Artificial Intelligence-Based Methods for Assessment of Accrued Damage and Remaining Use-Life in Automotive Underhood Electronics

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Motivation

- Electronics in automotive Underhood applications is exposed to sustained period of high temperature vibration.
- Almost 20% of the failure in the electronic components are based on vibration and shock loads.
- Different safety and driver assist features are enabled through electronics control systems.
- Failure of safety-critical electronic systems may adversely affect safe operation of the vehicle.
- Methods are needed for prognostication of accrued damage and impending failure of electronic components.
- Several data-driven techniques and physics of failure approaches are available, but AI-based physics predictions are scarce.

Literature Review Classifications

Author	Reported Methods
Gu 2008	Prognostics and Health management using Physics of Failure approaches
Scwabacher 2009, Vicare 2006	Data driven approaches using statistics and probability techniques
Lall 2009, Lall 2012, Lall 2014	Prognostics based on Resistance Spectroscopy measurements
Lall 2017-2022	Health Monitoring of electronic components from Strain Measurements
Liu J 2009	Model based approaches
Simone 2021, Wei Zang-2020	Machine and Deep Learning Based Models

Shortcomings of the State of Art for PHM

1. ***Physics of failure (PoF) approaches***
   a. Needs knowledge of a product's life cycle loading and failure mechanism.
   b. Scalability to complex systems is time-consuming-difficult.
   c. Presence of noise in the measurements reduces the efficiency.
2. ***Model Based Approaches***
   a. Multi-physics models, physical degradation laws needed.
   b. Insufficient when the complexity of the system increases and when the failure identification is difficult.
3. ***Data Driven Approaches***
   a. Correlation to the underlying damage is tenuous.
   b. Data-vectors probed may limit the visibility into unforeseen failure modes.

Objectives

- Health monitoring of the PCB from non-destructive measurements captured at different locations at different acceleration levels.
- Identify different feature vectors in predicting failure of the package using in-situ measurements.
- RUL estimation using a combined Physics of Failure and Deep Learning approach for SAC305, solder alloy PCB subjected to high strain-rate loads

Test Setup-Vibration

Figure 1: Shaker with the heating chamber on top

- **Natural frequency- 340 Hz**
- **Frequency Range of vibration from 330 Hz to 350 Hz**

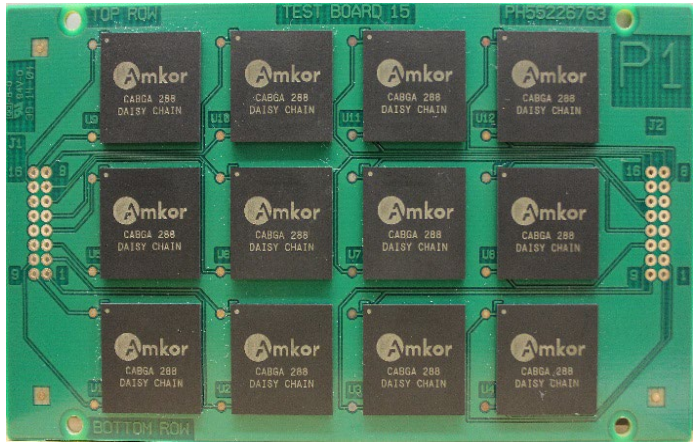


Figure 2: PCB board with packages

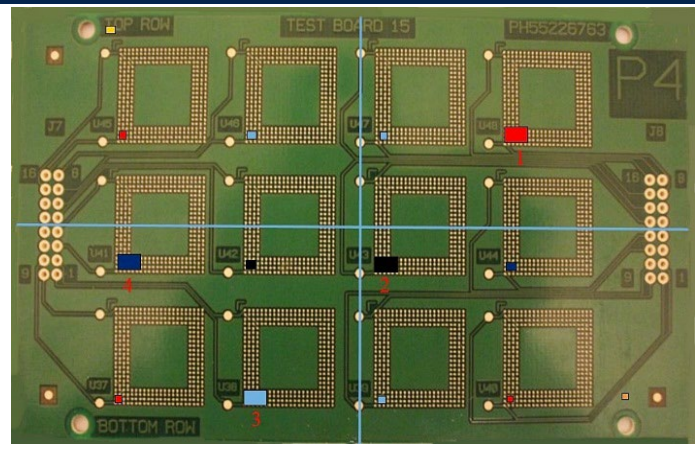


Figure 3: Schematic diagram of the symmetric position of strain gauges on the packages

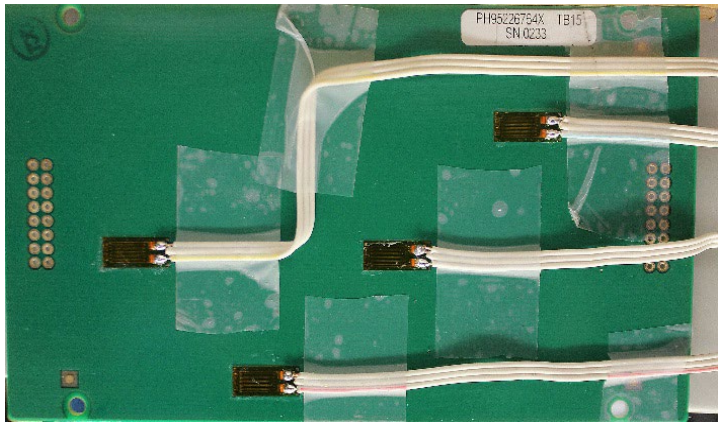


Figure 4: PCB board with strain gauges fixed to the back side of the board

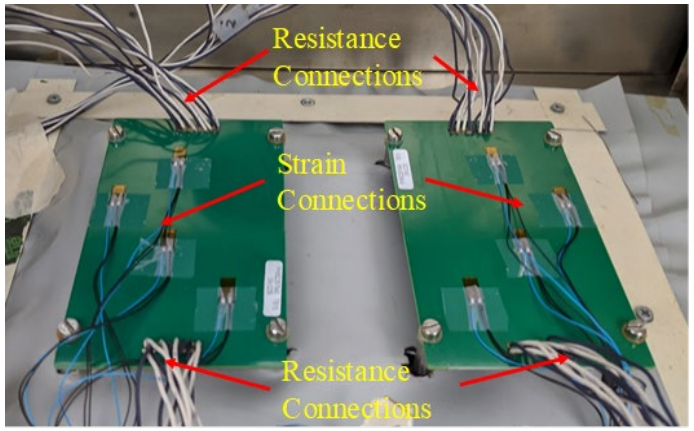


Figure 5: PCB board inside the heating chamber

Vibration Data Acquisition

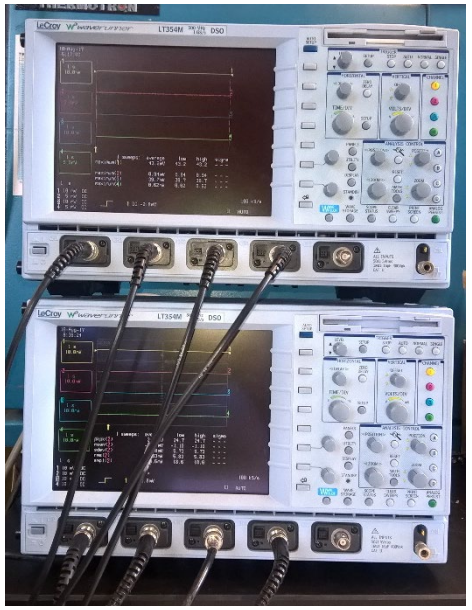


Figure 6: Oscilloscope for Data Acquisition

Figure 7: Signal condition Amplifier

- There are **119 strain signals** captured at different **instances of vibration**
- The **Red instances** represent the strain signal captured **before failure** of electronic package
- The **blue represents** after **failure strain** signals

- **Vibration Acceleration level- 5G**
- **Ambient Temperature- 55 Degree Celsius**

Table 1: Time Series taken for analysis

SL:No	Time (Minutes)
1	0
2	1
3	4
.	.
.	.
108	7360
109	7600
110	7840
.	.
.	.
117	10120
118	10600
119	11000

Red Series- Before Failure

Blue Series- After Failure

Vibration Strain Signal

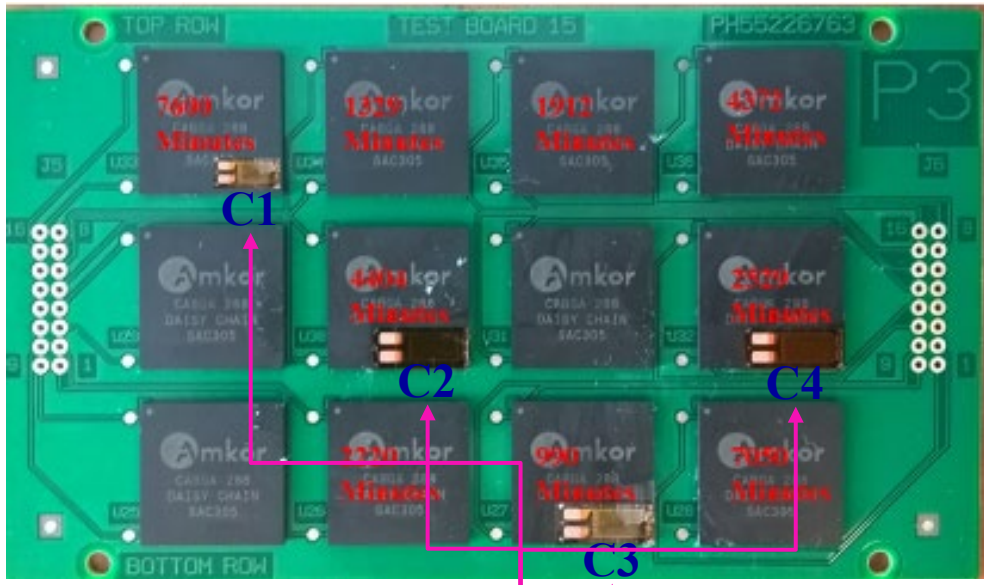


Figure 8: Failure Time of electronic packages on the board

C1, C2, C3 and C4 are strain signals from **different locations** of the PCB

Sampling frequency is at 10,000 Hz and Sampling Time is for 100 Sec

Splitting of each strain signal (C1 to C4) has been done similar to Figure 9

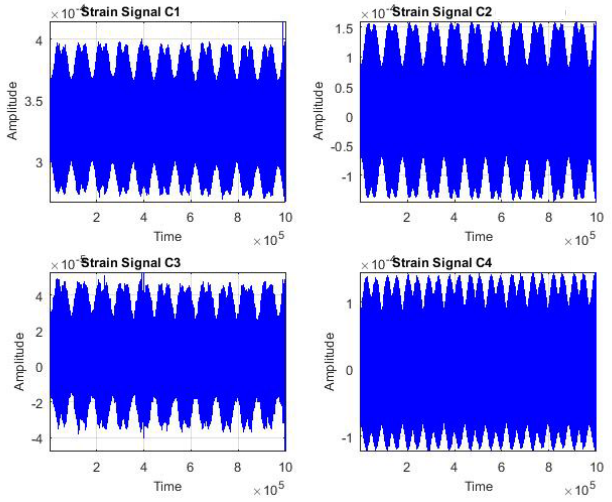


*Figure 9: Strain Signal of all traces **(C1-C4)***

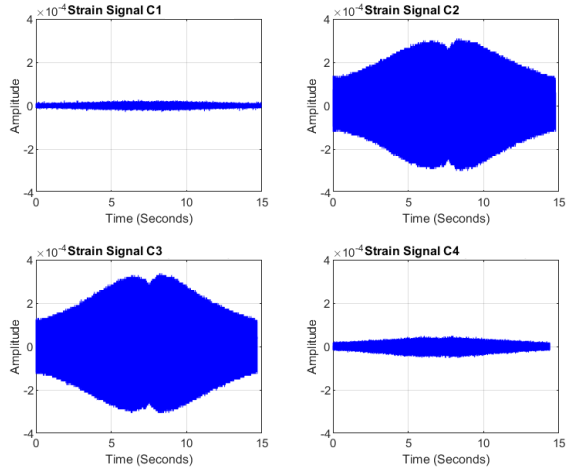
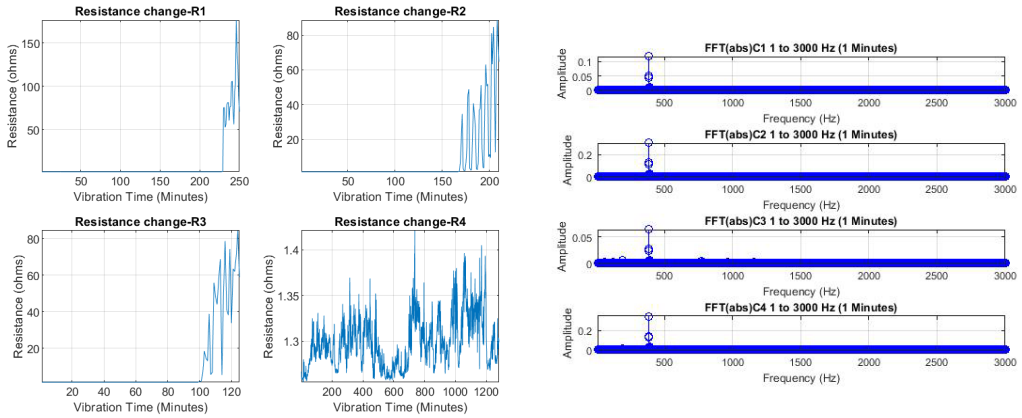


