APPLICATION OF AN INTEGRATED HIGH-PERFORMANCE COMPUTING RELIABILITY PREDICTION FRAMEWORK TO HMMWV SUSPENSION SYSTEM

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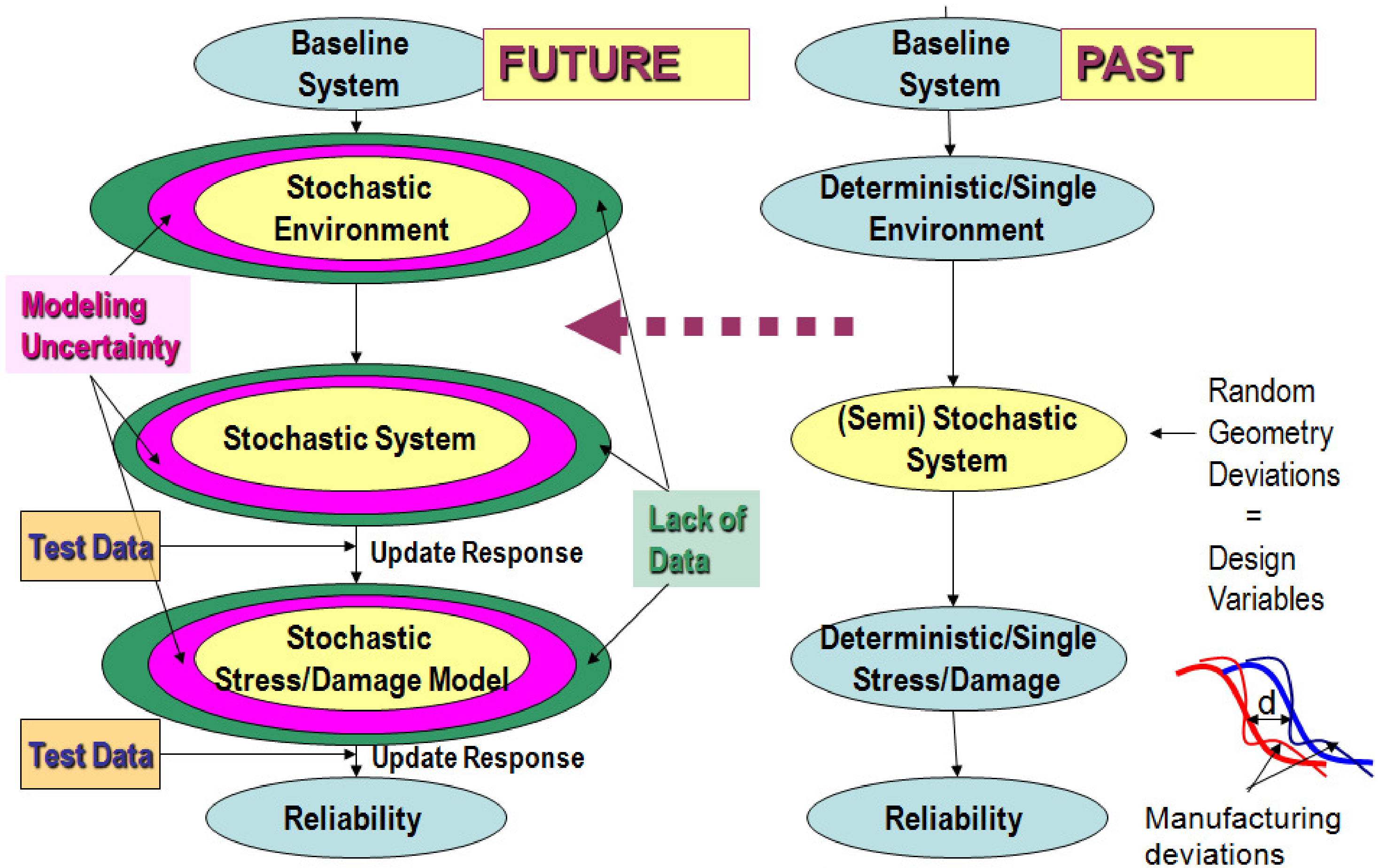
- Presentation Scope:
  - To present on overview of an integrated HPC stochastic physics-based framework that has been developed for vehicle reliability prediction.
  - Illustrative application to the HMMWV system

    DISCLAIMER: The HMMWV dynamic model and the suspension system configuration used in this research are slightly different than the actual HMMWV hardware.

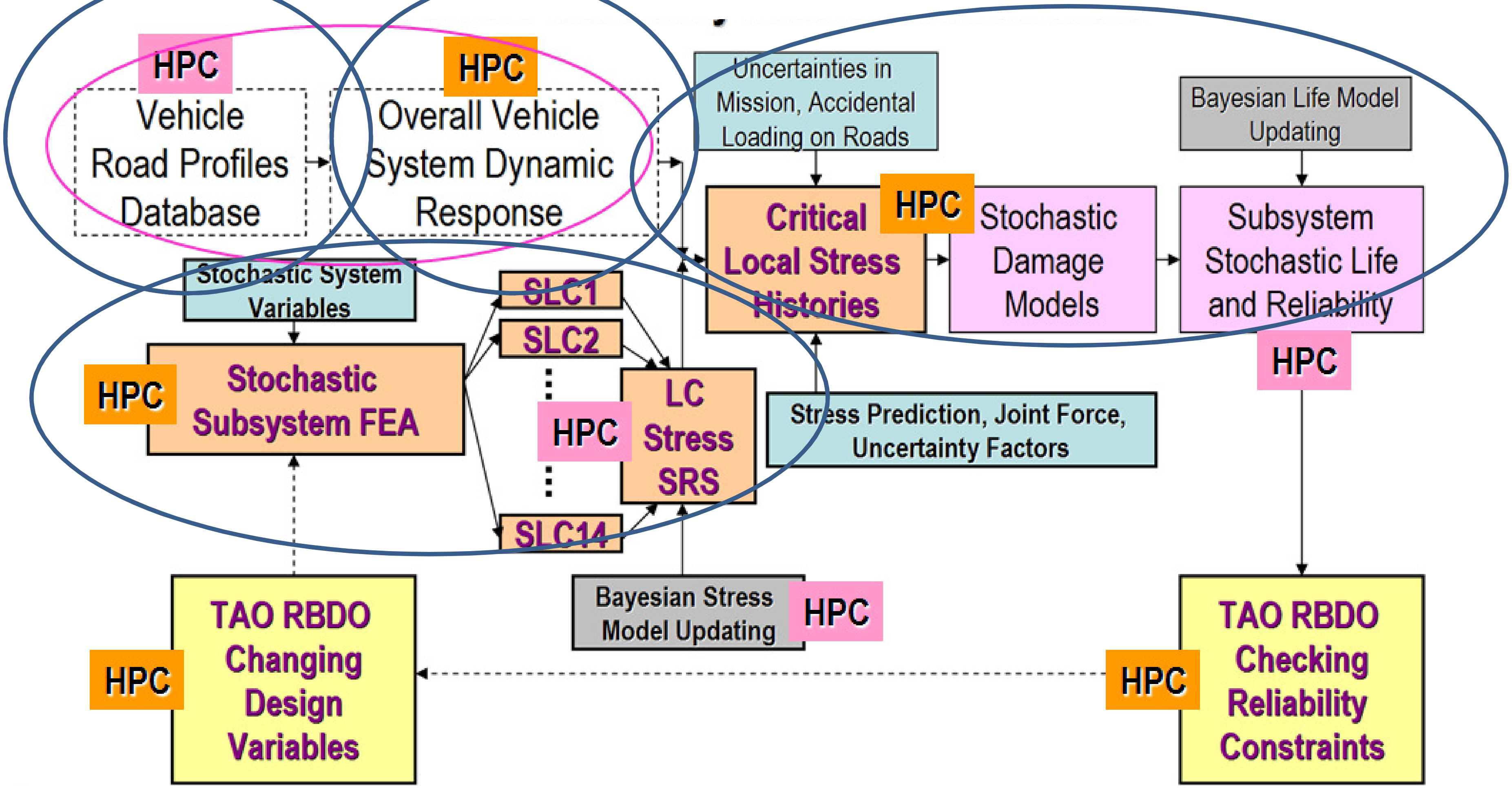
  - Focus on:
    - The front-left suspension system (FLSS)
    - Qualitative aspects and methodology, not on quantitative results

VEHICLE RELIABILITY PREDICTION MULTISTEP PROCESS



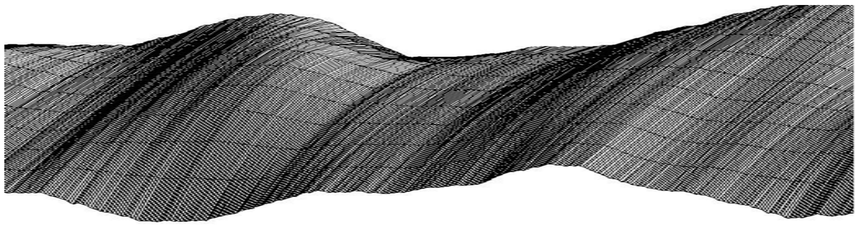
Note: HPC Future Need = 100…1,000 X Present HPC Need!

