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A novel approach to determine manufacturing processing parameters that are correlated to end -of-manufacturing test performance using multivariate analysis and iterative predictive modeling

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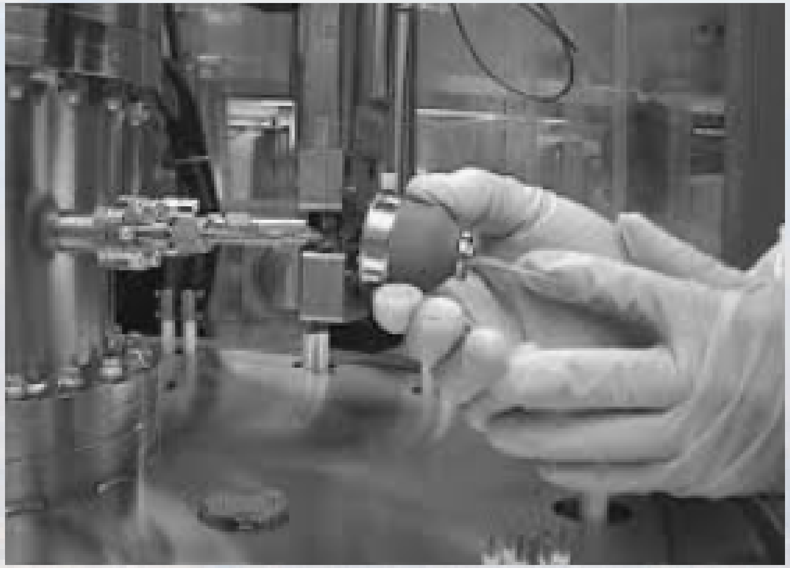
To be covered

- Analysis Overview
- Challenges and value
- Method
- Analysis Results



Analysis overview

- Goal of the analysis is to determine which manufacturing process parameters contribute most to specific end-of-line testing failures
- Data collected during the neutron generator (NG) manufacturing process is studied to determine which manufacturing operations contribute most two different types of end-of-line test failures
  - High Voltage Breakdown (HVB)
    - External to the NG (HVB wall)
    - Internal to the NG (HVB vac)
- The analysis methodology presented was developed using NG manufacturing data but can be applied to any manufacturing process

Challenges and value

- Challenges
  - Complexity manufacturing process
  - Validity of hypothesis that the data collected during the manufacturing process for process control purposes contains signal that can be extracted by multivariate methods to predict which units will fail for specific reasons during post manufacturing quality testing

- Value
  - The ability to predict which units being manufactured will later fail for specific reasons using data collected during manufacturing enables
    - operation specific optimization to reduce end-of-line material loss
    - development of in-line scrapping criteria to eliminate further processing of material destined to fail

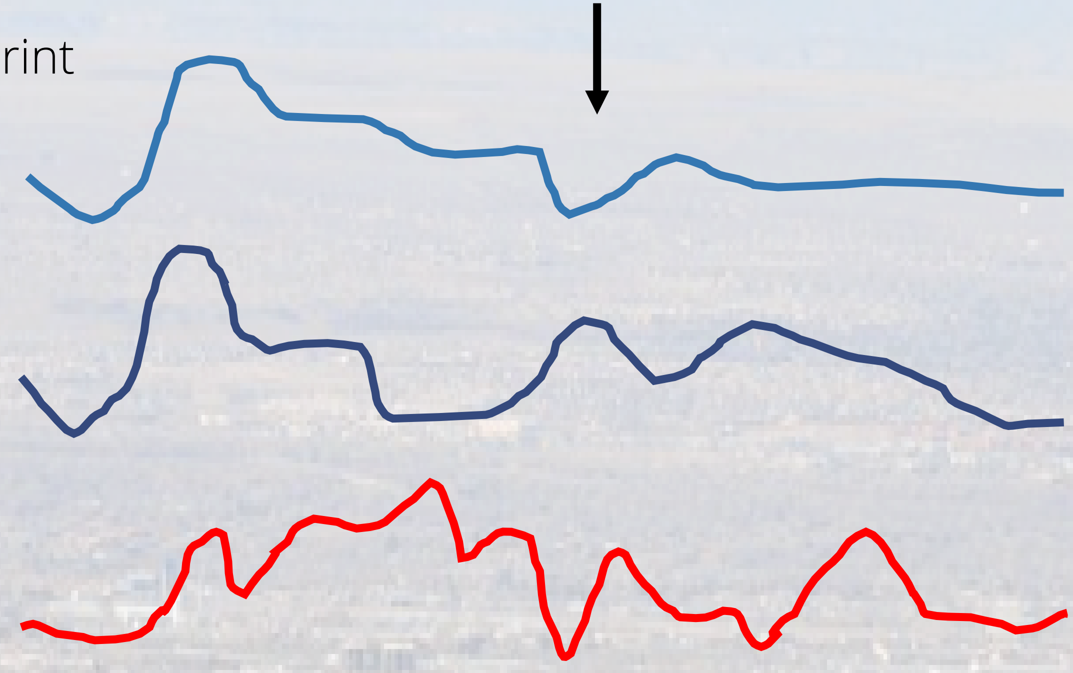
Multivariate modeling data

Modeling data for a unit consists of all data collected during manufacturing of the unit appended together to make a single 1Xn data array for each unit

n=number of variables in the fingerprint

<u>Analysis Array</u>
Rows: fingerprint for each unit
Columns: manufacturing data + end-of-line test results

Dimensions, Voltages Currents Fluxes Etc.



