Flight Control System using Neural Networks

Qasim Abdul-Aziz, Hassan H. Hashemi

***Abstract*—Despite all the research being done in an attempt to bridge the gap between control systems and artificial intelligence, there is still an immense risk of failure and instability that exists. One particular application that this research will look into and expand on is aircraft control mechanisms. This paper will examine the existing uncertainties within these systems that could be suspected as the cause of failure in the artificial control operation of an aircraft. This study will act as a further extension of research on the feedback linearization of an aircraft's control architecture using adaptive neural networks to decrease the probability of an uncontrolled error resulting from the nonlinearity of the aircraft's dynamic characteristics. The stability of previously implemented mechanisms to control aircraft systems will also be investigated. This research will require a thorough approach and understanding of various possible areas of malfunction and instability caused by multiple factors, including, external interferences and inefficiencies that accumulate within the controller that can mislead or cause an undesirable effect on the system. Examining similar areas where this study may be used for further research, while also discussing opportunities to apply these procedures to relatable applications will be analyzed, as it is of key importance for progression of this technology.**

***Index Terms*—artificial intelligence, flight control systems, neural networks, operational amplifiers**

I. INTRODUCTION

Flight control systems have been around for many decades now and are a prime example of how important system design is for vehicular control. In fact, most commercial jumbo jets fly using autopilot for more than 90 percent of the flight duration, while the pilot only takes control of the aircraft for less than 10 percent of it.

Essentially, a pilot has to worry about two primary transitions of flying: the first being when the plane is taking off and the second being when the plane is landing. This is the crucial point in the flight where the FAA does not wish for the autopilot to be engaged, even if it were technically able to [1]. The reason for this is that during takeoff and landing, there is a very low margin for error in keeping the flight safe. All the nonlinear inputs that a control system has to process can cause massive delays leading to instability, and causing an undesirable outcome. During the rest of a flight, including but not limited to ascending, cruising, banking, and descending, it is quite safe for an aircraft to be controlled completely using avionic control systems.

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Q. Abdul-Aziz is an MSc student of California State University, Fullerton, CA 92831, United States (email: qasimak96@csu.fullerton.edu)

H. H. Hashemi is a Professor of Electrical Engineering Department, California State University, Fullerton, CA 92831, United States (email: hhashemi@fullerton.edu)

This research takes a look at the "takeoff" portion of a flight and attempts to integrate deep learning and control systems to improve flight performance for a standard commercial aircraft. When an aircraft is in the stage of taking off from the ground, it is in a vulnerable position as it has to deal with many uncertainties and disturbances that can cause the aircraft to lose control. It has been well understood that an implementation of a control system with an adaptive neural network can provide a favorable outcome, even when heavy constraints are put on the control architecture [2].

A. Evolution of Artificial Intelligence

Artificial intelligence is the term used to define the idea of providing intellect to a machine. This form of intellect varies depending on the use of the machine; however, the basic structure remains the same. This enables researchers and engineers to install similar systems into various applications allowing them to "learn" from the tasks they are meant to complete [3]. Over the past several decades, artificial intelligence has grown into numerous fields including engineering, medicine, and data science.

Deep learning has become a dominant choice for engineers and scientists attempting to extract commonalities from extensive amounts of data, and predict specific events before they occur by recognizing patterns in the complexity of the input data [4]. This type of artificial intelligence can help in a plethora of applications where humans may not be able to identify trends due to the nonlinearities and size of the data. The foundation of deep learning is built on neural networks and their ability to learn; they are stacked layers of neurons that are interconnected, giving them the ability to distinguish features in a given set of data. Neural networks have become exceptionally useful tools in applications from predicting the price of stocks to predicting seasonal rain patterns for agricultural purposes [5], [6]. Creating these algorithms using mathematical statements would have taken months if not years to develop, while the accuracy would still be below satisfactory. With the help of deep learning, there is no limit to the complexities a system can identify, and therefore, integrate into its predictions and functionality.

