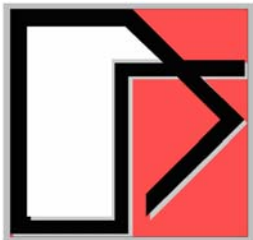


# Stochastic Interference and Visualization Tools for Risk-Based In-Flight Engine Fault Diagnostics and Prognostics

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Ghiocel Predictive Technologies Inc.

Ghiocel Predictive Technologies Inc.



**HCF Conference, New Orleans, LO, March 8-11, 2005**

## **Objective of the Presentation:**

To present innovative stochastic inference and visualization techniques applicable to in-flight engine PHM.

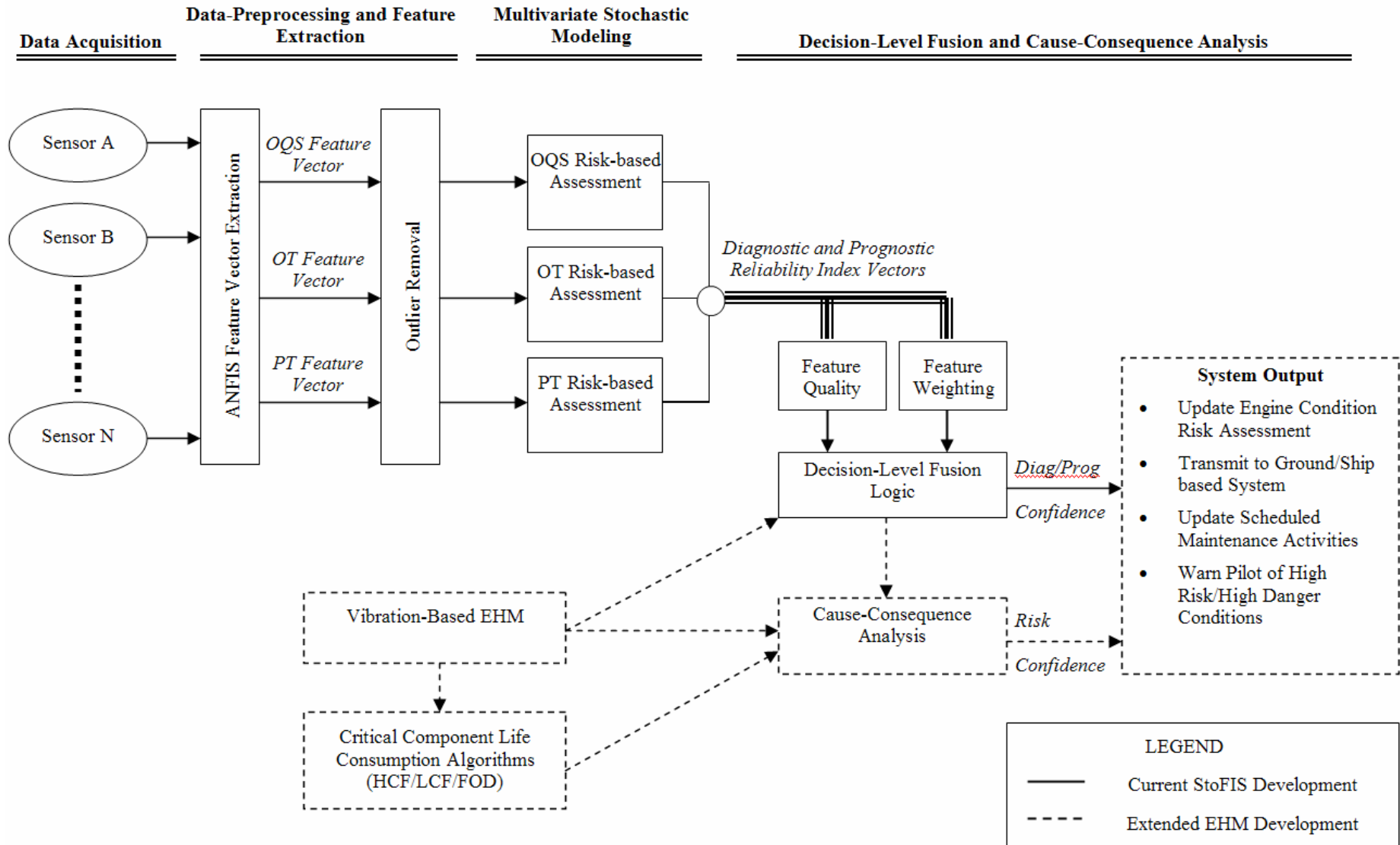
## **Acknowledgement:**

Collaborative effort with STI Technologies, Inc., a continuation of USAF sponsored StoFIS development (JSF Endorsement)

# Presentation Content

1. Stochastic-Neuro-Fuzzy System (StoFIS) for Engine Fault Diagnostics/Prognostics
2. Stochastic Fault Simulation
3. Stochastic Inference Models
4. Visualization Tools for High Dimensional Outputs
5. Concluding Remarks

# 1. Stochastic-Neuro-Fuzzy Inference System (StoFIS) for Engine Fault Diagnostics/Prognostics

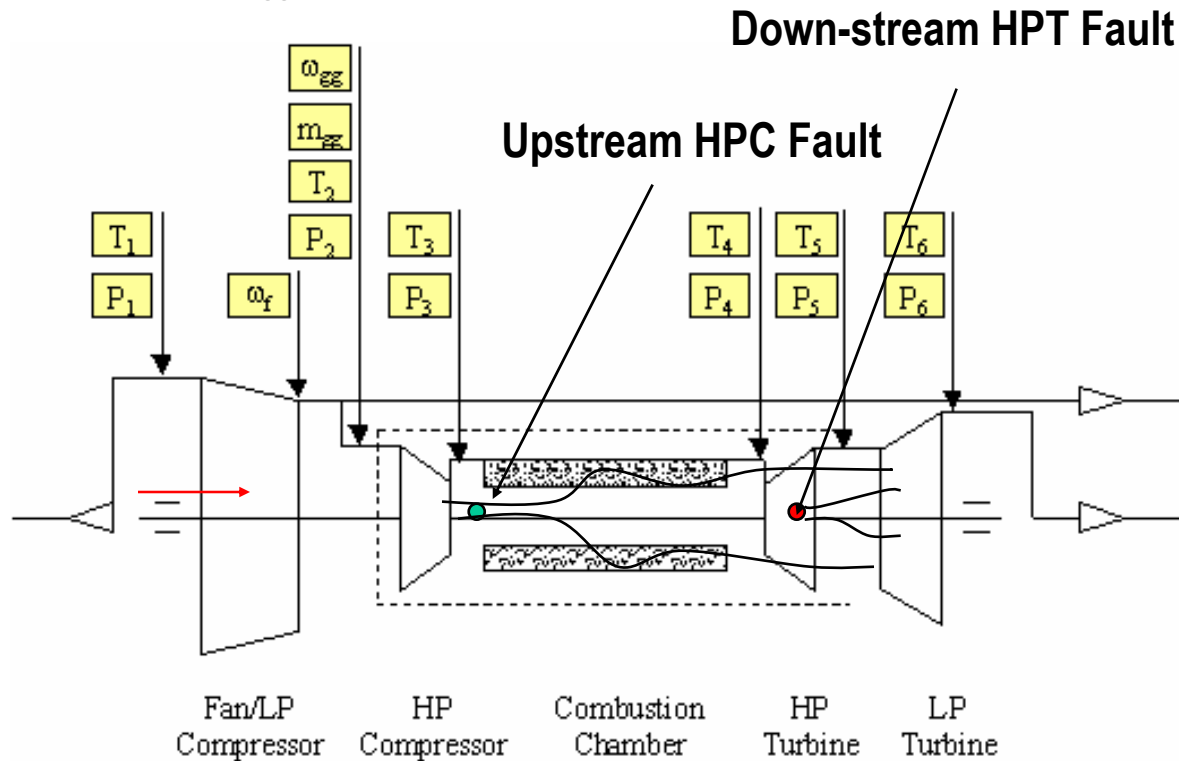


# 2. Stochastic Fault Simulations

## Generic In-Flight Turbofan Engine GPA Models

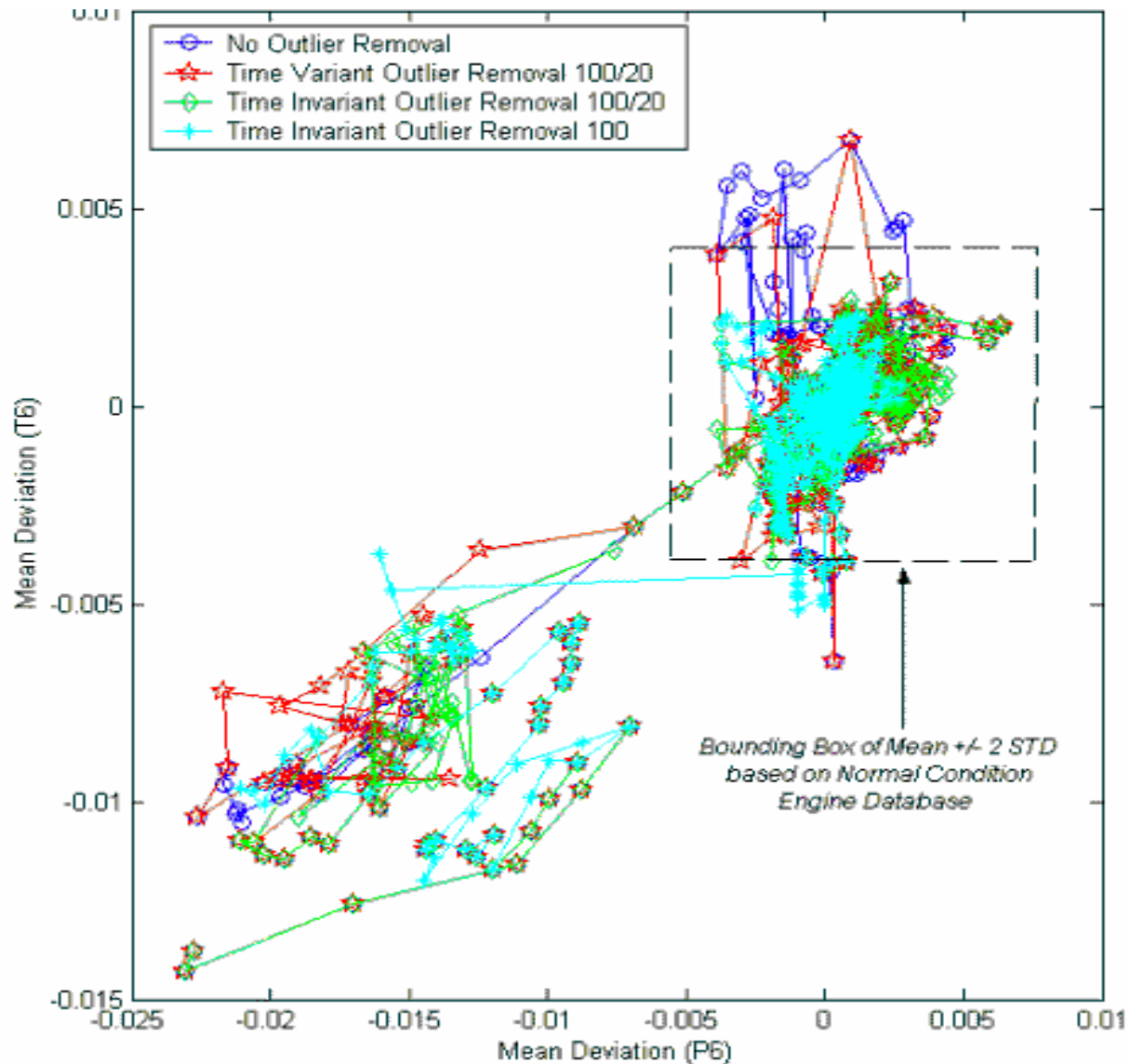
Develop Generic GPA Models for Simulating Engine Functional Faults

$$P_n, T_n = \text{fn}(P_1, T_1, \dot{m}_{gg}, \omega_f, \omega_{gg})$$



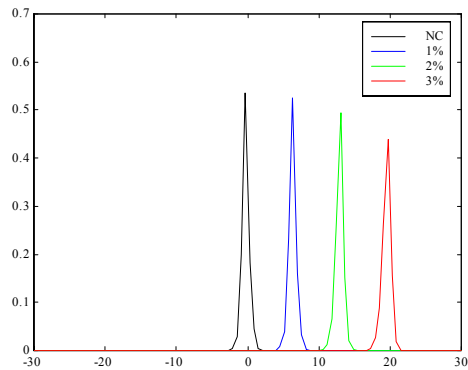
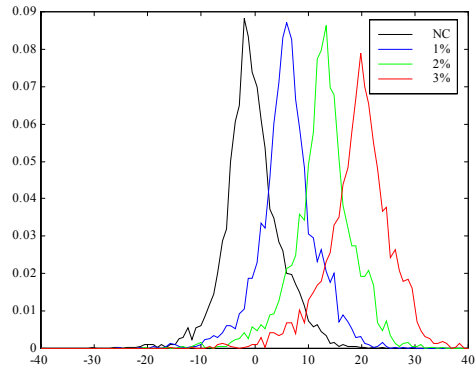
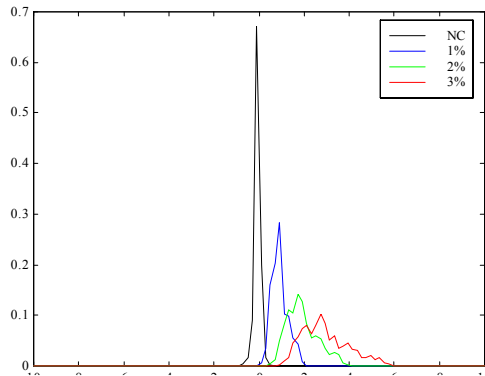
**Overall Engine GPA Model**

