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STATISTICAL CALIBRATION: A BETTER APPROACH TO INTEGRATING SIMULATION AND TESTING IN GROUND VEHICLE SYSTEMS.

David Aguilar
Mark Andrews, PhD
Brian Leyde
SmartUQ LLC
Madison, WI

ABSTRACT

Computer models and simulations have become an indispensable tool for solving complex problems in many parts of vehicle development including powertrain engineering, mobility assessment, survivability analysis, and manufacturing and life cycle assessment. As computational power has increased and model accuracy has improved, engineers have come to depend on simulations to investigate and characterize systems. This raises the importance of model calibration and validation. Calibration is the process of tuning model parameters which are not directly measured in physical tests. These parameters maybe physical properties (material and soil properties, manufactured dimensions, engine operating points) which are difficult to measure or entirely non-physical model parameters. Calibration is necessary to ensure that models and simulation results are as close to physical reality as possible given modeling limitations and assumptions. This paper presents a calibration framework which implements automated statistical calibration using kriging emulators. Through a combination of advanced experimental designs and numerical techniques, this framework greatly reduces the computation required to fit emulators. The utility of this framework is demonstrated with examples including the calibration of turbo machinery simulations. Several different methods within the framework are also demonstrated: agreement and linkage based calibration, and automated sensitivity analyses.

INTRODUCTION

Computer models and simulations have become an indispensable tool for solving complex problems in many parts of vehicle development including powertrain engineering, mobility assessment, survivability analysis, and manufacturing and life cycle assessment. As computational power has increased and model accuracy has improved, engineers have come to depend on simulations to investigate and characterize systems. This raises the importance of model calibration and validation.

Calibration is the process of tuning model parameters which are not directly measured in physical tests. These parameters maybe physical properties (material and soil properties, manufactured dimensions, engine operating points) which are difficult to measure or entirely non-physical model parameters. Calibration is necessary to ensure that models and simulation results are as close to physical reality as possible given modeling limitations and assumptions [1].

Next generation simulation tools are including even more detailed physics, greater complexity, and more parameters. Physical tests, though relatively expensive and slow, have also benefited from advances in electronics and are now able to produce massive amounts of data. Extremely detailed vehicle telemetry is common and handling it has become a question of big data analysis. These trends towards more complex models and large physical test data sets present new challenges and opportunities when calibrating models [2].

Traditional automated calibration methods rely on computing correlation coefficients, R^2 values etc., or calculating an error term and then using optimization techniques to maximize the correlation or minimize the error. For complex simulations, where there are many possible calibration parameters, this becomes a computationally intensive high-dimensional optimization problem. Thus it is often necessary to limit the number of parameters being considered via experience/domain expertise or analytic methods such as sensitivity analysis. Similarly, when large quantities of test data are available, it is often necessary to create summary variables or selective sub-samples again requiring significant expertise and data handling capability.

Statistical calibration methods have several important advantages over more traditional approaches. First, it allows for all sources of uncertainty, including the remaining uncertainty over the fitted parameters. Second, it can determine the discrepancy between the model and the observed data for optimized calibration parameters. Determining model discrepancy is useful for highlighting inadequacies in models and, by demonstrating low discrepancy, model validation [3].

Unfortunately, statistical calibration methods are also computationally intensive, exacerbating the increase in computational difficulty from increasing the number of calibration parameters. This paper presents a calibration framework which implements automated statistical calibration using kriging emulators. Through a combination of advanced experimental designs and numerical techniques, this framework greatly reduces the computation required to fit emulators. This allows accurate emulators to be constructed for large numbers of input points and high dimensional system. These emulators are then used as surrogates for the physics-based model in the statistical calibration process. Evaluating the emulator in place of the physics-based model can reduce the computational effort and time required for statistical calibration by orders of magnitude [4].

The utility of this framework is demonstrated with a closed form analytical examples with structural similarity to an engine exhaust model and with a GT-Power [5] model of a single cylinder diesel engine [6]. Several different methods within the framework are also demonstrated: agreement and linkage based calibration and automated sensitivity analyses.

EXAMPLE: CLOSED FORM EQUATION

As a test example consider the following function:

$$y(x,c) = c_1 \frac{exp\big(c_2 * (x_1 + x_2)\big)}{3} + c_3 x_4 \sin(c_4 x_3) + c_2 c_4 x_3 \tag{1}$$

where $x = (x_1, \ldots, x_4)$ and $c = (c_1, \ldots, c_4)$ are calibration parameters. The surface produced by this function has similar complexity and structure to that of many semi-cyclical gas flow and concentration models such as engine exhaust streams.

