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Using artificial neural network on flight distance prediction for paper plane

Tian-Syung Lan[1], Pin-Chang Chen[2] and Chih-Hsien Chuo[1]

Abstract

This study shows how to apply the essential principles of paper plane on the flight experiment. It applies three basic structures of paper plane including nose, wing, and rudder movements to predict the optimal flight distance. This study employs the artificial neural network model for data analysis and prediction. The data collected from the flight distance of paper plane are calculated and analyzed in the artificial neural network model in order to predict the optimal flight distance of paper plane. This study is intended to discover the essential principles and basic structures of manufacturing paper plane and provide theoretical and practical contributions in hands-on experiments and aviation science.

Keywords

Artificial neural network, flight distance, paper plane, prediction model, experiment

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Introduction

Paper plane involves the exploration into origami skills and flight principles. The manufacturing of paper plane can be referred as a kind of craft skill such as origami, paper cutting, and paper sculpture. It also can be referred as a kind of scientific creation. The improvement based on errors and experiments after modification and testing is the process of creation and invention. It means that paper plane is an interesting practice-based experiment which is conducted for the acquisition of scientific knowledge.[1]

Although paper plane is small and simple in appearance, it has the basic flight structure which consists of frame, wings, air level, vertical tail, flap, and elevator like a real plane. The basic requirement of paper plane is the ability of moving forward and rising up. It also requires the abilities of resistance against wind and turbulent airflow. In other words, the manufacturing and flight of paper plane can reveal the scientific principles of a real plane.[2]

The actual operation and flight of paper plane nearly involve all the flight functions of a real plane including gliding, straight flight, turning flight, and up-and-down rolling. With relevant flight principles, paper plane can be used for the experimental operation and adjustment of flight. The flight experiment of paper plane can illustrate the basic knowledge and concepts about flight, such as velocity and pressure, elevating force, force and counterforce, gravity, and weight.[3] This study uses paper plane for research experiment which comprised the three basic structures according to the basic scientific principles, concepts, and structures of plane. The three basic structures are the head including the prepositive weight and gravity; the wing including carrying capacity, elevating force, resistance, pressure, and angle of attack; and the elevator including rise, fall, and turn. This study employs artificial neural network (ANN) model for data analysis and prediction. The data collected from the flight distance of paper plane are

[1]Yu Da University of Science and Technology, Miaoli, Taiwan
[2]CTBC Financial Management College, Tainan, Taiwan

Corresponding author:
Pin-Chang Chen, CTBC Financial Management College, No. 600, Section 3, Taijiang Boulevard, Annan District, Tainan 709, Taiwan.
Email: chenpc@ctbc.edu.tw

calculated and analyzed in the ANN model in order to predict the optimal flight distance of paper plane.

Some recent researches on the field of neural networks have been conducted. He et al.[4] described the adaptive neural network control of an uncertain robot with full-state constraints. He et al.[5] found that adaptive impedance control was developed for an n-link robotic manipulator with input saturation by employing neural networks. He et al.[6] stated that a neural network controller was designed to suppress the vibration of a flexible robotic manipulator system with input dead zone. These researches have provided important references and hints for the research objective of this study. This study is intended to look for the best neural network architecture and algorithm to develop an ANN forecasting model on flight distance prediction for paper plane.

Literature reviews

Flight principles of paper plane

The basic structure of paper plane is the elevating force generated by the combination of nose, wing, and tail. Because of the prepositive weight in the nose, the gravity is located in the first half of frame. When the paper plane flies, the prepositive weight would make the paper plane fall in the form of a parabolic curve.[7]

The paper plane is hurled with one hand over the shoulder as well as the hurler's body leaning to one side. By rotating the shoulder joint and stretching the arm, the hurler hurls the paper plane with the maximum strength. The paper plane is powerless by itself and depends on the strength of hurling. Moreover, the paper plane does not have any sustainable force because paper plane flies in a straight line. The flight of the paper plane is supported by the initial force. The force would gradually disappear due to resistance.[8] In particular, the elevating force will disappear more quickly when the elevating structures like the elevation board are applied. The planes like hurled glider are completely driven by the strength of hurling and the change in airflow. Therefore, paper plane must have a streamline form. The weight and gravity center of paper plane must reach certain balance proportion. As a result, paper plane would be able to fly continually with the optimal proportion of elevating force and resistance.[9]

