Probabilistic Sensitivity Analysis for Launch Vehicles with Varying Payloads and Adapters for Structural Dynamics and Loads

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This paper examines Probabilistic Sensitivity Analysis (PSA) methods and tools in an effort to understand their utility in vehicle loads and dynamic analysis. Specifically, this study addresses how these methods may be used to establish limits on payload mass and cg location and requirements on adaptor stiffnesses while maintaining vehicle loads and frequencies within established bounds. To this end, PSA methods and tools are applied to a realistic, but manageable, integrated launch vehicle analysis where payload and payload adaptor parameters are modeled as random variables. This analysis is used to study both Regional Response PSA (RRPSA) and Global Response PSA (GRPSA) methods, with a primary focus on sampling based techniques. For contrast, some MPP based approaches are also examined.

Nomenclature

$S_{\mu i}$	=	Probability Sensitivity of the response with respect to the random variable *i* distribution mean parameter normalized to the standard deviation over the probability of failure
$S_{\sigma i}$,	=	Probability Sensitivity of the response with respect to the random variable *i* distribution standard deviation parameter normalized to the standard deviation over the probability of failure

I. Introduction

NASA Marshall Space Flight Center desires to develop Spacecraft and launch vehicles systems that maximize payload to orbit and minimize weight and costs, while achieving schedule milestones and maintaining high standards for safety. To achieve this goal, probabilistic sensitivities may be used to help identify the significant input parameters and significant uncertainty drivers on the structural dynamic and loads response of a launch vehicle system. Probabilistic sensitivities may be used in design, analysis, manufacturing and testing to help identify the important parameters that should be focused on, the tolerances and requirements that are important, and testing that should be performed to reduce the significant uncertainties driving loads and dynamic responses.

The purpose of this paper is to demonstrate Probabilistic Sensitivity Analysis (PSA) methods and tools on a launch vehicle with varying payloads and adapters. A realistic, but manageable, integrated launch vehicle analysis with varying payload and adapter subjected to liftoff type loads is used to demonstrate PSA. While the current analysis is made manageable by reducing its complexity, it is set up with the intent of expanding to more realistic (i.e. complex) models, random variable sets and loads analysis simulations in the future so that this method can be used

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to understand the general sensitivity of the vehicle response to structural parameters. Several PSA methods are investigated, including methods currently available in NESSUS, a Probability Analysis software tool with a GUI interface. Both regional response PSA (RRPSA) and global response PSA (GRPSA) methods will be discussed.

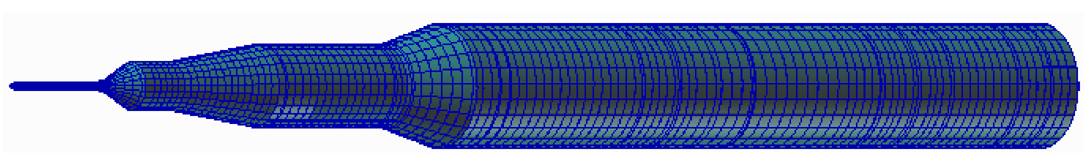
The primary PSA methods discussed herein are sampling based analysis, such as Monte Carlo, since current loads processes and heritage data are based on Monte Carlo analyses. Since numerous load responses are generated for each run in loads analysis, advanced probabilistic techniques are less attractive since these advanced methods generally process only one response variable at a time. There is much interest in defining Probabilistic Sensitivities near the enclosure limit (i.e. 99.865/50 limit or 3-sigma limit) for loads analysis.

NASTRAN is used to predict normal modes and load responses. A Matlab mode tracking tool is used to track normal modes.

This paper is organized as follows. The PSA Model is presented in Section II. PSA Methods are discussed in Section III. Results are given in Section IV. Conclusions are given in Section V, including a recommendation of the PSA method to use for Launch Vehicle Loads and Dynamic Analysis.

