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Estimation of Angle of Attack with Artificial Neural Networks from Aerodynamic Model

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Abstract
Some data loss is likely to occur in a system that is saturated during acceleration or does not have sensitive sensors on it. These data losses directly or indirectly affect the flight performance of the system. Angle of attack measurements are likely to be problematic due to sensor noise and bias levels. Angle of attack is important in controlling aircraft. In order to solve such cases, it is recommended to measure the angle of attack measurement as a black box with the solution of Artificial Neural Networks (ANNs). For the proposed solution, it is necessary to train the artificial neural network. This training data is provided via the aerodynamic database. According to the aerodynamic database, angle of attack, aircraft speed and aerodynamic surface deflection are a function of accelerations. By using this relation, an artificial neural network is obtained, to which the measured accelerations, aerodynamic surface deflection and aircraft speed are inputs and the output is the angle of attack. In the study, in addition to measuring the performance of the artificial neural network, a method for preparing data for ANN training is also discussed. According to the results obtained, it is seen that measuring like a black box with ANN provides an advantage over a saturated sensor, but it carries some error costs. When the training data is evaluated in terms of performance, choosing a data set with a Gaussian distribution significantly reduces both the preparation time of the data set and the training cost.

1. Introduction

Linear control system design approaches are effective in most non-linear aerodynamic systems. One of the assumptions of this design is that the system behaves linearly within certain intervals. Determining these intervals is important for the designer. The parameters that cause the aerodynamic character to be nonlinear are generally the speed of the system, altitude, the angle of attack, and the side slip angle. The designer uses the aerodynamics database to determine the appropriate ranges while preparing the necessary state spaces for linear controller design. Controller designs are prepared in accordance with the state spaces created for each condition. Afterwards, methods such as gain scheduling can be preferred to prevent jumps in controller commands caused by sudden transitions between intervals during the flight. It is necessary to know the parameters in determining the linear range in order to work with the controller designed in the range specific to the situations found at the time of flight. While some of these parameters can be measured, some parameters are calculated by different methods. While the speed and altitude of the system can be calculated by low-cost methods, calculating the angle of attack and side slip angle may require costly methods or sensors. For this reason, providing the angle of attack and side slip angle calculations at low cost can become an engineering problem for experimental operations. Expensive sensors are often not an option for disposable systems. For systems not equipped with expensive sensors, most designers try to make angle-of-attack estimations with observers. For these predictions, aerodynamic data and various filters are needed to provide this during the flight. This causes a computational cost on the system. When all these are evaluated, a simpler, cost-effective and faster solution is sought. In this study, presenting a solution using artificial neural networks is evaluated. However, some assumptions and equations, which are flight mechanics equations, are used to train and prepare artificial neural networks.

The main subject of flight mechanics equations is calculations such as forces and moments, acceleration, angular velocity, position, velocity. Combinations of velocity defined in body frame obtained by these calculations provide the true angle of attack and true side slip angle. Moments and accelerations are affected by parameters such as thrust,

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aerodynamic character, flight altitude, aerodynamic wing deflection, angular velocities and angle of attack, and are a function of these. Thus, a cycle that affects each other is defined.

This entire loop is modeled in a simulation environment. One of the cornerstones of this modeling is the aerodynamic database. With this database, the necessary coefficients for calculating accelerations and moments are obtained. Computational Fluid Dynamics (CFD) is often the most basic way of doing this. Sometimes it can be used for relatively fast and compact tools as DATCOM. In this study, the database is prepared with DATCOM. Aerodynamic databases may need different parameters according to the aerodynamic coefficient to be calculated. These values are aerodynamic surface deflection angles, projectile speed, altitude and angular velocities. These tables are used in mathematical models to maintain flight mechanics equations and calculate aerodynamic forces and moments. As a result, they all become functions of each other according to the aerodynamic database and flight mechanics equations. In this way, there are possibilities to be calculated with a function in terms of each other. However, for some parameters in a real flight this is not necessary. However, while there is no parameter to measure the angle of attack during a real flight, acceleration and angular rate are easily measured by instruments. In this study, online or offline estimation of angle of attack with artificial neural network is explained.

This article is organized as follows: The second section describes the related work, angle of attack estimation via ANN is presented in the third section, in the fourth section the results are evaluated, and the fifth section describes the conclusion of the study.

2. Related Work

A study has been carried out to use the aerodynamic model as an artificial neural network instead of look-up tables in simulation. However, this study is not suitable for online estimation. An artificial neural network solution is presented to shorten the simulation time for simulation environments and aerodynamic force and moment calculations are performed [1]. There are studies with time-dependent integration, algebra-based and complementary filter methods for calculating the angle of attack. However, among these, it is stated in the literature that the filter method is better [2]. These studies need improvement in terms of time cost effectiveness. In addition, possible instrument saturations and disruptive effects cause drawbacks in solutions based on the velocity in the body axis frame. There are recent research outcomes in different subjects and fields in which the artificial neural network is used as a black box virtual sensor [3]. These studies are about virtual sensors on topics such as spark ignition engines [4] and automatic transmission slip [5] In another work, the use of artificial neural networks as virtual sensors is presented [6]. In this study, contrary to the studies reported before, artificial neural networks operate in a structure that corrects errors in parameter estimation instead of doing parameter estimation itself. In addition to correcting this error with an artificial neural network, there are LTI and nonlinear Takagi-Sugeno (TS) fuzzy models. A combination of these three methods is used. In a study, a comparison of Smart-ADAHRS (Air Data, Attitude and Heading Reference Systems) and conventional ADAHRS is given. Smart-ADAHRS performance is tested in flight testing for ultralight aircraft [7]. In that study, The aerodynamic angle of attack and side slip angle are calculated by combining data from a single conventional probe and GPS/INS measurements into a linear estimation, which is assessed by an linear estimator, and a non-linear value calculated by an artificial neural network. In this study, there is no data that improves the selection of training sets and angle of attack estimation is based on both neural network and linear estimation. However, it contains experimental data performed on the aircraft.

