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# Adaptive neuro-fuzzy inference system based autonomous flight control of unmanned air vehicles

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A R T I C L E I N F O

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A B S T R A C T

In this paper, an ANFIS (adaptive neuro-fuzzy inference system) based autonomous flight controller for UAVs (unmanned aerial vehicles) is described. To control the position of the UAV in three dimensional space as altitude and longitude–latitude location, three fuzzy logic modules are developed. These adjust the pitch angle, the roll angle and the throttle position of the UAV so that its altitude, the heading and the speed are controlled together. The implementation framework utilizes MATLAB's standard configuration and the Aerosim Aeronautical Simulation Block Set which provides a complete set of tools for rapid development of detailed six degree-of-freedom nonlinear generic manned/unmanned aerial vehicle models. To demonstrate the performance and potential of the controllers, the Aerosonde UAV model is used. Flight Gear open source flight simulator and Gauges Block Set are deployed in order to get visual outputs that aid the designer in the evaluation of the controllers. Steep turn maneuvers which are used for basic training of pilots are applied to test the performance of the fuzzy logic controllers. Despite the simple design procedure, the simulated test flights indicate the capability of the approach in achieving the desired performance.



## 1. Introduction

Unmanned aerial vehicles (UAVs) are remotely piloted or self-piloted aircrafts that can carry many different types of accessories such as cameras, sensors and communications equipment. They have a very wide range of applications that include both civil and military areas. Some important features that make them very popular are their low cost, smaller size and their extended maneuver capability because of absence of a human pilot.

In literature, there can be found many different approaches related to the autonomous control of UAVs; some of the techniques proposed include fuzzy control (Banks & Hayward, 2001; Doitsidis, Valavanis, & Tsourveloudis, 2004; Verbruggen, Zimmerman, & Babuska, 1999), adaptive control (Andrievsky & Fradkov, 2002; Aström & Wittenmark, 1989; Schumacher & Kumar, 2000), neural networks (Sundararajan, Li, & Sratchandran, 2001), genetic algorithms (Cordon, Gamide, Herrera, & Magdelen, 2004) and Lyapunov theory (Ren & Beard, 2003). In addition to the autonomous control of a single UAV, research on other UAV related areas such as formation flight (Schiller & Draper, 1991) and flight path generation (Dathbun, Kragelund, Pongpunwattana, & Capozzi, 2002) are also popular.

The main objective of the work reported in this paper is to evaluate the performance of ANFIS (adaptive neuro-fuzzy inference system) based controllers in relation to the autonomous operation of UAVs. For this purpose, three fuzzy modules are designed, one module is used for adjusting the bank angle value to control the latitude and the longitude coordinates, and the other two are used for adjusting elevator and throttle controls to obtain the desired altitude and airspeed values. The work is a follow of the work reported at a conference (Kurnaz, Kaynak, & Konakoğlu, 2007).

The performance of the proposed system is evaluated by using the standard configuration of MATLAB and the Aerosim Aeronautical Simulation Block Set (Aerosim, Baldonado, Chang, Gravano, & Paepcke, 1997). Aerosim Aeronautical Simulation block set provides a complete set of tools for rapid development of detailed six degree-of-freedom nonlinear generic manned/unmanned aerial vehicle models. As a test air vehicle Aerosonde UAV (Aerosonde – Global Robotic Observation System) is utilized. This particular choice is made because the specifications and the flight parameters of Aerosonde UAV are openly available. Furthermore, the great flexibility of the Aerosonde, combined with a sophisticated command and control system, enables its deployment and command from virtually any location. Flight Gear (Gear Open-source Flight Simulator), which is an open source flight simulator and Gauges Block Set (Matlab Simulink Gauges Block Set) are employed in order to get visual outputs that aid the designer in the evaluation of the controllers.

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The paper is organized as follows. Section 2 starts with a basic introduction of ANFIS and then explains the design of the controllers which are used for the autonomous control of the UAV. The inputs and the outputs of each controller are described and the membership functions used are given. The hybrid learning algorithm adopted in this work is described in Section 3 and a representative simulation study and its results are presented in Section 4. In the final sections of the paper some concluding remarks and suggestions for future work are made.

