Autonomous Landing and Go-around of Airliners Under Severe Weather Conditions Using Artificial Neural Networks

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Abstract— We introduce the Intelligent Autopilot System (IAS) which is capable of autonomous landing, and go-around of large jets such as airliners under severe weather conditions. The IAS is a potential solution to the current problem of Automatic Flight Control Systems of being unable to autonomously handle flight uncertainties such as severe weather conditions, autonomous complete flights, and go-around. A robust approach to control the aircraft's bearing using Artificial Neural Networks is proposed. An Artificial Neural Network predicts the appropriate bearing to be followed given the drift from the path line to be intercepted. In addition, the capabilities of the Flight Manager of the IAS are extended to detect unsafe landing attempts, and generate a go-around flight course. Experiments show that the IAS can handle such flight skills and tasks effectively, and can even land aircraft under severe weather conditions that are beyond the maximum demonstrated landing of the aircraft model used in this work as reported by the manufacturer's operations limitations. The proposed IAS is a novel approach towards achieving full control autonomy of large jets using ANN models that match the skills and abilities of experienced human pilots.

I. Introduction

Human pilots are trained to perform piloting tasks that are required during the different phases of the flight. They are trained to perform landing under difficult weather conditions such as strong crosswind, and abort landing by executing a go-around if needed.

In contrast, Automatic Flight Control Systems (AFCS/Autopilot) are highly limited, capable of performing minimal piloting tasks. Although modern autopilots can perform auto-land, they cannot handle complete flight cycles automatically, they must be engaged and operated manually by the human pilots to constantly change and update the desired parameters, and they cannot handle severe weather conditions, such as strong crosswind components combined with wind shear, gust, and turbulence. The reason for such limitations of conventional AFCS is that it is not feasible to anticipate everything that could go wrong with a flight, and incorporate all of that into the set of rules or control models "hardcoded" in an AFCS.

This work aims to address this problem by creating an Intelligent Autopilot System (IAS) with the capability to handle landing, and go-around under severe weather conditions using Artificial Neural Networks. The IAS is a novel approach which introduces the possibility to transfer human intelligence and intuitions required to pilot an aircraft under such conditions, to an autonomous system. By using this approach, we aim to extend the capabilities of modern autopilots and enable them to autonomously adapt their piloting to suit multiple scenarios ranging from normal to emergency situations. This work builds on previous work by the authors [1][2][3] which introduced the ability to follow a flight course and land autonomously under calm conditions, however, this approach was not able to handle landing under severe weather conditions. Therefore, this paper provides a new approach to enable the system to cope under such difficult conditions, or to safely abort when impossible to land.

This paper is structured as follows: part (II) reviews related literature on wind effects during the cruise, and landing flight phases. Part (III) explains the Intelligent Autopilot System (IAS). Part (IV) describes the experiments, Part (V) describes the results by observing the behaviour of the Intelligent Autopilot System in a flight simulator, and part (VI) provides an analysis of the results. Finally, we provide conclusions.

II. Background

A. *Wind Effects on Autonomous Flying*

Wind disturbance causes the UAV to drift from the desired course, and when added to the accumulated errors of the navigation systems, maintaining a desired flight path or course becomes a significant challenge [4][5].

In [6], the physical properties of the Vehicle Dynamic Model (VDM) are used to study the effects of wind on navigation systems in addition to the control inputs within the algorithm of the navigation filter. In [7], an approach to tackle strong wind effects during flights is proposed by estimating wind effects that are steady and strong in nature, and delivers a maneuvering strategy to tackle such conditions [7].

B. Crosswind Landing

To tackle crosswind during an approach, two methods are used, the first method is known as Crabbing where a certain degree of drift or crab is induced to change the orientation of the aircraft's nose heading towards the direction of the wind [8]. The second method is known as Wing-down, in which a steady sideslip is induced to tackle the drift caused by the crosswind [8]. In practice, it is common to combine both methods, following degrees which could vary during the approach phase [9]. For the Boeing 777 of which a simulated model is used in this work, the maximum crosswind components are 45 knots for a dry runway, and 40 knots for a wet runway [8].