3. Estimation of Angle of Attack with Artificial Neural Networks

3.1 Aerodynamic Model and Flight Mechanics

In this study, a simple tail-controlled mini-projectile system [8], whose features are given in the table below, is considered. DATCOM is used to obtain the aerodynamic coefficients.

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Table 1 – Aerodynamic Model Features

Parameter	Value	Unit
Diameter	40	mm
Length	180	mm
Mass	0.9	kg
I_{xx}	$1.17e^{-4}$	$kg.m^2$
I_{yy}	0.001	$kg.m^2$
I_{zz}	0.001	$kg.m^2$

The most fundamental component is the aerodynamic model to simulate at the highest level of fidelity. In a high-level system design, computational fluid dynamics programs are used for this model data. However, because of its fast prediction tool based on semi-empirical method, DATCOM is preferred for obtaining the aerodynamic data. With the help of this tool, aerodynamic coefficients are obtained under certain flight conditions using the basic geometric information of the projectile.

Table 2 – Aerodynamic Model Flight Conditions

Parameter	Range	Unit
Mach Vector	[0.1 0.2 0.3 0.4 0.5 0.6]	-
β Vector	[-5 0 +5]	Degree
α Vector	[-15 -10 -5 -1 0 +1 +5 +10 +15]	Degree
δ Vector	[-5 -1 0 1 5]	Degree
Altitude Vector	[0 500 1000 1500 2000 2500 3000 3500 4000]	Meter

The flight conditions, which are given at Table 2 – Aerodynamic Model Flight Conditions, are used to drive DATCOM. As a result of this, aerodynamic coefficients are created according to combinations of flight conditions specified in the table. Aerodynamic force and moment terms in Equations 1-6 are calculated with air density ρ, reference area S, chord length c and speed of projectile relative to air $V_{B/W}$.

$$\mathbf{X = \frac{1}{2} C_x \rho V_{B/W}^2 S} \tag{1}$$

$$\mathbf{Y = \frac{1}{2} C_y \rho V_{B/W}^2 S} \tag{2}$$

$$\mathbf{Z = \frac{1}{2} C_z \rho V_{B/W}^2 S} \tag{3}$$

$$\mathbf{L = \frac{1}{2} C_{M_x} \rho V_{B/W}^2 Sc} \tag{4}$$

$$\mathbf{M = \frac{1}{2} C_{M_y} \rho V_{B/W}^2 Sc} \tag{5}$$

$$\mathbf{N = \frac{1}{2} C_{M_z} \rho V_{B/W}^2 Sc} \tag{6}$$

Aerodynamic coefficients, which are used in equation 1 – 6, are obtained from the following equations.

$$\mathbf{C_x = -C_A} \tag{7}$$

$$\mathbf{C_y = C_Y + C_{Y_r} r \frac{c}{2V_{B/W}}} \tag{8}$$

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$$\mathbf{C_z = -C_N - C_{N_q} q \frac{c}{2V_{B/W}}} \tag{9}$$

$$\mathbf{C_{M_x} = C_{LL} + C_{L_p} p \frac{c}{2V_{B/W}}} \tag{10}$$

$$\mathbf{C_{M_y} = C_M + C_{M_q} q \frac{c}{2V_{B/W}}} \tag{11}$$

$$\mathbf{C_{M_z} = C_{LN} + C_{N_r} r \frac{c}{2V_{B/W}}} \tag{12}$$

The parameters and definition of the aerodynamic coefficients in the above equation are explained in the Table 3 and Table 4. The coefficients in the table are extracted from a previously prepared database during the simulation. Instantaneous flight conditions not included in the database are found using linear interpolation.

Table 3 – Definition of The Aerodynamic Coefficients

Symbol	**Definiton**
C_A	Axial force coefficient (body axis)
C_Y	Side force coefficient (body axis)
C_{Y_r}	Side force coefficient derivative with yaw rate
C_N	Normal force coefficient (body axis)
C_{N_q}	Normal force coefficient derivative with pitch rate
C_{LL}	Rolling Moment coefficient (body axis)
C_{L_p}	Rolling moment coefficient derivative with roll rate
C_M	Pitching Moment coefficient (body axis)
C_{M_q}	Pitching moment coefficient derivative with pitch rate
C_{LN}	Yawing Moment coefficient (body axis)
C_{N_r}	Yawing moment coefficient derivative with yaw rate

