Evaluating and Quantifying Uncertainty

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References

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Measurement Uncertainty — Pitot Tube MEASUREMENT EQUATION

• Airspeed
$$v = \sqrt{\frac{2\Delta R_s T}{p}}$$



- △ Difference between total and static pressures
- T Air temperature
- *R*_s Specific gas constant for dry air
- *p* Static air pressure

Measurement Uncertainty — Pitot Tube INPUTS & UNCERTAINTY EVALUATION

INPU	TS		
	ESTIMATE	STD. UNC.	MODEL
Δ	1.993 kPa	0.0125 kPa	Gaussian
р	101.4 kPa	1.05 kPa	Lognormal
Т	292.8 K	0.055 K	Gaussian
Rs	$287.058{ m Jkg^{-1}K^{-1}}$	$0.114823{ m Jkg^{-1}K^{-1}}$	Gaussian

EVALUATION

- NIST Uncertainty Machine (uncertainty.nist.gov)
- Gauss's Formula (GUM) and Monte Carlo Method (GUM-S1) produce same results: v = 40.6 m/s and u(v) = 0.25 m/s

Measurement Uncertainty — Pitot Tube

NIST UNCERTAINTY MACHINE - INPUT

Delta	р	Т		Rs	
Update quantity nar	nes				
Delta Gaussian (M	lean, StdDev)		• 1.993	0.	.0125
p Lognormal (N	Mean, StdDev)		• 101.4	1.	05
T Gaussian (M	lean, StdDev)		• 292.8	0.	.055
Rs Gaussian (M	lean, StdDev)		• 287.0	58 0.	.114823
Number of realiza	tions of the output qua	antity: sqrt(Delta*Rs*T	/p)		

		sgrt(Delta*Rs*T	/p)		

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Measurement Uncertainty — Pitot Tube NIST UNCERTAINTY MACHINE — OUTPUT

===== RESULTS ======	si -			
Monte Carlo Method				
Summary statistics for sample of size 5000000				
ave = 40.6462 sd = 0.2462 median = 40.6456 mad = 0.246	Probability Density			
Symmetrical coverage intervals	op op			
99% (40 , 41.3) k = 2.6 $95%$ (40.2 , 41.1) k = 1.8 $90%$ (40.2 , 41.1) k = 1.8 $68%$ (40.4 , 40.9) k = 1	re 0.5			
ANOVA (% Contributions)				
w/out Residual w/ Residual				
Delta 26.73 26.73	40.0 40.5 41.0			
p 73.14 73.13 T 0.02 0.02	Output quantity (Y)			
Rs 0.11 0.11				
Residual NA 0.01	Download binary R data file with Monte Carlo values of output quantity Download a text file with Monte Carlo values of output quantity Download text file with numerical results shown on this page			
Gauss's Formula (GUM's Linear Approximation)	Download JPEG file with plot shown on this page Download configuration file			
y = 40.6448 u(y) = 0.2462				

• *Observation equation* expresses measurand as known function of parameters of probability distribution of inputs

ALUMINA COUPONS



- Rupture stress in flexure test modeled as Weibull random variable with shape α and scale σ_C
- MEASURAND Weibull mean value $\eta = \sigma_{\rm C} \Gamma(1 + 1/\alpha)$

Measurement Uncertainty — Tensile Strength RESULTS

- Maximum likelihood estimates $\widehat{\alpha} = 10.1$, $\widehat{\sigma}_{\mathsf{C}} = 383 \,\mathsf{MPa}$
- $\widehat{\eta} = \widehat{\sigma}_{\mathsf{C}} \mathsf{\Gamma}(1+1/\widehat{\alpha}) = 365 \,\mathsf{MPa}$



- Monte Carlo (exact)
- Statistical Theory (approximate)



Experimental or computational process that, by comparison with a standard, produces an estimate of the true value of a property of a material or virtual object or collection of objects, or of a process, event, or series of events, together with an evaluation of the uncertainty associated with that estimate, and intended for use in support of decision-making — NIST TN 1900, §2

Measurement Uncertainty HEAT CAPACITY OF AMMONIA

We think our reported value is good to 1 part in 10000

We are willing to bet our own money at even odds that it is correct to 2 parts in 10000

Furthermore, if by any chance our value is shown to be in error by more than 1 part in 1000, we are prepared to eat the apparatus and drink the ammonia

— C. H. Meyers, 1930s

Told by D. P. Johnson, reported by H. Ku, 1973 Quoted by T. Doiron & J. Stoup, 1997 Doubt about the true value of the measurand that remains after making a measurement

— NIST TN 1900, §3

- Measurement uncertainty described fully and quantitatively by probability distribution on set of values of measurand
- Probability distribution represents state of knowledge:
 - Subjective construct that expresses how firmly metrologist believes she knows measurand's true value
 - Characterizes how degree of her belief varies over set of possible values of measurand

Uncertainty Quantification MATHEMATICAL MODELS & COMPUTER CODES

- Simulator $\mathcal S$ is model for system $\mathcal W$ in physical world
- Since S reproduces W only imperfectly or incompletely, its output is surrounded by margin of doubt (*uncertainty*)
- In many cases, each evaluation of S, and each observation of W, are very costly: impracticable to characterize uncertainty using conventional Monte Carlo methods
 - Build *Emulator E* that approximates *S* and can express all recognized sources of uncertainty in play

Including model uncertainty and uncertainty associated with model implementation in computer code

- Calibrate emulator using only modest number of runs of ${\cal S}$ or observations of ${\cal W}$

Simulator

• Costly evaluations of simulator φ_S to be calibrated using costly observations of physical world



Emulator

• Gaussian random function A_{α} whose evaluations are much less expensive than simulator's — inherits simulator's bias



Bias Estimation & Correction

• Bias is persistent effect modeled as another Gaussian random function B_{β} that is used to correct emulator



Bias-Corrected Emulator

• Uncertainty quantification is by-product of Bayesian procedure used to estimate bias-corrected emulator



- Uncertainty quantification (for mathematical models and computer codes) can be done using same technical devices used to characterize measurement uncertainty
- Gaussian random functions (of several variables) provide flexible, general purpose emulators
- Bayesian approach (typically employing Markov Chain Monte Carlo sampling) enables uncertainty quantification relying on modest numbers of evaluations of costly simulator and of costly observations of physical world system