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Application of ANFIS Method to the Non-nulling Calibration of Multi-hole Pitot Tube

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Abstract

In this paper, ANFIS method was first applied to multi-hole pitot tube calibration modeling owing to its capability of efficient learning, easy implementation and excellent explanation through fuzzy rules. The results show that ANFIS method can help identify the dominant parameters and construct fuzzy learning system. After the determination of the ANFIS structure from the calibration data, the network of pitot tube calibration parameters was established and the correlation among non-dimensional pressure coefficients, flow angle and flow velocity were constructed as well. Due to its programmability, ANFIS can be integrated with real-time data acquisition system and wind tunnel, a large database consisting of flow properties, flow angles and the non-dimensional pressure coefficients can be efficiently established and is also helpful for shortening the calibration procedures.

Keywords: ANFIS; fuzzy logic; multi-hole pitot tube; non-nulling; calibration

Nomenclature

\( P_{\text{Total}} \) Total pressure

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1. Introduction

The multi-hole pitot tube has been widely used and regarded as one of the most economic and robust flow instruments for three-dimensional velocity measurements in the engineering applications. Based on the measurements of pressure ports and appropriate probe calibration methods, the multi-hole pitot tube can be used to measure the three velocity components, the static pressure, total pressures and flow angles. However, the main drawback for using multi-hole pitot tube is the time-consuming calibration procedures before implementation. To significantly reduce the time and costs associated with the calibration, the possible way is to establish automatic calibration traversing system and programmable calibration method in order to shorten the calibration process.

The purpose of the pitot tube calibration is to establish the mapping relationship between the pressure differences and the flow properties. Mainly, there are two methods (nulling and non-nulling method) for determining these relationships by using the calibration data. The conventional calibration technique, nulling method, usually focuses on finding the calibration curves based on the potential flow theory. The probe is calibrated in the wind tunnel with a known air speed and the probe is adjusted until the direction-sensing pressures are nulled so as to ensure the probe aligned with the flow. Although this nulling method is simple, it is not preferable due to tedious and lengthy procedures. Alternatively, the non-nulling calibration method has the potential to be more efficient owing to its programmability. The probe only needs to keep recording the pressure differences between each hole over a range of pitch angle and yaw angle under different air speeds. Eventually, a large database consisting of flow properties, flow angles and the non-dimensional pressure coefficients will be established by real-time data acquisition and used for analysis of non-nulling method.

Neural network method is the most common non-nulling technique for the model construction of pitot tube calibration. It consists of a series of simple and highly interconnected processing elements and the interconnections between neurons approximate the arbitrary functions. Because of the capability of universal approximation, neural network method is suitable for dealing with highly nonlinear problems. Rediniotis et al. [1,2] developed a novel neural-network-based calibration method and applied to multi-hole pitot tube calibration. The Back Propagation (BP) training algorithm is a gradient-based method and used to establish the calibration model. However, some inherent problems are often encountered, e.g., low convergence speed during the training process, the unavoidable local minima, etc. Fan et al. [3] used the Differential Evolution (DE) algorithm to tackle the shortcomings of BA algorithm for pitot tube calibration modeling. The method has been empirically demonstrated to be an effective and robust optimization method that outperforms some of traditional Evolution Algorithm (EA). Additionally, some researchers were also trying to improving the accuracy and convergence efficiency of neural network method especially when applying to air data system [4, 5, 6].

Besides the neural network method, the methods based on neuro-fuzzy models are more potential not only in the academia but also in the industrial applications. Neuro-fuzzy modeling can be regarded as a graybox technique between neural network and qualitative fuzzy models. It eliminates the disadvantage of the normal feedforward multilayer network that is difficult to understand or to modify [7]. One of the most famous neuro-fuzzy network in scientific areas is Adaptive Network-based Fuzzy Inference System (ANFIS) first developed by Jang [8]. ANFIS implements a Takagi-Sugeno fuzzy system [9, 10] in the network architecture and applies a mixture of plain back-propagation and least mean squares procedure to train the model. It also makes use of neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS). The main features of ANFIS method include fast and accurate learning, strong generalization capabilities, easy implementation, excellent explanation through fuzzy rules and incorporation with linguistic and numeric knowledge [11, 12]. Therefore, ANFIS has the capability to efficiently identify the nonlinear system and was applied to calibration modeling of multi-hole pitot tube in this paper.
The aim of this study is to use ANFIS for dominant parameters selection and construct fuzzy learning system. After the determination of the ANFIS structure by analyzing the calibration data, it was used to build up the network for pitot tube calibration parameters. The non-dimensional pressure coefficients were used as inputs and correlate to pitch angle, yaw angle and flow velocity. Finally, the resulting calibration model was validated by checking data and verified its accuracy by comparing with the relevant non-nulling results.

