Anomaly Detection & Failure Prediction in Aerospace Vehicles:

Modeling of Variability for Vehicle Monitoring Systems

IS Workshop

Intelligent Systems Program

Intelligent Data Understanding

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Problem Statement

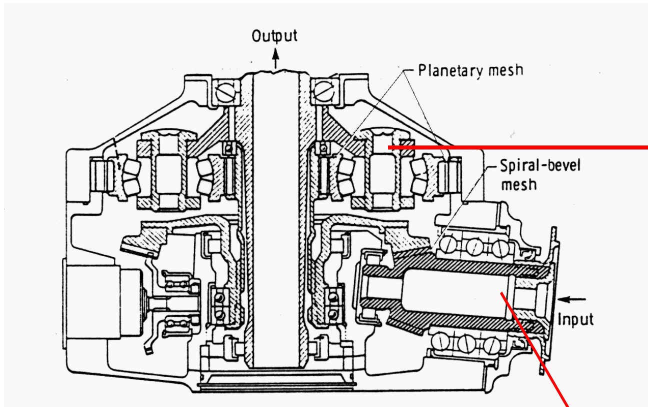
- Problem:
  - Vehicle health monitoring systems are corrupted with high rates of false alarms and missed detections
  - Vehicle monitoring systems are designed without a complete understanding of the variability of systems and input signals
  - Yet, anomaly detection algorithms must work within this highly variable environment

- Research Hypothesis:
  - Understanding of variations and the distributional characteristics of healthy systems as well as failure signatures are a necessary precursor to the development of successful anomaly detection algorithms

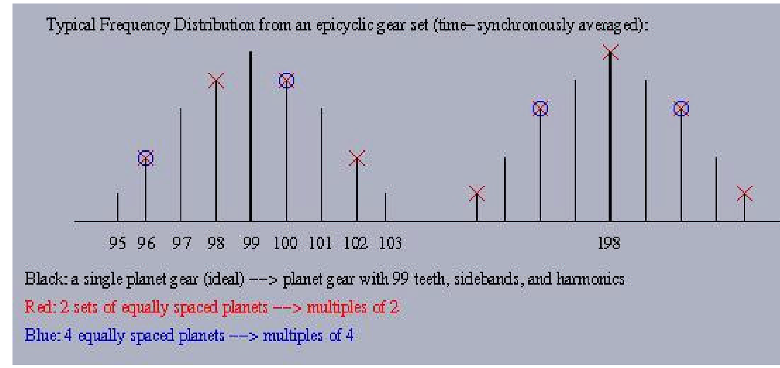
- Proposed Approach:
  - ***Data Understanding Problem****:*
    - Develop accurate models and understanding of data variance, noise sources, and failure signatures: two types of variability (system and operational) (PI: Irem Tumer)
  - ***Machine Learning Problem:***
    - Develop anomaly algorithms that take these factors into account for reliable detection (PI: Todd Leen)

Systems Variability Examples:
Design, Manufacturing, & Assembly Variations

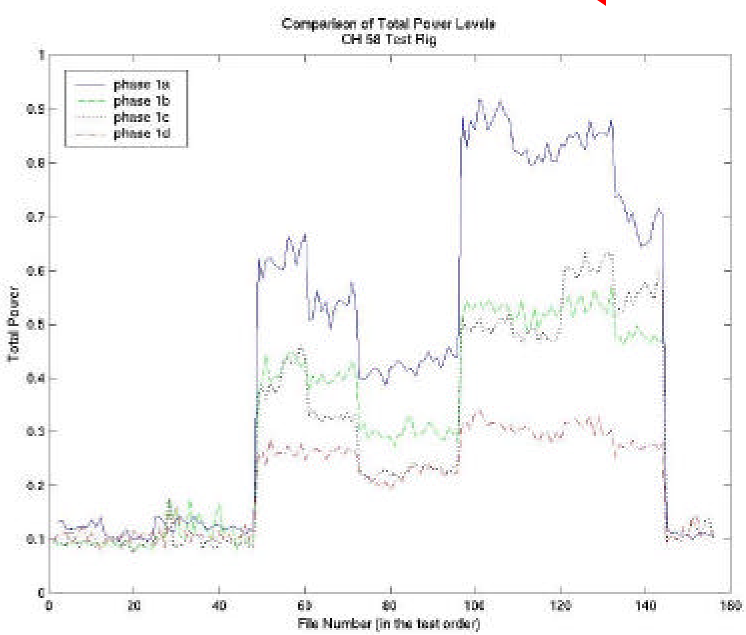
Helicopter transmission:



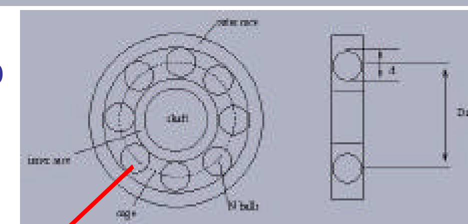
Variability in frequency response due to spacing variations:

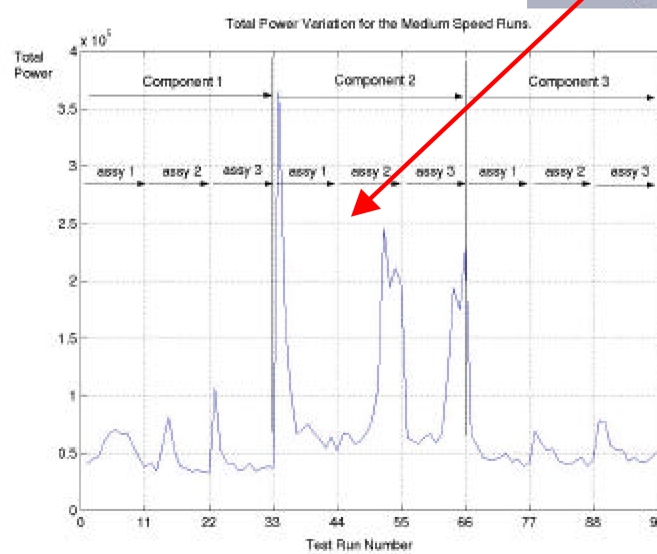


Variability in vibration levels due to assembly variations:



Variability in vibration levels due to bearing manufacturing variations:



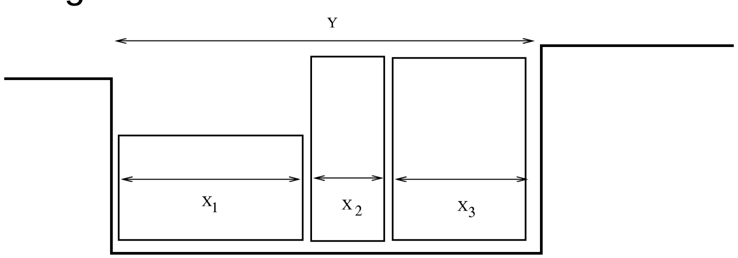


System & Failure Variability Modeling *Approach*

Two types of system variability:

1. Variation from component variability with process capability pre-knowledge:

   • Pre-knowledge of distributional characteristics for design parameters
   • Sensitivity analysis to determine significance



2. Variation from variability in rare failure events without known distributions:

   • Experiments to determine failure characteristics and distribution
   • Simulation to determine effect of variability on monitoring metric
   • Failures: corrosion, fatigue, fracture, wear, …

Two types of traditional approaches:

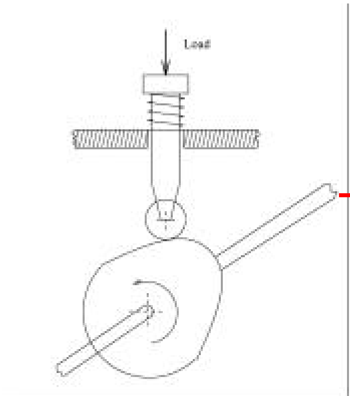
1. Low-order Taylor-series models for variance and mean: →

$$m_y = g(m_{x_1}, m_{x_2}, \ldots, m_{x_n}) + \frac{1}{2}\sum_{i=1}^{n} \frac{\partial^2 g}{\partial x^2} Var(x_i) \qquad Var(y) = \sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i}\right)^2 Var(x_i)$$

