the connection weight between node x_i in X and node y_j in Y; $x(i)$ the value of node x_i; b_y the bias for layer Y, and J the total number of nodes in Y.

Furtherly, the output value of node z in the output layer, namely the predicted noise value, z^{op} can be calculated by

$$z^{\mathrm{op}}=f_z\left(\sum_{j=1}^{k} w_{jk}y(j)+b_z\right) \quad k=1 \tag{5}$$

where f_z is the transfer function for layer Z; w_{jk} the linked weight between node y_j in Y and node z in Z; b_z the bias for layer Z; k takes the constant value of 1 when there is only one node in Z, as Fig.1 shown.

After calculating forward layer by layer according to Eqs.(4, 5) for each sample n, the total output squared error E of the prediction can be expressed as

$$E=\sum_{n=1}^{N}\left(z_n^{\mathrm{op}}-z_n^{\mathrm{ep}}\right)^2 \tag{6}$$

where z_n^{op} and z_n^{ep} are the output and actual noise value of sample n, respectively.

After measuring the output error, the gradient of this error is calculated and the initial weights and biases are constantly adjusted in the direction of descending gradient as Eqs.(7—10) describe, until the training goal or the upper limit of iteration is satisfied

$$w_{ij}(t+1)=-\eta\frac{\partial E}{\partial w_{ij}(t)}+w_{ij}(t) \tag{7}$$

$$w_{jk}(t+1)=-\eta\frac{\partial E}{\partial w_{jk}(t)}+w_{jk}(t) \tag{8}$$

$$b_y(t+1)=-\eta\frac{\partial E}{\partial b_y(t)}+b_y(t) \tag{9}$$

$$b_z(t+1)=-\eta\frac{\partial E}{\partial b_z(t)}+b_z(t) \tag{10}$$

where t and $t+1$ are the iteration numbers (there are different values for network weights and biases corresponding to different iterations); η is the defined learning rate for adjusting weights and biases.

2.2 Optimization of the initial parameters using the genetic algorithm

The learning method of gradient descent presented previously enables the network to gradually adjust along the direction of local improvement. Although the required solving time has been effectively reduced, inappropriate initial weights and biases can increase the possibility of falling into local optimum in complex search landscapes[15]. The genetic algorithm is a stochastic search technique that simulates natural selection and utilizes genetic mechanisms. With superior global search capability, it has great performance in effectively obtaining optimal (or sub-optimal) solutions[16]. Hence, the genetic algorithm is employed to improve the network performance by optimizing the initial parameters, namely the weights and biases between layers. As illustrated in Fig.2, the specific implementation is organized as follows.

Step 1 Data normalization: Normalize the original sample to a new dataset with an interval of 0—1 by Eq.(11) for the quantization uniformity

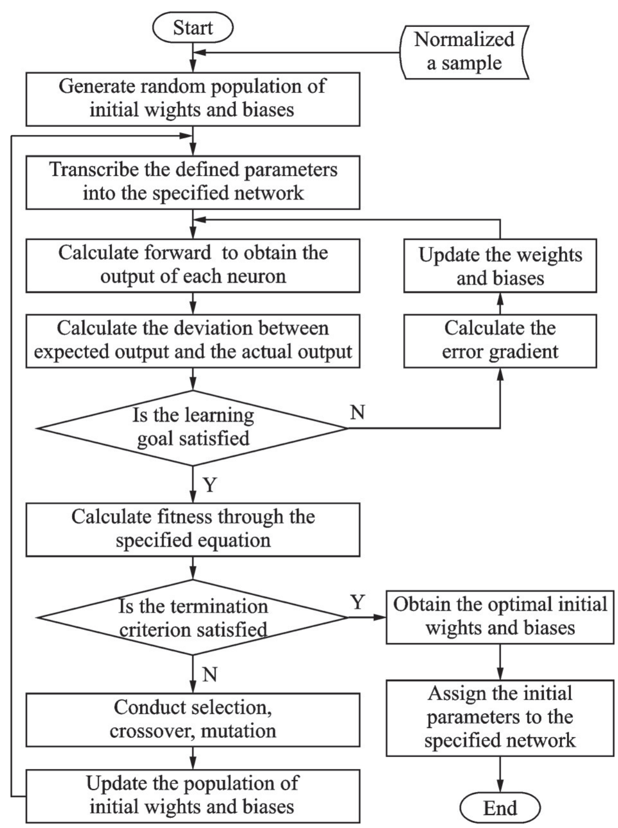

Fig.2 Flow chart of the optimized neural network

$$s_n' = \frac{s_n - s_{\min}}{s_{\max} - s_{\min}} \tag{11}$$

where s_n' is the normalized value of sample n; s_n its original value; $s_{\min}$ and $s_{\max}$ are the minimum and the maximum among all samples, respectively.