Table 4 – Function of The Aerodynamic Coefficients

Symbol	**Function**
C_A	$f(M, \alpha, \beta, \delta_e, \delta_r, \delta_a)$
C_Y	$f(M, \alpha, \beta, \delta_e, \delta_r, \delta_a)$
C_{Y_r}	$f(M)$
C_N	$f(M, \alpha, \beta, \delta_e, \delta_r, \delta_a)$
C_{N_q}	$f(M)$
C_{LL}	$f(M, \alpha, \beta, \delta_e, \delta_r, \delta_a)$
C_{L_p}	$f(M)$
C_M	$f(M, \alpha, \beta, \delta_e, \delta_r, \delta_a)$
C_{M_q}	$f(M)$
C_{LN}	$f(M, \alpha, \beta, \delta_e, \delta_r, \delta_a)$
C_{N_r}	$f(M)$

$$\mathbf{F_x = ma_x = \frac{1}{2} C_x \rho V_{B/W}^2 S} \tag{13}$$

$$\mathbf{a_x = \frac{1}{2m} (-C_A) \rho V_{B/W}^2 S} \tag{14}$$

$$\mathbf{F_y = ma_y = \frac{1}{2} C_y \rho V_{B/W}^2 S} \tag{15}$$

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$$\mathbf{a_y} = \frac{1}{2m}\left(\mathbf{C_Y} + \mathbf{C_{Y_r}}\mathbf{r}\frac{c}{2V_{B/W}}\right)\boldsymbol{\rho}\mathbf{V_{B/W}^2}\mathbf{S} \tag{16}$$

$$\mathbf{F_z} = \mathbf{ma_z} = \frac{1}{2}\mathbf{C_z}\boldsymbol{\rho}\mathbf{V_{B/W}^2}\mathbf{S} \tag{17}$$

$$\mathbf{a_z} = \frac{1}{2m}\left(-\mathbf{C_N} - \mathbf{C_{N_q}}\mathbf{q}\frac{c}{2V_{B/W}}\right)\boldsymbol{\rho}\mathbf{V_{B/W}^2}\mathbf{S} \tag{18}$$

Equations 13 – 18 show that the accelerations are functions of the parameters M, α, β, ω, δ_a , δ_e and δ_r. Here, angle of attack, α, is the angle between the reference line on an object and the vector representing the relative velocity with respect to the air.

3.2 Preparation of The Dataset for The Artificial Neural Network (ANN)

This section specifies the inputs and outputs of the ANN and explains how to collect datasets for training. As mentioned earlier, ANN is supposed to estimate the angle of attack, which is a parameter that cannot be easily measured using measurement devices. For this estimation, the relevant measurable parameters are taken as input. An ANN structure is planned with accelerometer, gyro and aerodynamic surface deflection angles as inputs. The output is determined as the angle of attack. The side slip angle effect is ignored in an acceleration in the Z-axis direction of the body. This acceleration directly contributes to the angle of attack estimation. For this reason, data is prepared as zero side slip angle, β, in the study.

In total, two types of data sets are preferred for training. The first of these is a large data set calculated at fixed intervals. It has a total of 102,487 data points. The other is a data set containing about 10,000 rows of data. While preparing this data set, the parameters are created in accordance with the Gaussian distribution with a standard deviation around a mean. It is expected that the conditions required for training will be covered in approximately by 10,000 rows of data. The data ranges of the first dataset are given in Table 5 and 6.

Table 5 – Equispaced Data Points Data Set for Inputs

$V_{B/W}$	δ_e	δ_r	δ_a	$\mathbf{a_x}$	$\mathbf{a_y}$	$\mathbf{a_z}$
[140: 10: 200]	[-5:1:5]	[-5:1:5]	[-5:1:5]	Measured Variable		

Table 6 – Equispaced Distribution Data Points Data Set for Output

α
[−15: 3: 15]

Table 7 – Normal Distribution Data Points Data Set for Inputs

$V_{B/W}$	δ_e δ_r δ_a	$\mathbf{a_x}$	$\mathbf{a_y}$	$\mathbf{a_z}$
$N(\mu = 170, \sigma = 10)$	$N(\mu = 0, \sigma = 5/3)$	Measured Variable		

Table 8 – Normal Data Points Data Set for Output

Symbol
α
$N(\mu = 0, \sigma = 5)$

The test data set consists of 500 data points. These data points are generated by Gaussian distributions of adjustable parameters.

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3.3 Training

The inputs of the trained ANN are velocity, aerodynamic wing deflection and accelerometer data. A two - layer structure is used in the first attempt. Each layer contains ten neurons. The activation functions of the layers are selected as "sigmoid" and "tanh", respectively, in the neural network. After an evaluation in section 3.2, an ANN is obtained as a result of training with a three-layered structure. In this structure, a layer architecture with "sigmoid" "sigmoid" "tanh" order is preferred.

Figure 1: The ANN Inputs and Outputs

Keras, a Python package that offers an interface to TensorFlow, is used to train the ANN. The work is done on the computer equipped with AMD Ryzen 3600 6- Core Processor, 16.0 GB RAM.