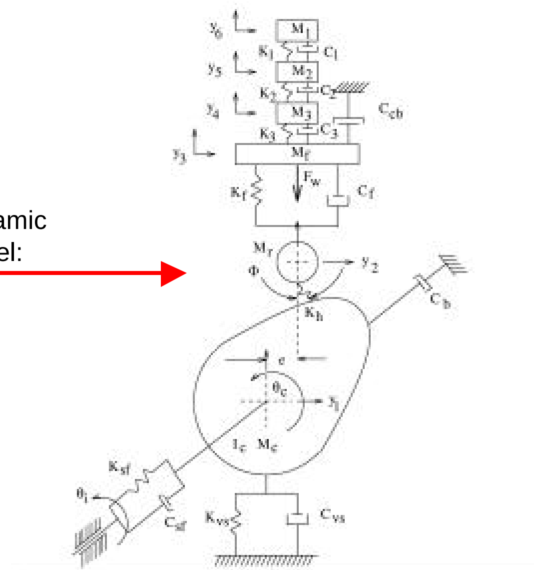
2. Monte Carlo models of variations and failure distributions: → Histograms and models of distributional characteristics for nonlinear and complex system dynamics

System & Failure Variability Modeling
FY02 Results

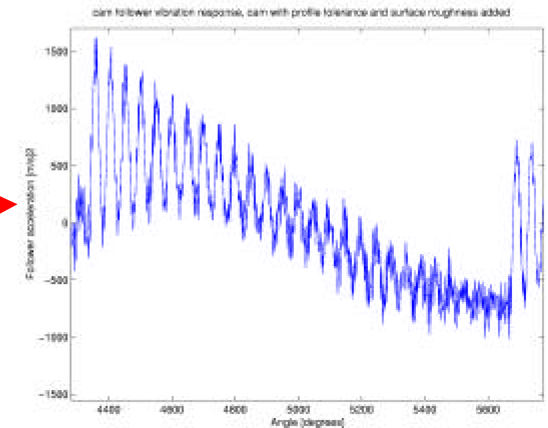
Cam-follower system:



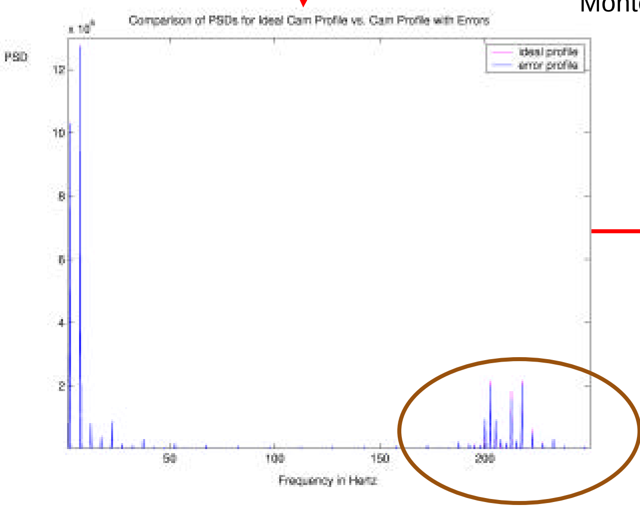
Dynamic model:



Vibration response:

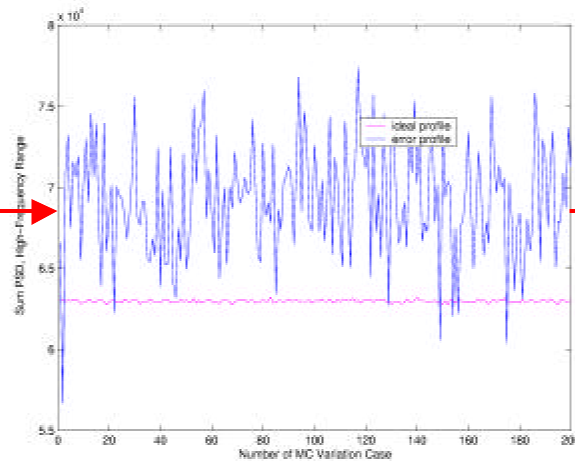


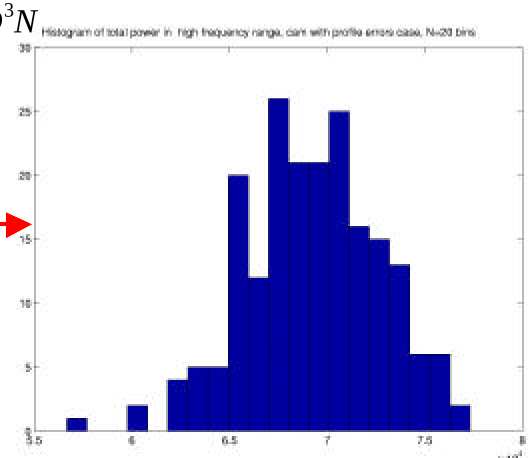
Monitoring Metric: Total Power



Monte Carlo simulation of spring constant variability:

