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April 18, 2014

Paula Wilson  
IDEQ State Office  
Attorney General's Office  
1410 N. Hilton  
Boise, ID 83706

**RE: Docket No. 58-0102-1201 - Negotiated Rulemaking  
Idaho's Fish Consumption Rate  
Probabilistic Risk Assessment**

Dear Ms. Wilson:

Clearwater Paper Corporation appreciates the opportunity to comment on Docket 58-0102-1201 as noted above. We value the work the Idaho Department of Environmental Quality (IDEQ) has done on this very important matter. We have attended previous meetings and look forward to participating further as this rulemaking proceeds.

During the April 2, 2014, rulemaking meeting, one agenda item was a presentation by Dr. Paul Anderson outlining the application of a software tool that uses probabilistic risk assessment (PRA) in setting human health water quality criteria (HHWQC). We are offering the following comments in support of IDEQ using a PRA approach to revise Idaho's HHWQC.

***Monte Carlo (i.e., PRA) methods are well accepted tools in technical decision making*** – The use of simulation approaches to solving mathematical and physical problems dates back to the late 1940's when it was developed at Los Alamos National Laboratory to assess nuclear safety. Simply stated, simulation approaches (also named Monte Carlo methods) make use of tracking the outcome of discrete events by simulating their probability of occurrence. By keeping track of various outcomes by using known probability distributions for pertinent inputs, the result of an analysis yields statistically based outcomes – not just one number but rather a distribution of outcomes.

NASA was an early user of Monte Carlo methods in predicting the failure rates of space mission subsystems and components. By simulating the reliability of rocket subsystems, the reliability and performance aspects of an entire mission can be assessed statistically (see Attachment A for an example). IBM has also been a long-time leader in the use of Monte Carlo methods (Attachment B).

Probabilistic methods have also been used for several decades when evaluating the potential human health risks associated with chemicals in the environment. The United States Environmental Protection Agency (EPA) started publishing guidance on using PRA more than a decade ago<sup>1</sup> as did the State of Oregon<sup>2</sup>. So while application of PRA to derive HHWQC is relatively new, using a probabilistic approach (i.e., a Monte Carlo approach) to establish HHWQC criteria makes use of the historically proven and generally acceptable approach of simulation science. Other states, such as Florida, have used this method in the context of setting fish consumption/water quality rules<sup>3</sup>.

***PRA represents the best science in assessing risk*** – Humans are physically different from one another and have very distinct water and food consumption patterns. Some healthy adults weigh 90 pounds while some weigh 300 pounds. Some adults drink three to four liters of water a day while some drink little or no water. Some adults don't eat fish while some eat a lot. By evaluating these types of differences among humans, the risk of drinking surface water and eating fish from Idaho rivers and lakes can utilize the best scientific approach to make informed risk policy decisions.

Looking at the risk from eating fish, high consumers will always have more risk from this pathway than other consumers who do not eat fish. Similarly, those who eat more beef will always have more risk from that pathway than others who eat less beef. In order to make an informed and reasonable decision about a population of fish consumers, the best choice is using a methodology to predict risk across the entire population. This result is inherent when using PRA to develop HHWQC in Idaho – a PRA approach is clearly the most comprehensive and accurate science-based tool to assess risk.

***Using PRA to set HHWQC would represent all Idaho fish consumers*** – When IDEQ completes their fish survey work, their results can be statistically combined and a distribution of fish consumption can be developed for the entire state. This distribution can be easily represented mathematically and used in a PRA analysis to evaluate the risks to all Idaho fish consumers – those who eat very little fish as well as those that eat many fish meals a week. Implicit in the use of PRA for developing HHWQC is the representation and modeling of all fish consumers in

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<sup>1</sup> USEPA. Guiding Principles for Monte Carlo Analysis. U.S. Environmental Protection Agency, Risk Assessment Forum, Washington, DC, EPA/630/R-97/001, 1997. USEPA. 2001. Risk Assessment Guidance for Superfund: Volume III - Part A, Process for Conducting Probabilistic Risk Assessment. EPA 540-R-02-002. Office of Solid Waste and Emergency Response, U.S. Environmental Protection Agency, Washington, DC. December.

<sup>2</sup> Oregon Department of Environmental Quality (ODEQ). 1998. Guidance for Use of Probabilistic Analysis in Human Health Risk Assessments. Waste Management and Cleanup Division, Oregon Department of Environmental Quality. Interim Final. January, updated November.

<sup>3</sup> Florida Department of Environmental Protection (FDEP) 2014. DRAFT Technical Support Document: Derivation of Human Health-Based Criteria and Risk Impact Statement. February 2014. Florida Department of Environmental Protection, Division of Environmental Assessment and Restoration.

Idaho. Please note Attachment C which is a visual representation of how fish consumers would be included when a state uses PRA in setting their HHWQC. This result is similar to work done in Florida using PRA. Note that the range of fish consumption that went into this PRA assessment was from essentially zero up to several hundred grams per day – all modeled in proportion to the expected number citizens from a state population eating that amount of fish. This same type of approach result would be available if Idaho uses PRA to set its HHWQC. An output of the PRA method will be a statistical basis for the distribution of fish being consumed in Idaho and would be developed from the current survey work by IDEQ and EPA. Basing HHWQC on a distribution of consumers would facilitate a better scientific understanding of risk and an informed establishment of rational and workable public policy choices.

***Using PRA facilitates transparency in HHWQC rulemaking*** – As noted above, using PRA puts a spotlight on all technical and public policy choices. Unlike a deterministic approach where “one size fits all” and the conservatism of several input parameters is compounded drastically, PRA allows a specific assessment of all the technical inputs and risk outputs and generates risk profiles for the entire population.

The PRA software tool (provided to IDEQ separately) was designed and developed to make transparency a focus. Each technical input and policy input is easily verified and a sensitivity analysis can be part of any HHWQC rule making.

Rather than make multiple highly conservative assumptions (e.g., daily drinking water intake, fish consumption rate) which leads to an unknown, but likely far greater level of protection than assumed by the HHWQC, PRA implicitly determines a range of outcomes that facilitate making reasonable public policy choices for risk to an entire population.

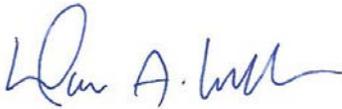
***PRA determines the risks for all Idahoans*** – As noted several times above, the use of PRA in setting Idaho HHWQC inherently calculates the risk to all Idahoans. Note Attachment D that is a sample output consistent with how a PRA tool would assess risk. If Idaho uses a PRA approach to set HHWQC, the risk results for all carcinogens and non-carcinogens will be available in results similar to Attachment D. Florida, for carcinogens, elected to protect the population “mean” at an excess lifetime cancer risk of  $1 \times 10^{-6}$  (one in one million) and concurrently protect the 90<sup>th</sup> percentile of the population at  $1 \times 10^{-5}$  (one in one hundred thousand) and additionally confirm highly exposed sub-populations were at no greater risk than  $1 \times 10^{-4}$  (one in ten thousand). This type of policy choice is easy to verify when using PRA and is easily estimated. A similar approach for non-carcinogens is also facilitated by using PRA.

The risk to all Idahoans is inherent and transparent if IDEQ chooses to use a PRA approach to set HHWQC.

In summary, Clearwater Paper urges IDEQ to use PRA when updating Idaho HHWQC with a new fish consumption rate. PRA is the best available science, assesses the risks of all Idahoans, is easily conducted using the software tool provided separately to IDEQ or using other available software, avoids an excessive compounding of conservatism and makes transparent the basis of the science and public policy choices used to establish HHWQC.

Please contact me at 509-344-5956 or [marv.lewallen@clearwaterpaper.com](mailto:marv.lewallen@clearwaterpaper.com) with questions.

Sincerely yours,

A handwritten signature in blue ink, appearing to read "Marv A. Lewallen".

Marv Lewallen  
Vice President – Environmental, Energy & Sustainability

C: Don Essig

W/ Attachment A  
Attachment B  
Attachment C  
Attachment D

# Learning About Ares I from Monte Carlo Simulation

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This paper addresses Monte Carlo simulation analyses that are being conducted to understand the behavior of the Ares I launch vehicle, and to assist with its design. After describing the simulation and modeling of Ares I, the paper addresses the process used to determine what simulations are necessary, and the parameters that are varied in order to understand how the Ares I vehicle will behave in flight. Outputs of these simulations furnish a significant group of design customers with data needed for the development of Ares I and of the Orion spacecraft that will ride atop Ares I. After listing the customers, examples of many of the outputs are described. Products discussed in this paper include those that support structural loads analysis, aerothermal analysis, flight control design, failure/abort analysis, determination of flight performance reserve, examination of orbit insertion accuracy, determination of the Upper Stage impact footprint, analysis of stage separation, analysis of launch probability, analysis of first stage recovery, thrust vector control and reaction control system design, liftoff drift analysis, communications analysis, umbilical release, acoustics, and design of jettison systems.

## Nomenclature

Alpha	= angle of attack
BDM	= Boost Deceleration Motor
Beta	= sideslip
CM	= Crew Module (part of Orion)
DOF	= degrees of freedom
FPR	= Flight Performance Reserve (includes FPR at nominal mixture ratio and fuel bias)
FS	= First Stage
GRAM	= Global Reference Atmosphere Model
H/S	= heavy/slow
ISS	= International Space Station
J-2X	= Ares I Upper Stage engine
LAS	= Launch Abort System
L/F	= light/fast
LH2	= liquid hydrogen
LOX or LO2	= liquid oxygen
MAVERIC	= Marshall Aerospace Vehicle Representation in C 6DOF simulation
MBLI	= moment-based load indicator
MECO	= main engine cutoff
PEG	= Powered Explicit Guidance
PID	= proportional-integral-derivative
PMBT	= Propellant Mean Bulk Temperature
POST	= Program to Optimize Simulated Trajectories
Q or Qbar	= dynamic pressure
Qalpha/Qbeta	= dynamic pressure times angle of attack and dynamic pressure times sideslip
Q*alphaTotal	= dynamic pressure times total angle of attack
RCS	= Reaction Control System
RSS	= root sum square

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<sup>1</sup> Aerospace Engineer, Flight Mechanics & Analysis Division/EV40, AIAA Member.

<sup>2</sup> Aerospace Engineer, Control Systems Design & Analysis Branch/EV41, non-AIAA Member.

TVC = Thrust Vector Control  
US = Upper Stage

## I. Introduction

The Ares I launch vehicle is currently planned for first test flight in 2013, with crewed flights to the International Space Station (ISS) one or two years later. The crew will fly onboard the Orion spacecraft that Ares I takes to orbit. The Ares I launch vehicle is currently at the Preliminary Design Review stage. The current schedule is subject to delay depending on the funding profile available (and has already been delayed due to budget considerations). Ares I is being designed so that, some time later, it will also be able to take Orion into a low-inclination orbit for rendezvous with the Ares V-delivered Earth Departure Stage and Lunar Surface Access Module (which one would be launched first has not been determined). The two missions (ISS and lunar) have differing payload requirements for Ares I, which leads to slightly different flight profiles and trajectory attributes. Ares I uses a Shuttle-derived 5-segment solid rocket booster, with a new Upper Stage that has an Apollo-derived J-2X engine. These two stages are used to insert the Orion into a -11x100 nm orbit at a mean altitude of 70 nm. Orion uses its on-board propulsion to circularize at 100 nm and to proceed on its mission from there. Since the perigee is negative, the Ares Upper Stage naturally burns up upon re-entry with the debris falling in the Indian Ocean.

A large NASA effort is ongoing for design of the Ares I. Contractors ATK (First Stage), Boeing (Upper Stage), Pratt & Whitney/Rocketdyne (Upper Stage Engine), and Boeing (Instrument Ring) are supporting the design effort along with NASA support contractors. During vehicle design, a high-fidelity 6-degree-of-freedom simulation is where the vehicle is functionally integrated in order to determine whether the design will be able to achieve the goals envisioned. This simulation resides within the guidance, navigation, and control discipline areas, because the simulation is used to develop the guidance and control approaches and to demonstrate that they can fly the integrated vehicle successfully in the presence of expected navigation uncertainties and vehicle and environmental variations. In order to demonstrate that the vehicle will be successful, the simulation must be exercised in ways that demonstrate how much the flight can vary. For example, what is the trajectory that will lead to the worst structural loads that the vehicle will have to withstand? What trajectory will lead to the worst aerothermal environments? And so on.

One way to develop “design” trajectories (or worst-case trajectories for design) is to vary individual parameters between their extremes, and to stack them with each other in single simulations, to see how the vehicle flies as a result. A problem with this approach is that it is quite difficult to determine how statistically bad the resulting simulation is. Another approach, which is more available currently than in the past due to computer speed, is to run Monte Carlo simulations. In this approach, everything that is known to vary is randomly varied across its range and a large number of simulations are run. After the simulations are finished, the results show statistically what the various parameters do. A user may choose the 99% value for design, or the 95% value, or the 99.73% value with 90% confidence (also called 10% consumer risk), as desired depending on how much design surety is required.

The approach used in this paper is to run the MAVERIC (Marshall Aerospace Vehicle Representation in C) simulation in Monte Carlo mode to answer the necessary design questions. Besides developing the simulation capability for the launch vehicle, and determining the vehicle and environmental uncertainties appropriate for the simulations, it is necessary to decide what vehicle models to use for the baseline that is being varied. At an early design stage, vehicle models are not what they will be when they are built and tested, so it is critical that heavier and slower models be simulated (for determining parameters such as payload performance and tower clearance) as well as lighter and faster models (for maximum aeroheating and structural loads, among other needs). Another reason to model more sluggish and more sporty vehicle models is that manufactured components will differ in ways that can be measured prior to launch. Engines vary and will be put on test stands prior to vehicle assembly, masses vary and components will be weighed, and solid propellant grain varies and will be tested.