Artificial Neural Networks (ANNs) were used to estimate a mapping relationship between the given situation, and the human pilot inputs while performing the crabbing maneuver [10] [11]. In addition, the possibility of using conventional Control Theory fault tolerance techniques, that are used for Proportional Integral Derivative (PID) controllers to tackle the crosswind landing challenge, is being investigated such as applying the Integral Windup handling methods [12].

Introducing intelligent autonomy to the aviation industry through developing intelligent control techniques that fit into an overall flight management system capable of making the highest level of decisions, is expected to significantly enhance safety, and lower costs [13].

In addition of having limited capabilities, modern autopilots can contribute to catastrophes since they can only operate under certain conditions that fit their design and programming, otherwise, they cede control to the pilots, and with the lack of proper situational awareness and reaction, the result could be fatal [14]. Although the civil aviation sector that uses medium to large jets equipped with such autopilots, is the largest with the highest risk and costs, the current focus of the relevant and recent research efforts is on investigating and developing autonomous autopilots for Unmanned Aircraft Systems especially small and micro drones by introducing solutions that may not be suitable for Large jets such as airliners. Therefore, we propose a solution that can be applied to multiple aircraft categories including airliners and cargo airplanes. We believe that manned aircraft especially airliners require significant attention to enhance safety by addressing the limitations of modern autopilots and flight management systems, and the human error factor as well. A review of the Autopilot problem, Artificial Neural Networks, autonomous navigation and landing are presented in our previous work [1][3].

III. The Intelligent Autopilot System

The IAS is made of the following components: a flight simulator, an interface, a database, a flight manager program, and Artificial Neural Networks. The IAS implementation method has three steps that start with pilot data collection which is a process [1][2][3] that records human pilot demonstrations in a flight simulator of the piloting tasks to be learned by the IAS. The recorded demonstrations are transformed into training datasets for the ANNs.

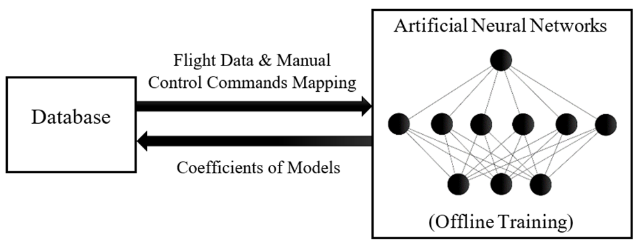

Fig. 1. Block diagram illustrating the IAS components used during training.

In this paper, we discuss: A. Training, and B. Autonomous Control. In each step, different IAS components are used. The following sections describe each step and the components used in turn. The approach applied to allow the IAS to learn from human teachers is covered in our previous work [1][2][3].

A. Training

1) Artificial Neural Networks

Artificial Neural Networks are used to generate learning models from the captured datasets through offline training. Fig. 1 illustrates the training step.

Fourteen feedforward Artificial Neural Networks comprise the core of the IAS. Each ANN is designed and trained to handle specific controls and tasks by taking flight data as inputs, and producing control commands as outputs. Fig. 2 illustrates the main ANNs used during the different phases of the flight. The fourteen ANNs including the emergency situations ANNs are discussed in [1][2][3]. In this work, we introduce the Bearing Adjustment ANN as Fig. 3 illustrates.

The method for choosing ANN topologies in this work is based on an implication [15] which indicates that direct mapping problems requiring more than one hidden layer are rarely encountered, and compared to Deep Learning, this approach means that the system is more understandable and easier to test and verify compared to single deep solutions which are black-boxes unsuited for safety critical applications.

Before training, the dataset is retrieved from the database. Then, the dataset is fed to the ANN. Next, supervised feedforward training using the Hyperbolic Tangent (Tanh) function [16] which is selected given its ability to handle negative values, and the Backpropagation algorithm [16] are applied to train the ANNs.