## 2. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a five layered feed-forward neural network structure, as shown in Fig. 1. The functions of the various layers are well explained in the literature (Jang & Sun, 1997) together with its merits over the other types of neuro-fuzzy approaches and therefore will not be dwelled upon here. The only remark that is worth making is the fact that its special architecture based on Sugeno type of inference system enables the use of hybrid learning algorithms (explained below) that are faster and more efficient as compared to the classical algorithms such as the error back propagation technique.

### 2.1. Hybrid learning algorithm

The approach used in this work for updating the ANFIS network parameters is a hybrid learning algorithm which is a two level learning algorithm. In this approach, the parameters of ANFIS network are evaluated in two parts as input and output parameters.

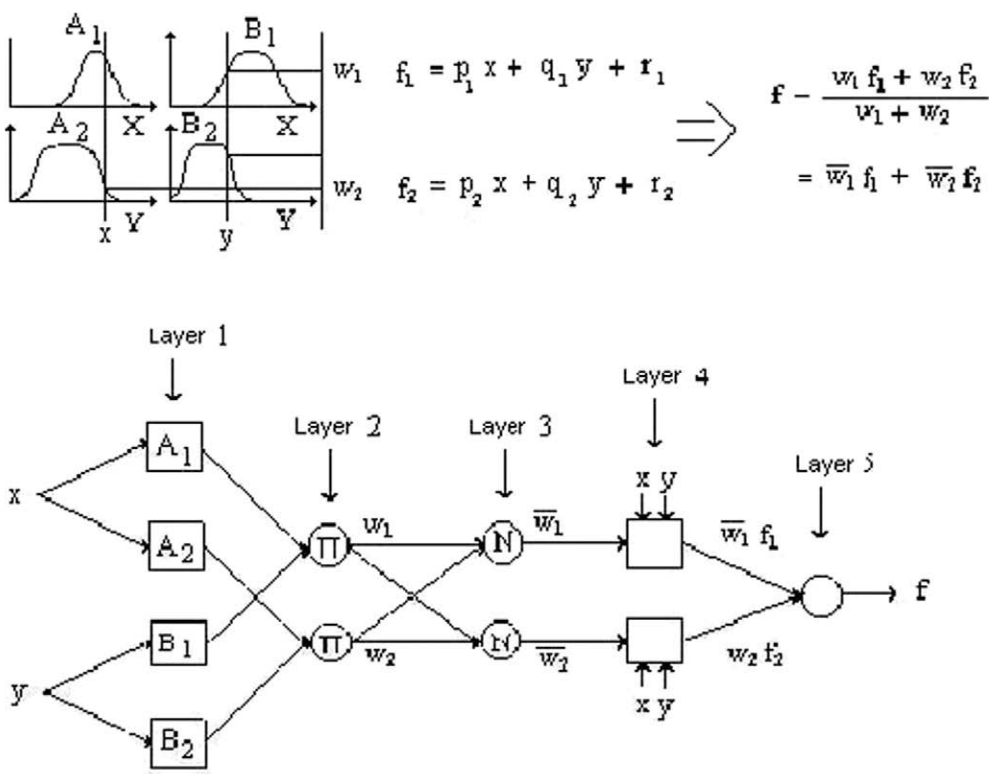


**Fig. 1.** Upper: 2-input, 2-rule Sugeno inference system. Lower: equivalent ANFIS architecture.

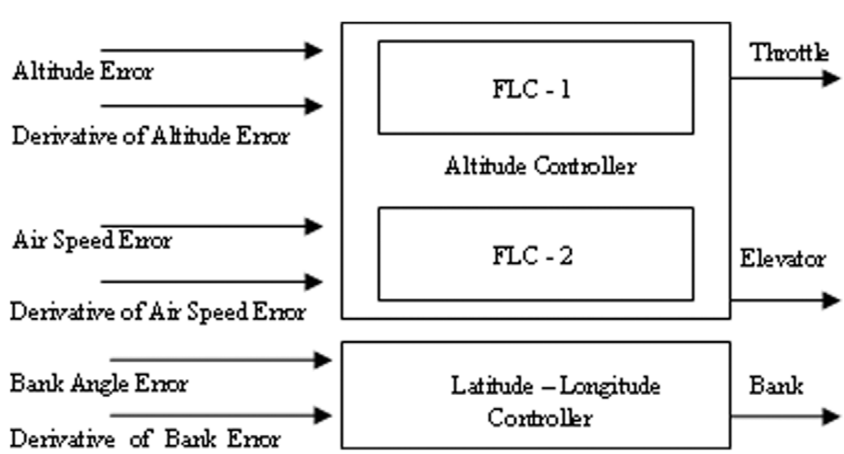


**Fig. 2.** ANFIS controller design.

Let us express the total parameter set as S = S1 + S2, where S1 is the set of input parameters (the parameters of the membership functions) and S2 is the set of output parameters (weights). During the forward pass of the hybrid learning algorithm, the parameters of the membership functions in the input stage (S1) are kept constant. In this manner, the output of the network becomes a linear combination of output parameters of the parameter set S2 and the well known Least Square Error (LSE) based training can be used.

During the backward pass of the hybrid learning algorithm, the parameter set S2 is kept constant and the error is back propagated. The parameter set S1 can now be updated using the well known gradient descent method.

## 3. Simulation studies

While simulating the ANFIS controllers, standard MATLAB/Simulink interface and Aeronautical Simulation Block Set (Aerosim) are used. Aerosonde UAV model is prepared in Aerosim block set and then the ANFIS based controller is adapted to the system. To see the visual outputs of the UAV, open source flight simulator Flight Gear and Gauges Block Set are used. By this way, the maneuvers of the aircraft can be seen.

ANFIS controller architecture is shown in Fig. 2. There are three Fuzzy Logic Controller (FLC) blocks in the architecture. These FLCs work together to achieve the altitude, the speed and the bank angle values as demanded by the reference trajectory. There are two