3.4 Comparison Criteria

The Mean Squared Error, Mean Absolute Error, Root Mean Squared Error, and R-Squared are used.
The average of the absolute difference between the actual and projected values in the dataset is represented by the Mean absolute error. It calculates the mean of the residuals in the dataset.

$$\mathbf{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{15}$$

Mean Squared Error is the average of the squared difference between the data set's original and predicted values. It computes the variance of residuals.

$$\mathbf{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{15}$$

Root Mean Squared Error is the square root of Mean Squared error. The standard deviation of residuals is calculated using this formula.

$$\mathbf{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{15}$$

The coefficient of determination, or R-squared, represents the proportion of the variance in the dependent variable explained by the linear regression model. It is a scale-free score, which means that regardless of how small or large the values are, the value of R square will be less than one.

$$\mathbf{R} = 1 - \frac{\sum y_i - \hat{y}}{\sum y_i - \bar{y}} \tag{15}$$

A lower MAE, MSE, and RMSE value indicates that a regression model is more accurate. A higher R square value, on the other hand, is considered desirable.

4. Results

4.1 ANN With Equispaced Distribution (ED)

It is seen that the performance of the ANN trained with the evenly distributed data model is sufficient. Increasing neuron number is not required for any layer. Some poor situations in the estimation performance are mainly due to the fact that they are not in the defined data range.

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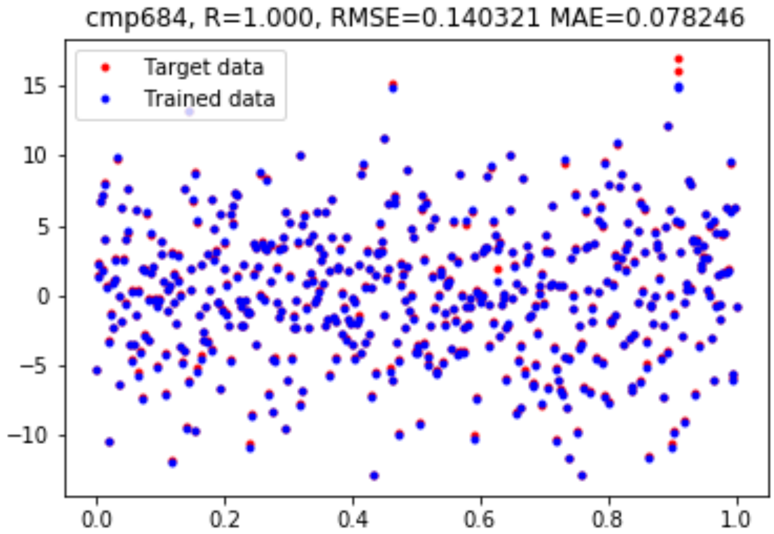

Figure 1: Performance on Test Data Set for Equispaced Distribution

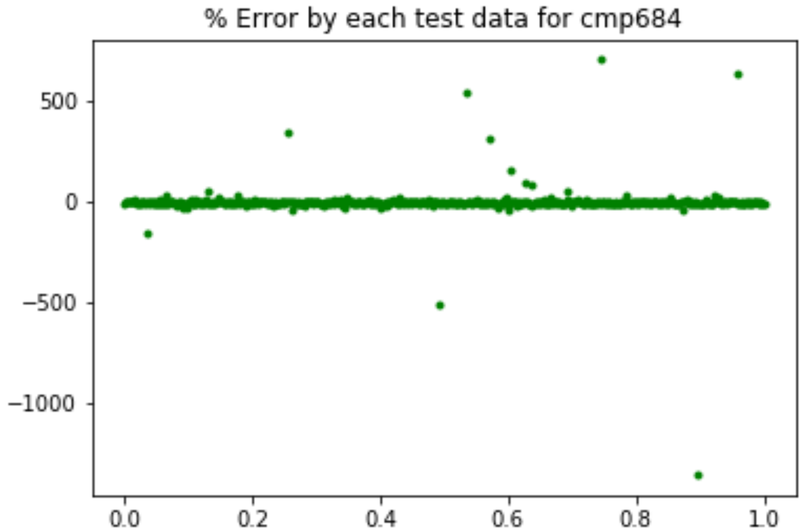

Figure 2: Error for Each Test Data on Test Data Set for Equispaced Distribution

4.2 ANN With Normal Distribution (ND)

In this section, first, the study for 1,000 data points is examined. As stated in the previous sections, these data are randomly generated data based on normal distribution. This study was collected at approximately one thousand times lower cost than ED.

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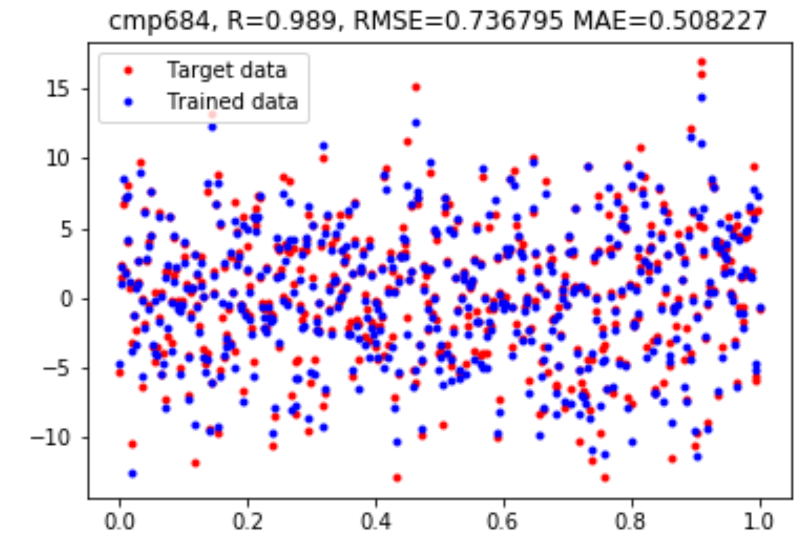

