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AN ANN-BASED INTEGRATED MODEL FOR AUTONOMOUS UAV FLIGHT CONTROL CONSIDERING EXTERNAL FORCES

Saewoong Min,* Chulwoo Rhim,** and Seongju Chang***

Abstract

This study presents an artificial neural network (ANN)-based integrated model designed to tackle the challenges of autonomous flight control in unmanned aerial vehicles (UAVs), with a particular focus on external forces such as wind speed. The proposed model offers multiple contributions to the field, including a reduction in UAV operation costs, simplified UAV control model establishment, and the ability to handle uncertainties and nonlinearities in different system environments. The model achieves high prediction accuracy (R^2 0.9710 and 0.9480) for UAV acceleration and path prediction, making it suitable for various UAVs including aviation systems. A dual-model approach is introduced, with Model 1 predicting the path with acceleration and wind speed, and Model 2 predicting the acceleration of the UAV with path and wind speed. This comprehensive approach enhances the autonomous flight control process. The proposed model enables the prediction of future UAV paths and stable control using established autonomous flight mechanisms even when following a new path. Although the study focuses on wind speed as the primary external force, there is potential for further improvement by incorporating additional external forces and data sources, such as gyro sensors, temperature, barometric pressure, and image data. In conclusion, the proposed model provides a valuable contribution to the field of autonomous UAV control, and future work can include refining the model with other external forces and data sources to enhance its accuracy and reliability in various environments.

Key Words

Unmanned aerial vehicles, autonomous flight control, artificial neural network, aviation systems

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Nomenclature

UAV	Unmanned Aerial Vehicle
GPS	Global Positioning System
RADAR	Radio Detection and Ranging
LiDAR	Light Detection and Ranging
IMU	Inertial Measurement Unit
LSTM	Long Short-Term Memory
NN	Neural Network
ANN	Artificial Neural Network
PID	Proportional, Integral, Derivative
HVAC	Heating, Ventilation, & Air Conditioning
RNN	Recurrent Neural Networks
NAR	Nonlinear Autoregressive
NARX	Nonlinear Autoregressive Network with Exogenous Inputs
NIO	Nonlinear Input-Output
NED	North East Down
R^2	The Coefficient of Determination
Stdev	Standard Deviation

1. Introduction

1.1 Research Context

The research context of this study is focussed on the challenges of autonomous flight control of unmanned aerial vehicles (UAVs), particularly in the face of technical and theoretical challenges posed by external forces and limitations of global positioning system (GPS) signals. As drones become increasingly commercialised for civilian use in various fields, such as logistics, monitoring, and agricultural operations, critical safety concerns arise with the potential for GPS errors, bad weather conditions, and unstable flight resulting in disastrous accidents. Moreover, as drones are subject to aviation safety regulations and various safety measures, such as no-fly zones and flight approvals, studies on autonomous aerial manoeuvring have become more prevalent [1]. Research on UAVs is being conducted in various fields, encompassing logistics, farms, indoor environments, agricultural operations, military agencies, emergency situations, and disaster scenarios [2]–[10].

In the pursuit of autonomous flight, UAVs heavily rely on various equipments. To achieve autonomy, UAVs employ sensors for environment perception, path planning, and motion control [11]. Numerous sensors, including those associated with the Internet of Things, computer vision [12]–[16], radio detection and ranging (RADAR), and light detection and ranging (LiDAR) [16]–[18], are being utilised in research. Cameras are relatively accessible sensors, which provide useful information similar to human vision. However, extracting valuable information for autonomous driving requires substantial AI processing capabilities [19]. Moreover, the recognition ability of cameras varies depending on light intensity [20]. Challenges, such as hardware limitations and processing capacity, hinder the widespread implementation of computer vision systems [19]. Thus, some applications still encounter accuracy challenges, and incorporating computer vision systems into various systems and workflows introduces additional complexities [11].

Due to the lower resolution in RADARs compared to cameras, the sensors in RADARs are generally not well-suited for object recognition applications [20]. As a result, researchers in the field of autonomous vehicles often integrate RADAR data with other sensory information, such as cameras and LiDAR, to overcome the limitations of the system's sensors [20]. By combining multiple sensor inputs, the researchers aim to compensate for the coarse resolution of RADAR and enhance the overall object recognition capabilities of the AV system [20].

However, despite LiDAR's advantages in dealing with light, the method has a weakness when it comes to adverse weather conditions [21]. The primary drawbacks of LiDAR are high cost and large size [21], [22]. These challenges encompass factors, such as cost, meeting reliability and safety standards, long measuring distances, adverse weather conditions, image resolution, and compact integration size [21]. To address these challenges, researchers have explored various solutions including different laser sources, scanning methods, and ranging principles [21]. Recent efforts by companies have focussed on miniaturising and reducing the weight of LiDAR, indicating the potential future availability of compact and affordable LiDAR systems for the general public [21].

Along with developments in LiDAR, there has also been a recent surge in research on autonomous aerial manoeuvring to develop UAVs capable of operating without direct human intervention [23]–[25]. To overcome the limitations of various sensors, this study proposes a novel approach that focuses solely on acceleration, disregarding traditional sensors. The proposed approach utilises an artificial neural network (ANN)-based integrated model to predict UAV acceleration, taking into account external forces like wind speed to enable autonomous flight and accurate path tracking. By considering these factors, the proposed method aims to enhance the accuracy of path tracking and ultimately improve the safety and efficiency of UAV operations. The main objective of this study is to introduce an innovative approach to tackle the challenges associated with autonomous flight control in UAVs, specifically emphasising the prediction of UAV acceleration while considering external forces such as wind speed to facilitate autonomous flight and precise path tracking.

UAVs have been a subject of extensive research in the field of control systems. Numerous studies have been conducted to enhance the manoeuvrability and control precision of UAVs [26]. One study focussed on developing a stable and accurate controller for achieving fast and agile maneuver control of UAVs [27]. This was accomplished by integrating ANN-based existing controller with advanced capabilities. The proposed approach incorporated online learning of system dynamics, which effectively addresses challenges related to unmodelled dynamics and operational uncertainties [27]. The experimental results demonstrate the superior performance of the proposed controller compared to conventional controllers, particularly in enabling fast and agile manoeuvring even at high speeds [27]. The study presented the details of the developed controller, which highlighted its potential to advance the field of UAV control [27], but did not account for external forces. Thus, it remains unclear whether the developed model can be effectively employed within constrained environments or applied in specialised settings. Another work proposed an intelligent UAV path planning framework that combines ANN and artificial potential fields (APF) [28] to generate optimal collision-free paths [29]. The implementation results demonstrated improved performance compared to existing methods, resulting in optimal and safe paths for UAVs [29]. However, the research was conducted under ideally limited conditions. In another study, an adaptive neural network-based intelligent control method is proposed to stabilise an UAV system (UAS) in complex environments with uncertainties and disturbances [30]. The controller, based on a radial basis function (RBF) network [31], successfully handles system dynamics uncertainties and disturbances as confirmed through computer-based simulations [30]. These previous studies focussed on achieving a stable UAV flight in a constrained environment, but did not consider the influence of external forces. Therefore, the current study investigates the autonomous navigation of UAVs, considering external forces such as wind.

The originality and novelty of this study lie in the development of an integrated model based on ANNs. By harnessing the capabilities of ANNs, UAV acceleration can be accurately predicted and external factors can be incorporated for enhanced flight control. This integrated model offers a novel solution to the existing challenges in autonomous UAV flight control. The contribution of this research is threefold. Firstly, an ANN-based integrated model that predicts UAV acceleration is proposed, which takes into account external forces such as wind speed. This model provides a more accurate understanding of the UAV's dynamics, enabling precise path tracking and enhancing flight control. Secondly, a dual-model structure is introduced, which further enhances the UAV's flight control capabilities. By integrating multiple models where each type is specialised in handling specific flight scenarios, the dual model can effectively adapt to changing environmental conditions and ensure safe and efficient