*Figure 10: Splitted strain signal **(C1)***

Vibration Resistance and Frequency Plots



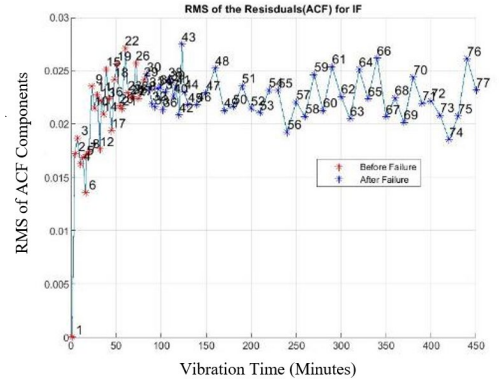
Test Matrix (F)- FFT(Strain Signal)

$$Row: 1 \quad FFT\ at\ SL\ No:\ 1$$
$$\vdots \qquad\qquad \vdots$$
$$Row: 119 \quad FFT\ at\ SL\ No: 119_{119\times10^4}$$

Test Matrix (X)-Strain Signal

$$Row: 1 \quad Strain\ Signal\ at\ SL\ No:\ 1$$
$$\vdots \qquad\qquad \vdots$$
$$Row: 119 \quad Strain\ Signal\ at\ SL\ No: 119_{119\times10^6}$$

Feature-1	Feature-2	Feature-3	Feature-4	RUL
Row-1	Row-2	Row-3	Row-4	Prediction
rms of Residual of ACF	mean of Residual of ACF	Variance of ACF Residual	kurtosis of ACF Residual	RUL- Drop Number



FFT of Vibration Strain Signals (C1-C4)

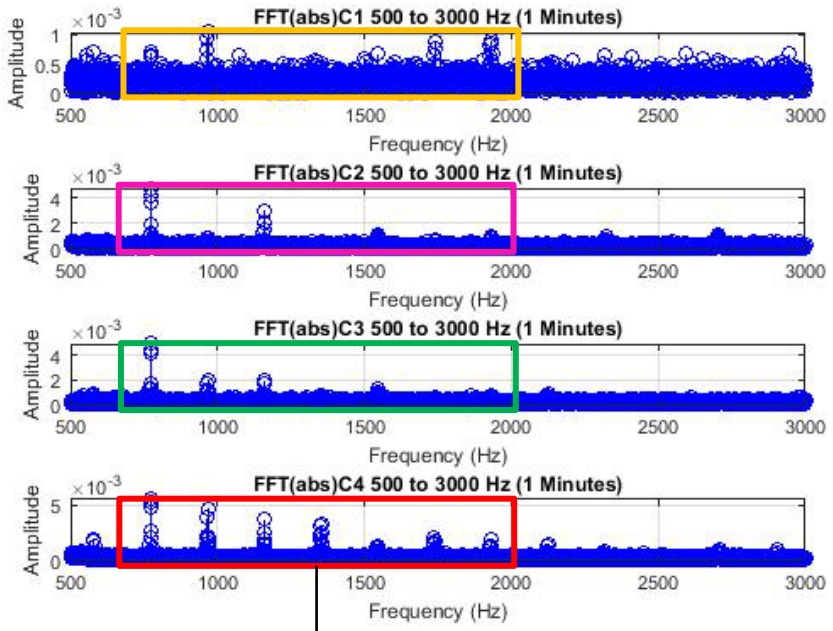


*Figure 12: FFT (Abs) of the strain signal (C1-C4) from **500- 3000 Hz** at **1 Minute***

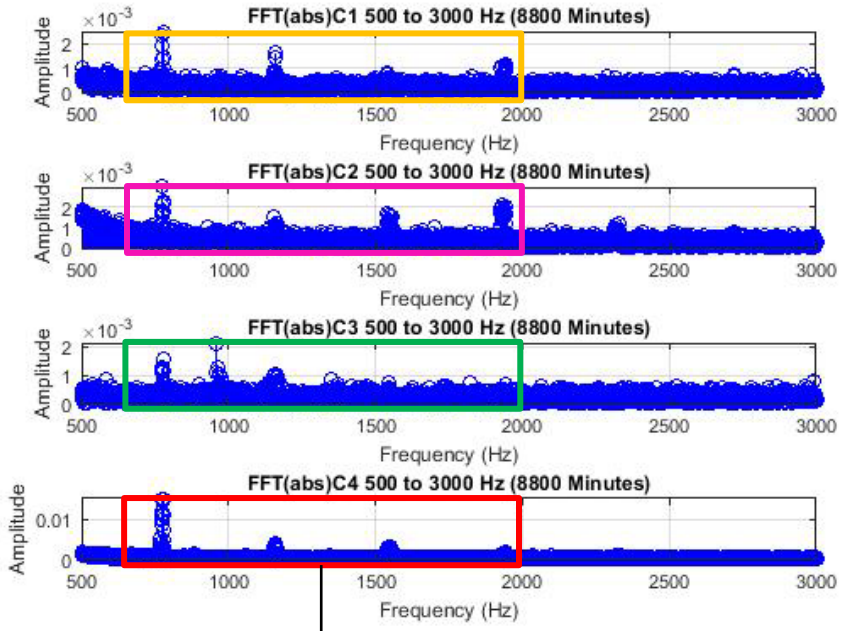


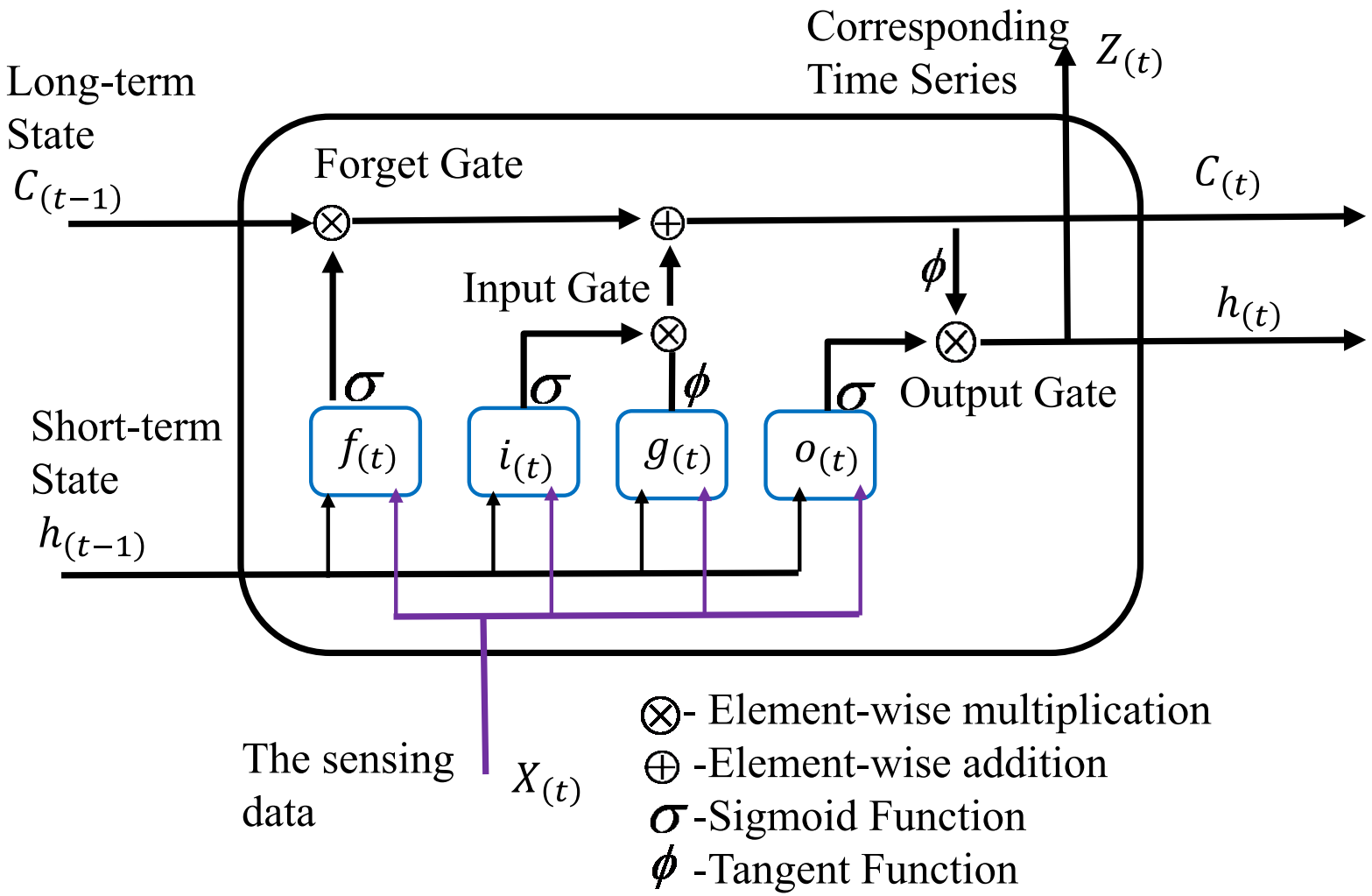
*Figure 13: FFT (Abs) of the strain signal (C1-C4) from **500- 3000 Hz** at **8800 Minute***

FFT of Before Failure Strain Signal

- Corresponding frequency components for strain signal C4 at **1 and 8800 minutes of vibration**
- **Lower frequency components** change considerably with vibration time
- This behavior is **same for C1, C2, and C3** as well.

FFT of After failure Strain Signal

LSTM


Corresponding
Time Series
$Z_{(t)}$
Long-term
State
$C_{(t-1)}$
Forget Gate
$C_{(t)}$
Input Gate
ϕ
$h_{(t)}$
σ
σ
ϕ
σ
Output Gate
Short-term
State
$h_{(t-1)}$
$f_{(t)}$
$i_{(t)}$
$g_{(t)}$
$o_{(t)}$
The sensing
data
$X_{(t)}$
⊗- Element-wise multiplication
⊕ -Element-wise addition
σ -Sigmoid Function
ϕ -Tangent Function

Vibration Statistical Feature Vectors for Experimental Strain

$$P_i = \frac{e^z}{1+e^z} = \frac{e^{\alpha+\beta_i x_i}}{1+e^{\alpha+\beta_i x_i}}$$

$$Z_i = \ln\left(\frac{P_i}{1-P_i}\right)$$

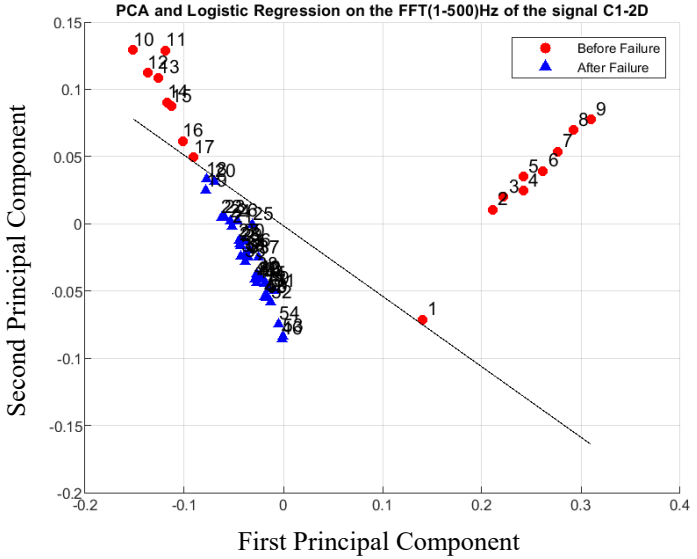
$$= \alpha + \beta_1 x_1 + .. + \beta_n x_n$$

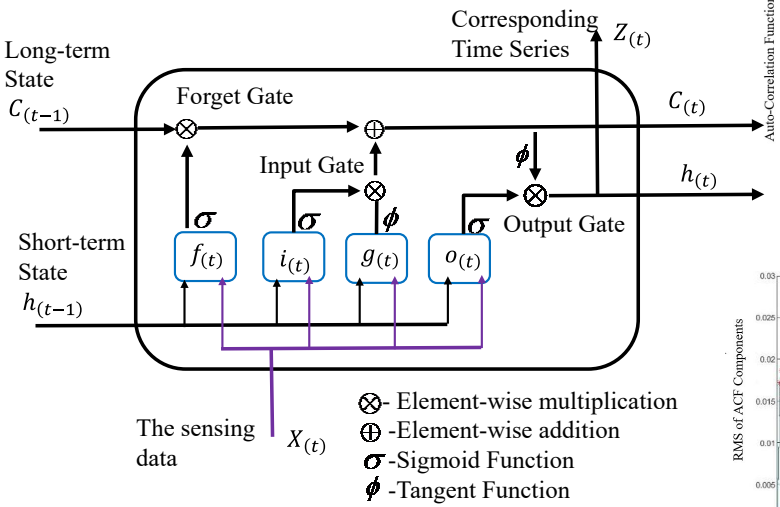
x_1=First Principal Component
x_2=Second Principal Component
P= is the probability of the event.

