REPAIRABLE SYSTEMS RELIABILITY MODELLING

MASTERS THESIS PROJECT

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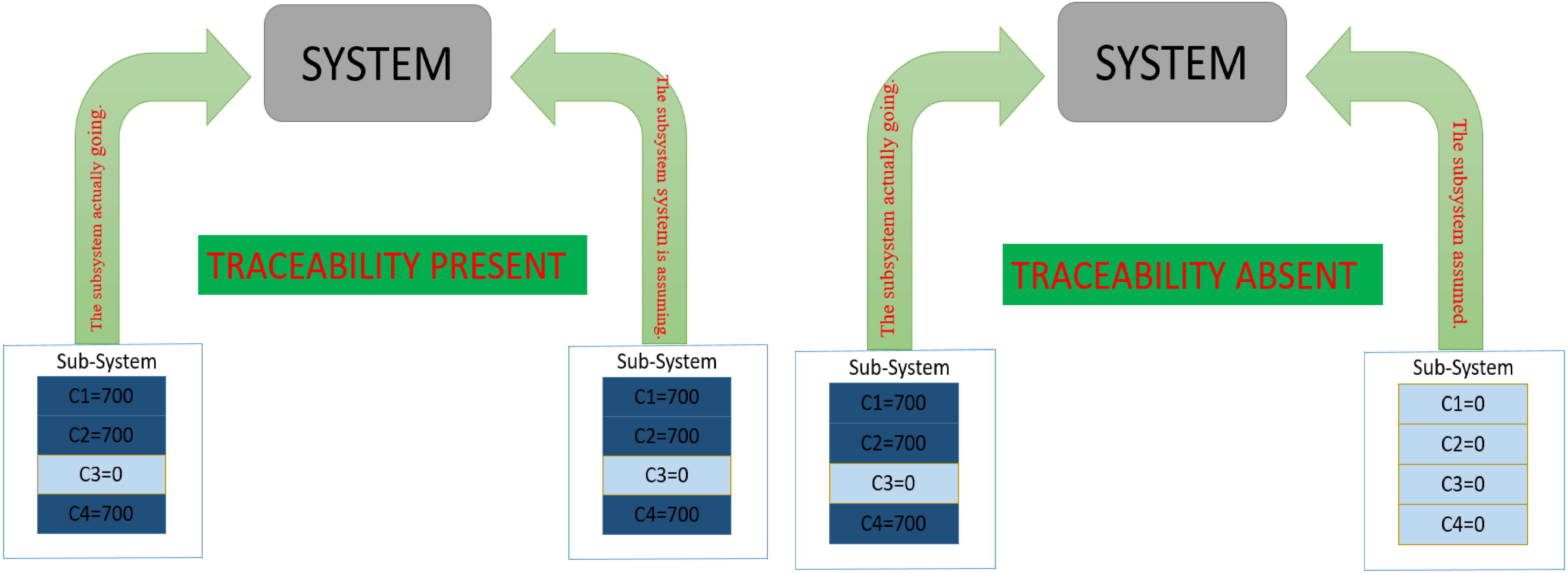
Outline