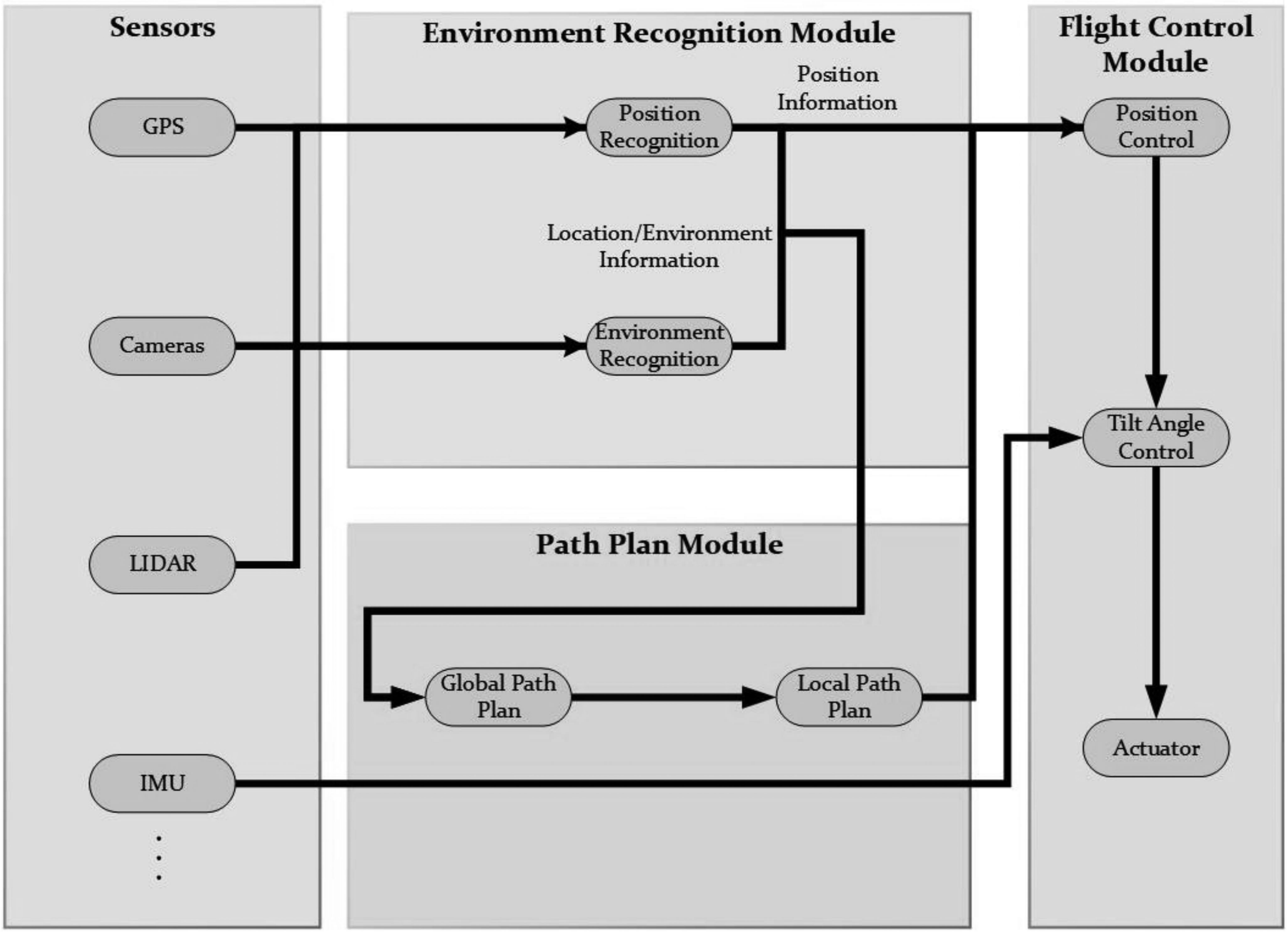


Figure 1. Environmental recognition and path planning process for an autonomous flight of UAVs.

operations. Lastly, this research contributes to the field of autonomous aerial manoeuvring by addressing the technical and theoretical challenges posed by external forces and GPS limitations. The study provides insights and solutions that can be applied in the development of autonomous UAVs, ensuring their reliability and safety in real-world applications.

The dual-model structure introduced in this study consists of Model 1 for predicting the path with acceleration and wind speed and Model 2 for predicting the acceleration of the UAV with path and wind speed. This model provides more precise predictions for both acceleration and path, enhancing UAVs' autonomous flight control. Furthermore, the proposed model demonstrates high prediction accuracy and can be easily applied to different UAVs and aviation systems, making it a versatile solution for a wide range of applications. By addressing uncertainty and nonlinearity in varying system environments, the proposed model simplifies the establishment of UAV control models, which reduces operational costs. In summary, this study aims to tackle the challenges of autonomous flight control of UAVs in the face of technical and theoretical challenges posed by external forces and limitations of GPS signals. This is done by proposing an innovative ANN-based integrated model that predicts the acceleration of UAVs and offering a dual-model structure for enhanced flight control.

The structure of this paper is organised as follows: Section 1 provides a comprehensive review of related literature in autonomous flight control and ANN-based models. Section 2 presents the methodology, detailing the proposed integrated model, and the dual-model structure. Section 3 discusses the experimental setup and presents the results and analysis. Finally, Section 4 explores the implications of the findings and their significance in the context of autonomous UAV flight control, and concludes the paper.

1.2 UAV Flight Methods

UAV can perform autonomous flight through a combination of sensors, an environmental recognition module, a path planning module, and a flight control module. Figure 1 illustrates how these components work together to enable autonomous flight [11]. In the context of autonomous flight control, UAVs typically rely on a combination of sensors, including GPS, cameras, LiDAR, and inertial measurement units (IMU), to gather information about their location and surrounding environment. After, this information is processed by an environment recognition module, which generates a path plan for the UAV to follow. If obstacles are detected along the path, the path planning module adjusts the plan accordingly. By integrating these

Table 1
Related Works

Authors	Topic	Method	Contribution
Son [32]	Predicting position in environments where GPS signals are unavailable	Vision	This study proposed vision-based method for predicting position in GPS-denied environments. Contribution to the development of autonomous navigation systems for environments, such as tunnels and indoor spaces, where GPS signals may not be available.
Zhong *et al.* [33]	Estimating the real-time location of UAVs	Vision	The proposed method utilises a single camera and ArUco markers to achieve localisation accuracy within 8 cm of the target location in real time.
Hidaka *et al.* [34]	Autonomous flight control of UAVs	Vision	This study proposed a method for achieving autonomous flight control of UAVs in a wider space by configuring a single coordinate system for combining images from two cameras.
Ma *et al.* [35]	Trajectory prediction for aircraft	LSTM	A model is proposed that predicts the trajectory of an aircraft using time, altitude, longitude, latitude, speed, and heading data.
Zeng *et al.* [36]	Trajectory prediction model for aviation terminal safety	LSTM	This study proposed position trajectory prediction method to prevent low altitude, collision, and flight path deviation by incorporating input parameters such as position, trajectory, speed, and aircraft type.
Conte *et al.* [37]	Predicting the orbital flight time of drones for efficient traffic management	NN	The work developed a prediction model for the orbital flight time of drones based on corner angle, relative orientation, and wind strength to improve traffic management of drones.
Collotta *et al.* [38]	Real-time control of hexacopter trajectory using a neural network	NN	This study developed a real-time system for controlling the trajectory of a hexacopter using a neural network, resulting in reduced errors in the coordinates of the hexacopter.
Xue [39]	4D trajectory prediction of small UAVs with wind speed consideration	ANN	The model utilises the location, speed, and wind speed data of small UAVs to predict their 4D trajectory with high accuracy, achieving a prediction error of less than 2.0 meters.
Wu *et al.* [40]	Prediction of aircraft trajectory	Backpropagation NN	The proposed model uses past position and velocity data along with current altitude to predict the future position and altitude of the aircraft with an accuracy of less than 1 min for time and less than 50 m for altitude.

various modules, the UAV's flight can be controlled with the primary driver of flight being the location of the UAV.

1.3 Related Works

Table 1 presents a summary of various studies conducted on UAV trajectory control. A wide range of approaches has been proposed for UAV trajectory prediction, which can be categorised into state estimation, aerodynamic model-based, data-based, and combination methods [36]. Initially, UAVs were controlled using mathematical models in which the Newton–Oiler equation was used to calculate the flight path, and the proportional–integral–derivative (PID) control model was used for stable conditions [41]. However, despite being the most widely used technique currently, the mathematical model has its limitations. Thus making it difficult for the model to maintain stability without the assistance of experienced experts [42]. Non-linear control methods have been widely used for the control system of UAVs [38]. Various methods, such as Lyapunov function [43], backstep [44], and nonlinear dynamic inversion [45], have been applied to improve the posture, trajectory, and control of UAVs. However, these methods that rely only on approximate nonlinear models may degrade the performance of UAVs [38] and are often too complex to design. To address these challenges, a study proposed a real-time system based on ANNs [46] for controlling the trajectory of UAVs [38]. ANN has the advantage of reducing economic costs and effort in identifying and modeling dynamics, as well as designing real-world control

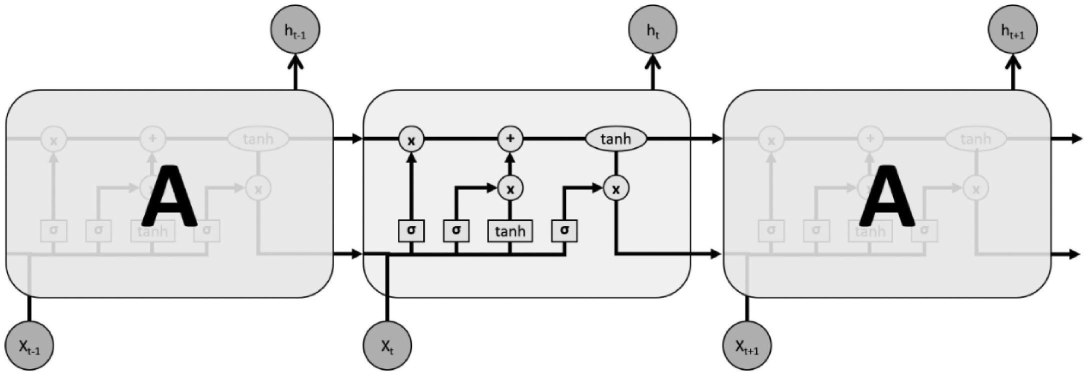


Figure 2. Typical structure of LSTM model.

laws to handle uncertainty and nonlinearity in systems and environments.