Figure 3: Performance on Test Data Set for Normal Distribution with 1,000 Data

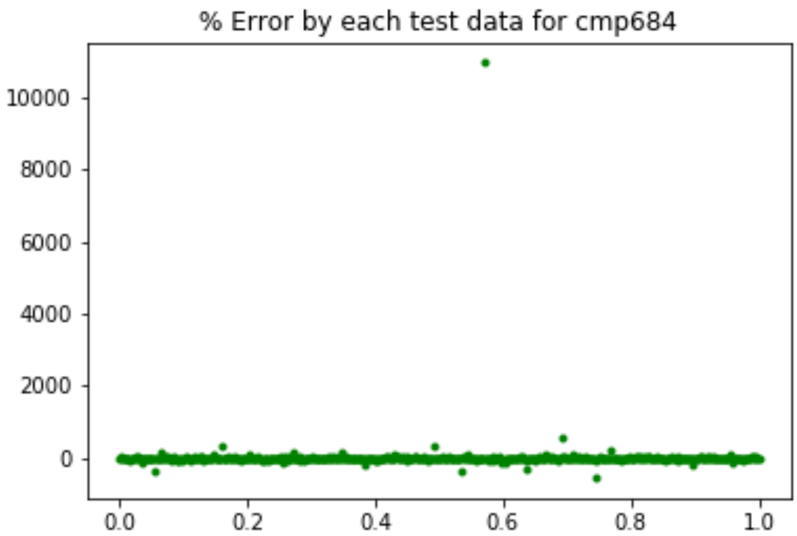

Figure 4: Error for Each Test Data on Test Data Set for Normal Distribution with 1,000 Data

Although a significant amount of time has been gained from the data collection period, the test performance of the trained ANN structure is not at the desired level. At this stage, the test data will be tested with a normal distribution with more samples. 10,000 rows of data is prepared for the new training.

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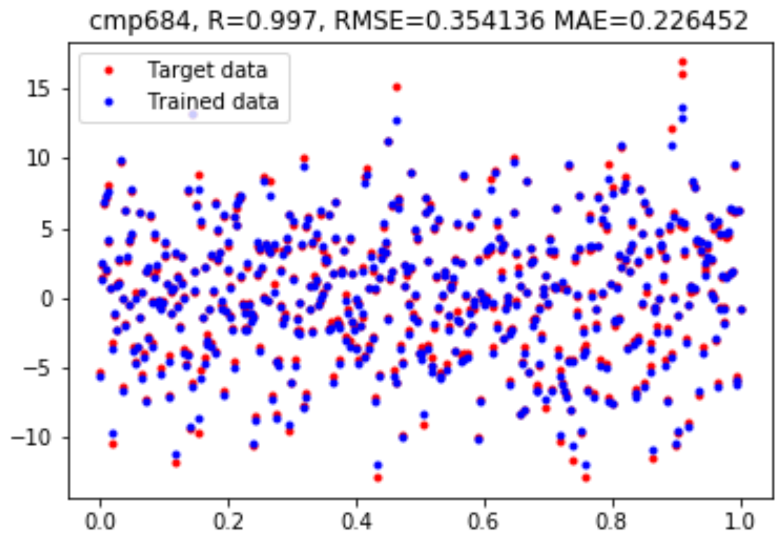

Figure 5: Performance on Test Data Set for Normal Distribution with 10,000 Data

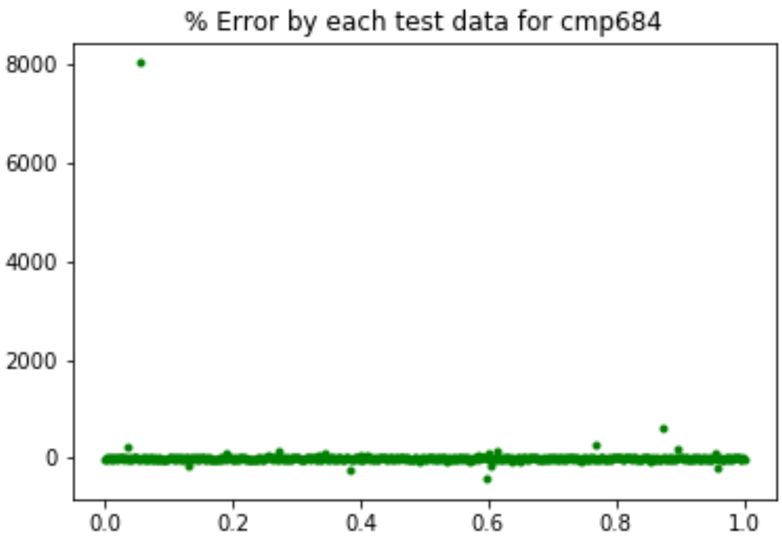

Figure 6: Error for Each Test Data on Test Data Set for Normal Distribution with 10,000 Data

The expected improvement in performance does not occur. Therefore, it is tested again with an increase in the number of the layers.