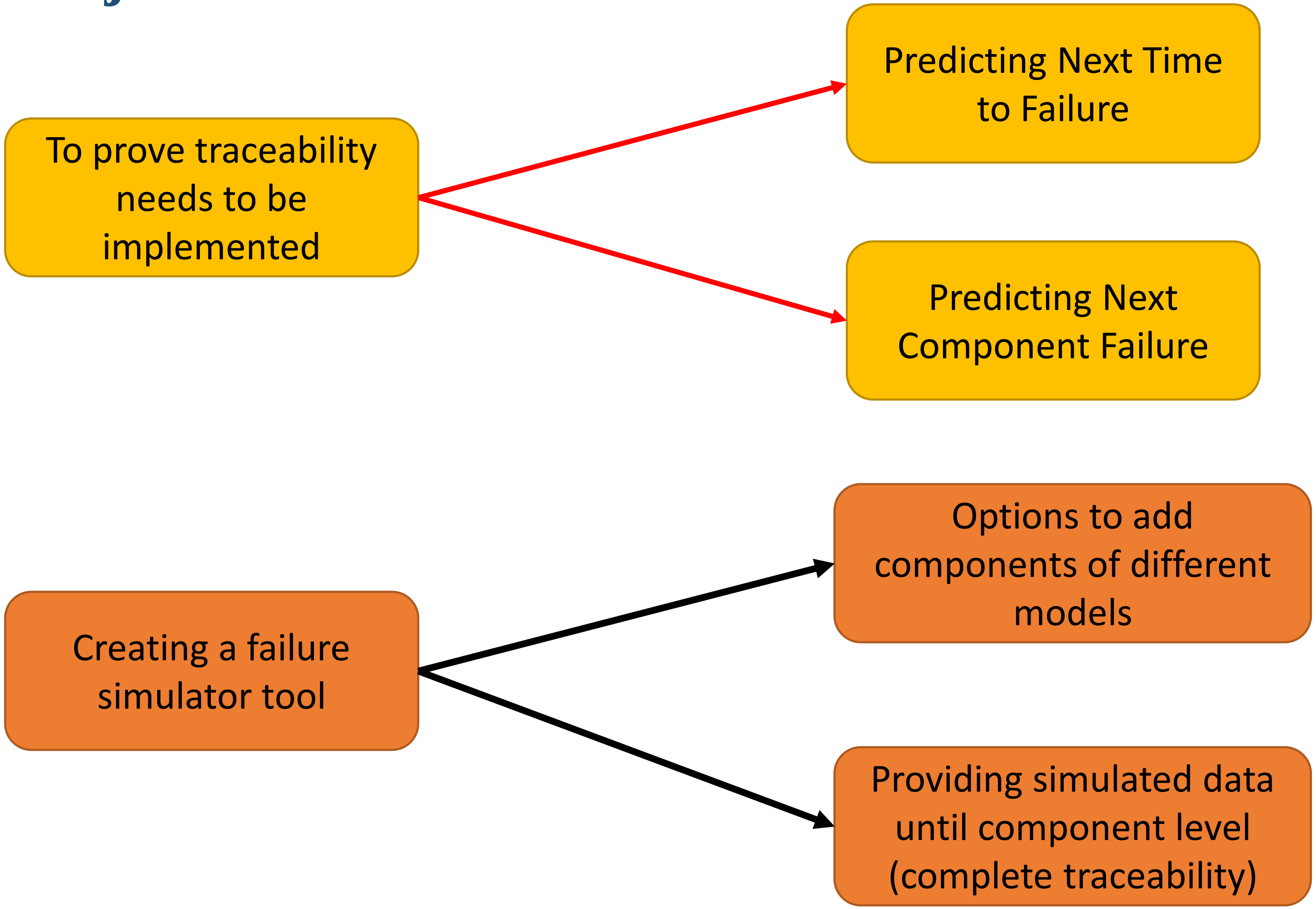
- ❖ Introduction
- ❖ Predicting the next time to failure
- ❖ Predicting the next Failed Component
- ❖ Creating a Simulator Tool
- ❖ Conclusion
- ❖ References

Introduction

Introduction:



Objectives:


To prove traceability needs to be implemented
Predicting Next Time to Failure
Predicting Next Component Failure
Creating a failure simulator tool
Options to add components of different models
Providing simulated data until component level (complete traceability)