On the other hand, GPS and IMU sensors are not effective in tunnels, indoors, and under bridges due to GPS instability [33]. Although some methods use GPS for autonomous flight control, GPS is often not available on bridges [34]. To address this issue, researchers such as Zhong *et al.* [33], Hidaka *et al.* [34], and Son [32] have utilised camera images for UAV localisation. Zhong *et al.* utilised [33] only one camera and ArUco markers to achieve real-time UAV localisation with an error of less than 8 cm while Hidaka *et al.* demonstrated autonomous flight control in a wider space by creating a coordinate system that combines images from two cameras [32]. In addition, Son studied image-based location prediction in indoor environments where GPS signals are not detected [39].

Furthermore, Ma and Tian [35] and Zeng *et al.* [36] predicted UAV trajectories using long short-term memory (LSTM) models (Fig. 2). In particular, Ma and Tian utilised one-dimensional convolution to extract spatial correlation and LSTM to extract temporal and spatial correlation for trajectory prediction [35]. Zeng *et al.* applied LSTM for trajectory prediction to prevent aviation accidents at air terminals with inputs such as location, trajectory, speed, and aircraft type [36]. The approach used in these two studies reduces accidents during flight operations at air terminals.

In the meantime, some studies have utilised neural networks to predict UAV trajectories. Collotta *et al.* [38] proposed a real-time system based on a neural network model for controlling UAV trajectory, showing improved accuracy in the predicted path. In addition, Xue [39] predicted trajectories using angular velocity, angular acceleration, tilt angle, external force, and inertia of the UAV, highlighting the difficulty in creating control models due to intellectual property issues and manufacturing cost constraints. Furthermore, Wu *et al.* [40] predicted longitude, latitude, altitude, and velocity values for the next time step using data from previous time steps with an error rate of less than 1 min for time and less than 50 m for altitude. Lastly, Conte *et al.* [37] predicted the trajectory flight time for drone traffic management based on corner angle, relative direction, and wind strength of the UAV.

Neural networks are capable of handling uncertainty and nonlinearity in various systems and environments [38]. These characteristics allow for accurate trajectory predictions even in GPS-unutilized environments [33], address the instability of PID control [42], and help overcome manufacturers' reluctance to share control models [39].

Table 2
Data Set

Classification	Parameter
Time	*time*
Acceleration	*acc_x*
Acceleration	*acc_y*
Acceleration	*acc_z*
Position	*latitude*
Position	*longitude*
Position	*altitude*
Position	*North*
Position	*East*
Position	*Down*
Wind speed	*wind_speed*
Wind direction	*wind_direction*

2. Methodology

2.1 2.1. Dataset Description

In this study, the data set used for training and testing the proposed model consists of sensor readings from UAVs. The data set includes five variables: time, acceleration, angular velocity, position, and tilt angle. Table 2 shows the specific parameters for each variable, including the accelerations along x, y, and z axes (acc_x, acc_y, and acc_z); latitude; longitude, altitude; positions in North, East, and Down directions; wind speed; and wind direction. The data set consists of 7,618 sets of 12 typed data obtained from 262 test flights. The data was averaged over 1 min and 27 s with a time interval of 3 s, resulting in a cumulative flight time of approximately 6.40 h. The data set was obtained from ShawnWuPlus [47].

2.2 Artificial Neural Network

In the current paper, ANNs were employed to predict the path of UAVs. Previously, ANNs have been extensively utilised to address a variety of problems and have shown their effectiveness in numerous research areas. For instance, they have been applied to HVAC defect detection in buildings [48], photovoltaic prediction [49], airtightness measurement in buildings [50], prediction for wheel loading [51], and heating energy prediction [52]. Time series data analysis is an inherent part of daily life, and various algorithms exist to predict such data. Notable neural network structures for time series prediction include recurrent neural networks (RNNs), nonlinear autoregressive (NAR) models, NAR with exogenous inputs (NARX) models, and nonlinear input–output (NIO) models [53], [54]. Each of these structures exhibits distinct advantages and disadvantages depending on the characteristics of the data being used.

These neural network structures excel at handling dynamic input data, particularly time series data, and have demonstrated exceptional performance in predicting nonlinear patterns. Dynamic models derived from these networks find utility in predicting and controlling various systems, ranging from robotics and manufacturing engineering to chemical processes and aviation systems. Moreover, beyond the realm of engineering, past data-driven predictions find applications in diverse fields, such as financial analysis, consumption analysis, and biology [55].

Time series prediction encompasses various fields, including information processing, dynamic systems, and digital signal processing. Systems that can represent all their objective functions and constraints linearly are referred to as linear systems, while those that cannot are considered nonlinear models [56]. Time series data can be categorised as discrete or continuous data, where the future values are stochastically determined based on past conditions [57]. The time series condition function of the NIO model is classified according to (1) below:

$$y\,(t) = \; f\,(x\,(t-1)\,,\; x\,(t-2)\,, \ldots, x\,(t-d)) \tag{1}$$

The NIO model shares a neural network structure that is highly similar to NARX Fig. 3, which is an equation that involves the variables $y(t)$ and $x(t)$. NARX is a valuable neural network for predicting the value of $y(t)$ based on the preceding value of $x(t)$. In contrast, the NIO model comprises tapped delay lines, layered feed-forward networks, and sigmoid transfer functions within its hidden layers [57].

NARX, an RNN, incorporates feedback connections across multiple layers within the network [58]. In this study, the NARX network model was implemented using the MATLAB, as depicted in Fig. 4. The predictions were obtained by training ten hidden neurons with Bayesian regulation [59], employing a delay count of 2, and utilising a sigmoid transfer function [60]. The structure of the NARX neural network comprises of tapped delay lines, a two-layer feed-forward network, and a sigmoid transfer function in the hidden layer [57].

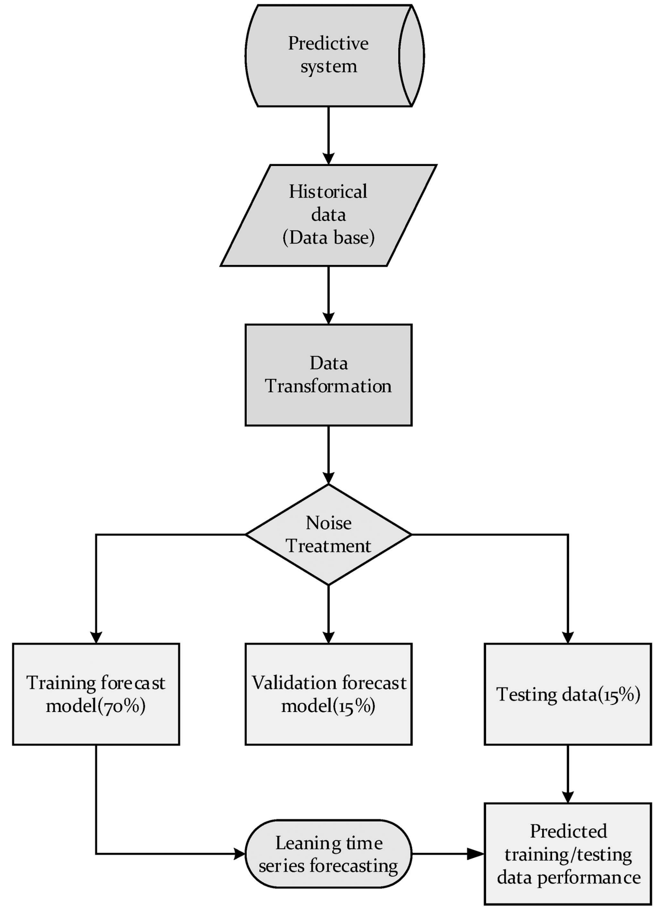


Figure 3. Predictive flowchart diagram for NARX and NIO.