Manufacturing process data for unit 1

Manufacturing process data for unit 2

Manufacturing process data for unit 3

Fingerprint created from all manufacturing data

Multivariate modeling theory

Assumes a relationship exists between a set of measured variables and the properties of interest

Observation = Structure + Noise

- Variables X (set of observations)
- Response Y = F(X) (set of possible responses)

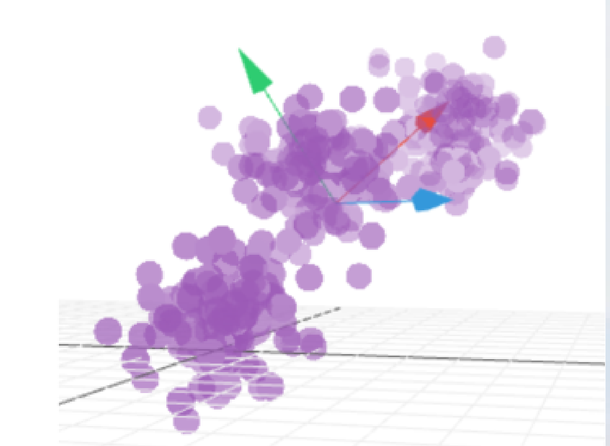
Finds the structure in the data representing the correlation between F(X) & X

Goal of the modeling is to extract the structure in the data that correlates to the observed responses while minimizing noise

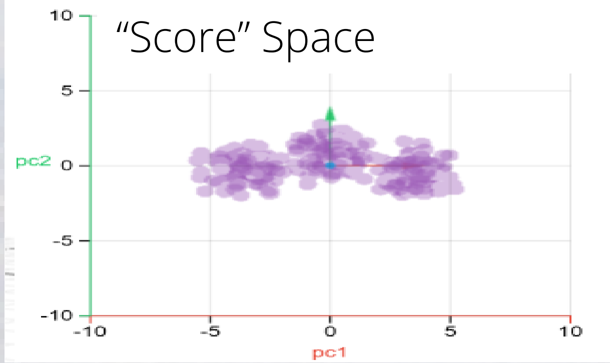
Analysis is accomplished through successive transformations in which the data is projected onto axes or "Principal Components" (PC's) representing the direction of maximum variation of the data

Each PC is orthogonal to the other PC's and centered on the mean of the data and is aligned to the direction of the maximum variation of the data

With each successive transformation to a new PC, more of the variance in the data is explained and a smaller portion of the variance remains unexplained



Original Data



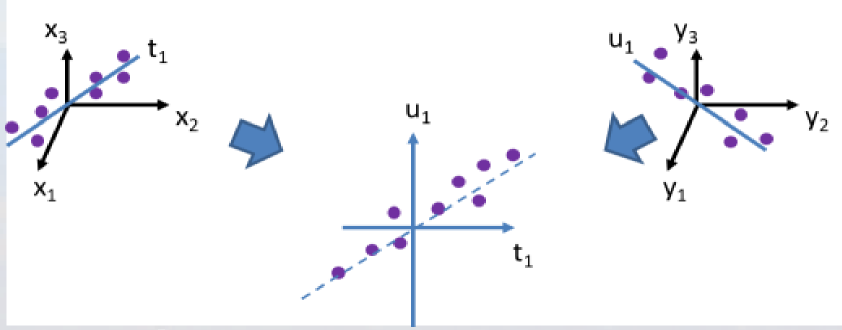
Projection of original data onto PC1 & PC2

Partial Least Square Regression (PLSR)

- Data is arranged in a NXn matrix for modeling
- PC's are calculated by modeling both the X and Y matrices (variables and responses) simultaneously using known data
  - Uses PCA on the variables (X^TY)
  - Uses PCA on the responses (Y)
  - Creates a transformation designed to maximize the covariance between X & Y
- Each interactively calculated PC has a characteristic linear equation for the relationship of the response to the variables :

$$Y = b0 + b1x1 + b2x2 + b3x3 + \ldots_{PLS}$$

  - The loadings indicate the contribution of each variable to the PC calculation
- Using an optimal number of PC's, a "Prediction Value" (PV) is calculated by the PLS prediction model that indicates how well matched new input data is to one of the response groups in the modeling



Method

- Create a manufacturing processing “fingerprint” for each unit by concatenating all the manufacturing process data for a unit
  - 1 X 1059 matrix for each manufactured unit
- Build PLS* models to differentiate HVB data from normal data
  - HVB wall vs. normal
  - HVB vac vs. normal
- Analyze the regression coefficients for the PC used to differentiate HVB wall (or vac) units from normal units to identify suspect operations responsible for the difference in performance

*PCA models were used for one product because data was insufficient for PLS Modeling