VEHICLE RELIABILITY IMPLEMENTATION CHART



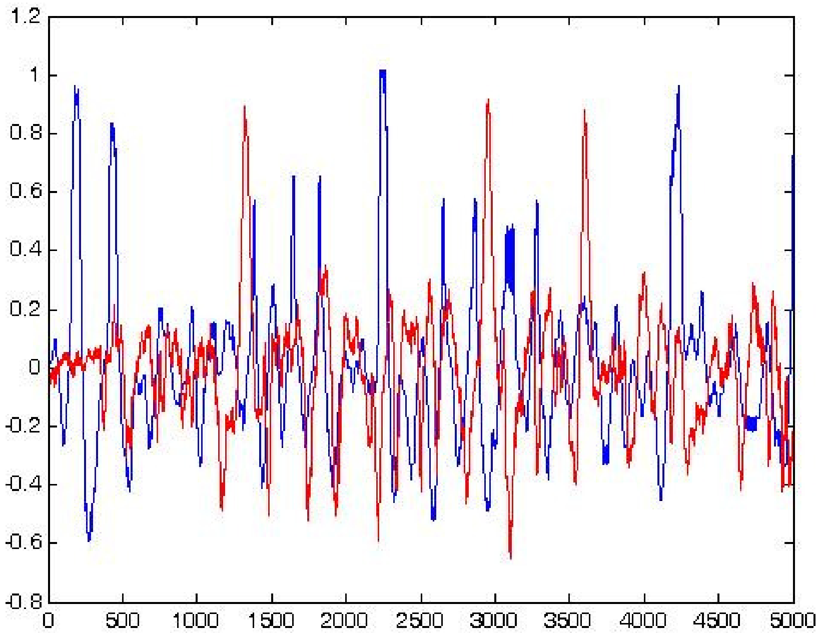
Stochastic Road Surfaces

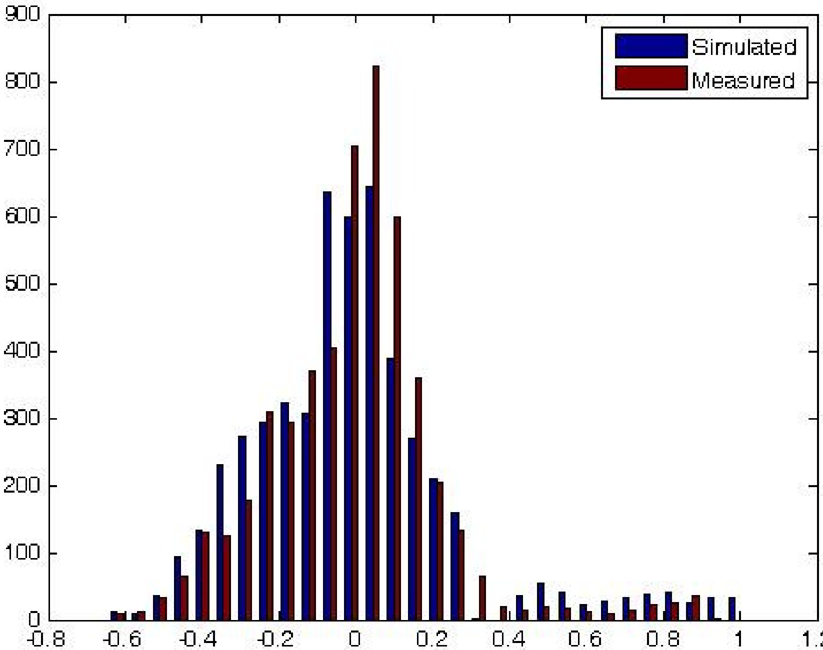
High Spatial Transverse Correlation



Low Spatial Transverse Correlation

Simulated vs. Measured Road Profiles





•With topography Effects; Smooth and Rough Stochastic Roads

Vehicle Behavior to Stochastic Road Surfaces

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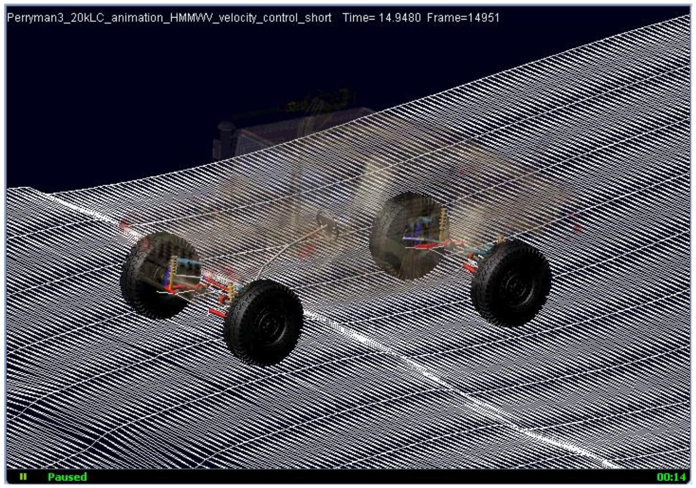
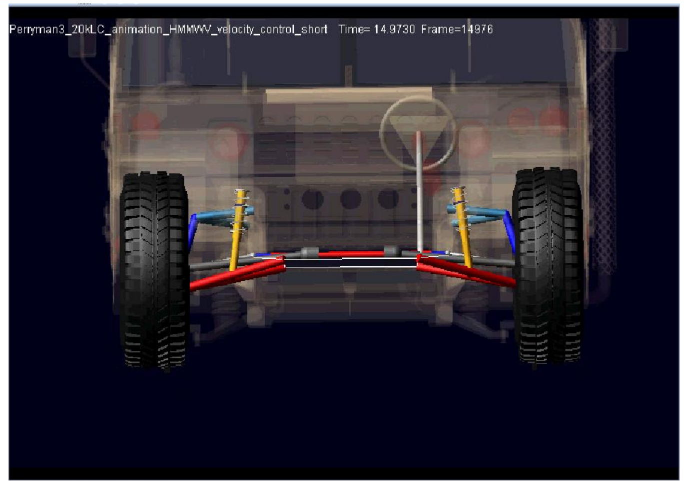
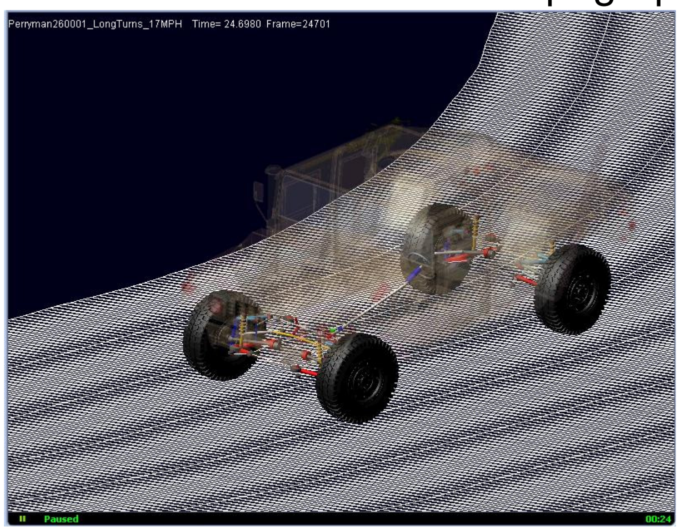
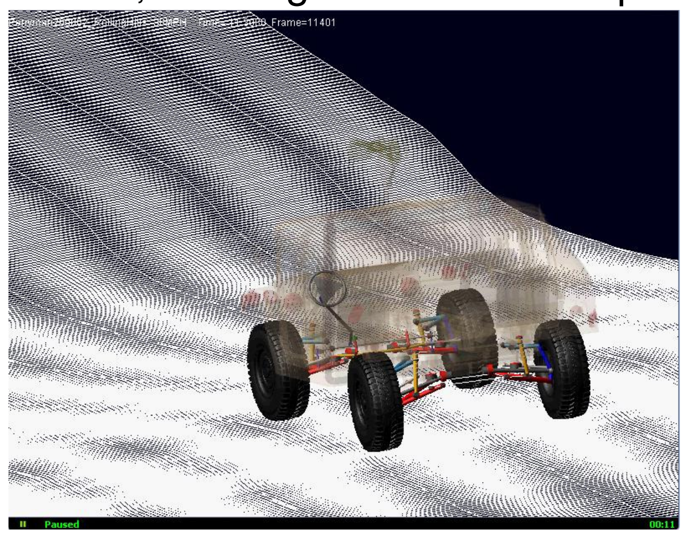




Flat road with no topography Effects; Passing a Random Bump

Using HMMWV Model





With topography Effects; Smooth and Rough Stochastic Roads

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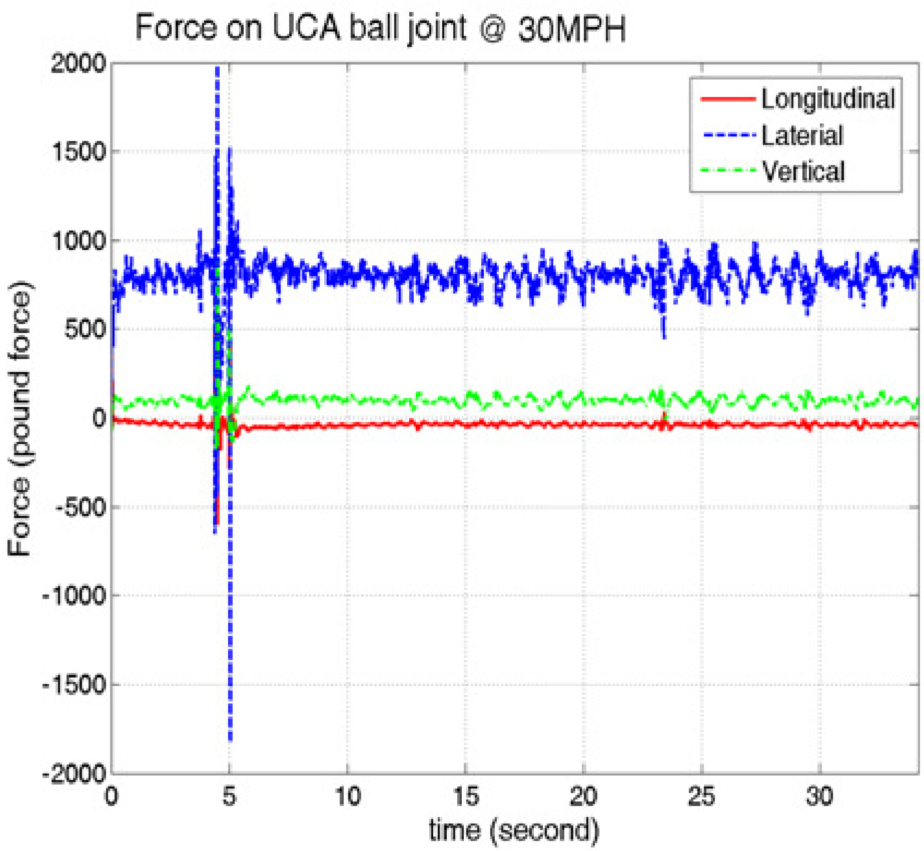
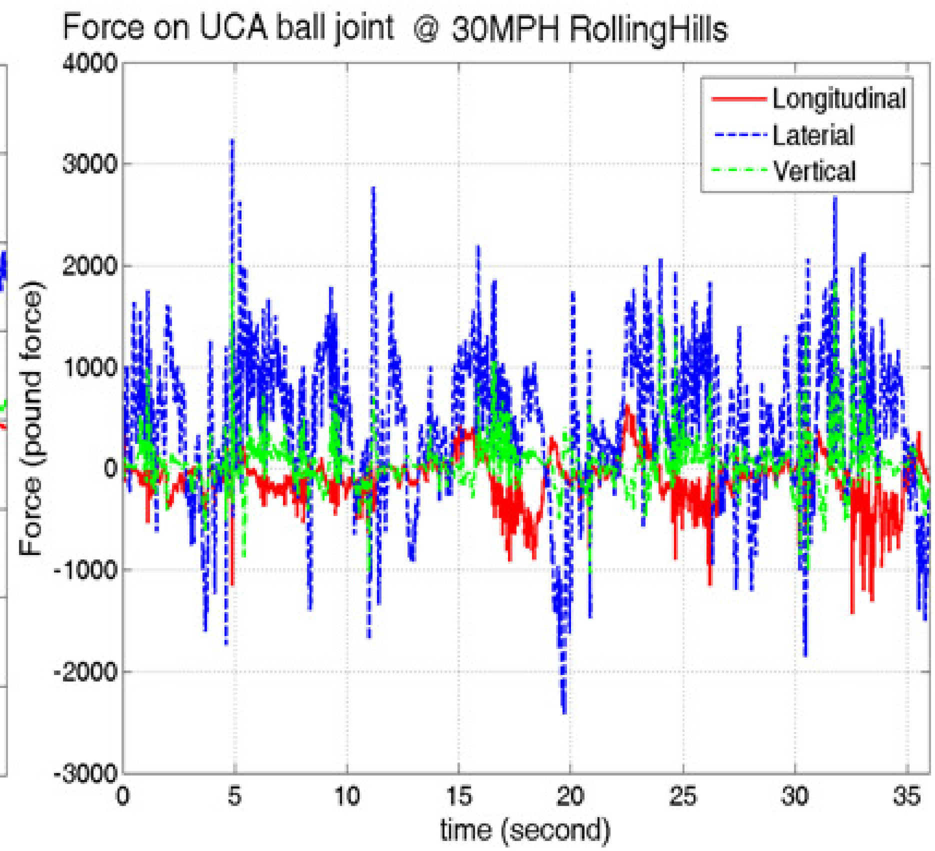
Effects of Road Topography on FLSS UCA Ball Joint Forces



Straight Road Segment

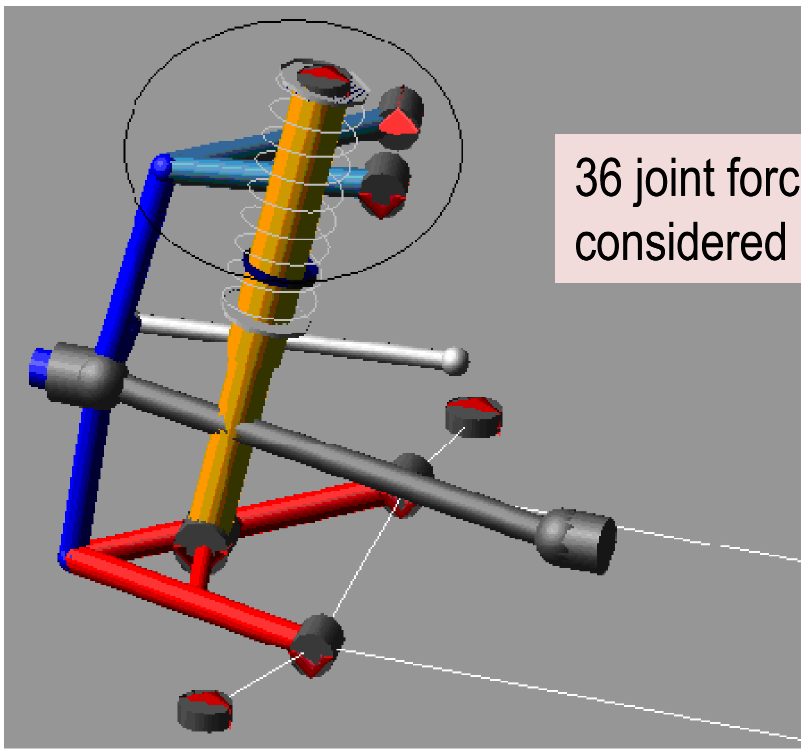


Rolling Hills Segment

FLSS ADAMS RBD Model and SPARTACUS FE Model

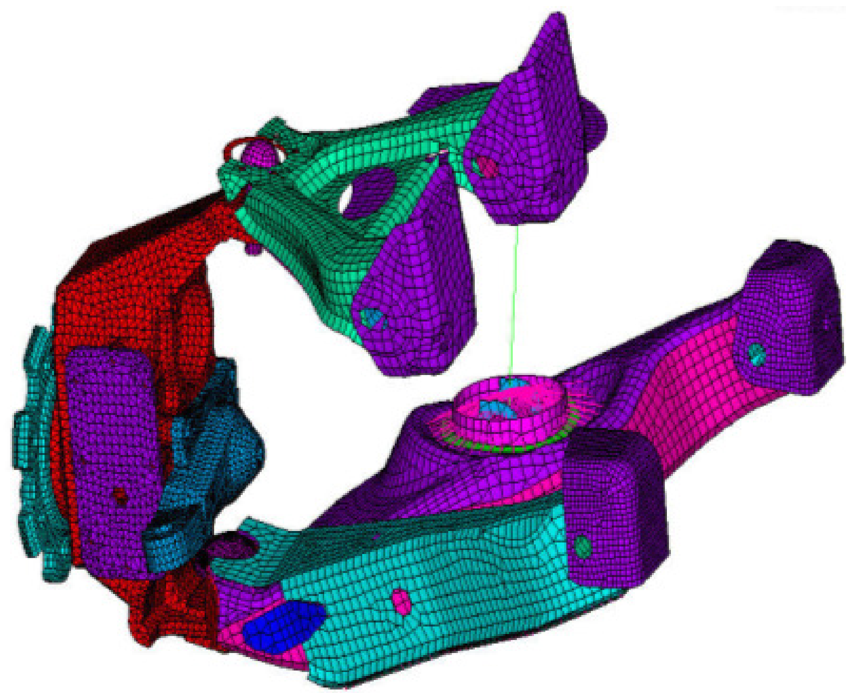
(36 Joint Component Forces/Moments Considered for FLSS)