The NARX process is illustrated in Fig. 5. The NARX model is represented by (2), where $y(t)$ is predicted based on the historical data of $x(t)$ and $y(t)$ with a lag of d.

$$y(t) = f(x(t-1), \ldots, x(t-d), y(t-1), \ldots, y(t-d)) \tag{2}$$

2.3 Experimental Framework

In this study, an ANN model was utilised to predict the acceleration of UAV for path tracking with given desired flight paths and wind speeds. The accuracy of the predicted acceleration profile was verified through a series of experiments for on-track flights. Among the data entries summarised in Table 2, acceleration was identified as the most critical variable for UAV control. This is because position, angular velocity, and tilt angles are all directly affected by acceleration. Therefore, the position was predicted solely by acceleration and wind speed. Since the utilised data sets were in the format of time series, historical data was used to predict position.

In the first experiment, the input data set for the ANN was X_1 and output data was Y_1, which indicated the position of the UAV:

X_1 = [acc_x, acc_y, acc_z, wind_speed, wind_direction]
Y_1 = [north, east, down]

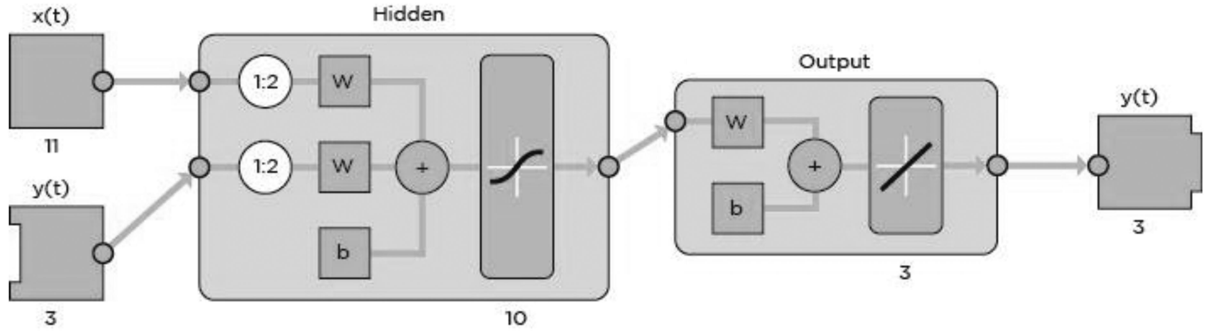


Figure 4. Standard NARX network model MATLAB.

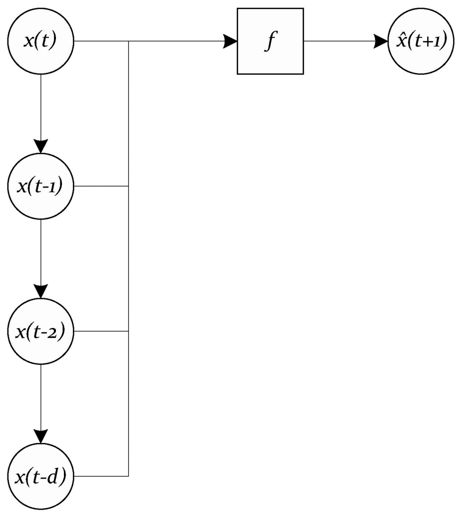


Figure 5. Predicting future from the past data.

As shown in Fig. 6, the input data of X_1 consisted of acceleration to x, y, and z axes, as well as wind speed, which is an external force used to predict the position of the UAV. Of the total input data, 85% was used for training and testing, with the remaining 15% reserved for validation. The resulting ANN model was named Model 1.

In the second experiment, the input data set for the ANN model was X_2 and output data was Y_2:

X_2 = [north, east, down, wind_speed, wind_direction]

Y_2 = [acc_x, acc_y, acc_z]

As shown in Fig. 7, the input data of X_2 was composed of the position of the UAV and wind speed, which is an external force used to predict the acceleration of the UAV. Of the total input data, 85% was used for training and testing, with the remaining 15% reserved for validation. The resulting ANN model was named Model 2.

For the third experiment, the input data of the ANN model was X_3 and output data was Y_3:

X_3 = [predicted_acc_x, predicted_acc_y, predicted_acc_z, wind_speed, wind_direction]

Y_3 = [north, east, down]

As shown in Fig. 8, the input data of X_3 consisted of the acceleration of the known dataset (*i.e.*, the predicted acceleration of the UAV from the second experiment) and wind speed, which is an external force used to predict the position of the UAV. The training data predicted the position of the UAV at known acceleration and wind speed, while the test data were the acceleration values predicted in the third experiment. The purpose of this experiment was to predict the acceleration for a desired path not included in the training data and to verify the actual flight path through Model 2.

The fourth experiment involved using Model 1 and Model 2 to generate a predicted path based on the desired flight path of the UAV. The desired and predicted flight trajectories were then compared and verified for accuracy.

In the present study, the ANN approach is utilised to predict the acceleration of UAVs during autonomous flight along a specified path and assess the accuracy of the path achieved based on the predicted acceleration as illustrated in Fig. 9. The proposed methodology involves the development of two models: Model 1, which predicts the path using acceleration and wind data, and Model 2, which predicts the acceleration using path and wind data.

To evaluate the performance of the models, the desired path is input into Model 2 to predict the corresponding acceleration. This predicted acceleration is then fed into Model 1 to compare the resulting predicted path with the desired path.

This study leveraged ANN models to predict UAV acceleration and evaluate path accuracy during autonomous flights. The subsequent chapters delve into the theoretical foundations, data analysis, and experimental results to substantiate the effectiveness of the proposed approach.

3. Result

Pearson's correlation analysis was conducted to analyse the relationship of the selected variables as shown in Fig. 10. The results showed a high correlation between North and latitude, East and longitude, and Down and altitude, as they are represented in the same coordinate system. The acceleration of x showed a high correlation with pitch, and the acceleration of y showed a high correlation with roll. This suggests that controlling the force of x and y is necessary to balance the aircraft. The acceleration of z and yaw were expected to show a high correlation, but a weak correlation was observed, possibly due to the little change in the center of gravity in the direction of z. Since the UAV can be viewed as a flat hexahedron, even if a force

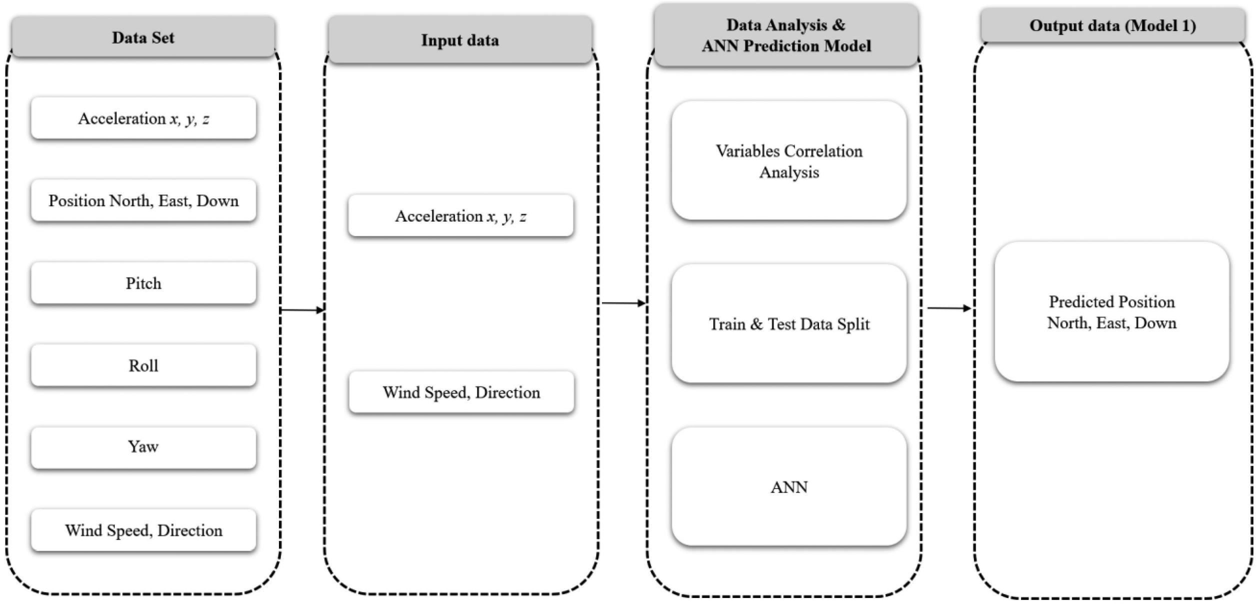


Figure 6. Position prediction process with acceleration and wind data (Model 1).