When it comes to failures, with crewed systems, abort capability is necessary. Understanding how the vehicle behaves dynamically in situations where a failure causes dynamic deviation is another necessary analysis. Knowing what will happen depends on understanding how the trajectory and attitude can vary, and again Monte Carlo simulations offer a reliable approach. These simulations help to evaluate various abort triggers for use as abort cues, and also help to determine how much time is available for escape.

This paper discusses first the simulation and modeling of Ares I used in MAVERIC, without describing each model in detail. Next the paper describes the uncertainty modeling and the determination of what simulations are needed (along with the corresponding vehicle models). The customers for the Monte Carlo results are listed, followed by an overview of many of the products and their uses.

## II. Simulation and Modeling of Ares I

The MAVERIC simulation models the Ares I launch vehicle in high fidelity, and the fidelity level will increase as the project progresses. The guidance and control algorithms are modeled as they are intended to be incorporated into the flight software. The control approach is described elsewhere<sup>1,2,3</sup>. In brief, the guidance uses an open-loop phase (pitch, yaw, and roll versus altitude) followed by a closed-loop design. An optimization procedure<sup>4</sup> and linear tangent steering were evaluated for the closed-loop design. The current baseline is the Shuttle version of linear tangent steering, Powered Explicit Guidance<sup>5</sup> (PEG). Comparison between the two closed-loop approaches did not show any advantages for the more complicated optimization approach. Some reasoning for choosing PEG as opposed to a more advanced guidance appears in Ref. 6. Another reason that advanced methods were not chosen for guidance or for flight control is that the Ares I launch vehicle is intended to use technology advances only where necessary. Guidance functions adapt to adjust the trajectory plan for the changing azimuth through the launch window. A steering function acts between the guidance and control to make sure that the guidance commands will not result in large attitude or attitude rate errors to the control system and that the rate and acceleration commands to control will be limited. This is critical in order to keep from causing actuator hard-over commands from the flight control that could lead to loss of stability. By staying within the control limits, overshoot of the desired attitudes is also minimized. The flight control design for pitch and yaw is a classical proportional-integral-derivative (PID) controller that uses rate gyros on multiple vehicle locations along with mathematical filters in order to control the vehicle in the presence of its vibrational modes. The control design for the reaction control system (RCS) is a phase plane design.

Navigation is currently modeled with sensor models that have initialization error and accelerometer and gyro errors that cause cumulative state vector error as the vehicle ascends into orbit. The error parameters included in the current model will be listed later in the paper. More advanced navigation models are being prepared for upcoming versions of MAVERIC. Ares I navigation is discussed in more detail in Ref. 7. MAVERIC contains models of the propellant slosh and of the flex (vibrational) behavior that have been checked against independent models. The thrust vector control dynamics models are based on Shuttle experience applied to Ares I. A dynamic thrust vector uncertainty model is also included. Propulsion modeling is as furnished by the Ares I propulsion experts. Since the First Stage uses Shuttle-heritage capabilities, the modeling of the First Stage propulsion is very well known. Besides modeling the overall thrusts and flow rates during the two stages, MAVERIC models in detail the uncertainties in shutdown for the First Stage and in startup and shutdown for the Upper Stage. This is because the modeling of these is very important to analyzing the success of stage separation and of orbit insertion accuracy and attitude control after insertion.

For stage separation, MAVERIC models the various components (booster deceleration motors, propellant settling motors, booster tumbling motors, and the dimensions of the vehicle components that must separate) along with uncertainties in the performance of the different components, the direction their thrust is pointing, various lateral and axial forces and torques that interact with the vehicle at this time, and failure cases associated with each component. MAVERIC outputs clearances during the simulation so that the success of the stage separation event can be examined. MAVERIC models the J-2X plume effects on the First Stage after separation, to support analysis of First Stage recovery. Stage separation is also currently being modeled in an independent simulation called CLVTOPS.

MAVERIC models time latencies and RCS behavior. Integration step size is currently 0.005 seconds, in order to correctly model the vibrational modes effects on the GN&C. MAVERIC does not model the sub-system behavior of the various systems, but rather only models the behavior of systems that lead to effects on the overall vehicle dynamics. For example, the voting logic within the flight computers is not modeled, but the error in output that ultimately influences the vehicle is modeled. MAVERIC does not model aeroelastic effects. MAVERIC models the vehicle as a rigid body in terms of generating forces and torques (although the effects of vehicle flex on the flight control are modeled). Aeroelastic effects are evaluated by the structural analysis discipline. MAVERIC models light to moderate wind gusts using the Global Reference Atmosphere Model (GRAM)<sup>8</sup> 2007. Extreme wind gusts are taken into account by the structural analysis discipline.

## III. Uncertainties

Uncertainties can be divided into two categories: those that are unknown now but will be known before flight day, and those that are unknown when the vehicle launches. Items in the first category include a certain portion of the First Stage burn rate uncertainty (the grain used in the flight vehicle is tested before flight), some mass

uncertainty (including manufacturing uncertainty since components will be weighed, and including some current levels of design mass uncertainty), a portion of the axial force coefficient (assuming that wind tunnel tests and higher fidelity vehicle models improve on knowledge of this parameter), and some of the uncertainty in J-2X performance (the engine will be hot-fired prior to flight).

Parameters in the flight day unknown category (the second category) include remaining unknowns for the items in the first category, navigation uncertainties, dynamic thrust direction uncertainties, and many others. Although all the aerodynamic parameters have larger uncertainty now than they will on flight day, only axial force coefficient affects the overall payload performance and items such as maximum dynamic pressure directly. The rest of the aerodynamic parameters are primarily of interest to control system design as far as dynamic simulation is concerned. The control system must be able to control the vehicle with the full range of aerodynamic parameter uncertainty, whether the vehicle model is heavy/slow or light/fast. For this reason, the aerodynamic parameters other than axial coefficient are all considered to be flight day unknowns.

Since a mean monthly wind profile is being used to design Ares I trajectories and since the payload will not be changed each day after the wind is measured several hours before launch, the wind variations within a month are considered to be “flight day unknowns”. Similarly, the First Stage Propellant Mean Bulk Temperature (PMBT) variation during a month is considered as a flight day unknown. Also, since the plan is to fully load the propellant tanks and not offload based on some knowledge of J-2X mixture ratio uncertainty derived during the engine test, all of the mixture ratio uncertainty is considered as flight day uncertainty and goes into calculation of the flight performance reserve (FPR), that amount of extra propellant needed to ensure the orbital delivery is made even with all the uncertainties included. Table 1 lists the uncertainties that are known before launch and that can be used in the trajectory design. Table 2 lists the parameters that are modeled with flight day uncertainty. Some parameters appear in both tables because, of the total uncertainty, some will be determined before flight. The list of uncertainties covered continues to increase as the design matures.

**Table 1. Deterministic Parameters (Known Prior to Flight Day).** *Includes parameters that still have some uncertainty on flight day but are known better by then than they are now. Also includes parameters that vary from vehicle to vehicle but are known better once the vehicle is assembled.*

First Stage burn rate	J-2X thrust	J-2X specific impulse
Axial forebody coefficient	First Stage dry mass	Interstage dry mass
Upper Stage dry mass	J-2X mass	Orion mass
Program manager’s reserve		

#### IV. Vehicle Model Choices and Monte Carlo Simulations

In order to decide what combination of vehicle models, missions, months of launch, and any other parameters are needed for obtaining the necessary results, previous Monte Carlo runs were used, run for each month of the year, for both missions, and for other differing conditions. Three target parameters were identified for analysis.

1. Performance. What combination yields the lowest vehicle performance? This case drives the derivation of the FPR, since other cases would result in more fuel left over than this case. The goal is to find the worst combination of heavy and slow (underperforming) that might make up a known vehicle combination. This case also drives the liftoff drift analysis since it is most sluggish in leaving the launch pad. This vehicle is called H/S in the following discussion.
2. Loads. What combination yields the lightest and fastest vehicle that we might need to fly? This case drives the highest maximum dynamic pressure, the highest structural loads, the highest acceleration, the highest heat rates, the fastest liftoff for umbilical release analysis, worst-case aborts within the atmosphere, and probably the worst-case First Stage gimbal angles and rates. This vehicle is called L/F in the following discussion.
3. Upper Stage acceleration. The Orion spacecraft design has panels that encapsulate the Service Module during atmospheric ascent and carry structural loads during this portion of flight. These panels are jettisoned once the high heating part of ascent is finished, and the rest of the Service Module/Spacecraft Adapter has to carry the remaining structural load for Upper Stage flight into orbit. The highest axial acceleration for Ares I is during First Stage flight, but for this particular purpose we need the highest acceleration that occurs during Upper Stage flight. This occurs with a light/fast Upper Stage and a light payload along with a heavy/slow First Stage (which leads to the Upper Stage having to do more of the

work and results in a lower amount of remaining propellant and thus an even lighter Upper Stage). This vehicle model is called “hybrid” in the following discussion.

**Table 2. Flight Day Uncertainty Parameters**

First Stage internally generated roll torque	TVC-induced roll torque	Dynamic thrust vector uncertainty	Flex frequency (first mode) and amplitude
Uncertainty in mode shape	Mode slope at the gimbal point	Slosh mass, location, damping, and frequency	First Stage Propellant Mean Bulk Temperature PMBT (variation within the month)
First Stage burn rate	First Stage loaded propellant	First Stage specific impulse	First Stage tailoff model
First Stage engine location	First Stage engine alignment	J-2X mixture ratio, thrust, and specific impulse	J-2X thrust misalignment and engine location
J-2X shutdown transient thrust profile	J-2X ignition transient thrust profile	J-2X shutdown delay time	J-2X shutdown side load
Effect of engine inlet pressure and temperature on engine parameters	Variation of engine inlet pressure and temperature (oxygen and hydrogen)	Loaded propellant (oxygen and hydrogen)	Total stack aerodynamics (axial, normal, lateral, pitch/yaw/roll moments)
Upper Stage stack aerodynamics (moment and force terms)	Navigation initialization (position, velocity, and attitude)	Accelerometer errors (bias repeatability, scale factor, misalignment, noise, each axis)	Gyro errors (bias repeatability, scale factor, misalignment, random walk, each axis)
Atmospheric density, temperature, pressure	Winds aloft	RCS fuel per tank, thrust, flow rate, plume effects, moment arm, each stage	Boost Deceleration motors BDM (burn rate, PMBT, ignition interval, loaded propellant, thrust vector alignment)
Mass properties: uncertainties in all dry masses, center of mass, inertia	Uncertainty in J-2X plume effect on FS after separation	Propellant settling motors (burn rate, PMBT, loaded propellant, ignition interval, thrust alignment)	Thrust vector control (scale factor, damping ratio, position limit, rate limit, position error at startup)
J-2X TVC: time to gimbal capability	J-2X engine inertia	Boundary of J-2X engine nozzle while in interstage, including misalignment and vibration	Upper Stage TVC misalignment
Time delay to stage separation	First stage nozzle pointing error when in null position	Center of mass/center of percussion uncertainty	Side force from First Stage thrust at staging

Table 3 shows the combinations of models for obtaining the desired results, along with what each run is targeting. Flying to different parts of the rendezvous launch window does not in general affect the flight parameters significantly. Since the lunar mission has a 90-minute design launch window, an extra case must be run in order to understand the effect of the launch window on the Upper Stage impact footprint. The 10-minute ISS launch window does not have a significant effect on the impact footprint. The ISS mission has a lighter payload, so its loads and heating parameters are typically slightly worse than for the lunar mission. In some previous studies, August was the worst month for dynamic pressure, but July was the worst for heating, so both are on the list. For each Monte Carlo set, 2000 random simulations were made.

The approach to designing the three different vehicle models was to take the various parameters that are in the pre-flight-determined category (Table 1) and to determine the partial derivative of the item of interest with respect to each parameter. For example, for First Stage burn rate, the partial of payload with respect to burn rate supplies the necessary information for the H/S model, the partial of maximum dynamic pressure with respect to burn rate supplies the L/F model, and the partial of Upper Stage maximum acceleration with respect to burn rate supplies the hybrid model. It should be noted that worst dynamic pressure does not necessarily imply the other goals of the

light/fast model will be met. For example, the worst-case vehicle model for maximum acceleration may not be the same as that for maximum dynamic pressure. This nuance was not considered for the current vehicle modeling, but will be in the future.

**Table 3. Combinations of Vehicle/Mission Models for Generating Monte Carlo Worst Cases**

Vehicle	Mission	Month	Launch window	What is the need?	Identifier
L/F	ISS	August	Closure	Max Q, max acceleration, FS footprint	TD6-A
L/F	Lunar	February	Closure	Dynamic pressure*total angle of attack, MBLI	TD6-B
H/S	Lunar	February	Closure	Worst performance, FPR, liftoff drift, US footprint	TD6-C
H/S	Lunar	February	Open	Worst performance, FPR, liftoff drift, US Footprint	TD6-D
hybrid	ISS	February	Open	Worst US acceleration	TD6-E
L/F	ISS	February	Closure	Dynamic pressure*total angle of attack, MBLI, compare with lunar, US footprint	TD6-F
L/F	ISS	July	Open	heat rate, compare with L/F August	TD6-G
L/F	Lunar	August	Open	Max Q, max acceleration, comparison between ISS and lunar	TD6-H

Table 4 shows the effects of the various pre-flight-determined quantities on the parameters of interest for the three vehicle models described above. It is easy to see which parameters have a large impact on the vehicle models. It is also easy to see that some of the parameters could be zeroed out without much effect. The J-2X performance parameters affect the maximum dynamic pressure because the entire trajectory is re-optimized to take the model changes into account.