Prediction value:
Y = b0 + b1x1 + b2x2 + b3x3 +…. where regression coefficients b1, b2, etc. are the relative contributions of each variable (value from operation) to the total prediction value

Data

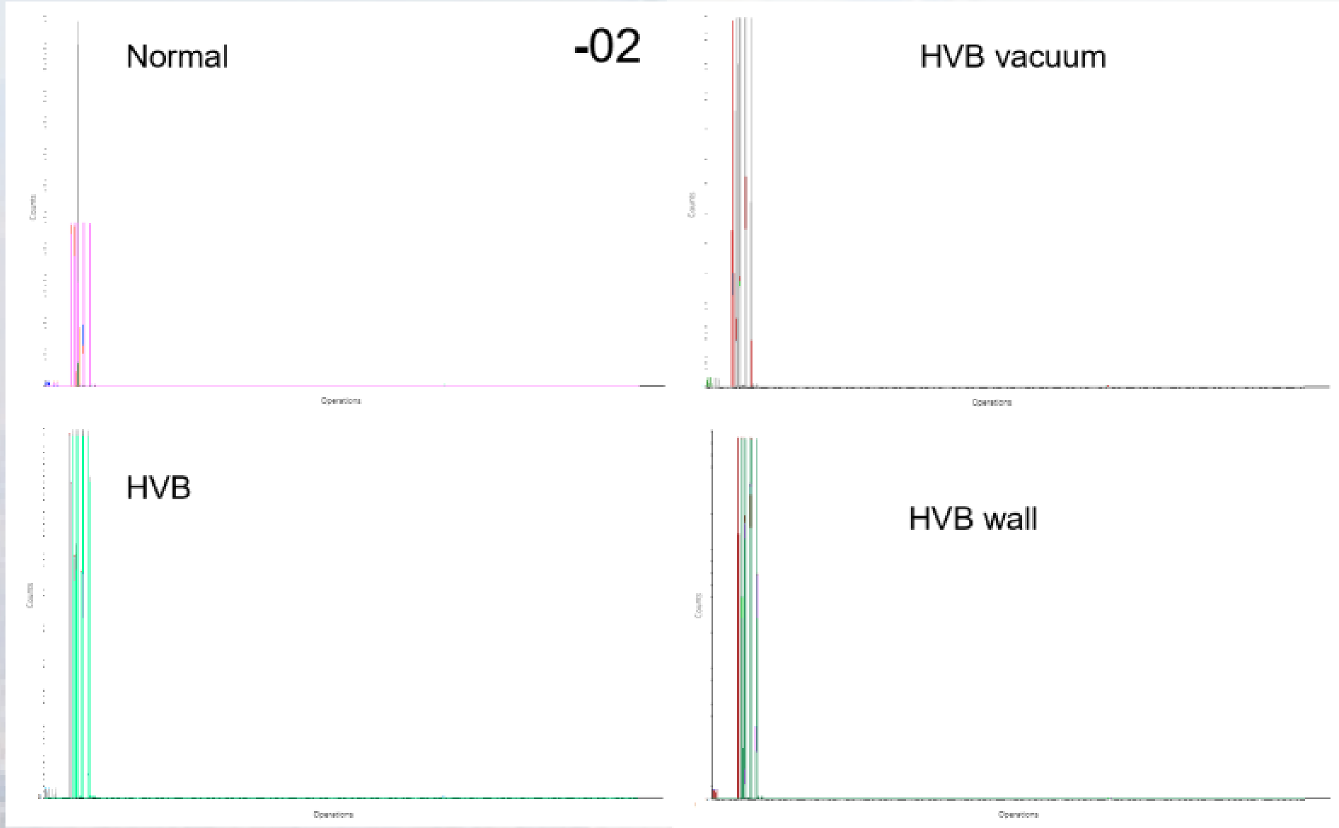
Manufacturing process data for NG's determined to be normal, HVB wall, or HVB vacuum at end of line test