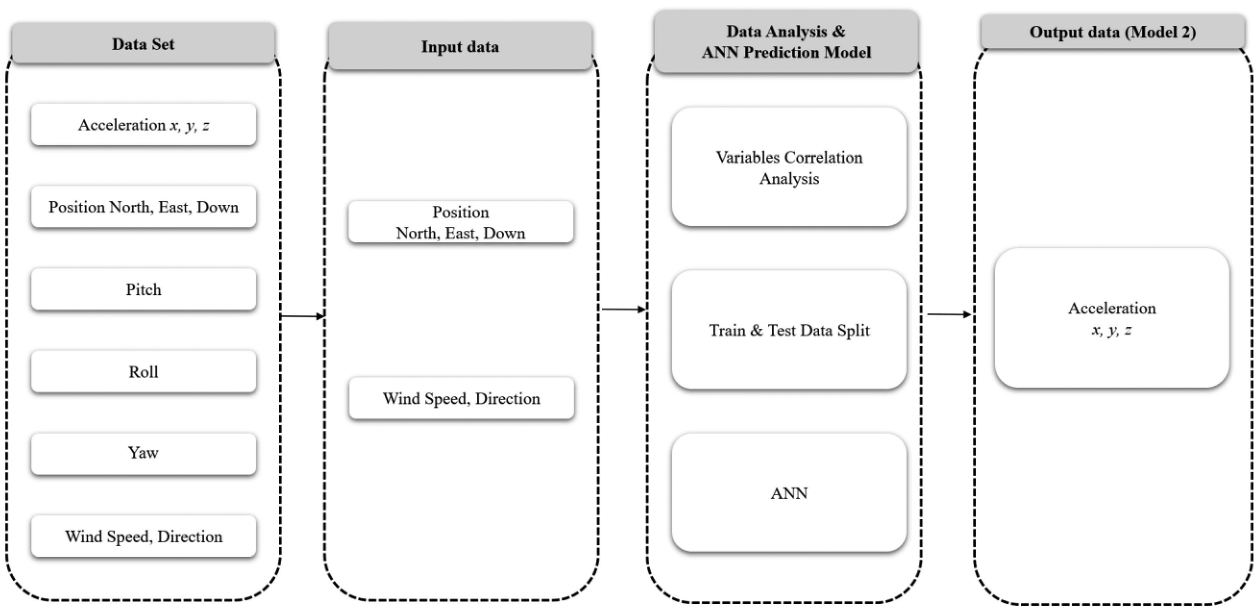


Figure 7. Acceleration prediction process with position and wind data (Model 2).

is applied to the direction of z, the turning force is small, resulting in a weak correlation.

3.1 Position Prediction by Acceleration and Wind

The accuracy of the position prediction model using acceleration and wind as input variables was evaluated. Table 3 presents the statistical values of the predicted position variables including North, East, and Down. The R^2 values for North, East, and Down are 0.9930, 0.9917, and 0.9780, respectively. The scatterplots of the actual and predicted values for each component are shown in Fig. 11. The maximum and minimum values for North, East, and Down are also presented in Table 3, as well as the standard deviations for each component. The accuracies of the position predictions are in the order of North, East, and Down.

The plots of the actual and predicted values for North, East, and Down are shown in Fig. 12. The North component was sufficiently predicted with only a slight error where the slope sign changed. The East component showed some errors where the slope sign changed and in areas with slight slope in early and mid-term flight states. However, relatively less error was found in areas with a steep slope. The Down component showed a slight error within the first 180 s, with a maximum error of 0.53 m at 90 s. The error profile in areas with no other movement was 0.25 m or less, showing only an average error of 0.0998 m.

The path of the UAV according to the North–East–Down (NED) coordinate system is presented in

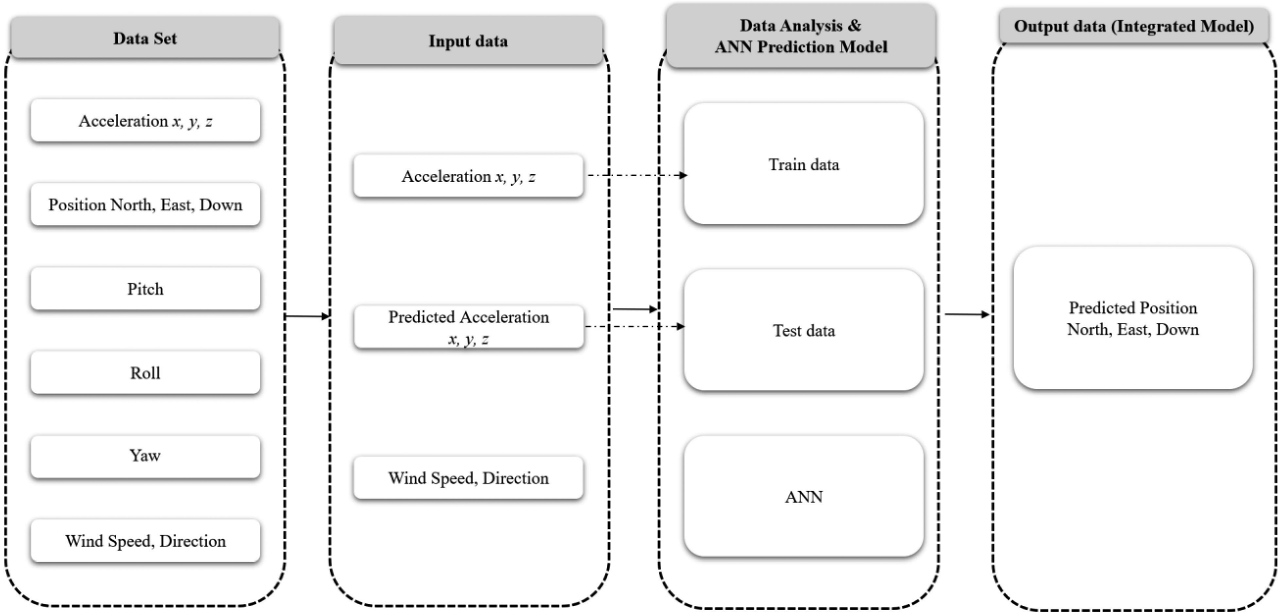


Figure 8. Position prediction process with the predicted acceleration and wind.

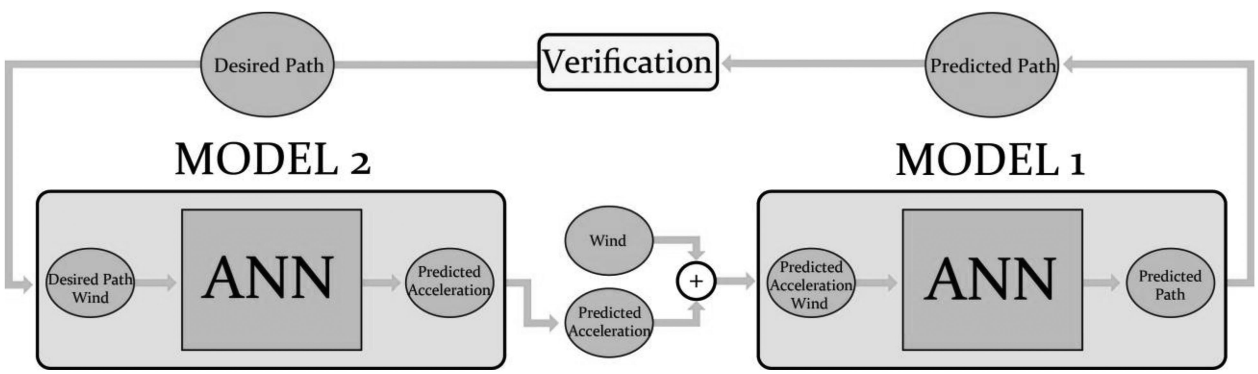


Figure 9. Experimental diagram.

Table 3
Statistical Values of Predicted Position Variables

	North	East	Down
R^2	0.9930	0.9917	0.9780
Maximum (m)	51.692	13.658	2.2439
Minimum (m)	−132.27	−67.826	−30.490
Range (m)	183.96	81.484	32.732
Stdev (m)	23.081	18.229	6.4848

Fig. 13. The actual and predicted position differences were not significant, indicating that the performed position prediction was successful.

Table 4 shows the average distance difference values for North, East, and Down, as well as for the total distance. The average error values for North, East, and Down are 1.303 m, 1.207 m, and 0.5834 m, respectively, with a total average error of 2.2637 m. The standard deviations for North, East, and Down are also presented in Table 4, with a small standard deviation for the Down component. Overall, the error rate is within 1.3 m, and the R^2 values for North, East, and Down are 0.9930, 0.9917, and 0.9780, respectively. These results indicate that the path prediction accuracy is satisfactory.

In conclusion, the proposed model evaluated the accuracy of position and acceleration predictions for a UAV using an acceleration and wind input variables. The results showed that the model was successful in predicting the position of the UAV, with R^2 values of 0.9930, 0.9917, and 0.9780 for North, East, and Down components, respectively. The scatterplots of the actual and predicted values indicate that the North component was sufficiently predicted, while the East component had some errors in areas with slight slope. The Down component had a slight error in the first 180 s with a maximum error of 0.53 m at 90 s. Overall, the error was within 1.3 m, indicating that the path prediction accuracy was satisfactory. Therefore, this study provides a useful framework for predicting UAV position and acceleration with acceleration and wind input variables, which could be valuable for various applications in the field of UAVs.