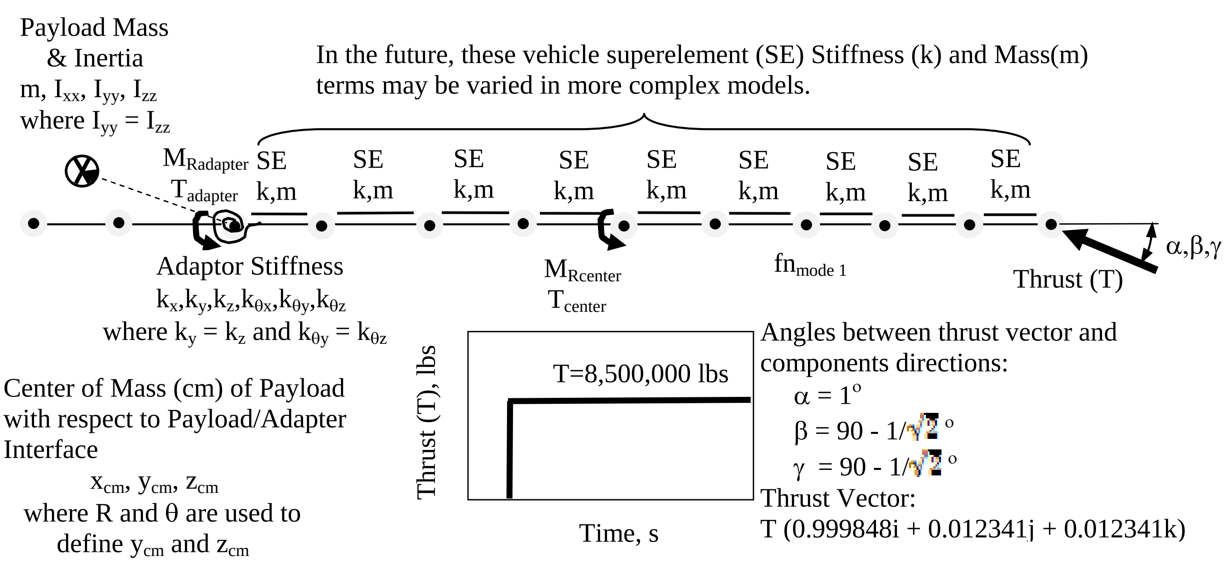
II. The PSA Model

A realistic, but manageable, integrated launch vehicle system with varying payload and adapter subjected to liftoff type loads is used to demonstrate PSA with the intent of expanding to more complex models, random variable sets and loads analysis simulations in the future. A sketch of the model is shown in Fig. 1. Figure 1a depicts a 3D rendering of a 2D generic Apollo launch vehicle. Figure 1b shows a simplified schematic of the model. Payload and Adapter terms are varied. Payload and Adapter random variables are shown in Table 1. The integrated vehicle



Origin (0., 0., 0.) 100" forward of LAS tip (X – Aft, Y-Starboard, Z-up)

1a – 3D Rendering of 2D NASTRAN Finite Element Model



1b – Schematic of Varying Payload and Adapter on Integrated Launch Vehicle

Figure 1. PSA Integrated Launch Vehicle System with Varying Payload and Payload Adaptor

model normal modes will be evaluated to a 100 Hz cutoff. Load responses will be evaluated for a liftoff-like thrust step load input applied to the vehicle base at an incidence angle. The step load excites all the modes in the model. The responses investigated for PSA are the first structural dynamic mode, the maximum resultant My-Mz moment and maximum torque at the vehicle center and the maximum resultant My-Mz moment and maximum torque at the adapter as shown in Table 2.