B. Existing Flight Control

Understanding faults in previous technology is important as innovation can only occur when proper requirements are met. One of those requirements is to be able to produce better results with research and development. On June 1, 2009, a quite sad and unfortunate display of unstable flight control had caused a severe accident of a commercial flight. The system of the aircraft had lost control when severe turbulence struck the aircraft. Due to this, the autopilot pulled the aircraft into a steep incline and the aircraft lost its speed and began to stall. A last-minute effort by the flight crew to return the aircraft to a safe trajectory had failed and the flight ended in a terrible accident [7], [8]. The implementation of breakthrough and progressive technology

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can help with the safety of aerial vehicles and diminish the possibility of an accident.

Reference [9] was one of the first to use neural networks and deep learning in flight control systems. That research study used neural networks to manipulate various controls on an aircraft through a flight simulator, but the results achieved were not satisfactory for a safe flight. There is a strictly low margin of error that can exist for a flight to be considered safe, and that was not achieved in any previous research study. Since this research focuses on takeoff, that portion of flight should be directly compared to the results of previous research studies [9]. The issues they faced could possibly be caused by the neural network not having optimum control of the elevator, the training data being inaccurate, or having a slow response network. Any combination of these deficiencies, along with other unknown shortcomings, can result in an unstable and unreliable mechanism.

There have also been implementations of neural networks in flight control using linearization techniques of nonlinear inputs in feedback loops. Since the problem statement was the same, the researchers attempted to derive linear models for use in their systems. The neural networks were trained on the linear models and integrated into the system; this allowed for faster response times as well as a more cost-effective design. This research also used state-space models for linearization and included algorithms to counter inversion errors and bound dead-zone occurrences [10]. Various additional computations needed to be done in order to maintain a stable system after the linearization of the data. The use of neural networks here is not used precisely as a nonlinear control system, but rather as an algorithm for detecting trends in the data. This practice voids many of the advantages that are associated with the integration of neural networks; hence, it is not a justifiable utilization of the system.

There are many attempts at flight control using various designs built on nonlinear control architecture. These developments have contributed significantly to the flight control systems available in aircraft used for commercial and private purposes. Due to the evolution of artificial intelligence, these previous control mechanisms are starting to become obsolete in their functionality. Modern aircraft are rapidly advancing in their technology and require exceptionally complex systems to operate, and there's a certain limit to the ability that standard control systems can yield. Previous designs of control-based architecture in flight control systems have had issues with deviations in mathematical models and flight dynamics when faced with highly nonlinear inputs. In the case of simpler nonlinear inputs, standard control procedures have definitely had issues; however, they have at times, also been known for functioning considerably well [11].

II. Methodology

The methodology of this research has been extended over the domain of deep learning to incorporate neural networks within the structure of the control system. Multiple software packages have been carefully selected to be used in this study to ensure an effective and meaningful result is obtained.

A. *Overall Structure*

The architecture of the system is rather simple. It consists primarily of a neural network, a controller, and a simulator that is used to collect the training data as well as test the system. It can be seen from Figure 1 that the structure is oversimplified as shown, and it is broken down into more detail later on. The core of the entire system is the brain, which is termed as the "neural network," and it is where most of the processing is done. The controller, on the other hand, is primarily for merging all the subsystems into one functioning system that is capable of operating in synchronization with the neural network and the simulator. The simulator was chosen specifically due to its accurate representation of aerodynamics in flight under various climate and weather conditions. It is a useful and well-known tool for portraying the effect that nonlinear disturbances have on the system, and how the system will suppress these undesirable effects to allow for safe operation of the aircraft.

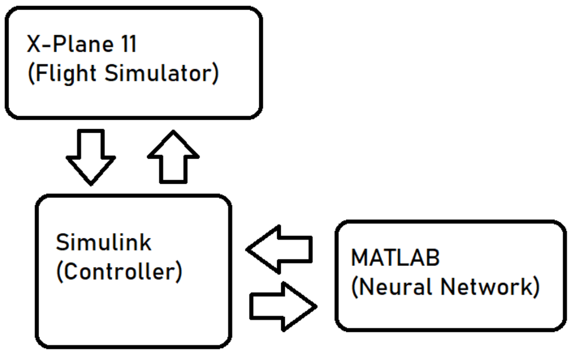

Figure 1. Overall structure of system depicting the flow of data.