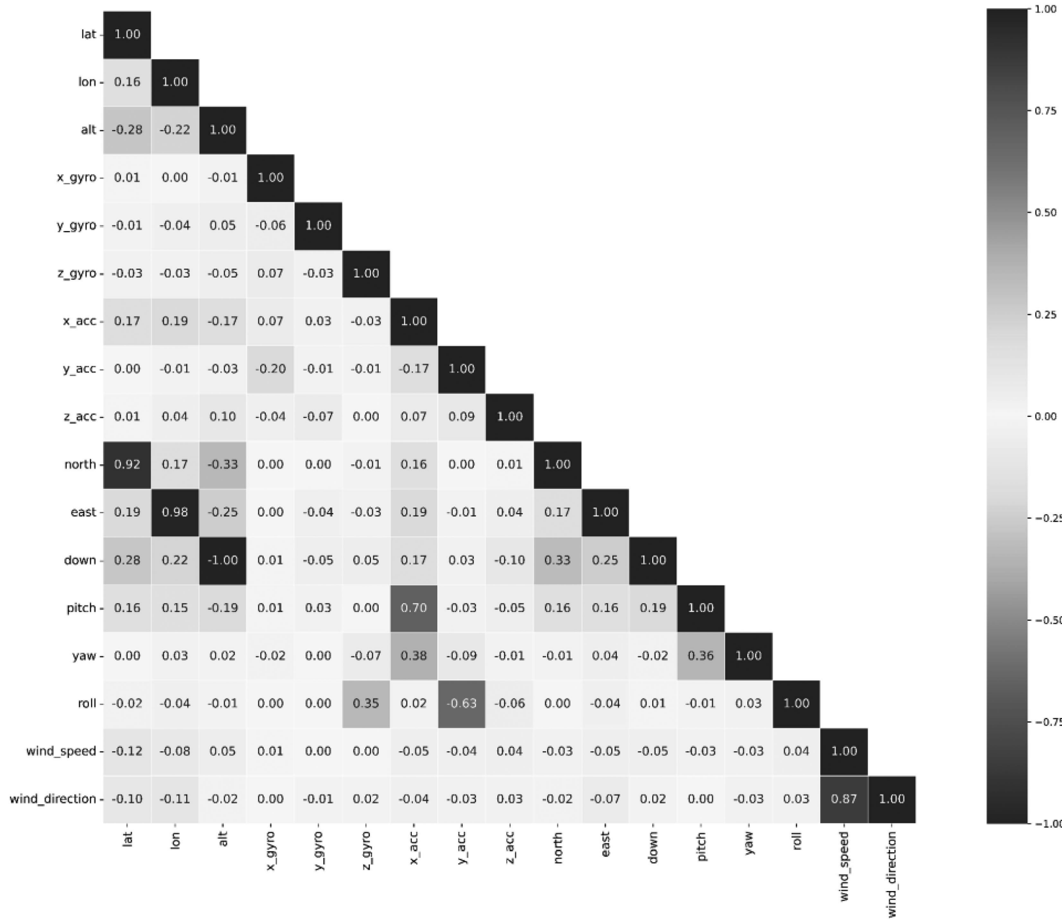


Figure 10. Correlation among data components.

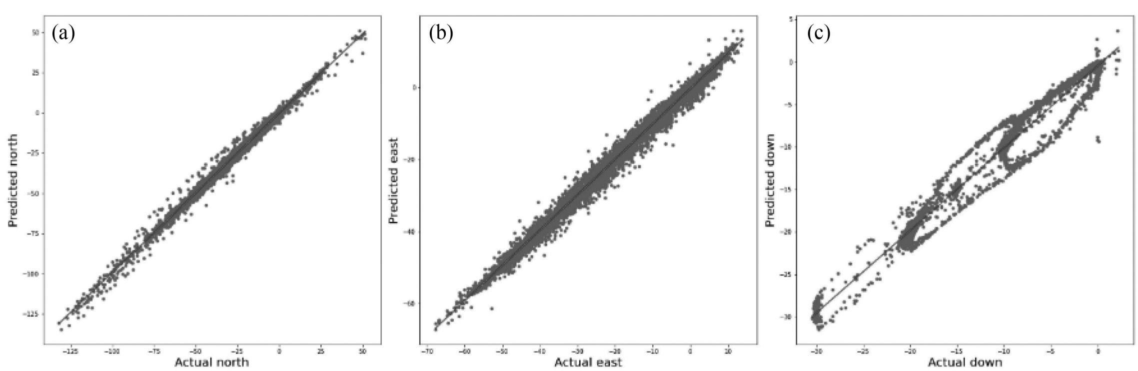


Figure 11. Scatter plot of actual and predicted North (a), East (b), Down (c).

Table 4
Statistical Values of Position Difference

	Distance Difference(m)	North Difference (m)	East Difference (m)	Down Difference (m)
Average	2.267	1.303	1.207	0.583
Stdev	1.561	1.430	1.157	0.834

3.2 Acceleration Prediction by Position and Wind

Acceleration prediction using position and wind data is evaluated in this study. The R^2 value for the x, y, and z components of acceleration are shown in Table 5, with values of 0.9119, 0.8974, and 0.3669, respectively. Fig. 14(a) shows the scatterplot of actual and predicted values of the x component of acceleration, which represents linearity

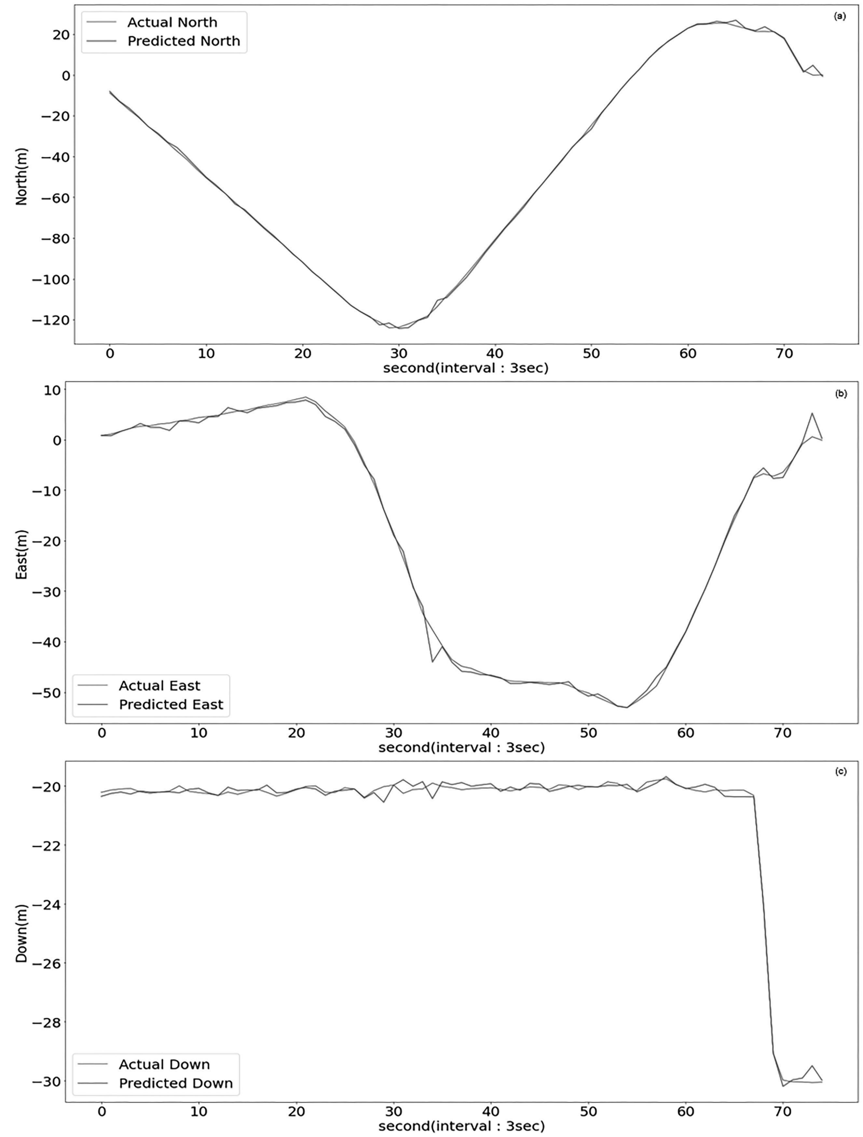


Figure 12. Plot of actual and predicted North (a), East (b), and Down (c).