ANN

The ANN is applied as the research method in this study. ANN, as its name indicates, is a model which imitates the neurons and neural networks of human brain. ANN originated in the 1940s when scientists began to design an artificial computer characterized with such complicated human brain behaviors as thinking, analysis, and induction according to the neural system of human brain.[10]

The feature of ANN is that it has a processing mode similar to that of human brain, including memory, learning, and induction. ANN can learn from many accumulated data and acquire the wisdom similar to human brain. Scientists have become increasingly convinced that the simulated biological system can significantly accelerate the development of artificial intelligence. ANN has the modes of memory and cumulative learning, so it has a stronger ability to offer experience and information for analysis and induction. Additionally, the processing mode of ANN is efficient. Due to the parallel processing mode, ANN is capable of high-speed calculation.[11]

As the learning based on the neural system of human brain, ANN applied in various fields derived from the essence of life science and engineering science. ANN plays an important role in different areas, such as computer science, artificial intelligence, biomedicine, automatic control, video processing, phonetic recognition, neural science, physiology, psychology, and cognitive science.[12]

Back-propagation neural network (BPN) is the most representative and widely applied neural network model. The concept of BPN was discussed by Werbos in 1974 and Parker in 1982. The basic principle of BPN is using the gradient steepest decent method to minimize the error function and infer the Delta Rule. The BPN processing is divided into two stages including learning process and recall process. In the stage of learning process, the learning model is adopted to obtain weighted values and threshold values. In the stage of recall process, the weighted values and threshold values are used to apply model simulation and obtain the forecasting results. The BPN model can be explained using formulas (1) and (2) as follows

$$u_i(k+1) = \sum_{j=1}^{N} W_{ij}(k)a_j(k) + \theta(k) \tag{1}$$

$$a_i(k+1) = f(u_i(k+1), u_i(k), a_i(k)) \tag{2}$$

After a new activation value is generated, it is sent to other neurons. The two preceding formulae are collectively called the system dynamic formula, where k indicates the number of updates, u_i represents the input value of the neuron number i, W_{ij} indicates the weighted value between neuron number i and neuron number j, θ_i denotes the internal threshold value of neuron number i, Nindicates the number of neurons connected to neuron number i, and $f(\bullet)$ describes the activation function derived from the simplified bio-effect in the neural cells.

The BPN processing steps are repeated until the error value no longer changes significantly and the convergence is achieved. The BPN model stores the weighted and threshold values when the learning process is completed. The weighted and threshold values are applied in the recall process in order to obtain the forecasting results.[10]

Methodology

This study obtains relevant data from the flight experiment of paper plane. The factors which affect the flight distance of paper plane are taken as the input variables. The flight distance is taken as the output variable. As the variables which influence the flight distance of paper plane are non-linear, this study adopts Alyuda Neuro Intelligence software as ANN simulation tool. This software is able to seek the optimal parameters and algorithms to train, analyze, test, and obtain the forecasting results. The research process of this study is as follows:

Step 1 (Analysis). The factors which affect the flight distance of paper plane are taken as the input variables. The variables are classified and ranked according to the experiment sequence. This study takes 70% of the input data as the training values, 15% as the validation values, and 15% as the testing values.

Step 2 (Preprocessing). To prevent excessive or inadequate data from resulting in an excessive error value which would reduce the accuracy of prediction, the numeral values of the data are set between "1" and "−1."

Step 3 (Design). The quantity of the input layer, hidden layer, output layer, and the artificial neurons of the network are defined in the establishment of the ANN framework. The number of hidden layers and the artificial neurons would have direct influence on prediction performance. ANN adopts the trial-and-error learning methods to achieve the best predicted results.

