

# Neural Network Trained Controller for Manned Mars Missions

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## Abstract

- We submit a new method for atmospheric entry into the Martian atmosphere using a neural network trained controller
- Traditionally the controller for atmospheric entry is an algorithm with internal logic with a specific purpose, such as following a reference trajectory<sup>1</sup>
- The Neural Network is to be trained with real data from Apollo missions, then the results compared against the Apollo algorithm to determine the robustness of the controller
- Results from a previous research group were promising, and the use of a different type of neural network may yield better results

## Introduction

- Atmospheric entry is an unavoidable design challenge that must be faced by any mission with a goal of landing on Mars
- As manned missions may become feasible in the future, there will demand for more accurate and robust landing algorithms
- To understand the problem better it is best to understand the derivation of the governing equations of the entry problem
- The Apollo algorithm was reconstructed in MATLAB using a 1966 paper by Raymond Morth and the results from the simulation nearly perfectly replicated the real mission data

## Literature Review

As seen in the diagram on the left, the reentry capsules generate lift by using a misaligned center of mass.

The derivation for the equations seen to the right can be found in *Introduction to Astrodynamics Reentry*. Although I will not cover the full derivation of the equations, it is helpful to understand what they mean. The first three of the equations are kinematic equations that describe the motion of the spacecraft over some planetary body. They are best interpreted as the spherical components of the velocity of the spacecraft, with respect to the center of the planet. The second and third equations are then divided by  $r$  to translate them to latitude and longitude. The last three equations are similar in form but are more involved. They can be understood to be the forces acting on the spacecraft and again are converted to spherical coordinates.

The most important take away from the equations is the bank angle,  $\sigma$ . The bank angle is the only control which the onboard computer has over the spacecraft as it enters through the atmosphere, and there have been several different approaches to best control the bank angle as a function of time.



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## Approaches

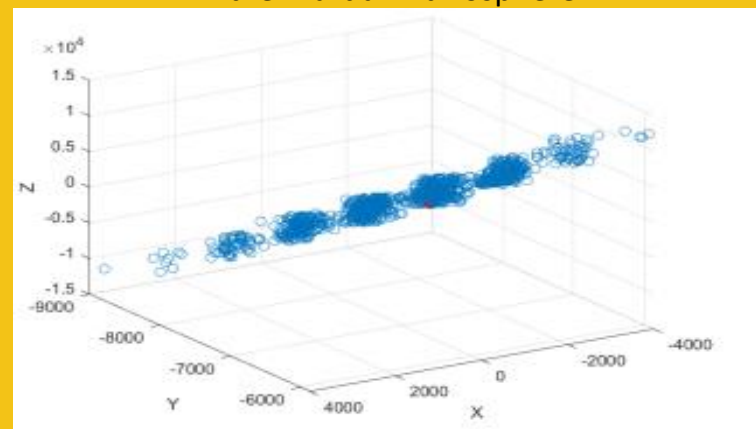
- There have been many different approaches to determine the best way to control the bank angle as the spacecraft descends through the atmosphere
- The most well-known is the Apollo algorithm which has a predetermined trajectory stored within the flight computer. Throughout the course of atmospheric entry, the computer checks the current state of the spacecraft and adjusts the bank angle accordingly to maintain a flight path along the predetermined trajectory
- Another approach is the predictor-corrector method which numerically integrates an energy form of the given equations to determine the predicted trajectory in real time and control the bank angle to avoid any high-g maneuvers