**Table 4. Parameter Effects for Vehicle Model Definitions (Heavy/Slow, Light/Fast, and Hybrid)**

Parameter	Payload effect for 1 sigma positive variation (lb)	Maximum dynamic pressure effect for 1 sigma positive variation (psf)	Upper Stage maximum accel. effect for 1 sigma positive variation (g)
First Stage burn rate	317	15.93	-0.009
J-2X thrust	273	1.75	0.014
J-2X specific impulse	228	-0.06	-0.007
Drag coefficient	-153	-4.89	0.004
First Stage mass	-78	-0.81	0.002
Interstage mass	-3	-0.03	0.000
Upper stage mass	-97	-0.17	-0.000
J-2X mass	-28	-0.05	0.000
Ares margins—ISS/lunar	Assumed allocated to mass for heavy vehicle model	-1.44/-1.37	-0.0008/-0.0005
Program reserve—ISS/lunar	Assumed required to take to orbit for heavy vehicle model	-0.54/-0.75	-0.0012/-0.0018
Orion mass—ISS/lunar	Maximum required mass used	-1.02/-0.51	-0.0023/-0.0004
99.73% RSS effect—ISS/lunar	1,437 (lunar only)	47.0/46.9	0.052/0.052

The vehicle model chosen is one that yields a 99.73% variation in the parameter of interest from the mean value. Since this vehicle model is made up of a number of variations, there is a multi-dimensional choice as to what combination of parameters is chosen that causes the 99.73% variation. Once the 99.73% value is determined (Table 4), the vehicle model that leads to the most likely vehicle is the one chosen. Any parameters with uniform distributions are taken at their maximum values, since each value is equally likely. Taking the maximum value for the uniformly distributed parameter means that Normally-distributed parameters do not need to contribute as much to the overall result, and so are closer to nominal values. The maximum-likelihood value is then taken for the Normally-distributed parameters, which leads to the parameters that have the largest influence on the result being the ones that are dispersed the most. The result in each case is confirmed by designing a trajectory for the new vehicle model in the trajectory design tool (Program to Optimize Simulated Trajectories—POST).

## V. Customers

Table 5 lists a partial set of current customers for the Monte Carlo results.

**Table 5. Monte Carlo Dispersion Customers**

Customer	Uses	Customer	Uses
Aerothermal	Plot files (Mach, alpha, beta, etc.); US re-entry also	Thrust Vector Control	Maximum gimbal angles, gimbal rates, actuator power
Environments	Development and verification of winds modeling	Acoustics	Uses standard dispersion output
First Stage Reentry	First Stage separation states to initialize analysis	Main Propulsion System	Results of flight performance reserve analysis; acceleration and fuel dispersions
Flight Mechanics	FPR, orbit insertion accuracy, flight control analysis, GN&C requirements values, upper stage reentry footprint, navigation accuracy, guidance analysis, input for liftoff drift, umbilical removal, adequacy of RCS/TVC designs	Orion Loads	Trajectory data at Mach 1, trajectory data at max Q, trajectory data at all high dynamic pressures for loads evaluation, and trajectory data at various times for abort analysis.
Venting	Plot files; time history plots of alpha and beta as function of Mach. Alpha versus beta ellipses	Ares Stage Separation	Stage separation clearance dispersions
Abort Trajectories	Dispersed states at max dynamic pressure, First Stage, LAS jettison, etc.	Aerodynamics Panel	Variation of aerodynamic angles for which various data are needed
Abort Test Booster Project	Mach, alpha, beta, altitude, axial accel, dynamic pressure at max-drag, max-dynamic pressure, FS separation, and LAS jettison flight conditions	Orion	Altitude and acceleration as function of Mach for dispersions and reference trajectories, for acoustics. Heat rate at LAS jettison, conditions at Service Module panel jettison.
RCS	Acceleration angles with respect to body axes, confirmation that RCS design is adequate, requirements if not	Structural Loads	Qalpha/Qbeta ellipses at various altitudes; list of specific 99.73% trajectory results; MBLI results
ESM Fairing	Nominal and dispersed data at Encapsulated Service Module fairing jettison	Range Safety	Trajectory envelopes; velocities on the envelopes
Fuel slosh	Slosh amplitude and time history plots	Communications	Azimuth and elevation to Tracking and Data Relay satellites

For some customers where it is not clear which of the Monte Carlo cases provides their worst case, all trajectories are made available and these customers pick what is worst for them by examining outputs of interest. For example, the aerothermal analysis discipline runs the trajectories from the Monte Carlo runs through their thermal evaluation model while examining the heating on various body points. Similarly, for First Stage recovery, a

separate 6DOF Monte Carlo simulation is used to model the random behavior of the booster as it is re-entering the atmosphere. The large set of state vectors resulting from the post-stage separation point serve as initialization states for the re-entry simulation. There is no current single parameter that can be used to define the worst case for First Stage recovery. Orion uses the Monte Carlo results to determine the statistics of normal vehicle conditions that the spacecraft might need to abort from. The overall statistical results provide the bounds for which the Launch Abort System should be qualified. Other discipline areas, such as acoustics, take the output statistics and examine them for cases that are worst for acoustic design (in this case, load indicators, accelerations, and aerodynamic angles as a function of Mach number). For the various staging or jettison events (stage separation, ullage settling motor jettison, encapsulated service module panel jettison, launch abort system jettison, and Orion separation), the Monte Carlo results provide the range of conditions for which successful clearance and operation must be demonstrated.

## VI. Analyses

### A. Load Indicators

All results below are for a particular set of vehicle design parameters at a stage in the design process and will change as the design is refined. Any parameters that are judged to be outside the acceptable range will be worked during the design process. Figure 1 shows the maximum dynamic pressure variation for the nominal trajectories for the dispersion vehicle models. It can be seen that this indicator is significantly higher for some vehicle/mission combinations than it is for others. Figure 2 shows the variation of maximum dynamic pressure during Monte Carlo runs for the worst case. It is interesting to see how large a Mach range there is for the maximum dynamic pressure. Figure 3 shows the variation of maximum dynamic pressure times total angle of attack ( $Q \cdot \alpha_{Total}$ ), a key structural load indicator, for the worst case. Note that the highest dynamic pressures are seen in the summer, but due to wind variations the highest  $Q \cdot \alpha_{Total}$  is in February. Also of interest is that the highest  $Q \cdot \alpha_{Total}$  is quite a bit larger in 6DOF versus 3DOF simulation. 3DOF simulation captures all the wind variations, but assumes the vehicle is always pointed in the desired direction. When the flight control is included, the high dynamic pressure

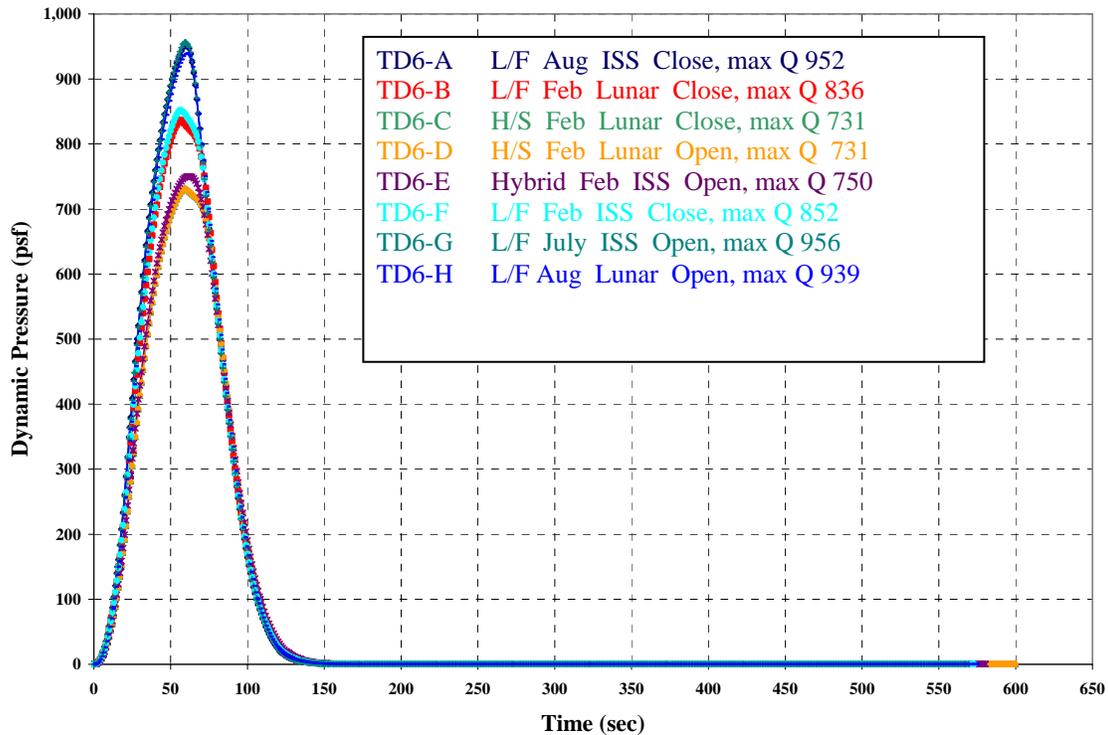


Figure 1. Maximum Dynamic Pressure Variation for Dispersion Nominals. The list of trajectories is in Table 3.

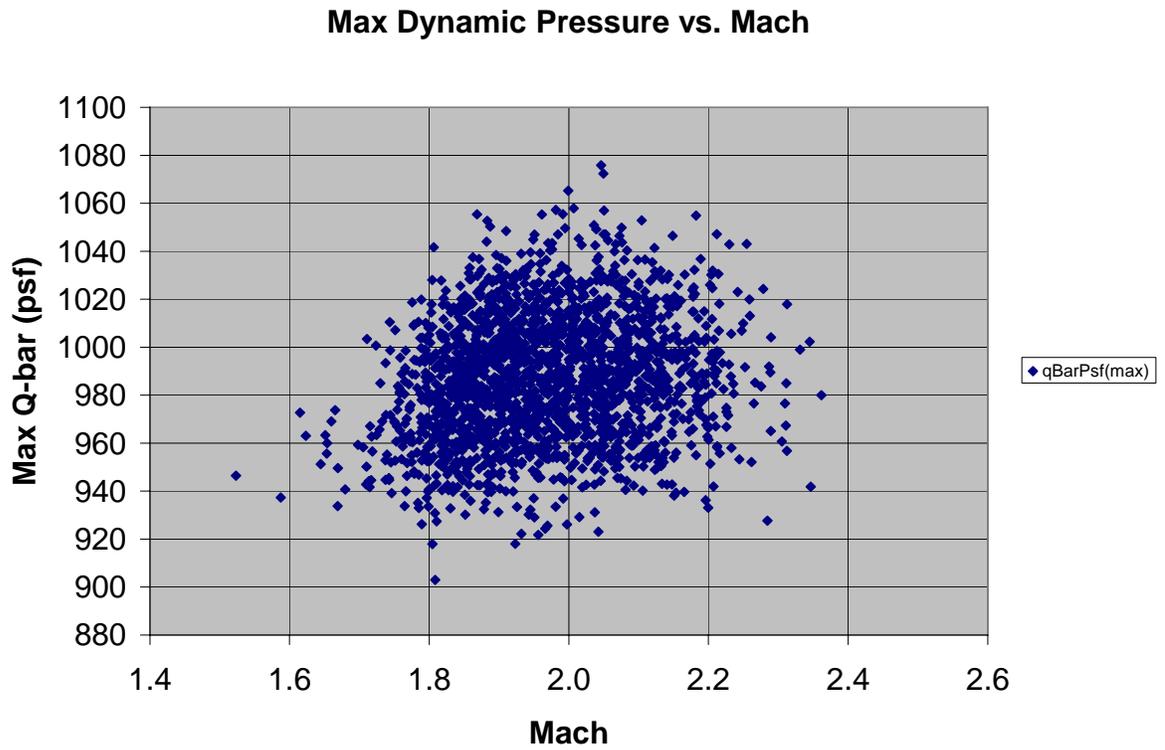


Figure 2. Maximum Dynamic Pressure versus Mach for Highest Dynamic Pressure Case (L/F ISS July)

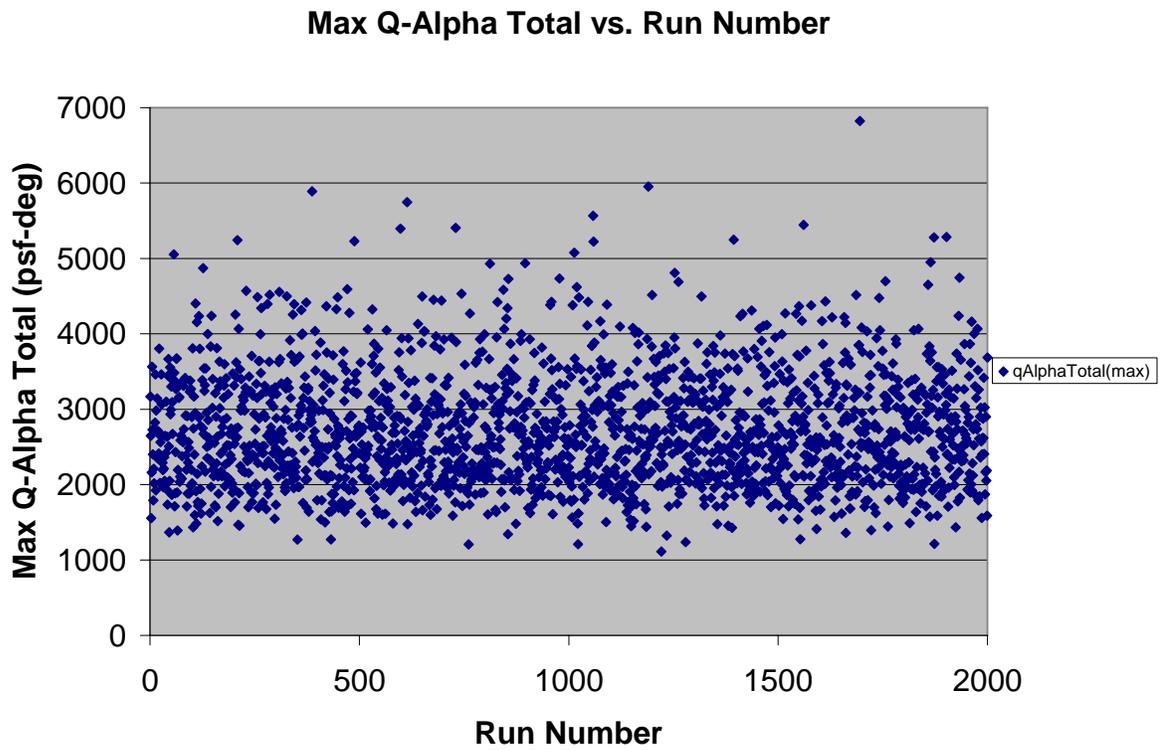


Figure 3. Variation in Peak of Dynamic Pressure times Total Angle of Attack for Worst Case (L/F Lunar February)

and strong winds make it difficult to fly without attitude error. A degree or two of attitude error at a high dynamic pressure results in a substantial increase in  $Q \cdot \alpha_{Total}$  for the worst cases. A more refined load indicator, called the moment-based load indicator (MBLI), has been derived as a measure of the dynamic load on each portion of the vehicle. MBLI envelopes are shown in Figure 4. The MBLI is normalized so that a value of about 1.0 would imply the vehicle exceeds its load limits and safety margin.