ADAMS Model



36 joint forces considered

SPARTACUS Model



Stochastic FEA for Stress Computation

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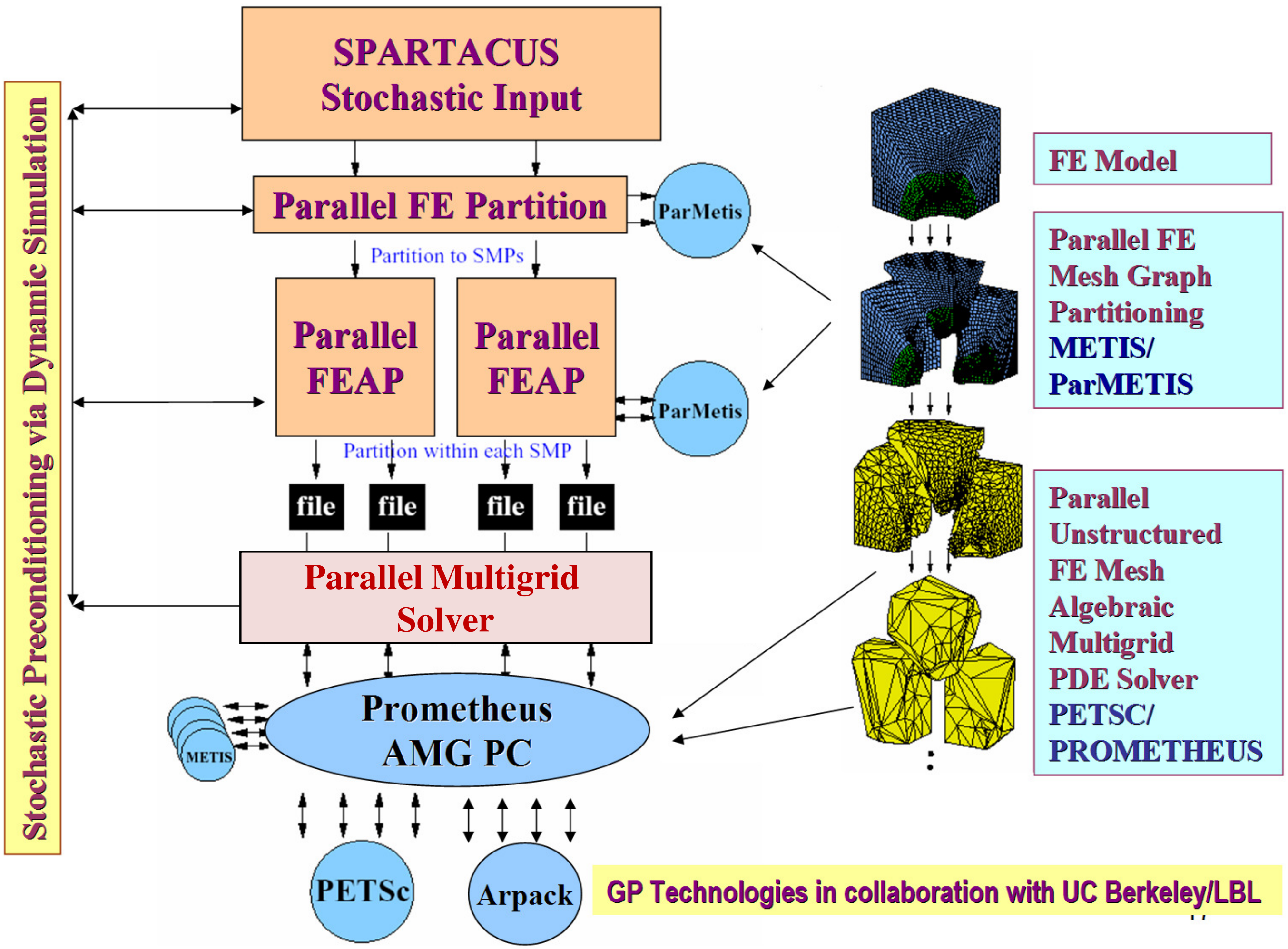
Stochastic PARallel Tool for Analysis of Computational Unstructured-Mesh Solids (SPARTACUS). Applicable to Large-Size FE Models.



GP Technologies in collaboration with UC Berkeley/LBL

Scalability for FEA Problems with100,000 to 20,000,000 Dofs

Scalability for FEA Problems with100,000 to 20,000,000 Dofs

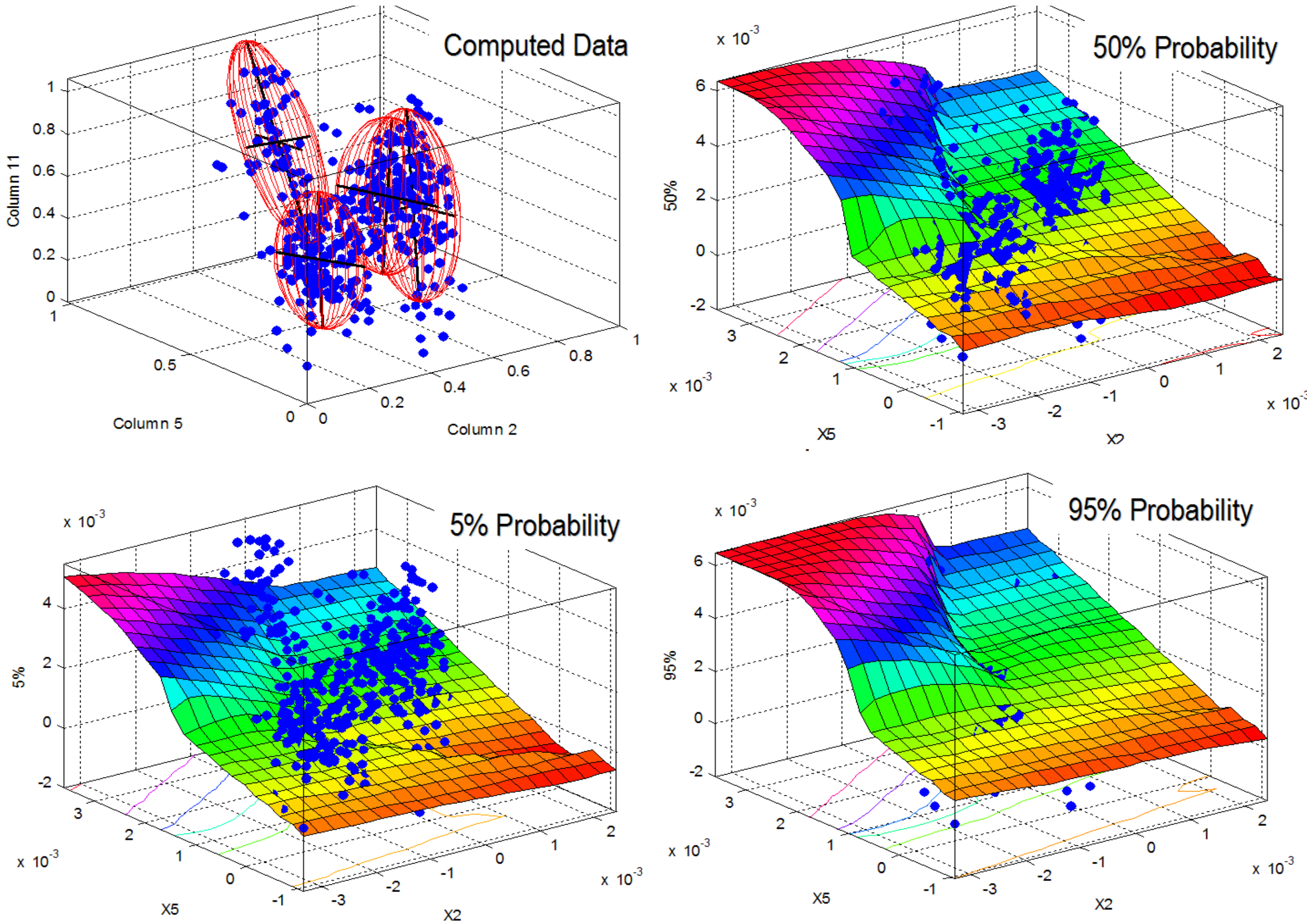
Block Jacobi

Num Procs / Equations	100 k	500 k	1 M	5 M	10 M	20 M
6	2.68	14.81	31.24	196.32	443.74	1084.97
12	3.84	10.9	21.66	118.51	260.54	661.36
18	3.61	10.14	19.99	99.99	207.76	508.6
24	4.91	10.42	21.14	92.37	187.42	450.98

Parallel Multigrid

Num Procs / Equations	100 k	500 k	1 M	5 M	10 M	20 M
6	3.31	18.53	36.7	174.71	339.25	686.57
12	3.88	11.95	21.51	95.87	178.3	373.51
18	4.5	11.44	17.74	69.49	126.8	259.5
24	6.01	9.55	18.58	57.26	100.68	205.7

10 D Stochastic Surface Using High-Order Stochastic Field Models



Sensitivity Studies: Effects of Road Topography on FLLS Joint Forces and Stresses

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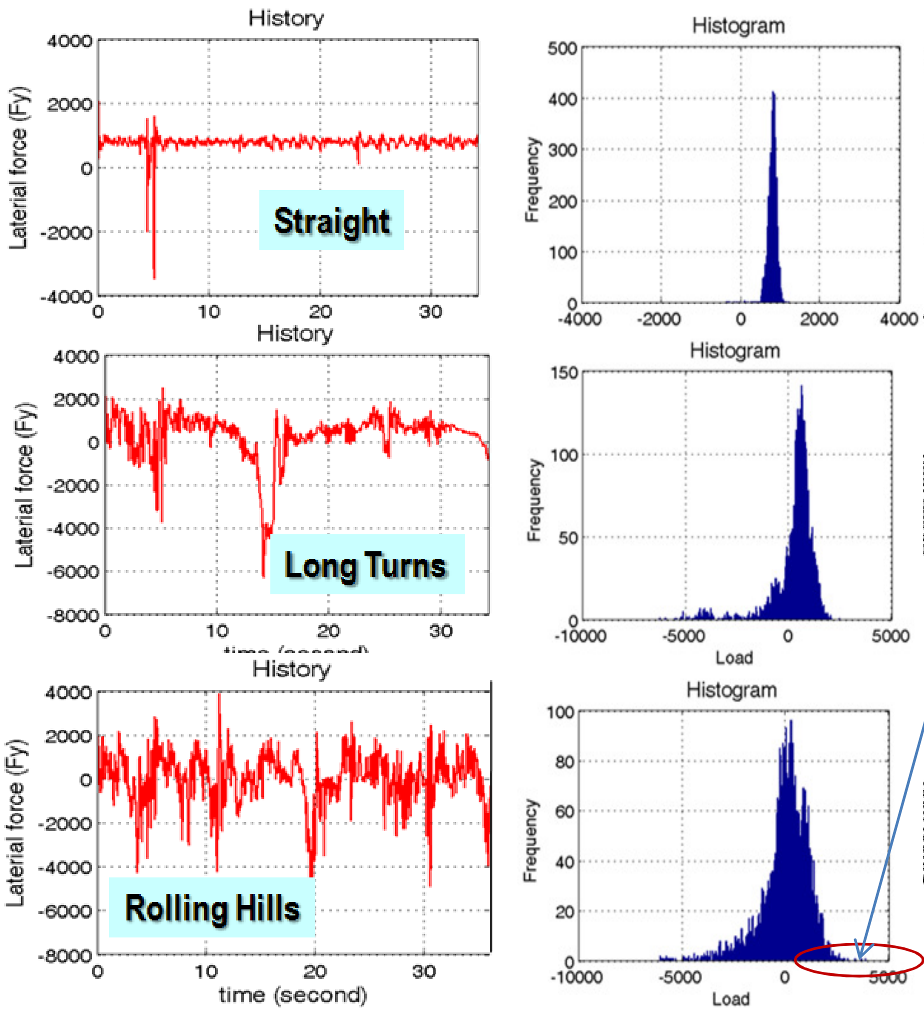
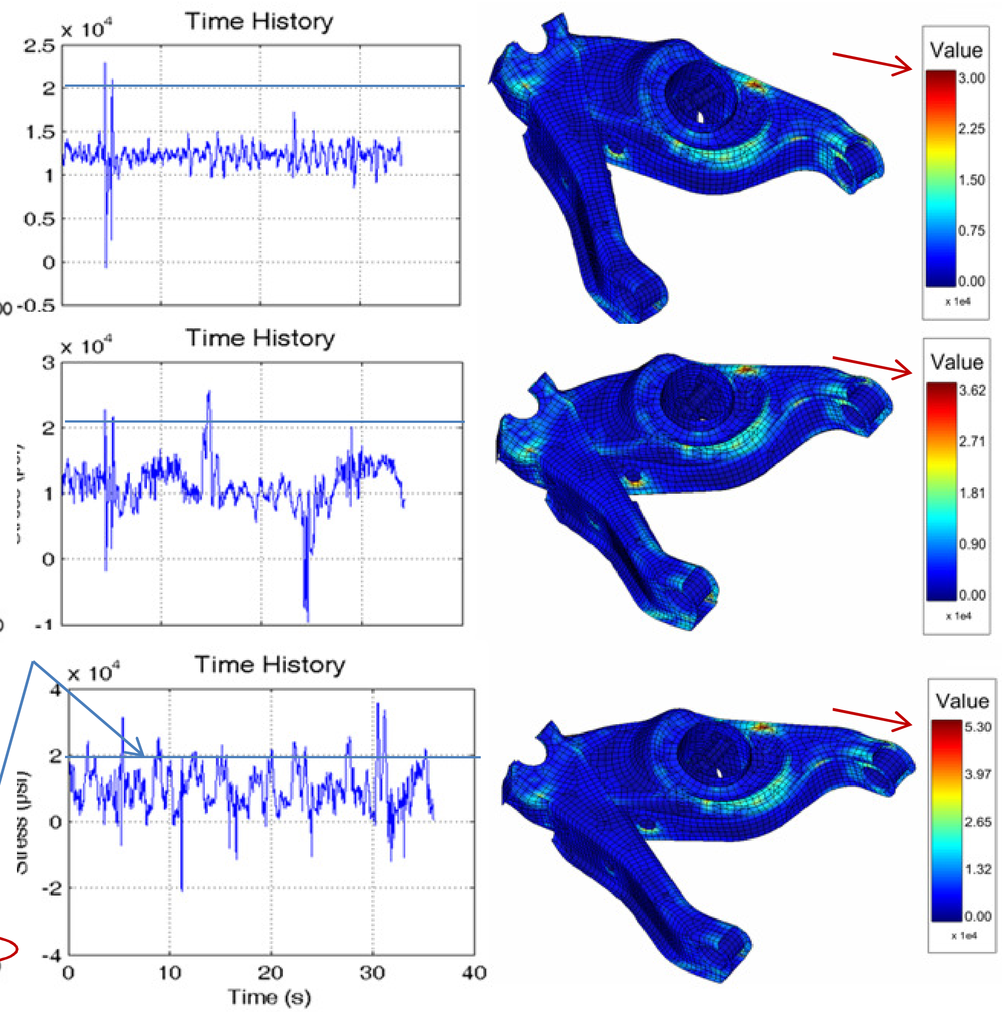
Moderate Roughness Road at 30 mph: Straight, Long Turns, Rolling Hills