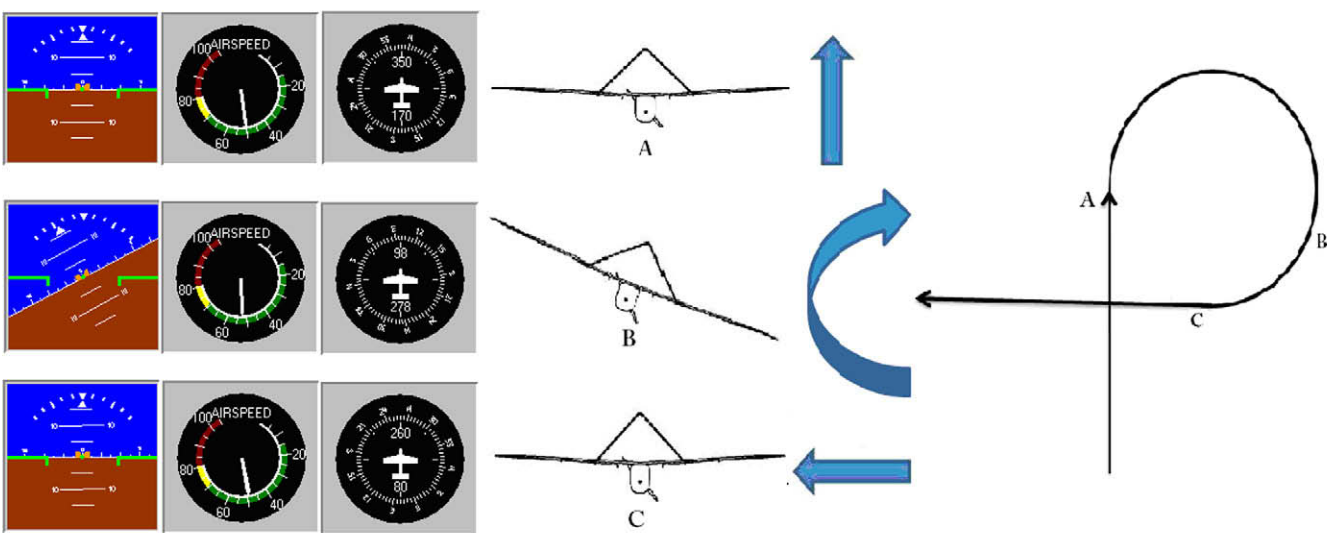


**Fig. 3.** The steep turn Maneuver with Aerosonde UAV.

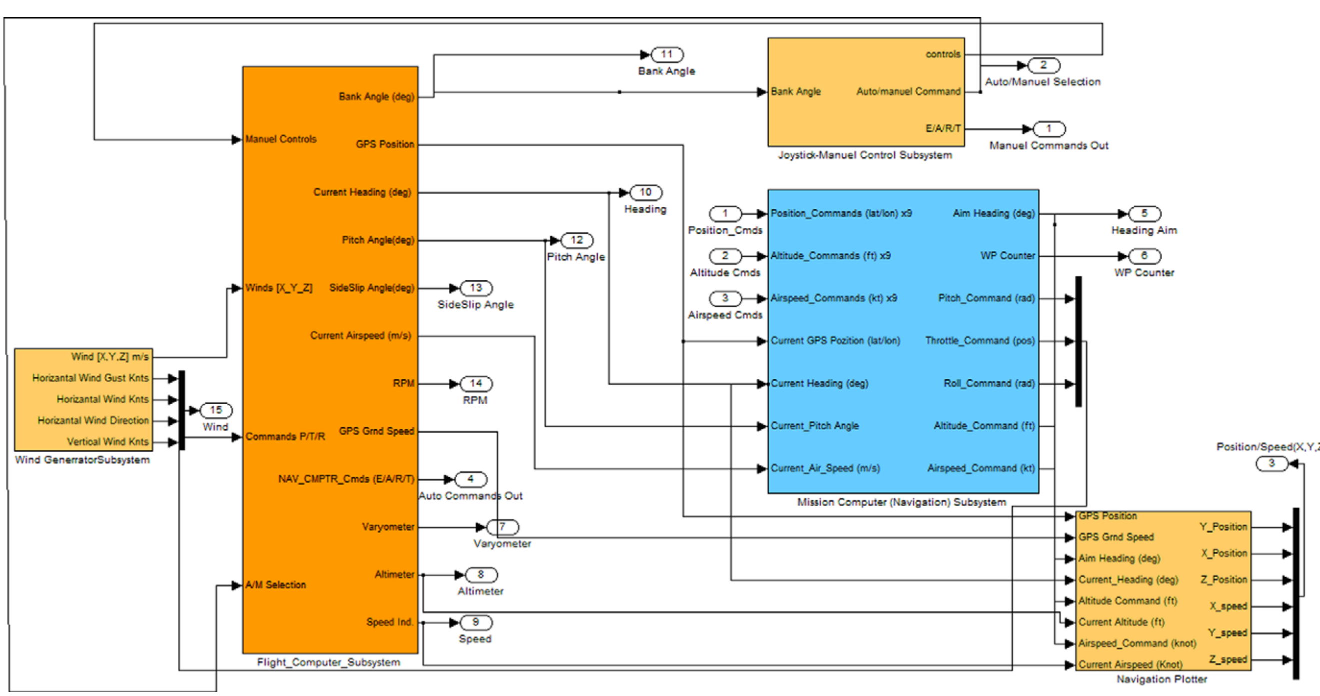


**Fig. 4.** The SIMULINK block diagram used in simulation studies.

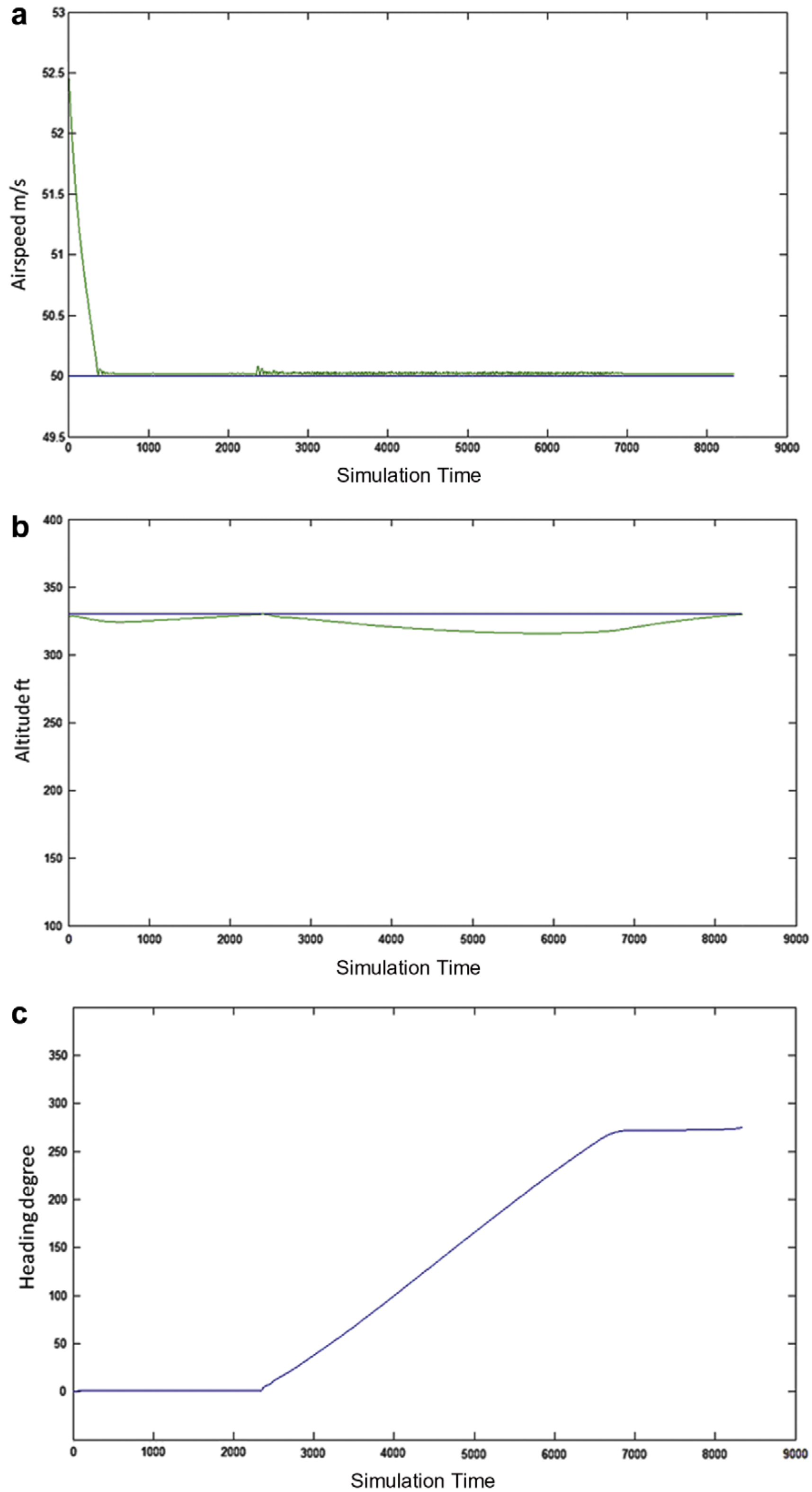


**Fig. 5.** Typical simulation results.

main subsystems in controller. One of them is the Altitude Controller. The inputs to this subsystem are the altitude error, which is the difference between the desired altitude and current altitude, the derivative of the altitude error, the air speed error, which is the different between the desired airspeed and the current airspeed, and the last input is the derivative of air speed error. The function of the Altitude Controller subsystem is to reach the desired altitude and the desired air speed and therefore it controls the throttle and the elevator position as outputs. The second subsystem is the Latitude–Longitude Controller subsystem. The inputs of this subsystem are the bank angle error and its derivative. The duty of the subsystem is to reach and hold the desired bank angle to achieve