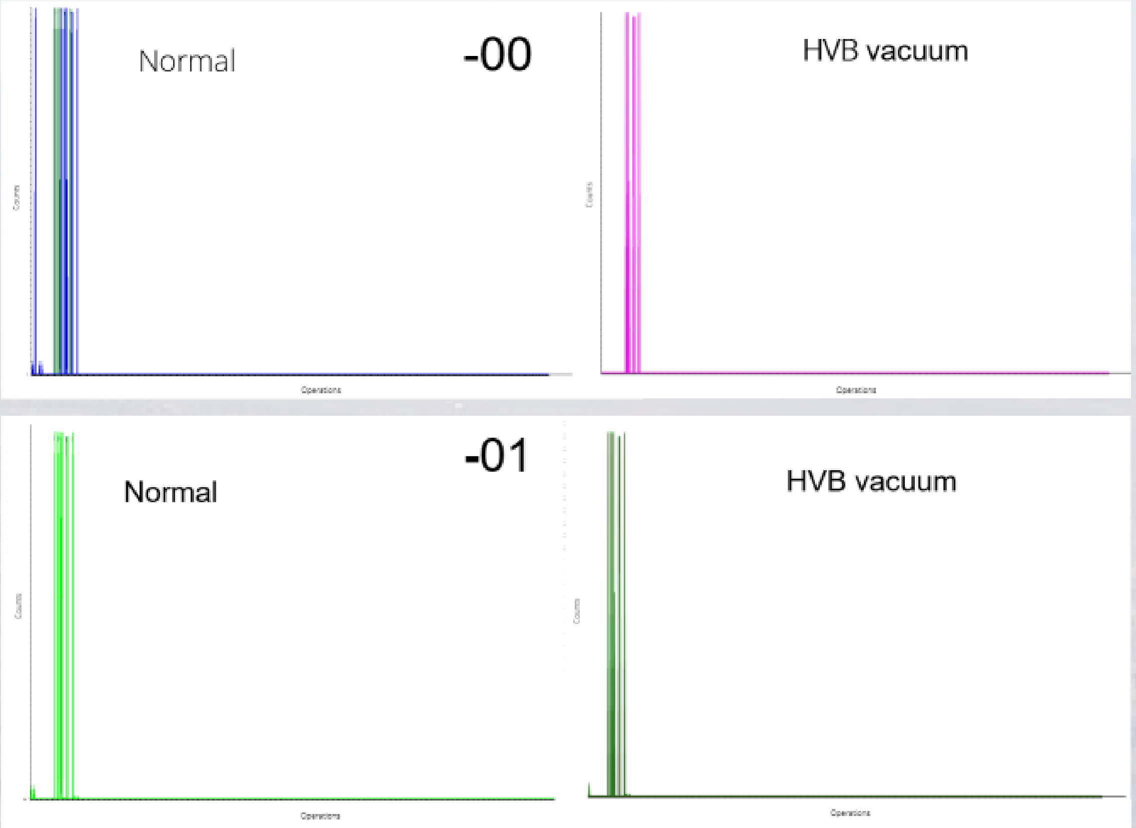
- Product-02
- Product-01*
- Product-00

*Not enough data for PLS HVB vac modeling, used PCA

Product	Normal	HVB	HVB wall	HVB Vacuum
-00	1186	32	0	32
-01*	1179	3	0	3
-02	3300	86	71	14

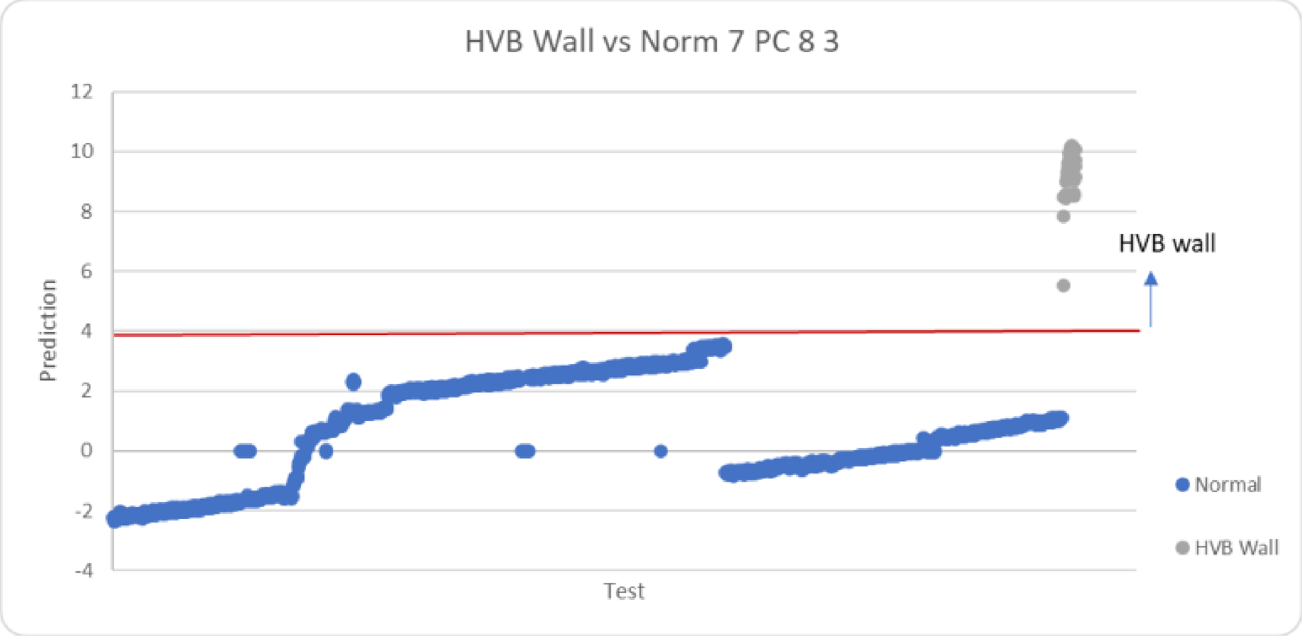
Data Fingerprints:

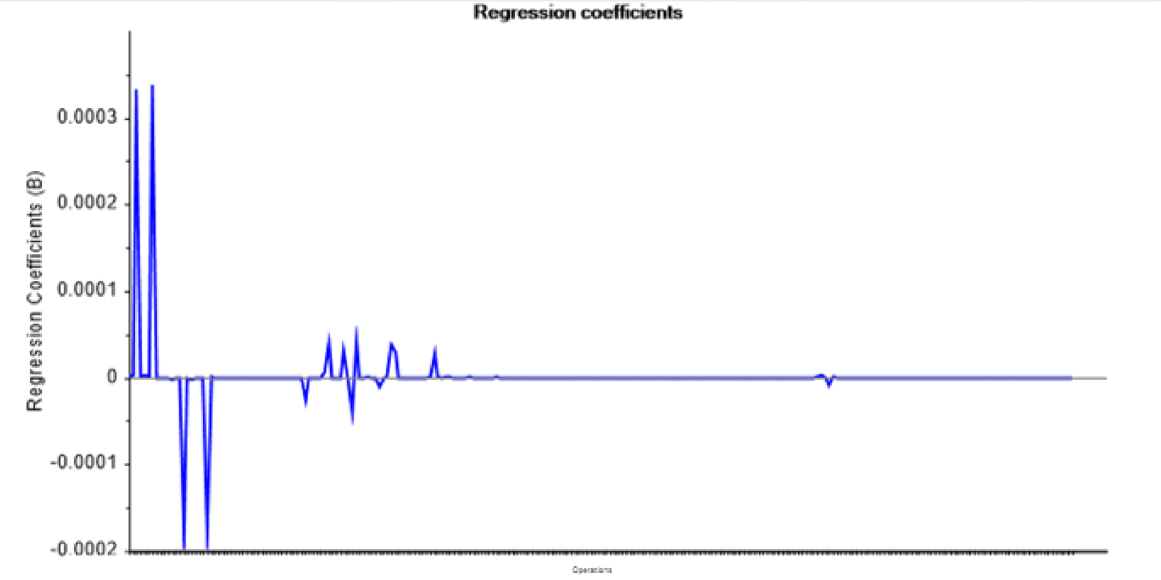




Not enough -01 data for PLS modeling, PCA was used instead (only 3 HVB vac)