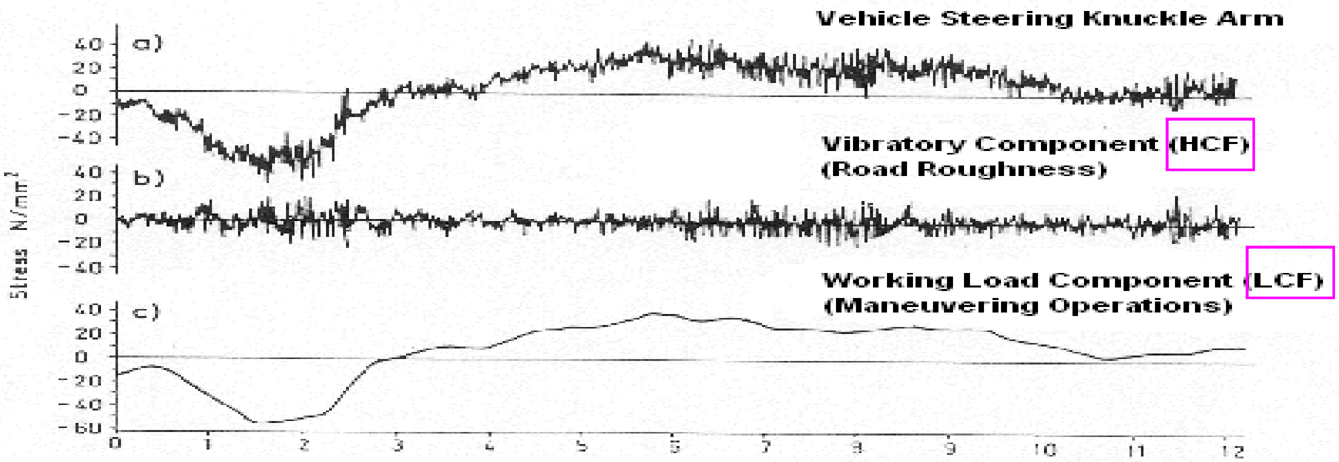
LCA Ball Joint Force

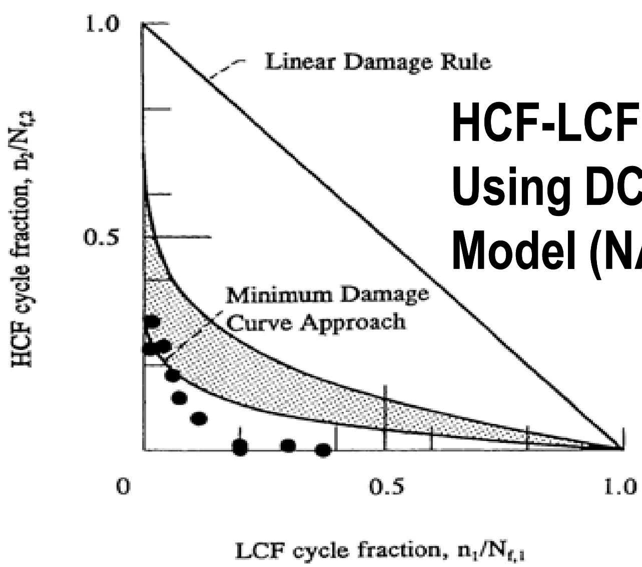


Critical Location Von-Mises Stress Variations

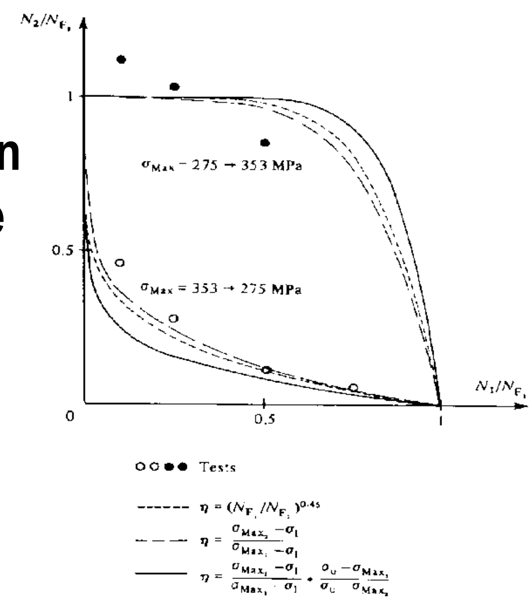


Interactive Fatigue Damage Mechanisms for Vehicle on Rough Terrain





HCF-LCF Interaction Using DCA Damage Model (NASA GRC)



Simultaneous Corrosion-Fatigue Model. Validated Against Field Data.

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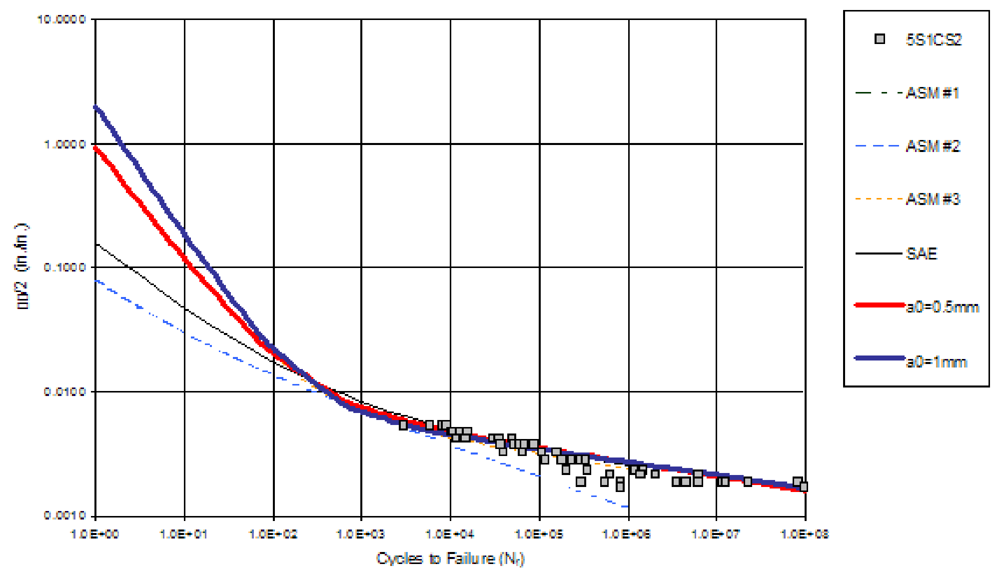
Crack Initiation



Strain-Life Curve:

$$\frac{\Delta\varepsilon}{2} = \frac{\sigma_f'}{E}(2N_f)^b + \varepsilon_f'(2N_f)^c$$

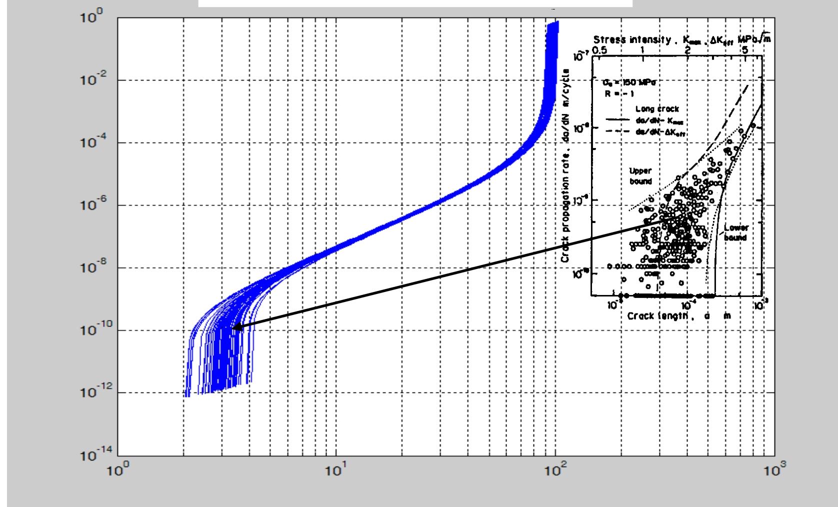
Ramberg-Osgood Curve:

$$\frac{\Delta\varepsilon}{2} = \frac{\Delta\sigma}{2E} + \left(\frac{\Delta\sigma}{2K'}\right)^{1/n'}$$

Uncertain Parameters

$$a(t) = IDS + [\sum_{n,t} a(n)^{\alpha} + p(t)^{\beta}]^{\gamma}$$

Crack Propagation



Forman FCG Model (NASA JPL, 1996)

$$\frac{da}{dN} = \frac{C(1-R)^m \Delta K^n (\Delta K - \Delta K_{th})^p}{[(1-R)K_C - \Delta K)]^q}$$

$$\Delta K_{CF} = \psi(t)\Delta K_F$$

$$\psi(t) = \sqrt{1 + \frac{p(t)}{a(n)}}$$

Uncertain Parameters

Sensitivity Studies: Effects of Damage Mechanism Model on Life Predictions

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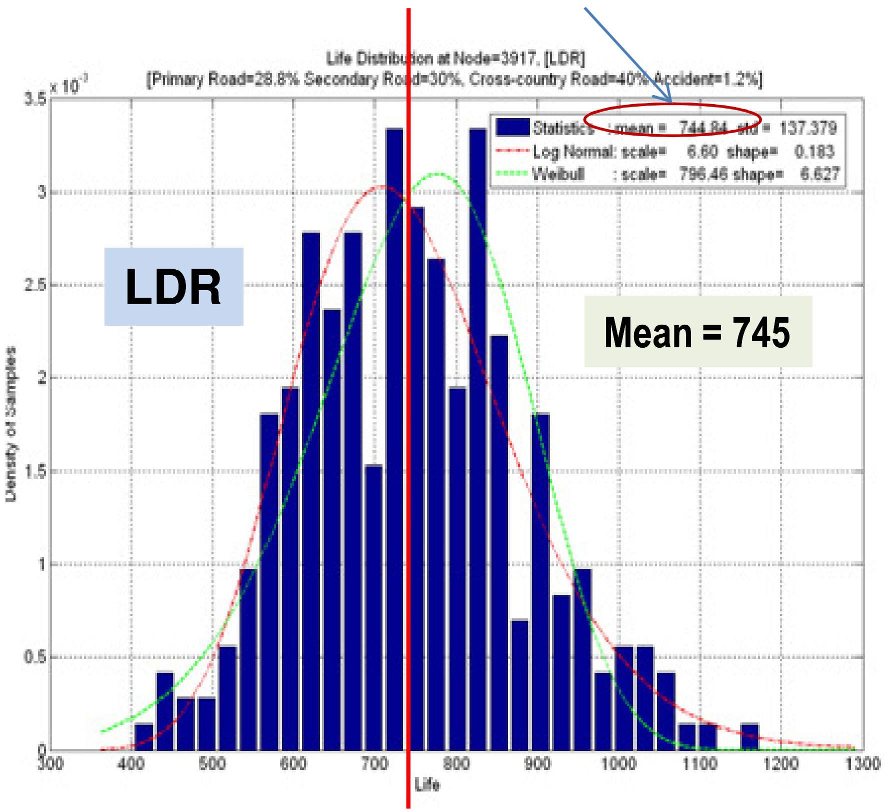
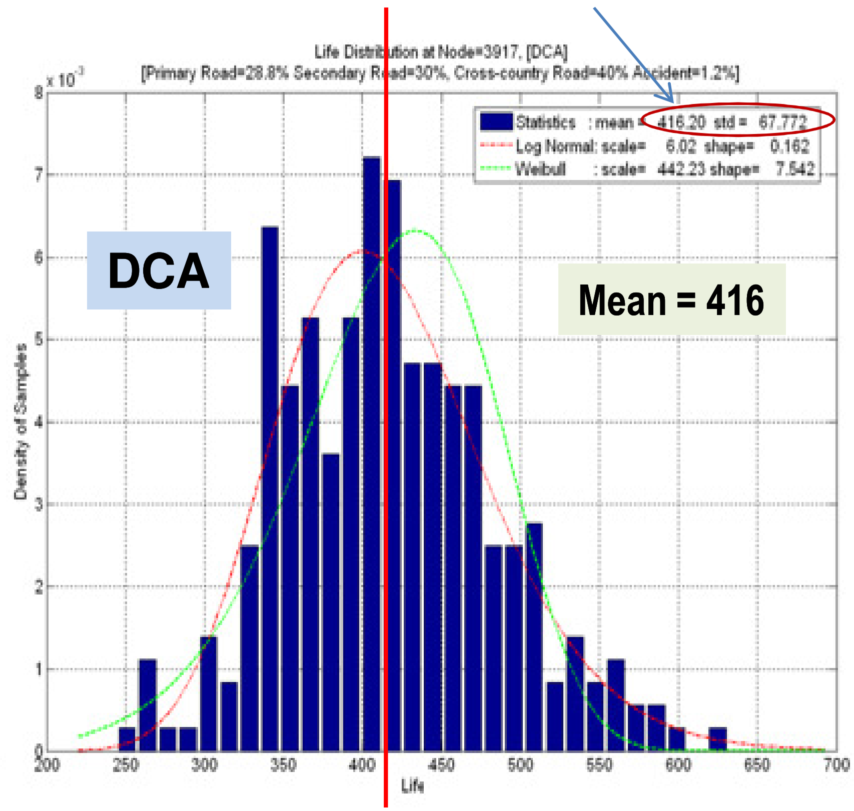
Predicted FLSS Life Using LDR and DCA Damage Models