Table 5
Coefficient of determination of accelerations

	Acceleration x	Acceleration y	Acceleration z
R^2	0.9119	0.8974	0.3669

and a performance level of 0.9119 as indicated in Table 5. Fig. 14(b) represents that the prediction performance regarding the magnitude of x-acceleration is somewhat low although the prediction on the direction of acceleration was feasible to some extent.

Similarly, Fig. 15(a) shows a performance level of 0.8974 for the y component of acceleration. Fig. 15(b) shows that the prediction performance regarding the magnitude of y-acceleration is somewhat low even though the prediction on the direction of acceleration is feasible.

On the other hand, Fig. 16(a) shows the scatterplot of actual and predicted values of the z component of acceleration, which does not represent linearity compared to the x and y components. The R^2 value for the z component of acceleration in Table 5 indicates the lowest performance level of 0.3669. Fig. 16(b) suggests that the prediction of z-acceleration was the worst. The reason for this poor performance is that it is difficult to learn patterns regarding the direction of the wind, which is parallel to the xy plane and not related to the z-plane. Therefore, the z-acceleration prediction was shown to be less accurate than anticipated. However, if the direction of the z-axis is applied to the direction of wind speed, it is expected to improve the prediction performance.

In conclusion, the proposed model exhibits high accuracy in predicting the x and y components of acceleration although the prediction performance regarding the magnitude of acceleration is somewhat low. The prediction of the z component of acceleration is the worst due to the difficulty in learning patterns regarding the direction of wind. However, if the direction of the z-axis is applied to the direction of wind speed, it is expected to improve the prediction performance.

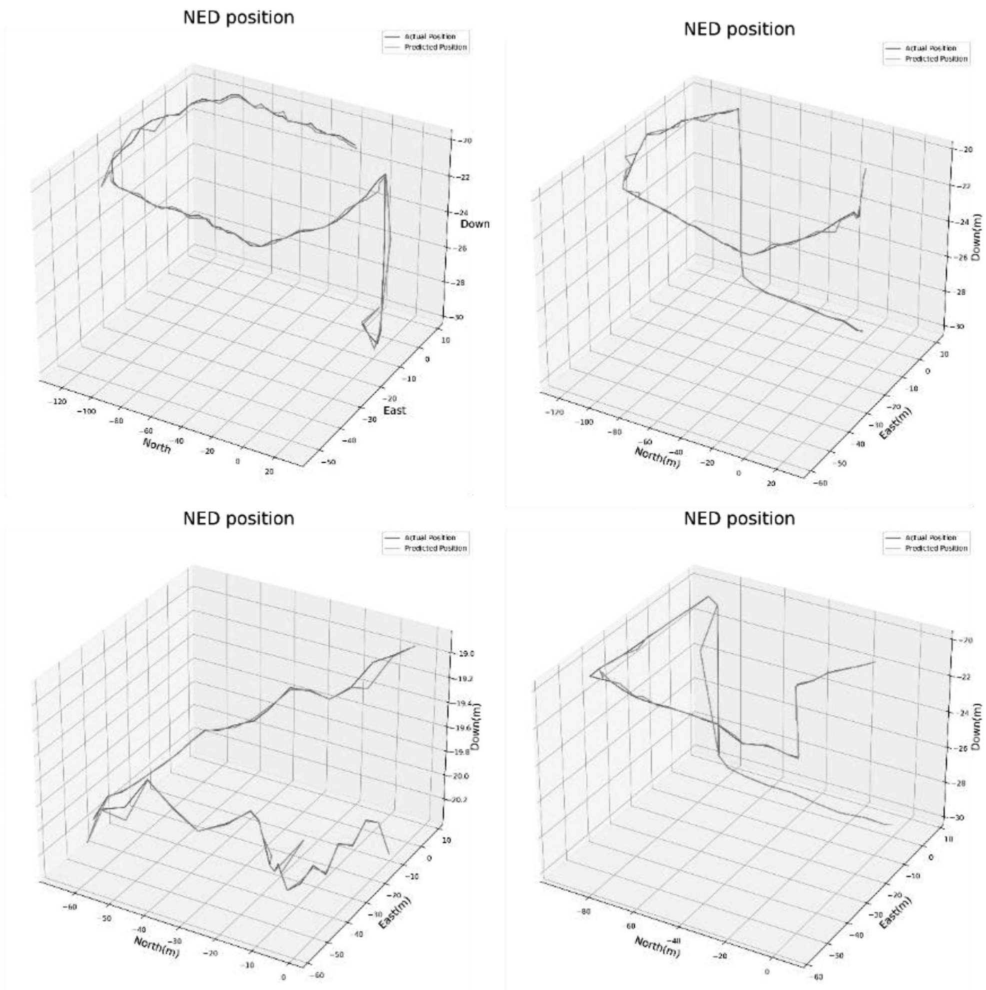


Figure 13. Paths of actual and predicted NED position (interval: 3 s).

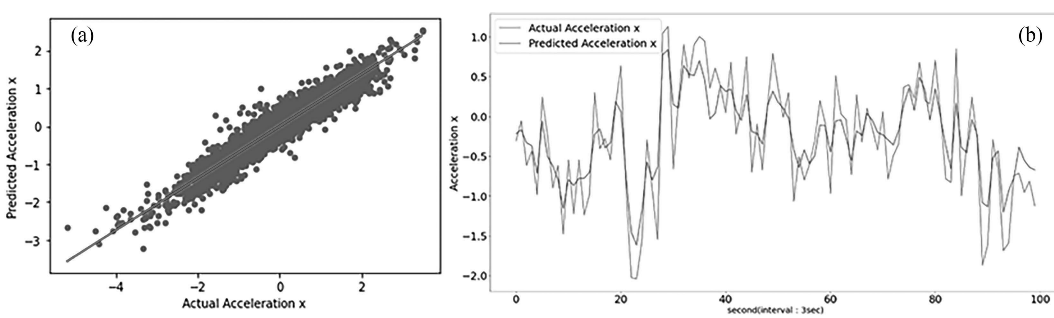


Figure 14. (a) Scatter plot and plot (b) of actual and predicted acceleration x.

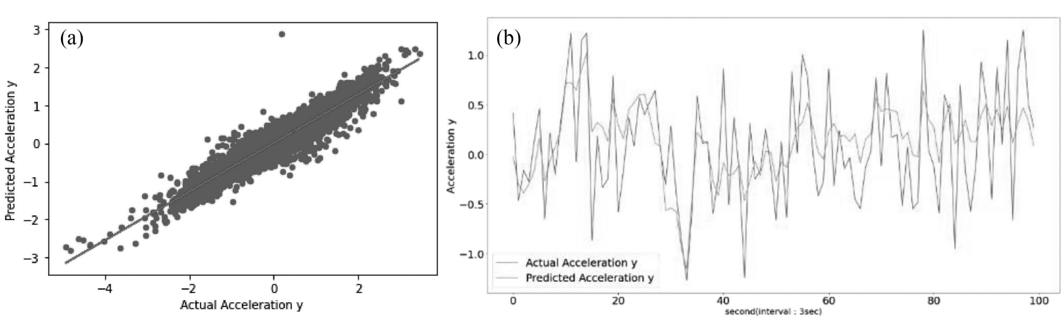


Figure 15. (a) Scatter plot and plot (b) of actual and predicted acceleration y.

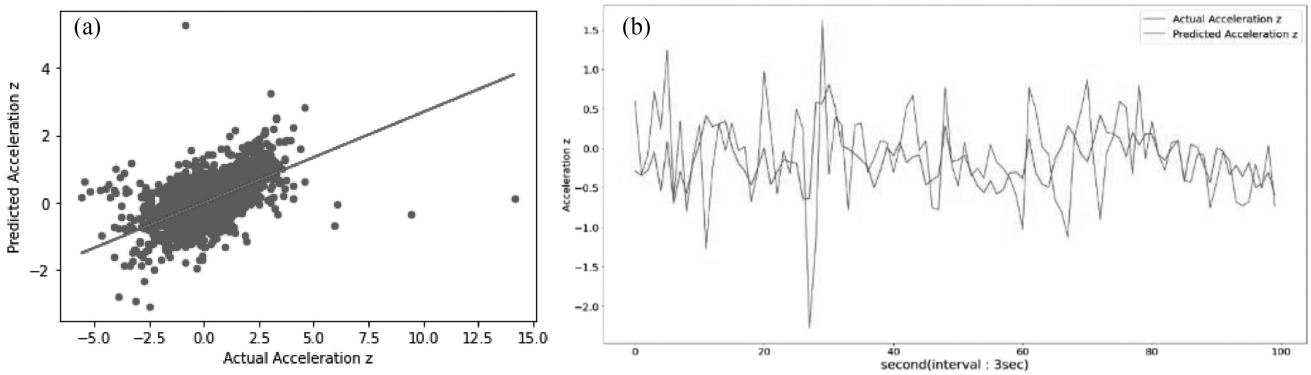


Figure 16. (a) Scatter plot and plot (b) of actual and predicted acceleration z.