HVB wall vs Normal Analysis Results: -02



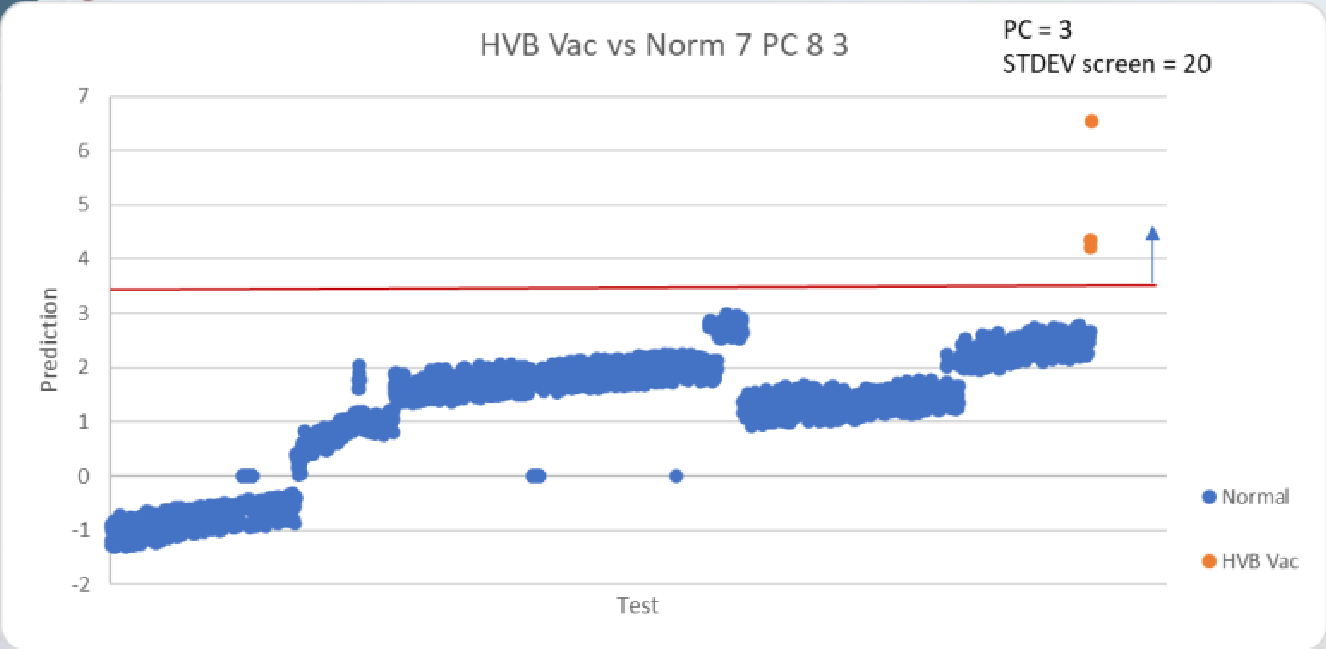


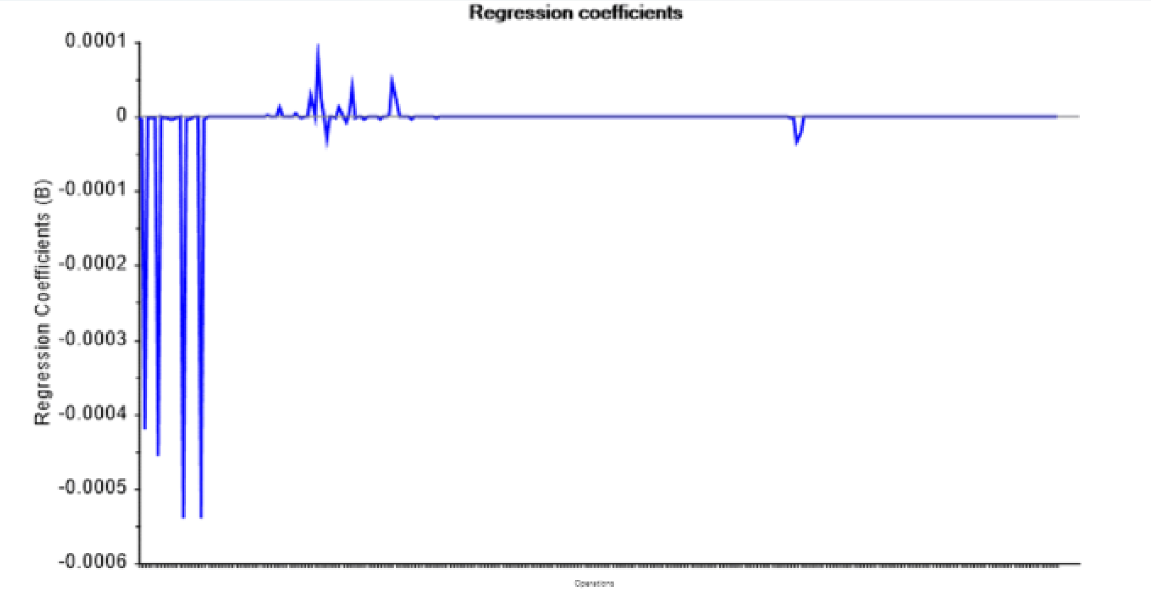
HVB wall -02 Operation (sorted by ABS magnitude of coefficients)
Operation 291
Operation 294
Operation 293
Operation 9
Operation 75
Operation 3
Operation 4
Operation 5
Operation 256
Operation 1
Operation 7
Operation 290
Operation 8
Operation 276
Operation 265

<u>Tested on:</u>
3246 Normal
43 HVB wall
Test data was not part of modeling data set

Iterative modeling: select data to model on, test model on new data, add failing test data back into the modeling data, repeat (until good prediction is obtained)