# Typical Engine Fault in A 2D Projection

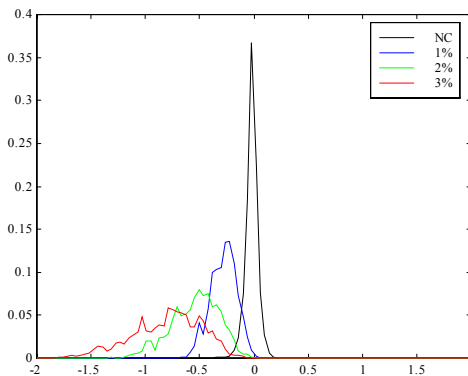
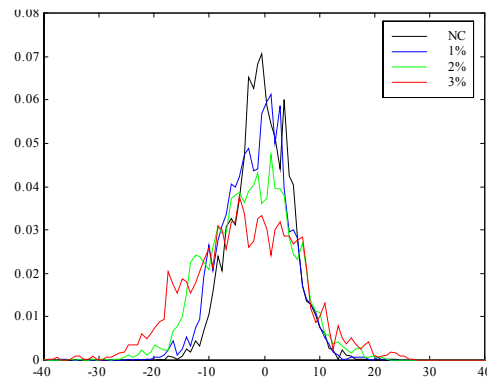
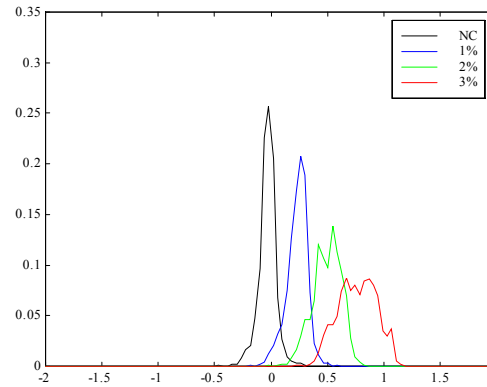


# Probability Density of Engine Parameter Deviations

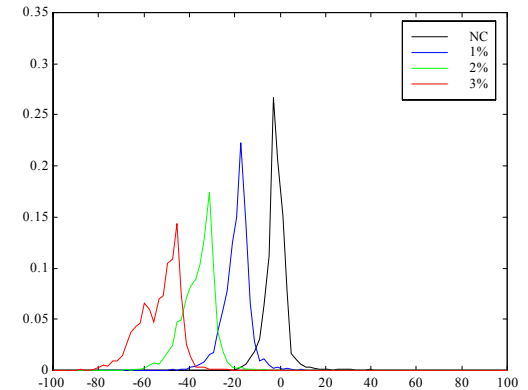
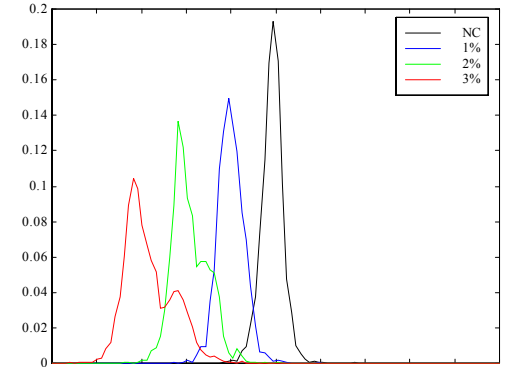
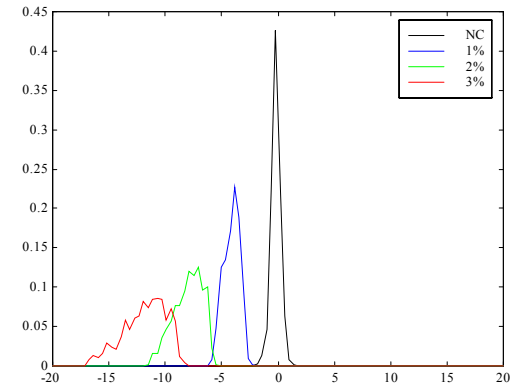
Fault #4: Drop in High Pressure Turbine Capacity



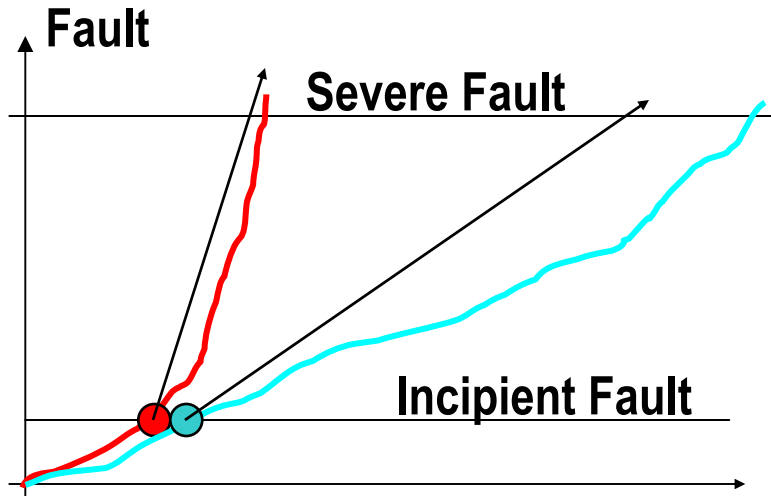
Fault #2: Drop in Low Pressure Turbine Capacity



Fault #7: Drop in High Pressure Compressor

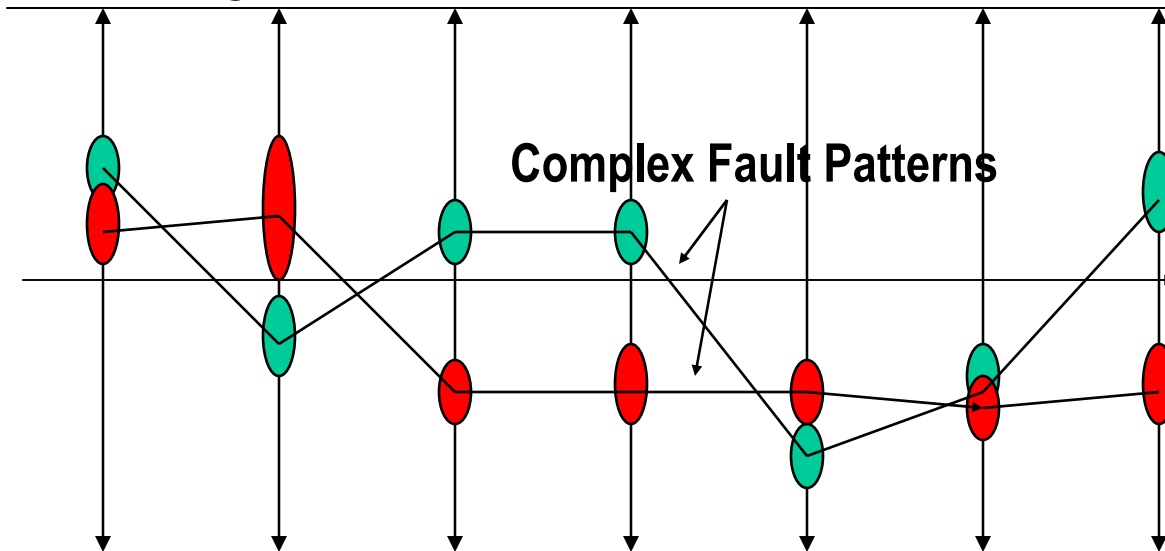


# Real PHM Problems Are Often in High-Dimensions...



Data Fusion? Or Stochastic Physics?

● Single Fault Parameter



**Current Practice:**

Using 1D Selected Fault Parameters ...  
Health Index based on subjective data fusion...  
Difficult to understand stochastic fault physics...

**Future Need:**

Using High-Dimensional Parameter Space..  
Health Index based on High D fault patterns...  
Helps to understand stochastic fault physics...

We need to capture the complex stochastic fault patterns:

RESPONSE:

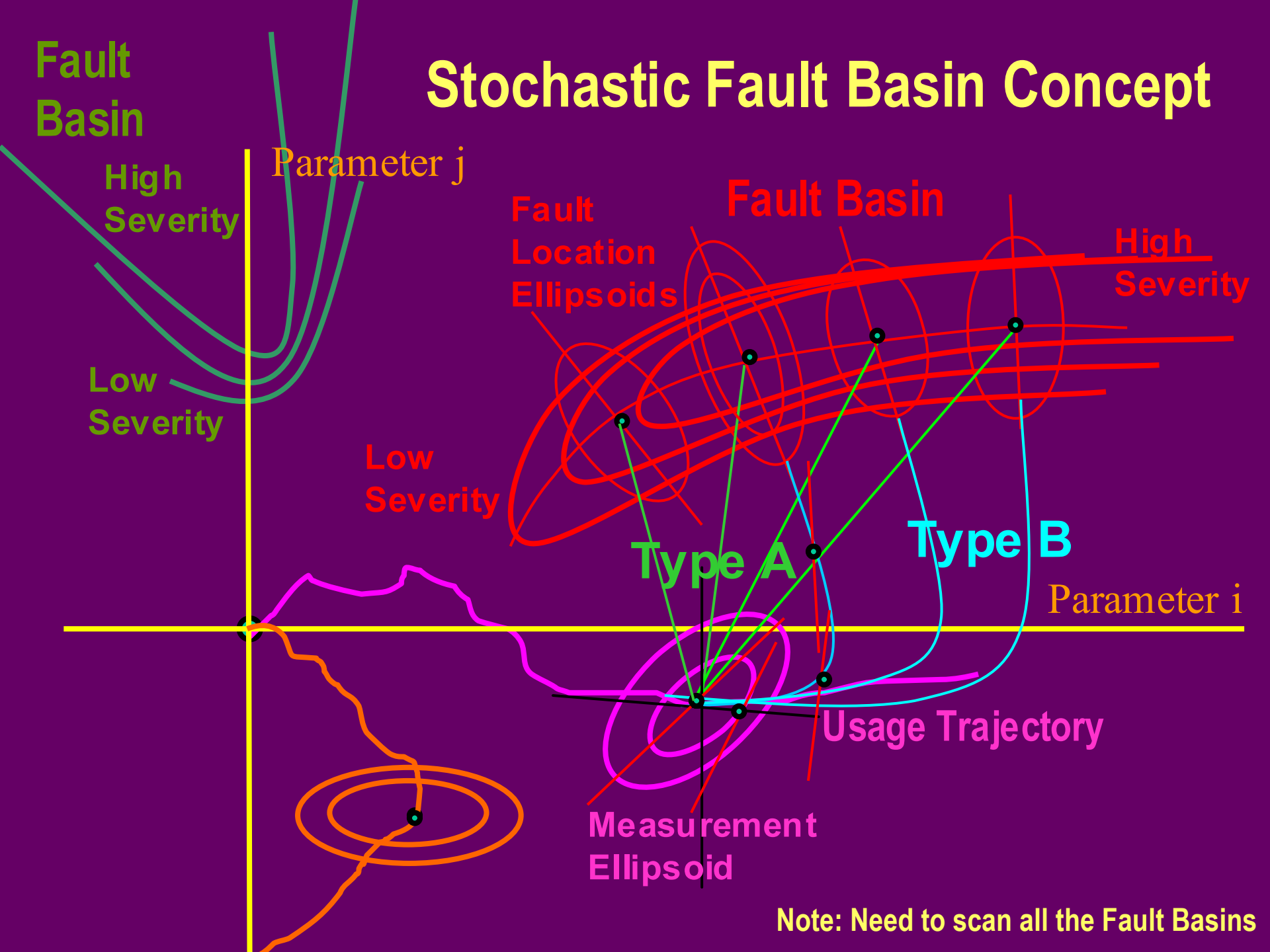
- 1) Accurate estimation of the HD stochastic input-output relationship
- 2) Stochastic pattern mapping in "2D health visualization maps"

RISK COMPUTATIONS:

- 3) *Multidimensional Reliability Model*

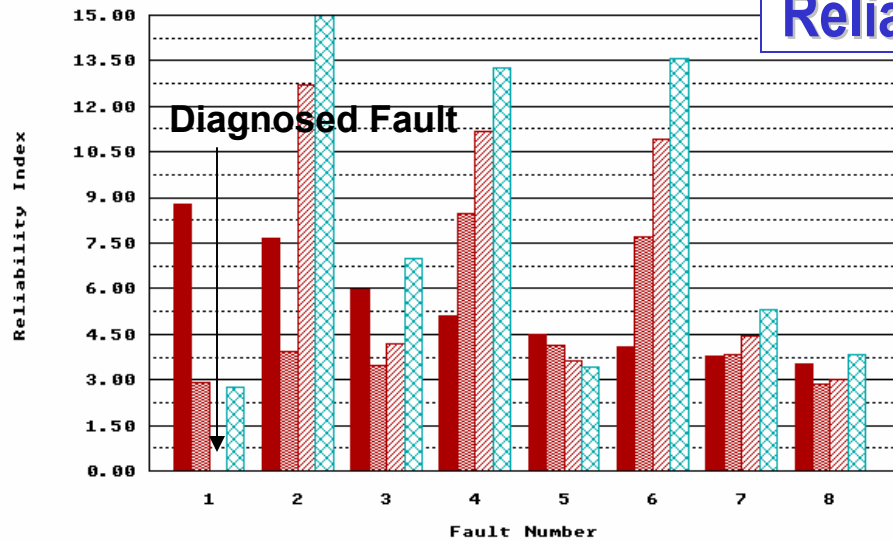


# Stochastic Fault Basin Concept



Quasi-static GPA Model - Lpt 2% Eff.Drop

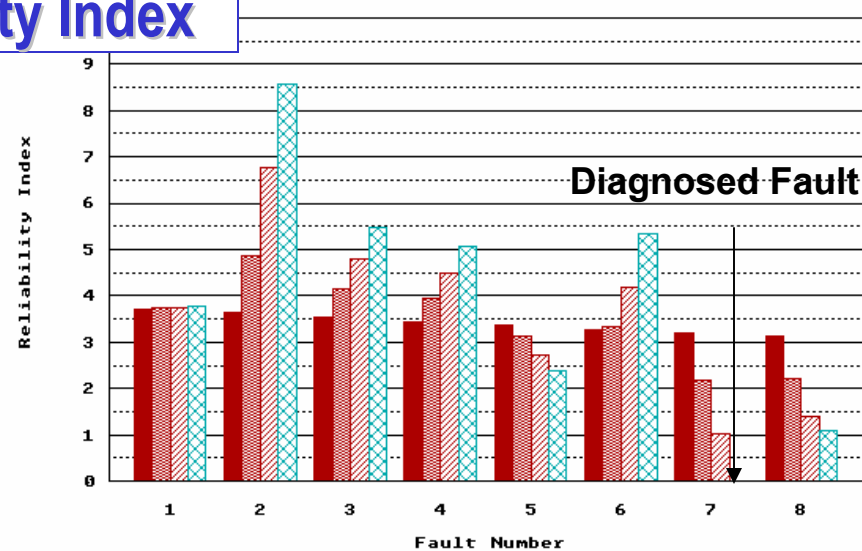
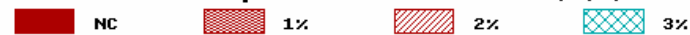
Reliability Index for 8 Faults -0,1,2,3%