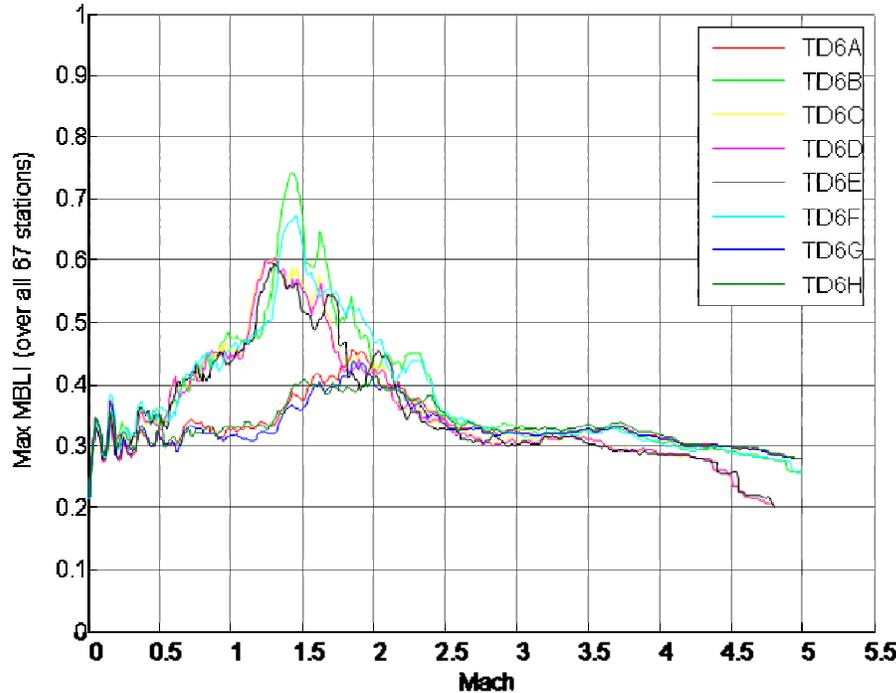


Figure 4. Maximum Moment-Based Load Indicator (MBLI) for all 67 Vehicle Locations and all 2000 Monte Carlo runs

### B. Launch Probability due to Winds Aloft

These results can be used to estimate launch probability due to winds aloft. Suppose the current value of  $Q \cdot \alpha_{Total}$  being used for structural design is 6400 psf-deg. If it is assumed that the winds are measured on launch day with a balloon and then the launch occurs within a few hours, a  $Q \cdot \alpha_{Total}$  criteria is needed for the go-no go decision. Suppose an increase of up to 600 psf-deg is allocated to wind persistence (the variation of the wind between the measurement and the launch time) and another 400 psf-deg is allocated to margin. Then for all simulations where the measured  $Q \cdot \alpha_{Total}$  is below 5400 psf-deg using the measured wind, the decision would be go for launch. Using these criteria leads to Table 6 for a particular set of runs. These criteria will need to be refined as the detailed design proceeds.

Table 6. Launch Probability due to Winds Aloft—selected mission models

Mission	Launch Probability (percent)	Mission	Launch Probability (percent)
L/F ISS August	100	Hybrid ISS February	99.95
L/F Lunar February	99.6	L/F ISS February	99.8
H/S lunar February	99.95	L/F ISS July	100
		L/F Lunar August	100

### **C. Monte Carlo Products**

Besides scatter plots, products from the Monte Carlo dispersion runs include tables of statistics for all parameters of interest (there are currently over 100 of these), statistics of key parameters at each mission event of interest, envelope plots of various parameters (worst case and various percentages), calculations of correlations of the outputs with respect to the various input uncertainties, time histories of parameters, squatcheloids (plots of angle of attack versus sideslip at a particular altitude, or plots of dynamic pressure times each of these aerodynamic angle quantities at various altitudes), and summary comparisons of the different cases.

### **D. Fuel Remaining**

Determination as to whether the flight performance reserve (FPR) is sufficient involves examining the worst-case liquid oxygen and liquid hydrogen remaining. If the flight runs out of either of these for more than an allowed number of runs, then some additional propellant must be set aside for FPR and withheld from use in designing nominal flight with maximum payload. Figure 5 shows an example of a way to do this calculation. The desire is to minimize the total amount of propellant (LOX + LH2) needed to meet the required percentage for FPR coverage. The figure shows a scatter plot of propellant remaining for a sample Monte Carlo run. In the case shown, all of the data points show both LO2 and LH2 remaining. This means that FPR can be reduced while still meeting the required success percentage. The two probability curves at the lower left represent propellant remaining for 99.73% with 10% consumer risk (90% confidence) and 99.73% with no consumer risk considered (simply pull the 99.73% value from the Monte Carlo experimental data). They represent a movement of the origin of the graph that would occur if the total LH2 and LO2 available were changed. If the origin were moved to a point above these curves, there would be quite a few cases that run out of oxygen. If the origin were moved to a point to the right of these curves, hydrogen failures would occur. As these curves are moved to the left and down, they represent adding more propellant and pushing the scatter plot up and to the right. A line segment of constant total propellant remaining is shown. Finding the minimum constant that satisfies the FPR probability requirement will minimize the total propellant needed. Integrating the probability distribution of the remaining propellant and determining the likelihood of running out of propellant allows this constant to be minimized. For the optimum shown, some failure cases are still allowed (shown on the plot).

### **E. Orbit Insertion Accuracy**

Orbit insertion accuracy is shown in Figs. 6 and 7 (it is generally not impacted significantly by which mission/vehicle model is being flown, except that a longer ascent allows the navigation errors to grow slightly). The orbit plane error is primarily due to the navigation attitude initialization error, and the in-plane energy error is primarily due to the uncertainty in the amount of impulse obtained during the J-2X shutdown transient.

### **F. Impact Footprint**

Figure 8 shows impact footprint areas for the Upper Stage for the different missions and for various other assumptions as to the altitude where the Upper Stage breaks up and the pieces that it breaks into. The Upper Stage was propagated in 6DOF from the end of the dispersed ascent until the breakup altitude. The toe and heel of the footprint were determined through use of a postulated heavy/low drag piece of debris and a light/high drag piece. These results will be used to help refine the design to ensure that none of the pieces fall on any populated land masses.

### **G. Stage Separation**

One of the fertile areas for Monte Carlo analysis is stage separation, a key part of ascent that must be examined in detail to ensure success. Monte Carlo analysis for Ares I stage separation is currently being performed in two independent simulations. Figure 9 shows examples of the motion of the outside of the J-2X nozzle with respect to the interstage boundary for two cases, one nominal (with the various uncertainties and variations included) and the other with a boost deceleration motor (BDM) failure. When one BDM fails, a large side torque results that moves the interstage closer to the J-2X nozzle as the interstage is pulled back from the Upper Stage. Despite an expected high reliability for the BDMs, since the vehicle is crewed, it is being designed to succeed even in the presence of a

failure. These results help in determining what combination of systems and timing will lead to successful separation.

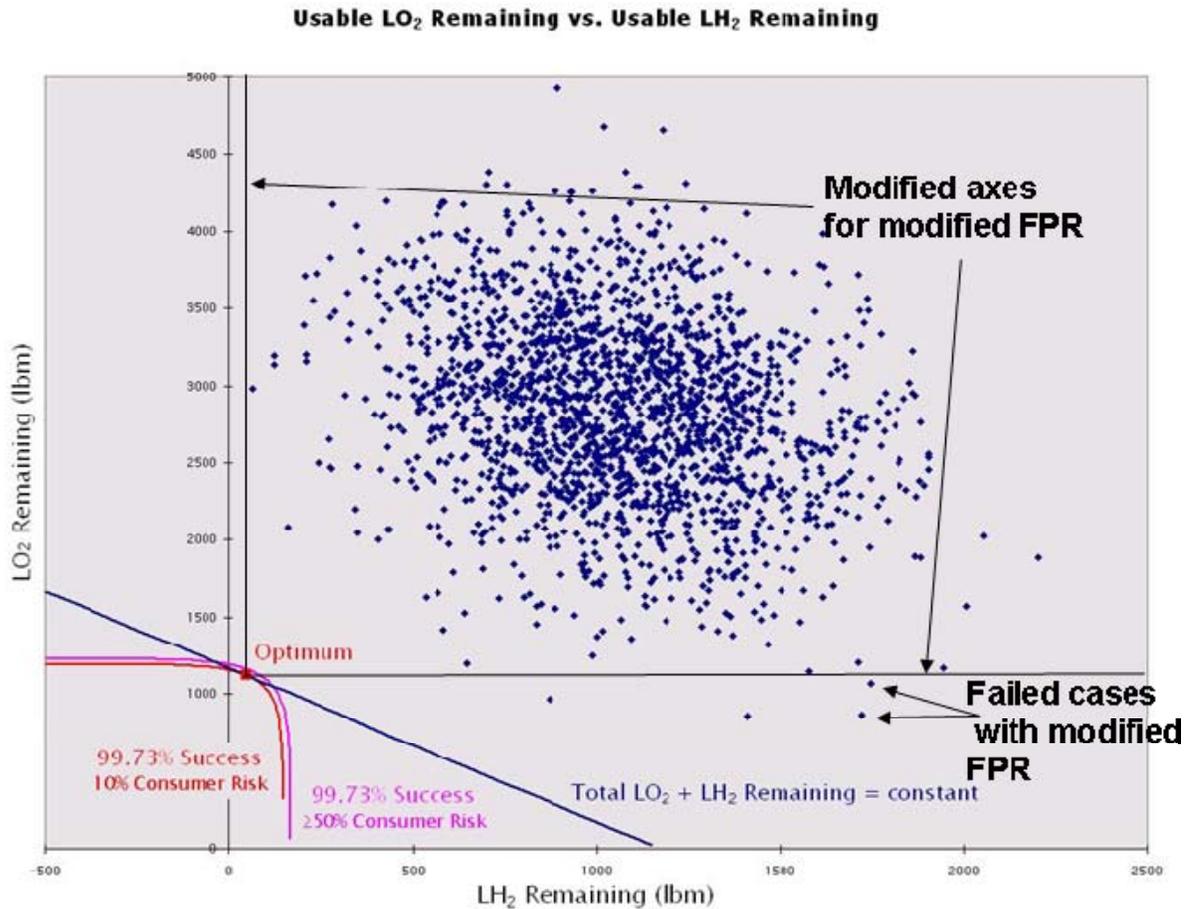


Figure 5. Propellant Remaining and Flight Performance Reserve Calculation Example

## H. Failure and Abort Analysis

Another important area for Monte Carlo analysis is examination of the effects of various failures. Although these failure modes are expected to be unlikely, since the vehicle is crewed, successful abort is desired for any situation where it is possible to abort safely. For any failure that affects vehicle dynamics (for example, a thrust vector control failure that is hard over, fails in place, or fails to null; a nozzle failure; or a First Stage case or field joint burn through), a Monte Carlo run will generate statistics of the starting conditions for the failure (since it can occur at any time on any flight). The value of using various parameters for abort triggers (make the decision to abort if this value is exceeded) can readily be evaluated, as well as the ability to depart from the vehicle before certain structural parameters are exceeded. For example, Fig. 10 shows envelopes for yaw rate around the Monte Carlo runs that were adjusted so that there would be no false alarms even with wind gusts. Figure 11 shows a way Monte Carlo results can be used to analyze aborts. Using the various triggers such as the one shown in Fig. 10, for a particular thrust vector control actuator failure near the time of maximum dynamic pressure, one can measure the time available. In Fig. 11, the first abort trigger limit to be passed is graphed, and the y axis shows the time duration between the moment the trigger value is reached and the structural load indicator limit is exceeded (hence the time available to abort, not considering the possibility of an explosion after the limit is reached).

Figure 12 shows an example of a flight parameter at the presumed time when the crew module and launch abort system (CM/LAS) would depart from the failing launch vehicle (assuming it takes 0.55 seconds after the trigger is passed before the CM/LAS leaves). This information can be used to help with CM/LAS modeling for ensuring the abort will be successful.