Step 4 (Training). The algorithm is selected, and the learning rate and learning cycles are set according to the ANN framework. The training process goes on repeatedly until the ANN achieves convergence.

Step 5 (Testing). Once the ANN model has been well trained, the output data are obtained as the predicting result.

Step 6 (Evaluation). The correlation and R-squared values are evaluated to compare the predicted values and the actual values in order to obtain the best forecasting performance.

Data analysis

In this study, 240 paper planes with various structures are taken as the samples. The three basic structures which influence the flight distance of paper plane are taken as the input variables. The three basic structures include the size of the nose, the width of the wing, and the angle of the elevator. With these three factors as the input data and the flight distance as the output data, this study aims to find out the best combination of the three basic structures in order to achieve the optimal performance of flight distance.

The three basic flight structures of paper plane are mutually combined, with the length of the nose being 1, 2, 3, 4, 5, and 6 cm, the width of the wing being 2, 3, 4, 5, 6, 7, 8, and 9 cm, and the elevator being at the angles of 25°, 45°, 65°, 90°, and 105°. In this study, 240 paper planes are used for the experiment.

Among the three influencing factors, the length of the nose includes the location and size of the prepositive weight and the location of gravity center. It plays an essential role in the forward hurling of paper plane. A longer nose indicates a heavier nose and a more front gravity center of paper plane. The width of wing determines the elevating force (including resistance and pressure) and the loading capacity of paper plane. A narrower wing indicates less resistance, which would facilitate the flight in terms of velocity and distance. On the contrary, a wider wing implies greater resistance and elevating force, and a lower speed which is good for hovering. The elevator angle can be regulated and controlled for the upward and downward flight of paper plane. Moreover, it would create an adequate angle of attack for the wing and generate the elevating force for the paper plane.

Alyuda Neuro Intelligence software is employed to analyze and predict the data. There are different neural network training algorithms including Quick Propagation, Conjugate Gradient Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg–Marquardt, Online Back Propagation, and Batch Back Propagation provided by the Alyuda Neuro Intelligence software. This study uses 50 test samples in order to find the best training algorithm among the candidate methods. After the test simulation, the Quick Propagation outperformed other methods which has been chosen as the neural network training algorithm for this study. The simulation process is shown in Figures 1–4 as follows.

According to the results, the optimal length of the nose is between 2 and 6 cm, the width of the wing is between 4 and 8 cm, and the angle of the elevator is between 25° and 65°. The correlation coefficient of the samples was 0.952 and that of the relevant samples was 0.905. It indicates a close and positive correlation which demonstrates that the predicted results of the proposed model are reliable.

Conclusion

Paper plane is a kind of powerless plane. It means that the three basic structures must be taken into