## Reliability Index

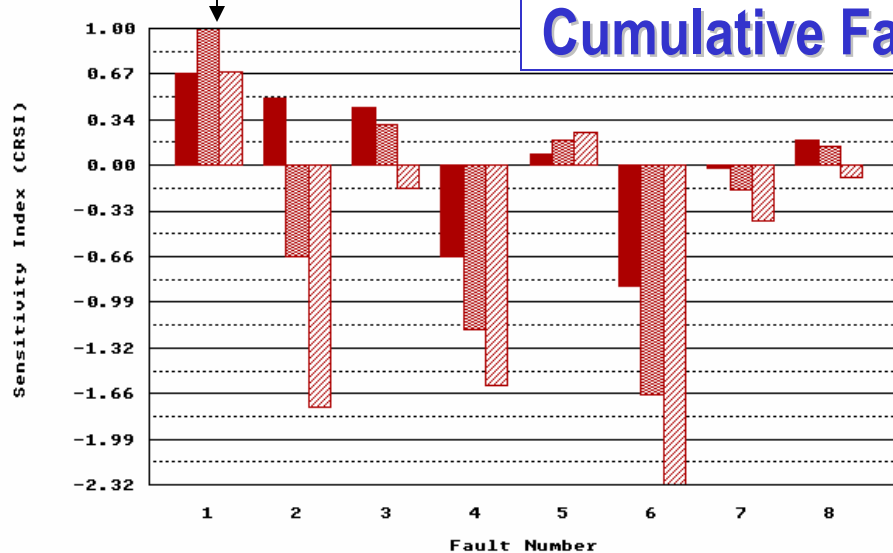
Quasi-static GPA Model - Fan 3% Eff.Drop