Predicting Time to Next Failure

Using LSTM

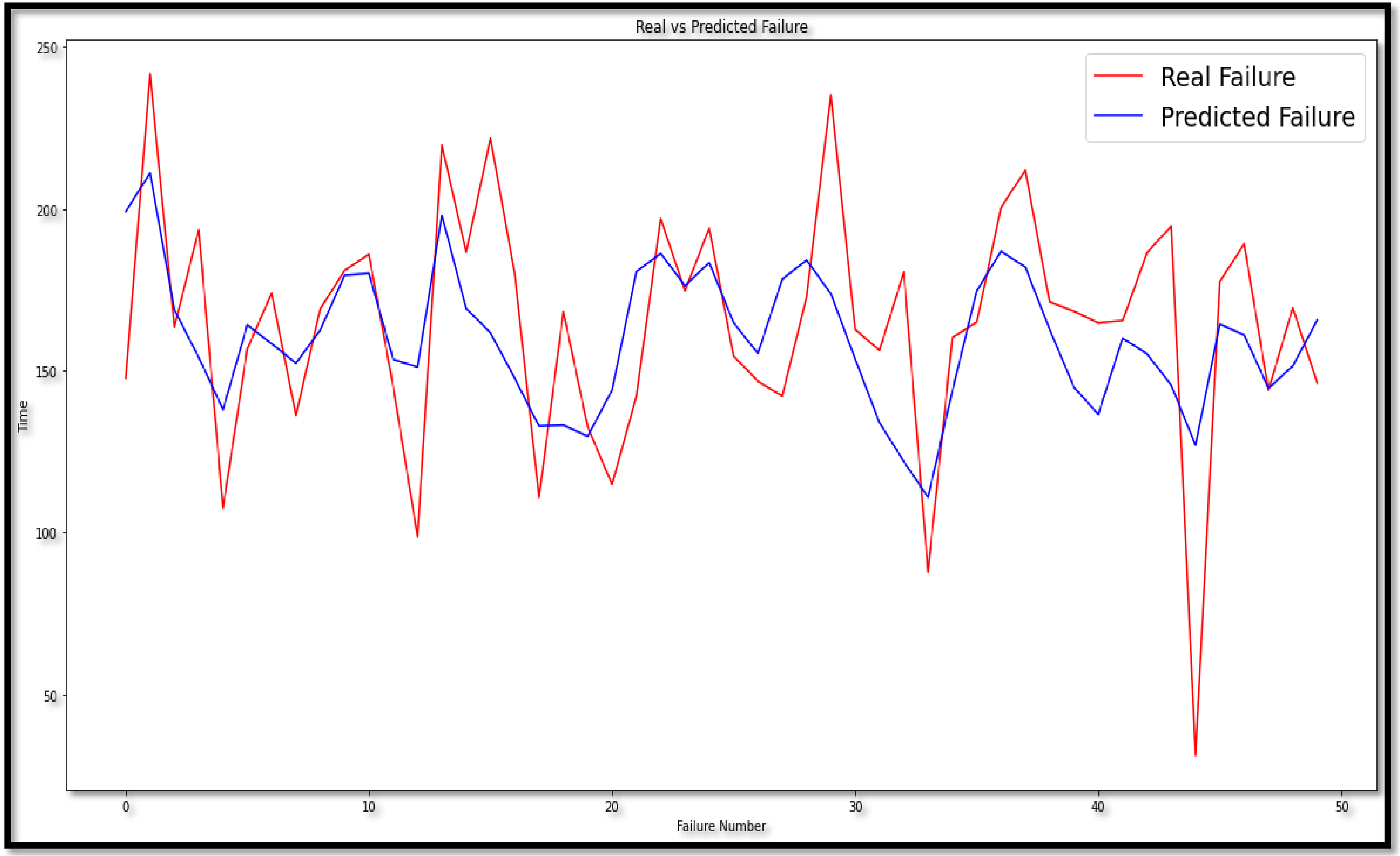
Scale the data so that all values are between 0 and 1

