The value of an engineering simulation solution is intrinsically tied to the level of engineering insight it provides. While the validity of the modeling approach, the model inputs, and simulation processes are critical considerations, engineering insight fundamentally depends on the quality and volume of simulation data produced. With the advent of high-performance computing, engineering simulations can now be deployed at-scale to explore the design space, understand the sensitivity of each parameter, and optimize engineering design under uncertain conditions.

As a case in point, suspension system design is a challenging analytics task, due to the essential need for tradeoffs between competing design objectives and the uncertainty surrounding each aspect of the bridge. For example, ride quality and handling have different optimization norms; the firmer the suspension means better control of body movements but lower ride quality. Additionally, each objective comes with its own form of uncertainty such as material properties of the concrete, steel and aluminum and the loading applied to the bridge. So how does one handle the uncertainty surrounding the design objectives using an engineering simulation?
Sources of uncertainty

Before diving headlong into the value that UQ brings to the MSC portfolio, let’s identify various sources of uncertainty which can be divided into two broad categories, aleatoric and epistemic.

Aleatoric is derived from the Latin alea or dice, referring to a game of chance. Aleatoric uncertainties stem from the natural variability of things and cannot be reduced by more information or making changes to the process under consideration. Many simulation models contain aleatoric or random inputs. In Additive manufacturing aleatoric uncertainty is often found in the types of materials and the 3D printing process used. Below are some sources of layer-by-layer aleatoric uncertainty found in a powder bed method such as selective laser sintering (SLS).

- Variability in the radius of powder particles
- Fluctuation of laser scan speed
- Variation of mechanical and material properties of the powder
- Uncertainty of the absorption coefficient
- Variation in the temperature boundary condition
- Measurement errors

These sources of uncertainty can affect the material properties of the completed part leading to part-to-part variation in structure and tensile strength. UQ would be able to capture the uncertainties at the layer-by-layer level to better understand what causes the final material properties variation.

Epistemic uncertainty originates from knowledge that is currently unknown, as it is expensive or difficult to obtain. In the context of simulation models, it can be divided into two main categories: data uncertainty and model uncertainty. Data uncertainty is the result of only having access to a limited amount of data or data with imprecise measurements. For example, in vehicle dynamics simulations, interactions between the road and the tire has an impact on the predicted vehicle operation. Model input parameters related to the road type, soil properties, and tire inflation levels are impossible to comprehensively measure. Another source of data uncertainty is test data that is used for model calibration. Model outputs calibrated against this test data can be impacted by these uncertainties.
Model uncertainty comes from a model’s inability to fully capture the behavior of the underlying system due to the approximations and assumptions made when building a model. These could be related to the formulation of the governing equations, an empirical assumption or perhaps the choice of a certain numerical solution algorithm. Better knowledge or understanding of a system can lead to a decrease in the epistemic uncertainty.

**Challenges in quantifying simulation model uncertainties**

**Large numbers of variables**
Quantifying simulation uncertainty is a multi-dimensional problem. A simulation model consists of multiple models and sub-models each consisting of multiple input variables. Furthermore, the effect of these uncertainties on a large number of output responses needs to be tracked. Capable uncertainty quantification methods would therefore have to solve high dimensional problems that require large datasets. This is especially true for systems simulation models like Adams that are assembled from various parts and sub-systems with a large set of parameters in each.

**Limited computational resources**
While high performance computing systems are pervasive in the simulation industry today, the load on these systems needs to be judiciously managed to cater to the needs of multiple different simulation stakeholders within the organization. To capture the uncertainty in a complex system, a sizable number of simulation runs is needed. This requires an intelligent trade-off as handling large data sets can be computationally expensive but limiting the number of simulation runs can lead to inaccurate results.

**Limited modeling capabilities**
While engineering simulation is an integral part of the engineering development process, truly predictive virtual prototypes are still not the norm for various simulation applications. Models need to be supplemented with information gathered from physical prototyping to calibrate the model response and to improve the fidelity of various sub-models through empirical information. This presents unique model uncertainty quantification challenges due to the presence of both simulated and empirical information in the model.

**Limited experimental resources**
Experimental information can obviously reduce the epistemic model uncertainty that practitioners frequently encounter. However, experimentation and physical testing have the obvious overhead of cost and time and would need to be utilized prudently. Furthermore, using testing to reduce the uncertainty in simulation models runs counter to industry-wide initiatives, to substitute tests with simulations.