When training is completed, the learning model is generated, and the free parameters or coefficients represented by weights and biases of the model are stored in the database.

2) Database

An SQL Server database stores the free parameters or coefficients represented by weights and biases of the generated learning models.

B. Autonomous Control

Once trained, the IAS can now be used for autonomous

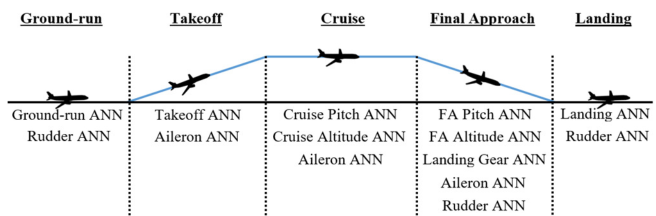

Fig. 2. The ANNs used during the different phases of the flight.

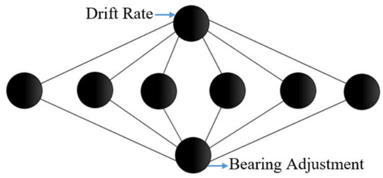

Fig. 3. Input, output, and the topology of the Bearing Adjustment ANN.

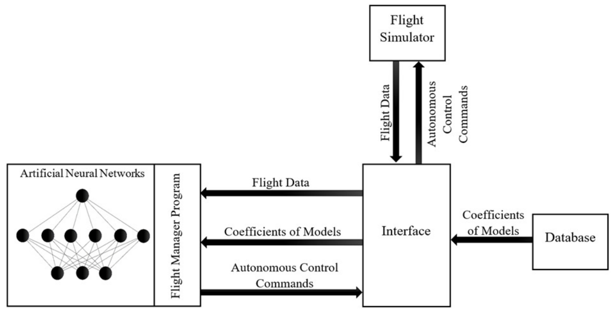

Fig. 4. Block diagram illustrating the IAS components used during autonomous control.

control. Fig. 4 illustrates the components used during the autonomous control step.

1) The Flight Simulator

The simulator of choice in this work is X-Plane 10 which is an advanced flight simulator that has been used in many research papers such as [17] [18] [19].

2) The IAS Interface

The IAS Interface is responsible for data flow between the flight simulator and the system in both directions over the network using UDP packets. Here, the Interface retrieves the coefficients of the models from the database for each trained ANN, and receives flight data from the flight simulator every 0.1 second. The Interface organizes the coefficients into sets of weights and biases, and organizes data received from the simulator into sets of inputs for each ANN. The relevant coefficients, and flight data input sets are then fed to the Flight Manager and the ANNs of the IAS to produce outputs. The outputs of the ANNs are sent to the Interface which sends them to the flight simulator as autonomous control commands using UDP packets every 0.1 second.

3) The Flight Manager Program

The Flight Manager is a program which resembles a Behaviour Tree [20]. The purpose of the Flight Manager is to manage the ANNs of the IAS by deciding which ANNs are to be used simultaneously at each moment. In addition, it generates a flight course to the destination airport of choice based on stored GPS waypoints.

The go-around maneuver is performed to abort landing, by going to takeoff thrust levels, pulling up to climb, and retracting the landing gear. This is performed when the pilot decides that proceeding with landing might be unsafe, and therefore, it is favorable to climb, go around through a given flight course which brings the aircraft back to the point that precedes the final approach phase, and reattempt landing.

Landing safety check techniques are used to ensure that the aircraft is within safe landing conditions, otherwise, go-around is initiated. These techniques, such as the Runway Overrun Prevention System (ROPS)[1] from Airbus, analyze multiple parameters continuously including the available landing runway data and condition to ensure safe landing.