Step 2 Population initialization: Randomly generate an initial population consisting of many individuals, each of which includes a series of connection weights and biases for different layers.

Step 3 Fitness calculation: Define the fitness F as the mean squared error (MSE) of all samples in the testing dataset, and the function can be expressed as

$$F = \frac{1}{N}\sum_{n=1}^{N}\left(z_n^{\mathrm{op}} - z_n^{\mathrm{ep}}\right)^2 \tag{12}$$

where N is the sample number in test dataset.

Step 4 Generation evolution: Update the population through evolutionary manipulations, including selection, crossover, mutation and retention. Calculate the fitness values of individuals and record the best one with the least fitness in each generation. Repeat this step until the prespecified termination condition is satisfied.

Step 5 Initial network parameters setting. Set the initial weights and biases of the constructed network according to the best individual obtained in Step 4 and assign them to the network.

Step 6 Application: Train the network and apply it to effectively obtain reliable prediction results.

3 Experiment Results and Analysis

3.1 Data preparation

Samples of Nanjing Lukou International Airport (ICAO code: ZSNJ) were collected from a computer simulation software named Aviation Environmental Design Tool (AEDT) to train and verify the proposed method. As shown in Table 1, the raw data includes the information about longitude, latitude, altitude, wind speed at each observation point, as well as the corresponding values of weighted effective continuous perceived sound level, L_{WECPN}. For the acquisition of L_{WECPN}, noise observation points were selected within 20 km away from the taxiway center; the wind speed is set as 3.70, 8.17 and 9.26 km/h successively under the premise that other meteorological conditions remain unchanged. After normalization, the collected samples (2 040 in total) were randomly split into the training (60%), the testing (20%) and the validation (20%) datasets, allowing a supervised learning process to be performed.

Table 1 Part of the sample data

Latitude/(°N)	Longitude/(°E)	Elevation/m	Wind speed/(km•h^{-1})	L_{WECPN}/dB
31.64	118.77	5.91	3.70	35.29
31.82	118.98	5.91	3.70	48.89
31.71	118.90	5.91	3.70	59.47
31.64	118.77	2 624.67	8.17	31.66
31.72	118.98	1 640.42	8.17	59.52
31.77	118.92	656.17	8.17	71.91
31.78	118.77	5.91	9.26	41.78
31.78	118.98	5.91	9.26	68.22
31.73	118.88	5.91	9.26	82.64
⋮	⋮	⋮	⋮	⋮

3.2 Optimal initial network parameters

There is no doubt that the node number of the hidden layer and the selection of transfer functions are critical factors that determine the network performance. In order to reduce the prediction error as far as possible, comparative tests were carried out by training the network for each value in the nodes number range of 10—20 in Y using different transfer functions combinations. In terms of the transfer functions, the widely used sigmoid (sig) function and linear (lin) function are considered in this paper. Fig.3 illustrates the average results of 20 runs with the learning rate of 0.01. It is obvious that the combination of lin-lin with 14 nodes in Y performs best in terms of MSE, meaning that a minimum prediction error can be obtained using a linear transfer function for both the hidden layer and the output layer. In addition, it can be observed that as the neuron number of the hidden layer changes, the lin-lin combination shows higher stability in prediction error.

Given the preferred node number of Y and

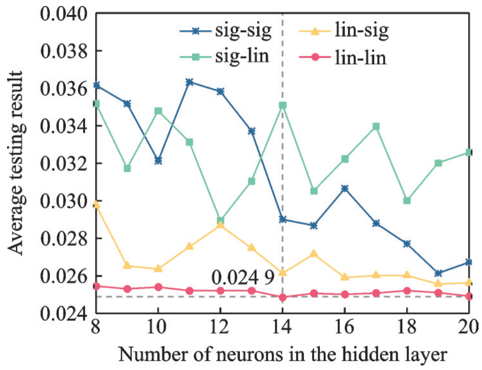

Fig.3 Comparation of network performance using different transfer functions and node numbers in the hidden layer

transfer functions for different layers, the initial weights and biases can be optimized according to the solution process described in Section 2. The specific parameters of the genetic algorithm were set based on computational results regarding accuracy during plenty of experiments. Using binary encoding, the population size and the maximum of generation were all defined as 100. The strategies of Roulette-wheel selection, two-point crossover, discrete mutation, and elitism were adopted, and the rates for crossover, mutation and retention were assigned to be 0.85, 0.01 and 0.85, respectively. Fig.4 shows the output fitness curve of the genetic algorithm. When the generation number reaches about 29, there comes a converged solution and a minimum MSE approaching to 0.011 2, at which time the optimal initial weights and biases are obtained. Compared with the original minimum value of 0.024 9 (Fig.3), an improvement resulted from the genetic algorithm optimization is preliminarily indicated by the generated error reduced by about half.