Create input array of 80 values an output as 81st value

Feed the data into LSTM with dropout layers

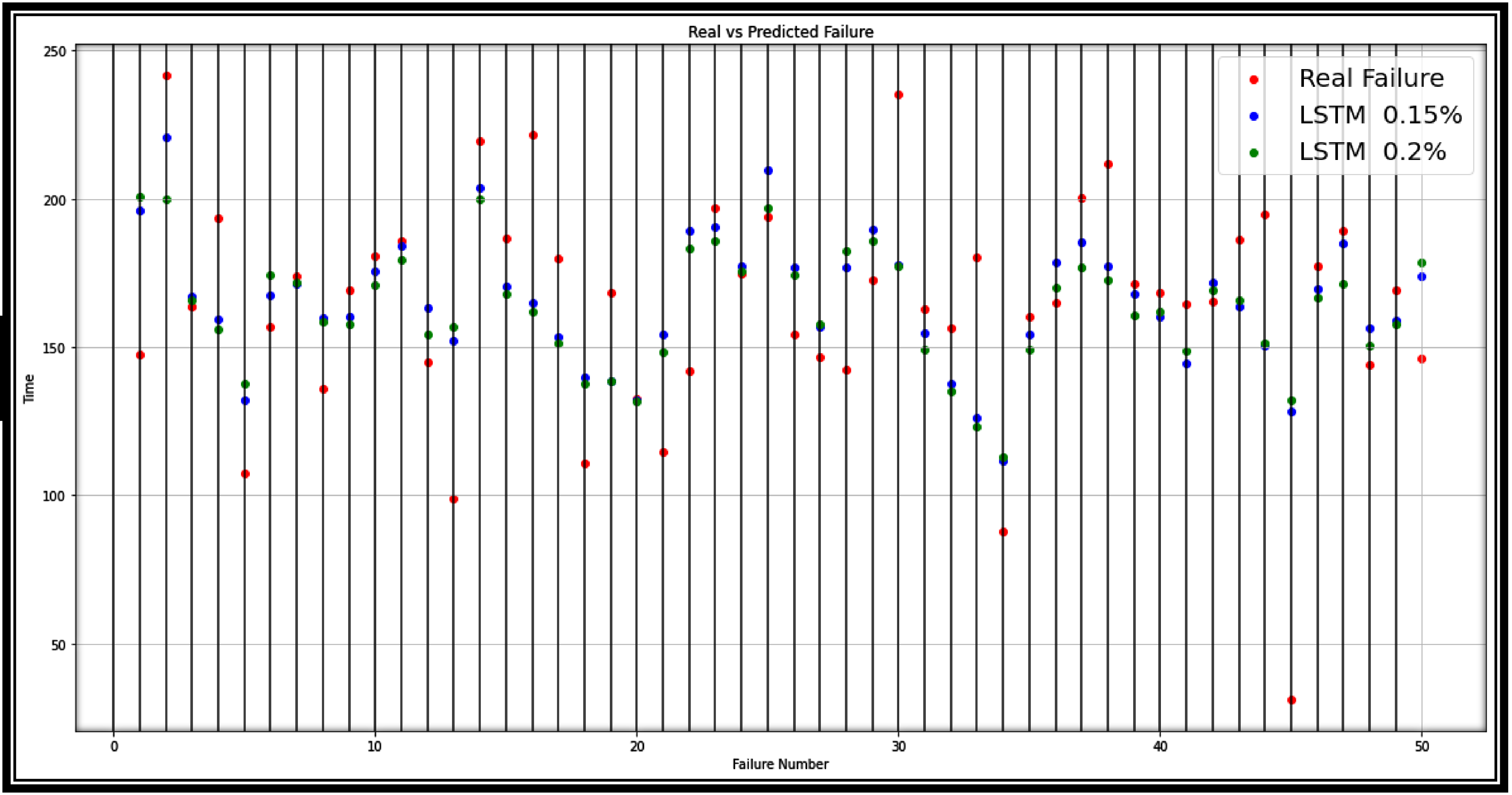
Tune number of layers, dropout % for better accuracy

Predict the value and re-scale it to get actual output.



Results with different dropouts

```
rmse_LSTM20  30.987
rmse_LSTM15 29.3641
```



Predicting Next Component

Using language Modelling

Tokenize the components and create numerical sequences

Define sequence length, here = 50. Split them into array of inputs and a single output.

RNN with embedding layers with **sparse categorical_crossentropy** as loss function

Predict the output from the model giving the past list of 50 components as input.