Simulation data were collected by evaluating the function with an optimal LHD DOE of 300 points cover the full ranges of x and c. Simulated ‘field data’ were collected by evaluating the function with a DOE of 70 points covering the full range of x while fixing all c values at ‘true’ values of (2,1, -1, 1).

To determine the ‘unknown’ true values of the calibration parameters from the simulated field data an agreement-based statistical calibration method was employed. Calculating the calibration parameters took approximately 2 seconds per iteration. We replicated the calibration process 100 times, taking approximately 3.5 minutes, to reduce noise from the stochastic nature of the calibration process. The averaged results are summarized in Table 1. The calibration parameter estimates are very close to the true values, indicating a good fit.

Table 1: Summary of estimated calibration parameters over 100 replications.

Parameters	True value	Mean	Std. Error
c_1	2	2.02	0.065
c_2	1	0.99	0.018
c_3	-1	-1.04	0.056
c_4	1	0.99	0.033

The discrepancy of the calibrated model from the simulated field data was calculated and plotted in Figure 1. The discrepancies are small and centered around zero indicating, as is expected in this case, that the emulator is capable of fully explaining the field data.

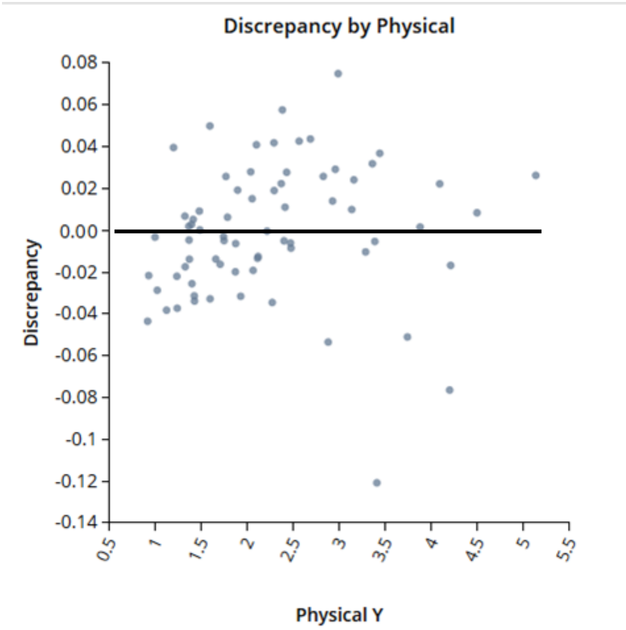

Figure 1: Result point calibration discrepancy plot

EXAMPLE: LINKAGE VS AGREEMENT BASED CALIBRATION METHODS IN A 1D ENGINE MODEL

In this example a single cylinder direct injection compression ignition engine was modeled using GT-Power. The piston geometry is shown in Figure 3 and the GT-Power model information flow in Figure 2. Seven Inputs were parameterized: Bore, Stroke, Connection Rod Length, Inlet Diameter, Compression Ratio, Injected Mass, and Injection Duration. The output of interest was the Break Mean Engine Pressure (BMEP) at 2000 [RPM].

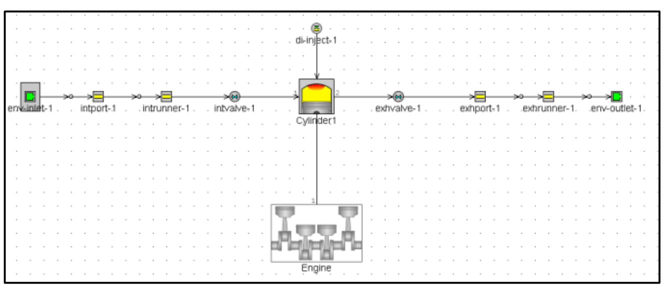

Figure 2: GT Power model diagram.

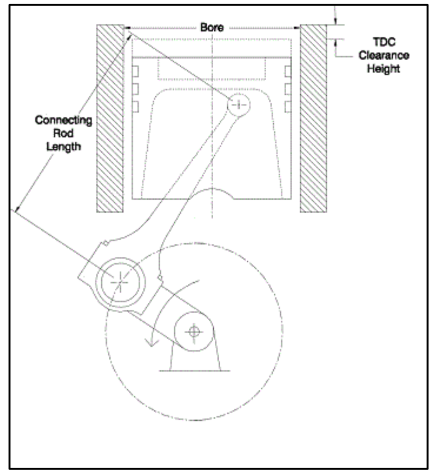

Figure 3: Cylinder geometry diagram.