Sensitivity Studies: Effects of Vehicle Weight Increase on Predicted FLSS Life

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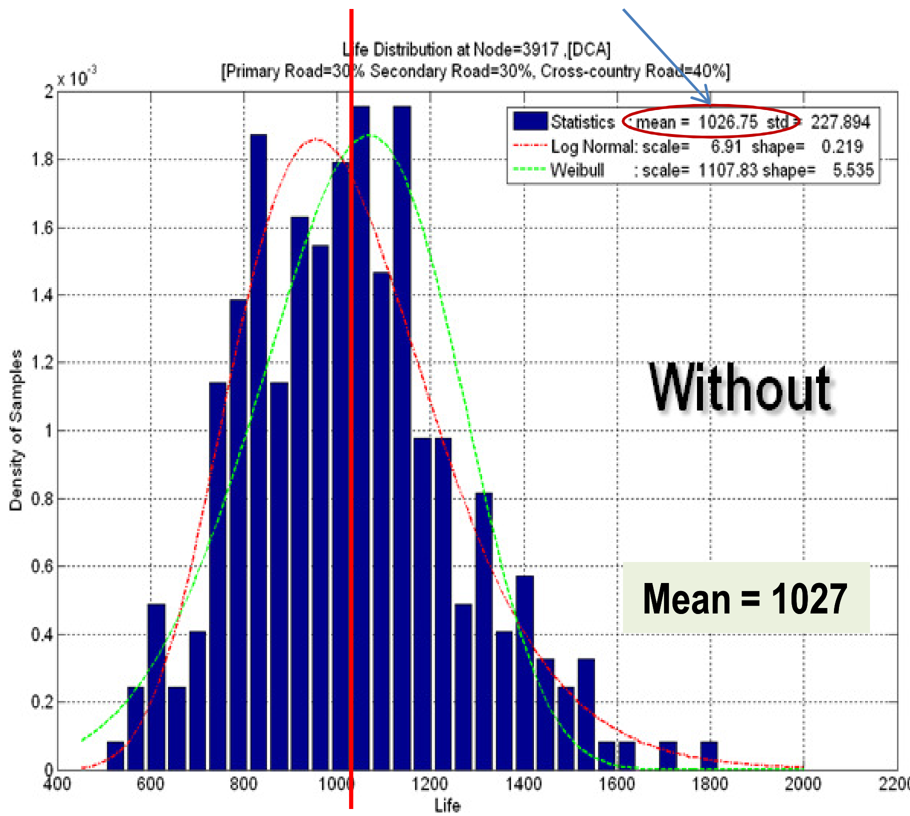
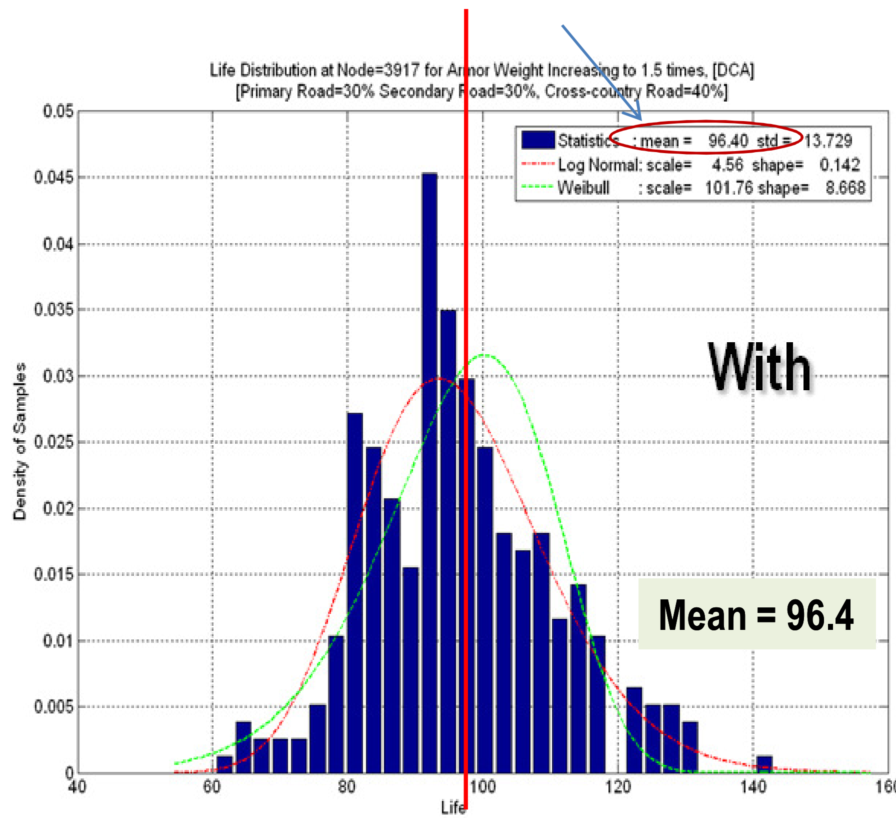
Predicted FLSS LCA Life Without and With Armour Weight Increase (50% of total vehicle weight)





Bayesian Updating (BU) vs. Bayesian-Probability Transformation Updating (BPTU). Many Test Data

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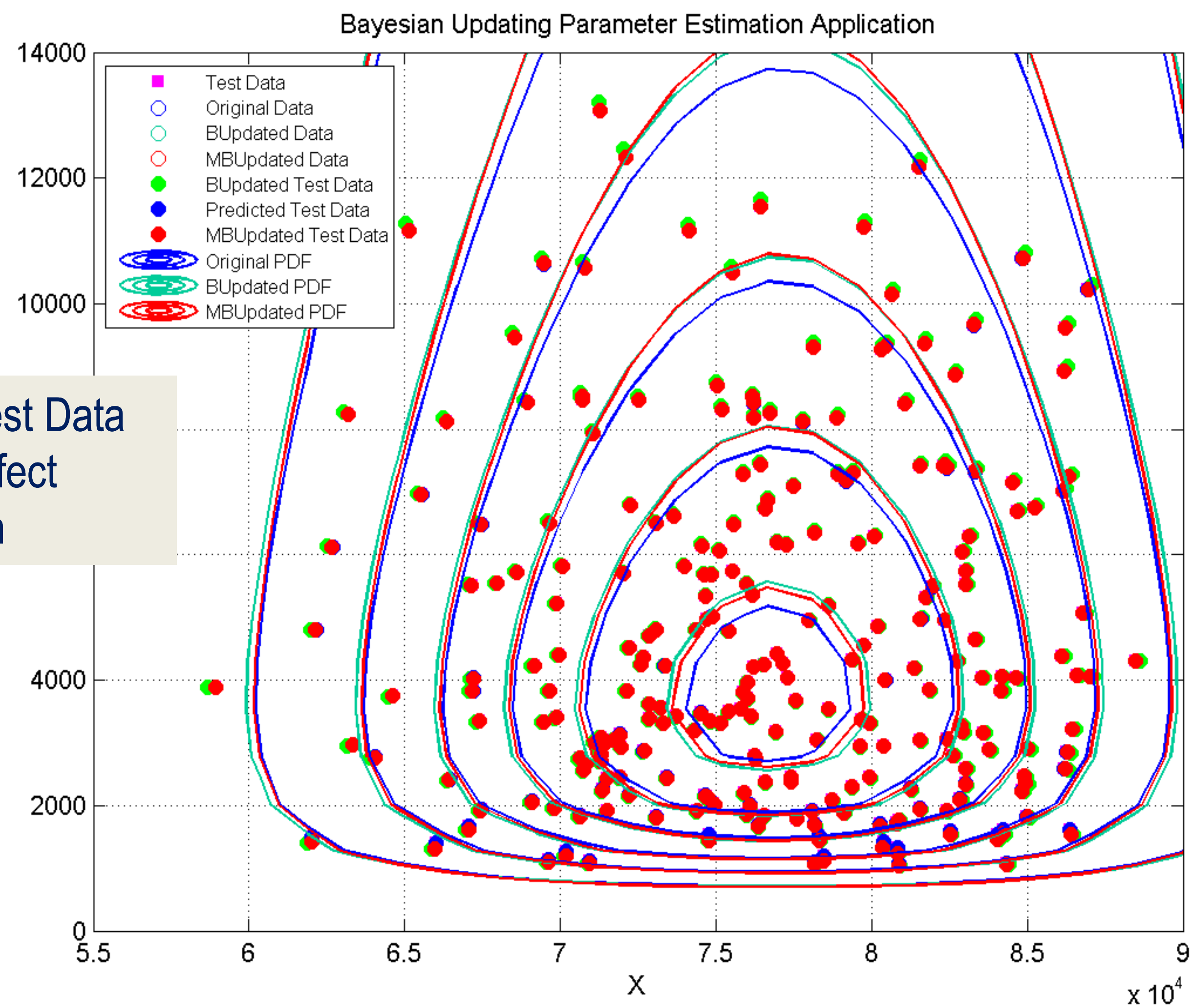
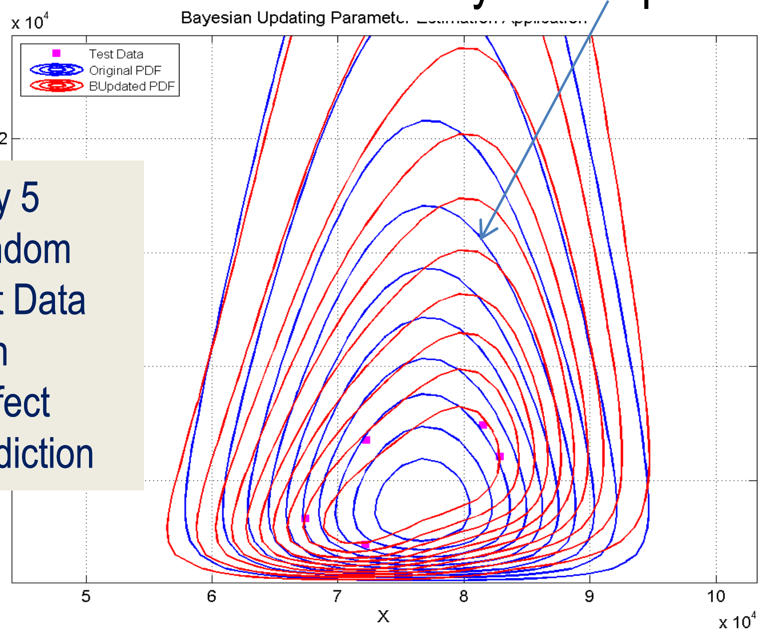
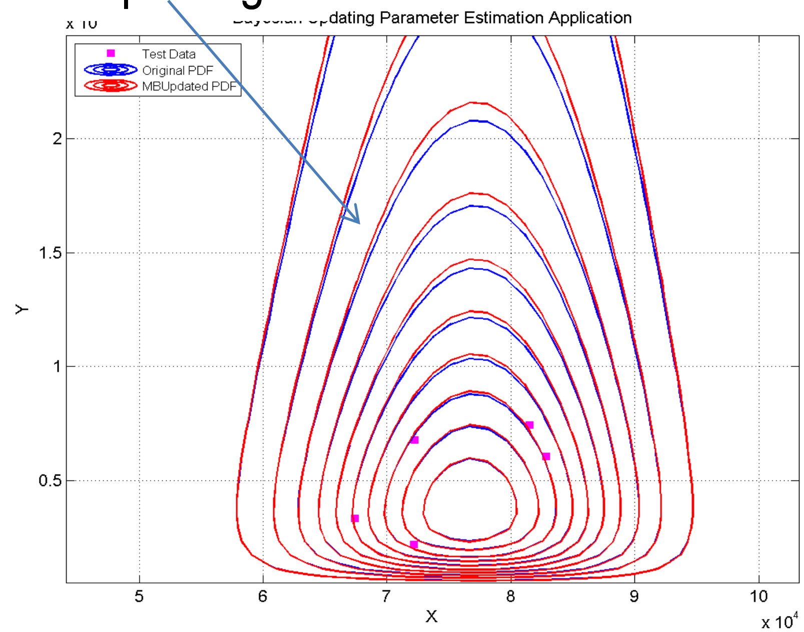


All 250 Test Data Have Perfect Prediction

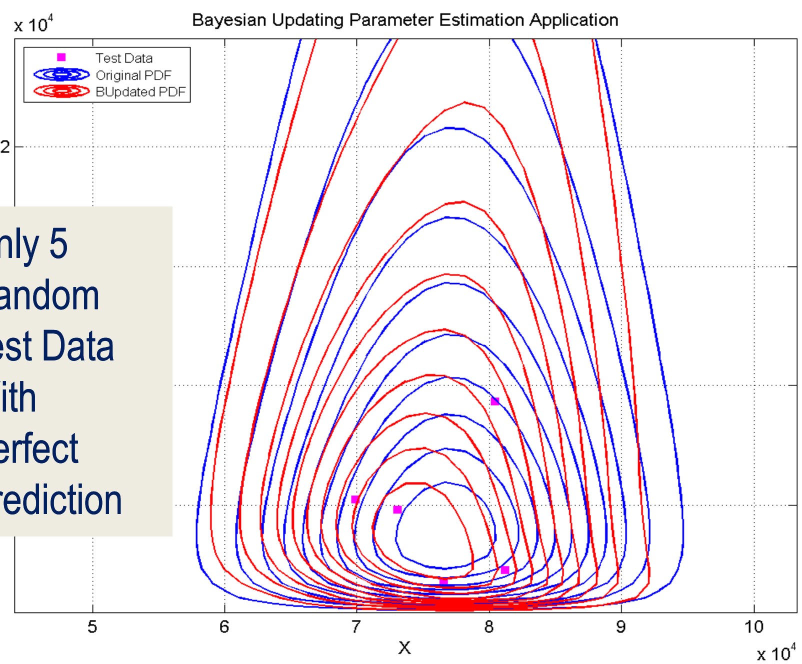
Bayesian Updating vs. BPT Updating

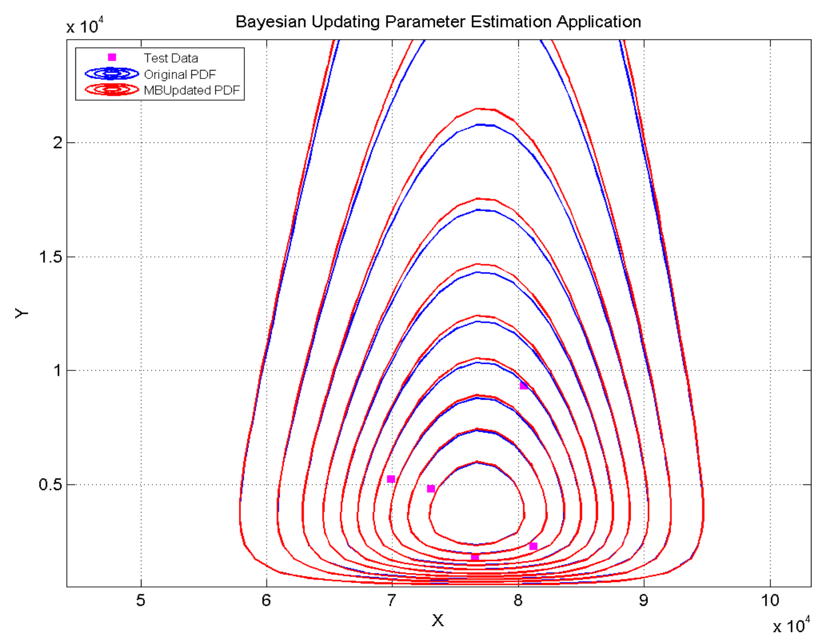
Only 5 Random Test Data With Perfect Prediction