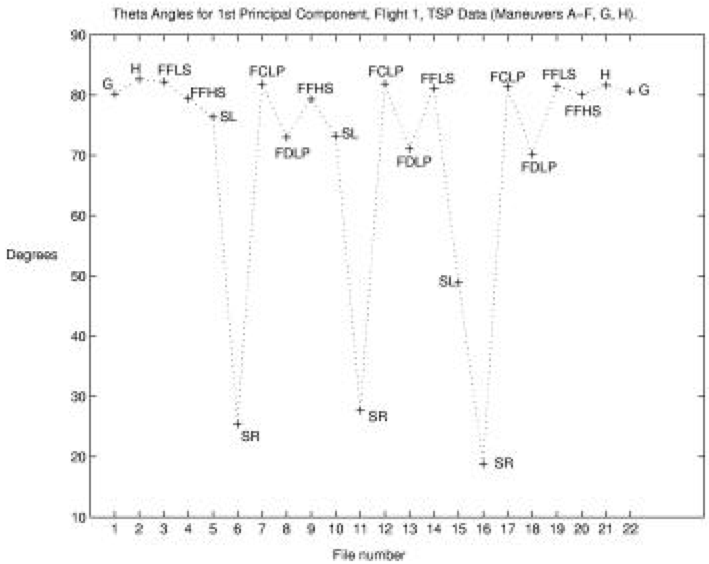
$$k = \frac{d^4 G}{8 D^3 N}$$

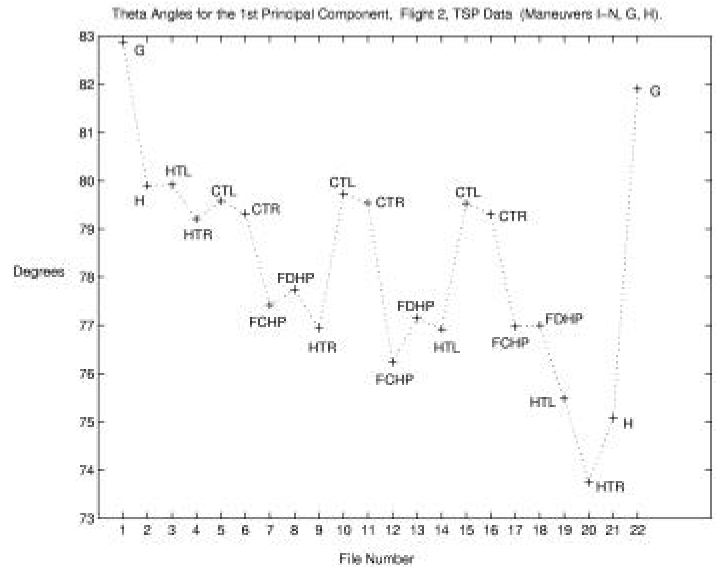




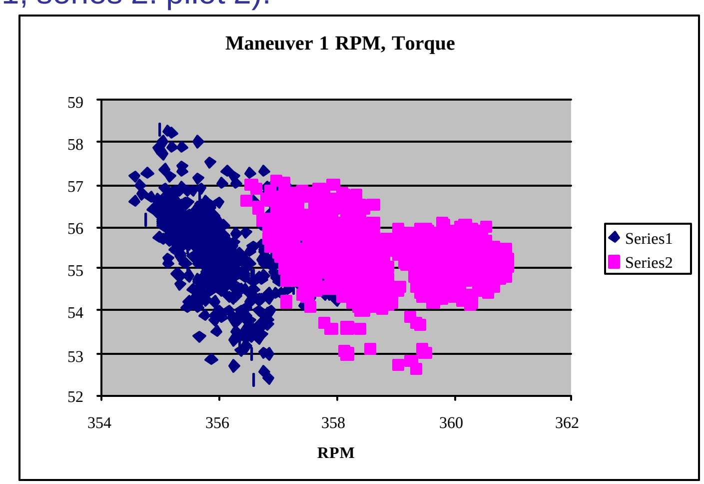
Operational Variability Examples: *Flight Maneuver Variations*

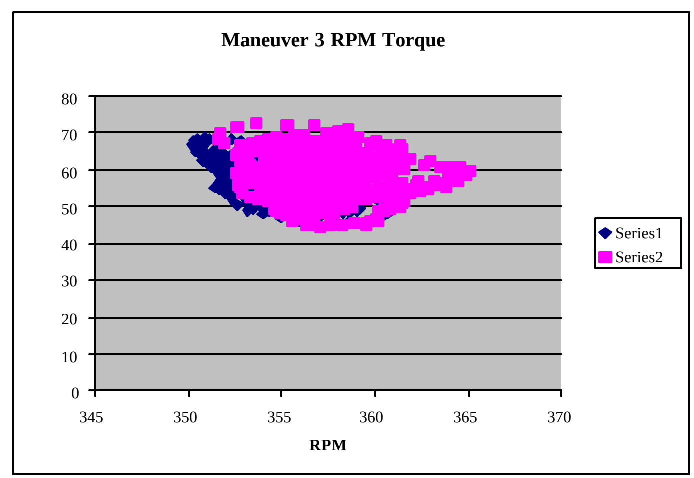
Variation of PC1 angles for all maneuvers and flights:





Clustering of vibration (RMS) data based on pilots and different flights (series 1: pilot 1; series 2: pilot 2):

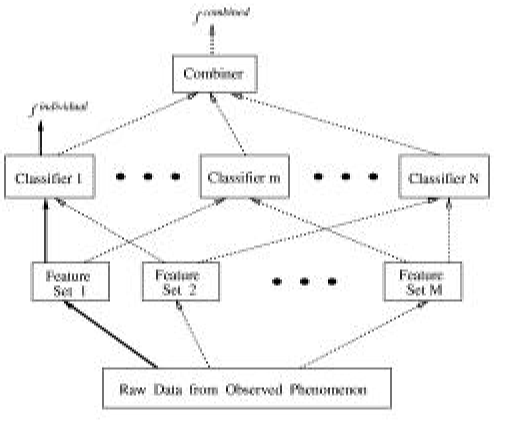




Maneuver & Anomaly Classification
Approach

- Hypothesis:
  - Focusing on smaller windows (maneuver states) reduces/eliminates operational false alarms and missed detections due to maneuvering and torque changes
  - Reverse classification: vibration features can be used to discriminate between maneuvers
    - For example: If there is a mismatch between maneuvers/regime information from aircraft bus data and maneuver identification from the vibration data, then it is possibly a failure event!

- Proposed Approach:
  - Ensemble Classifiers (Nikunj Oza & Kagan Tumer):
  - 2 days x 2 pilots x 2 flights/pilot x 22 maneuvers/flight x 194 revs of the planetary gear



  - 30 inputs
    - Revolutions per minute of planetary gear
    - Torque (average, standard deviation, skew, kurtosis)
    - Six accelerometers (rms, skew, kurtosis, clipping)
    - Which pilot was flying (2 possibilities)
  - Output:
    - The maneuver being performed (14 possibilities)
  - Training/Testing:
    - 23000 randomly-chosen revolutions of data for training, remaining (11144) for testing.