A 200 point optimal LHD, Figure 4, was used to collect simulation data from the engine model based on the ranges for the seven input parameters specified in Table 2.

Table 2 GT Power Model Input Parameters

Input Parameter	Lower Limit	Upper Limit	Unit
Bore	70	110	[mm]
Stroke	60	100	[mm]
Rod Length	120	190	[mm]
Comp. Ratio	10	20	[-]
Inlet Diam	35	45	[mm]
Injected Mass	50	110	[mg]
Injection Duration	10	25	[deg]

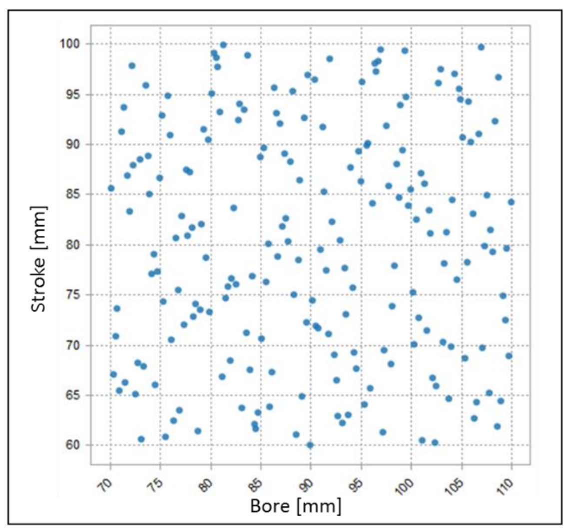

Figure 4: Simulation DOE Optimal LHD with 7 dimensions and 200 Runs

The simulated 'experimental data' consisted of a 100 run optimal LHD covering the entire range for six of the input parameters and holding the fuel injection mass constant at 60 [mg].

Two separate statistical calibration techniques were used to calculate optimal calibration parameters to match the simulation and field data. The first was agreement-based calibration, which is well suited for noisy, low bias settings. The second was linkage-based calibration, which is well suited to high bias settings.

As would be expected when using unbiased simulated field data, the agreement based method did significantly better than the linkage-based method with calculated fuel mass injection values of 59.95 [mg] and 65.04 [mg] respectively. This is reflected in the discrepancy by physical plots shown in Figure 5 and Figure 6. While both methods had small relative discrepancies, the agreement based method produces discrepancies that appear more or less randomly centered around 0. The linkage based method resulted in increased bias and a clear pattern in the discrepancy values.

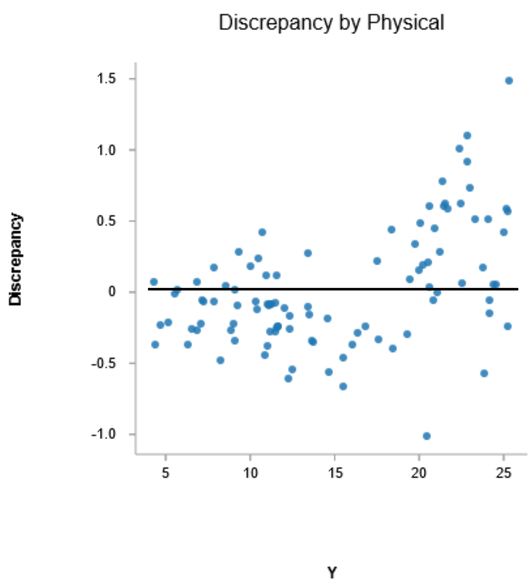

Figure 5: Discrepancy plot for the agreement-based calibration.

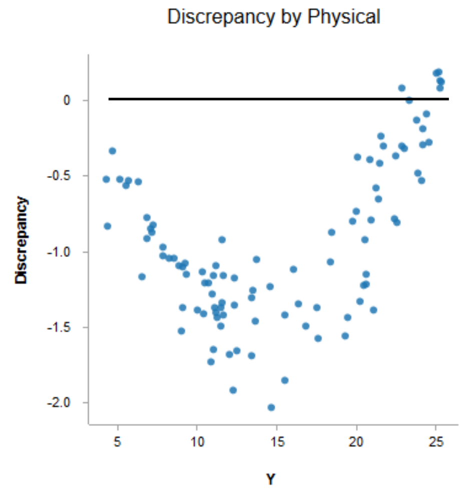

Figure 6: Discrepancy plot for the linkage-based calibration

In addition to testing the effects of the two different calibration methods, the 200 points from the simulation DOE were also used to construct an emulator. This highlights the utility of using expensive data sets for multiple purposes. The emulator took 0.9 [s] to construct and was relatively accurate with a CV Error of 0.28 [-]. Once constructed the emulator was used to explore the model design space, Figure 7, and test the domain wide sensitivity of the BMEP to the input variables, Figure 8.