During final approach and just before touchdown, and at a specific altitude that ensures the possibility for the aircraft to climb safely before touchdown, the Flight Manager of the IAS initiates the continuous landing safety check. The selected altitude at which this process starts is equal to or slightly greater than 60 (ftagl) based on preliminary empirical testing. First, the Flight Manager checks if the angle between the aircraft and the centerline of the landing runway is less than a specific degree based on the runway's width. Then, it checks if the beginning of the landing runway has been reached. Finally, it checks if the remaining distance to the end of the runway is safe for landing. The parameters used during this checking process can be modified based on the available information about the landing runway such as its width and length. If the Flight Manager detects an unsafe landing, it generates a go-around flight course based on the available GPS coordinates as Fig. 5 illustrates, changes the flight status from final approach to takeoff, and activates the takeoff ANN.

Fig. 6 illustrates the process which the Flight Manager follows to handle the go-around process. The methods used by the Flight Manager to handle the different tasks including generating flight courses, managing flights, and handling emergency situations is discussed in [2][3].

4) Artificial Neural Networks

The flight data input received through the Interface is used by the ANNs' input neuron along with the relevant coefficients to predict the appropriate output. The Interface sends the relevant output layer value to the flight simulator as autonomous control command.

Since this work aims to expand the capabilities of the IAS to handle landing under severe weather condition including strong crosswind components, wind shear, gust, and turbulence, the Bearing Adjustment ANN is introduced to predict the necessary adjustment of the aircraft's bearing based on the drift rate either towards or away from the path line to be intercepted. Based on preliminary empirical testing, the desired drift rate towards the path line is 0.0025 degrees every decisecond. First, the average rate of change of the

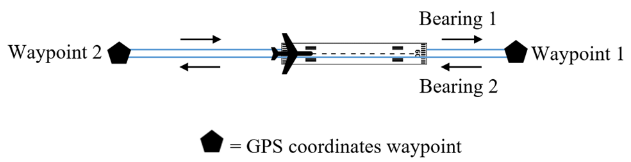

Fig. 5. The generated go-around flight course represented by the blue lines. The aircraft navigates to waypoint 1, then to waypoint 2, and finally, back to the landing runway.

[1] Airbus ROPS. http://www.aircraft.airbus.com/support-services/services/flight-operations/fuel-efficiency-and-runway-overrun-protection-systems/

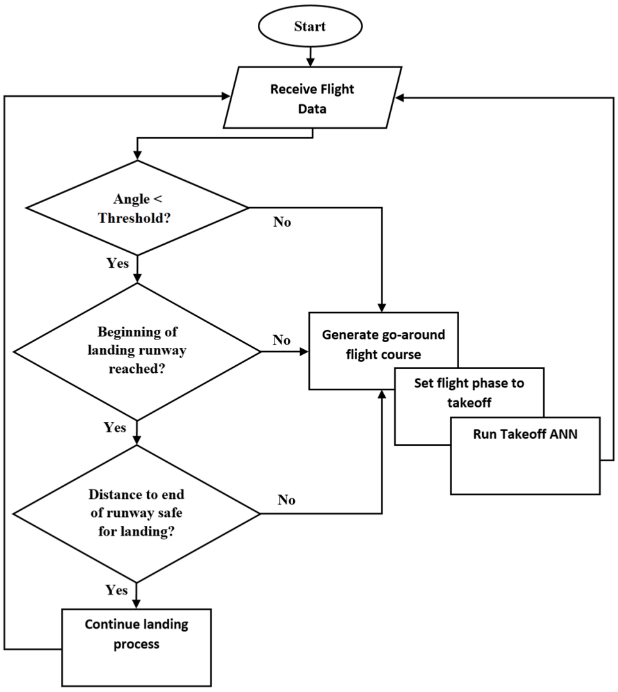

Fig. 6. A Flowchart illustrating the process which the Flight Manager program follows to check the landing conditions, and initiate a go-around if necessary.

angle -between the aircraft and the path line to be intercepted- is calculated using (1) [21].

$$A(x) = \frac{f(x) - f(a)}{x - a} \quad (1)$$

where $x - a$ is the change in the input of the function f, and $f(x) - f(a)$ is the change in the function f as the input changes from a to x. Then, the result is added to the difference between the bearing of the path line to be intercepted, and the aircraft's current bearing to generate the required bearing to be followed. The difference between the latter and the current bearing of the aircraft is fed to the Aileron ANN [1][3] which takes the difference as input, and predicts through its output neuron, the appropriate control command to the ailerons, to bank, and intercept the path line.