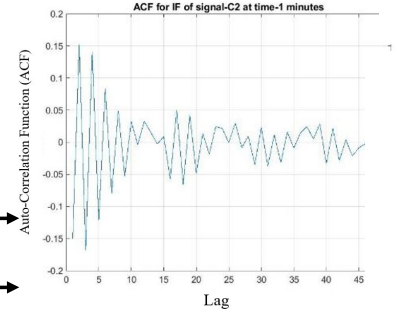
Logistic Regres
using PC(1-2)
FFT(1-500)Hz

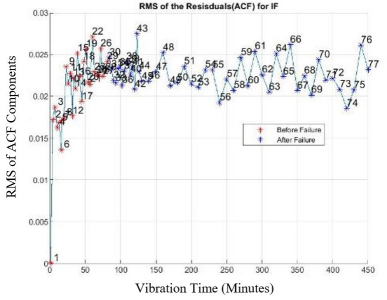
Logistic Regression using first two Principal Components

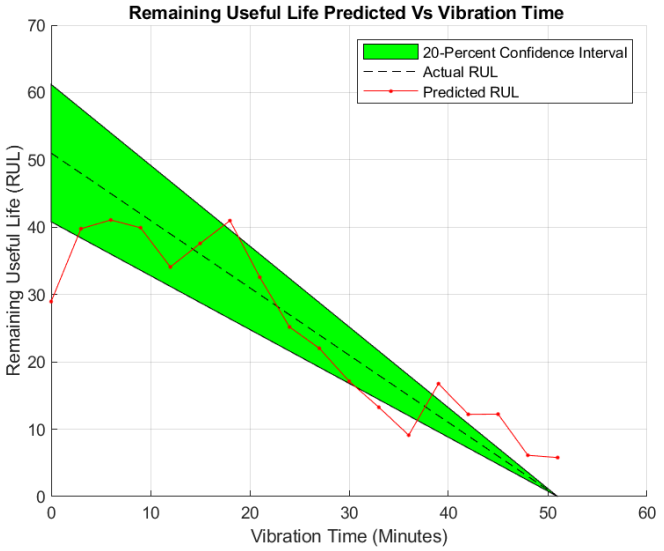
$$Z_i = \alpha + \beta_1 x_1 + \beta_2 x_2$$



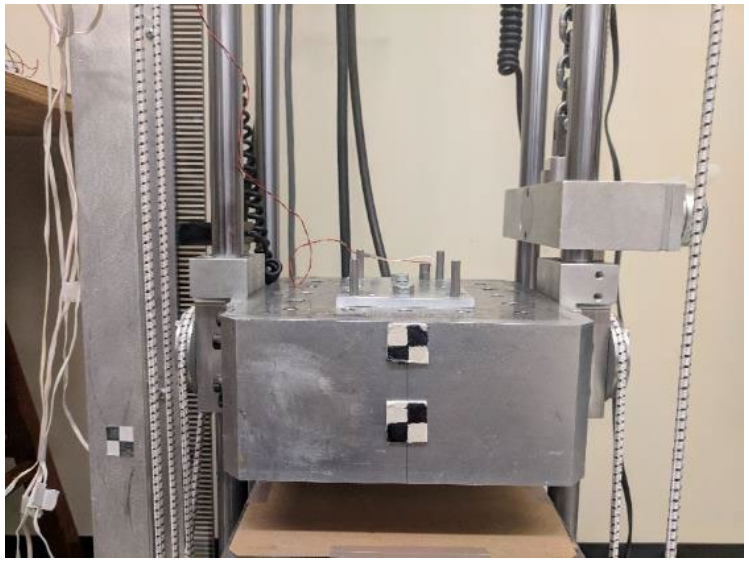


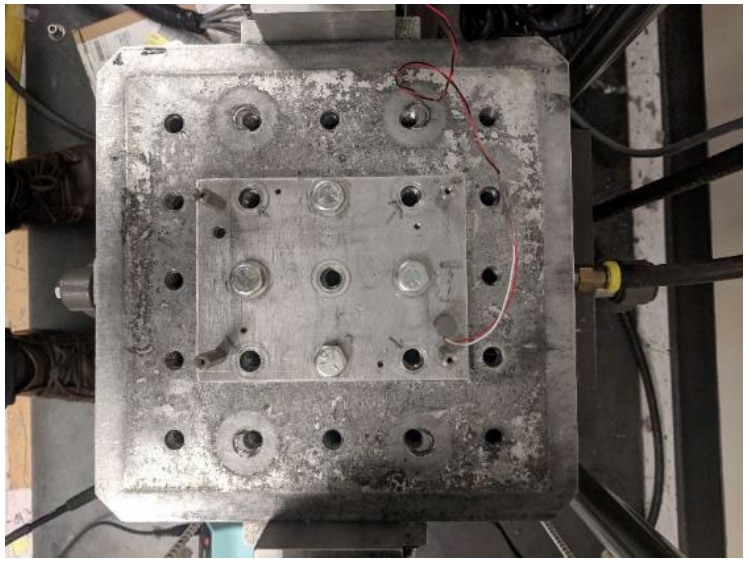


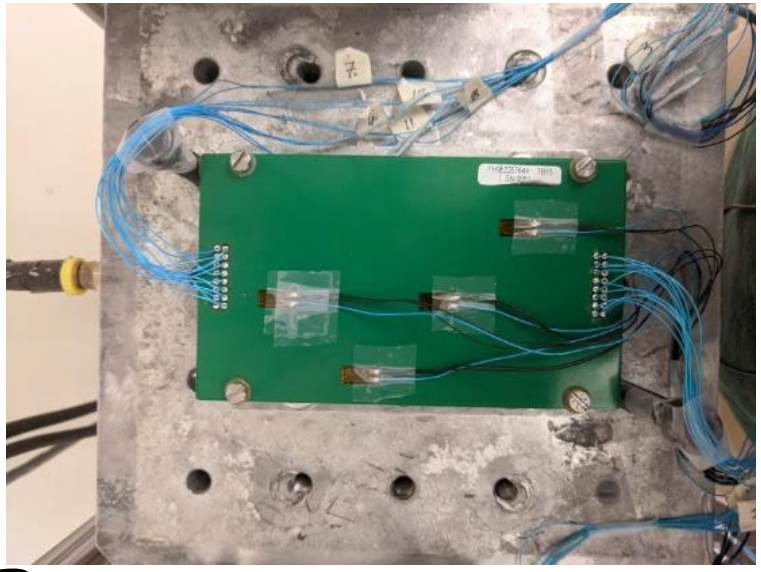


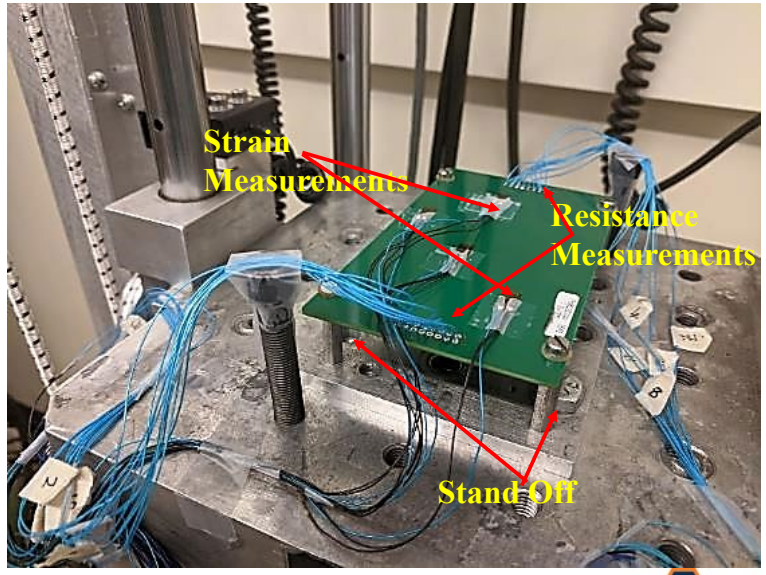


Experimental Setup – Mechanical Shock



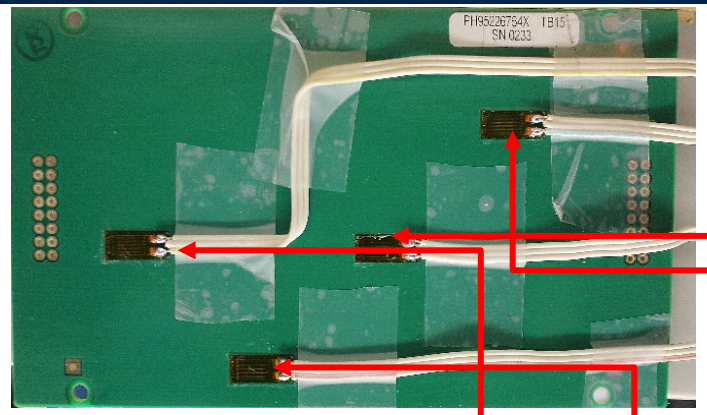




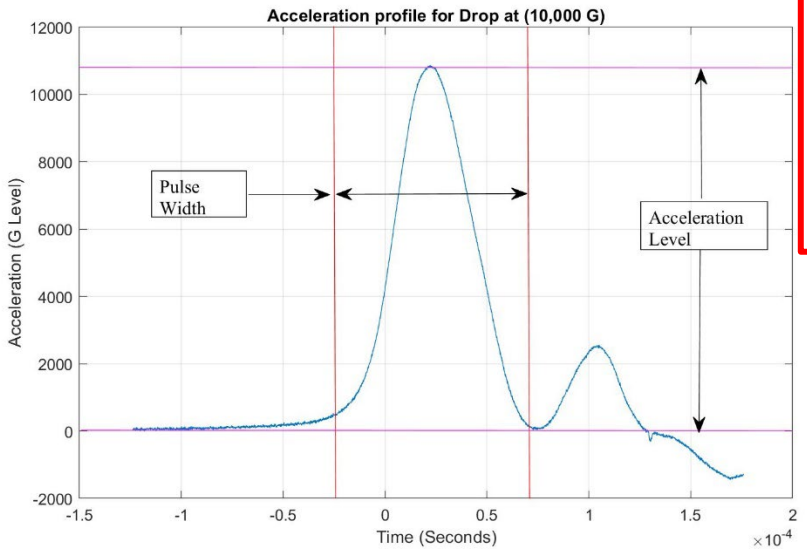


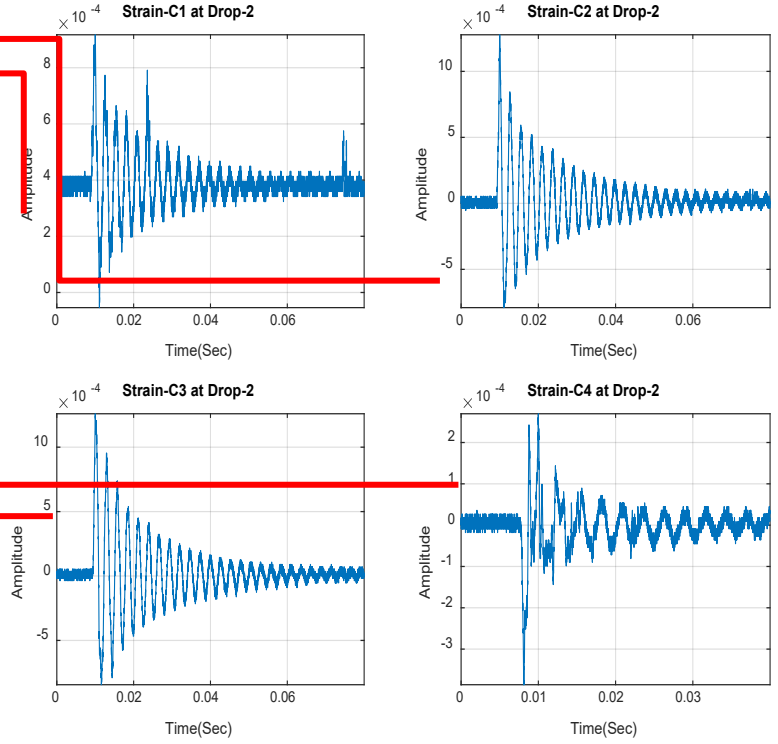
Shock Acceleration Profile

C1=400µm
C2=1200µm
C3=1200µm
C4=300µm



Positions of the Strain gauges and corresponding strain signals



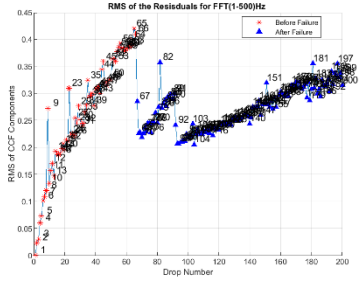


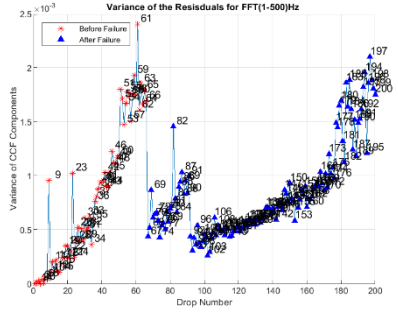
Acceleration Levels= 1500, 3000, 5000,7500,10000 G
Pulse Width= 0.1 milliseconds