B. *Software Used for Realization of System*

As this research focuses on the control of an aircraft through a simulator—a few applications were required to accurately construct the architecture of the system. This was exceptionally challenging as it was critical to ensure the software would be capable of cooperating with each other successfully in real-time.

MATLAB

The brain of the system which is comprised of neural networks used by the various components of the controller was developed through MATLAB. This software works specifically well for engineering applications that require low latency and high accuracy. MATLAB is a primary choice for systems that need to be linked through a controller and require a more dynamic characteristic when training using deep learning. It is also pre-equipped with various toolboxes that can help train and test numerous deep learning applications, and also fuse them with electrical/mechanical mechanisms [12], [13]. The neural network used in the system was trained in MATLAB using flight data extracted from the simulator. During the testing phase, the trained neural network was used to process inputs and produce outputs correlating to the data that it had been trained on.

To realize a system capable of controlling an aircraft for takeoff, the proper readable inputs and controllable outputs need to be selected, as shown in Figure 2. The two primary outputs that are being manipulated by the controller are the throttle of dual engines and the elevator yoke control. As for inputs, the optimum inputs for understanding proper vector control are altitude, speed, and climb-rate. By using these inputs, the network was able to anticipate the trajectory of flight, allowing it to make adjustments as needed to maneuver the aircraft in case of disturbances or deviations.

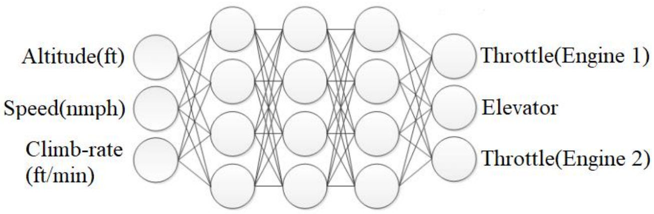

Figure 2. Neural network model. A theoretical representation of the neural networks' inputs and outputs. The hidden layers can also be seen here. The number of hidden layers and nodes is much larger in the actual neural network; this figure is for representational purposes only.

Simulink

The controller of the system was developed using Simulink. As Simulink is integrated within MATLAB, the architecture of the network was able to directly communicate with Simulink and each model. This procedure allowed for a low latency connection functioning in real-time, so each model could execute its respective functions in synchronization with the rest of the system. Due to this, the system was able to produce outputs virtually instantly with varying inputs. Previous research papers indicate how developers used Simulink to create toolboxes within the software that are capable of allowing realism in network communication. This is essential when simulating a physical connection between nodes as it accounts for effects that would normally be negated [14]. This is an outstanding example of how accurately a designer could potentially produce a virtual system that can be used to simulate real-world operations through Simulink. Countless realistic applications could be replicated with remarkable accuracy using Simulink, including electrical and mechanical systems.

X-Plane 11

The simulator or testing software that was used in this research is widely used by multiple aerospace firms to simulate their aircraft designs in flight by testing its aerodynamics and control [15], [16]. As this is one of the most accurate virtual representations of an aircraft in flight that can be virtually observed—it has become a popular choice for companies to test their aircraft and tweak the overall design before it is sent to the factory for production.

"X-Plane 11" was used in this research for collecting the training data as well as testing the system. The aircraft had to be flown through the transition of taking off, so the required data could be collected to train the neural network to learn the procedure. It is then tested on the simulator to examine the accuracy in comparison to a human pilot. As the primary goal of this research was to suppress the effects that stormy weather, which includes wind gusts, heavy rain, and varying humidity levels have on the aircraft during takeoff, it was of utmost importance that an additional control system be integrated into the architecture. This would provide the neural network with a feedback loop that would monitor differences between the desired and current trajectory of flight. Then, it would react with an equal force to nullify the difference and bring the aircraft back on the desired trajectory.

