SPACE DEBRIS SYMPOSIUM (A6)
Modelling and Orbit Determination (9)

Author: Dr. Joseph Gangestad
The Aerospace Corporation, United States

QUANTIFYING REENTRY UNCERTAINTY: STATISTICS, DRIVERS, AND BEST PRACTICES

Abstract

Several high-profile reentries—including UARS, ROSAT, Phobos-Grunt, and Cosmos 2261—sparked renewed interest for the space-debris community to provide reliable reentry predictions. However, the prediction problem must address two questions: 1) where and when will a reentry occur, and 2) how well do we know that it will reenter there and then? Much effort has been directed at answering the first question but less at the second, which focuses on estimating the uncertainty of a prediction.

This paper reports on a quantitative investigation into reentry-prediction uncertainty for uncontrolled debris from low Earth orbit. A combination of Monte Carlo and design-of-experiments methodologies was used to investigate how input variability (such as model settings and state uncertainty) propagate to output metrics (such as the mean or median reentry time) and how the inputs rank in their effect on those metrics. Reentry-time distributions generated in the Monte Carlo process exhibit non-Gaussian shapes, suggesting that uncertainty is best captured by quoting reentry time in percentiles, as opposed to the more traditional plus-minus notation. The main drivers on reentry uncertainty were identified—including ballistic coefficient uncertainty and atmospheric activity—as were parameters that have a less significant effect, such as state uncertainty. Pinpointing the drivers on reentry uncertainty provides stakeholders with insight into how investments in modeling translate into improved prediction precision.

In the second part of the analysis, uncertainty estimates were generated for real-world reentries, using archived data to tune the input uncertainties (e.g., past performance of solar-activity predictions). These settings were validated against a database of more than 100 historical reentries. The results have been compiled into a set of candidate "best practices" for generating uncertain reentry predictions. By taking a Monte Carlo approach, which requires variation only on inputs, an end user is free to use whatever propagation tool is preferred for each individual run, and the uncertainty of the prediction emerges from the ensemble of runs. In contrast to some earlier analyses, these best practices have been designed for end users who may have no access beyond the front end of a reentry-prediction tool; for example, the F10.7 level would be varied instead of atmospheric density, which is often inaccessible except through source code. These best practices provide a wide range of users the opportunity to deliver reentry predictions—with uncertainty—while leveraging the resources already available, instead of requiring the development of entirely new tools.