Sampling Frequency= 1 MS/s
Sampling Time= 1 seconds

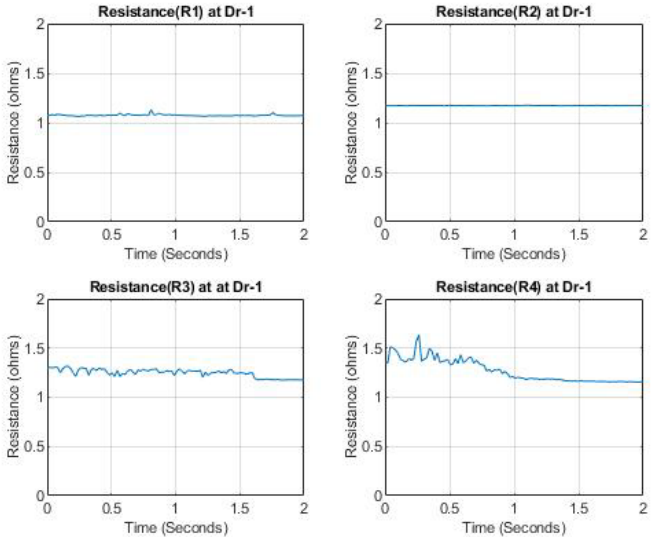
G-Level= 10000g

Shock Resistance and Feature Vectors

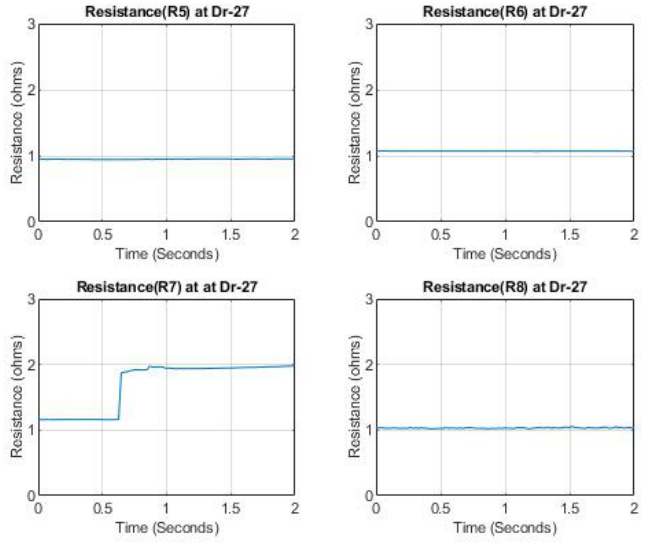




Resistance Variation for Drop Number-1

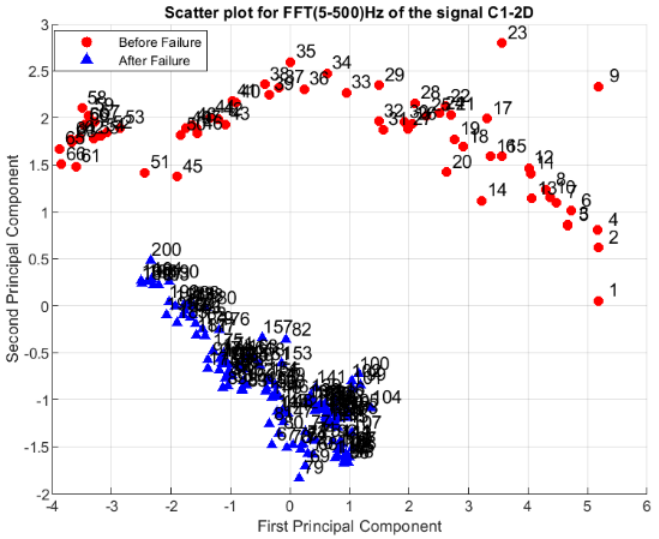


Resistance Variation for Drop Number-27

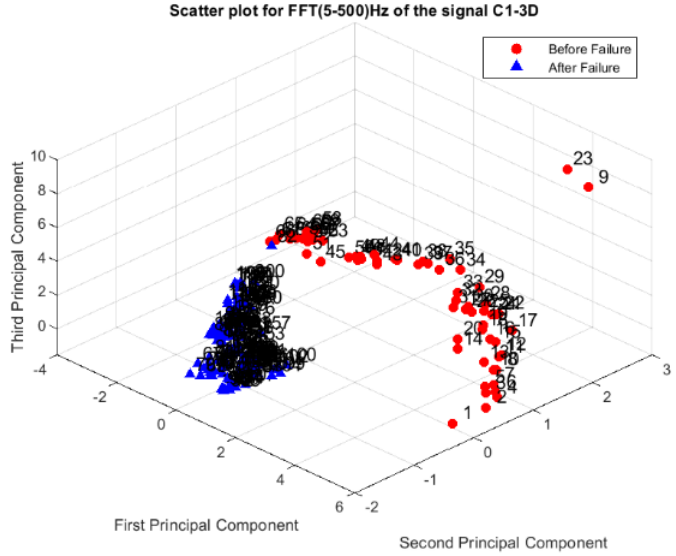


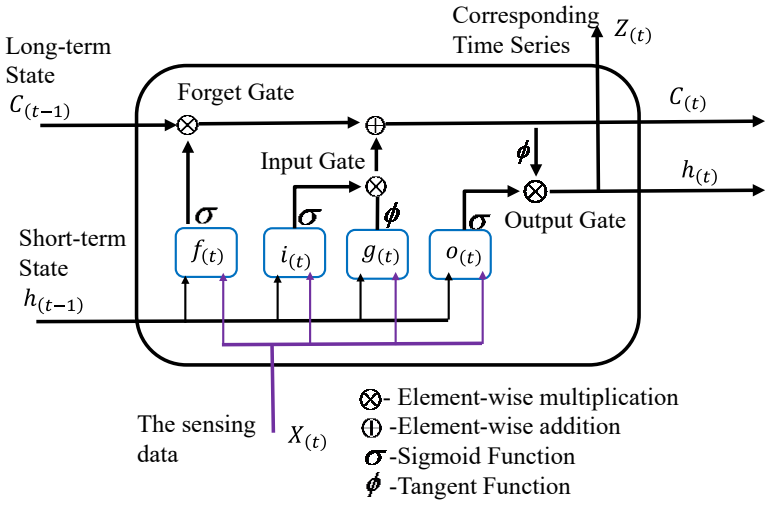
Feature-1	Feature-2	Feature-3	Feature-4	RUL
Row-1	Row-2	Row-3	Row-4	Prediction
rms of Residual of CCF	mean of Residual of CCF	Variance of CCF Residual	kurtosis of CCF Residual	RUL- Drop Number

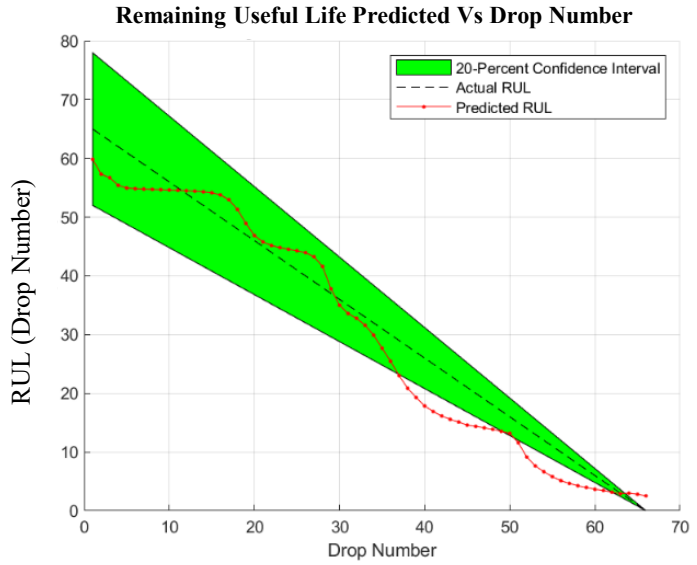
Shock Statistical Feature Vectors for Experimental Strain



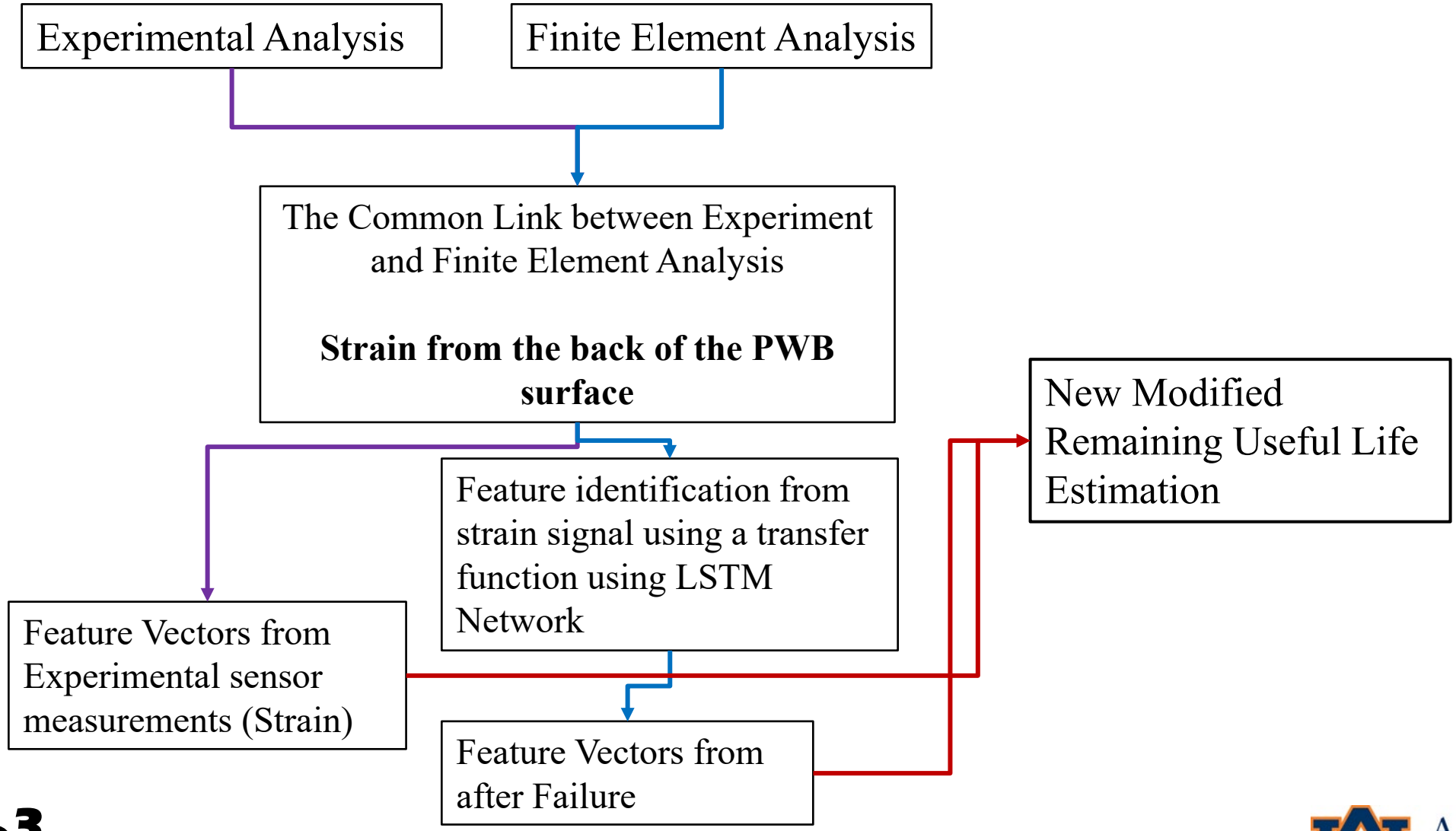
Plot of Principal components for FFT for (1-500) Hz