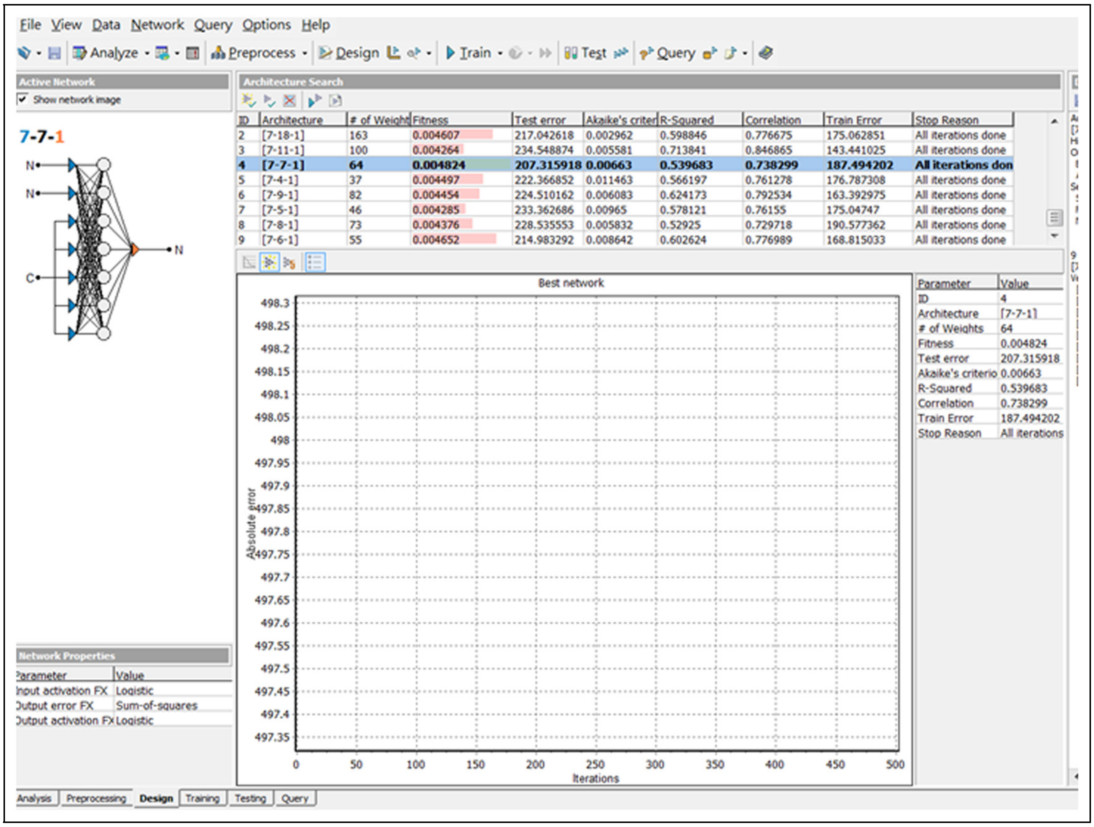

Figure 1. Neural network design.