HVB vacuum vs Normal Analysis Results: -02



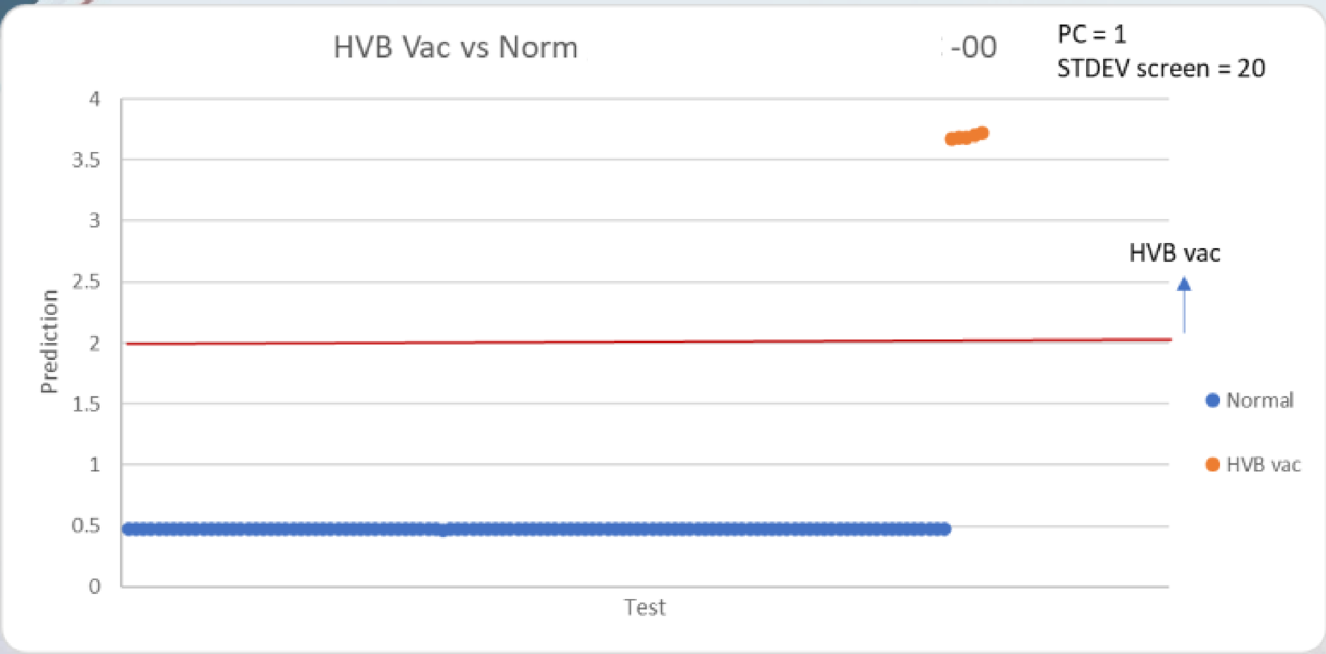


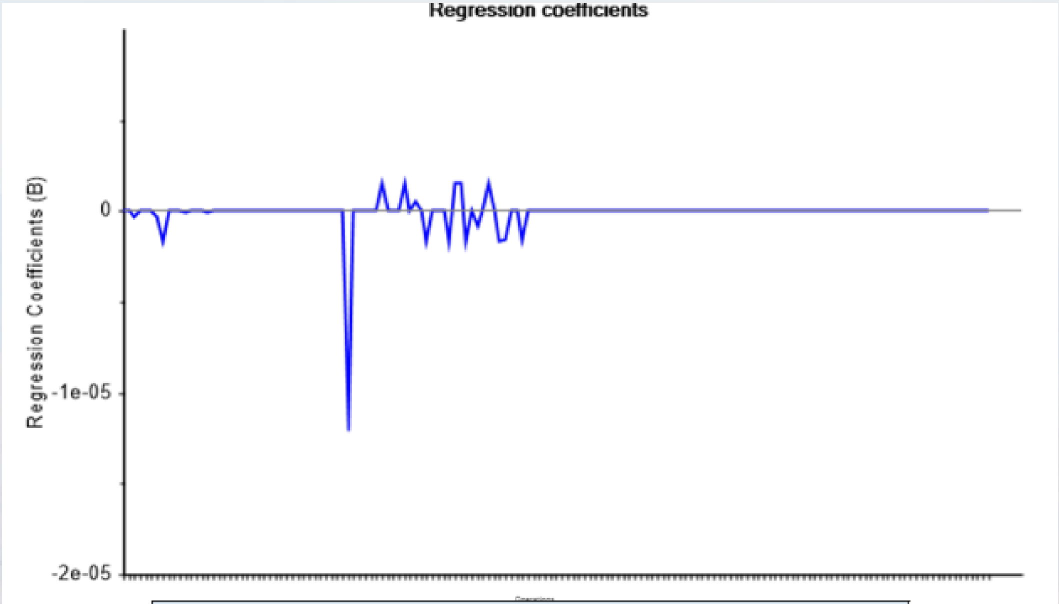
HVB vac -02 Operation (sorted by ABS magnitude of coefficients)
Operation 294
Operation 293
Operation 291
Operation 1
Operation 2
Operation 3
Operation 290
Operation 289
Operation 4
Operation 7
Operation 8
Operation 287
Operation 10
Operation 265

Tested on:
3246 Normal
4 HVB vac
Test data was not part of modeling data set

Iterative modeling: select data to model on, test model on new data, add failing test data back into the modeling data, repeat (until good prediction is obtained)