2. Calibration of multi-hole pitot tube

2.1. Calibration instruments and method

Five-hole pitot tube used in this paper has several possible geometries and the most widely used probes are spherical and conical types. The pitot tube calibration conducted in this experiments is conical shape as shown in Fig. 1. Each probe tip contains five pressure ports, with one located at the center and the other four pressure ports are symmetrically arranged as a ring downstream. Each port is connected to the pressure measurement instrument in order to calculate the pressure difference between the center and other ports. The velocity vector can be fully characterized by four variables including pitch angle, yaw angle, static pressure coefficient and total pressure coefficient. The calibration process can be fully automated and the data-acquisition system is operated to collect the data at each orientation. After the acquisition of pressure and flow properties, the data set can be used to establish the calibration model and represented as the aerodynamic properties of the probe. The non-dimensional pressure coefficients, $C_{P,\text{Pitch}}$ and $C_{P,\text{Yaw}}$, are introduced and regarded as the input or independent variables. The output parameters are pitch angle, yaw angle and velocity coefficient ($C_V$). The input and output parameters are defined as below.

\begin{align}
C_{P,\text{Pitch}} &= (P_3 - P_2)/(P_1 - \bar{P}) \\
C_{P,\text{Yaw}} &= (P_5 - P_4)/(P_1 - \bar{P}) \\
C_{P_{\text{Total}}} &= (P_1 - P_{\text{Total}})/(P_1 - \bar{P}) \\
C_{P_{\text{Static}}} &= (\bar{P} - P_{\text{Static}})/(P_1 - \bar{P}) \\
C_V &= C_{P_{\text{Total}}} - C_{P_{\text{Static}}} = 1 - (P_{\text{Total}} - P_{\text{Static}})/(P_1 - \bar{P}) \\
\bar{P} &= (P_2 + P_3 + P_4 + P_5)/4
\end{align}

2.2. The architecture of ANFIS

Adaptive-Network-based Fuzzy Inference System, ANFIS is a powerful technique that integrates the benefits from the reasoning capability of fuzzy logic and the learning skill of neural network. It can serve as a basis to construct a set of fuzzy if-then rules whose membership function parameters are tunable. It can use either a back propagation gradient descent algorithm alone or combined with least squares method to estimate the parameters of membership function and minimize the error. Neural-Fuzzy systems are fuzzy systems that use artificial neural networks theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. It
adjusts the parameters and structures of fuzzy inference system by introducing neural learning rules. Therefore, it has several advantages when applying this method for system identification including refinement of fuzzy if-then, unnecessary human expertise, selectable membership functions and efficient convergence. ANFIS has been successfully implemented to different areas including decision making, pattern recognition, modeling and identification, data analysis, etc. ANFIS is based on Takagi-Sugeno inference model and uses hybrid learning algorithm to identify the consequent parameters of Sugeno-type fuzzy inference systems. The total system consists of five layers (fuzzy, product, normalized, de-fuzzy and total output) and constructs the relationship between the input and output of each layer. Every node of these layers calculates the normalized weight. For a first-order Sugeno fuzzy model as shown in Fig 2, a typical rule set with two fuzzy if-then rules, two inputs \((m, n)\) and one output \(f\). It can be expressed as below and calculation procedures are illustrated as Fig. 3:

Rule 1: if \(m\) is \(A_1\) and \(n\) is \(B_1\), then \(f_1 = p_1 m + q_1 n + r_3\) 
Rule 2: if \(m\) is \(A_2\) and \(n\) is \(B_2\), then \(f_2 = p_2 m + q_2 n + r_2\)

Where \(p_1, p_2, q_1, q_2, r_1, r_2\) are linear parameters and \(A_1, A_2, B_1, B_2\) are nonlinear parameters.