Results

```
1/1 [==============================] - 0s 45ms/step
Predicted Failure: C21 Actual Failure: C21
1/1 [==============================] - 0s 38ms/step
Predicted Failure: C53 Actual Failure: C53
1/1 [==============================] - 0s 39ms/step
Predicted Failure: C33 Actual Failure: C11
1/1 [==============================] - 0s 39ms/step
Predicted Failure: C33 Actual Failure: C31
1/1 [==============================] - 0s 39ms/step
Predicted Failure: C34 Actual Failure: C54
1/1 [==============================] - 0s 39ms/step
Predicted Failure: C34 Actual Failure: C36
1/1 [==============================] - 0s 39ms/step
Predicted Failure: C34 Actual Failure: C22
1/1 [==============================] - 0s 41ms/step
Predicted Failure: C34 Actual Failure: C35
1/1 [==============================] - 0s 42ms/step
Predicted Failure: C33 Actual Failure: C12
1/1 [==============================] - 0s 41ms/step
Predicted Failure: C51 Actual Failure: C32
1/1 [==============================] - 0s 43ms/step
Predicted Failure: C52 Actual Failure: C13
1/1 [==============================] - 0s 47ms/step
Predicted Failure: C51 Actual Failure: C44
1/1 [==============================] - 0s 37ms/step
Predicted Failure: C52 Actual Failure: C34
1/1 [==============================] - 0s 47ms/step
Predicted Failure: C51 Actual Failure: C43
1/1 [==============================] - 0s 43ms/step
Predicted Failure: C52 Actual Failure: C11
1/1 [==============================] - 0s 69ms/step
Predicted Failure: C52 Actual Failure: C45
1/1 [==============================] - 0s 60ms/step
Predicted Failure: C52 Actual Failure: C21
```

Using Classification algorithm

DATA FORMAT

C1=0 ; C2=0; C3=0

C1=50 ; C2=50; C3=0

C1=0 ; C2=150; C3=100

C1=25 ; C2=175; C3=0

C1=50 ; C2=0; C3=25

C1=0 ; C2=100; C3=125

C1=40 ; C2=140; C3=0

DATA GENERATED

X	Y
20,20,20	3
40,40,40	3
60,60,10	1
80,80,30	1
100,100,50	1
140,140,90	1
10,160,110	3
30,180,5	2
50,200,25	2
130,20,80	1
10,110,135	3

Results

	Actual	Predicted
0	9	6
1	9	9
2	9	10
3	9	9
4	9	6
5	9	11
6	9	15
7	9	10
8	9	15
9	9	3

Creating A Tool For Failure Simulations

General Structure of the Tool (Interface)

Create your system.

↓

Add components to the system.

↓

Create dependencies if any among components.

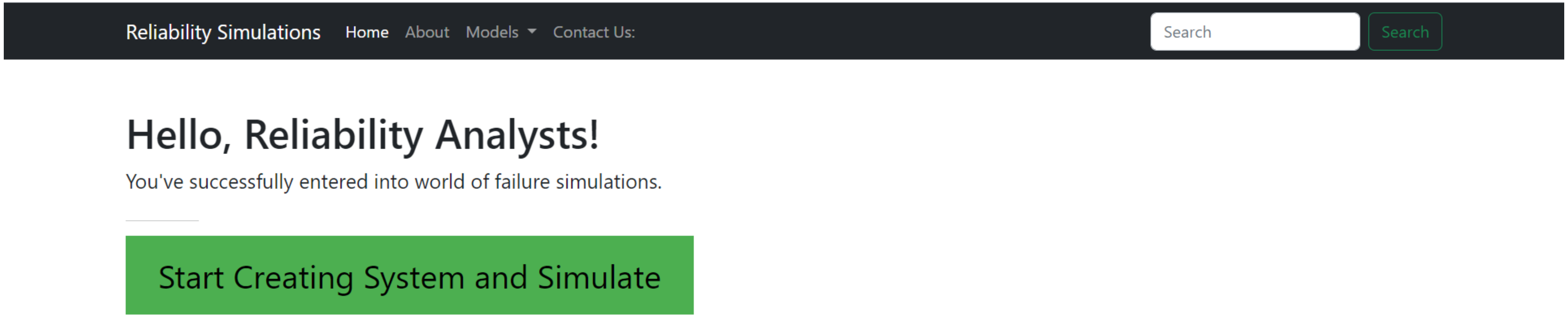
↓

Start Simulations and get results in form of tables and plots.