Table 6
Coefficient of Determination Desired and Predicted Path

	North	East	Down
R^2	0.9710	0.9480	0.8788

3.3 Predicted Path vs Desired Path by Predicted Accelerations and Wind

The accuracy of the predicted path using the predicted accelerations and wind data is evaluated in this study. The R^2 value for the desired and predicted paths in the North, East, and Down directions are shown in Table 6, with values of 0.9710, 0.9480, and 0.8788, respectively. Figure 17(a) shows the North values of both desired and predicted paths with an R^2 value of 0.9710, indicating no significant difference between the desired and predicted paths. Similarly, Fig. 17(b) shows the East values of both desired and predicted paths with an R^2 value of 0.9480, which is slightly lower than the North and desired paths. However, the predicted path seems to be more accurate. The R^2 value of the East component in Model 1 Table 6 was 0.9480, indicating no significant difference between the desired and predicted paths. On the other hand, Fig. 17(c) shows the Down values of both desired and predicted paths, with an R^2 value of 0.8788. Although the value is less accurate than the North and East components, it shows higher results than expected considering that wind speed did not affect the z-direction.

Figure 18(a) shows the path of North–East in 2D, considering low accuracy of Down. The accuracy of the predicted path was high. Figure 18(b) is expressed as a path graph in 3D using NED's geographic coordinate system. The graph is shown for the duration of 210 s, and the predicted path has high accuracy especially for the desired path.

In conclusion, the proposed model accurately predicts the desired path in the North and East components with slightly lower accuracy in the Down component. However, the predicted path presents higher accuracy than expected considering the wind speed did not affect the z-direction. The proposed model can be used to predict the path of UAVs with high accuracy, especially for the desired path.

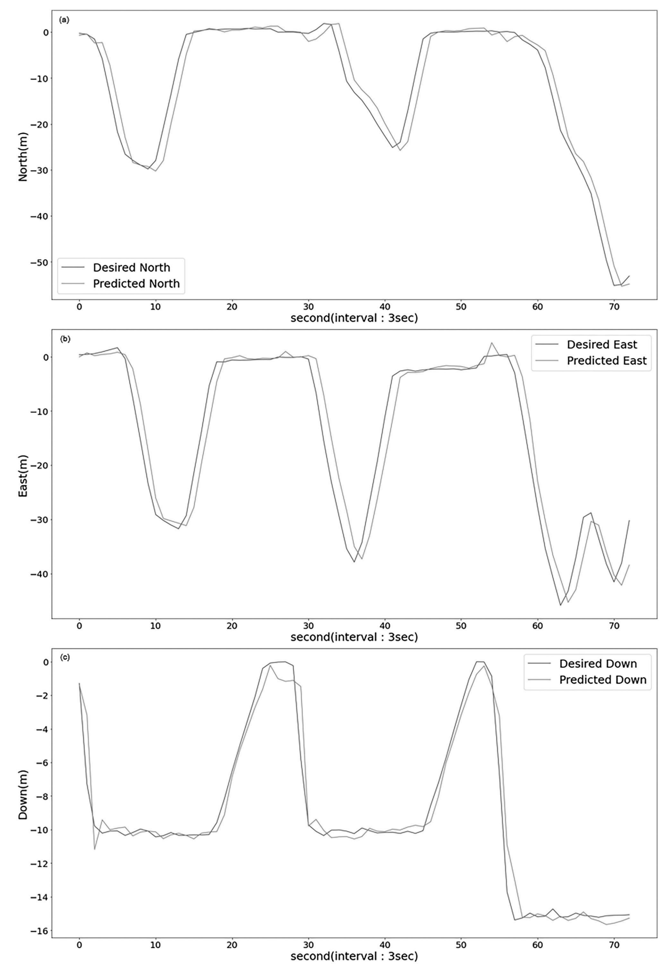
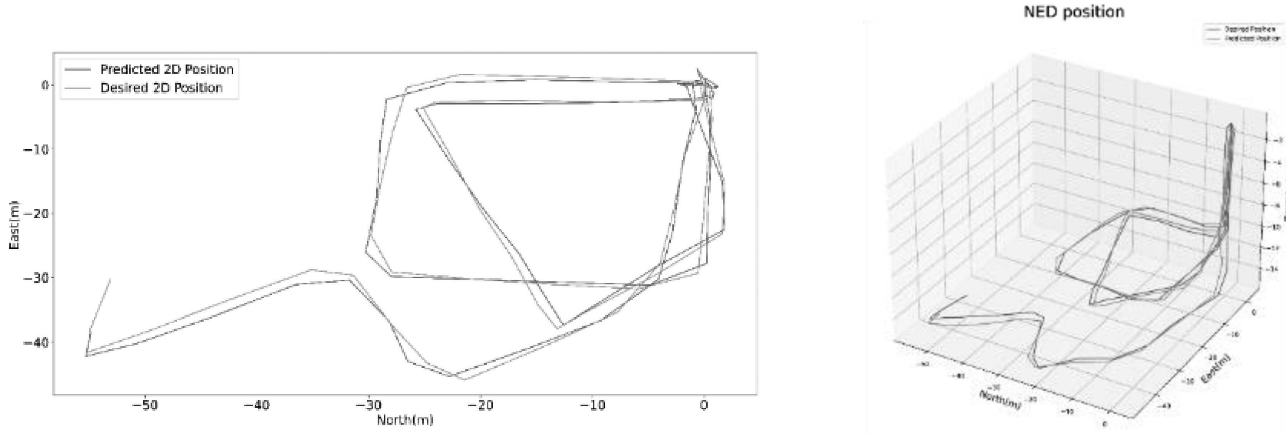


Figure 17. Plot of desired and predicted North, East, and Down path.

4. Discussion

The outcome interpretations of this study focussed on the evaluation of the accuracy of a model in predicting the position, acceleration, and path of a UAV using input variables, such as acceleration, path, and wind. In Section 3.1, it was shown that the model accurately predicted the position of the UAV. The R^2 values were reported as 0.9930, 0.9917, and 0.9780 for the North, East, and Down components, respectively. The scatterplots



(a) (b)

Figure 18. Plot of desired and predicted (a) 2D and (b) 3D paths.

of the actual and predicted values indicated that the North component was accurately predicted, while the East component had some errors in areas with a slight slope. The Down component represented a small error in the first 180 s, with a maximum error of 0.53 m at 90 s. Overall, the errors were within 1.3 m demonstrating satisfactory path prediction accuracy. This study provides a valuable framework for predicting UAV position using acceleration and wind input variables.

In Section 3.2, it was found that the proposed model achieved high accuracy in predicting the x and y components of acceleration. However, the prediction performance regarding the magnitude of acceleration was somewhat low. The z component of acceleration had the worst prediction performance due to the challenge of learning patterns related to wind direction. Nevertheless, the current paper suggests that by considering the direction of the z-axis in relation to the direction of wind speed, the prediction performance could be improved. In Section 3.3, a conclusive statement was suggested that the proposed model accurately predicted the desired path of the UAV in the North and East components, with slightly lower accuracy in the Down component. Surprisingly, considering that wind speed did not affect the z-direction, the predicted path showed higher accuracy than expected. The proposed model can be utilised to predict UAV paths with high accuracy, particularly for the desired path.

The study emphasises the successful application of the proposed model in predicting the acceleration of a UAV for achieving its desired path utilising input variables, such as acceleration, wind, and path. The findings suggest that the model has potential for various applications in the field of UAV.

5. Conclusion

In conclusion, this study proposes an ANN-based integrated model addressing the challenges of autonomous flight control in UAVs, especially considering external forces such as wind speed. The proposed model contributes significantly to the field in several ways:

(1) The model reduces the cost of UAV operations and simplifies the difficulty of establishing UAV control models by addressing uncertainty and nonlinearity in varying system environments.
(2) The model achieves high prediction accuracy (R^2 0.9710 and 0.9480), demonstrating its effectiveness in predicting UAV acceleration and path for various UAVs including aviation systems.
(3) The study introduces a dual-model approach, with Model 1 predicting the path with acceleration and wind speed, and Model 2 predicting the acceleration of the UAV with path and wind speed. This comprehensive approach enhances the control process of UAVs' autonomous flight.
(4) The proposed model enables the prediction of future UAV paths and stable control using established autonomous flight mechanisms even when following the desired path.
(5) While the external force was limited to wind speed in this study, the model offers potential for further improvement by incorporating additional external forces and data sources, such as gyro sensors, GPS, temperature, barometric pressure, and image data.

In summary, the proposed model can be applied to predict the position of UAVs and provide crucial information for necessary decision making of auto-flight even if the desired path is designated. By addressing the challenges of autonomous flight control, this study contributes valuable advancements to the field. Future work can include further testing and refinement of the proposed model with other external forces and data sources to enhance the accuracy and reliability of the model for autonomous UAV control in various environments.

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