IV. EXPERIMENTS

This work discusses the experiments conducted on the Bearing Adjustment ANN which aids the Aileron ANN to intercept a path line under severe weather conditions. This section also discusses the experiments conducted on performing go-around.

The experiments were conducted under severe weather conditions with the presence of high crosswind component, wind shear, gust, and turbulence.

Our previous work [1][2][3] provide detailed explanations of the experiments of autonomous ground-run, takeoff, climb, cruise, rudder control, maintaining a desired altitude and pitch, navigating from departure to arrival airports, landing, and handling emergency situations.

To assess the effectiveness of the proposed approach in this paper, the Intelligent Autopilot System was tested in two experiments: A. Path line interception during final approach, and B. Go-around.

The simulated aircraft used for the experiments is a Boeing 777 as we want to experiment using a complex and large model with more than one engine rather than a light single-engine model. The experiments are as follows:

A. Path line interception during final approach

The purpose of this experiment is to assess the behaviour of the IAS when intercepting a path line that represents the centerline of the landing runway during final approach under severe weather conditions.

1) Training

Based on preliminary empirical testing, a synthetic training dataset representing a correlation between the drift rate and the bearing adjustment was generated. The Bearing Adjustment ANN was trained until a low Mean Squared Error (MSE) value was achieved (below 0. 01).

2) Autonomous Control

After training the ANN on the relevant training dataset, the aircraft was reset to the runway in the flight simulator, and the IAS was engaged to test the ability of intercepting a final approach and landing path line under severe weather conditions autonomously. After the IAS took the aircraft airborne, and navigated to the destination airport, the output of the Bearing Adjustment ANN was used to assist the Aileron ANN to intercept the final approach path line. This was repeated 50 times under different and random weather conditions as table I shows, to assess consistency. The weather conditions included a 0.015 turbulence value, and rain precipitation around 0.3 mm during all attempts.

B. Go-around

The purpose of this experiment is to assess the behaviour of the IAS when performing go-around autonomously.

1) Training

For this experiment, the same approach [3] used to navigate autonomously from a given point A to a given point B is applied. Therefore, no additional training was required.

2) Autonomous Control

Just before touchdown, deviation from the path line is induced manually by stopping the IAS, and manually engaging the ailerons by the human pilot to deviate from the path line. Then, the IAS is started immediately. This approach was applied since the IAS excelled at landing within the safe zone of the landing runway regardless of how severe the weather conditions as long as these conditions are not exaggerated to a no-fly condition. To assess consistency, this was repeated 10 times under different and random weather conditions with minimum wind speed of 20 knots up to 35 knots, and random directions between 0 and 360 degrees including shear of 20 degrees. The weather conditions included a 0.015 turbulence value, and rain precipitation around 0.3 mm during all attempts. The following section describes the results of the conducted tests.

TABLE I
THE DIFFERENT WEATHER CONDITIONS USED FOR THE FINAL APPROACH PATH LINE INTERCEPTION EXPERIMENT.

Attempts Count	Wind Speed (knots)	Wind Gust (knots)	Wind Direction (degrees)	Wind Shear (degrees)
10	20	12	0	20
10	23	14	180	20
10	27	15	90	22
10	27	15	270	22
10	50	0	90	0

V. RESULTS

A. Path line interception during final approach

One model was generated for the Bearing Adjustment ANN with an MSE value of 0.0089. Utilizing the output value of the Bearing Adjustment ANN to enhance the path line interception performance, resulted in the system flying the aircraft using a technique known as crabbing, where although the aircraft flies in a straight line, the nose of the aircraft is pointed towards a bearing different from the bearing of the landing runway's centerline due to wind conditions. Unlike other systems where this technique must be explicitly hard-coded, here, the IAS naturally discovered the technique itself.