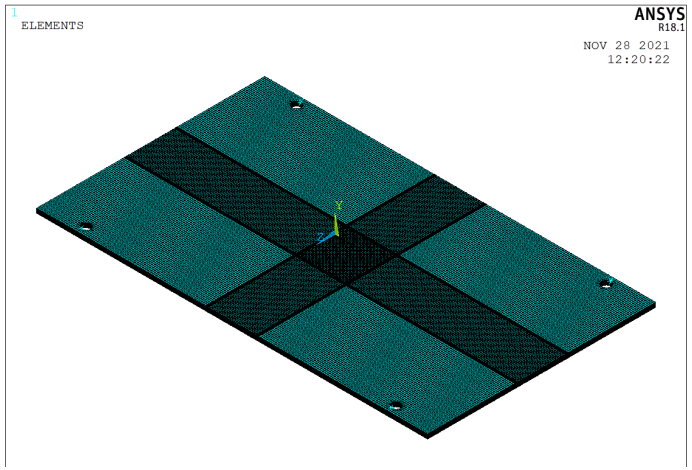


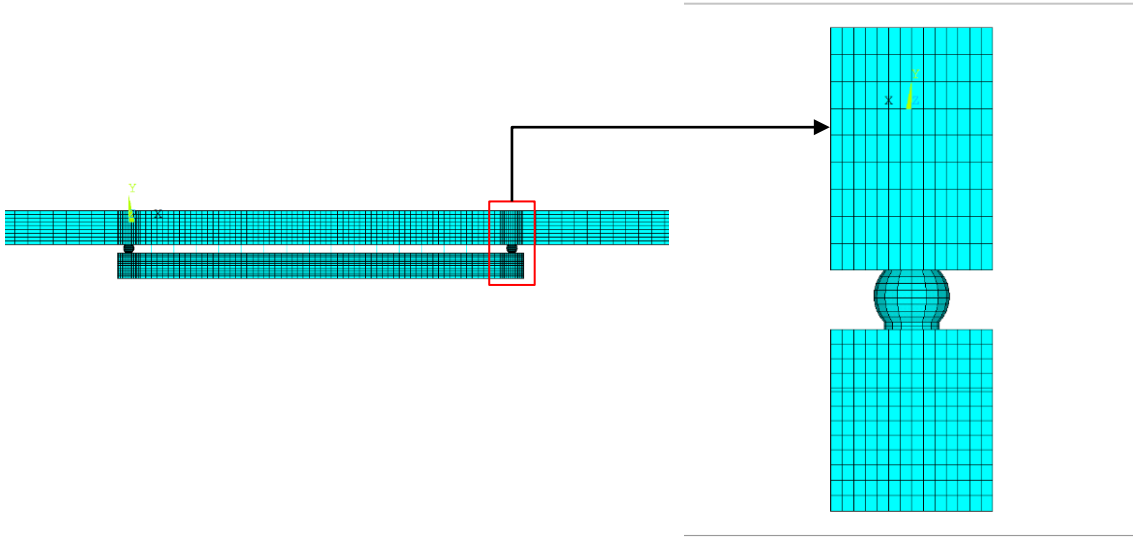


Modified Remaining Useful Life using Experimental and Finite Element Analysis



FEM Model for Vibration and Drop





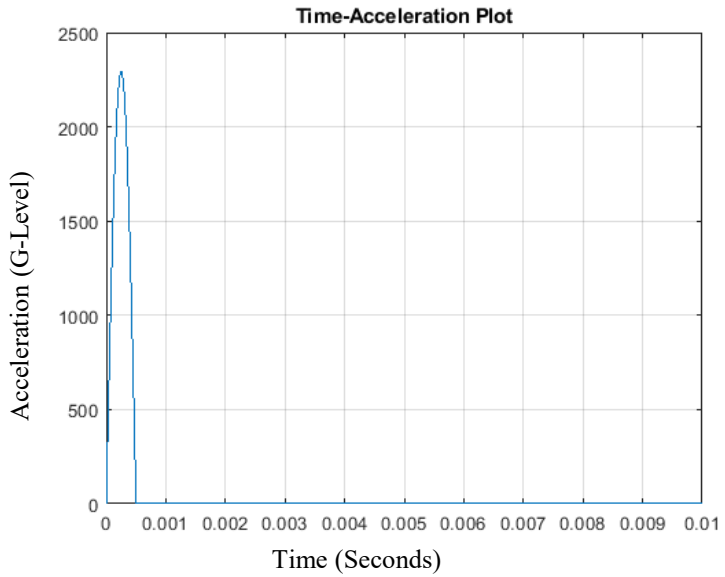
Package Assembly	E (MPa)	Poisson's Ratio	Density (tonne/mm^3)
Solder Joints	42000	0.34	8.40E-09
Mold Compound	23500	0.25	1.65E-09
Silicon Die	162000	0.28	2.33E-09
Die Attach	2760	0.35	7.80E-09
BT Substrate	17400	0.28	1.80E-09
Copper Pad	129000	0.34	8.82E-09
PCB	23.8	0.39	1.80E-09

Board Assembly	Element Type
PCB	SOLID 45
Copper Pad	SOLID 45
Silicon Die	SOLID 45
Die Attach	SOLID 45
BT Substrate	SOLID 45
Conner Joints	VISCO 107
Center Joints	BEAM 188
Mass Element	MASS 21

FEM Analysis-Vibration and Drop

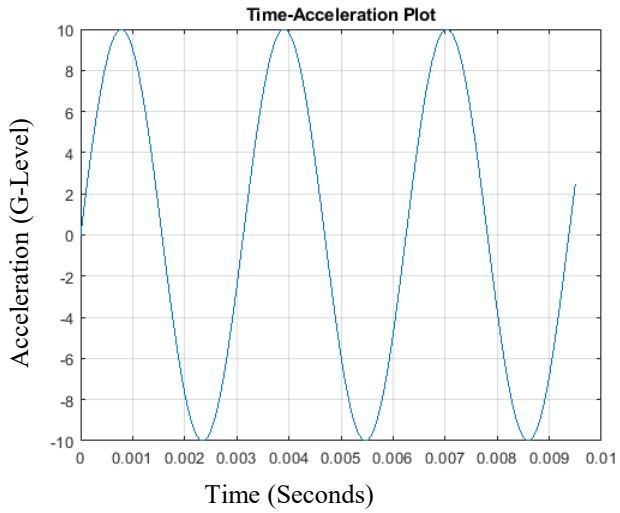
Anand Constant	0 Days	30 Days	60 Days	120 Days
S_0	0.294	0.29	0.279	0.243
Q/R	4500	4500	4500	4500
A	650	730	762	800
ξ	6.7	6.7	6.7	6.7
m	0.4637	0.4401	0.4213	0.361
h_0	163700	108000	91860	91400
$\hat{s}$	64.176	56.322	51.415	50.85
n	0.0055	0.0056	0.00551	0.00526
a	1.16	1.20	1.26	1.34

Anand Visco-Plastic Parameters of SAC305 Solder for different aging conditions



Time-Acceleration plot for Drop Experiments

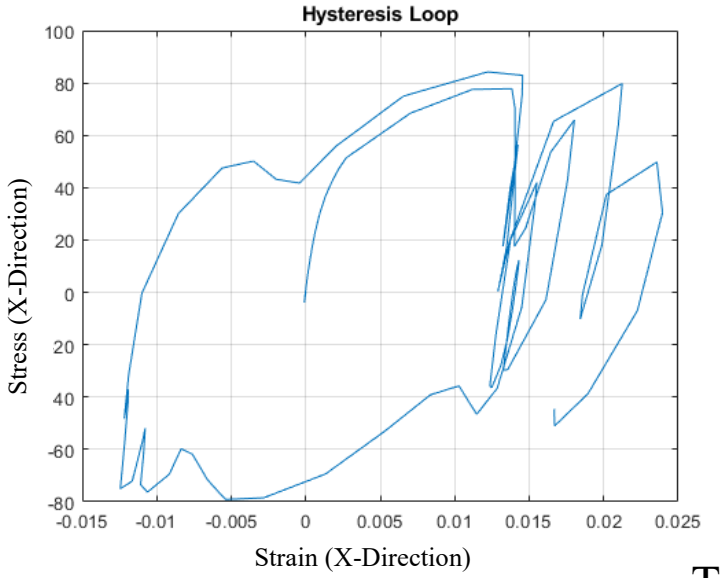
FEM Analysis using **Input-G** method



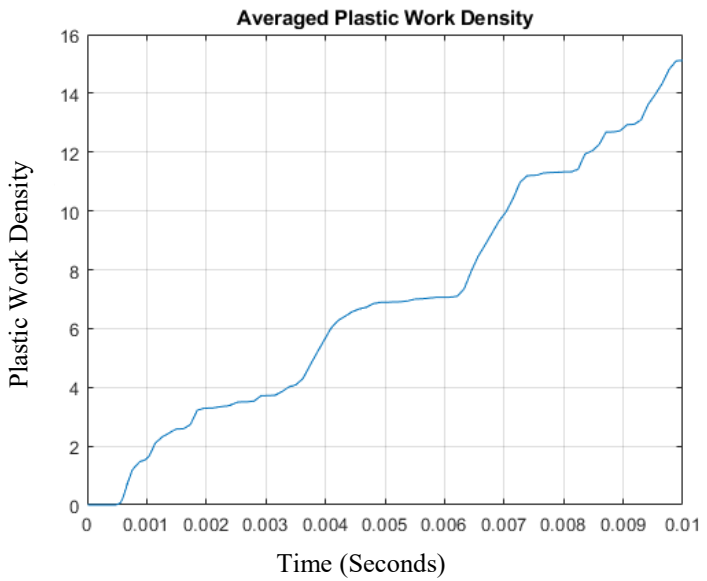
Time-Acceleration plot for Vibration Experiments

Average SJ Plastic Work and Hysteresis Loop

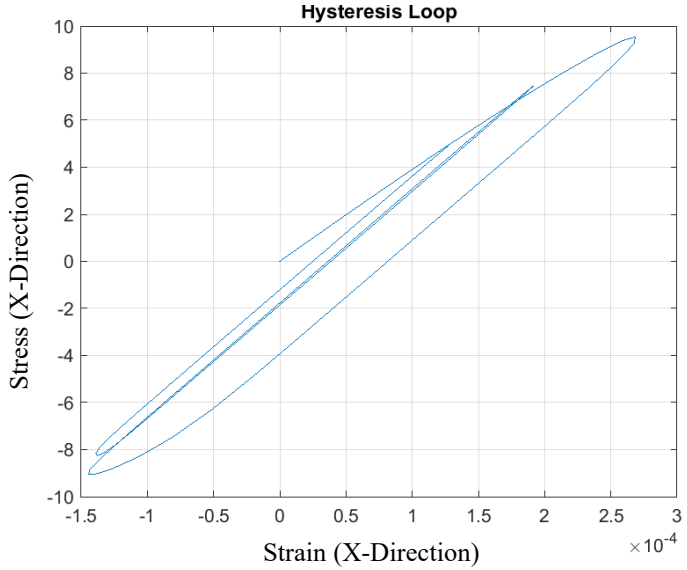
Vibration



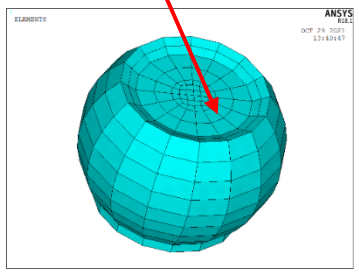
Average Plastic work of the **top layer** of the solder ball