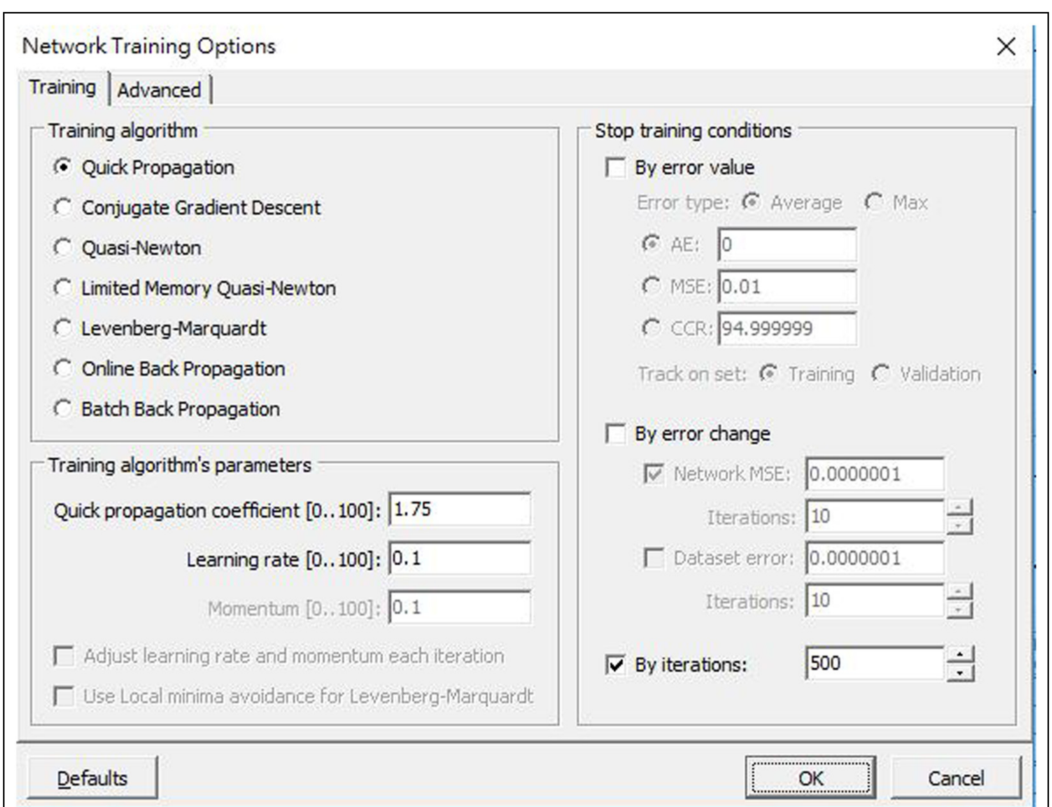

Figure 2. Training algorithm.

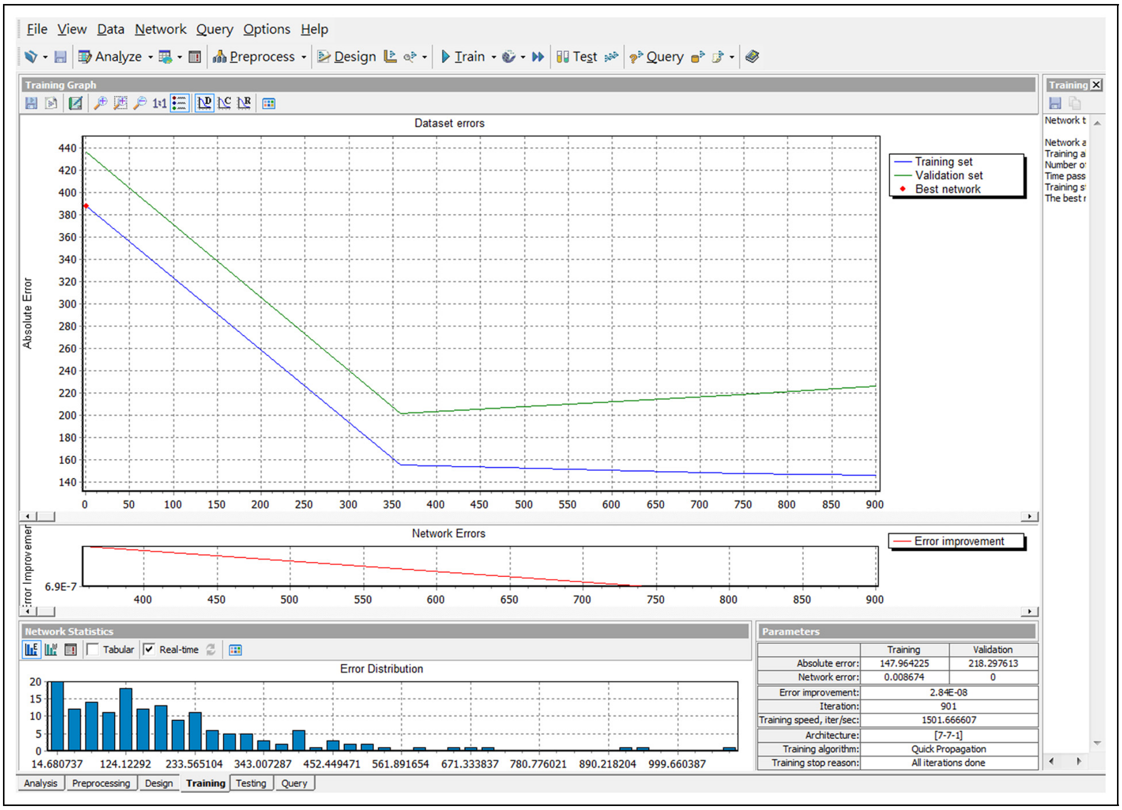

Figure 3. Data training.