Table 1. Input Random Variables for Varying Payload and Adapter

Random Variable	Units	Mean	Std Dev	COV	PDF	Description
Mass	lb-s^2/in	571.012	57.012	0.10	Normal	Payload Mass, m
XCG	in	-432	64.8	0.15	Normal	Payload CM x_{cm}
I11	lb-in-s^2	4.5E6	1.125E6	0.25	Normal	Payload Inertia I_{xx}
I22	lb-in-s^2	3.75E7	0.9375E7	0.25	Normal	Payload Inertia I_{yy}; $I_{yy} = I_{zz}$
KX	lb/in	1.0E7	0.3E7	0.30	Normal	Adapter Stiffness k_x
KY	lb/in	1.0E7	0.3E7	0.30	Normal	Adapter Stiffness k_y; $k_y = k_z$
KXX	in-lb/rad	0.35E+12	0.105E+12	0.30	Normal	Adapter Stiffness $k_{\theta x}$
KYY	in-lb/rad	0.35E+12	0.105E+12	0.30	Normal	Adapter Stiffness $k_{\theta y}$; $k_{\theta y} = k_{\theta z}$
RCG	in	24.00000	7.2	0.30	Normal	Payload CM, Radius R
THECG	degrees	0.0	109.5	-	Normal	Payload CM, Angle θ

Table 2. Responses for Launch Vehicle

Response	Units	Description
FREQ1	Hz	First Structural Mode Frequency of vehicle – Unconstrained
MRCTR	lb-in/rad	Resultant Moment = $\sqrt{My^2 + Mz^2}$ at center of vehicle
TCTR	lb-in/rad	Torque = Mx at center of vehicle
MRADPT	lb-in/rad	Resultant Moment = $\sqrt{My^2 + Mz^2}$ at Adapter
TADPT	lb-in/rad	Torque = Mx at Adapter

III. PSA Methods

PSA methods may be categorized as regional response PSA (RRPSA) and global response PSA (GRPSA) methods. RRPSA is defined as a PSA for the case that the interest is among a partial range of a response distribution, either at the tail of the distribution or within a localized range of the distribution. GRPSA is defined as a PSA for the case that the interest is among the entire distribution of a response.

Variance decomposition is a decomposition of the variance of a response to its variation sources. It highlights the difference between the main effect with response to only one random variable vs. the total effect that includes the individual effect of the random variable as well as its interaction with other random variables. Variable decomposition is a GRPSA.

The following Probability Sensitivity Analyses are performed herein:

1) Using NESSUS, perform RRPSA on Monte Carlo sample-based analysis, averaging the Probabilistic Sensitivities over all the failure cases.

2) Using NESSUS, perform RRPSA on an advanced reliability Most-Probable-Point (MPP)-based method, such as AMV+, utilizing importance levels derived from the direction cosines inherent in the MPP-based process.

3) Using NESSUS, perform GRPSA using Variance Decomposition. Evaluate first-order factors and total factors, where total factors incorporate both the first-order factors and the partial variance interaction terms. Perform Variance Decomposition using Structured Monte Carlo and for Fourier Amplitude Sensitivity Test (FAST).

4) Perform RRPSA on Monte Carlo sampled-based analysis using several "locally accurate" surrogate model formulations, such as moving least squares and Kriging.

IV. Results

The results of PSA are given herein. Results, similar to example cases shown in Figures 2-5, will be given.