Reliability Index for 8 Faults -0,1,2,3%



Quasi-static GPA Model - LPT 2% Eff.Drop

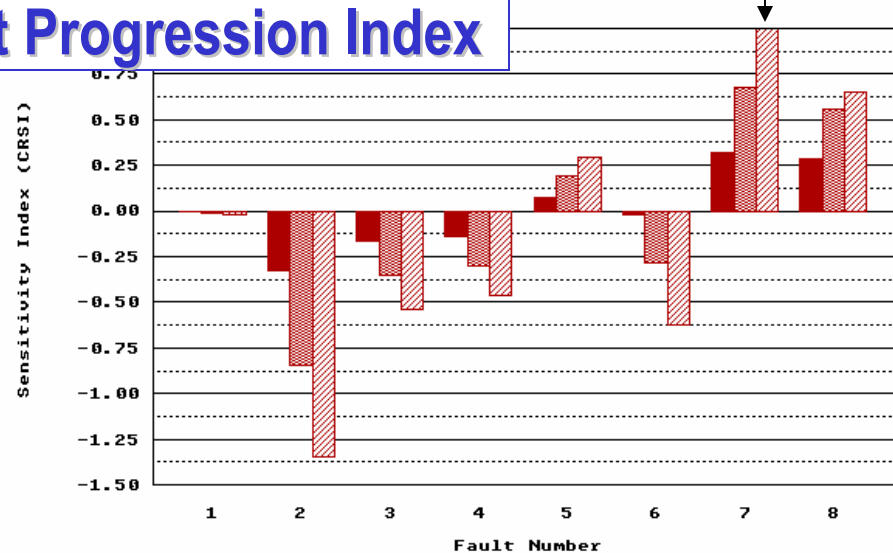
Reliability Index for 8 Faults - 1,2,3%



## Cumulative Fault Progression Index

Quasi-static GPA Model - Fan 3% Eff.Drop

Reliability Index for 8 Faults - 1,2,3%



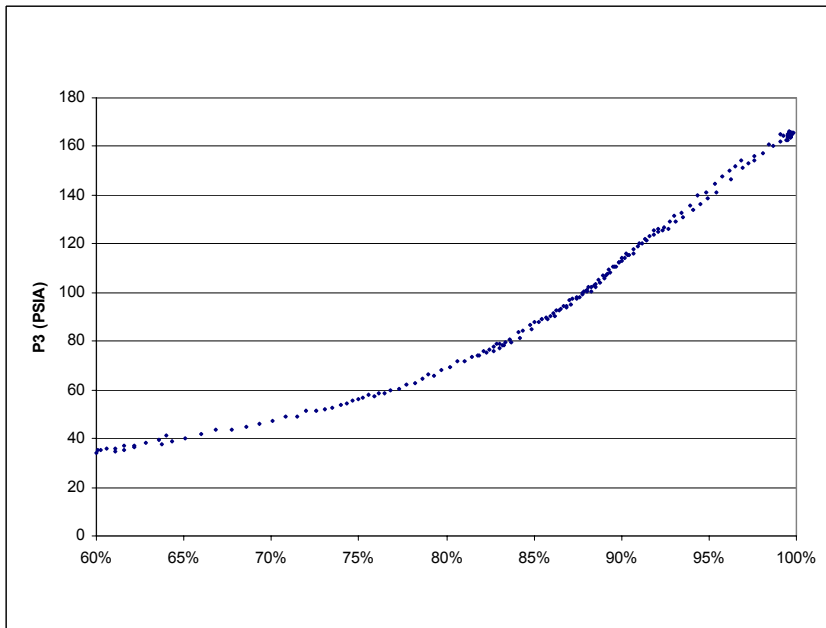
# 3. Stochastic Inference Models

## In-Flight vs. Ground Parameter Variations

Ground-test data

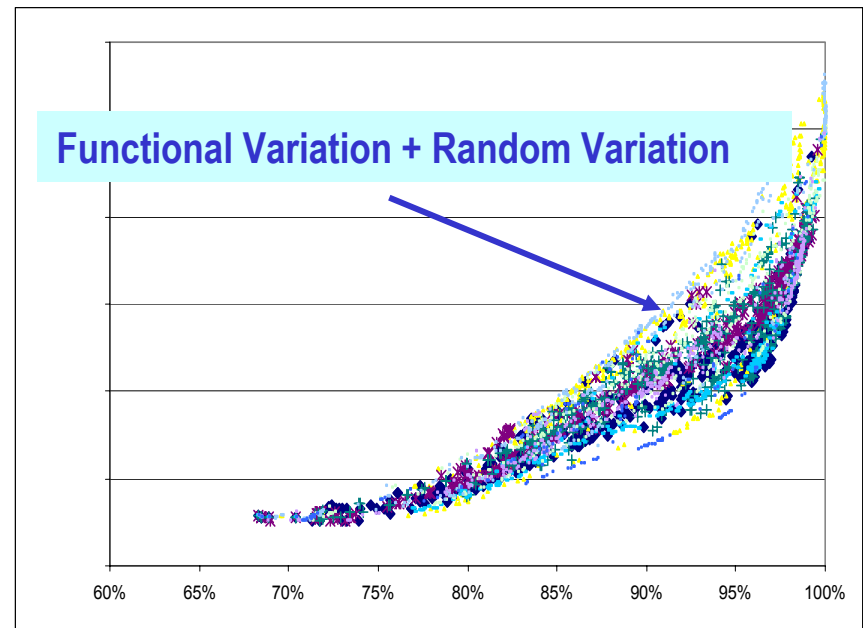
In-flight data

Comp. Pressure



Speed

Comp. Pressure

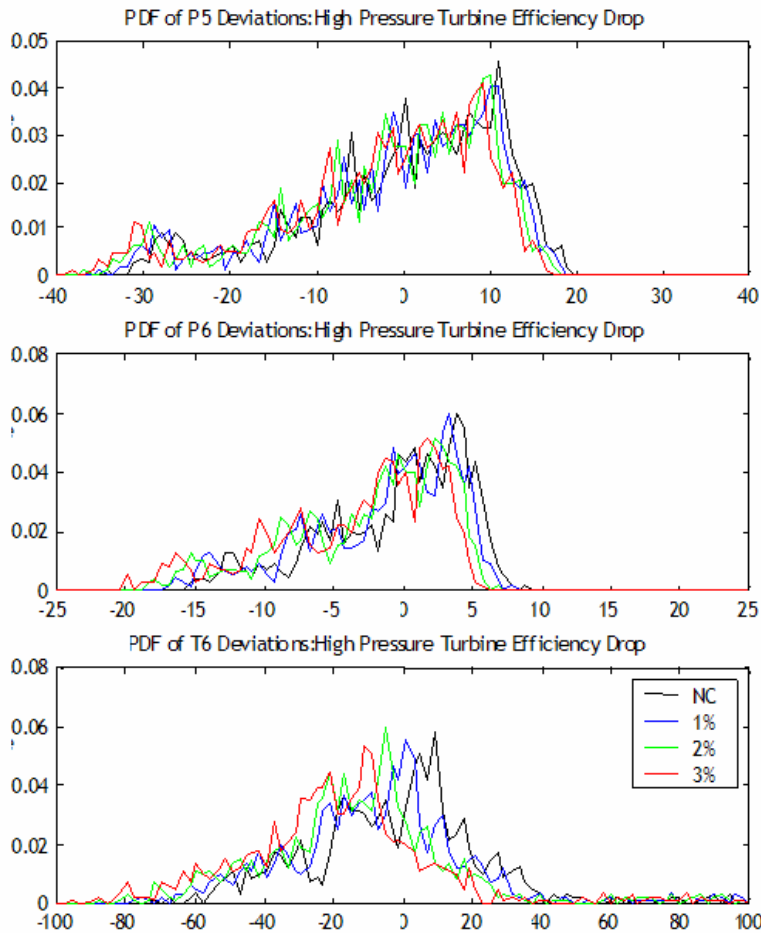


Speed

# Stochastic Approximation in High-Dimensions

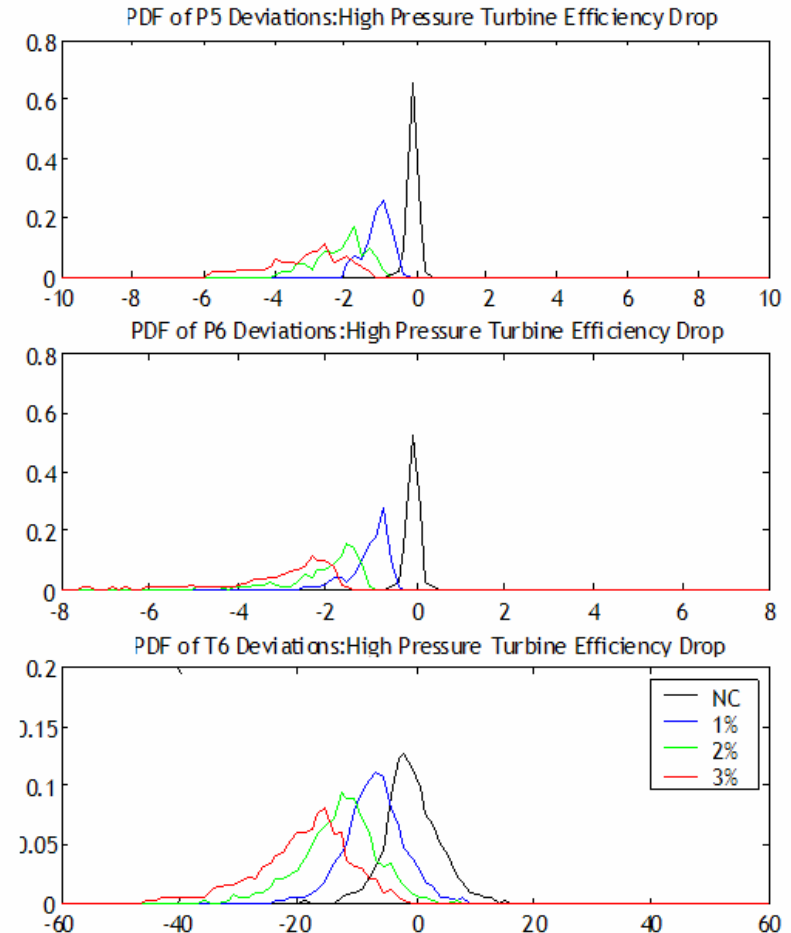
## One-Dimensional Function

### Function of 1 variable

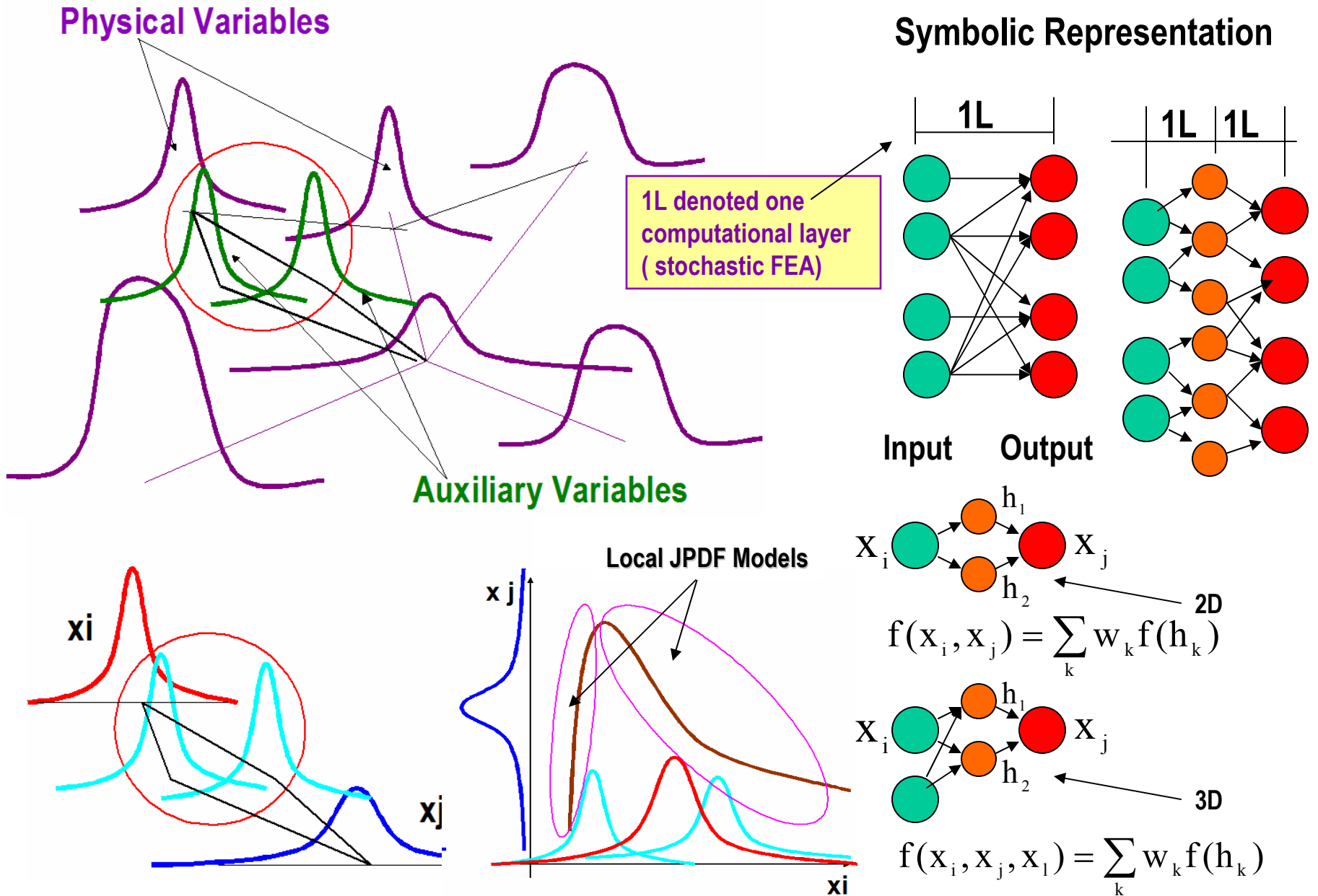


## Multidimensional Function

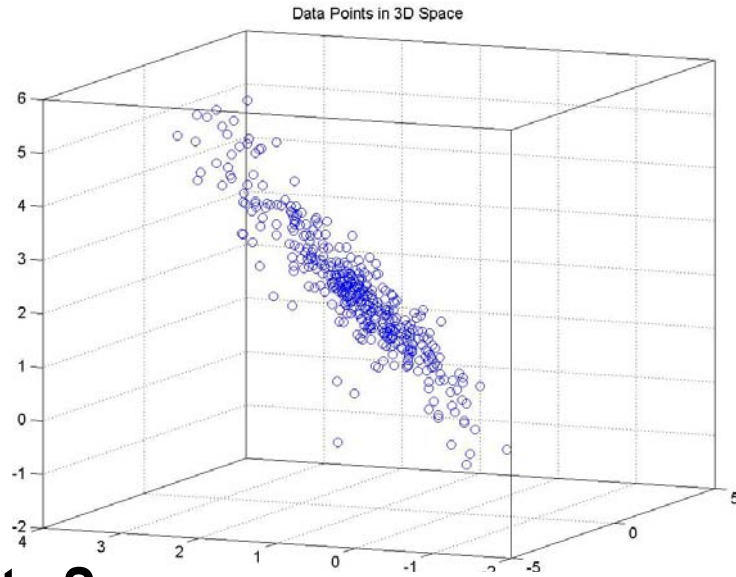
### Function of 5 variables



# 2L and 3L Hierarchical Approximation Models

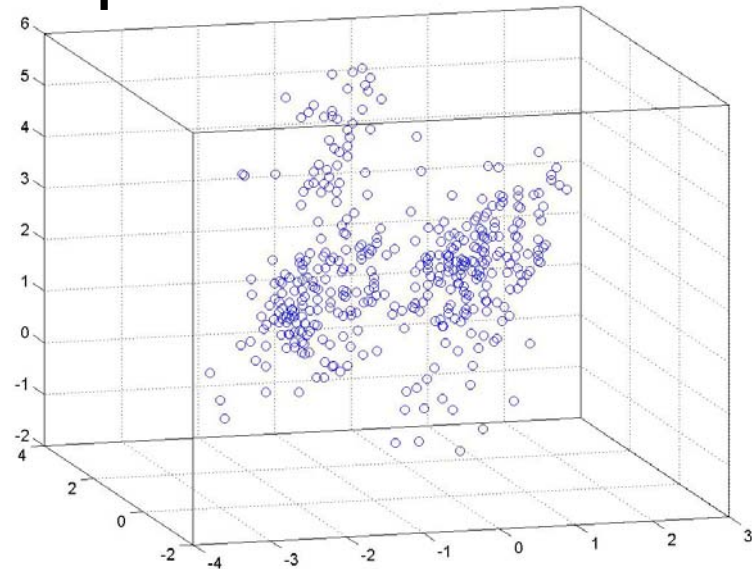


# HO Stochastic Field Approximation Using Local JPDF Models



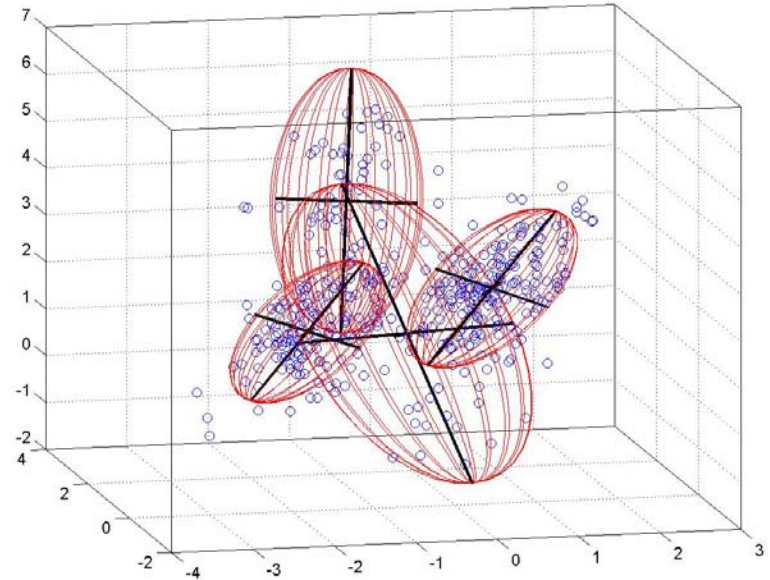
**Data Space**

Data Points in 3D Space

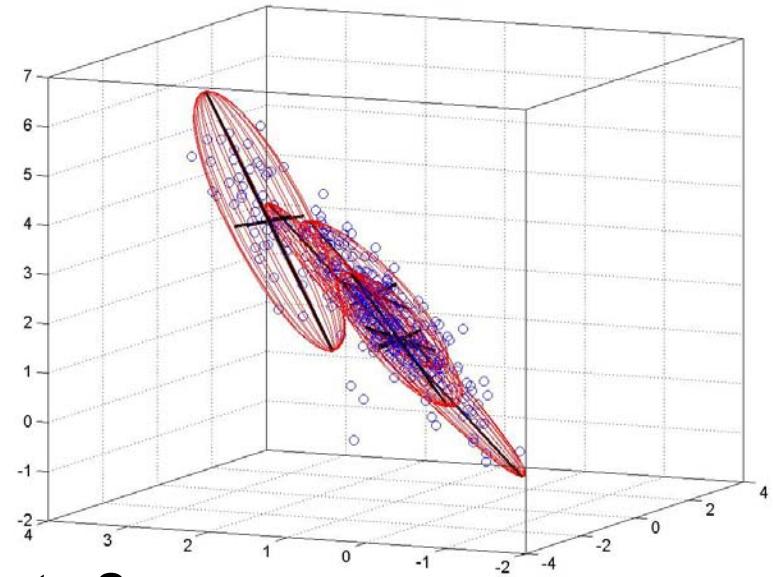


**State Space**

Data and Local PPCA Model



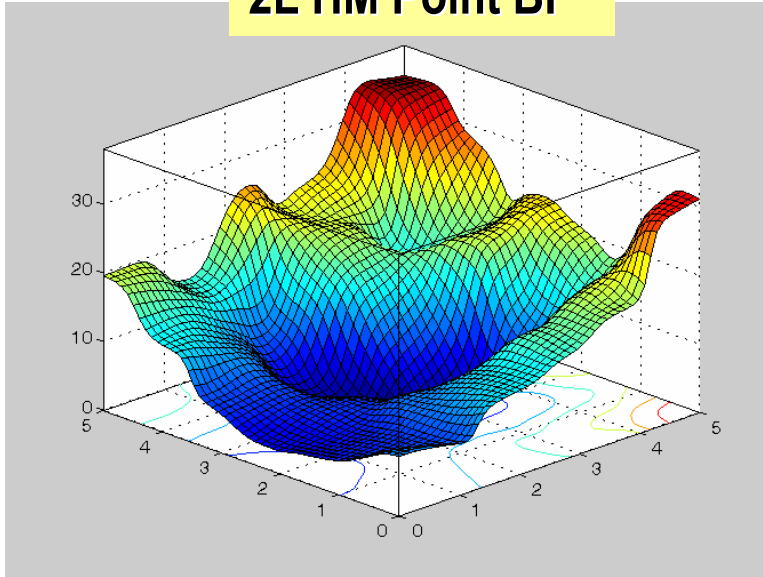
Data and Local PPCA Model



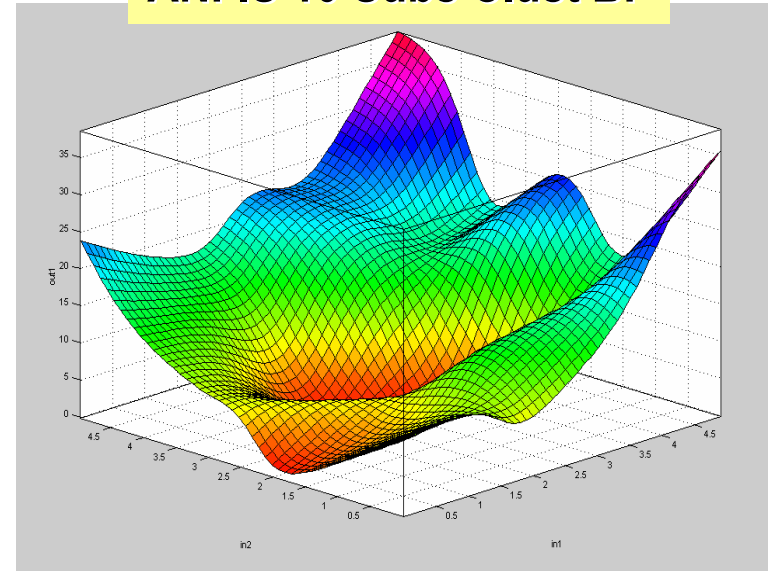


# Comparison of 2L and 3L (Bayesian) HM Models

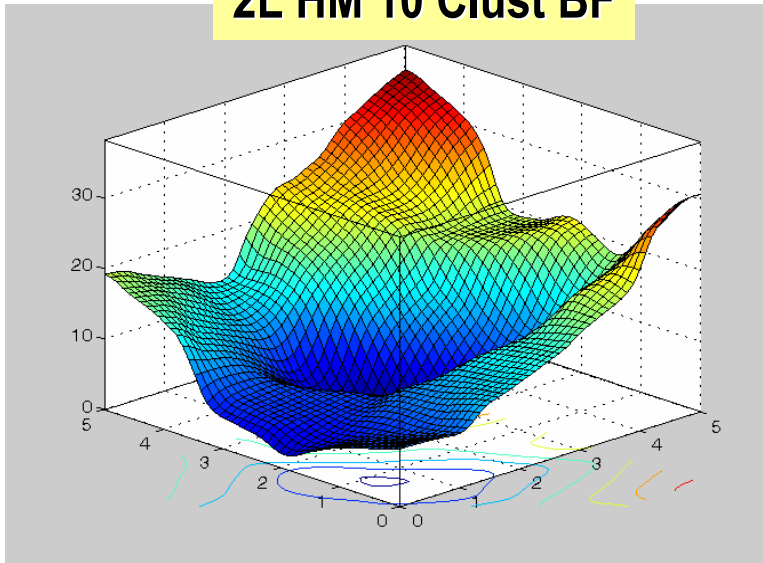
2L HM Point BF



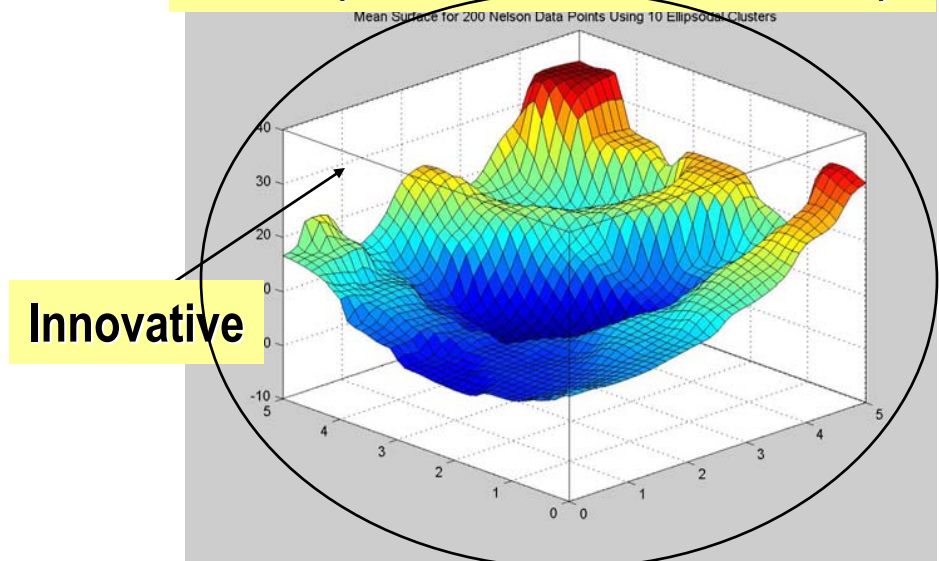
ANFIS 10 Subs Clust BF



2L HM 10 Clust BF



3L HM (10 Clust BF with Point BF)