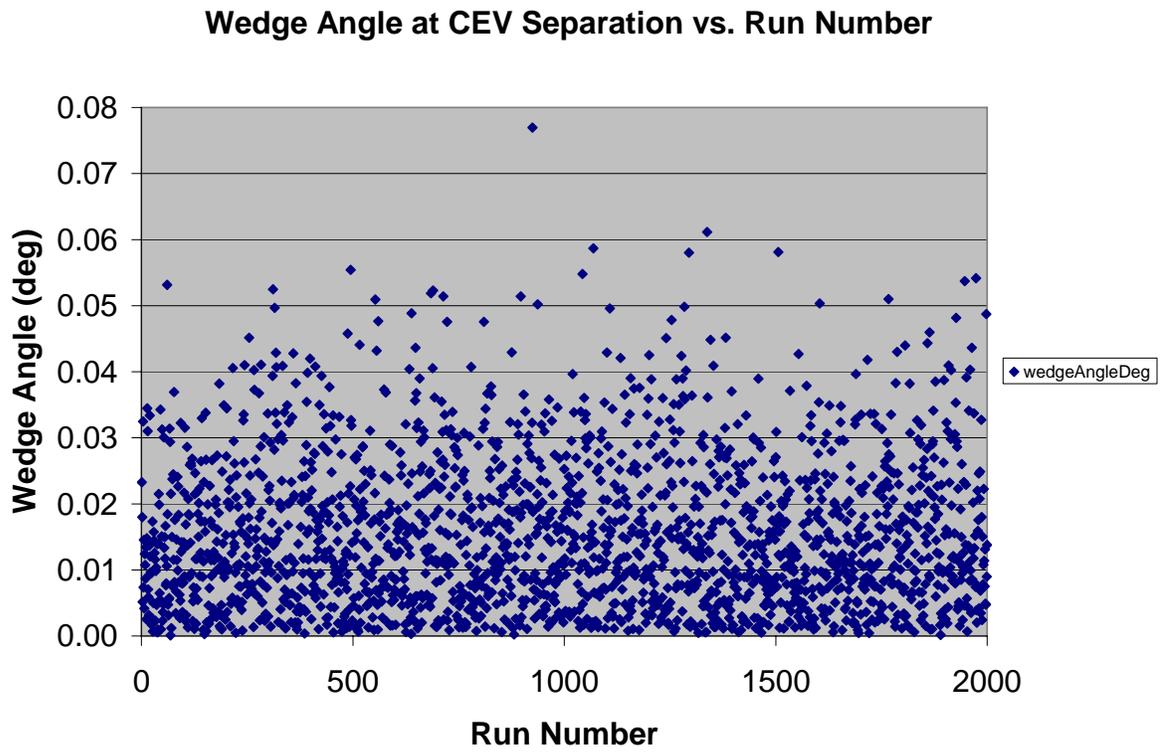


Figure 6. Orbit Plane Error at Insertion

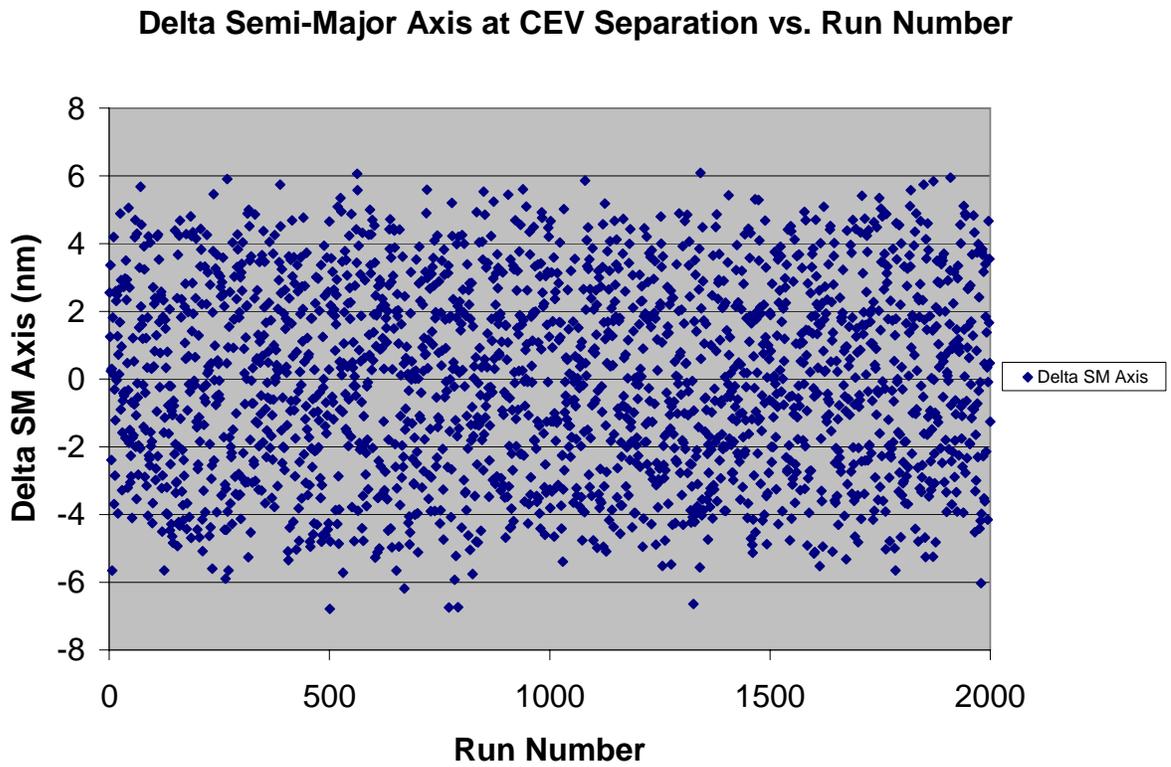
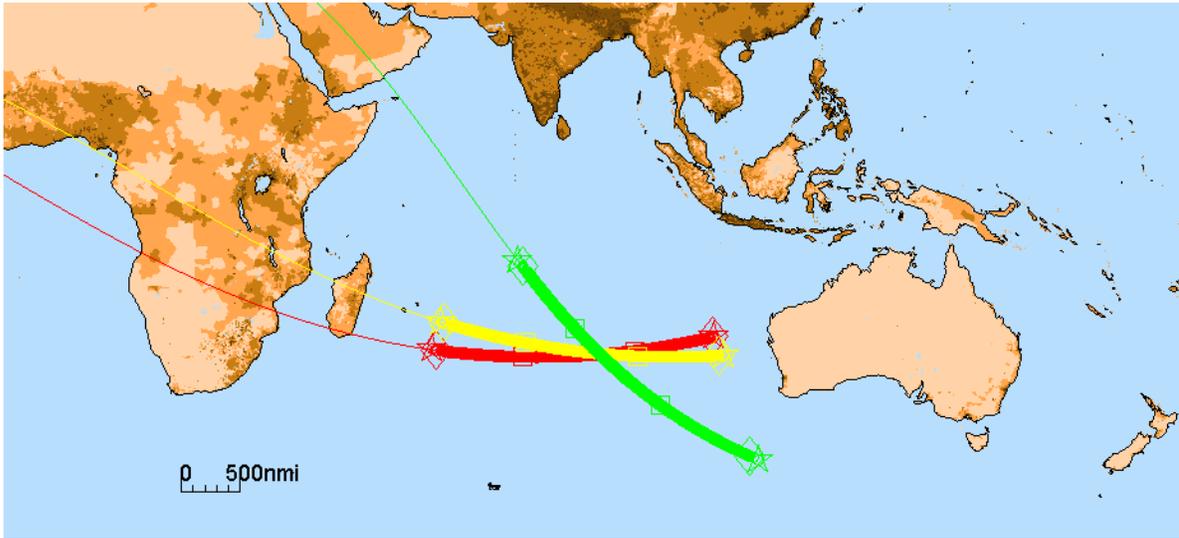
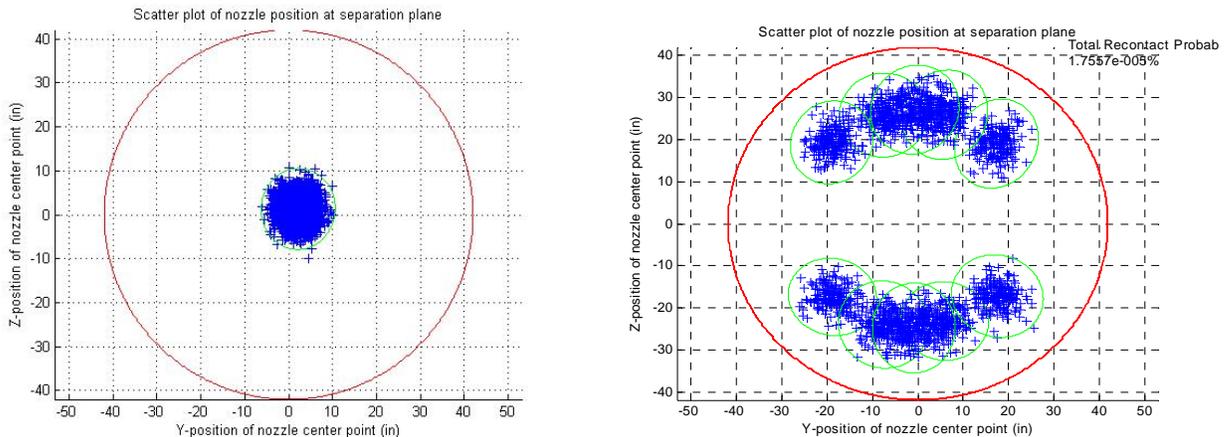


Figure 7. Semi-Major Axis Error at Insertion



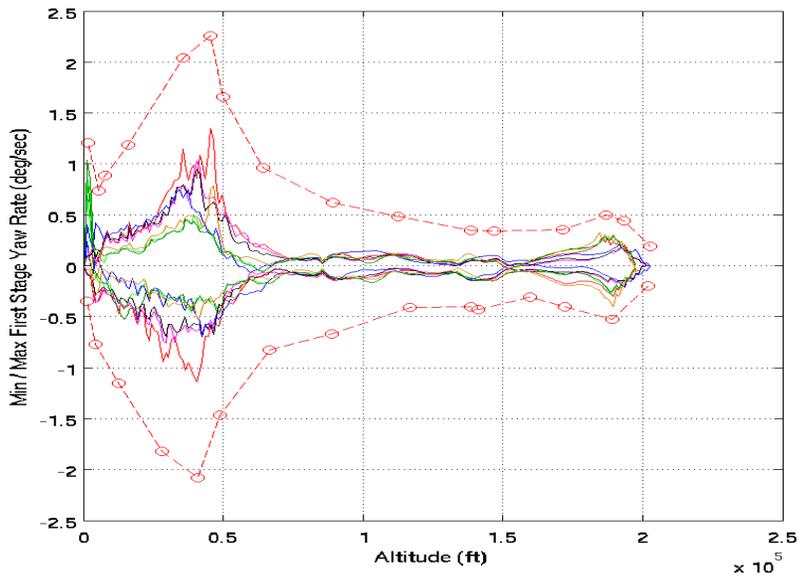
**Figure 8. Upper Stage Impact Footprint Areas.** Yellow = lunar mission, open of launch window, red = lunar mission, close of launch window, green = ISS mission, open of launch window, stars are worst case results, diamonds are 99.73% values with 90% confidence, squares are mean impact points of the high and low drag pieces.



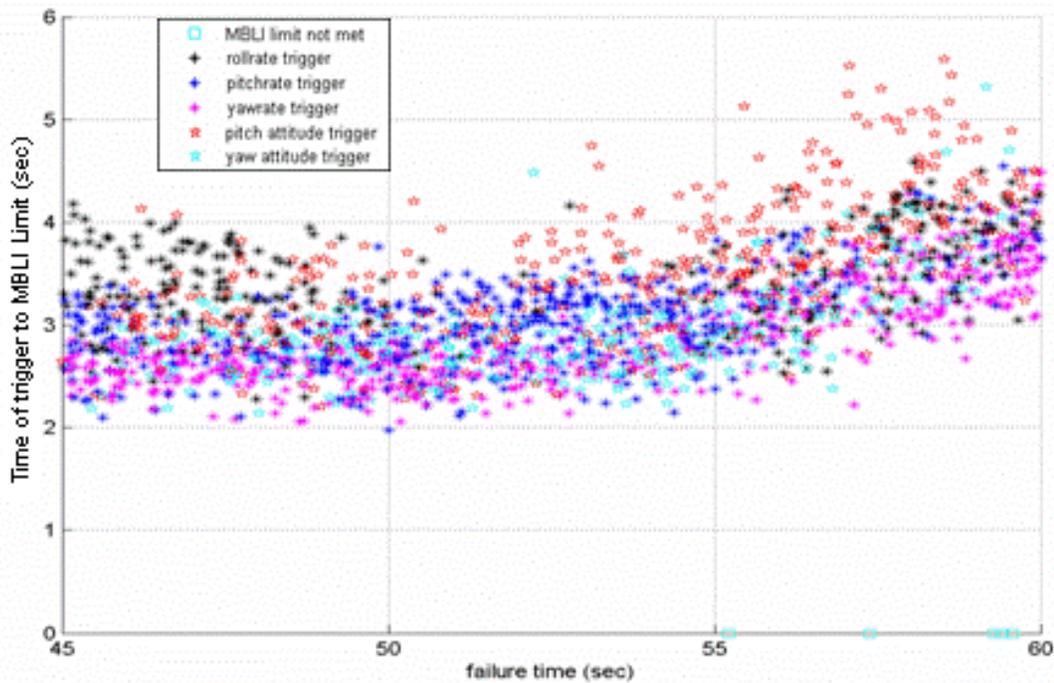
**Figure 9. Stage Separation Monte Carlo Results.** Left graph is no-failure case, right is one Boost Deceleration Motor failure. The outer circle represents the interstage that, if contacted, would damage the J-2X nozzle. The blue Monte Carlo marks indicate the nearest approach of the outside of the nozzle to the interstage. Clearance between the nozzle and the interstage is 42 inches at the start of the stage separation. The green ellipses are 99.73% ellipses.