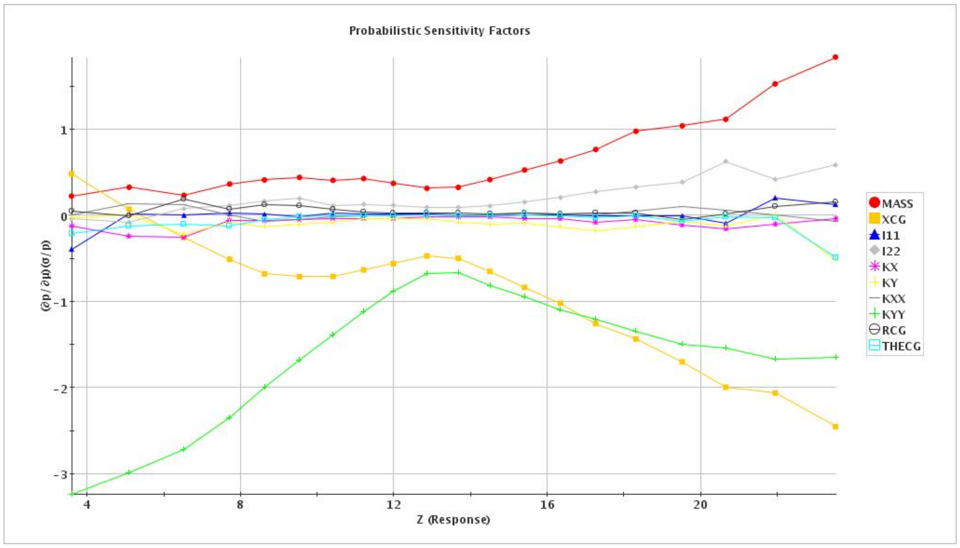


Figure 2. First Structural Mode PSA with respect to Mean, Normalized to (σ/P_f) for Several P_f Conditions for 10,000 Monte Carlo Runs – An Example.

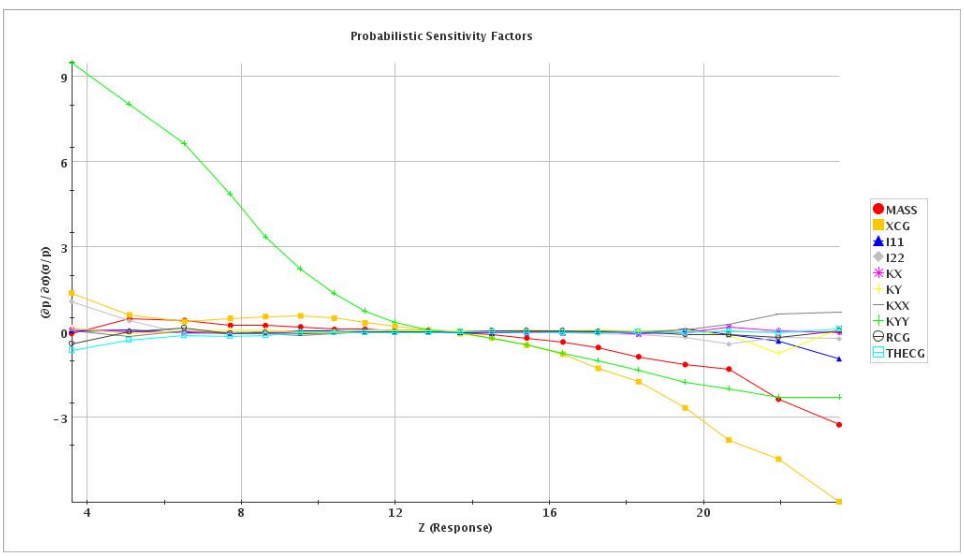


Figure 3. First Structural Mode PSA with respect to Standard Deviation, Normalized to (σ/P_f) for Several P_f Conditions for 10,000 Monte Carlo Runs – An Example.