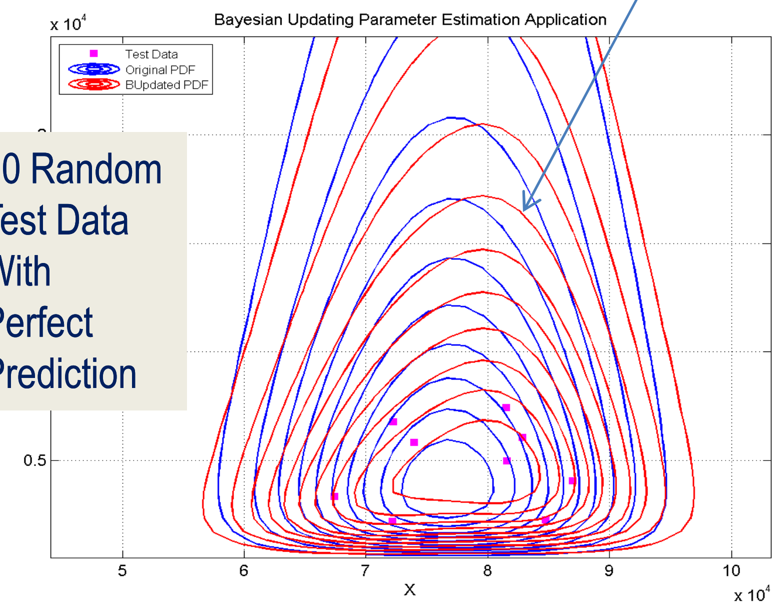
Only 5 Random Test Data With Perfect Prediction

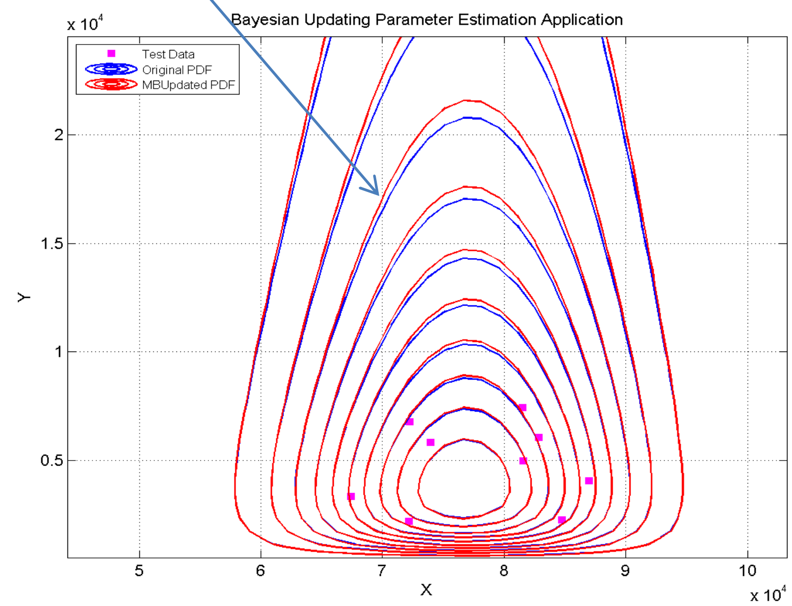




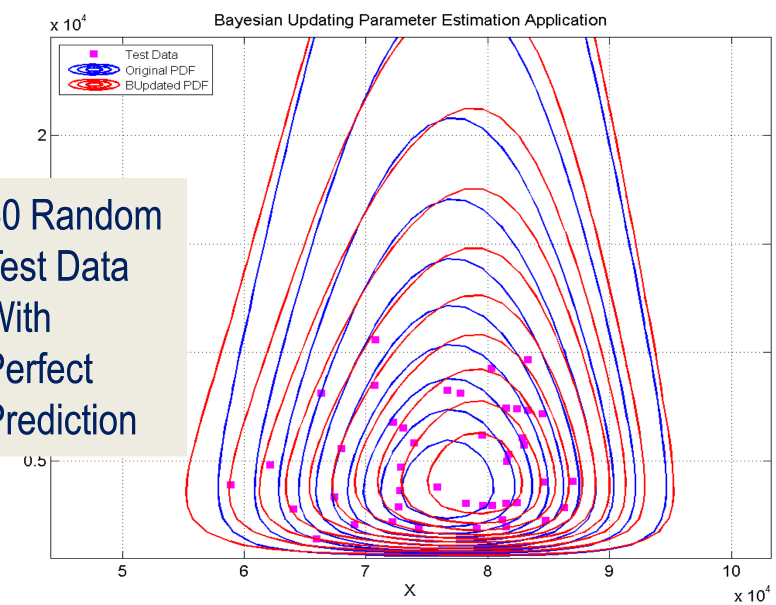
Bayesian Updating vs. BTU Updating

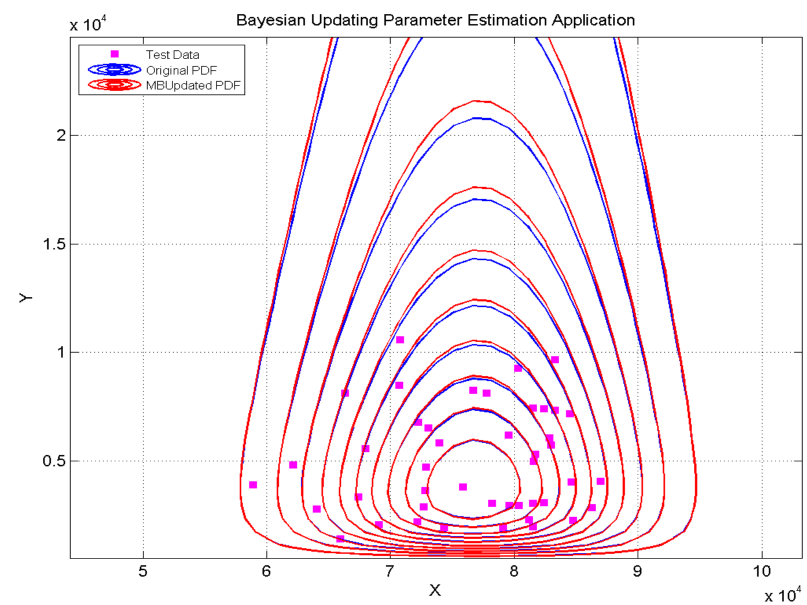
10 Random Test Data With Perfect Prediction



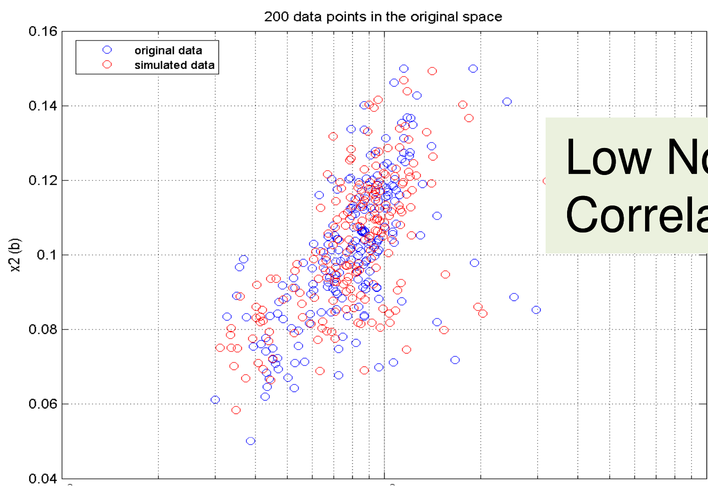


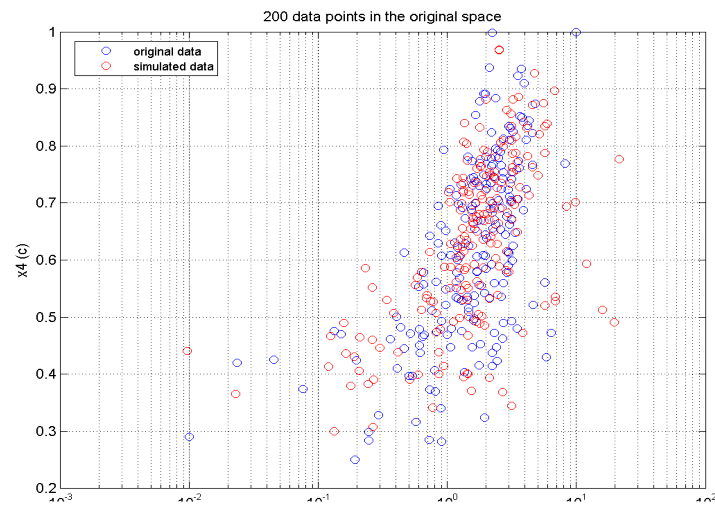
50 Random Test Data With Perfect Prediction



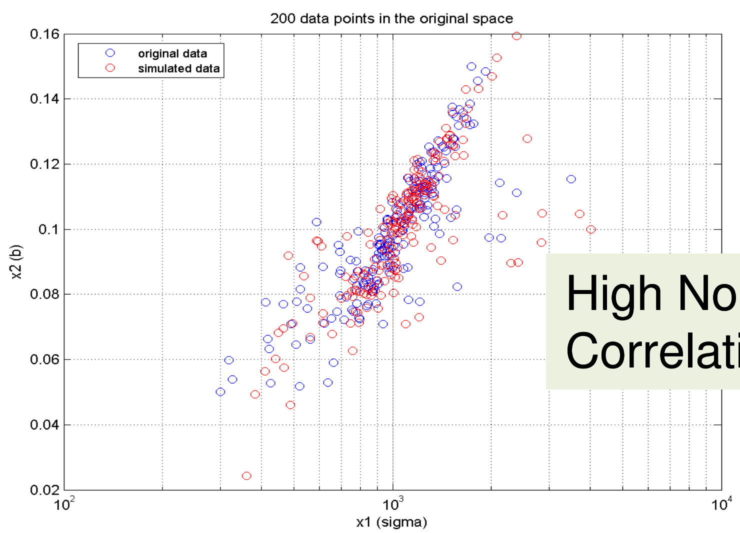


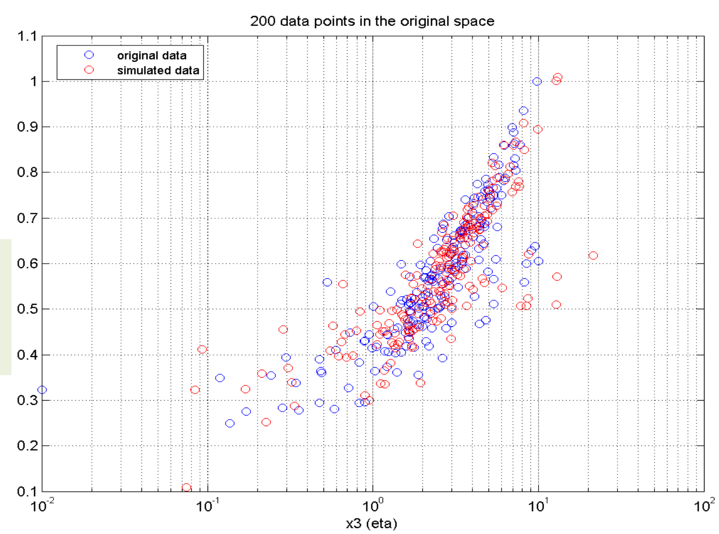
Statistical Strain-Life Curve. Effect of Nonlinear Correlation Between SLC Parameters (Sigmaf, Epsf, b, c)





Low Nonlinear Correlation





High Nonlinear Correlation

Statistical Strain-Life Curve. Effect of Nonlinear Correlation Between SLC Parameters (Sigmaf, Epsf, b, c)