### Our Method

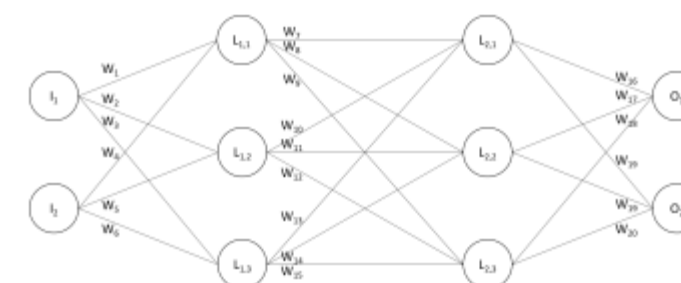
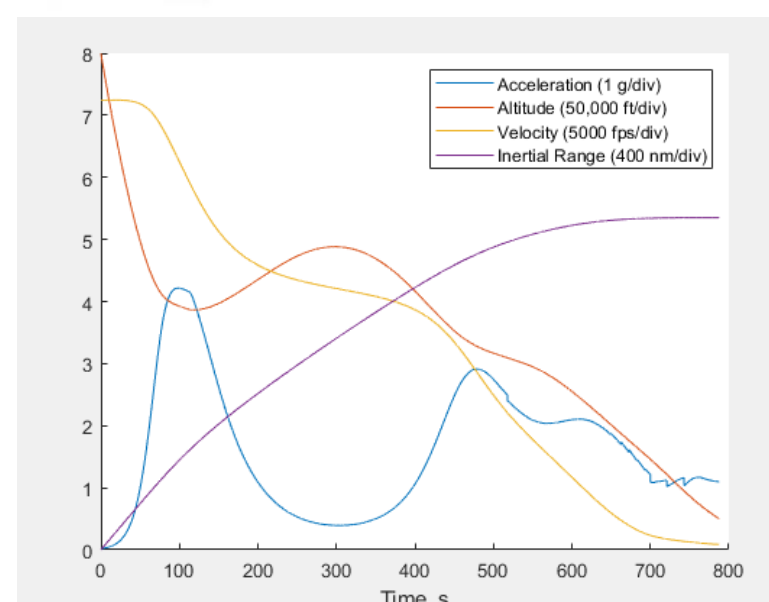
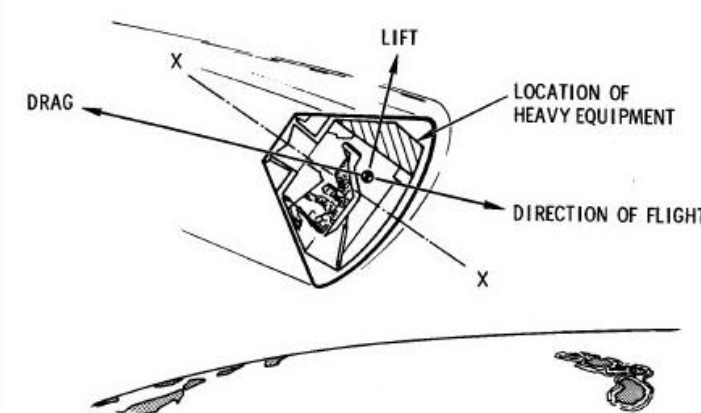
- Our method is to train a neural network to act as the controller of the bank angle throughout atmospheric entry. This was done by another group of students using an ANN, pictured below, to produce promising results, but we plan to use a CNN-LSTM to improve on those results

## Results

A previous research group produced promising results but when using a nonlinear model in Earth atmosphere the model failed to produce satisfactory results. Below is their results for the Martian Atmosphere



### COMMAND MODULE AERODYNAMICS



$$\dot{r} = V \sin(\gamma)$$

$$\dot{\theta} = \frac{V \cos(\gamma) \cos(\psi)}{r \cos(\phi)}$$

$$\dot{\phi} = \frac{V \cos(\gamma) \sin(\psi)}{r}$$

$$\dot{V} = -\frac{D}{m} - \frac{G}{m} \sin(\gamma)$$

$$\dot{\gamma} = \left( \frac{L}{m} \cos(\sigma) - \frac{G}{m} \cos(\gamma) + \frac{V^2}{r} \cos(\gamma) \right) / V$$

$$\dot{\psi} = \left( \frac{L \sin(\sigma)}{m \cos(\gamma)} - \frac{V^2}{r} \cos(\gamma) \cos(\psi) \tan(\phi) \right) / V$$

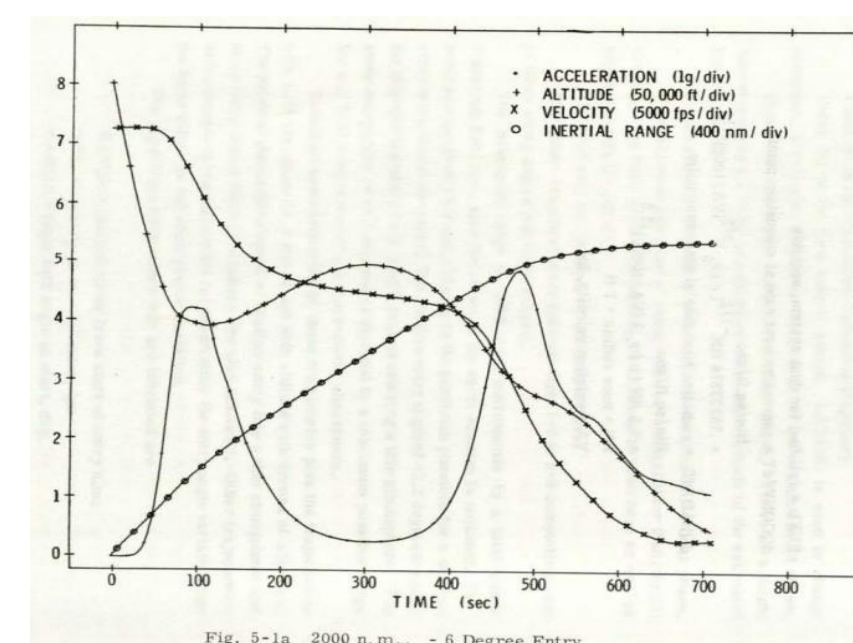


Fig. 5-1a 2000 n.m., - 6 Degree Entry

## Conclusion

- The practice of training neural networks to act as controllers for complex engineering solutions shows great promise given initial findings.
- Using a new neural network that is better suited to the problem at hand, it is possible the previous results can be improved

## Limitations

- Although this research was sponsored through a 10-week REU, more time was needed to fully develop the CNN-LSTM. Initial models could be verified, and previous results could be replicated, but more time is needed to run more tests and train the new network. Research on this project will continue into the next semester with the hope that progress can be made

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