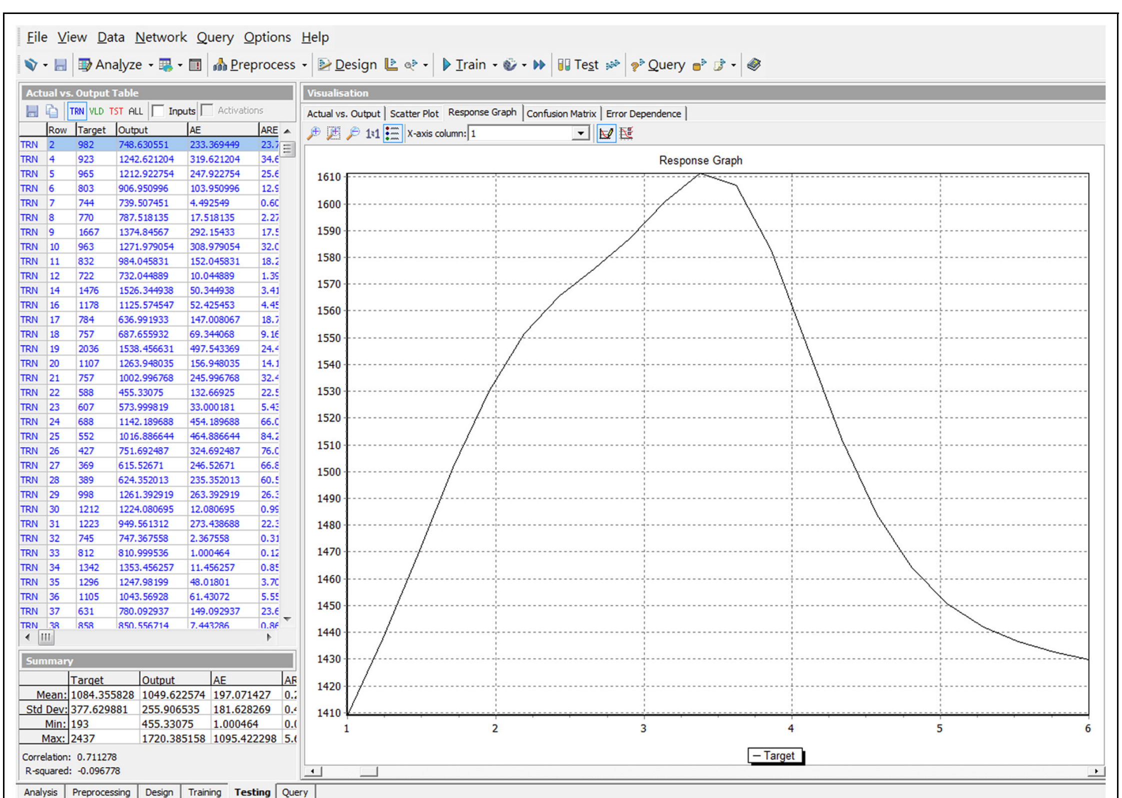

Figure 4. Data testing.

consideration. The additional weight of the nose is taken as the hurling force. The elevation angle is adjusted to affect the angle of attack of the wing in order to generate the elevating force. Therefore, the interactions of the three structures including the weight of the nose, the width of the wing, and the angle of the elevator are the key points for the flight distance of paper plane.

The traditional method of predicting paper plane's flight distance is manufacturing a lots of paper planes and applying a lots of the flight testing. The flight experiments might take a long time and spend a lot of expenses. Compared to the traditional method, the ANN method proposed in this study can provide reliable predicting results using ANN model simulation. The predicting results will be referred as important references for future paper-plane manufacturing.

In conclusion, the three basic structures of paper plane will affect the performance of flight distance. An excessively small nose, for instance, indicates that the prepositive weight is too light and that the gravity center moves backwards. An overly narrow wing will result in a weak elevating force. A high angle of rudder indicates that the resistance is excessive and the elevation is too fast. They would reduce the stability and flight distance of paper plane.

The three flight structures including the weight of the nose, the width of the wing, and the angle of the elevator are discussed in this study. This study is combined with the theory and practice to facilitate future inferences and follow-up research. However, there are many factors which influence the flight of a paper plane. It is suggested that other variables including anhedral angle, cathedral angle, and the location of gravity center might be considered for future studies.

Declaration of conflicting interests

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