DEEP LEARNING ATMOSPHERIC PREDICTION ALGORITHM FOR ENHANCED MARS EDL GUIDANCE. D. Amato[1], S. Hume[1], E. Roelke[1], B. Grace[1] and J. McMahon[1]. [1]3775 Discovery Drive, Aerospace Engineering Sciences, University of Colorado, 80303 Boulder, Colorado. Email: davide.amato@colorado.edu

Background: Epistemic uncertainty in atmospheric density and winds is a major cause of sub-optimal performance in the Entry, Descent, and Landing guidance of Mars vehicles. Current guidance algorithms rely on relatively simple on-board estimation methods adjusting a nominal exponential density profile through the estimation of scale factors and scale heights [1], Kalman filters [2, 3], or ensemble correlators [4, 5]. These methods generally do not achieve high prediction accuracy due to their simplifying assumptions (for instance, neglecting time and position dependence of atmospheric density). In addition, no approaches currently exist for the prediction of winds, which may considerably affect landing errors of high A/m vehicles.

Objective: We improve the robustness of current Mars EDL guidance algorithms to off-nominal dynamic environments by proposing a reliable on-board atmospheric estimation algorithm. The algorithm estimates density and wind profiles from the current altitude down to the surface at each guidance call, and provides associated prediction uncertainties.

Method: We choose a deep learning regression algorithm, the Long Short-Term Memory Network (LSTM), a particular type of Recurrent Neural Network that handles sequential time series of features efficiently [6]. The LSTM is trained on inertial measurements, such as the state and aerodynamic force histories. The training dataset is generated by running an extensive set of Monte Carlo simulations in which controlled EDL trajectories are generated by using the Fully Numerical Predictor-corrector Entry Guidance (FNPEG) algorithm during atmospheric entry. Each trajectory corresponds to a particular atmospheric density profile that is generated through the Mars Global Reference Atmospheric Model (GRAM) 2010. Particular attention is devoted to the processing of the network features (inputs) and targets (outputs) necessary to improve the performance of the network. In addition, we investigate the effect of introducing air data measurements as features and we quantify the uncertainty associated with network predictions through Gaussian processes [7].

Results: We train a sequence-to-one LSTM to predict the atmospheric density profile from 0 km to 150 km. The training and validation datasets consist of 4500 and 500 trajectories, respectively, each of which has a different GRAM-generated density profile. Figure 1 shows that the network is able to predict the density with a 6% RMS error on average. Further analysis shows that the prediction performance improves for altitudes of particular interest for guidance (less than 80 km). The accurate estimate of density is fed to the numerical predictor-corrector entry guidance, which results in greater landing accuracy. The proposed algorithm also shows significant promise for the prediction of horizontal winds.

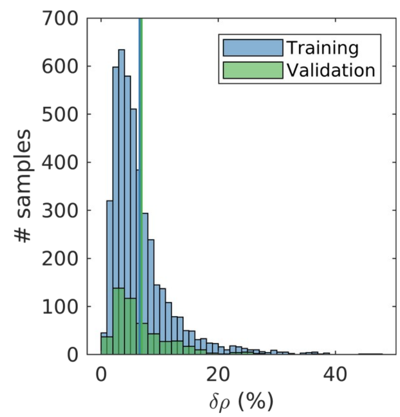

Figure 1: *Histogram of RMS relative density error along each trajectory sample. Blue and green histograms are for the training and validation sets, respectively. The mean RMS relative density error is 6%.*

Conclusions: We devised a deep learning algorithm improving the robustness of on-board Mars EDL guidance through the prediction of atmospheric density and winds from inertial and air data measurements. Improved knowledge of atmospheric characteristics is of considerable import to enhance the autonomy of Mars entry vehicles.

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