Layer 1 (Fuzzy layer): \(m, n\) are the input of \(A_1, B_1\) and \(A_2, B_2\), respectively. \(A_1, A_2, B_1, B_2\) are the linguistic labels used for dividing the membership functions in the fuzzy theory. The membership function between input and output are described as below.

\[
O_{1,i} = \mu_{A_i}(m), i = 1, 2 \tag{9}
\]
\[
O_{1,j} = \mu_{B_j}(n), j = 1, 2 \tag{10}
\]

Layer 2 (Product layer): the output, \(w_1, w_2\), are the product of the input signals and the weighting functions of next layer. The definition is as below.

\[
O_{2,i} = w_i = \mu_{A_i}(nm)\mu_{B_i}(n), i = 1, 2 \tag{11}
\]

Layer 3 (Normalized layer): the function of this layer is used to normalize weighting functions as the following process.

\[
O_{3,i} = \bar{w} = w_i/(w_1 + w_2), i = 1, 2 \tag{12}
\]

Layer 4 (Consequent layer): this layer includes linear functions, which are functions of the input signals. Every node in this layer is an adaptive square node with a node function.

\[
O_{4,i} = \bar{w}_i(p_i m + q_i n + r_i), i = 1, 2 \tag{13}
\]

Layer 5 (Output layer): Each output node computes the overall output by summing all the inputs, which represents the results of cleaning rates. The output can be expressed as below.

\[
O_{5,i} = \sum_i \bar{w}_i f_i = \sum_i w_i f_i/\sum_i w_i, i = 1, 2 \tag{14}
\]

Finally, the training results would be evaluated by using RMSE (Root Mean Square Error) and the definition is as below.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Y_{\text{observed}} - Y_{\text{predicted}})^2} \tag{15}
\]
Fig. 2. The first order Sugeno ANFIS architecture (Type-3 ANFIS)

![First order Sugeno ANFIS architecture](image)

**Fig. 3. ANFIS calculation procedures**

```
START

- Load training / checking data
- Generate initial FIS model

- Setup initial parameters and membership function
- Choose the method for FIS model optimization
- Determine the training and checking parameters

Import the training data into ANFIS

No

Training finished

Yes

The results are obtained

Import the checking data into ANFIS

No

Checking finished

Yes

- Output the FIS surface
- Generate the rules
- Adjust the membership function

STOP
```
3. Conclusion

After obtaining the calibration data, the distribution of non-dimensional pressure coefficient and air velocity is illustrated as Fig 4. The graphs show that the distribution begins to be distorted after the flow angles are over 30 degrees. Thus the following analysis is based on the flow angles ranging from -30 to 30. In Fig. 5 (a), it shows that the training is efficient because the training error is less than $7.2 \times 10^{-3}$ at the first epoch and stabilized after 60 epochs. The results are helpful for determining the iteration steps in order to save the computational time. Moreover, the FIS outputs were also examined to confirm the consistency between the training data and outputs. The results from Fig. 5 (b) show the outputs are highly consistent with the training data and the precise prediction of calibration model could be expected. Meanwhile, the FIS output surface also reveals the nonlinear feature of input data in Fig. 5 (c). Eventually, the RMSE from Table 1. were used to evaluate the correlation between the input and output parameters. The results demonstrate that the combination of non-dimensional pitch and yaw angle coefficient and yaw angle derived from the previous calculation can have better prediction for pitch angle than solely calculated from non-dimensional pitch and yaw angle coefficient. The prediction for air velocity can also have good results based on flow angle and flow angle coefficient. It can reach to a high consistency of 0.0068 after iteration.

![Fig. 4. Non-dimensional pressure coefficient vs. air velocity](image-url)
Fig. 5. (a) Training error (b) Training error vs. FIS output (c) The surface of FIS output

Table 1. Root Mean Square Error (RMSE) for different combination of non-dimensional parameters

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References