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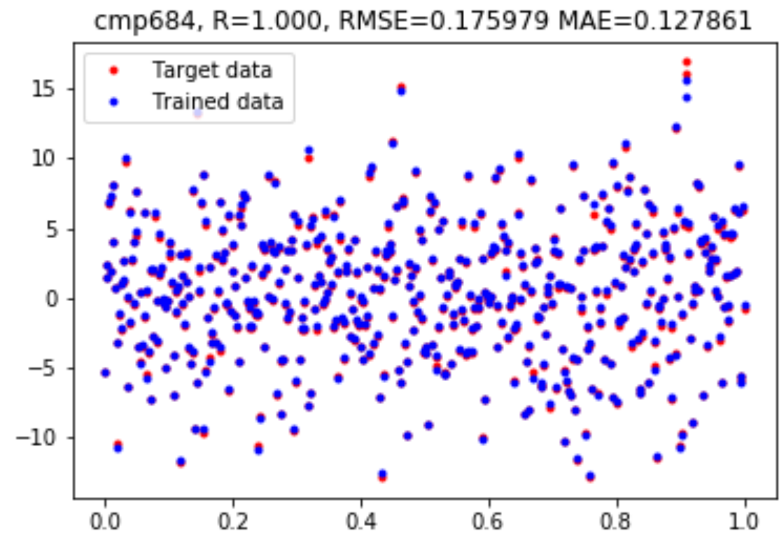

Figure 7: Performance on Test Data Set for Normal Distribution with 10,000 Data with 3 Layers

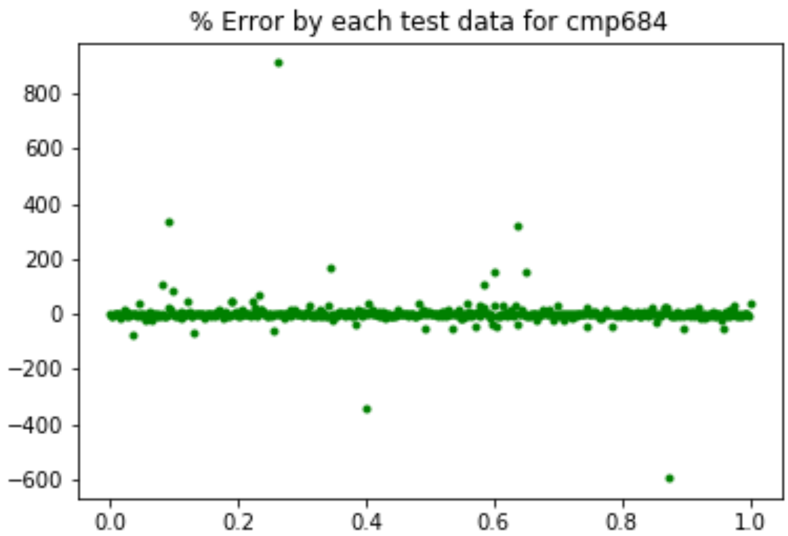

Figure 8: Error for Each Test Data on Test Data Set for Normal Distribution with 10,000 Data with 3 Layers

An improvement in performance is observed with the change in the number of layers. This can be considered sufficient for the user.

Table 9 – Summary of Comparison

	Train Data Preparation [s]	**ANN Training 2 Layers [s]**	**ANN Training 3 Layers [s]**
ED [102487 Data]	17115	410.5	528.4
ND [10000 Data]	1670	29.15	36.15

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There is no known instrument for measuring the angle of attack on projectiles. Known theoretical solutions make use of integrals of auxiliary instruments in practice, which accumulates errors and progressively degrades performance towards the end of the flight. Therefore, in this study, it is investigated whether it is possible to make a measurement using only the outputs of the instruments and the aerodynamic database. According to the study, the ED performance is considered suitable for the estimation of the angle of attack with artificial neural networks. However, training ANN with ED is costly. In the face of this problem, training ANN with ND is recommended as an alternative and a comparison is made in this regard. In the first study, an ANN with 1,000 rows of data is trained with ND, but sufficient performance is not observed. Then, ANN with 10,000 data is trained with ND, the performance has increased, but it was still not at the desired level. Finally, with 10,000 data points, the ANN training is repeated for a more complicated structure (three layers with ten neurons) and the system performance reaches an acceptable performance level.

To evaluate the performance of the virtual sensor, a 3-layer ANN trained with ND set is tested in an open-loop 6 DoF simulation model. For this evaluation, the elevator (δ_e) commands in Figure 9 are used. The commands are chosen as a step and sine function with an amplitude of one degree. According to these commands, the system generates responses in accordance with the open loop natural frequency. This creates the manoeuvre that changes the angle of attack. With the saturation in the sensors of the system, data is lost at the time of acceleration and a bias appears in the velocity component in the body-x axis. This causes the component in the basic formula in the following equation to be incorrect, and therefore the angle of attack is incorrectly calculated.