To add realism into the flight, the simulator needed to be adjusted. This was done by adding heavy rain and random wind gusts to the virtual world. These settings had a direct impact on the trajectory of the flight as the aircraft was constantly being forced off its commanded trajectory. "X-Plane 11" is an excellent software that adds realism to a simulated flight. This is extremely beneficial when studying effects caused by real-world circumstances on high-speed aerial vehicles. In Reference 9, it is shown that the research faced problems in the takeoff phase due to "stormy weather." It was recorded that the flight did a very insufficient job in taking off from the ground and maintaining a safe trajectory in the air. It is clear that the simulator did apply varying weather effects; however, the system was not able to react skillfully enough to neutralize the disturbance.

III. IMPLEMENTATION

Successful implementation of the system is dependent upon the functionality and reliability of the different components in the system. As there are innovations and improvements in the architecture of the system—it is expected to give an admirable result that will show improvement with respect to previous studies done in this field.

A. Input/Output Modules

The initial part, as well as the final part of the system, consists of primarily two components respectively, the input port and the output port. These two core mechanisms are heavily relied upon for accurate communication in real-time between the system and the simulator. The transmission and reception of the signals are done in synchronization to ensure the internal system can compute the required values simultaneously. One important point to note is that all communication done between the simulator and the system is through UDP, or "User Datagram Protocol," and not TCP, or "Transmission Control Protocol." This system employs the use of UDP as it does not require a confirmation from the receiver to the transmitter to ensure proper values are being received. This was not necessary and would slow down the response time of the system significantly. As the system and simulator were both running on the same computer—there was a very low chance (if any) of miscommunication [17].

B. Neural Network Modules

These modules are placed directly in the center of the system schematic and are made up of "Neural Network" and "MATLAB function" blocks. Each module has been trained separately in accordance with the data that has been provided to it, and each module can produce outputs that correlate with the data it has been trained on [18]. These are the foundation of the entire system as they are responsible for the elevator and speed control of the aircraft. In this specific study, they have been trained to take off an aircraft and maintain an acceptable climb-rate throughout the "ascending" phase. This was exceptionally challenging as developing a neural network that can operate within extremely critical margins requires a highly responsive system that can read, process, and transmit a control signal to the simulator before the aircraft experiences instability.

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This research study focused on the design of two neural networks, both working simultaneously to control two separate actuators on the aircraft. In Figure 3, the first and more complex artificial neural network can be seen. With an input of altitude and climb-rate—the network must output a corresponding value for the elevator yoke. The neural network calculates the required climb-rate from the altitude of the aircraft, and uses it to find the difference between the required and instantaneous climb-rate. That difference is then used to determine a suitable control signal for the elevator. The neural network uses this method to stabilize the climb-rate or it will vary depending on weather conditions at the time of flight. This network is trained on a commercial jet taking off on a standard runway in “clear” weather conditions. This includes no disturbances of any kind that may cause undesired forces on the aircraft itself to push it off course. Climb-rate was introduced specifically into this system to account for disturbances that would cause the aircraft to deviate from its assigned trajectory. However the elevator yoke is set, the vector on which the aircraft is traveling cannot be understood by the yoke itself, so climb-rate was opted as the primary indicator for determining the actual velocity vector of the aircraft.

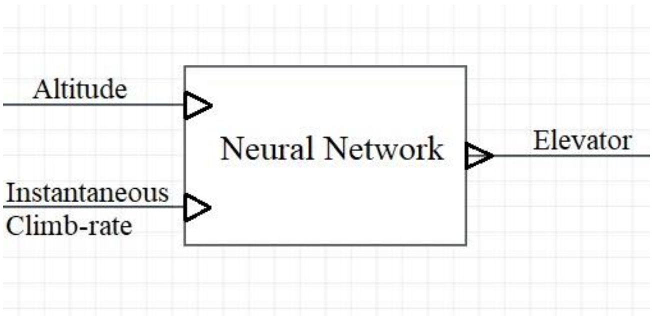

Figure 3. Elevator control network. This part of the system is responsible for calculating a suitable required climb-rate from the instantaneous altitude of the aircraft. The difference of the required and instantaneous climb-rate is then used to determine a suitable elevator yoke signal.