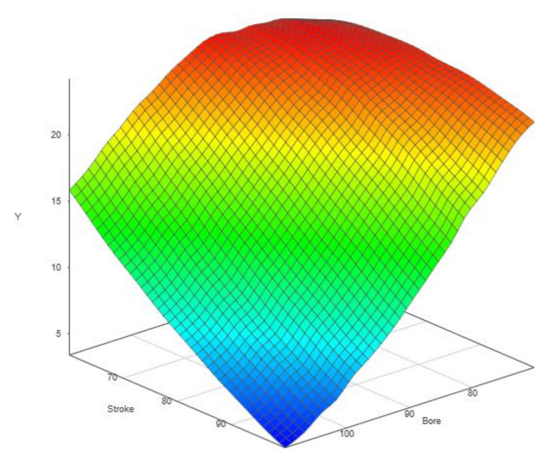

Figure 7: BMEP plotted as a function of Stroke and Bore while holding all other variables constant at the center of their ranges.

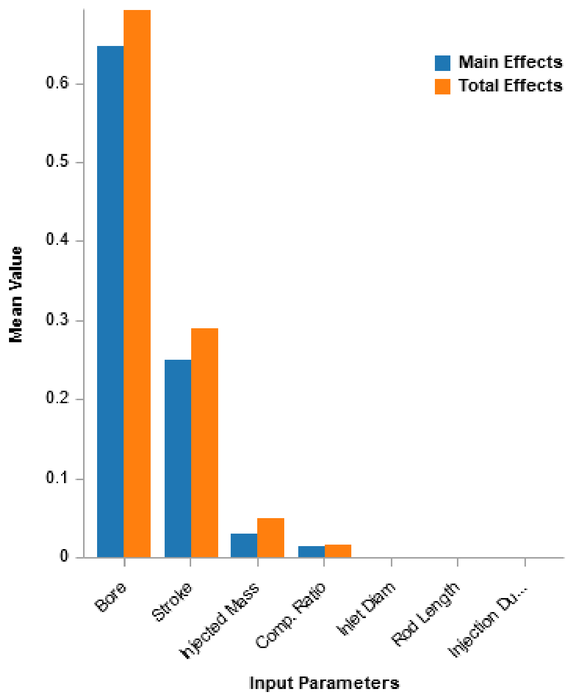

Figure 8: Main and total effect sensitivity indices for BMEP.

The sensitivity analysis results indicate that the variation in BMEP over the entire design region is mostly the result of changes in the Bore diameter, followed by Stroke length. Injected Mass and Compression Ratio each had a small impact while injection duration, air inlet diameter, and rod length all had negligible impact.

CONCLUSION

Calibration is the process of tuning model parameters which are not directly measured in physical tests. Calibration is necessary to ensure that models and simulation results are as close to physical reality as possible given modeling limitations and assumptions.

Statistical calibration methods allow all sources of uncertainty, including the remaining uncertainty over the fitted parameters to be included in the calculations. They also determine the discrepancy between the model and the observed data for optimized calibration parameters. Determining model discrepancy is useful for highlighting inadequacies in models and, by demonstrating low discrepancy, model validation.

The examples presented illustrate the importance of calibrating the model before performing additional analyses such as a forward propagation of uncertainty and using these data in a decision process.

For the 1D engine model, the agreement-based method did significantly better than the linkage-based method with calculated fuel mass injection values of 59.95 [mg] and 65.04 [mg] respectively. Without knowing the true values of the calibrated parameter, fuel mass injected, we may still determine that the agreement based calibration method is more accurate based on the smaller and more randomly distributed discrepancies. Though the superiority of agreement based methods is expected from the nature of the simulated field data being used in the calibration, this example highlights both the importance of selecting appropriate calibration measures and the necessity of using calibration methods which allow determination of the discrepancy of calibrated models.

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