$$\boldsymbol{\alpha} = \mathbf{atan}(\mathbf{w}/\mathbf{u}) \tag{15}$$

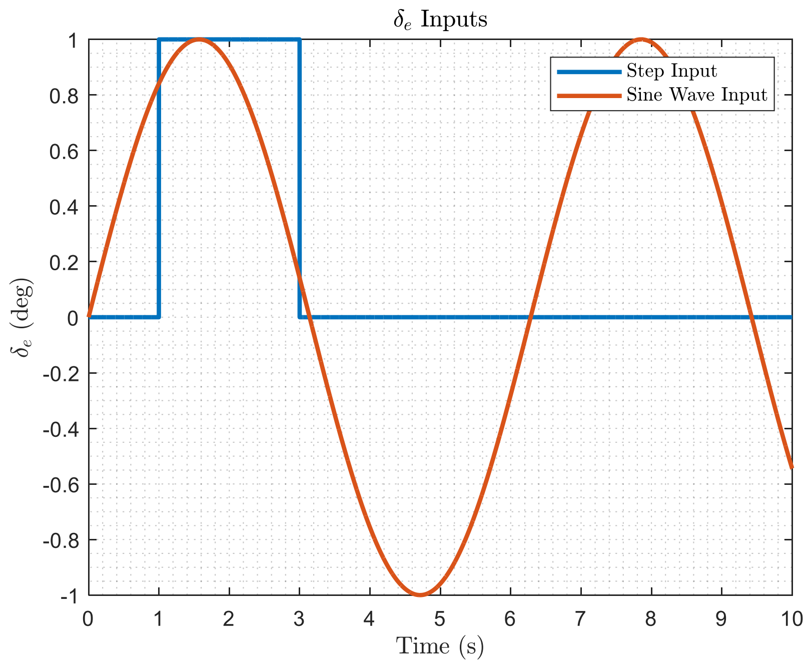

Figure 9: Elevator (δ_e) Commands for Comparison

According to the study, after a one-degree step command, the system reaches the negative angle of attack. If saturation, noise, and bias are absent, the calculation is successful. However, with a possible sensor saturation, there is a deviation from the correct value and the error increases over time. According to the study, after a one-degree step command, the system reaches the negative angle of attack. If saturation, noise, and bias are absent, the calculation is successful. However, with a possible sensor saturation, there is a deviation from the correct value and the error increases over time. If the system is wanted to be controlled in the later phase of the flight with the saturated sensor, it will cause bad results for the system performance. Thus, the angle of attack calculation with ANN is possible within certain tolerances for the designer who has the risk of saturation of the sensor and is looking for a cost-effective solution.

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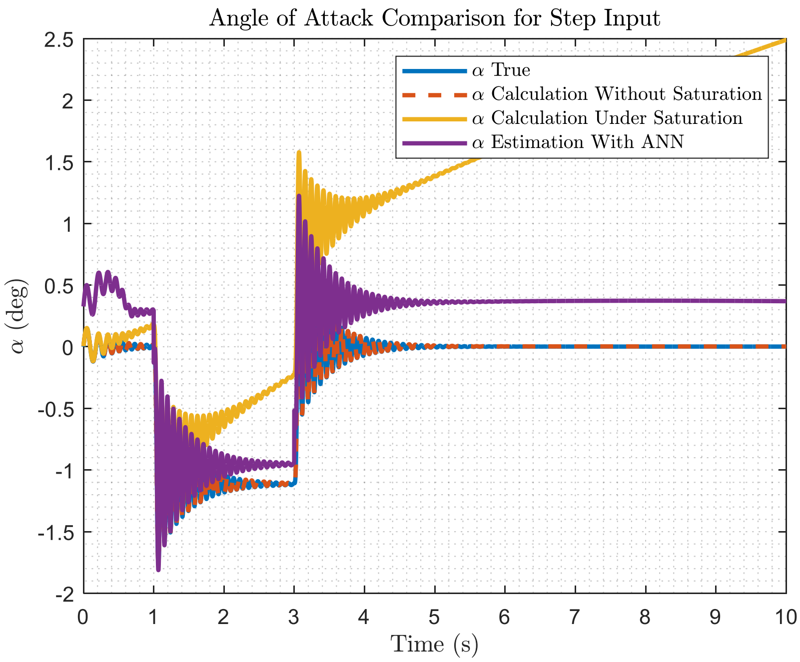