### I. Guidance Analysis

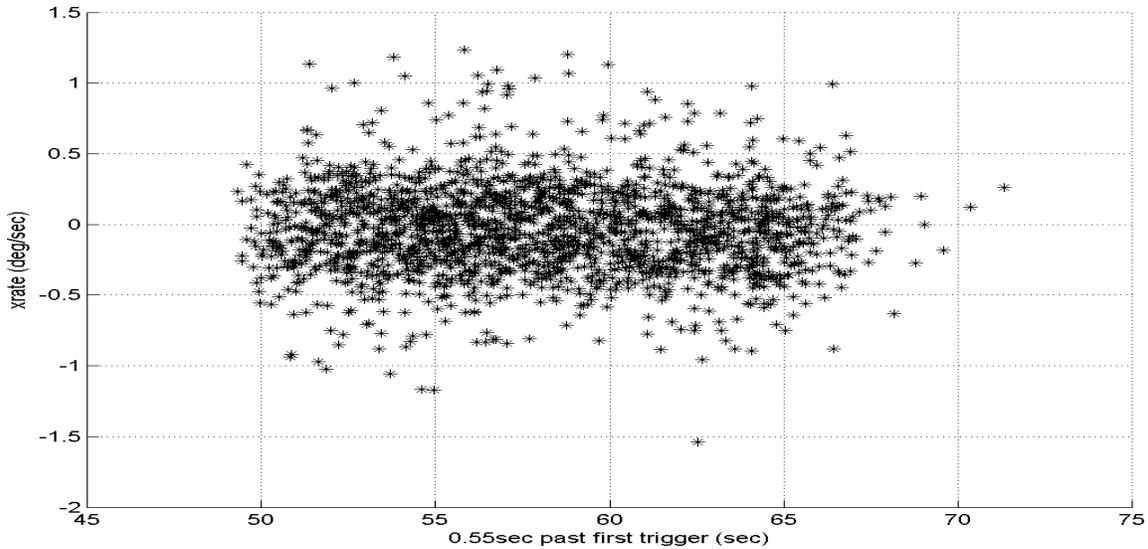
Monte Carlo analysis was also used to determine the guidance approaches that are best for Ares I. As an example of this, Monte Carlo runs were used to compare the use of different open-loop guidance independent variables. The guidance commands in the open-loop table are pitch, yaw, and roll. They may be a function of time, altitude, Mach number, speed, or other parameters. Analysis showed that time was not as good a parameter as a state variable, but that it did not matter much which state variable was used. This result agrees with Ref. 6. Altitude is currently being used since it is monotonic through staging. Monte Carlo analysis was also used to compare the Shuttle closed-loop guidance (Powered Explicit Guidance)<sup>5</sup> to a more complete optimization process as a closed-loop guidance approach. In addition, Monte Carlo analysis was used to compare various limits on guidance-commanded attitude rates and attitude accelerations for their effects on the flight control.



**Figure 10. Yaw Rate Envelopes for Monte Carlo Runs (solid curves) and Abort Trigger Envelope (dashed curve)**



**Figure 11. Time Available Before Vehicle Structural Failure After Abort is Triggered with Thrust Vector Control Failure.** *The failure mode was both actuators failing in place at their current value. Zero on the y-axis represents the time the first trigger value is passed, some time after the failure occurs. The first trigger to be exceeded is indicated for each Monte Carlo run on the plot. MBLI limit not met means that the load limit was never reached for those particular cases (blue squares at zero on the y axis). So in general the crew has at least 2 seconds to depart from the vehicle before structural limits are reached.*



**Figure 12. Attitude Rate at the Presumed Time of CM/LAS Separation from the Launch Vehicle for the Thrust Vector Control Errors in Figure 11.** *Time of flight is on the x-axis. These data can be used to assist in CM/LAS design for abort.*

## J. Flight Control Analysis

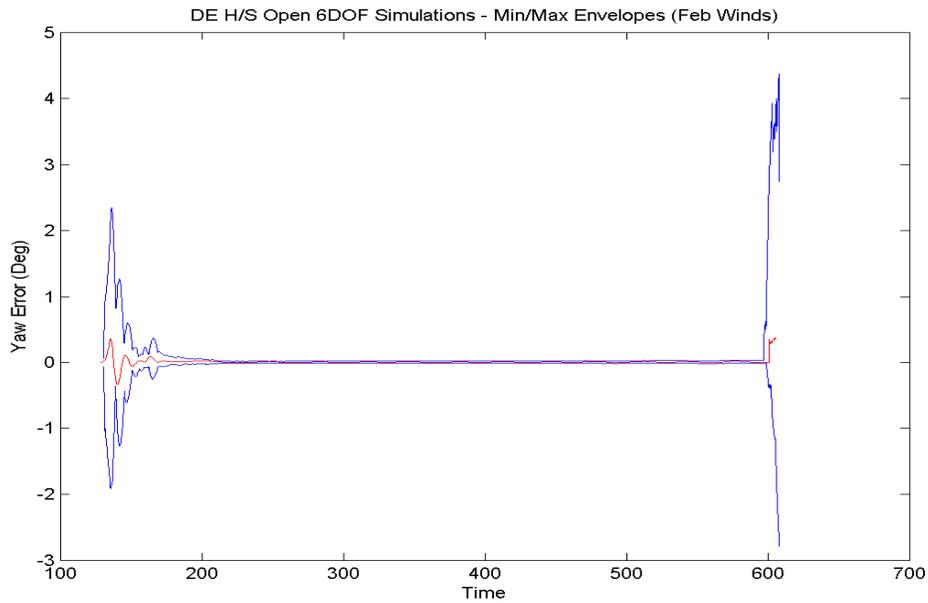
Development of the flight control design for each design cycle starts with stability analysis. Gains are derived that provide stability (along with the flex filters) and sufficient time response in the linear system. The flight control design is tested in the nonlinear, 6DOF time simulation (MAVERIC) to show that it successfully flies the vehicle and to verify stability and transient response characteristics. Many potential issues are discovered before the use of Monte Carlo simulations. But until all the uncertainties are encountered (winds, aerodynamic moments, TVC errors, lag times, etc.), it is not possible to be sure the flight control will succeed in general. When issues are found in the Monte Carlo results, they can be chased down in the runs that led to the problems. For example, Fig. 13 shows the yaw error envelope for Upper Stage flight (the red line is the nominal case). The errors at the start of Upper Stage flight result from transients due to the coast during staging before J-2X startup and due to the closed-loop guidance commands for steering to a different attitude. The significant error at the end of Upper Stage flight, just prior to insertion, was less understandable. The vast majority of runs had an error less than 1.5 deg at insertion, but many were higher than this value. It was determined that the integral gain was far too low to cover certain cases where dispersions were combined in a way that increased yaw disturbance torque towards the end of powered flight. The attitude integral gain was increased and the stability analysis repeated to verify margins. As can be seen in Fig. 14, this portion of the error can be removed with some work in the control design.

Another example is in Figs 15-16. Although some error is unavoidable if the vehicle is to remain stable (and since the winds are changing), some Monte Carlo runs show high error around 80 seconds into flight (Fig. 15). Similar to the upper stage anomaly, bad combinations of vehicle dispersions compounded by bad winds caused larger than expected pitch errors in this portion of flight. With some adjustment of the attitude proportional gain, this is improved (Fig. 16).

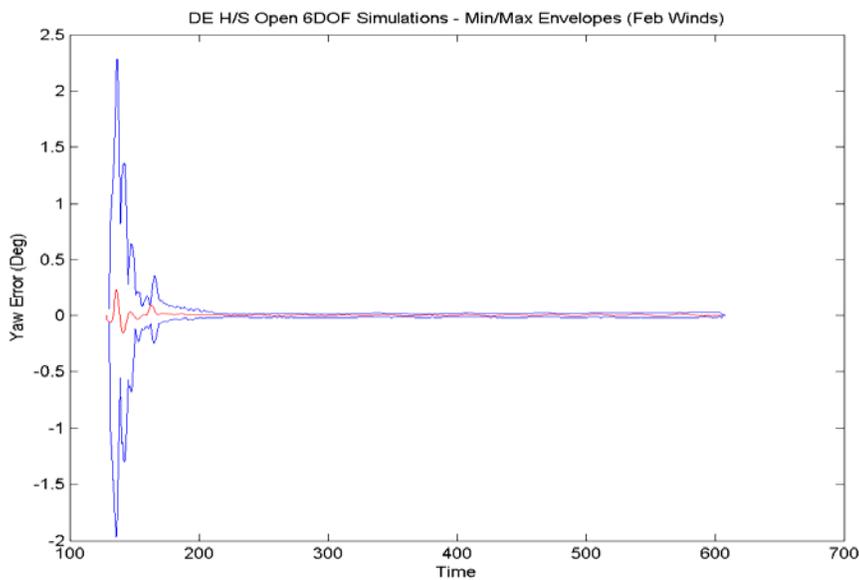
## VII. Conclusion

This paper describes how Monte Carlo simulation is being used to understand many of the issues involved with designing the Ares I launch vehicle. Starting with high fidelity simulation along with uncertainties in each input parameter of interest, the simulations needed are defined in order to examine worst case design points for each discipline area. Besides helping with vehicle design parameters, the simulation also assists with determining whether the design meets requirements in many integrated vehicle areas. Many of these were described in the paper.

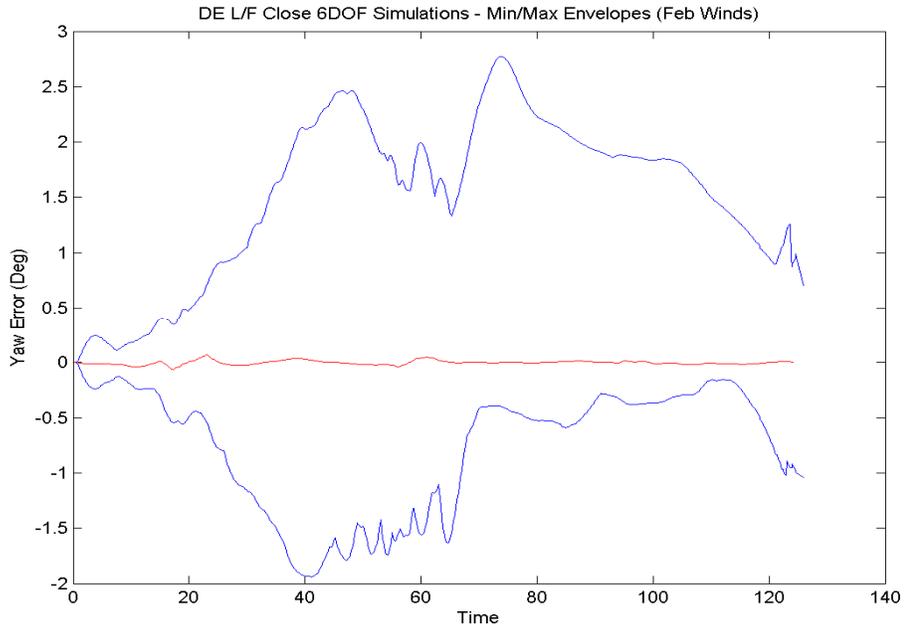
As the Ares I design matures, with each passing month, more uses for the data output from the Monte Carlo runs are discovered as the various subsystems look for their design cases. After the design is firm, Monte Carlo simulation will be used to assist in verifying that the Ares I meets its requirements.



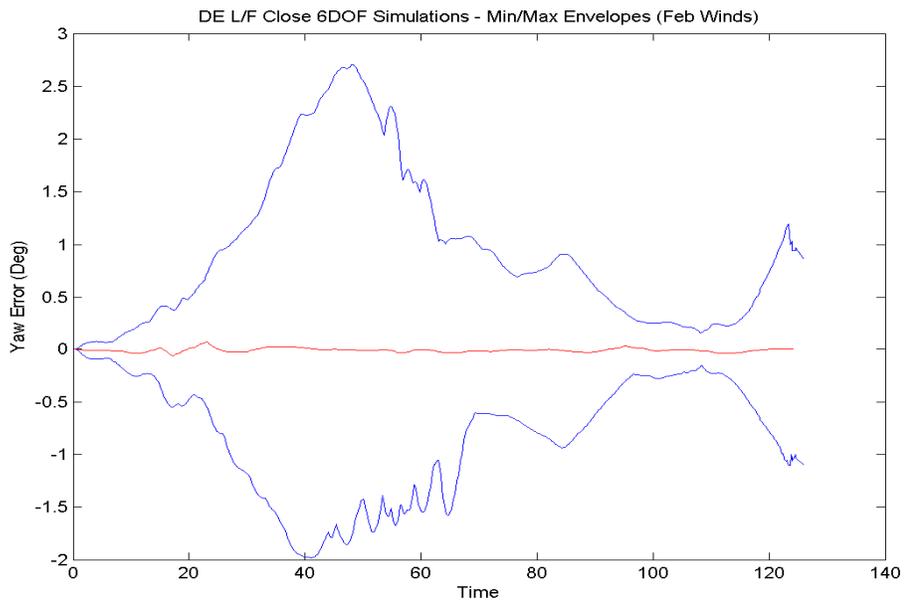
**Figure 13. Yaw error before flight control adjustment (lunar February H/S mission).** *This graph is for Upper Stage flight. The early excursions are expected from attitude deviations associated with stage separation as well as the closed-loop guidance commanding an attitude maneuver once it begins issuing commands. A few out of the 2000 Monte Carlo runs had significant attitude errors near MECO, although the vast majority of cases had less than 1.5 degrees error.*



**Figure 14. Yaw error after flight control adjustment for the case in Fig. 13.** *Note the improvement at the end of flight.*