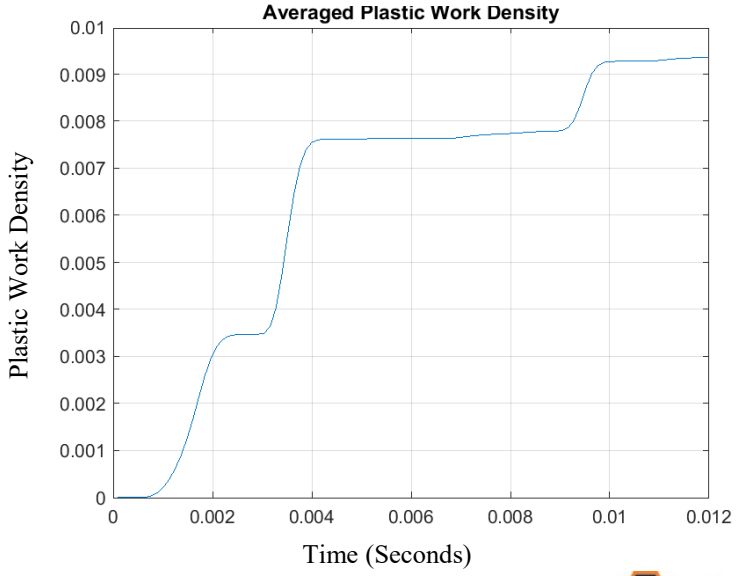


Shock

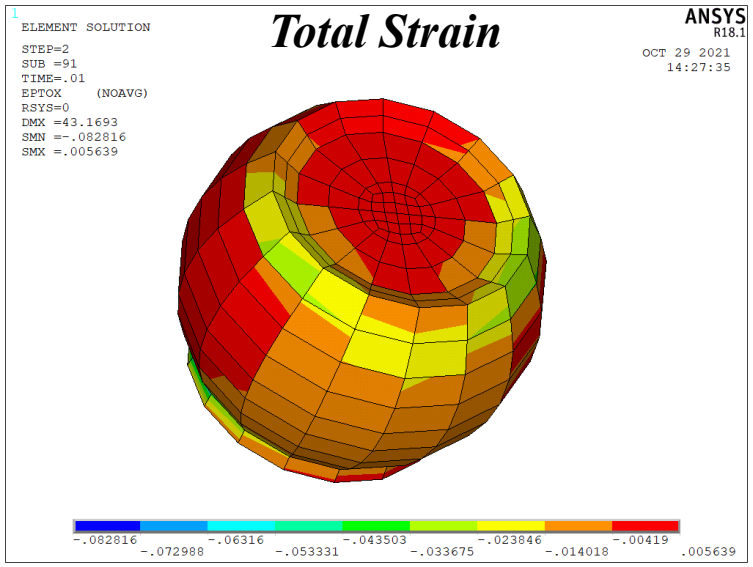


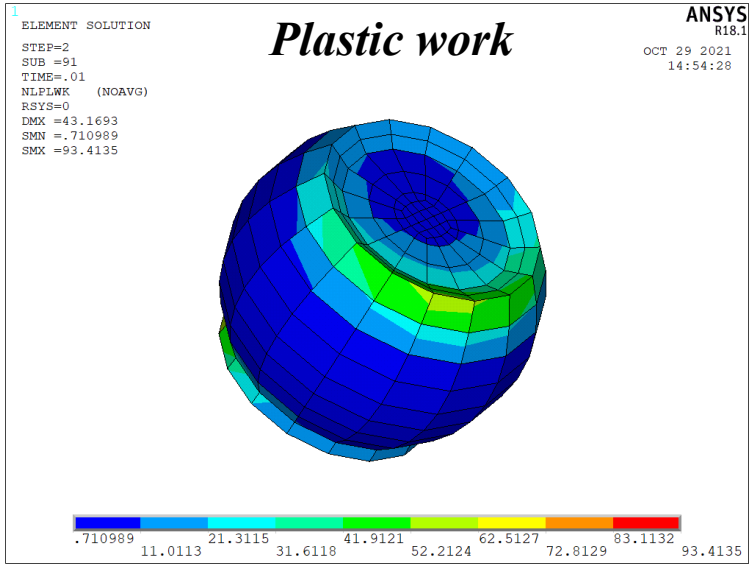
Top Layer

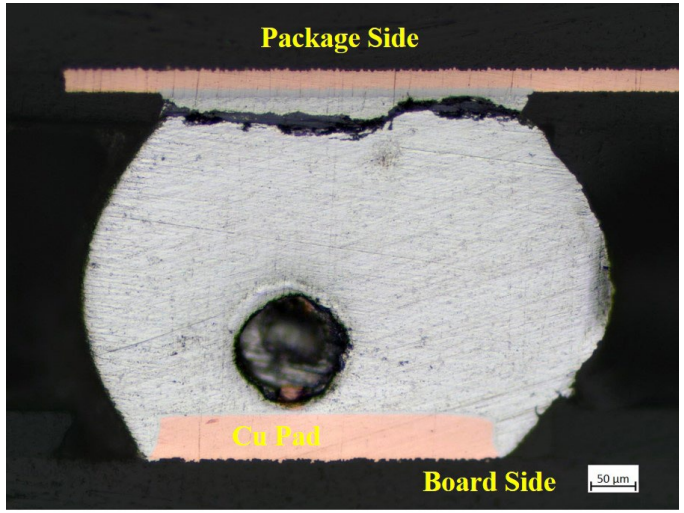


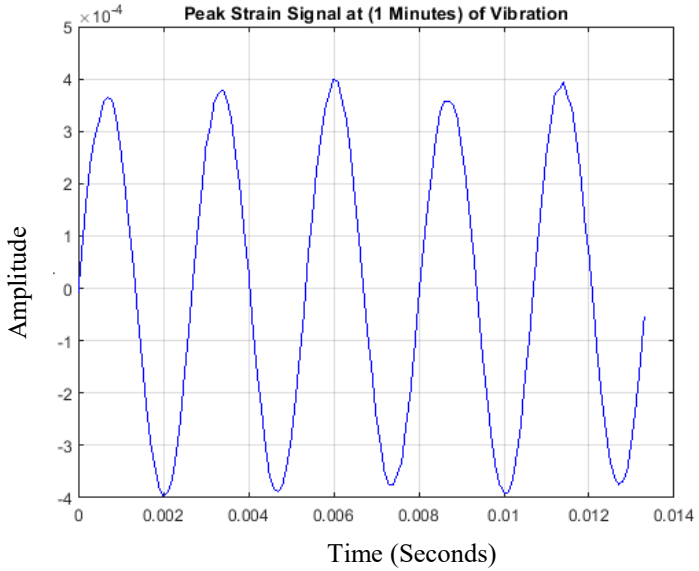


Vibration SJ Plastic Work and Strain



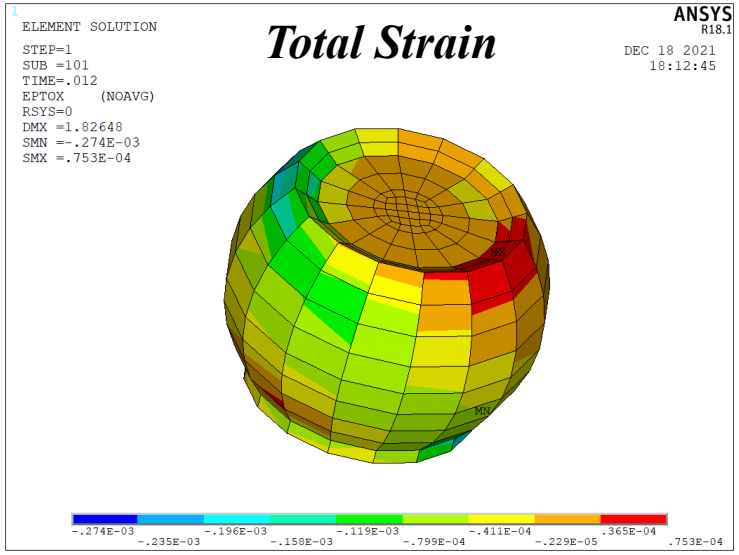


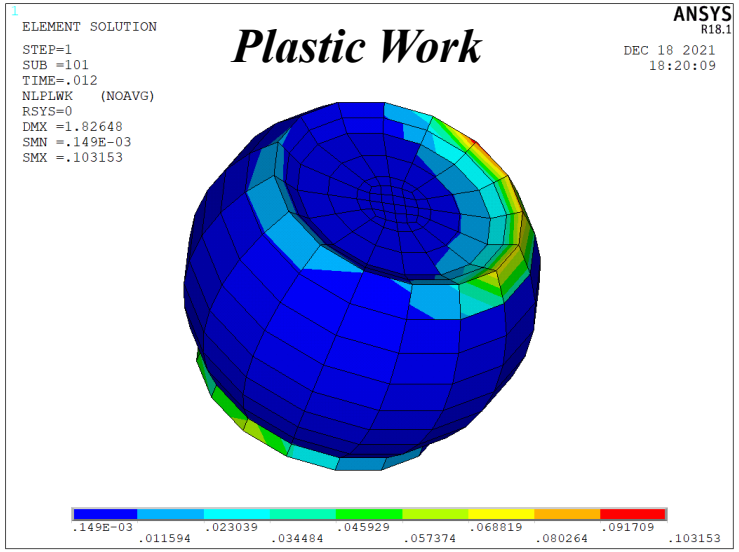


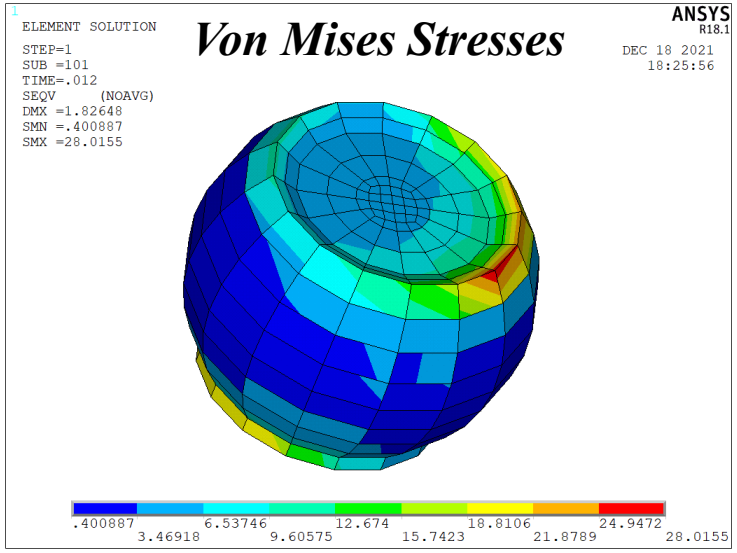


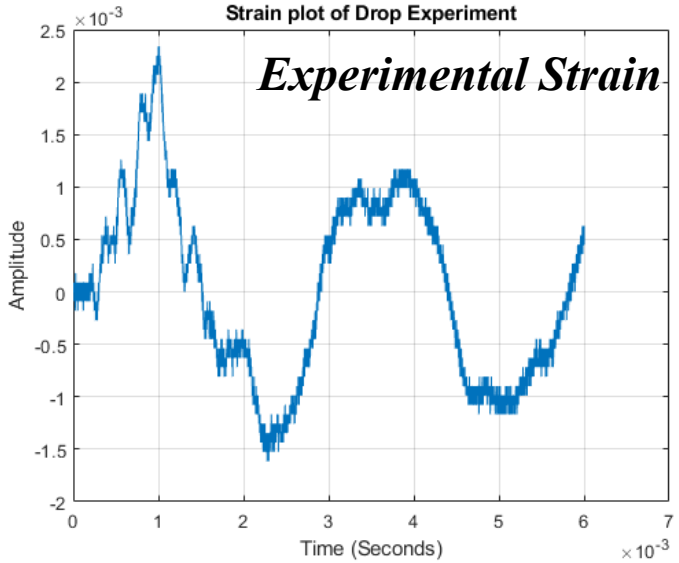
Experimental Strain

Shock SJ Stress and Strain

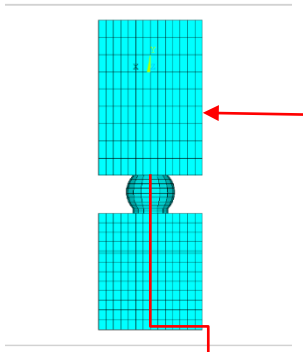




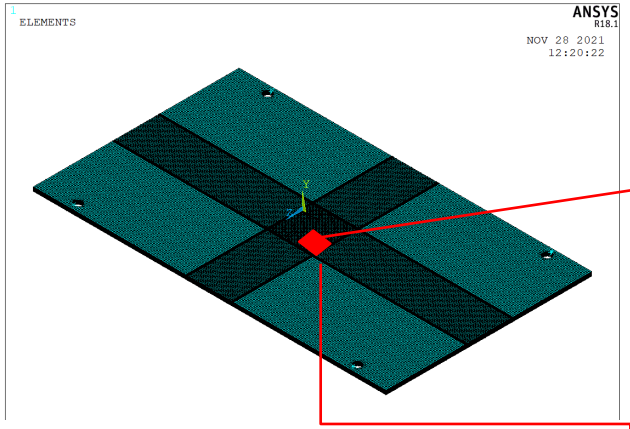




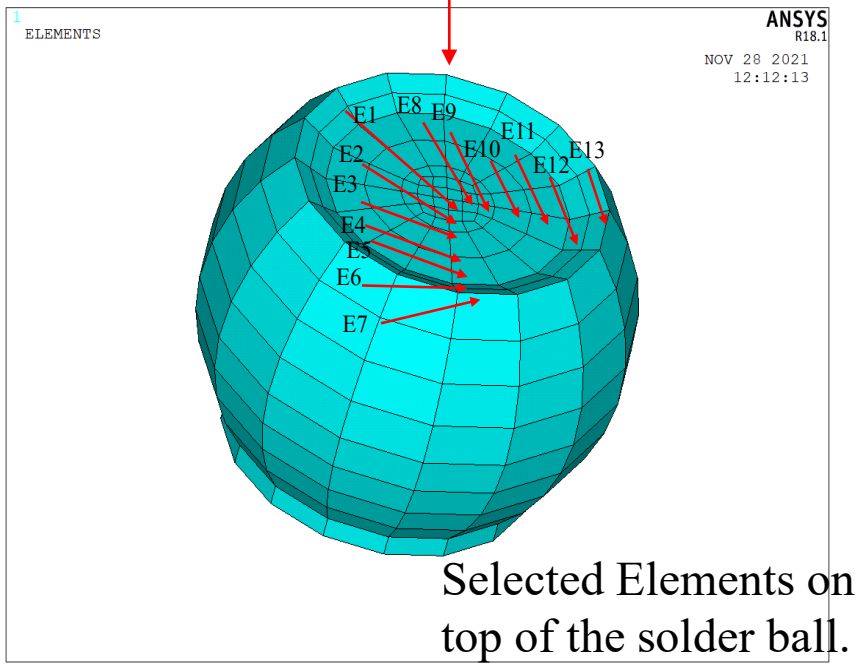
Statistical Analysis of the SJ FEM Predictions