Maneuver & Anomaly Classification
FY02 Results

OH58					
REVOLUTIONS	ML METHOD	MANEUVERS	PERCENT CORRECT	TORQUE, RPM	VIBRATION
Single revs	Neural Network	original	81.313 ± 0.093	65.997 ± 0.095	75.636 ± 0.082
		consolidated	93.472 ± 0.065	83.873 ± 0.060	88.806 ± 0.074
	Ensemble	original	83.807 ± 0.037		
		consolidated	$\boxed{94.620 \pm 0.025}$		
Window of 29	Neural Network	original	89.891 ± 0.359	70.558 ± 0.102	88.529 ± 0.187
		consolidated	96.828 ± 0.0644	86.766 ± 0.075	94.735 ± 0.108
	Ensemble	original	91.967 ± 0.086		
		consolidated	$\boxed{96.692 \pm 0.034}$		

AH1		ALL INPUTS		TORQUE, RPM	VIBRATION	BUS DATA
REVOLUTIONS	ML METHOD	MANEUVERS	PERCENT CORRECT			
Single revs	Neural Network	original	95.940 ± 0.135	64.952 ± 0.142	74.216 ± 0.164	89.706 ± 0.124
		consolidated	98.535 ± 0.097	73.500 ± 0.141	86.616 ± 0.133	95.423 ± 0.096
	Ensemble	original	98.184 ± 0.017			
		consolidated	99.804 ± 0.007			
Window of 29	Neural Network	original	97.817 ± 0.121	71.774 ± 0.247	82.571 ± 0.298	91.324 ± 0.129
		consolidated	98.529 ± 0.090	77.779 ± 0.250	92.540 ± 0.228	$\boxed{95.902 \pm 0.081}$
	Ensemble	original	99.308 ± 0.008			
		consolidated	$\boxed{99.546 \pm 0.008}$			

			P(tr == vib)	P(tr == bus)	P(vib == bus)
Single revs	Neural Network	original	59.810 ± 0.223	59.256 ± 0.188	69.815 ± 0.170
		consolidated	70.666 ± 0.198	70.573 ± 0.190	83.563 ± 0.124
Window of 29	Neural Network	original	69.438 ± 0.318	66.165 ± 0.318	78.600 ± 0.280
		consolidated	77.403 ± 0.272	75.508 ± 0.283	$\boxed{90.308 \pm 0.219}$

Able to separate maneuvers based on vibration data

- Confusion caused by hover maneuvers and coordinated turns: consolidated (better)
- Inputs: single revolutions vs. a moving window average (better)
- Methods: neural nets vs. ensemble classifiers (better); Features: Vib, Torque, RPM, bus data (better combined)
- Bus data alone provides good classification rates: can be used for regime identification? (Probability of classification agreement between vibration data and bus data for consolidated and windowed inputs: >90%)

Conclusions

- Technical significance and impact of *Year One* progress:
  - Enabled exploratory data analysis by collecting and processing helicopter vibration data
  - Established the necessity to understand baseline variations
    - Journal paper on mfg variability accepted for publication
    - Journal paper on triaxial PCA angle variability accepted for publication
  - Demonstrated feasibility of using Monte Carlo methods to model design variability
    - ASME Design Engineering conference paper accepted for publication
    - Journal paper submitted for review
  - Started collaboration to generate empirical distributions for unknown failure events to model their variability characteristics
    - 1 graduate student and 2 undergraduate students recruited, UMR, Prof. Dan McAdams
    - Efforts to set up experimentation have started in June 2002
    - Efforts to start testing of computational models started in August 2002
  - Demonstrated the classification of maneuvers from vibration data to develop classifiers that detect mismatch between expected & anomalous inputs
    - I.e., if we have misclassification/mismatch, it might be due to a failure event
    - Conference paper submitted for review to NIPS 2002
    - Journal paper in preparation
  - Started exploration of other vehicle domains (e.g., aircraft engines, spacecraft?) where variability is of concern
- Linkable URLs:
  - http://ic.arc.nasa.gov/people/itumer