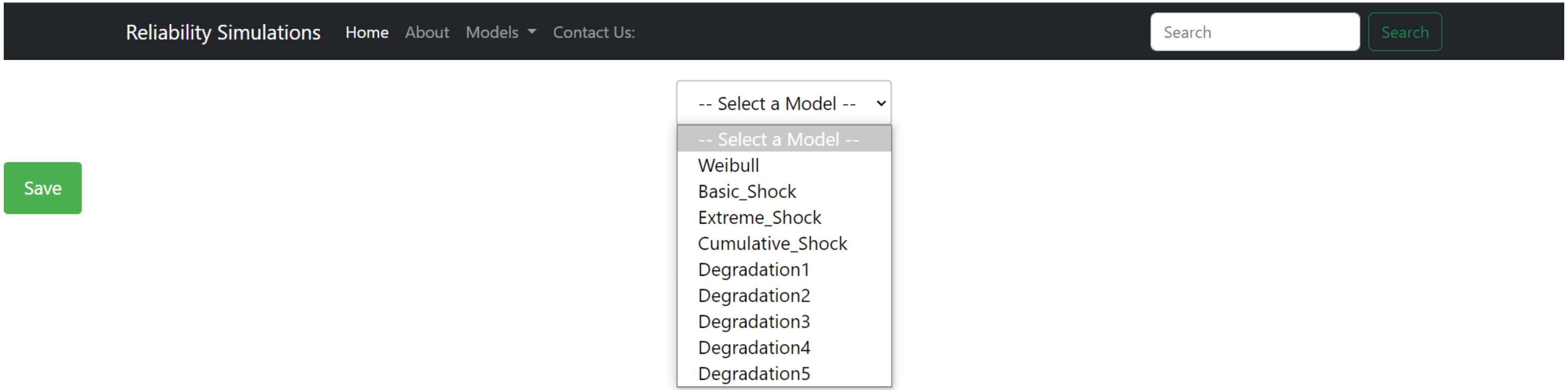
↓

Save data at component level as well as system level.