# 4. Visualization Tools for High-Dimensional Responses

## 1. Generative Topographic Maps (2D function)

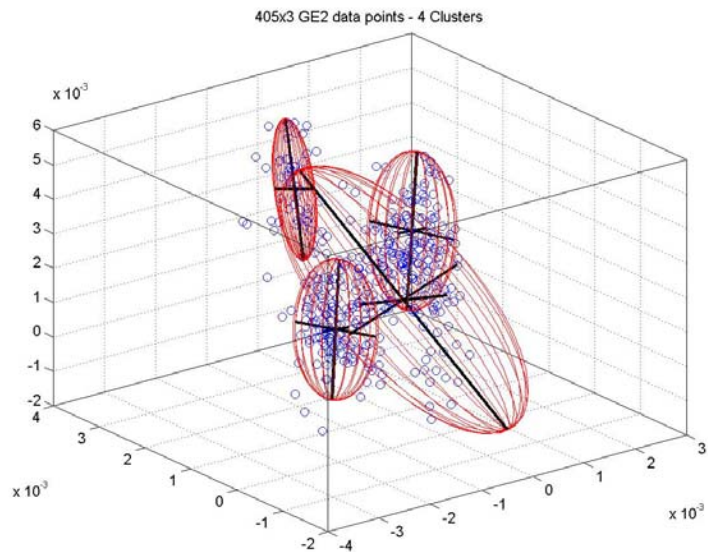
- If the posterior JPDF in latent space is unimodal and symmetric, then the mean and mode are closely-spaced, i.e. the map is uniformly colored.
- If the posterior JPDF is more complex, i.e. the mapping manifold is locally twisted or highly curved near a data point the posterior mean and mode are well separated, i.e. the map is non-uniformly colored.
- Magnification factors (measure of local nonlinear distortion of the mapping surface) shows the data clustering structure.

## 2. JPDF Map in Latent Space (2D function)

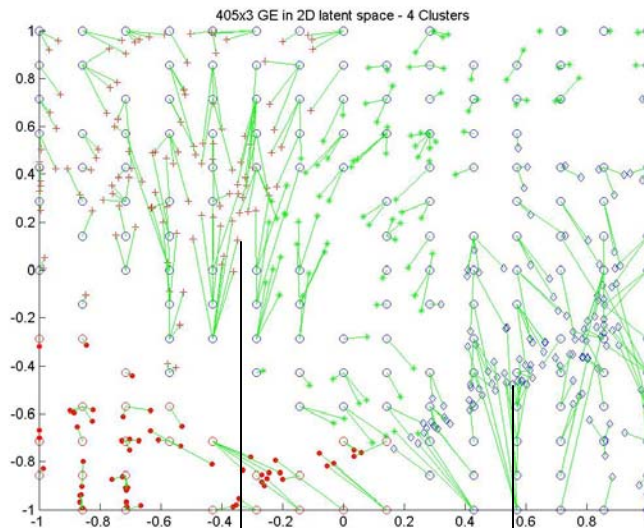
- This is a powerful tool totally new for describing high-dimensional, complex stochastic patterns. Statistical moments can be used as stochastic fault features for fault diagnosis. The use of KL expansion as a synthetic classifier.



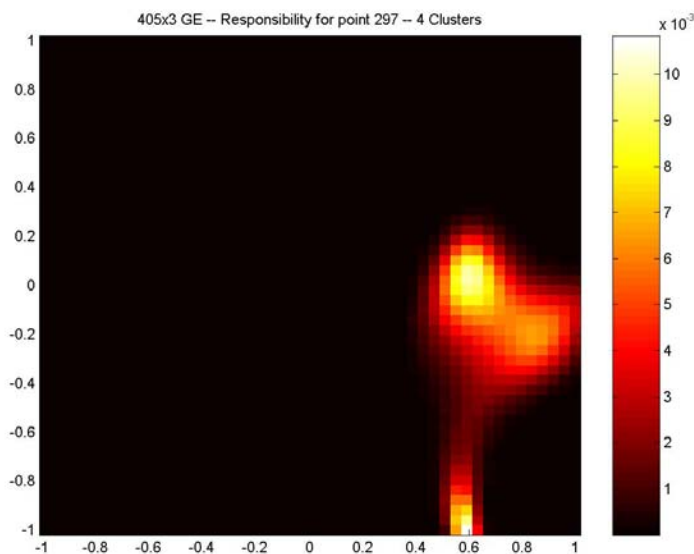
# Stochastic Generative Topographic Map



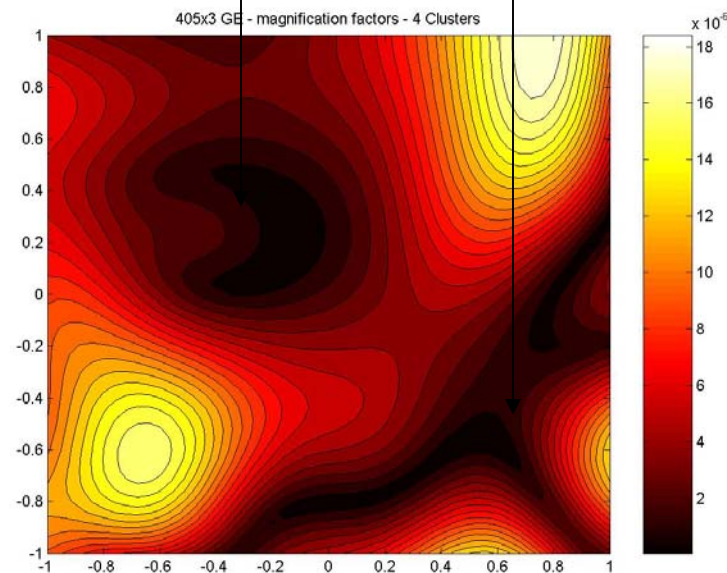
Sample Data in the 3D Original Space



Data in 2D Latent Space

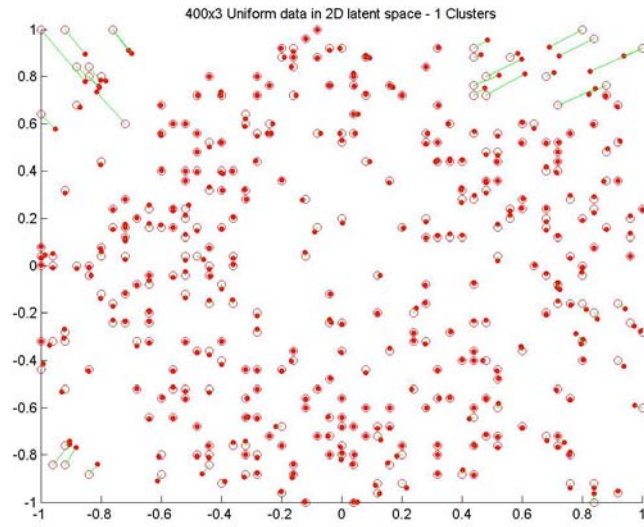
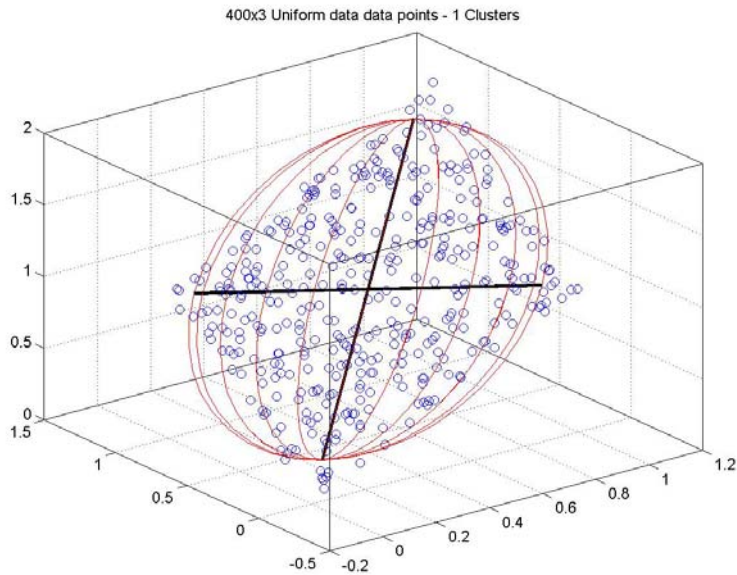


Responsibility of Data Point 297



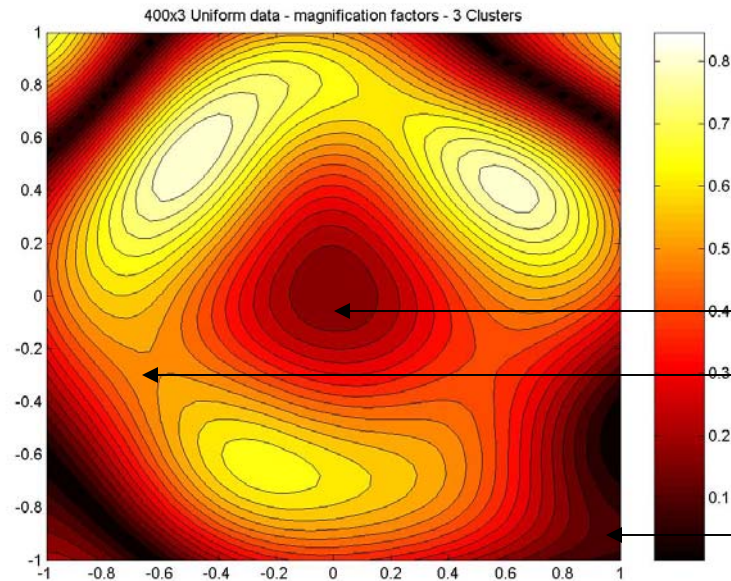
Magnification Factor Map (MFM)

# Stochastic Map Applied to Random Data Hyperplane

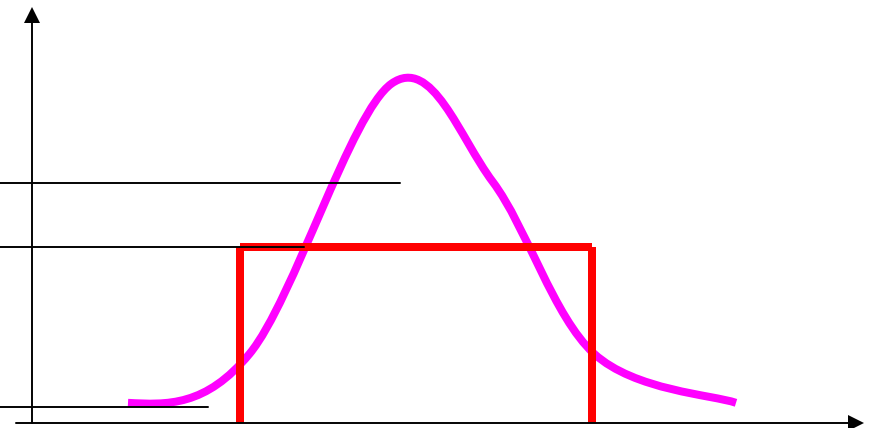


Uniform Random Points in 3D Data Space

Mean and Mode in the 2D Latent Space

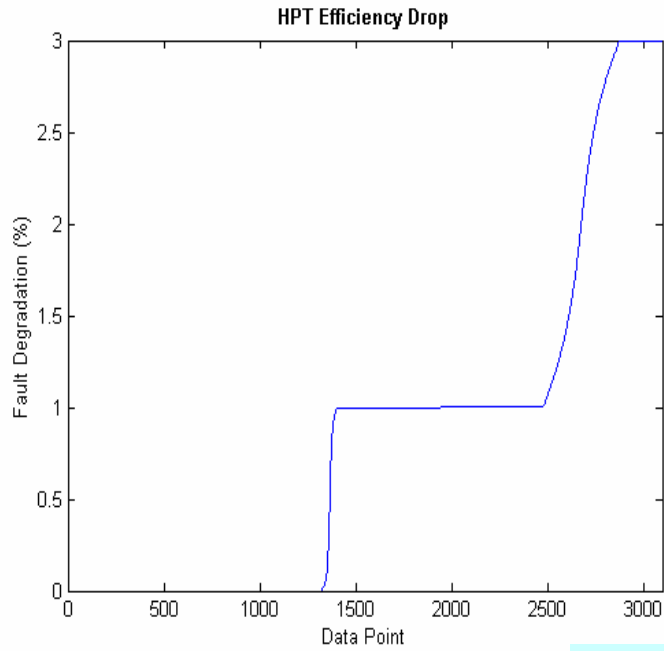


MFM (2D Visualization Map)