During the testing phase, the system was tested in clear as well as stormy weather conditions. The weather had many nonlinear effects on the aircraft that needed to be countered by the control system. Working against “stormy weather” is definitely an arduous task that flight control systems have had to deal with since they were invented, and these systems are known to have had terrible failures [7].

The second neural network module in the system was used for throttle control of the aircraft. Although the throttle control that exists in the aircraft’s control system is flawless, it is important to demonstrate that each segment of an aircraft can be controlled by deep learning techniques while providing equal or better performance. As shown in Figure 4, there are two limiters attached to the outputs of the neural network block. The purpose of these limiters is to ensure that under no circumstances should the throttle control signal ever be higher than the maximum or lower than the minimum permitted throttle. This is a safety feature that ensures the system does not overstress the aircrafts components.

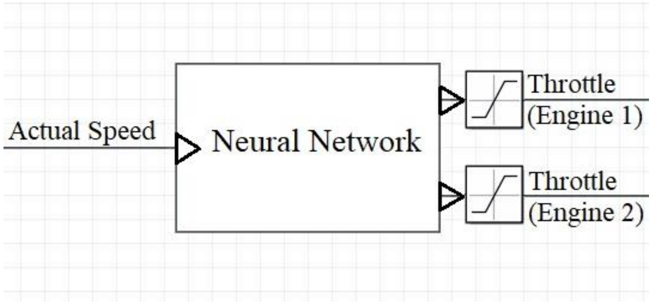

Figure 4. Throttle control network. This neural network runs parallel to the elevator control network. It is responsible for calculating a throttle control value at any given instantaneous speed.

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

When a neural network is being trained to compute certain data, it needs to have an activation function attached to each node; its responsibility is to apply a transformation to the weighted input. As the data in this research was mostly nonlinear, a nonlinear activation function was chosen that provided the most accurate training to the neural network. The activation function is the “sigmoid” function. In Equation (1), the mathematical statement of the activation function can be seen.

C. The Operational Amplifier

As mentioned earlier, the system was trained using data from the simulator under the conditions that the weather was clear; that ideally meant that there were no external effects due to rain, wind, or humidity on the aircraft. This did not seem to be a problem when the system was tested under these same weather conditions, however, when the simulator was configured for harsher weather, the flight failed rather quickly [9]. This was due to the fact that the aircraft had absolutely no idea of the effect that the weather had on it; as it was not able to identify the issue, it was not able to counter it.

To allow the system to react against nonlinear disturbances, an operational amplifier was placed after the neural network responsible for elevator control. Figure 5 shows the schematic representation of the operational amplifier used in this research. The input and output nodes are elevator control values and the variable resistor is manipulated by the subtractor. The purpose of the subtractor is to calculate the difference between the required and instantaneous climb-rate. That value is then used for “R1.” The ideology here is to vary the gain of the amplifier in proportion to the difference between the required and current trajectory. This would apply a controlled gain to the elevator signal causing it to vary depending on the value of “R1.”

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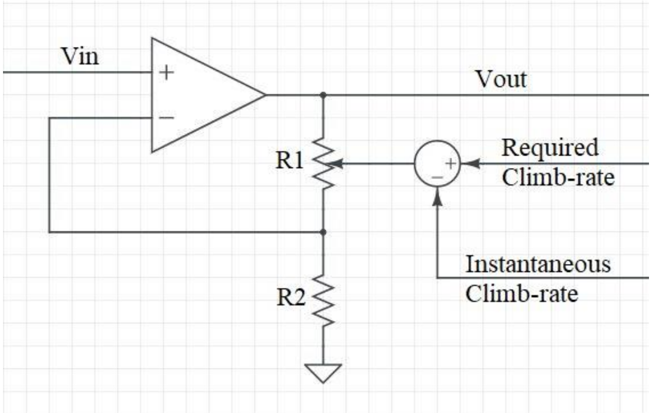