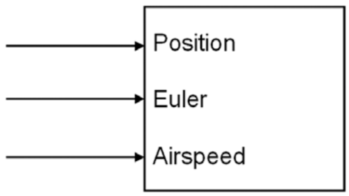


**Fig. 6.** The flight gear interface block.

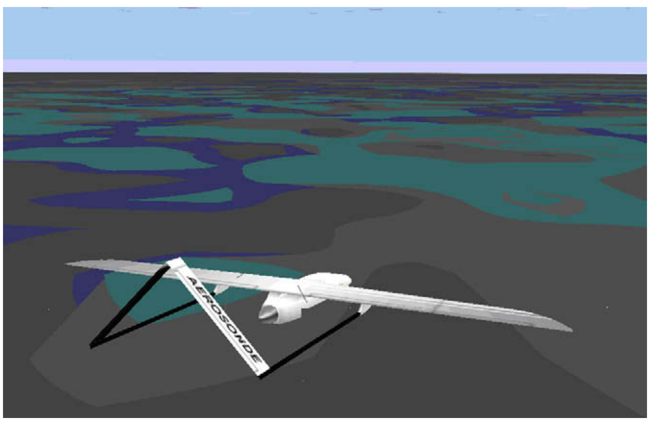


**Fig. 7.** The flight gear flight conditions.

the desired heading angle. In this way, the UAV can be guided through the desired latitude and the longitude.

Summarizing what is described above; the outputs of the two ANFIS controllers enable the air speed, the altitude and the heading to be controlled. That is to say, the attributes of the UAV is kept under control so the system guides the platform to the desired position in three dimensional space. To test how successful the designed controllers are, a test pattern is needed that changes the altitude and the heading of the UAV. It is described in the next section.

Another extra module used in simulation studies is the wind subsystem. The subsystem generates random wind effects as a canker to simulate the environment of UAV. The wind is represented by three dimensional vectors $[x,y,z]$. The limitations imposed in this subsystem are maximum wind speed 8 kn/h; maximum wind gust is ±2 kn/h for all altitudes. The use of the wind module enables us to see the effectiveness of the mission computer under simulated wind effects.

### 3.1. Reference trajectories

The efficacy of the ANFIS controllers is evaluated by demanding the Aerosonde UAV to execute some flight maneuvers autonomously. There are some basic maneuvers described in the aviation literature. One of them is steep turns. Steep turns aim to see the domination of the pilot over the control surfaces of the plane in basic training. There are several types of steep turn maneuvers. The one that is used here is a 270° turn which starts at a particular heading angle and finishes at a heading angle which is 270° from the start. As an example if the UAV starts a 270° right steep turn at 350° heading angle, 50 knots and 330 ft altitude as shown in Fig. 3, it must complete a 270° right turn and finish the turn at 260° heading angle, 50 knot airspeed and 330 ft also. It is to be noted that 330 ft is a rather low altitude for the Aerosonde considered. A steep turn at lower altitudes need more skills and can be dangerous because it is more difficult to keep the altitude level. If the controller can manage to complete the described turn with the same speed and the altitude values as at the start of the turn, this would indicate that the control surfaces of the UAV are effectively controlled by the FLCs and that the UAV can accomplish any other kind of maneuver demanded (turns, dives and climbs) with the same success as long as the maneuver is within its flight envelop.

It should here be noted that while in steep turn UAV must have maximum 30° bank angle. If the nose of the UAV comes under the horizon line, it starts to lose altitude and the air speed is increased. And if the nose comes over the horizon line, UAV starts to gain altitude and the airspeed is decreased. To see the nose position and the bank angle, an artificial horizon indicator is used. The controller changes the throttle position and the bank angle to preserve the initial flight values while going through the turn. Throughout the maneuver, the basic objective is to keep the nose in horizon line and to control the altitude and the airspeed.

### 3.2. Simulation results

In order to test the effectiveness of the ANFIS controllers, the Simulink test platform shown in Fig. 4 is used and extensive sim-