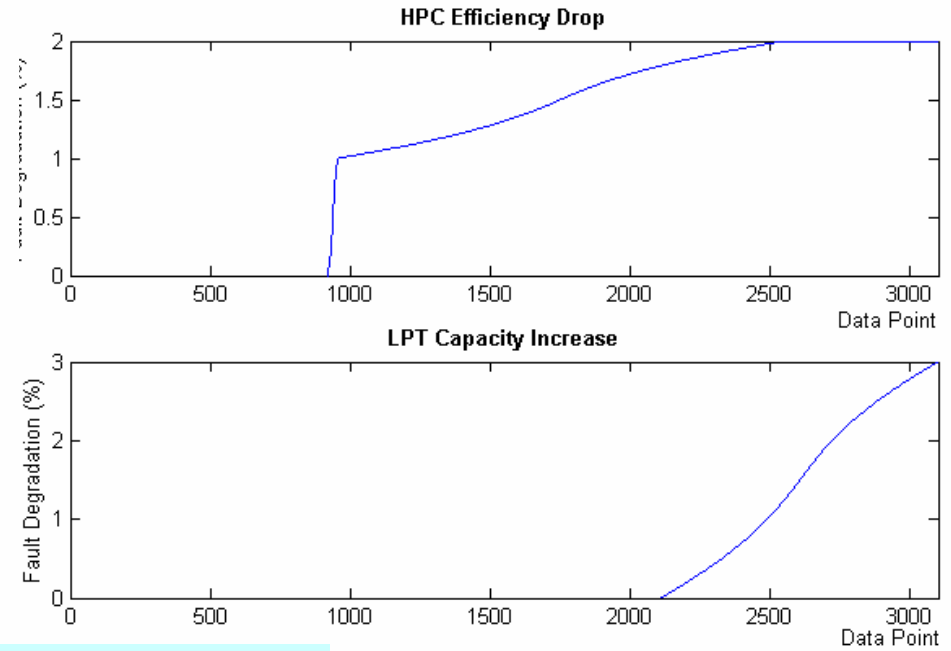


Uniform vs. Gaussian Data Points PDF

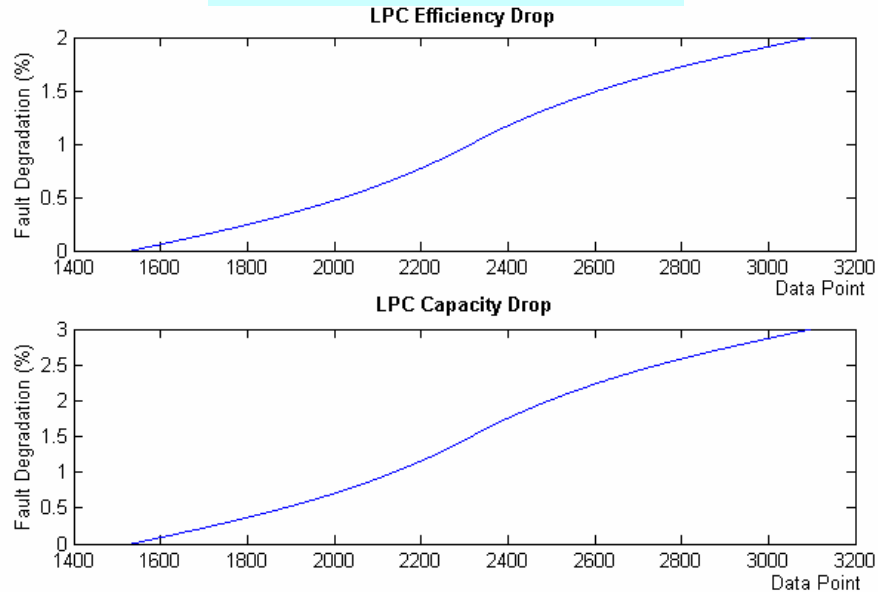
## Simulated Fault # 1

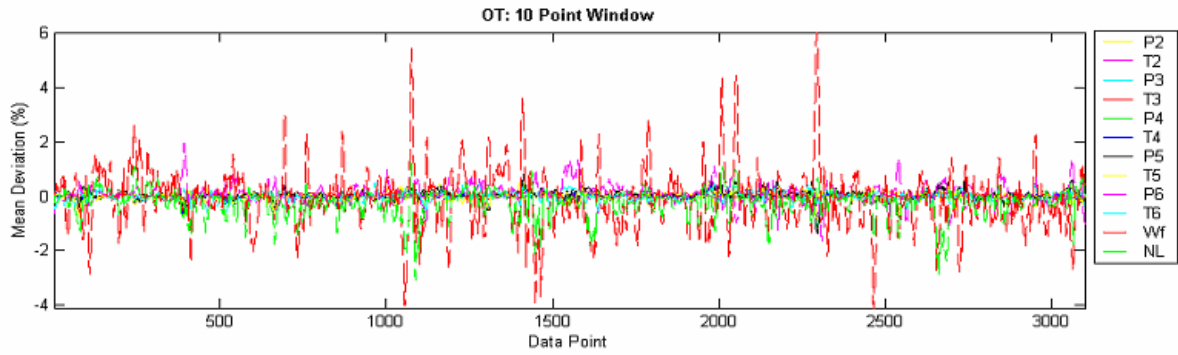


## Simulated Fault # 2

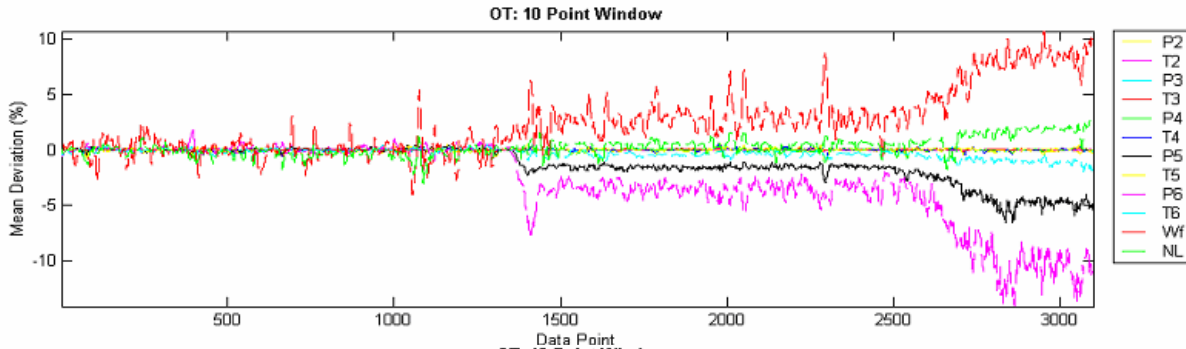


## Simulated Fault # 3

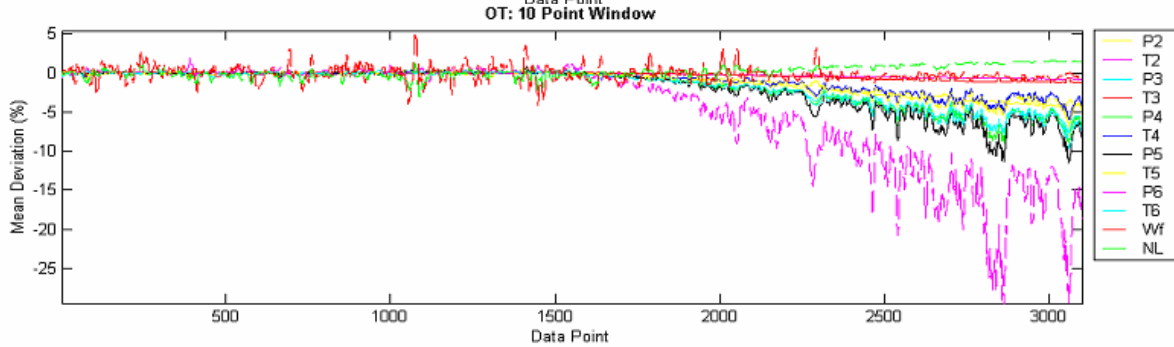




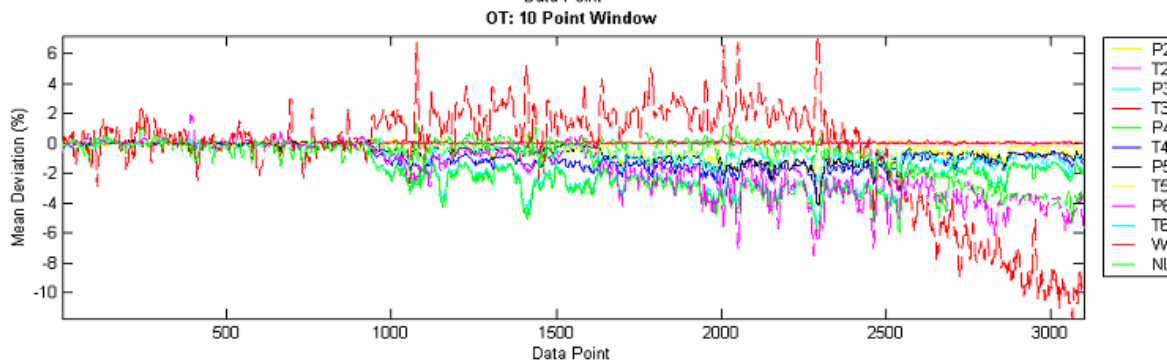
Normal Conditions



Fault #1 - HPT

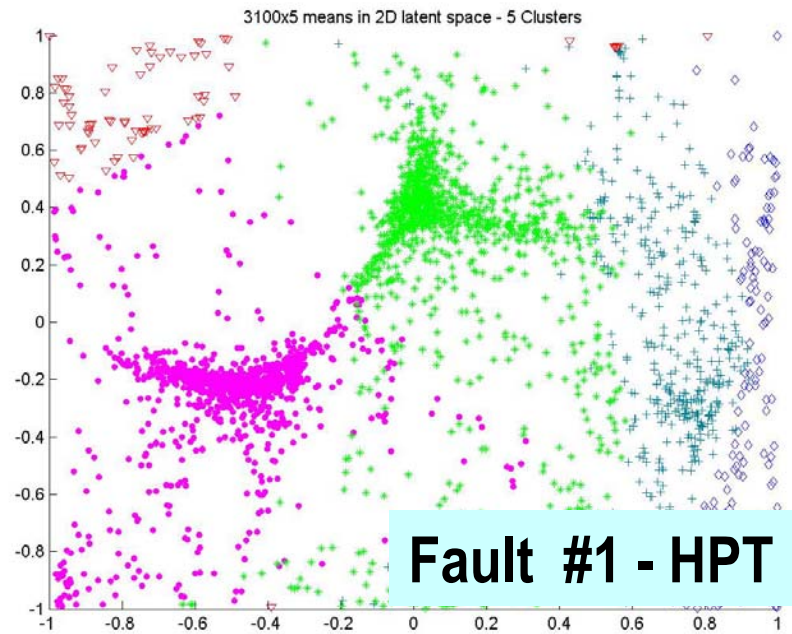
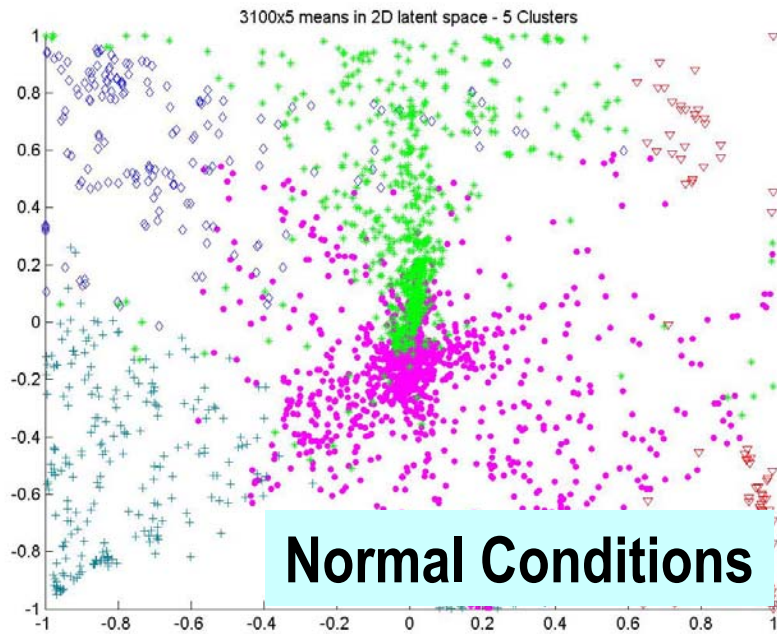


Fault #2 - HPC & LPT

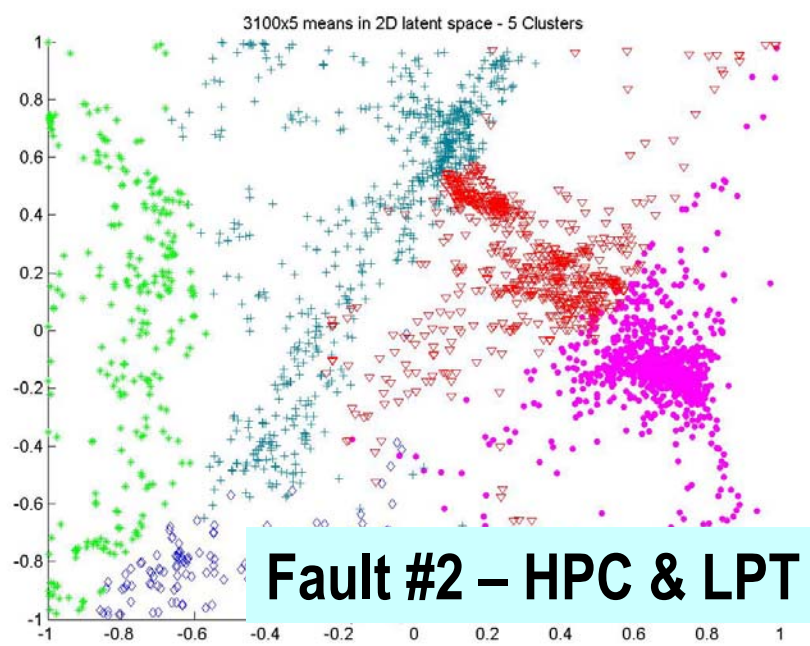
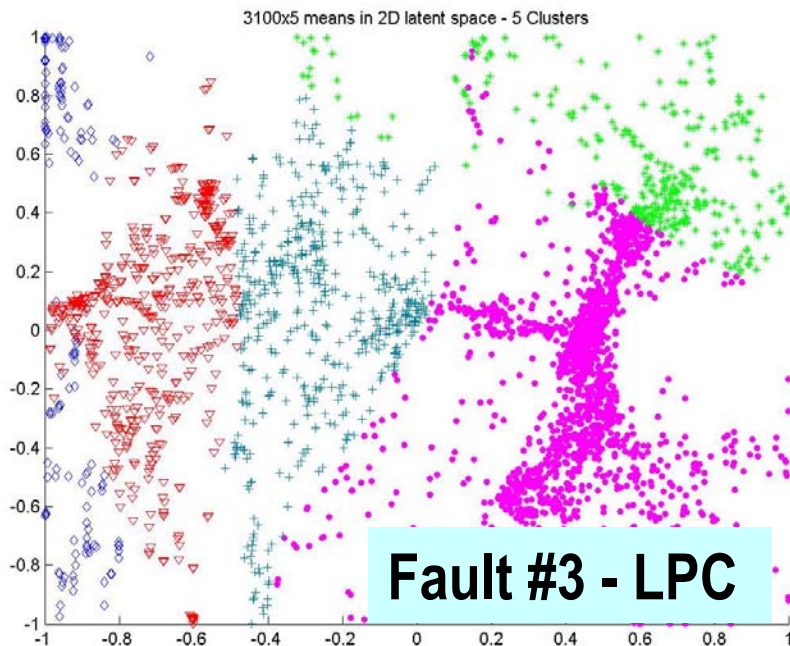