HVB vacuum vs Normal Analysis Results: -00



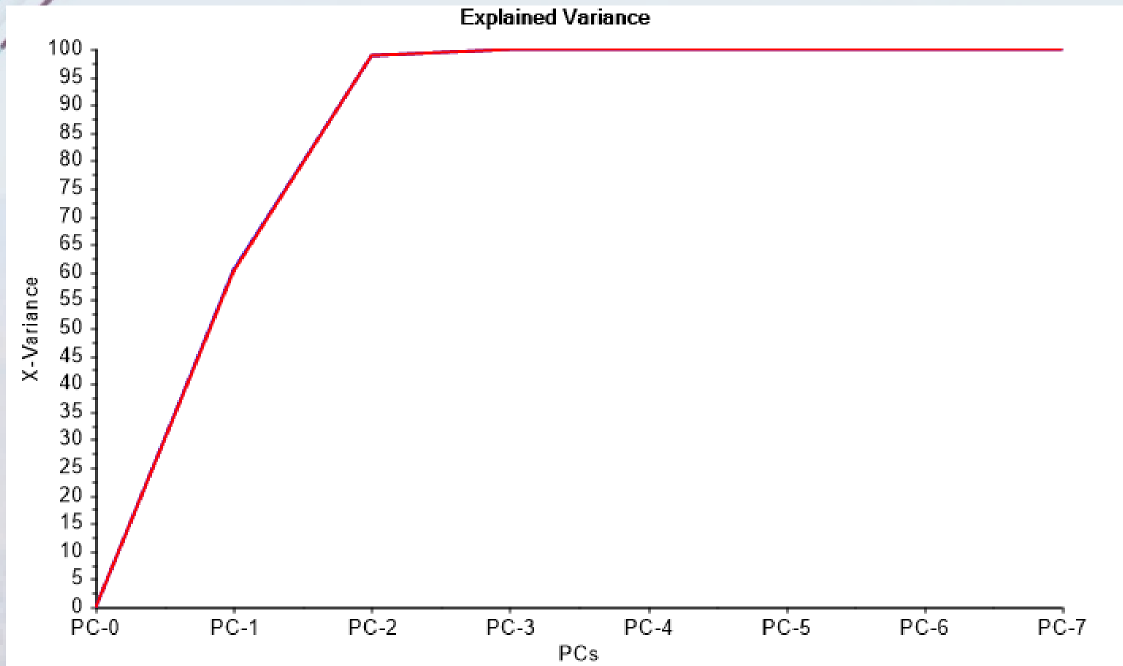


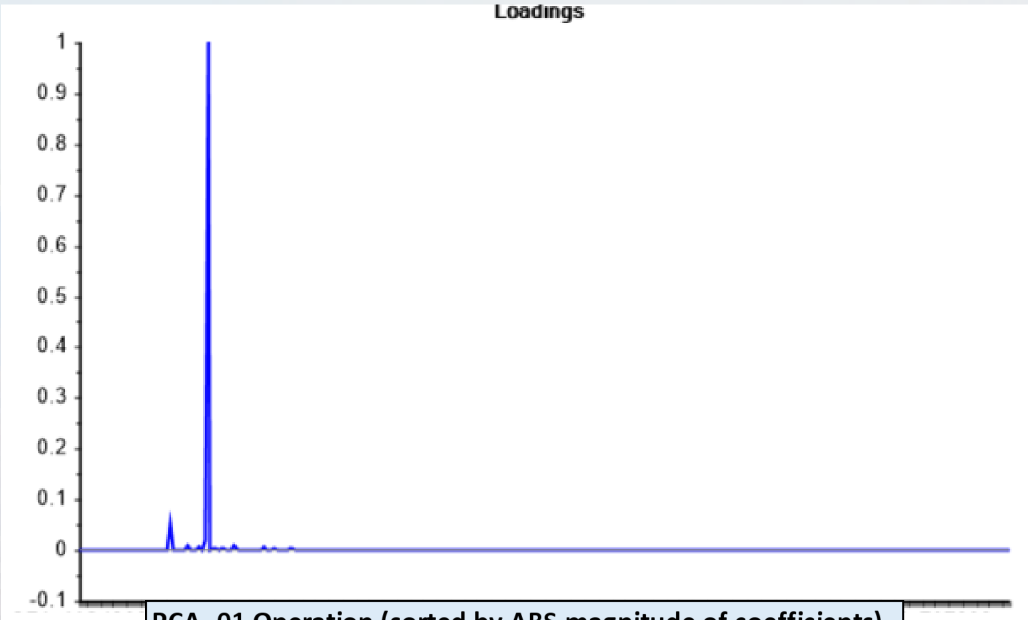
Operation HVB vac vs norm -00 (sorted by ABS magnitude of coefficients)
Operation 7
Operation 275
Operation 241
Operation 258
Operation 15
Operation 2
Operation 295
Operation 6
Operation 9
Operation 256
Operation 75
Operation 3
Operation 4
Operation 88
Operation 1
Operation 291
Operation 281
Operation 294

<u>Tested on:</u>
110 Normal
5 HVB vac
Test data was not part of modeling data set

Iterative modeling: select data to model on, test model on new data, add failing test data back into the modeling data, repeat (until good prediction is obtained)

HVB vacuum vs Normal Analysis Results: -01





PCA -01 Operation (sorted by ABS magnitude of coefficients)
Operation 5
Operation 7
Operation 9
Operation 75
Operation 256
Operation 4
Operation 3
Operation 6
Operation 2
Operation 106
Operation 283
Operation 13
Operation 8
Operation 289
Operation 274

<u>PCA Modeling on:</u>
1179 Normal
3 HVB vac

<u>Results less sure:</u>
Only 3 HVB vac fails in modeling

Important operations

Compare operations important for differentiating

- HVB from normal (Yellow)
- HVB wall from HVB vac (Blue)

	Important for Differentiation			
Operation	**PLS HVB wall -02**	**PLS HVB vac -02**	**PLS HVB vac -00**	**PCA Norm HVB vac -01**
Operation 291	X	X	X	
Operation 265	X	X		
Operation 241			X	
Operation 293	X	X		
Operation 281			X	
Operation 294	X	X	X	
Operation 7	X	X	X	X
Operation 75	X		X	X
Operation 273				
Operation 4	X	X	X	X
Operation 1	X	X	X	
Operation 5	X			X
Operation 258			X	
Operation 289		X		X
Operation 13				X
Operation 274				X
Operation 15			X	
Operation 9	X		X	X
Operation 3	X	X	X	X
Operation 275		X	X	
Operation 88			X	
Operation 256	X		X	X
Operation 2		X	X	X
Operation 6			X	X
Operation 295			X	
Operation 8	X	X	X	
Operation 276	X			
Operation 290	X	X		
Operation 287		X		
Operation 283				X
Operation 106				X

Funding

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