Though there are many model uncertainty challenges in engineering simulation, the right techniques can bound the uncertainty while also minimizing the volume of computational and physical data required.

**MSC Software and SmartUQ**
The strategic partnership between MSC software and SmartUQ will bring SmartUQ’s cutting edge uncertainty quantification techniques to the entire MSC product portfolio. The first product level integration with Adams is already in place. Adams users can now use SmartUQ to quantify the effect of environmental, physical or manufacturing uncertainties on their Multibody dynamics models. Integrations with Digimat and Nastran for materials and structural uncertainty quantification are also completed.

**SmartUQ - a powerful uncertainty quantification solution**
A true uncertainty quantification solution should include a range of functionality that empowers high-impact decision making, to improve design cycles.

**Design of experiments and data sampling**
Several data sampling techniques and a comprehensive library of advanced DOE (design of experiments) generators for both simulation and physical experiments is available in SmartUQ. A differentiator is a subsampling tool for Big Data applications and Adaptive Design, which maximizes sampling efficiency by using already gathered data to select additional data points.

**Emulation**
In lieu of expensive Monte Carlo sampling and hours long wait-times for analytic calculations, SmartUQ employs emulators or statistical predictive models to predict the behavior of complex black-box computational and physical systems. This approach enables extremely fast uncertainty propagation, sensitivity analysis, optimization, statistical calibration, and design space exploration.

**Statistical calibration**
SmartUQ quickly and automatically determines model calibration parameters even with limited simulation and test data. It provides model discrepancy measurements to identify opportunities for improvement and provides metrics for model validation. As a result, the tool is critical for decreasing design cycles by limiting the number of tests required to understand complex systems.
Sensitivity analysis
SmartUQ’s sensitivity analysis toolkit helps rapidly determine which factors have a relatively low or high impact on the design space, allowing engineers to focus efforts appropriately.

Optimization
Using adaptive sampling techniques and analytical models, this feature enables rapid search area reduction with multiple objectives as well as the ability to run through very large numbers of input parameters. It’s another tool for shortening test cycles.

Inverse Analysis: This capability, which determines the probability distribution of an input results in a set of outputs from a system, and helps verify hard-to-measure system properties.

Uncertainty Propagation: The heart of the system, this set of features helps engineers determine whether system outputs will meet requirements, what the extreme probabilities really are, and which inputs have the most significant effect on output distributions.

A detailed workflow of the Adams SmartUQ integration is shown below.

The workflow starts out with a design of experiment (DOE) in SmartUQ. With the DOE and the results from Adams, SmartUQ can generate an emulator that is a virtual representation of a system and can be quickly sampled to perform advanced analytics.

To start the analysis portion, a sensitivity analysis is performed to determine which parameters have the largest impact on the output parameters and which parameters are less important or can be ignored in future analyses. Next, an optimization procedure is performed to determine a design configuration that minimizes a certain vehicle response (e.g., roll angle and yaw rate). To verify the optimal input configuration, the input parameters are run through the Adams simulation model, and the emulator and simulation model results are compared. Finally, uncertainty propagation is performed to validate the design configuration.

As a form of reliability analysis, uncertainty propagation calculates the uncertainty in a system’s outputs based on the uncertainty associated with each of the system’s inputs. An array of different distribution options including normal distributions can be assumed for the system inputs. The uncertainty propagation draws 100,000 random samples from the distributions through the emulator. SmartUQ can make these predictions in about 10 seconds, whereas it would be computationally challenging to run 100,000 samples through the physics-based simulation to perform the uncertainty propagation.

Once the uncertainty propagation is completed, one can then determine the probability that the design will not exceed a specific performance metric. For example, there is a hypothetical risk of the vehicle tipping over or spinning out of control if the maximum yaw rate exceeds 29.5. Based on the above figure, the maximum yaw rate of 29.5 will not be exceeded approximately 98.6% of the time. If this is an acceptable rate, then decision makers can confidently move forward with the design. If this is not acceptable based on the severity of the outcome, then the results from the sensitivity analysis can be used to determine what manufacturing tolerances need to be tightened to achieve acceptable results.

The partnership between MSC Software and SmartUQ continues to evolve and will soon include multiple different products in the MSC product portfolio. By leveraging SmartUQ’s ground-breaking uncertainty quantification techniques, MSC software users can add a layer of knowledge and context to the simulation data that can help in identifying potential design problems or incorrect models.