Fault #3 - LPC

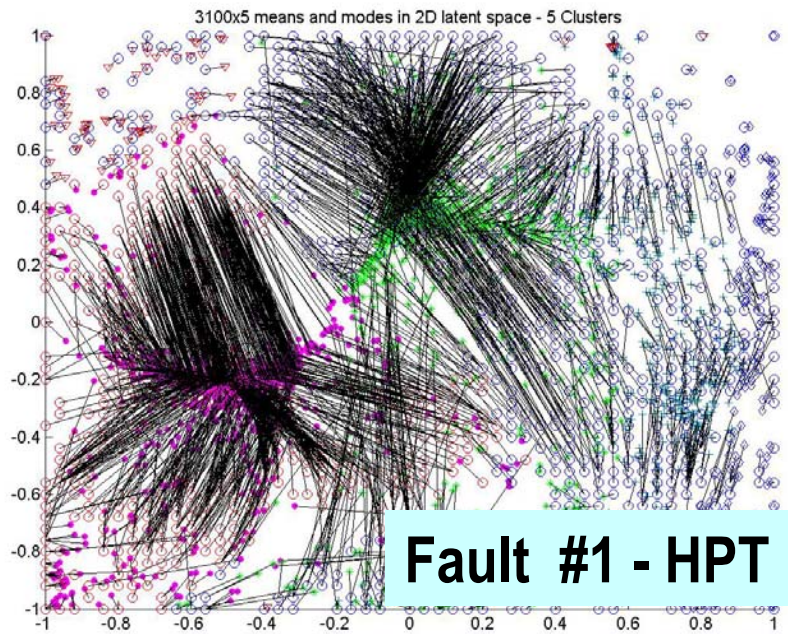
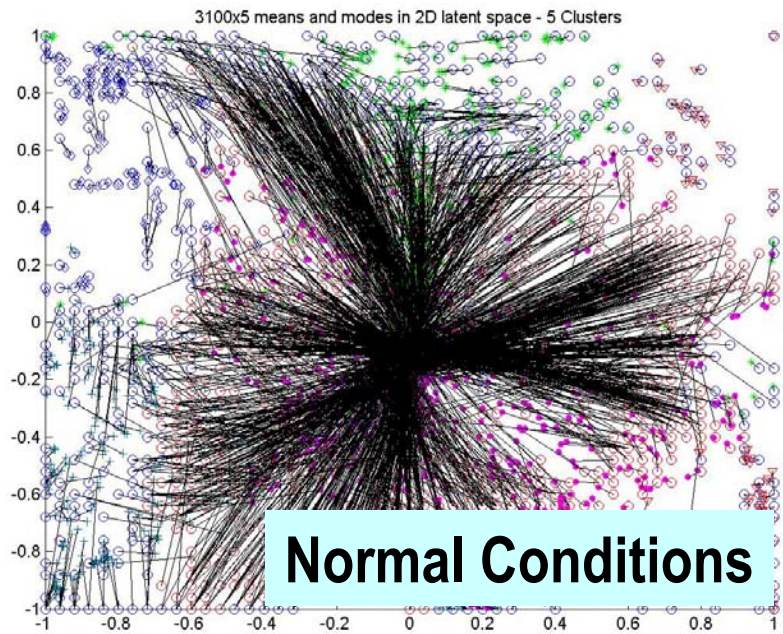




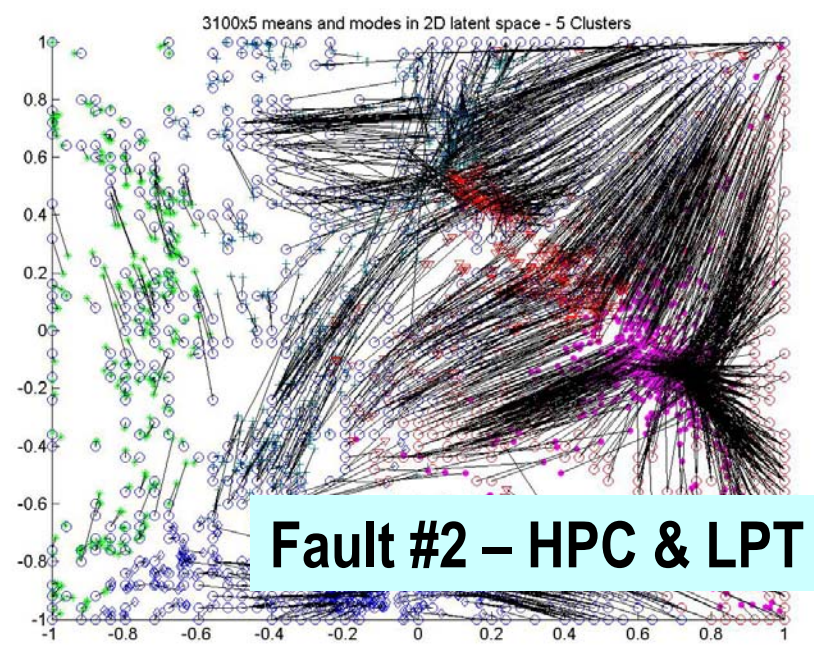
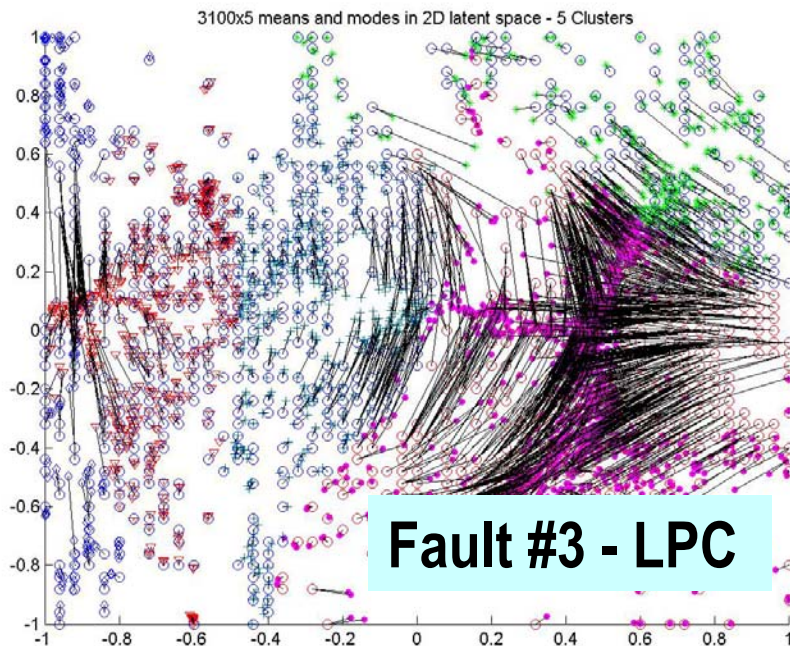
## Data Points in Latent Space