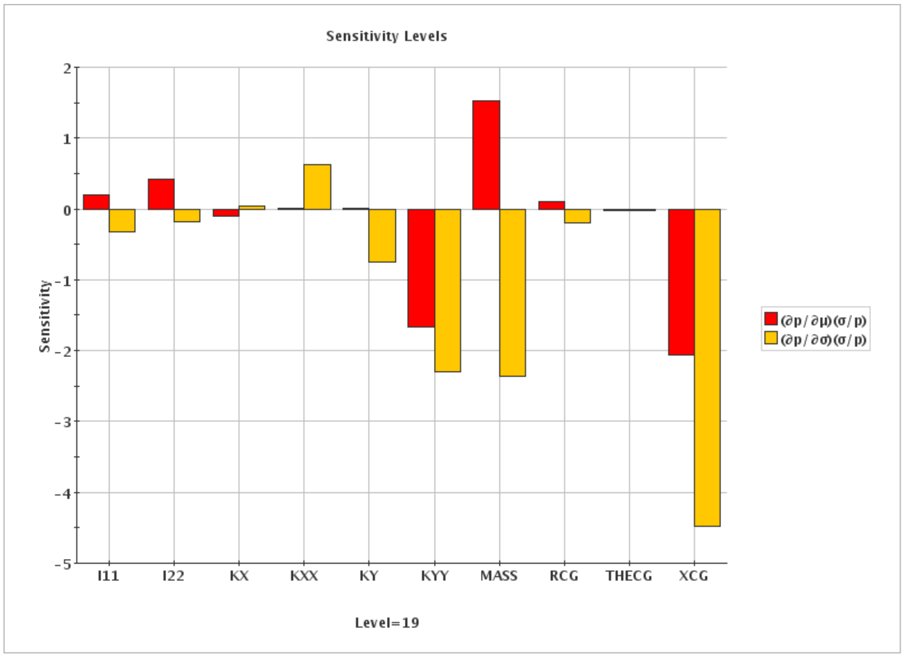


Figure 4. First Structural Mode PSA with respect to Mean and with respect to Standard Deviation, Normalized to (s/P_f) for Level=19 P_f Condition for 10,000 Monte Carlo Runs – An Example

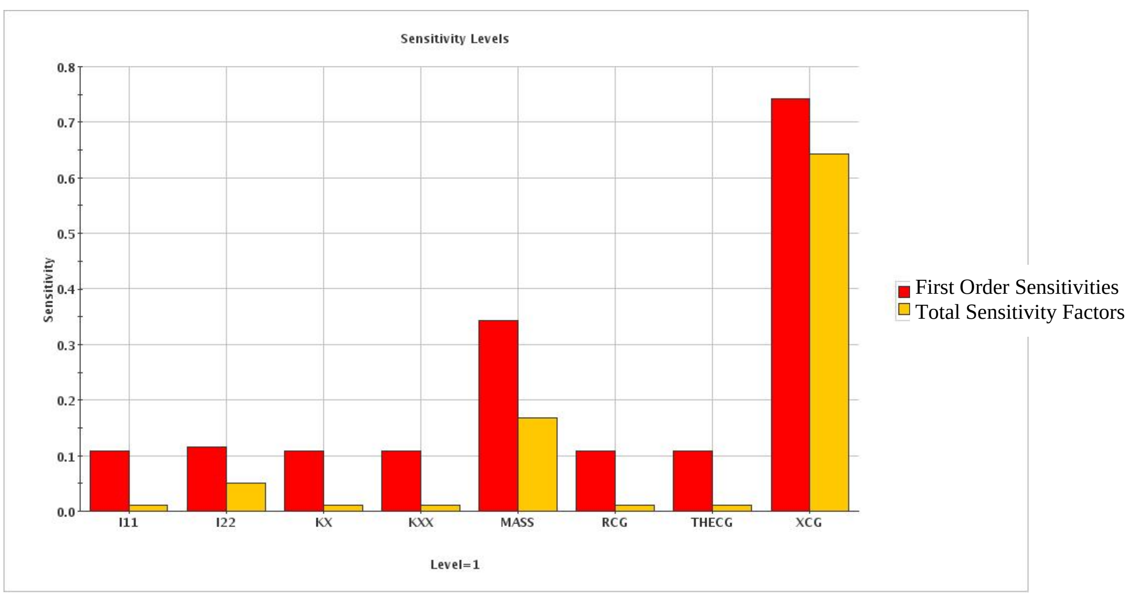


Figure 5. First Structural Mode Variance Decomposition with First Order Sensitivities and Total Sensitivity Factors for Level=1 P_f Condition for 10,000 Monte Carlo Runs – An Example

V. Conclusions

To be completed after results have been analyzed.

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