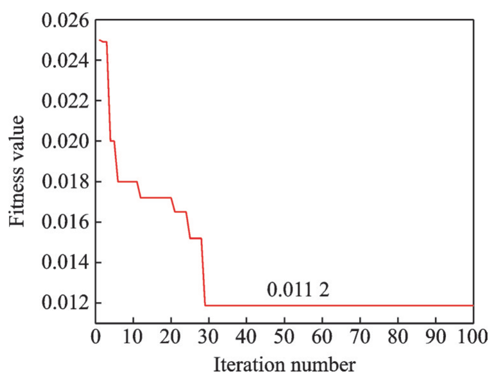

Fig.4 Fitness curve of the genetic algorithm

3.3 Results and analysis

The output (predicted) and actual values of noise level for 100 exemplars randomly selected from the testing dataset (408 in total) are illustrated in Fig.5. Generally, there is a good agreement between the predicted and the actual results using the optimized neural network.

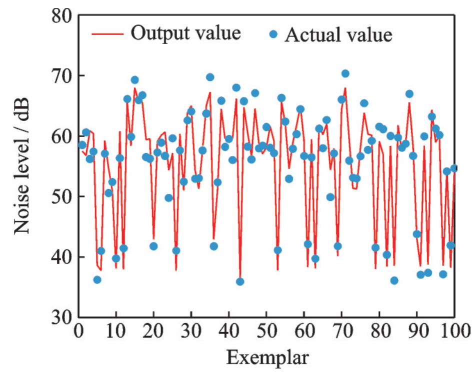

Fig.5 Comparison of the predicted and the actual values of noise level for 100 exemplars in the testing dataset

To further assess the advantage of the optimized neural network for airport aviation noise prediction, its performance was tested and compared with that of the original one using the validation data. Note that all tests were conducted with the same learning rate, and the gradient method was always used to learn from error. As for performance indicators, the mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), maximum absolute percentage error (Max-APE) and R^2 were selected and counted. The detailed numerical results are shown in Table 2.

Table 2 Performance comparison between the optimized neural network and the original one

Performance indicator	Original neural network	Optimized neural network
MSE	0.025 6	0.012 3
MAE	0.124 0	0.126 6
MAPE	0.084 5	0.041 9
Max-APE	0.154 9	0.091 6
R^2	0.647 5	0.835 6

Numerical results in Table 2 make it obvious that the optimized neural network has advantages in prediction performance. That is indicated by the reduction of all kinds of error including MSE, MAE, MAPE and Max-APE, as well as the significant increase of R^2. Consequently, it can be drawn that the accuracy and stability of the constructed neural network for airport aviation noise prediction is improved effectively by the introduction of the genetic algorithm.

4 Conclusions

In order to support targeted decision-making for reducing airport aviation noise and thus improving the sustainability of airport operation, a more effective model using machine learning method is developed for airport aviation noise prediction in this paper. Some conclusions are drawn as follows.

(1) The conducted neural network for airport aviation noise prediction performs best when 14 nodes are set in the hidden layer with a linear transfer function for both the hidden layer and the output layer.

(2) Using the optimized neural network, there is a good agreement between the predicted results and the actual ones for 100 exemplars of the testing dataset.

(3) The genetic algorithm shows significant efficiency in optimization performance of the constructed neural network, which is indicated by the reduced MSE, MAE, MAPE, Max-APE and the increased R^2.

The feasible, reliable and optimized method for airport aviation noise prediction proposed in this paper helps assess the environmental impact and further improve the sustainability of airport operation. Future studies can be carried out by identifying other influencing factors and placing them into the input layer. It is also meaningful to take the introduction of multiple hidden layers into consideration.

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Author contributions Miss **MA Lina** designed the study, conducted the analysis and wrote the original manuscript. Dr. **TIAN Yong** contributed data and model components for the optimized neural network. Mr. **WU Xiaoyong** contributed to the discussion and background of the study, also revised and modified the manuscript. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

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基于改进神经网络的机场航空噪声预测

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摘要: 探索一种有效的机场航空噪声预测方法对减轻机场噪声污染和提升机场运营的可持续性具有重要意义。为简便、经济地解决机场航空噪声预测问题,本文采用三层神经网络技术进行建模;基于对比试验中获得的最佳神经元个数和不同层间的传递函数,使用遗传算法对所构建的网络进行优化,以进一步提升网络预测性能。结果表明,本文提出的方法在机场航空噪声预测方面表现出了更高的精确度和稳定性,研究结果有利于评估未来机场航空器运行的环境影响,进而提高机场运营的可持续性。

关键词: 噪声预测;神经网络;遗传算法;可持续运输