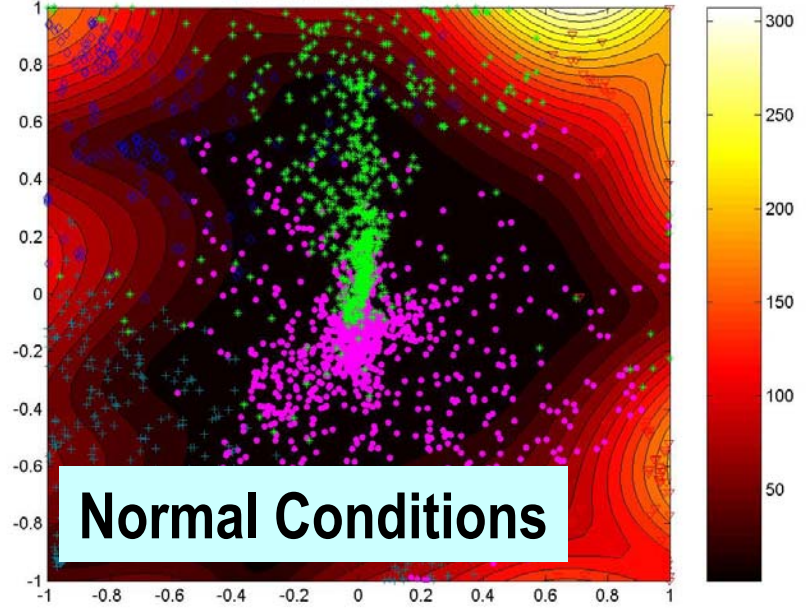


## Latent Data Space Means and Modes

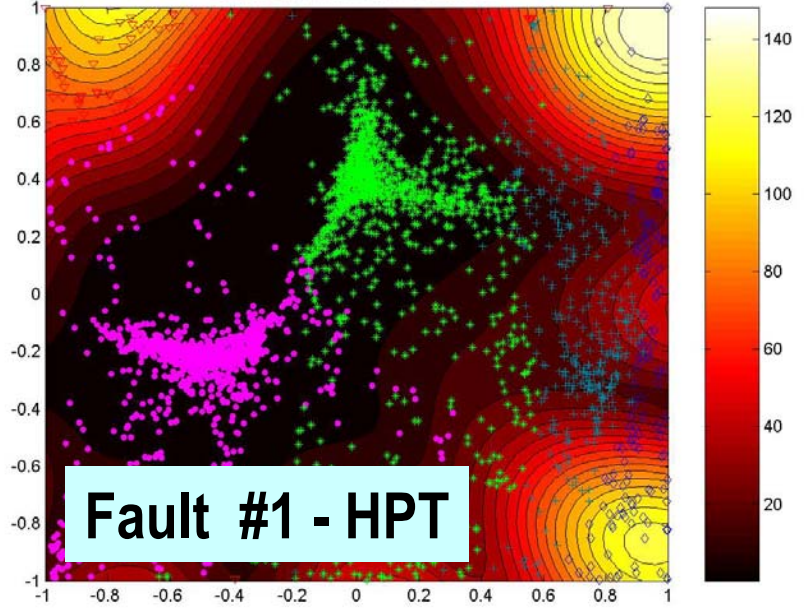




3100x5 M. F. with means - 5 Clusters

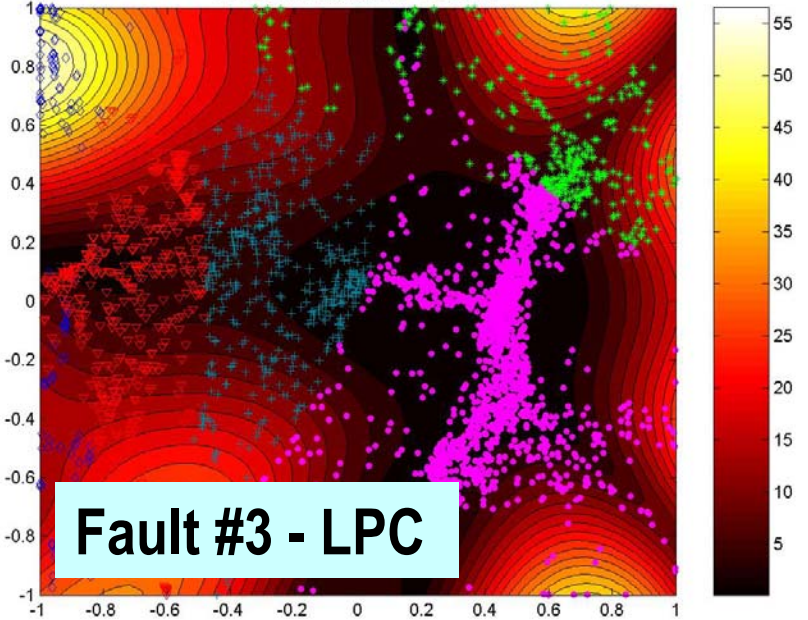


3100x5 M. F. with means - 5 Clusters

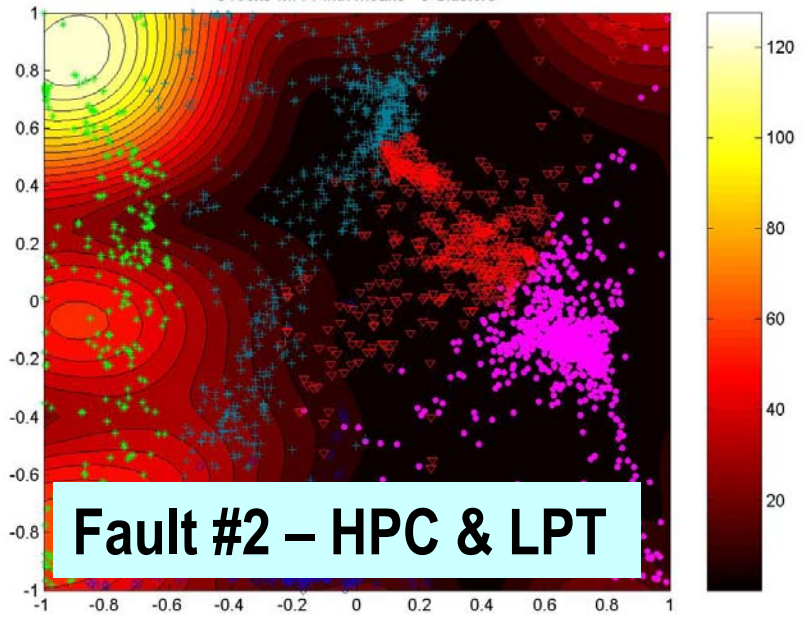


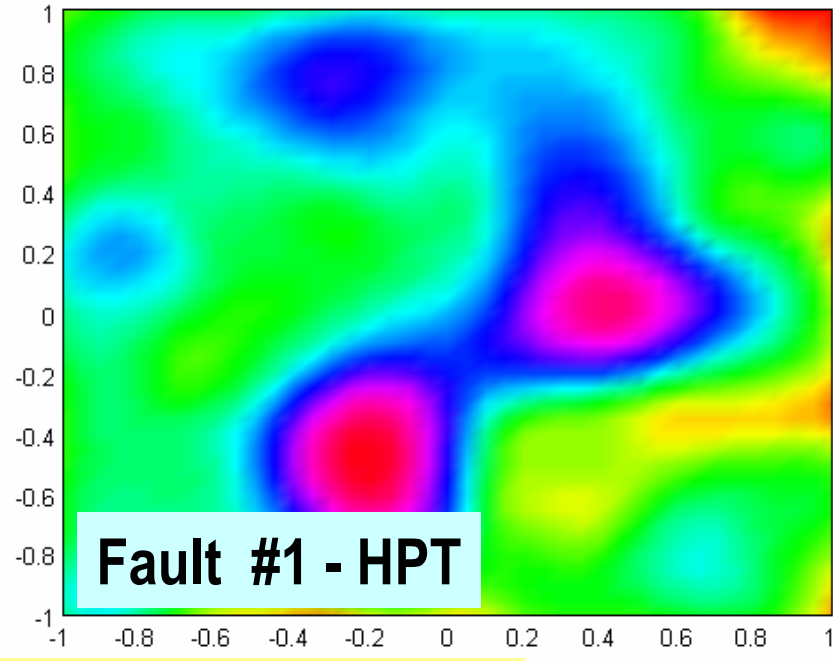
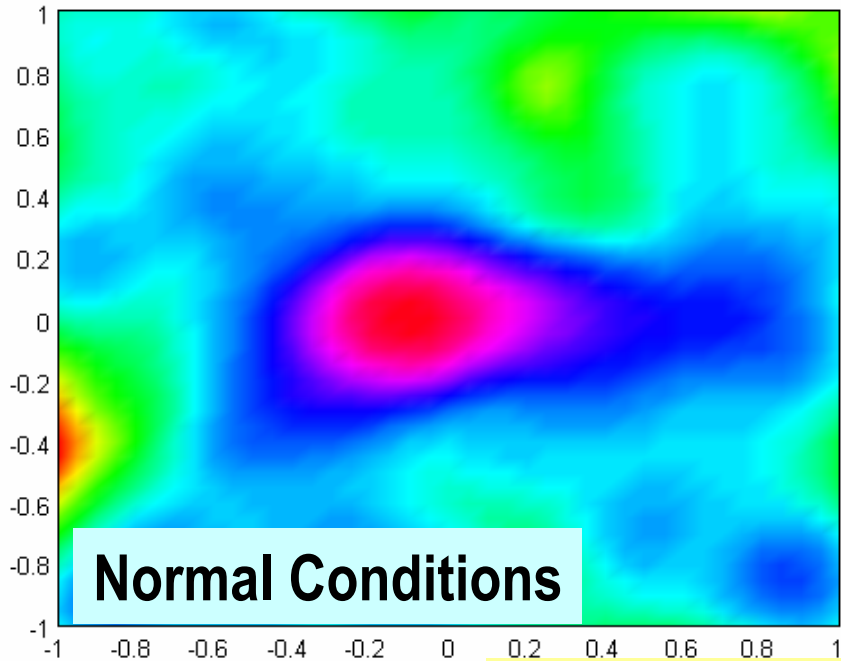
# Stochastic GTM

3100x5 M. F. with means - 5 Clusters

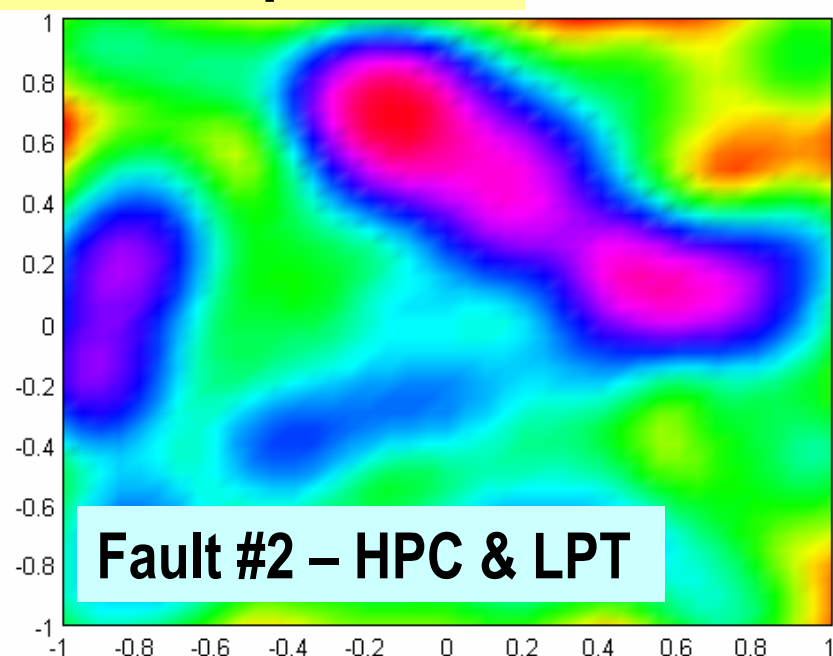
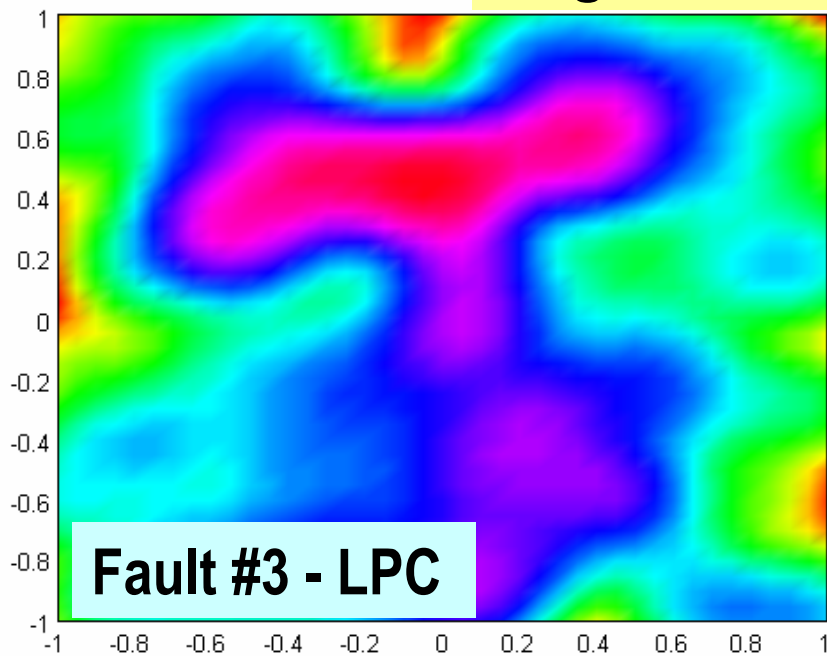


3100x5 M. F. with means - 5 Clusters



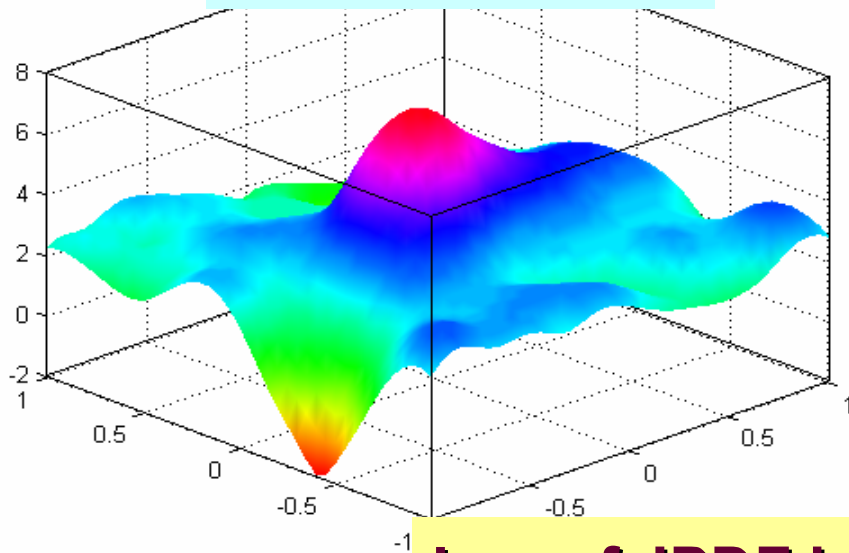


## Log of JPDF in Latent Space

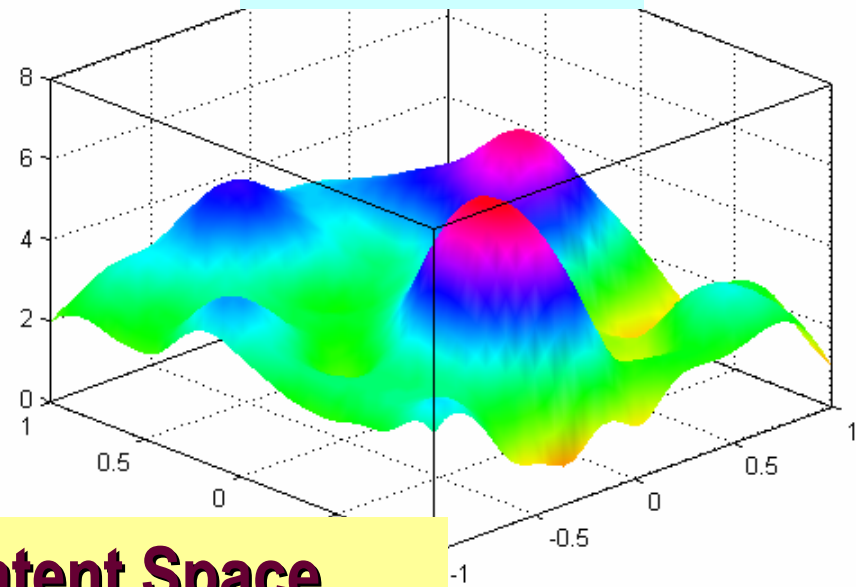




**Normal Conditions**

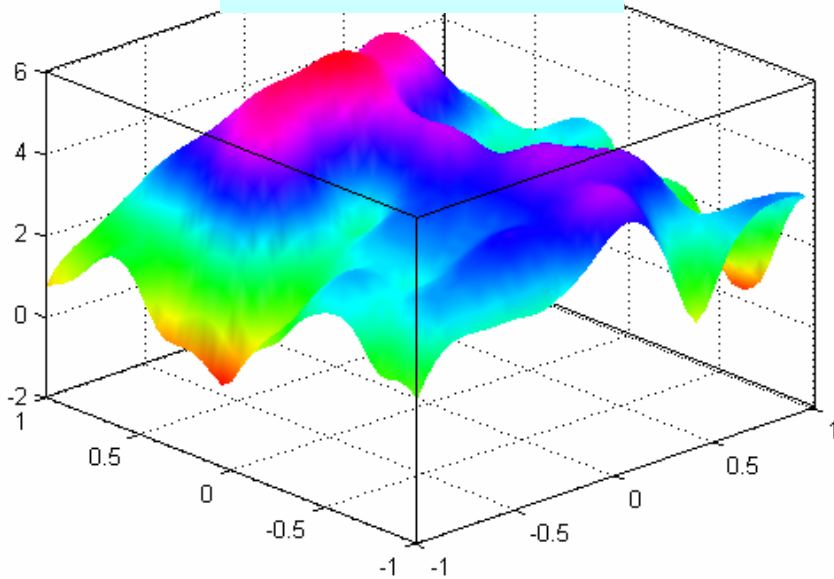


**Fault #1 - HPT**

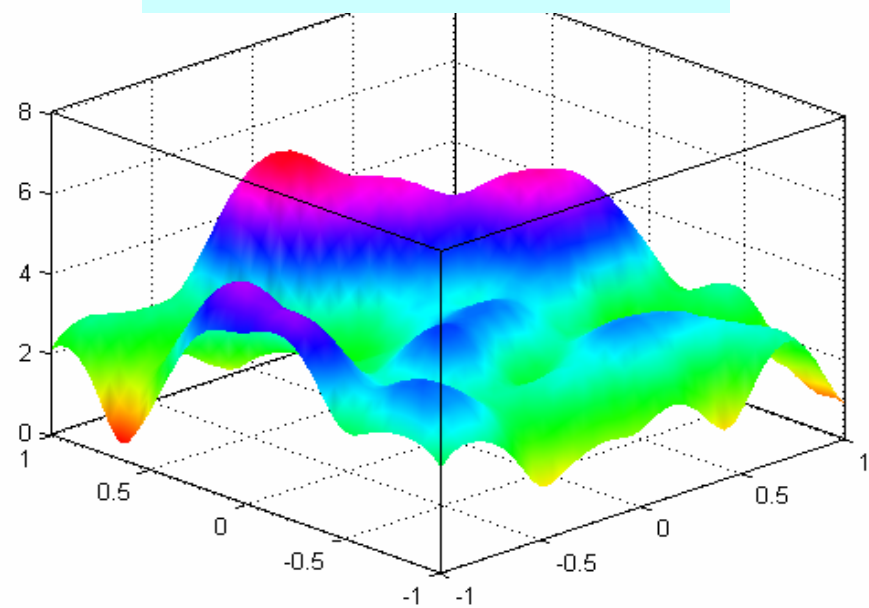


**Log of JPDP in Latent Space**

**Fault #3 - LPC**



**Fault #2 - HPC & LPT**





## 5. Concluding Remarks

1. Need to use accurate stochastic approximation tools for measured outputs that are high-dimensional stochastic functions of engine parameters.

We recommend the use of 3-level hierarchical stochastic approximation models. They proposed models train much faster than standard NN.

2. 2D Visualization Maps are extremely useful tools for complex fault diagnostic and prognostic problems.

We recommend the output pattern visualization using (i) Generative Topographic Maps and (ii) JPDF Map in latent space