Figure 5. Operational amplifier control system.

$$Gain = \frac{Vout}{Vin} = 1 + \frac{R1}{R2} \quad (2)$$
$$R1 = Required\ climb\ rate - Current\ climb\ rate \quad (3)$$

The primary function of the amplifier represented in Figure 5 is for nonlinear adaptive control of the elevator. It is used to force amplification to the output elevator control signal based on the difference in the required climb-rate and instantaneous climb-rate. The required climb-rate is calculated from the "Elevator Control Network," and the instantaneous climb-rate is sent directly from the decoder after receiving a signal. The higher the difference, the more rapidly the difference is decreased due to the higher gain of the operational amplifier. In Equations (2) and (3), it should be known that the resistor "R1" is the primary gain factor of the amplifier, as "R2" is at a constant value; however, "R2" can also be modified to scale the gain of the amplifier. This can be quite beneficial when tuning the amplifier to work with different types of aircraft, as it will directly adjust the sensitivity of the amplifier.

IV. RESULTS

The results collected had been extracted from the flight simulator data log file after multiple successful test-runs in varying weather conditions [15]. This study aimed to improve on and extend the introduction of neural networks in flight control systems, and this was accomplished by incorporating a secondary control module through an operational amplifier. This architecture provided the system with the advanced control that was vital for its performance.

In Figure 6, the result showing the altitude of the aircraft with respect to time can be seen, where two tests have been compared. The first test is when the flight had to take off during severe weather conditions, while the second test is when the weather conditions were clear. The curve for clear weather conditions is meant to be used as a reference as that is the curve on which the neural network was trained. In Figure 6, however, it quickly becomes clear that there is a slight deviation between the aircraft's trajectory during stormy weather conditions vis-a-vis the trajectory during clear weather conditions. This study successfully produced a positive result for elevator control and achieved a massive improvement over the result that was achieved by previously completed studies [9]. That research study was lacking in outputting a satisfactory result for aircraft elevator control in stormy weather conditions, and that is what the primary motive of this study was founded upon.

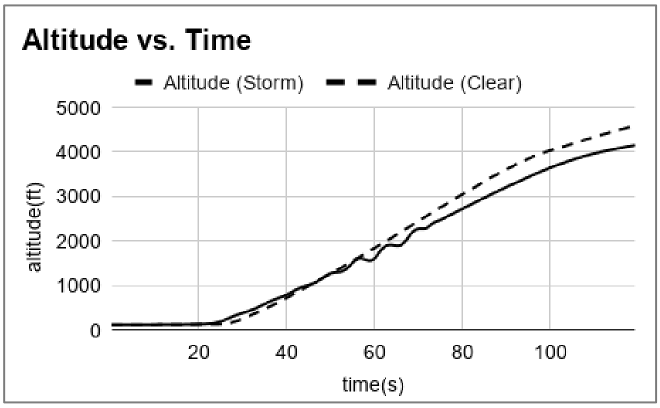

Figure 6. Altitude vs. Time graph. The primary focus of this paper was on this portion as there was a need of improving the attitude control of the aircraft using deep learning. It depicts the vertical trajectory of the aircraft in clear and stormy weather conditions with respect to time.

It is well understood that for safe travel in an aircraft, it is important that the aircraft be capable of controlling itself in case of any external disturbance including wind and rain. From the result that was obtained in this study, it is evident that there exists a minor deviation between the flight in stormy and clear conditions; however, it is also clear that the aircraft did manage to control itself after being affected by turbulence in mid-flight. This was a stunning display of responsive control in a crucial segment of the flight. There was another external effect throughout takeoff caused by varying air and rain resistance acting on the body of the aircraft. This is primarily what caused a slightly lower slope in the trajectory of flight. It is essential to note that the drifting effect significantly depends on the direction of the wind and it will almost always vary. In this case, it is assumed from the data, that the external disturbances were applying a downward force on the aircraft, and that is why it had a lower slope.