**Figure 15. Yaw Error Envelope (and nominal) Prior to Flight Control Adjustment (L/F lunar February mission)**



**Figure 16. Yaw Error Envelope (and nominal) after Flight Control Adjustment (L/F lunar February mission)**

### Acknowledgments

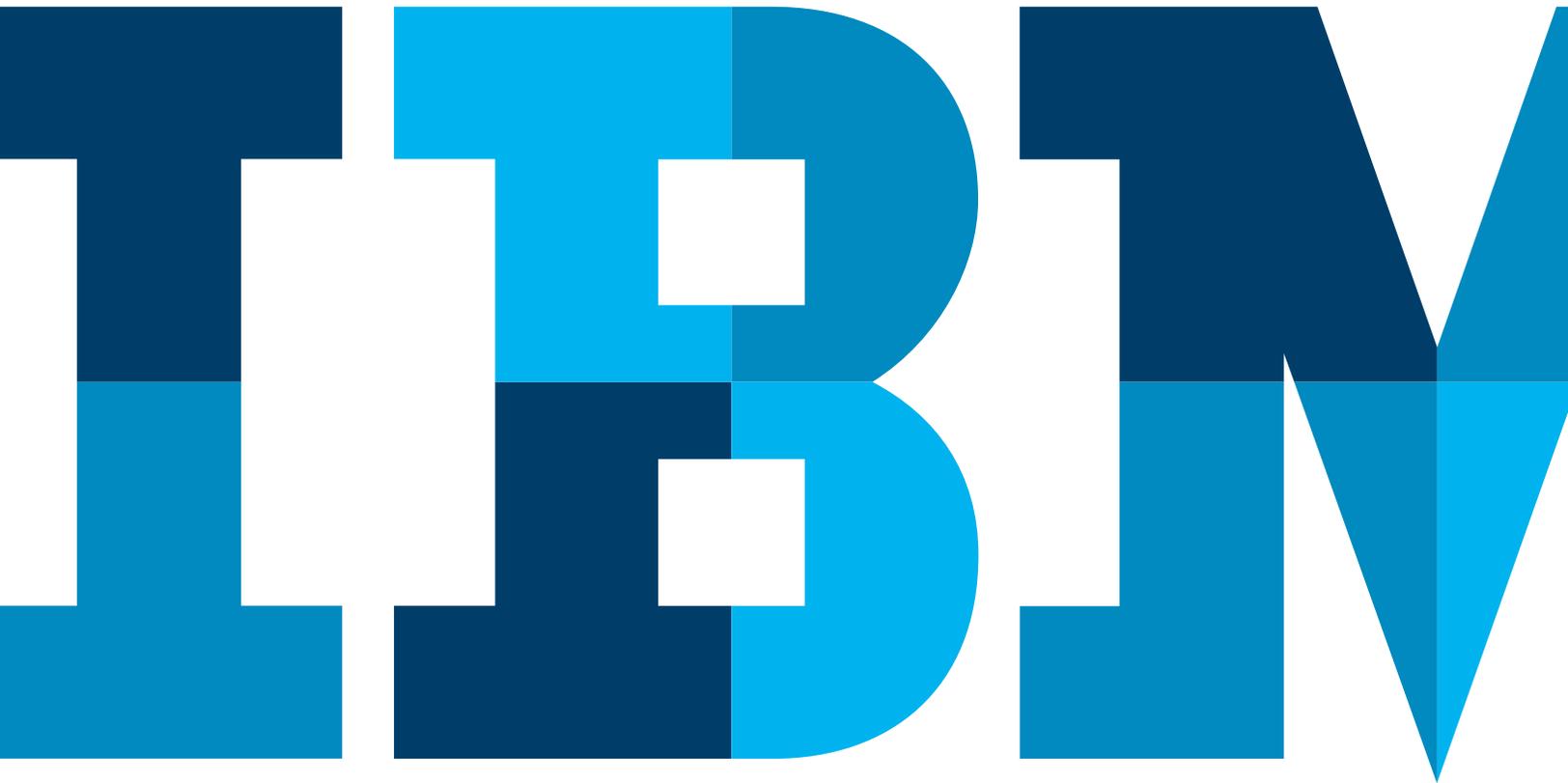
The authors thank the Ares GN&C team for producing the results shown in this paper. In particular, the authors are grateful to Stan Douglas, Dr. Greg Dukeman, Jim Hays, Ashley Hill, Dr. Young Kim, Robin Pinson, Terri Schmitt, Rob Stough, and Eric Waters. The authors are also grateful for Dr. Bernard Beard for assistance with the statistical calculations.

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# Better decision making under uncertain conditions using Monte Carlo Simulation

*Monte Carlo simulation and risk analysis techniques in IBM SPSS Statistics*



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  - 4 Addressing uncertainty with simulation
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## Introduction

IBM® SPSS® Statistics is one of the world's leading statistical software solutions, providing predictive models and advanced analytics to help solve business and research problems. For many businesses, research institutions and statisticians, it is the de facto standard for statistical analysis. Organizations use SPSS Statistics to:

- Understand data.
- Analyze trends.
- Forecast and plan.
- Validate assumptions.
- Drive accurate conclusions.

The SPSS Statistics environment offers a wide range of multivariate procedures for investigating complex data relationships. A number of procedures include advanced models such as general and generalized linear modeling capabilities. With general linear models, you can model relationships and interactions between many factors. The general linear model incorporates a number of different statistical models: analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), analysis of covariance (ANCOVA), repeated measures and more. General linear modeling is well suited for statisticians who analyze data with unique characteristics (for example, nested-structure data) or who describe relationships between a dependent and a set of independent variables to discover whether random effects introduce correlations between cases.

Regression models (for continuous dependent variables) are a family of classical predictive techniques, all of which involve fitting (or regressing) a line or curve to a series of observations to model effects or predict outcomes. With SPSS Statistics, you can also use regression models to predict categorical outcomes for more than two categories, easily classify data into two groups, accurately model non-linear relationships, find the best predictor from dozens of possibilities and more.

Predictive models, such as linear regression, require a set of known inputs to predict an outcome. In many real-world applications, however, inputs are not known with certainty, and users are interested in accounting for that uncertainty in their models. For example, when given a profit model that includes cost of materials as an input, users also want to account for uncertainty in materials cost and determine the likelihood that profit will fall below a target value. To deal with uncertainty in future input values, statisticians turn to simulation.

SPSS Statistics includes a simulation module designed to account for uncertainty in inputs to predictive models. This paper describes Monte Carlo simulation, the value of using Monte Carlo simulation for risk analysis and how SPSS Statistics and its new simulation module can help businesses use Monte Carlo simulation for risk analysis.

### Uncertainty in inputs into models

The development of a forecasting model requires making certain assumptions. These might be assumptions about the investment return on a portfolio, the cost of a construction project or how long it will take to complete a certain task. Because these are projections, it is not possible to know with certainty what the actual value will be, but based on historical data, expertise in the field or past experience, it is possible to estimate. Although this estimate is useful for developing a model, it contains some inherent uncertainty and risk, because the estimate is an unknown value.

Traditionally, companies address uncertainty in one of three ways:

- *Point estimates* use the most likely values for the uncertain variables. These estimates are the easiest, but they can return very misleading results. For example, consider what might happen if you decide to cross a river because its average depth is three feet. Or, suppose, because you have calculated that it takes an average of 25 minutes to get to the airport, you leave 25 minutes before your flight takes off. How likely are you to miss it?
- *Range estimates* typically calculate three scenarios: the best case, the worst case and the most likely case. These types of estimates can show you the range of outcomes, but not the probability of any of these outcomes. This approach also considers only a few discrete outcomes, ignoring hundreds of thousands of others. Simply put, it gives equal weight to each outcome, so there is no attempt to assess the likelihood of each outcome. Interdependence between inputs and the impact of different inputs relative to the outcome are ignored, oversimplifying the model and reducing its accuracy.
- *What-if scenarios* are usually based on the range estimates and typically are about exploring the effect of things you can control. What is the worst case? What if sales are best case but expenses are the worst case? What if sales are average, but expenses are the best case? What if sales are average, expenses are average, but sales for the next month are flat? This form of analysis can be time consuming, and it results in a great deal of data.

With each of the three traditional approaches, it is not possible to determine the probability of achieving different outcomes.

## Addressing uncertainty with simulation

A Monte Carlo simulation is a computer experiment involving random sampling from probability distributions of the inputs to obtain approximate solutions to problems, especially in the case of a range of values where each has a calculated probability of being the solution. When statisticians use the term “simulation,” they usually mean Monte Carlo simulation.

In this approach, uncertain inputs are modeled with probability distributions (such as the triangular distribution), and simulated values for those inputs are generated by drawing from those distributions. The simulated values are then used in a predictive model to generate an outcome. The process is repeated many times (typically thousands or tens of thousands of times), resulting in a distribution of outcomes that can be used to answer questions of a probabilistic nature to determine behavior, to analyze risk and more.

One of the strengths of Monte Carlo simulation is that it makes it possible to account for risk in quantitative analysis and decision making. Historical simulation (usually used in computing value at risk in financial scenarios, for example) consists of generating scenarios by sampling historical data associated with each risk factor included in the problem. This approach doesn't require any distributional assumptions.

Running simulations from known distributions based on historical data produces accuracy. For example, stochastic risk analysis uses a model and Monte Carlo simulation to analyze the effect of varying inputs on outputs of the model. It defines probability distributions to express the possible variation of the model input variables and uses the Monte Carlo simulation technique to calculate the effect of uncertainty on the model's key outputs. Stochastic analysis can be an invaluable decision-making tool for investment appraisal, business and strategic planning, marketing and sales forecasting, pricing models, along with many scientific applications.

If historical data exists, you still might not want to use historical simulation because Monte Carlo simulation has the advantage of allowing for a wider variety of scenarios than the rather limited results that historical data can provide. Therefore, you can fit probability distributions to the data and use it as the basis for input distributions for Monte Carlo simulation. For example, someone might have collected historical data on a product price and might want to create a distribution of possible future prices that is based on the data.

One of the reasons why risk analysis was not frequently applied in the past is that computers were not powerful enough to handle the demanding needs of Monte Carlo simulation. In addition, for each case, you had to develop a custom project appraisal computer model that represented the relationships between input and output variables using a combination of functions, formulas and data. Now, however, most of the computers and processors can handle intensive computation from Monte Carlo simulation.

## The value of Monte Carlo simulation for risk analysis

Existing statistical and modeling software solutions have different methods for addressing risk analysis. Some modeling solutions work in the Microsoft Excel environment. The advantage of this approach is that companies can easily incorporate risk management in everyday processes at all levels of their organization because spreadsheet models have been created for them.

Other statistical software products can act as standalone solutions for risk management, but they are designed mostly for banks and other types of financial institutions. They provide risk management tools for the management and control of market risk, credit risk, operational risk and liquidity risk, but it is not clear how a model is built within their framework.

Monte Carlo simulation solutions either provide functions to simulate from all of the standard probability distributions or offer two-dimensional Monte Carlo simulations. Econometric tools are available for performance and risk analysis, and other software has functions for calculating a risk model. Custom coding is necessary if you want to use these solutions for Monte Carlo simulation and risk analysis together.

Risk analysis can greatly benefit from Monte Carlo simulation. Consider a simple example of monthly sales as a function of advertising expenditures, the number of sales agents and the consumer confidence index (called “cci” in the model), which is an indicator of the general health of the economy. This process has several stages:

### 1. Set up the model and identify risk variables

Figure 1 demonstrates the data represented over 5 years of monthly sales data that was used to create the linear regression model, assuming that there are no time dynamics in the data and no correlation in the error terms.

advert	cci	agents	sales
11332.00	55.00	109.00	6709410.00
69477.00	93.00	113.00	7829320.00
59087.00	73.00	105.00	6943660.00
36364.00	53.00	118.00	7257860.00
50401.00	42.00	115.00	6481200.00
75382.00	102.00	107.00	7476770.00
75892.00	68.00	122.00	7364630.00
37461.00	73.00	116.00	6980820.00
73628.00	73.00	116.00	6840060.00
22951.00	91.00	98.00	6943570.00
55946.00	60.00	112.00	7149030.00

Figure 1: The data for monthly sales

Figure 2 shows the linear regression model generated after fitting the model with sales as a dependent (target) variable and advert, cci and agents as independent (predictor) variables. In the example, the advert, cci and agent variables are those for which the projected value is both probable and potentially damaging to the monthly sales value.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.711 <sup>a</sup>	.505	.479	275285.8758

a. Predictors: (Constant), agents, advert, cci

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.330E+12	3	1.443E+12	19.047	.000 <sup>b</sup>
	Residual	4.244E+12	56	75782313427		
	Total	8.574E+12	59			

a. Dependent Variable: sales  
b. Predictors: (Constant), agents, advert, cci

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	4627254.938	501272.059		9.231	.000	3623086.337	5631423.538
	advert	6.619	1.890	.331	3.502	.001	2.833	10.405
	cci	10331.400	1705.754	.573	6.057	.000	6914.363	13748.437
	agents	12747.541	4260.719	.284	2.992	.004	4212.295	21282.788

a. Dependent Variable: sales

Figure 2: Linear regression model with three risk variables

2. Specify probability distributions.

The specification of a probability distribution for each selected risk variable involves setting up a range of values and allocating probability weights. In general, analysts for the project should rely on judgment and subjective factors for determining the range of values and probabilities. Figure 3 illustrates some of the probability distributions used in the application of risk analysis.

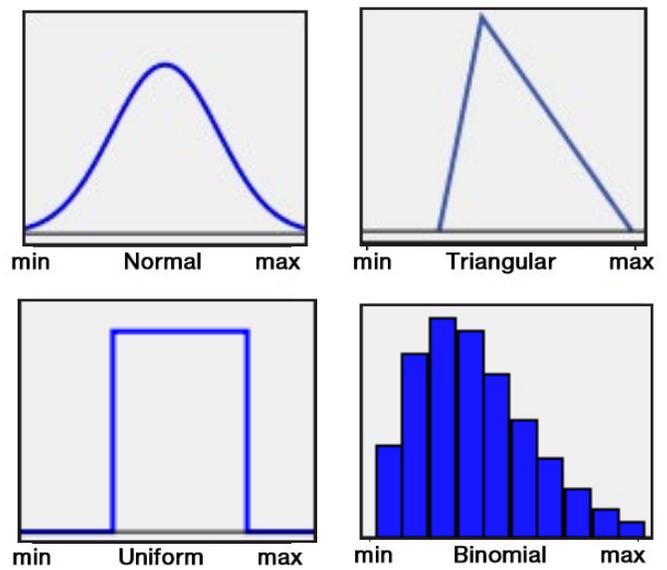


Figure 3: Probability distributions used in risk analysis

If historical data exists, you can skip this stage and conduct historical simulation directly. Or, you can fit distributions to the data for Monte Carlo simulation.

