

Leverage SmartUQ to achieve modern artificial intelligence and machine learning for simulation and digital twins

by Gavin Jones SmartUQ

Simulation is of course widely used to great benefit by engineers in all industries; however, the effective use of simulation does still face challenges which artificial intelligence and machine learning (ML) can help with.

Simulations can for example have long run times that limit the types of analyses that can be performed as well as the number of inputs, scenarios, and design possibilities that can be explored. The accuracy of simulations is also affected by uncertainty regarding, for example, initial conditions, boundary conditions, and model parameters. SmartUQ has best-in-class, unique tools to address all these challenges.



Fig. 1. SmartUQ's MultiView of an ML model showing prediction with a 95% confidence interval and uncertainty propagation.

ML models

One approach to address long simulation run times is to train an ML model to predict the results of the simulation. This is sometimes referred to as surrogate modelling. Once trained, such an ML model can predict the outcomes much more rapidly than the required run time for the simulation thus eliminating the limits on the types and depths of analyses that can be performed.

The effectiveness of this approach largely depends on the accuracy of the ML model's predictions compared to the simulation results: SmartUQ's ML models have best-in-class prediction accuracy.

The company has also developed unique ML model variants for situations common to engineering problems. For example, SmartUQ's Spatial/Temporal predictive model can rapidly create accurate ML models for data sets that have a spatial distribution to the outputs - such as for an FEA (finite element analysis) that needs to predict the stress at every node.





Design of experiments (DOEs)

Training an ML model of a simulation requires some simulations to be run to collect training data. This is particularly challenging for simulations with longer run times and larger numbers of inputs where it may not be possible to collect sufficient training data.

SmartUQ addresses this challenge in two ways. Firstly, its more accurate ML models require less data to achieve the desired prediction accuracy for a given problem. Secondly, by using modern DOEs such as Latin Hypercube Designs (LHDs), SmartUQ offers more efficient DOEs with unique options to minimize the amount of data



Fig. 2. SmartUQ sliced design of experiments with 5 inputs and 40 total samples.

About SmartUQ

required to train an accurate ML model, such as by allowing data to be collected in efficient batches (Fig. 2), or by permitting complicated constraints on the problem's input space.

The product also features adaptive sampling techniques that can use an existing ML model to intelligently decide where further data should be collected to have the largest effect on improving the ML model's accuracy.

Statistical calibration

Simulations and ML models that predict simulation results are only useful if their results agree well with physical data such as test or experimental results.

Calibrating simulation to physical data is key to creating and maintaining accurate digital twins. Typical approaches to calibrating simulation models can be time consuming and, worse, often unsuccessful because they only focus on parameter uncertainty either through a manual or an optimization process.

The goal of these approaches is to find the best values for model parameters to obtain the closest agreement with the available physical data. However, this approach ignores the role that model form error plays when there is disagreement between simulation and physical data. For example,

SmartUQ is a Machine Learning (ML) and Artificial Intelligence (Al) tool optimized for engineering applications from ideation and design to manufacturing and sustainment. By providing powerful tools and accurate ML models with user-friendly interfaces, SmartUQ makes it easy to perform predictive modelling, optimized sampling, uncertainty quantification (UQ), and model calibration. From Fortune 500 manufacturers to startups and engineering consulting firms, SmartUQ's best-in-class predictive modelling accuracy helps our customers go beyond analysis to include uncertainty in the decision-making process.

SmartUQ was originally developed to solve UQ challenges for a leading jet engine manufacturer because previous tools could not handle the complexity, scale, and high-dimensionality of their problems. Since then, SmartUQ has become a user-friendly general AI and machine learning tool with users across industry and government in Automotive, Aerospace & Defence, Turbomachinery, Heavy Equipment, Medical Device, Semiconductors, Consumer Electronics, Energy, and Oil & Gas.

The team is headed by world-class experts in statistics and engineering who take pride in creating game-changing solutions where no off-the-shelf solutions exist. Our software has helped our customers solve some of their most difficult analytics problems, saving millions of dollars and thousands of hours of work. **Visit smartuq.com** if a linear material model has been selected for a situation that would normally use a nonlinear material model, it may be impossible to select parameters to obtain results that agree well with the physical data.

SmartUQ's statistical calibration features account for parameter and model form uncertainty; they can also accommodate the uncertainty in calibration results arising from noise in the physical data being used.

Analytics

Once trained and calibrated (if required), the ML model is ready to be used for analysis. SmartUQ makes performing a large variety of analyses quick and easy. Sensitivity analysis helps identify the inputs with the greatest



Fig. 3. Results of global sensitivity analysis showing main effects (size of blue circles), total effects (size of orange circles), and strength of two-way interactions between inputs (line thickness).

influence on the outputs (see Fig. 3), while uncertainty propagation can quantify the ambiguity in results due to uncertainty in inputs, for example, the uncertainty in peak stress resulting from uncertainties in geometry and loading. SmartUQ's stochastic and reliability-based optimization can even take such input uncertainties into account as part of the optimization.

SmartUQ is available with both a userfriendly GUI or as a Python API.

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