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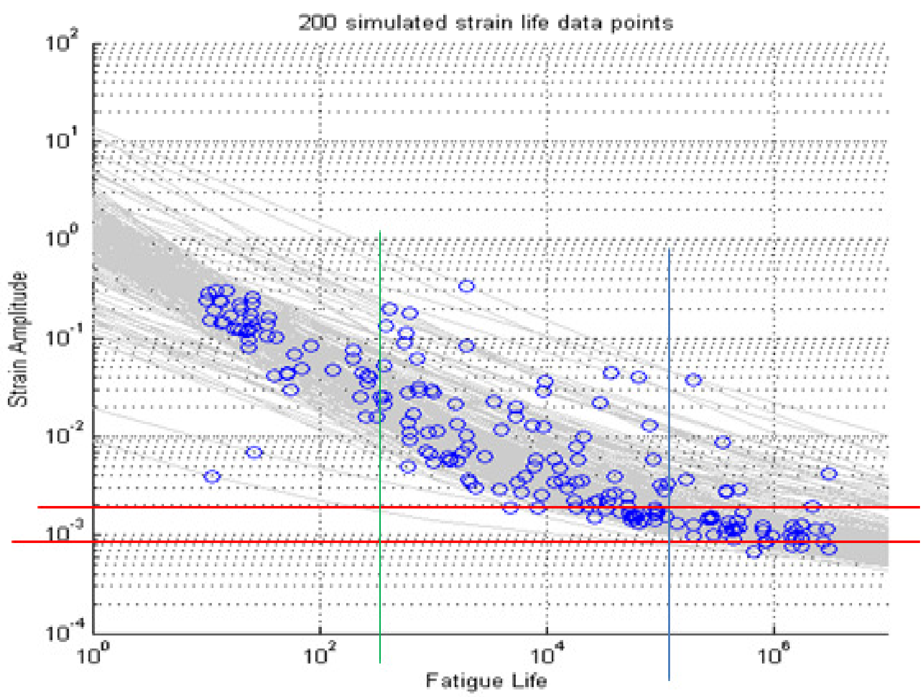
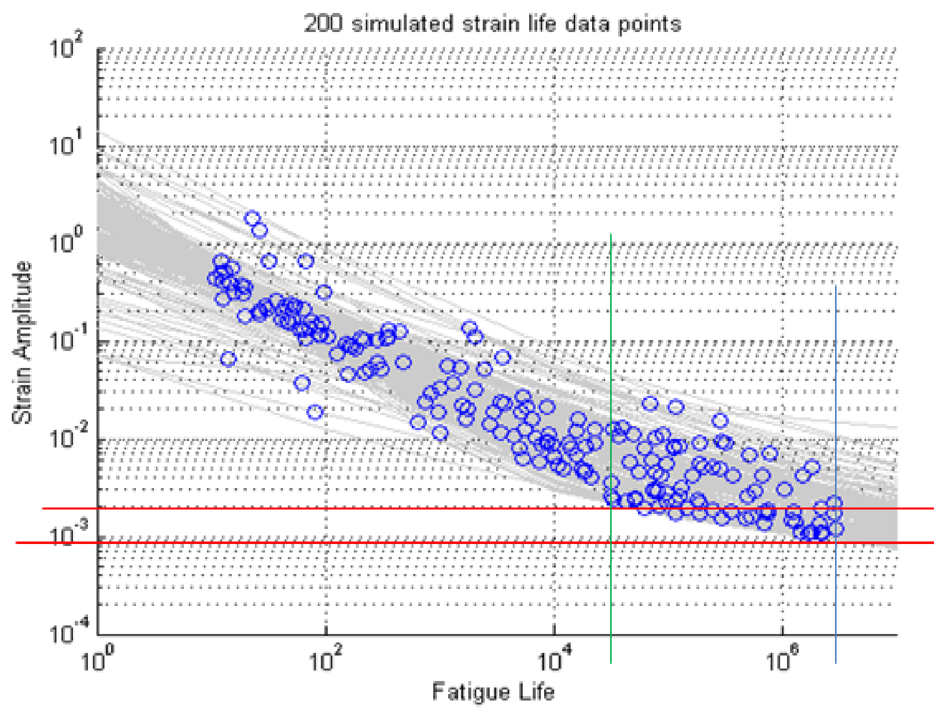
Low Nonlinear Correlation



High Nonlinear Correlation



Lack of Data Effects (250 simulations) on Life PDF, and 99% & 95% Reliability Life

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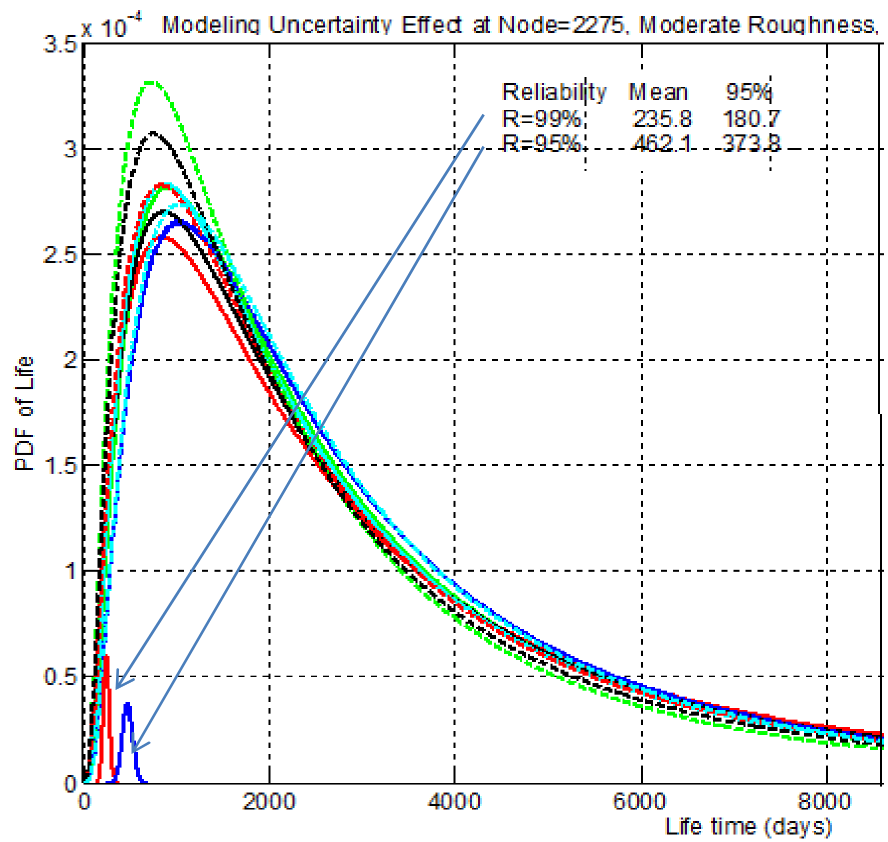
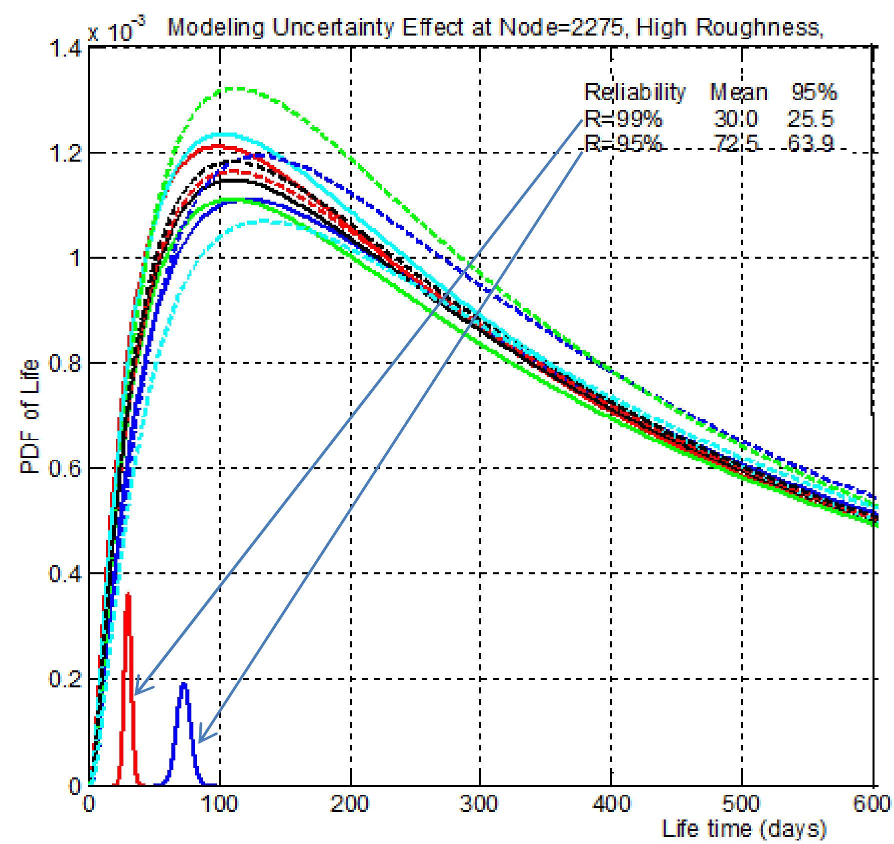
High Roughness



Moderate Roughness

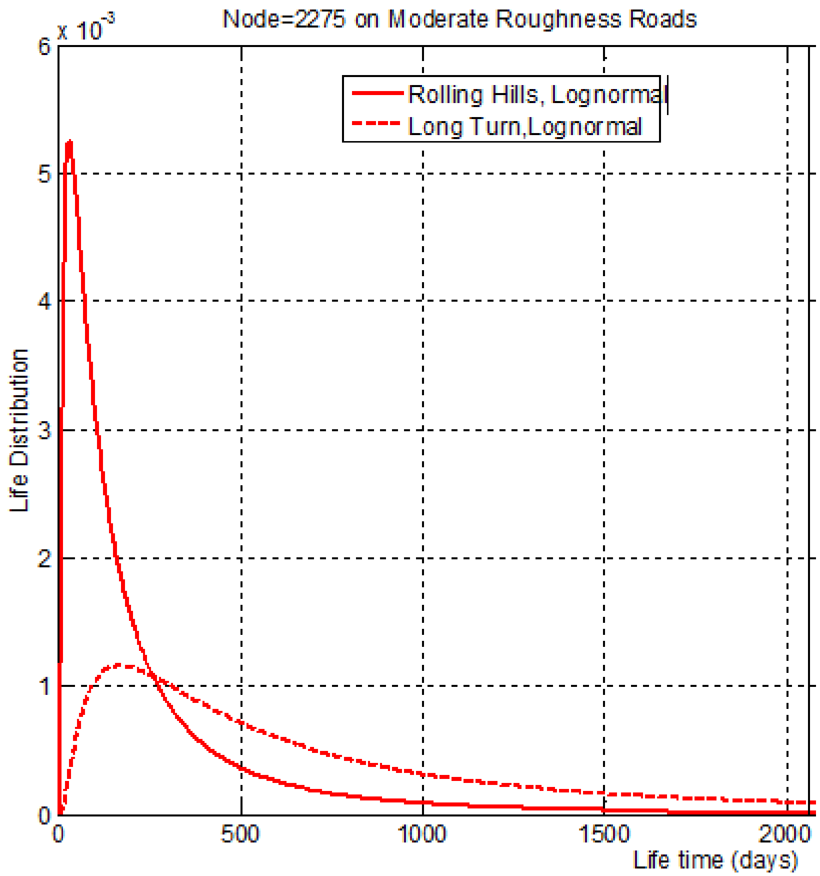


Effect of Limited FEA Simulations (250) on FLSS Life for Given Reliability

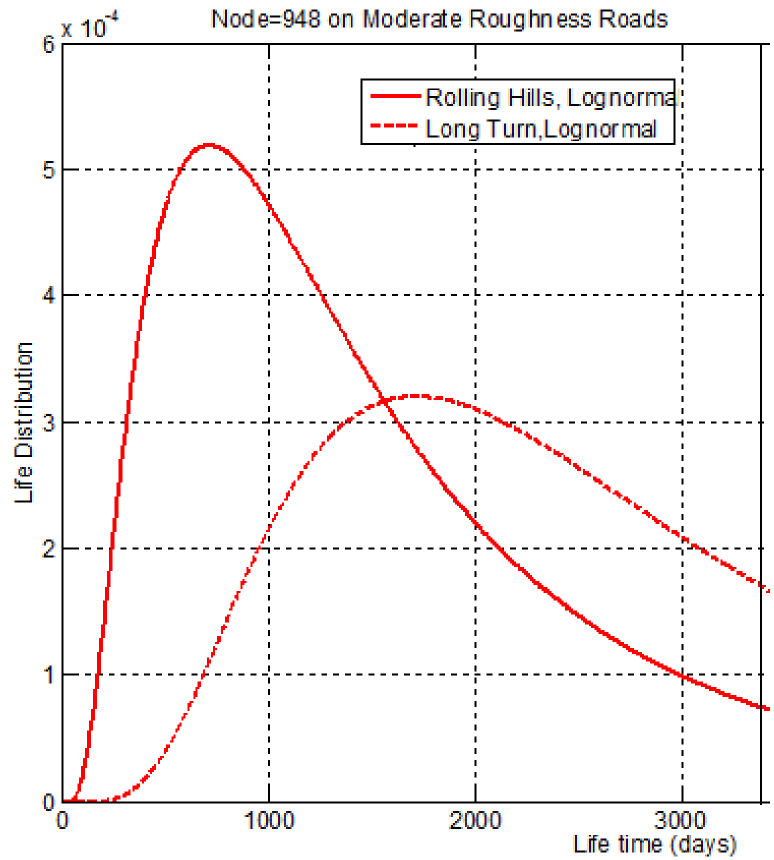
Road Profile Type (including topography)	Mean Life (days)	Life with Given Reliability 99% and 95% (days)	No Modeling Uncertainty	With Modeling Uncertainty	
			Deterministic	50% Confidence	95% Confidence
High Roughness	620	99%	31	30.0	25.5
		95%	72	72.5	63.9
Moderate Roughness	3200	99%	249	235.8	180.7
		95%	459	462.1	373.8

Sensitivity Studies for FLSS Predicted Life. Effects of Road Topography for Moderate Road Surface Roughness