Figure 10: Angle of Attack Comparison for Step Input

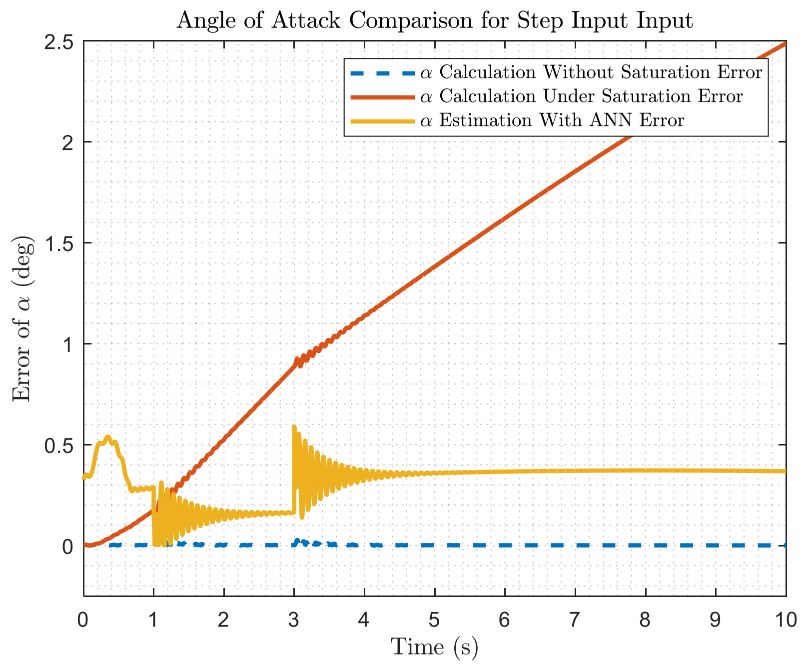

Figure 11: Error of Angle of Attack Comparison for Step Input

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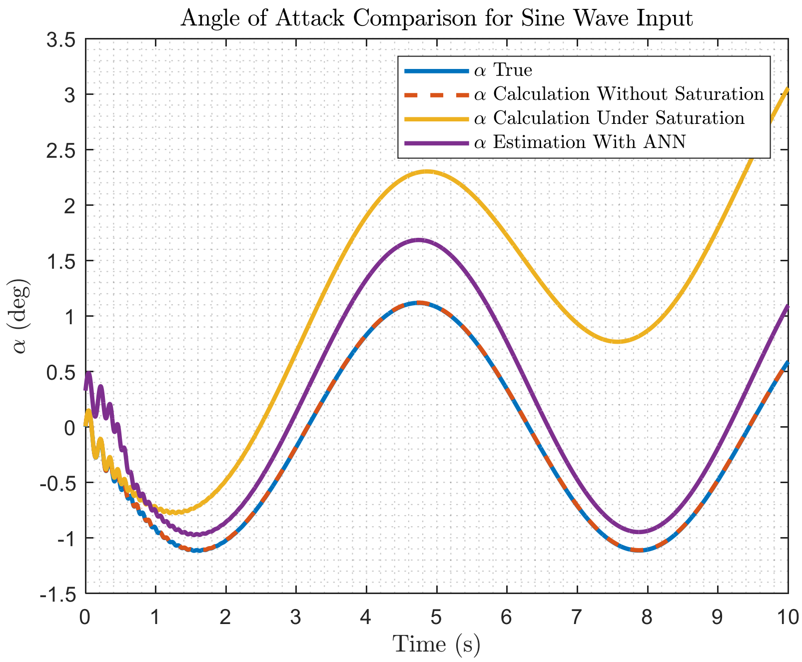

Figure 12: Angle of Attack Comparison for Sine Wave Input

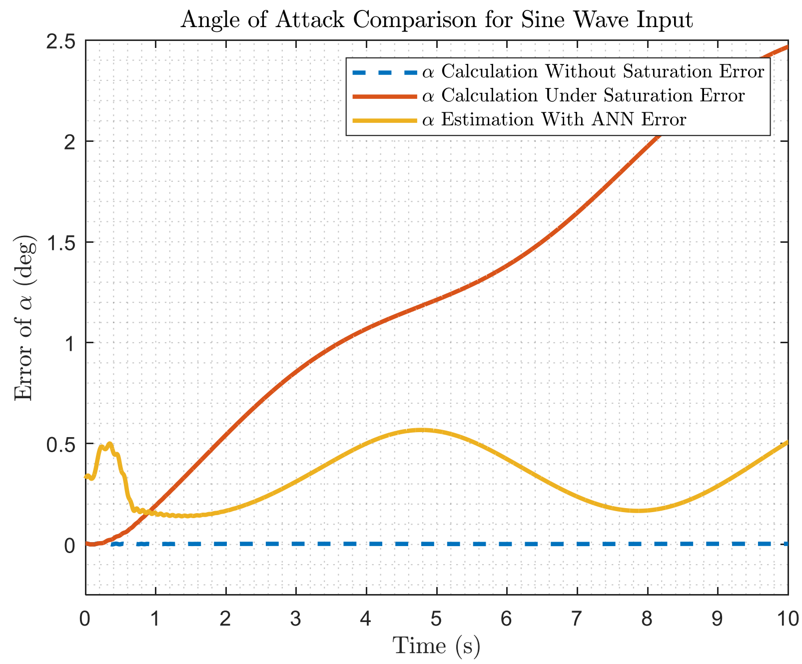

Figure 13: Error of Angle of Attack Comparison for Sine Wave Input

When the system is commanded with a sine wave, the open loop's response is to follow an angle of attack in sine wave format. As in the step command, data loss occurs with saturation in the system and this situation is observed as error growth in calculations. ANN seems to be successful when half a degree of error tolerance is accepted.

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5. Conclusion

In summary, in this study, angle of attack estimation was tested with ANNs. According to the study, the estimation of the angle of attack is possible with the knowledge of accelerometer, gyrometer and wing deflection angles. However, there is an assumption that the aerodynamic database is correct in all experiments conducted. It has been observed that the performance is improved as the sample frequency increases. However, for the time cost incurred, sampled data with normal distribution are tried and the estimation performance is found at the desired level.

In the future, the study can be tested as an online estimation method, filtered by comparing the estimated angle of attack and the angle of attack calculated from the state space matrices, and its positive effect on flight performance can be shown. Also, in the future, all angle of attack estimation methods can be experimentally compared with ANN and the time cost and performance on hardware can be evaluated.

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