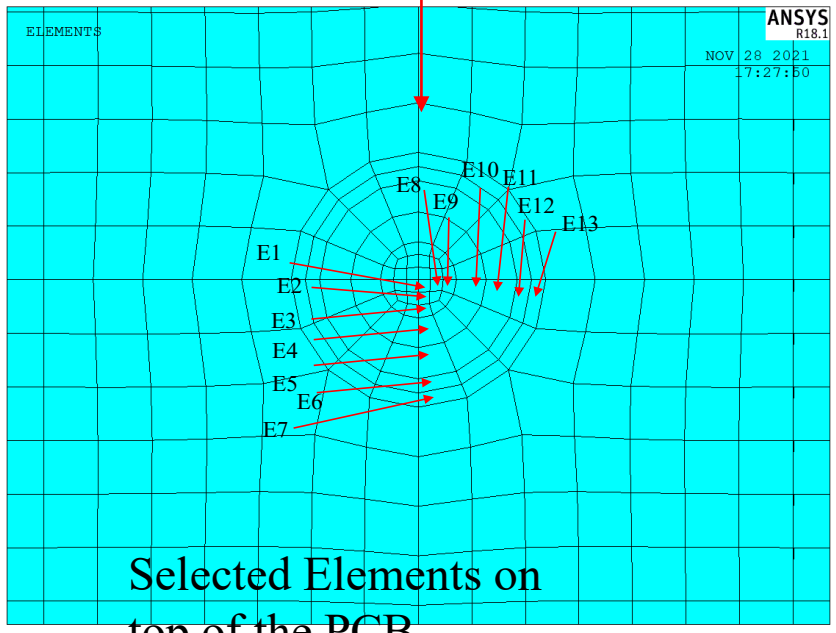
PCB Side



Strain Gauge Position

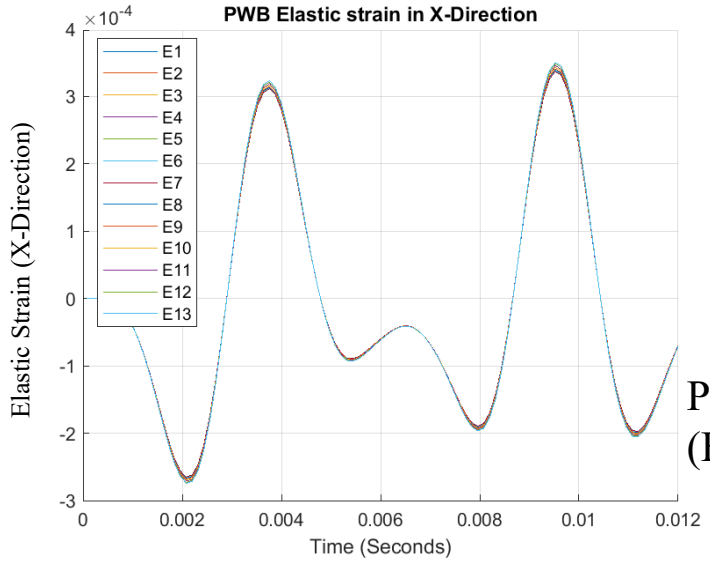


Selected Elements on top of the solder ball.



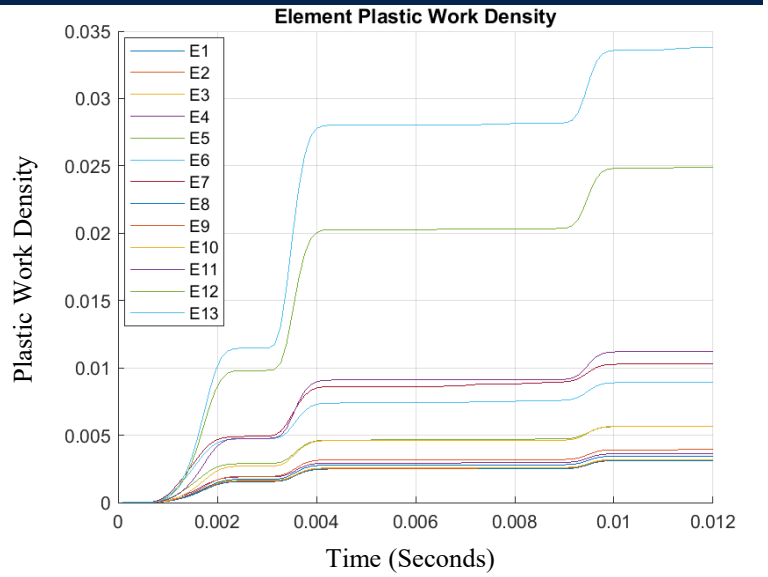
Selected Elements on top of the PCB.

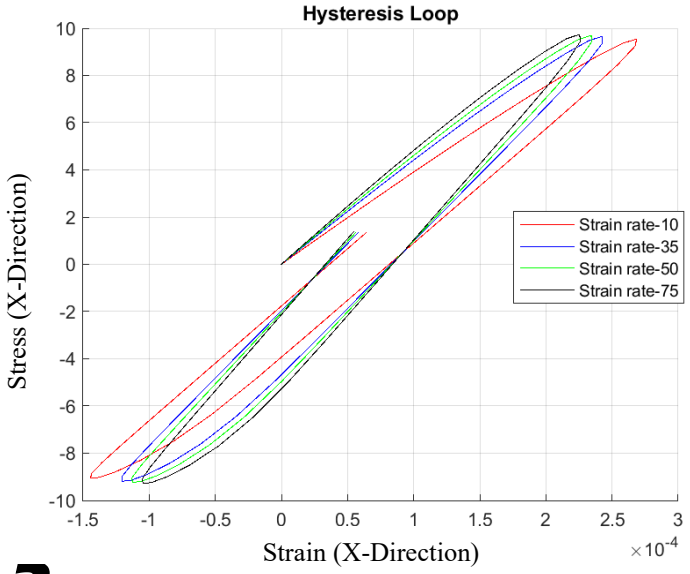
Vibration PCB x-Strain and Plastic Work



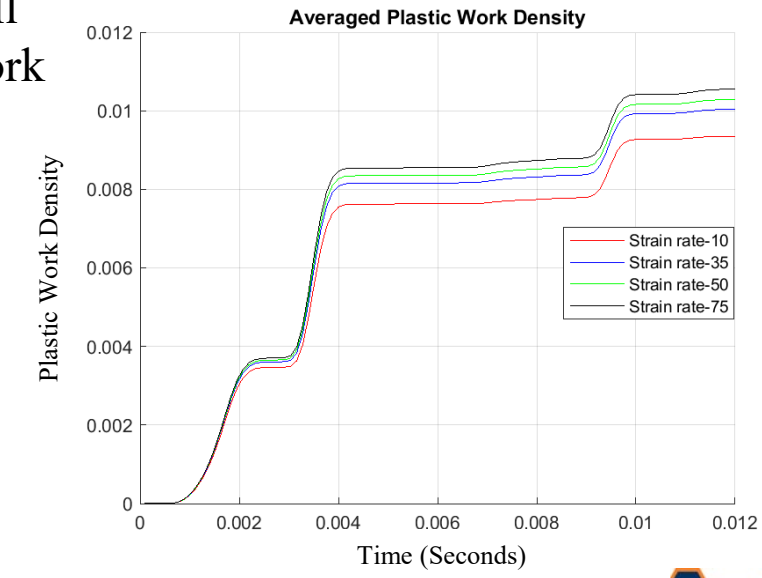
Strain Rate $10s^{-1}$

PWB Strain (E1-E13)

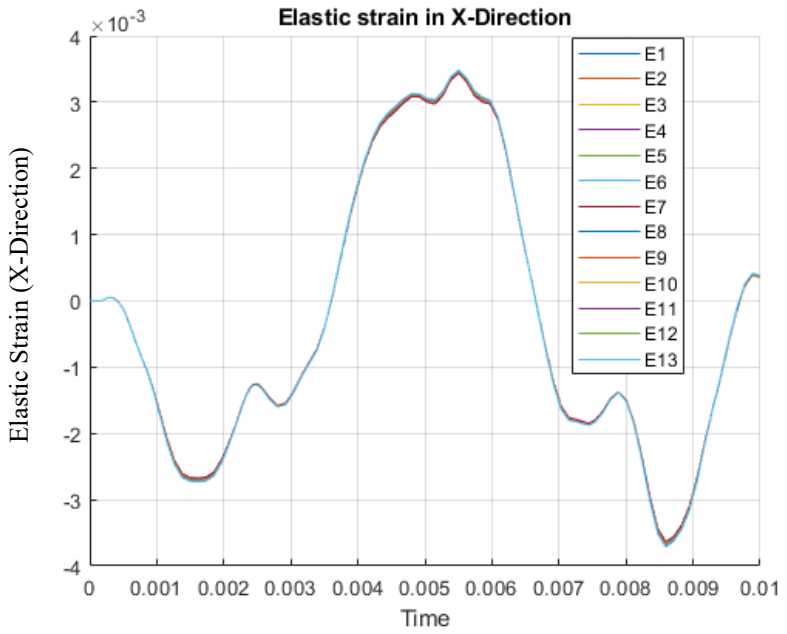




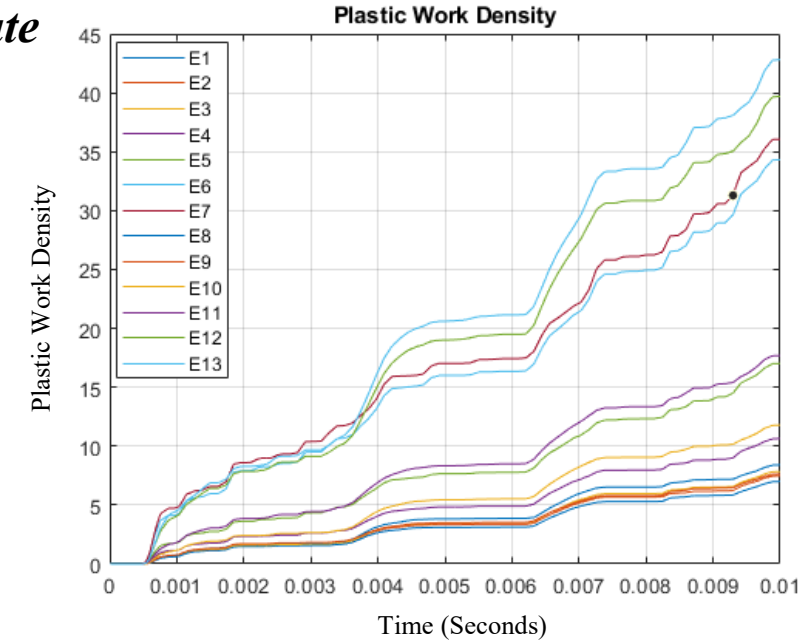
Solder Ball Plastic Work (E1-E13)



Shock PCB x-Strain and Plastic Work



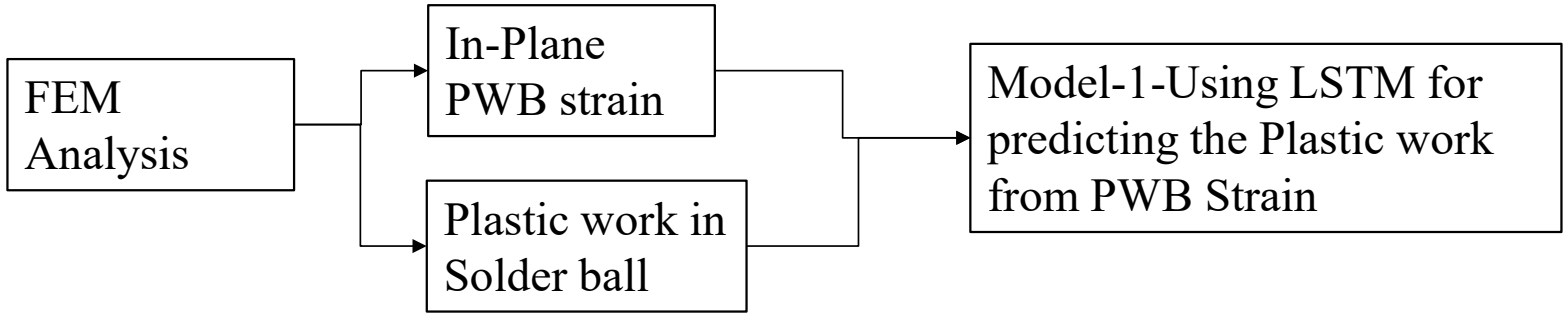
Strain Rate $10s^{-1}$

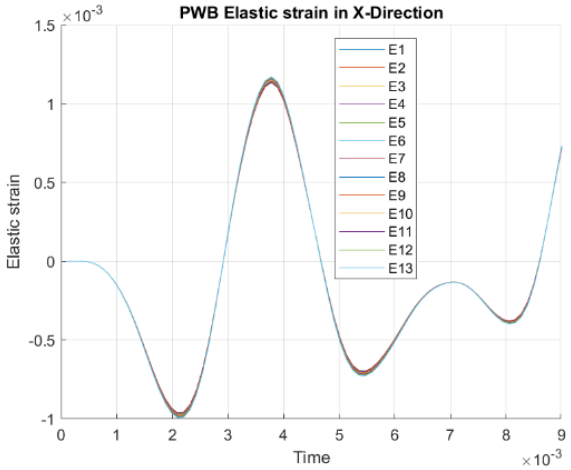


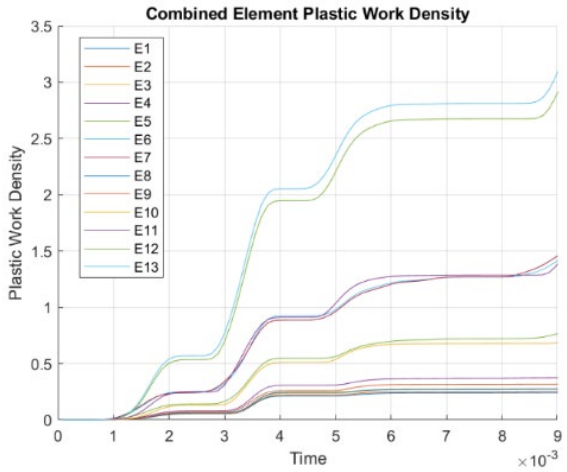
Strain from the top of the PWB in X-Direction Elastic strain for Elements (E1-E13)