Fig. 7 illustrates the different bearings the IAS followed under random severe weather conditions as table I shows, compared to the bearing of the landing runway (326 degrees), where the lines in the upper area represent bearings followed when the aircraft was pushed to the left side of the landing runway's centerline, which happens in the presence of east crosswind for example, and vice versa. The lines on top are the bearings the IAS followed under a sustained weather condition with a constant crosswind of 50 knots at 90 degrees. Fig. 8 illustrates the average rate of change of the angle when drifting towards the path line. Fig. 9 illustrates the angle representing the difference between the aircraft's position, and the centerline of the landing runway. Based on the width of the landing runway used in the experiments, a safe touchdown angle is between 0.045 and -0.045 which was found based on preliminary empirical testing.

B. Go-around

Fig. 10 illustrates the flight paths that the IAS followed autonomously back to the landing runway. Since no strict go-around path was applied, the IAS followed two different paths based on the aircraft's location with respect to the landing runway's centerline, where a position on the right of the runway due to wind blowing from the left would cause the IAS to bank right towards the next waypoint, and vice versa.

VI. ANALYSIS

As can be seen in Fig. 7 (Path line interception during final approach experiment), the IAS was able to produce a natural

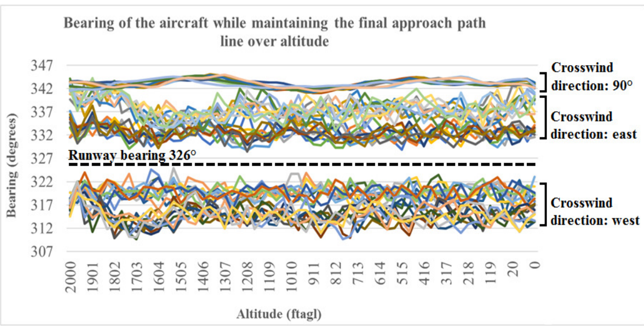

Fig. 7. 50 attempts showing Aircraft bearings (crabbing) during final approach under random severe weather conditions at table I shows, compared to the bearing of the landing runway (326 degrees). Lines in the upper area are bearings followed when the aircraft was pushed to the left side of the landing runway's centerline, and vice versa.

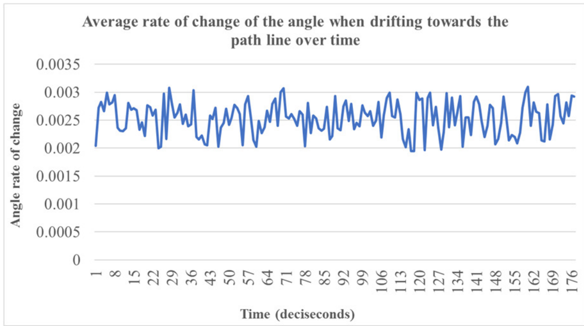

Fig. 8. The average of 20 different readings of the rate of change of the angle when drifting towards the path line in the presence of random and severe weather conditions at table I shows, compared to a desired rate of change of 0.0025 degrees every decisecond.

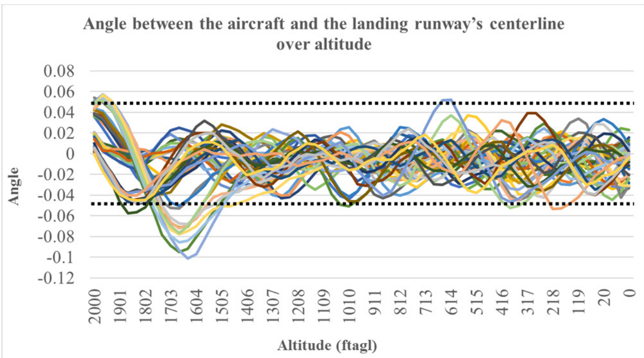

Fig. 9. 50 lines showing angle values between the aircraft's position, and the centerline of the landing runway (0 degrees) of all the attempts illustrated in Fig. 6. Based on the width of the landing runway used in the experiments, a safe touchdown angle is between 0.045 and -0.045, which is the area between the dotted lines (landing runway's safe touchdown zone).