Inputting external disturbances into the simulator to upset the attitude of the aircraft is an important step in examining nonlinearities that may offer challenges for flight control. One specific area that needs to be highlighted is how disturbances will vary and cause a distinct response in each case. A neural network based flight controller needs to be trained through multiple experiences in changing weather conditions for it to be able to react skillfully when faced with an unknown incident. Here the aircraft was trained in clear weather conditions and was competent enough to control its output for a smooth recovery when met with turbulence. A significant amount of additional training in numerous weather conditions should vastly improve the flight performance of the aircraft further.

While the system was controlling the elevator for the aircraft, it was also trained to control the throttle simultaneously. Figure 7 portrays the "actual speed" of the aircraft with respect to time. It can be seen that both curves shown are quite similar, but the aircraft in stormy weather did travel slightly faster at any instantaneous point aside from when the aircraft experienced mid-flight turbulence. This was most likely due to the lower climb-rate the aircraft was flying at, allowing for higher acceleration. Overall, the throttle control of the neural network remained trustworthy and reliable, leaving no doubt about its functionality

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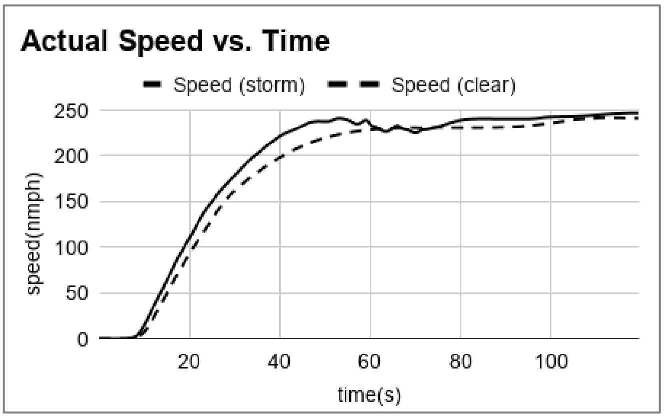

Figure 7. Speed vs. Time graph. A representation of how the speed of the aircraft varies in stormy and clear weather conditions with respect to time.

The first artificial neural network focused on elevator control, which is highly nonlinear, while the other was for speed control, which is relatively less complex. This data alone provides convincing evidence to the idea that practically all controls of an aircraft can be performed through the use of neural networks. Furthermore, the results achieved here invoke the possibility that with enough development, neural networks may even function considerably superior to humans in applications including flight control.

V. FUTURE ADVANCEMENTS & CONCLUSION

Although this paper has successfully reached a milestone, it has not entirely concluded the process of taking off in an aircraft. Moreover, there are many other stages of flight that still need to be developed. The study done here has opened a path for future innovators to integrate deep learning into the remaining control infrastructure of the aircraft to enable the possibility of autonomous flight. There are numerous areas that should be researched, including navigation control, altitude adjustment for dodging turbulence in the troposphere, banking control, and landing [19]. Systems that can suppress nonlinear effects in flight should be researched, and the most important two stages of flight, namely takeoff and landing, need to be improved further. As this project has successfully improved the process of taking off, there needs to be an ample amount of research concentrated on developing autonomous landing as well.

In conclusion, this research study turned out to be quite a success as it accomplished what it was designed to do. Realizing a system that can function normally with nonlinear disturbances is not a simple task in control systems; however, the use of neural networks has proved to be a sustainable option that can be implemented in flight control systems. Integrating control systems with deep learning is a type of adaptive control system; and by using neural networks to learn from training, it can allow for a significantly reduced response time in processing [20]. It has also been proven to operate with immense more stability than using deep learning without any additional control mechanism [9]. The main upside of this ideology is that it can be applied to practically any application, including the other stages of flight. Additional possibilities include integration into autonomous vehicles, including cars, trucks, and buses; as neural networks have been appearing in many studies involving driverless cars, there is a need for innovation in related vehicular control [21]. There are also theories for implementing artificial intelligence into robotics; however, that concept may not be ready to be realized as an actual system before conducting further research on improving the stability of neural networks.

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