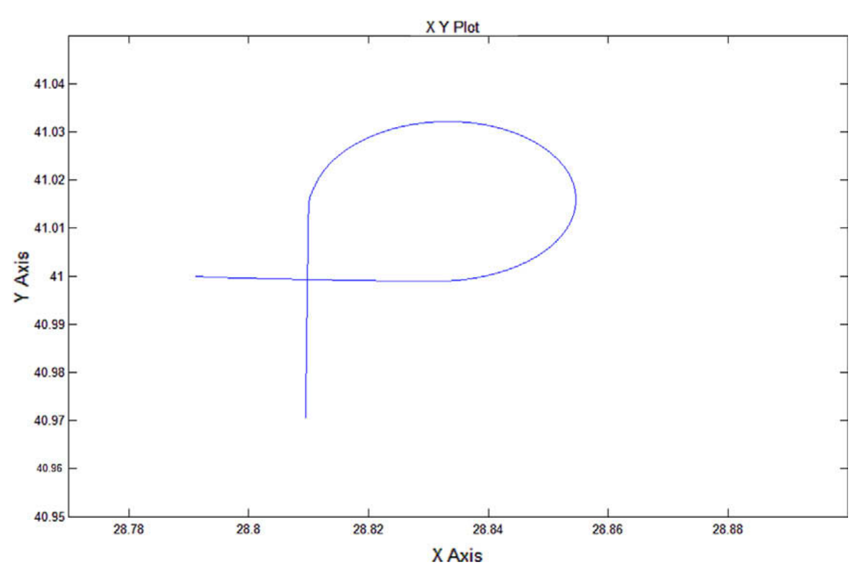


**Fig. 8.** GPS coordinate based simulation trajectory.

ulation studies are carried out with different atmospheric conditions. A typical result is shown in Fig. 5 which is for the steep turn described in the previous section under standard atmosphere conditions at that altitude and wind conditions which is produced by wind generation module described above.

### 3.3. Flight gear visual interface

In order to be able to visualize the flight of the air vehicle, the software Flight Gear v.9 was used. In this way, it was possible to see the effects of the even very small changes of the flight parameters in the flight conditions (that may not apparent from a study of the graphical simulation results). Fig. 6 depicts the block diagram of the interface between the Simulink and the Flight Gear, the inputs to the block being the aircraft states and the other information available as the outputs of the Aerosim block. UDP (User Datagram Protocol) is used for communication between the two software which run on different computers in a same network. A snapshot of the Flight Gear window is shown in Fig. 7.

## 4. Conclusions

The main purpose of the autonomous flight is to enable the UAVs to accomplish their mission autonomously, without any (or with minimal) input from the ground operator. Fuzzy logic controllers described in this paper grant autonomy to the UAV. The controllers provide the airplane with improved dynamic stability by regulating the flight parameters within limited ranges, at the same time tracking of UAV route. In this work a GPS based trajectory is produced by Simulink to see the maneuver as a flight pattern. We can see the result from this trajectory which is shown in Fig. 8.

The simulation results presented demonstrates the feasibility of ANFIS based controllers for autonomous flight control of UAVs. In order to be able to have a basis for comparison, well-tuned PID type and fuzzy logic type controllers are also designed. Although there are many control law architectures, the classic PID control approach augmented with online gain scheduling provides the ideal mix of robustness and performance for typical aircraft dynamics. The stability and control loops can be tuned to provide the desired performance and robustness specifications by adjusting a set of autopilot parameters or gains. But this is done through linear analysis – the nonlinear aircraft model is linearized for a representative set of flight conditions that cover the operating envelope of the aircraft. The linear dynamics of the closed-loop system (aircraft + autopilot) are analyzed in terms of stability and control responses (overshoot, settling time). By using fuzzy controllers, this difficult design process is avoided; nevertheless stable control and fast reaction time over conventional autonomous UAVs can be achieved as shown in this paper. The capability to do a dynamic planning of the desirable flight pattern is also important and this is done in this paper by using the current position of the moving UAV and the stationary target positions. The simulation studies presented verify that the UAV can follow the pre-defined trajectories despite the simplicity of the controllers. However, as seen by the simulation results, there exist some oscillations and errors when wind effects are added to the simulation environment while using fuzzy controllers.

It is seen that the performance of ANFIS type of controller is comparable to those obtained from the bank angle controller with a PI type controller and from PID type controller for speed controller despite the model-free approach of the ANFIS approach. However, PI and fuzzy type of altitude controllers have demonstrated superior performance. For some flight conditions, the ANFIS type controller has resulted in unstable performance. This has demonstrated that more stable learning algorithms need to be adopted. One possible solution could be the use of Variable Structure Systems theory based algorithms that are known for their stability (Topalov, Cascella, Giordano, Cupertino, & Kaynak, 2007).

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