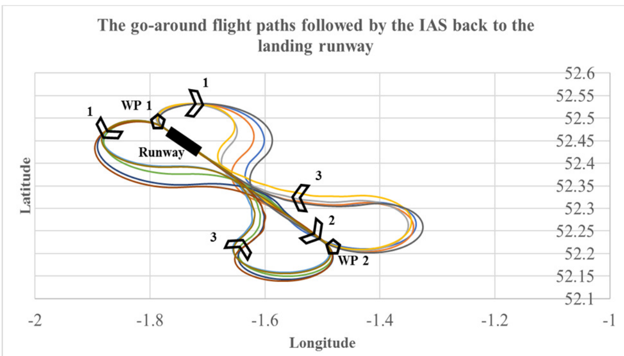

Fig. 10. The 10 go-around flight paths followed autonomously by the IAS back to the landing runway. The aircraft navigates to waypoint 1, then to waypoint 2, and finally, back to the landing runway. the IAS followed two different paths based on the aircraft's location with respect to the landing runway's centerline. Birmingham airport (BHX) was used.

crabbing behaviour in a direction that is perpendicular to the constantly changing speed and direction of wind without being explicitly trained to do so. In addition, the IAS was able to handle persistent strong crosswind of 50 knots at 90 degrees which is beyond the demonstrated crosswind landing of a Boeing 777 as the top lines in Fig. 7 show. Keeping the angle rate of change close to 0.0025 degrees despite the random severe weather conditions proved the effectiveness of the Bearing Adjustment ANN as Fig. 8 (Path line interception during final approach experiment) illustrates. In all the attempts, the IAS was able to touchdown within the safe landing zone with respect to the centerline of the runway as Fig. 9 (Path line interception during final approach experiment) illustrates. This compares extremely well with the previous version of the IAS without the Bearing Adjustment ANN, which was unable to land under the same conditions. Under most weather conditions the IAS piloted so well that go-arounds were not needed, therefore, manual intervention was required to induce a go-around maneuver by stopping the IAS just before touchdown, manually banking the aircraft away from the centerline, then restarting the IAS. The system was able to detect unsafe landings through the Flight Manager, and followed go-around paths back to the landing runway under random severe weather conditions successfully as Fig. 10 (go-around experiment) illustrates.

VII. Conclusion

In this work, a novel and robust approach is proposed to perform autonomous final approach path line interception, and go-around under severe weather conditions.

The experiments were strong indicators towards the ability of Supervised Learning with Artificial Neural Networks to capture low-level piloting tasks such as the rapid manipulation of the ailerons to intercept a path line under severe weather conditions.

The novelties presented in our work, and dedicated to introducing intelligent autonomy to large jets such as airliners are robust solutions that could enhance flight safety in the civil aviation domain. They provide solutions to the difficult problem of autonomous navigation and landing under severe wind disturbance by enabling autonomous behaviour that was not possible before.

The aviation industry is currently working on solutions which should lead to decreasing the dependence on crew members. The reason behind this is to lower workload, human error, stress, and emergency situations where the captain or the first officer becomes incapable, by developing autopilots capable of handling multiple scenarios without human intervention. We anticipate that future Autopilot systems which make of methods proposed here could improve safety and save lives.

References

[1] H. Baomar and P. J. Bentley, "An Intelligent Autopilot System that learns piloting skills from human pilots by imitation," *2016 International Conference on Unmanned Aircraft Systems (ICUAS)*, Arlington, VA, USA, 2016, pp. 1023-1031.

[2] H. Baomar and P. J. Bentley, "An Intelligent Autopilot System that learns flight emergency procedures by imitating human pilots," *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, Athens, 2016, pp. 1-9.

[3] H. Baomar and P. J. Bentley, "Autonomous Navigation and Landing of Airliners Using Artificial Neural Networks and Learning by Imitation," *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, Hawaii, USA, 2017.