Plastic Work from the top of the Solder ball Elements (E1-E13)

Statistical Feature Vectors from FEM Analysis

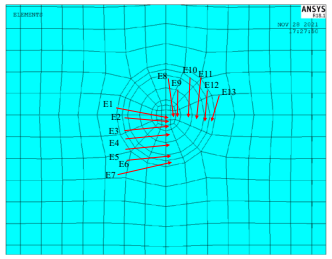




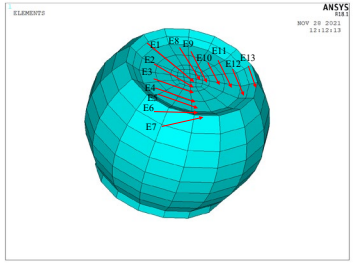


This is used as the training dataset for Model-1

PWB Elements



Solder Ball Elements



Training is carried out using FEM Analysis

Modified Remaining Useful Life Predictions

Feature-1	Feature-2	Feature-3	Feature-4	Prediction
Time Instant	Strain (PWB)	Strain rate (PWB)	Elastic Modulus	**Solder ball Plastic work density**

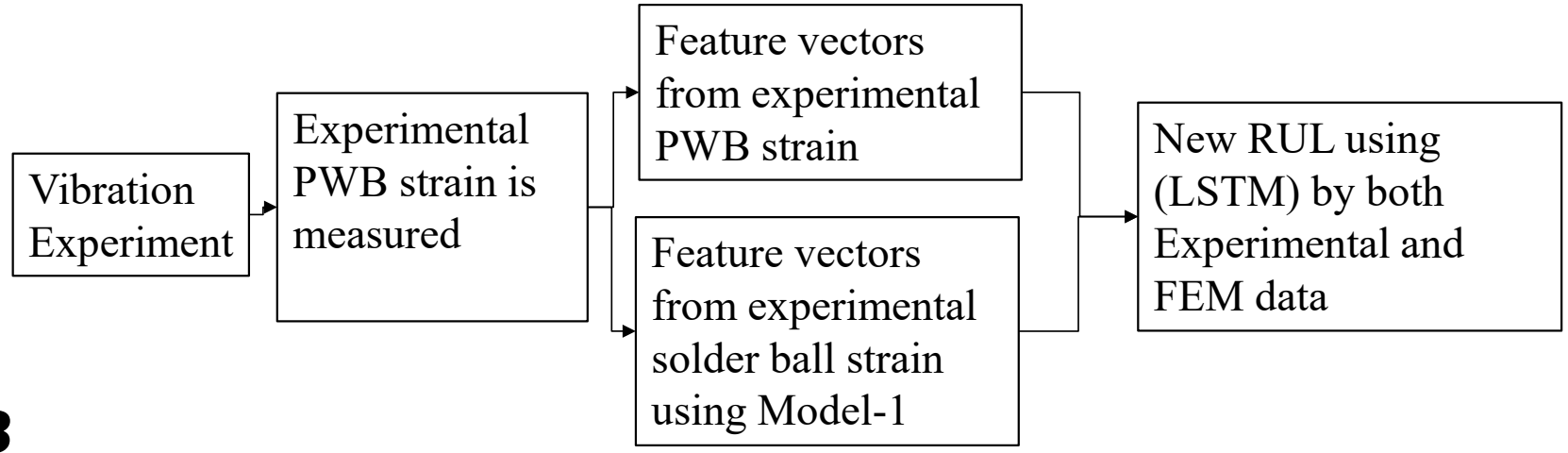
Testing Using **Model-1**

Stage-1

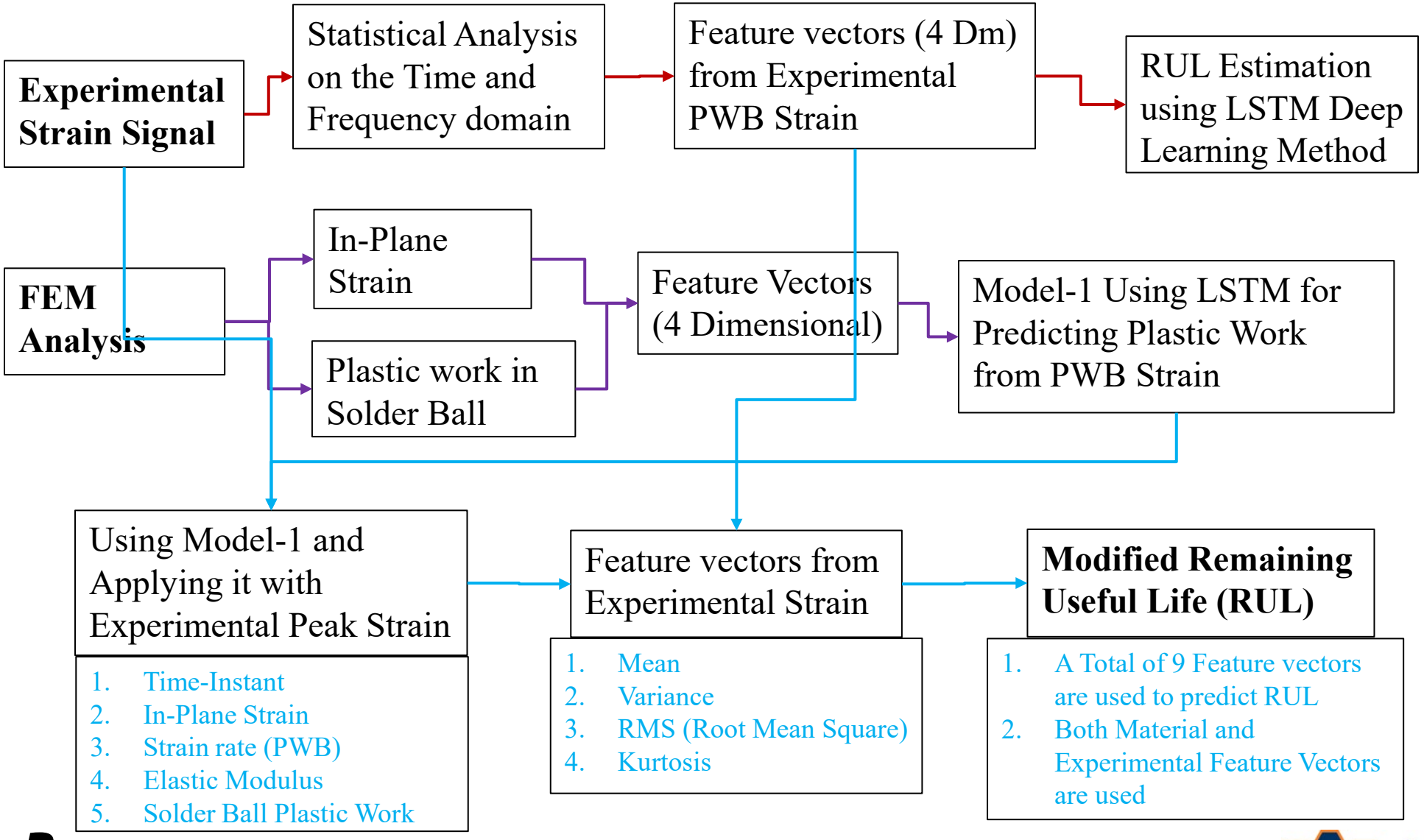
Using Experimental Data

Stage-2

Feature-5	Feature-6	Feature-7	Feature-8	Feature-9	Prediction
rms of Residual	mean of Residual	Variance of Residual	kurtosis of Residual	**Solder ball Plastic work density**	New Remaining Useful Life (RUL)

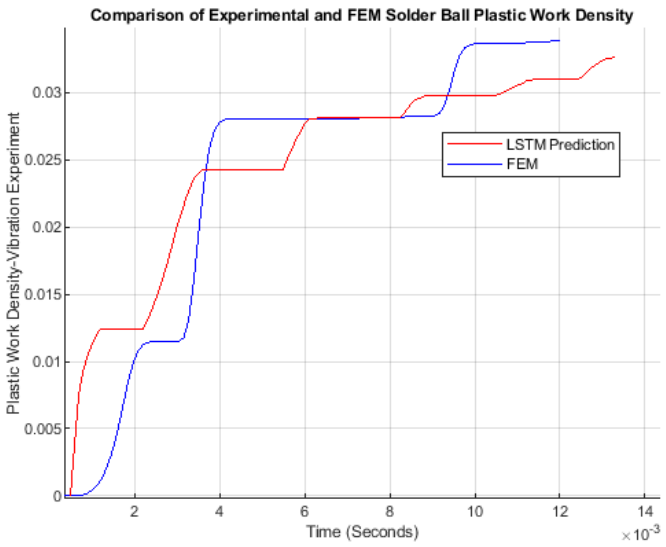


Workflow-Remaining Useful Life Predictions

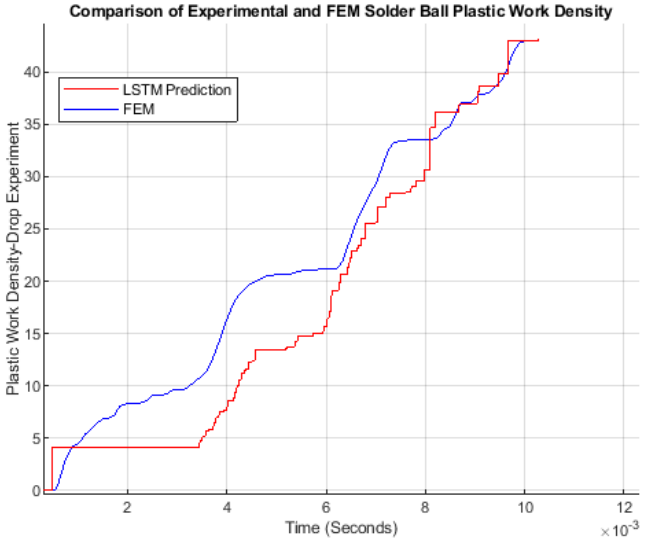


Modified Remaining Useful Life Predictions

Vibration

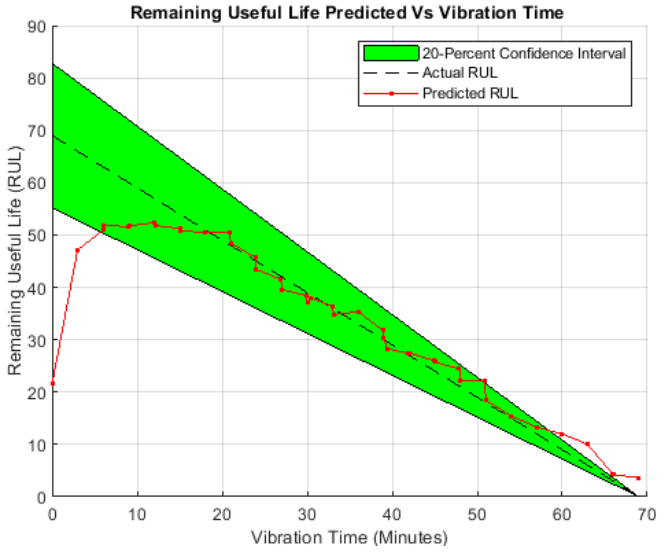


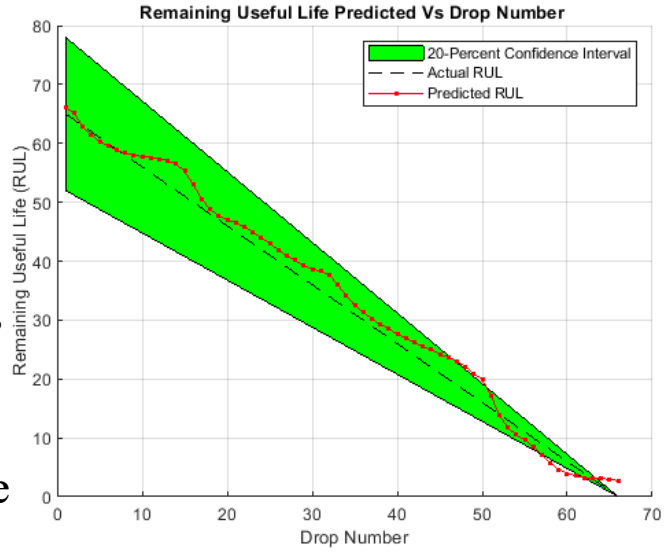
Shock



Prediction of Life of the Electronic Packages using a **Combination of Feature Vectors from FEM and Experiments**

The New RUL Estimation involves **Geometric and Material** characteristics of the Solder.





Summary and Conclusions

- Remaining Useful Life (RUL) estimation using Experimental and FEM based feature vectors was modelled.
- Long Short-Term Memory (LSTM) deep learning method was used to predict the remaining useful life of the packages.
- The methodologies proposed in the paper allow for successful separation of before failure and after failure strain signals using statistical methods on the Frequency matrices.
- The residuals of the Cross-correlation and Auto-correlation function showed an increasing behavior which was used to predict the failure of the packages.
- Feature vector identification for RUL estimation for different solder materials were also tested.