Governing Critical Location

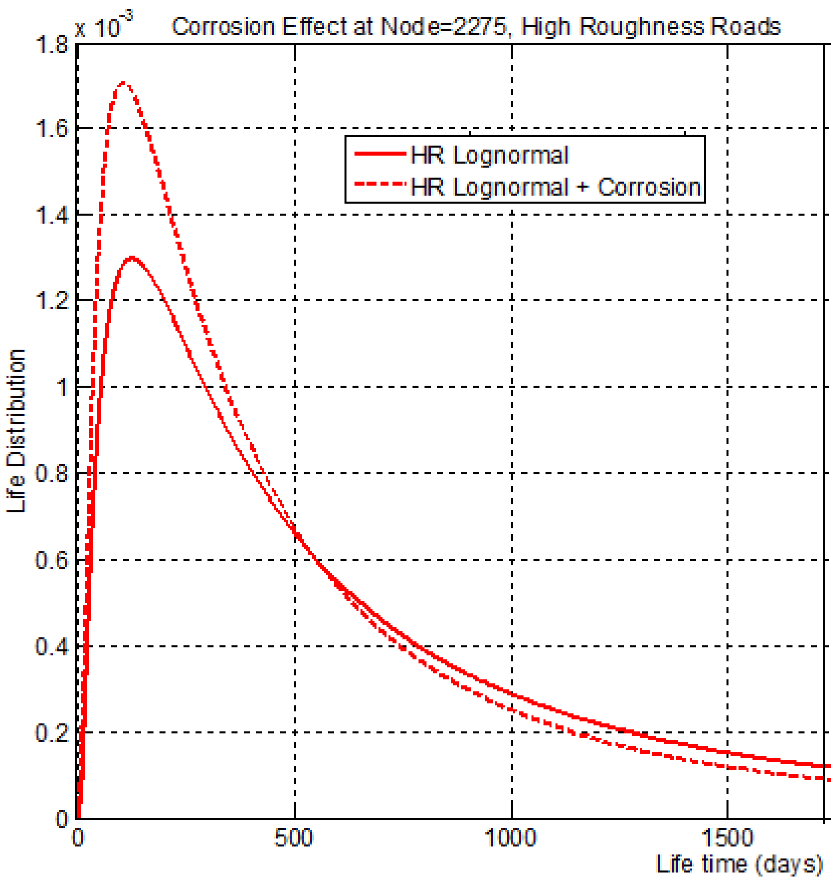


Other Critical Section

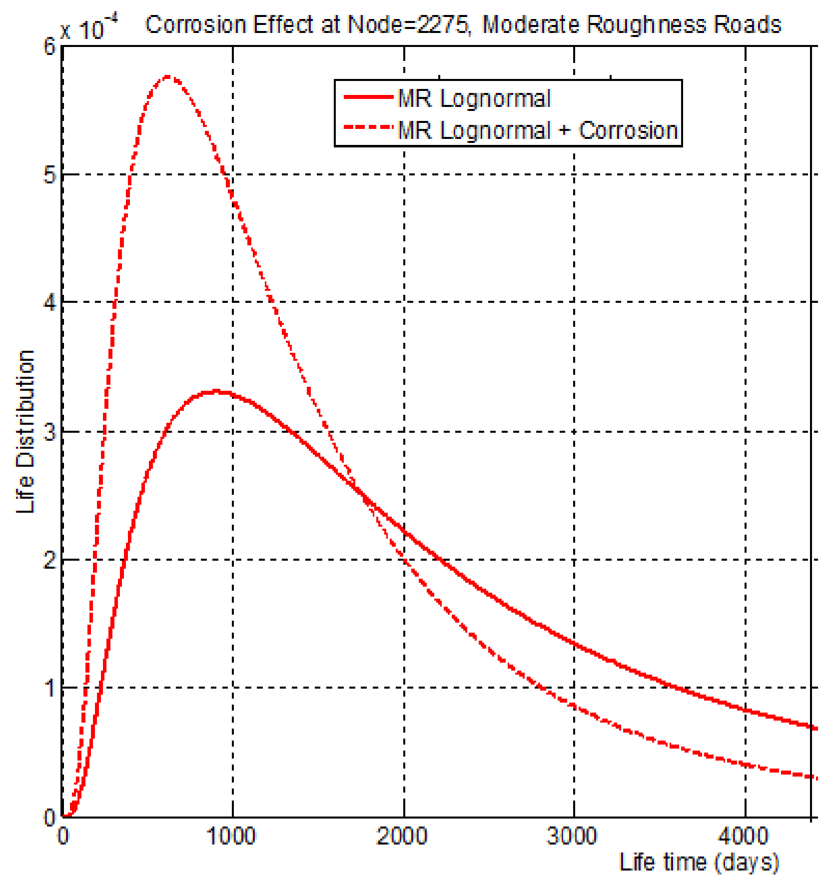


Sensitivity Studies for FLSS Predicted Life. Effects of Corrosion for Different Road Surface Roughness

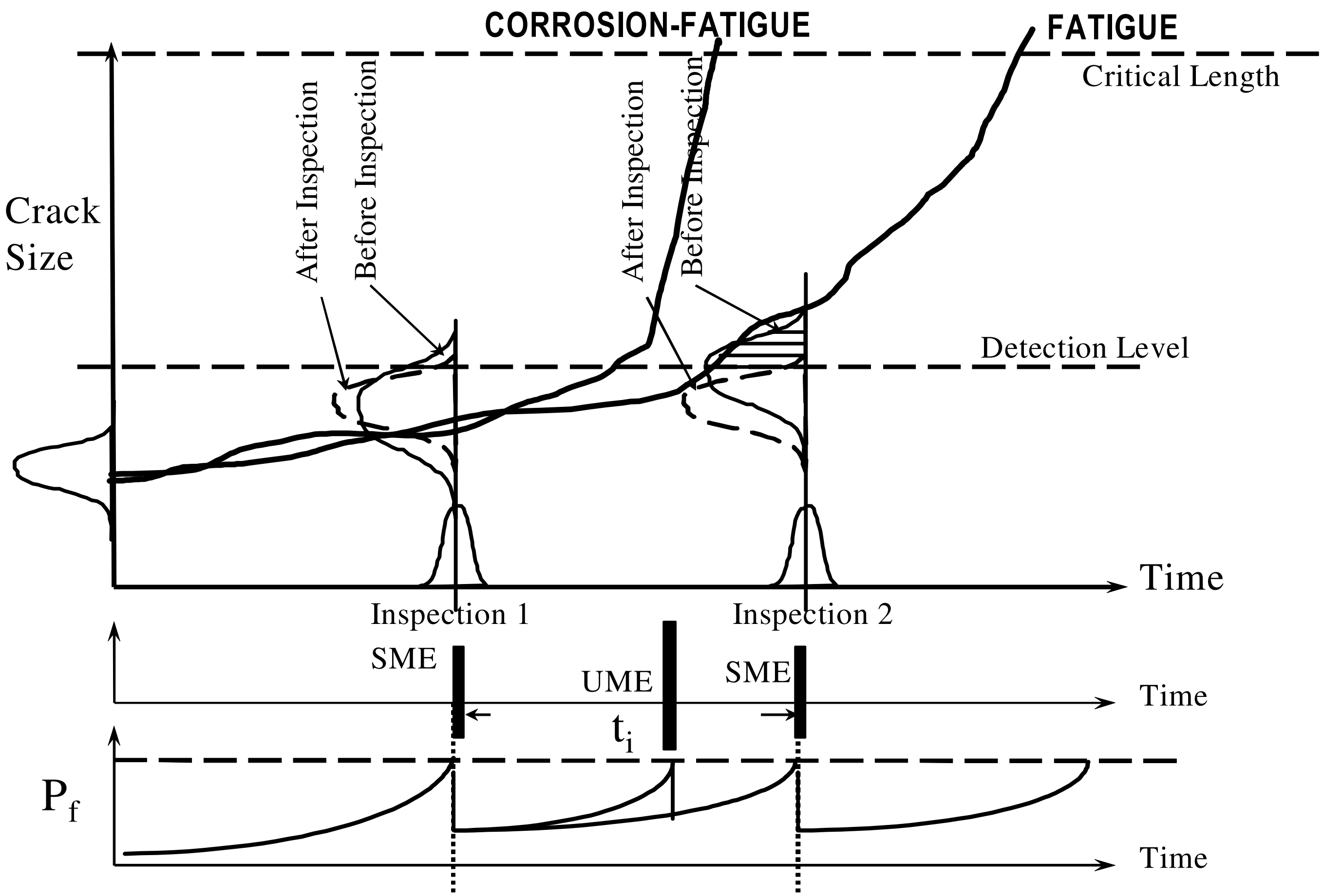
High Roughness



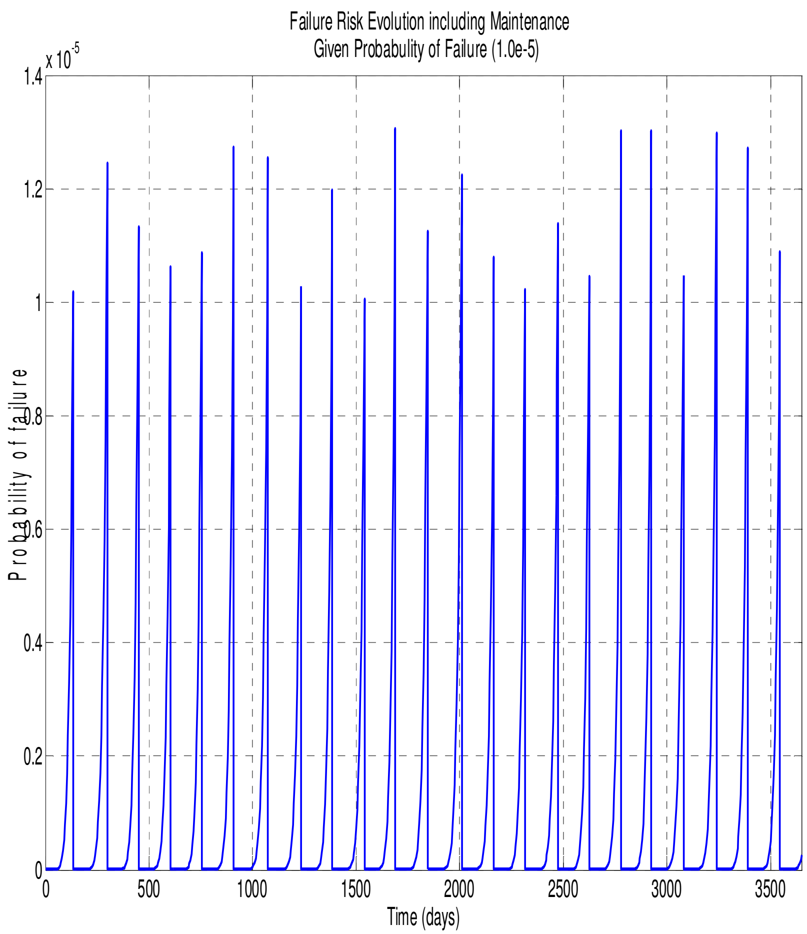
Moderate Roughness

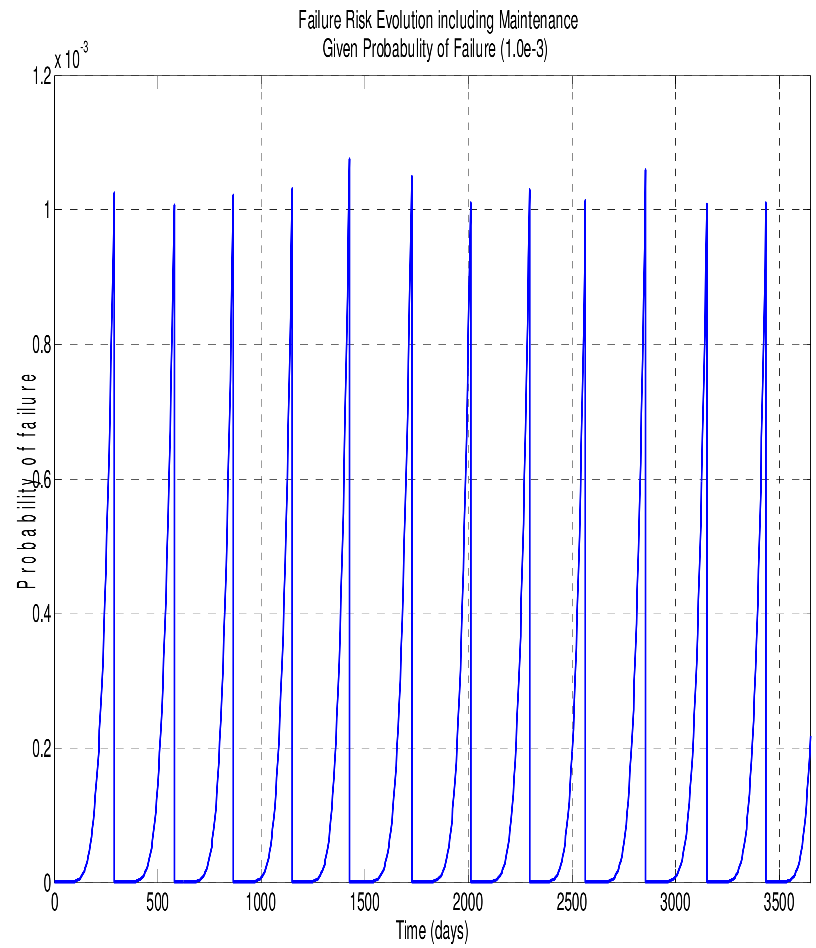


Risk-Based Maintenance Analysis Concept



Reliability-Based Maintenance Analysis Sensitivity Studies: Given POF





Maintenance Schedule (Inspections and Repairs) Given POF

Target Probability of Failure (POF)	Computed Probability of Failure (POF)	Number of Scheduled Maintenance Events	Mean Maintenance Interval (days)	Cumulative Number of Repairs per Component	Mean Hazard Failure Rate For Entire Period (per day)
1.0 E-05	1.1 E-05	23	155 (372) (1.02 years)	18	7.5 E-08
1.0 E-04	1.1 E-04	17	205 (492) (1.35 years)	15	5.3 E-07
1.0 E-03	1.0 E-03	12	285 (684) (1.87 years)	11	3.5 E-06

Sensitivity Studies Given Maintenance Schedule for Design Life of 20 Years

Sensitive Study Parameters	Average Maximum POF Per Interval	Average Hazard failure Rate	Number of Repairs Per 100 Parts
Maint. Interval=155 days	1.29003e-5	8.32275e-8	853
Maint. Interval=185 days	5.39682e-5	2.91720e-7	745
Maint. Interval=230 days	2.56768e-4	1.11638e-6	617
Visual Inspection *	3.4119e-4	1.84428e-6	382
Eddy Inspection *	5.39682e-5	2.91720e-7	745
Worst Skill Operator *	2.37889e-3	1.28589e-5	280
Best Skill Operator *	3.38781e-5	1.83125e-7	384
Rejection crack size = 0.0 in*	5.39682e-5	2.91720e-7	745
Rejection crack size = 0.15 in*	1.79505e-4	9.70295e-7	170

NOTE: * Constant maintenance intervals of 185 days were considered.

Summary/Concluding Remarks

An integrated HPC stochastic simulation framework has been implemented and demonstrated. This framework incorporates the following constitutive parts:

i) simulation of the stochastic operational environment,
ii) stochastic vehicle multi-body dynamics analysis,
iii) stress prediction in subsystems and components,
iv) stochastic progressive damage analysis, and
v) component life prediction including uncertainty from maintenance
vi) reliability prediction at the component and the system levels.

Remarks:

-The road surface roughness and the road topography variations impact severely on the HMMWV suspension predicted life. The non-Gaussian variations of road profiles have a significant impact on predicted fatigue life.

- The statistical nonlinear correlation patterns between the stochastic life model parameters, and the limited number of FEA simulations impacts significantly on FLSS reliability.

- Traditional Bayesian updating could often fail, especially when the number of test data is small. Including additional information on predicted data bias is key.