[4] H. Xiong, R. Yuan, J. Yi, G. Fan and F. Jing, "Disturbance Rejection in UAV's velocity and attitude control: Problems and solutions," *Proceedings of the 30th Chinese Control Conference*, Yantai, 2011, pp. 6293-6298.

[5] J. Smith, J. Su, C. Liu and W. Chen, "Disturbance Observer Based Control with Anti-Windup Applied to a Small Fixed Wing UAV for Disturbance Rejection", *Journal of Intelligent & Robotic Systems*, 2017.

[6] M. Khaghani and J. Skaloud, "Evaluation of Wind Effects on UAV Autonomous Navigation Based on Vehicle Dynamic Model", *Proceedings of the 29th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2016)*, pp. 1432 - 1440, Portland, Oregon, USA, 2016.

[7] S. Park, "Autonomous crabbing by estimating wind using only GPS velocity," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 52, no. 3, pp. 1399-1407, June 2016.

[8] G. van Es, P. van der Geest and T. Nieuwpoort, "Safety aspects of aircraft operations in crosswind", National Aerospace Laboratory NLR, Amsterdam, Netherlands, 2001.

[9] G. van Es et. al., "Safety Aspects of Aircraft Performance on Wet and Contaminated Runways", *the 10th annual European Aviation Safety Seminar (FSF)*, Amsterdam, March 16-18, 1998.

[10] R. Mori and S. Suzuki, "Analysis of Pilot Maneuver under Crosswind Condition using Neural Network," Mathematical Problems in Engineering, Aerospace and Sciences, June 25-27, 2008.

[11] R. Mori and S. Suzuki, "Analysis of pilot landing control in crosswind using neural networks," *2009 IEEE Aerospace conference*, Big Sky, MT, 2009, pp. 1-10.

[12] S. Ismail, A. A. Pashilkar and R. Ayyagari, "Phase compensation and anti-windup design for neural-aided sliding mode fault-tolerant autoland controller," *2015 International Conference on Cognitive Computing and Information Processing(CCIP)*, Noida, 2015, pp. 1-7.

[13] P. Salmon, G. Walker, and N. Stanton, "Pilot error versus sociotechnical systems failure: a distributed situation awareness analysis of Air France 447". Theoretical Issues in Ergonomics Science, 2015, pp.64-79.

[14] E. Atkins, "Safe Autonomous Manned and Unmanned Flight in Off-Nominal Conditions", [Presentation]. *Future Technologies Conference*, San Francisco, USA, 2016.

[15] J. McCaffrey, "Understanding Neural Networks using .NET", [Presentation]. The Microsoft 2014 Build Conference, San Francisco, USA, 2014.

[16] J. Heaton, *Artificial Intelligence for Humans, Volume 3: Deep Learning and Neural Networks*. St. Louis, MO, USA: Heaton Research, Inc., 2015.

[17] F. Wei, A. Bower, L., Gates, A., Rose, and D. T. Vasko, "The Full-Scale Helicopter Flight Simulator Design and Fabrication at CCSU", *57th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, 2016.

[18] M. Jirgl, J. Boril, and R. Jalovecky, "The identification possibilities of the measured parameters of an aircraft model and pilot behavior model on the flight simulator". *International Conference on Military Technologies (ICMT)*, 2015, vol., no., pp.1-5.

[19] A. Kaviyarasu, and S. Kumar, "Simulation of Flapping-wing Unmanned Aerial Vehicle using X-plane and Matlab/Simulink". "*Defence Science Journal*", 2014, 64(4), pp.327-331.

[20] K. Winter, I. J. Hayes, and R. Colvin, "Integrating Requirements: The Behavior Tree Philosophy," 2010 8th IEEE International Conference on Software Engineering and Formal Methods, Pisa, 2010, pp. 41-50.

[21] J. Steig, "Average Rate of Change Function", *Mesa Community College*, 2009. [Online]. Available: http://www.mesacc.edu/~marfv02121/readings/average/.