### 3. Run simulations

The model is processed and repeated until enough results are gathered to make up a representative sample of the near infinite number of possible combinations. During a simulation, the values of the risk variables are generated randomly according to specified probability distributions. In the example, the goal of the simulation was to look at the probability of reaching a monthly target sales goal of \$7,000,000. The results of the model (the “monthly sales” in the example) for each run are computed and stored away for statistical analysis (the final stage of the risk analysis process). Figure 4 shows the cumulative distribution function of monthly sales (based on 100,000 records of simulated data) where you can observe that the probability of reaching the monthly target sales goal of \$7,000,000 is 62 percent.

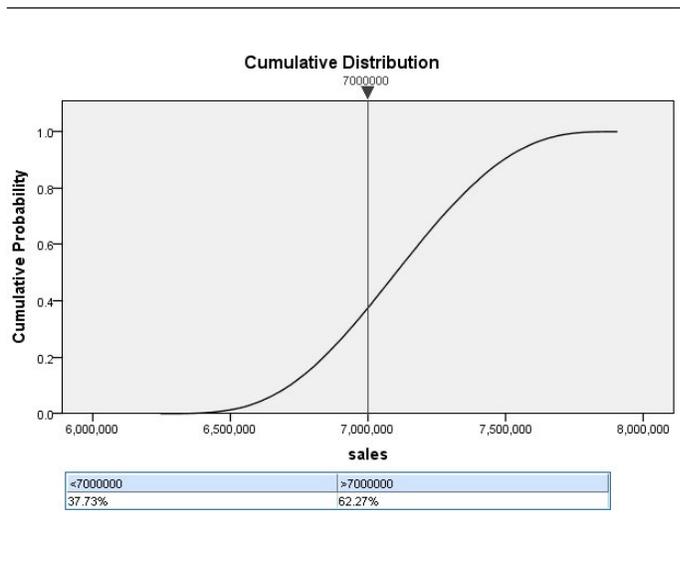


Figure 4: Cumulative distribution function of monthly sales

The example also looked at the effect of varying the number of sales agents over three fixed values: 110, 100 and 90 to analyze the effect on monthly sales of reducing sales staff. Varying an input over a set of fixed values, as done here for number of sales agents, is referred to as “sensitivity analysis.” Figure 5 shows the sensitivity analysis of varying the number of sales agents with respect to monthly sales.

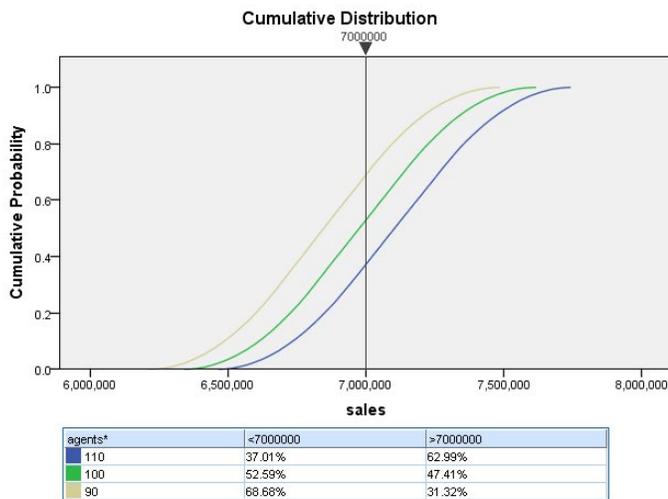


Figure 5: Sensitivity analysis

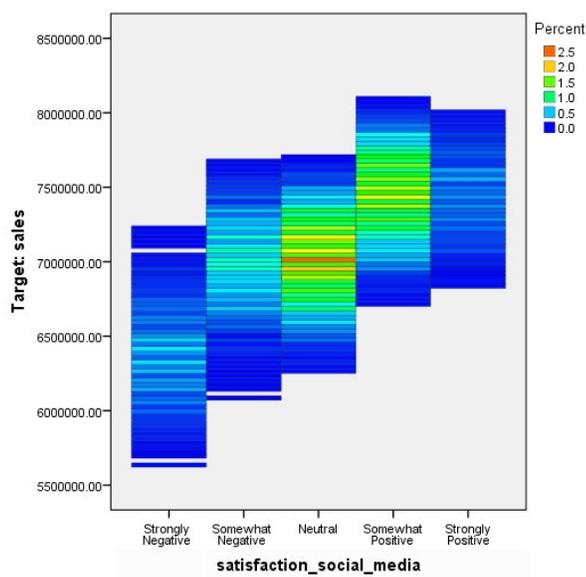
You can see that when you reduce your sales staff from 110 to 90, you decrease your chances of meeting your goal from 63 percent to 31 percent.

Next, the company decides to analyze the impact of customer satisfaction on monthly sales. It has obtained monthly satisfaction data from both a formal survey of existing customers and analysis of social media content. This data has been spread across five categories: Strong Negative, Somewhat Negative, Neutral, Somewhat Positive and Strongly Positive.

Specifically, the company wants to determine whether the satisfaction level measured from social media data has an impact on the sales target. An additional step can be taken to confirm this hypothesis.

#### 4. Fitting a categorical distribution

The original sales model can be expanded by including monthly satisfaction data. In the original story, the company wanted to know how likely it was to achieve a monthly sales target of \$7,000,000. For inputs with a categorical distribution, you can automatically compute a multiway contingency table from the historical data that describes the associations between those inputs. The contingency table is then used when data are generated for those inputs. After fitting categorical distributions and an associated contingency table to the monthly satisfaction level data, the simulation is rerun to generate scatter plots of the target with the inputs. Scatter plots that contain a categorical target and/or categorical input are displayed as heat maps, as shown in Figure 6.



*Figure 6:* The expanded model that includes satisfaction data shows that when the satisfaction level measured from social media data is “Neutral,” the monthly sales numbers are spread roughly evenly around the \$7,000,000 target. However, when the social media satisfaction level is “Somewhat Positive” the sales distribution shifts so that the bulk of the distribution (for that satisfaction level) exceeds the target. This suggests that customer satisfaction level as measured by social media data is an integral part of attaining the sales target.

## SPSS Statistics: Building better simulations and assessing risk with automation

The simulation functionality in SPSS Statistics is designed to account for the uncertainty of values of the inputs in predictive models. It helps users:

- Design a simulation. Users can specify all details required to run a simulation, such as the distributions for the simulated predictors and correlations for those predictors. When historical data is present, distributions and correlations for simulated predictors can be automatically determined from that data.
- Save specifications for a simulation to a simulation plan file.
- Run a simulation. The specifications for the simulation can come from a loaded simulation plan file or the user can simply provide the specifications in the associated user interface and run the simulation from that user interface.
- Load a simulation plan, modify any aspect of the plan, optionally run the modified simulation and optionally save the changes.

In addition to the procedures described in the previous section, SPSS Statistics includes a range capabilities to help users build better simulations, including:

**Simulating strings.** Non-numeric variables such as “male” and “female” can be simulated without recoding them as numeric variables. The software also supports fitting a categorical distribution to a string field in the active dataset. For example, if a model contains gender as an input, the user can load the model, fit the model inputs to the active dataset, and SPSS Statistics will fit a categorical distribution for string fields.

**Support for Automatic Linear Modeling (ALM).** Users can export models from ALM and use them as the starting point for the simulation.

**Association between categorical inputs.** SPSS Statistics can automatically determine and use associations between categorical inputs when generating data for those inputs. A multiway contingency table is computed for all inputs that are fit to a categorical distribution. This table is then used when generating data for the inputs.

**Ability to generate data in the absence of a predictive model.** In this case, the user simply specifies which variables to simulate and either fits them to the active dataset or manually specifies their distributions.

How does it work? Here are two examples.

#### **Modeling impact on profit due to uncertainty of cost of materials**

Paul is an analyst at a large manufacturing company and is responsible for financial modeling and forecasting. Given the current instability in markets, Paul's managers want him to include risk in the cost of materials in his profit model. For this scenario, many statisticians use a relatively simple profit model: estimates of the maximum, minimum and most likely value for cost of materials. This has the limitations described previously for range estimates.

Using the new simulation dialog in SPSS Statistics, Paul enters his profit model in the expression builder and specifies "cost of materials" (one of the predictors in the model) as a simulated predictor. Paul only has estimates of the maximum, minimum and most likely cost, so he chooses a triangular distribution to model his cost variable. Because there is some uncertainty in his estimates of the maximum, minimum and most likely cost, Paul plans to run his simulation multiple times, varying the parameters of his cost distribution in each simulation. He is able to save his specifications in a simulation plan so that his scenario analysis does not have to be completed in just one session, and he is able to vary the parameters for his triangular distribution more easily after reloading his simulation plan.

#### **Modeling energy usage accounting for uncertainty in temperature**

It can be a challenge to model or predict energy usage needs for a utility company that purchases energy from other providers when demand exceeds on-site production capacity. Consider Pamela, who is responsible for that task in her utility company. She models energy needs with a regression model that she has built in SPSS Statistics. Pamela has saved the model to an XML file, which enables her to quickly apply the model to a given set of inputs—something that she does daily.

One of the primary sources of uncertainty in Pamela's model is temperature. Although she can easily use what-if analysis to get point estimates of energy needs for specific temperatures, she is most interested in the likelihood that energy needs will exceed production capacity on a given day, necessitating the purchase of additional energy from an outside provider.

Pamela has access to historical temperature data that she plans to use to model uncertainty in daily temperature, so she starts up SPSS Statistics and loads that data.

She opens the simulation dialog, loads her regression model and specifies that temperature is a simulated predictor. She then chooses to automatically fit (autofit) the temperature distribution from the historical data. Because she also has temperature forecasts for the current day, she can customize the parameters of the autofit distribution if she chooses. She specifies values for the fixed predictors and obtains a distribution of energy usage, from which she can easily determine the probability that energy needs will exceed on-site production capacity by a given amount.

## Conclusion

Monte Carlo simulation helps address the challenges of dealing with uncertainty in predictive and forecasting models and assessing risk. SPSS Statistics is designed to help you use Monte Carlo simulation in risk analysis. Using the simulation module in SPSS Statistics, you can simulate data according to parameters you specify and then use that simulated data as input for predicting an outcome. You can also modify the parameters used to simulate the data and compare outcomes. For example, you can simulate various advertising budget amounts and see how that affects total sales. Based on the outcome of the simulation, you might decide to spend more on advertising to meet your total sales goal. With automation, features for saving simulation plans and support for predictive modeling, the simulation module in SPSS Statistics smoothly combines risk analysis and Monte Carlo simulations in one software solution.

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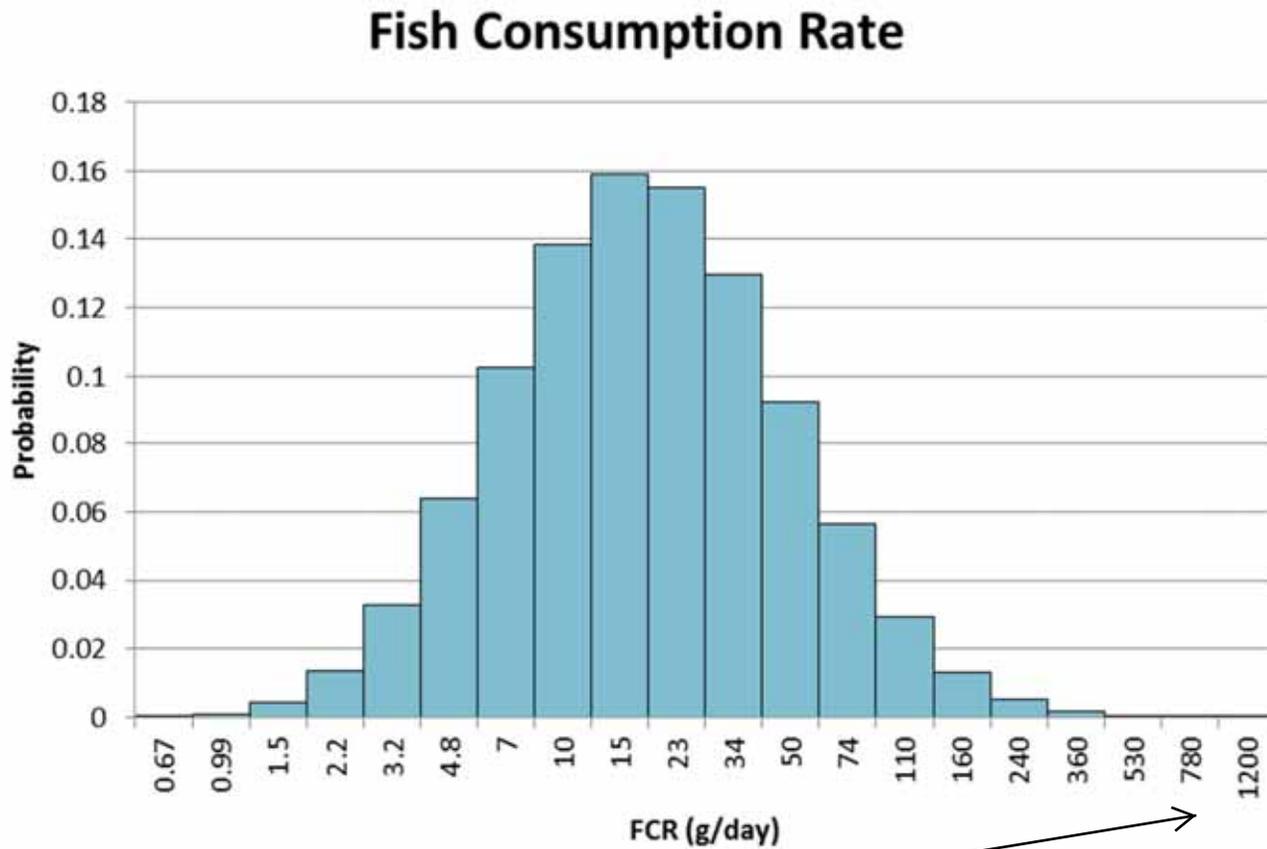
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# Attachment C - Example Fish Consumption Rate Distribution



Very high fish consumers are included in a PRA analysis

# Attachment D - PRA Calculates Risks for an Entire Population

## Heptachlor Excess Lifetime Cancer Risk