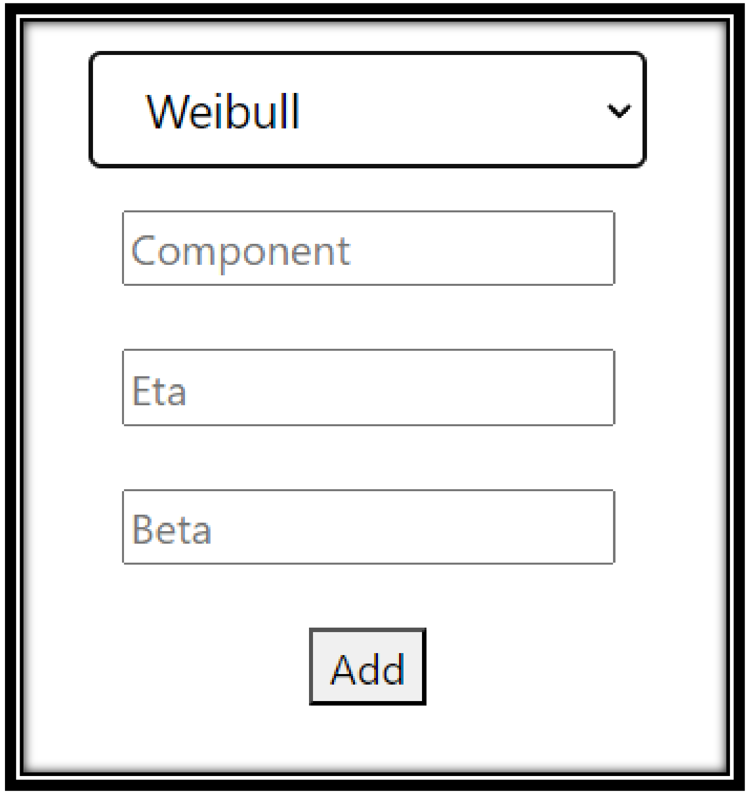
Welcome Page

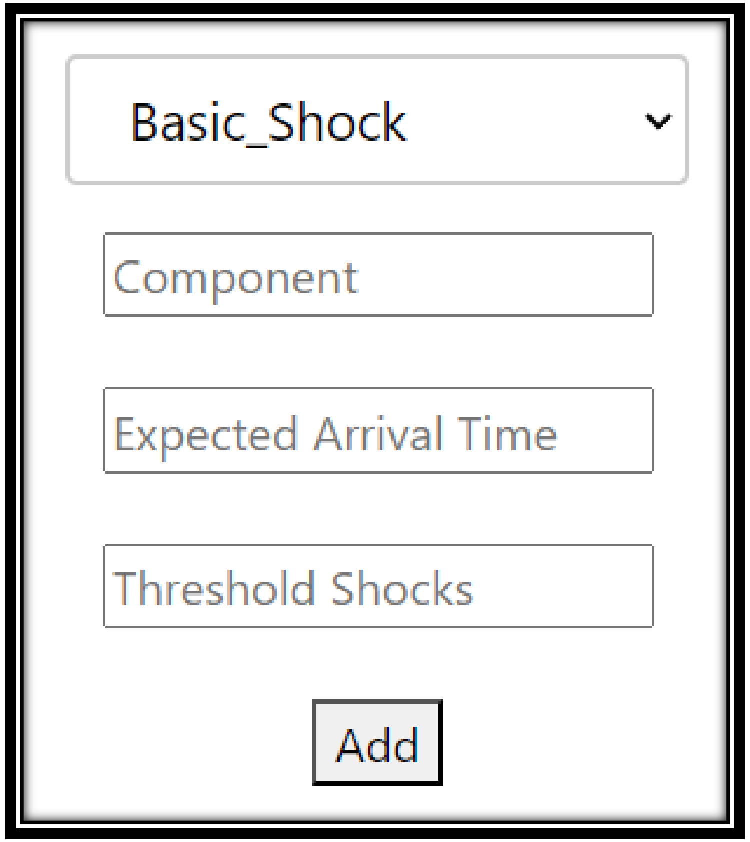


Create your System

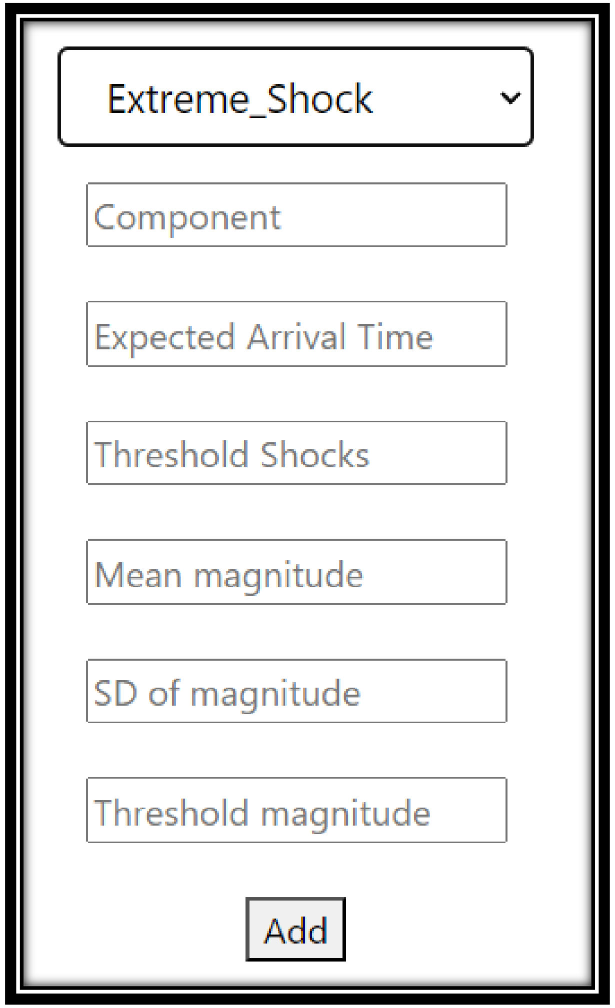


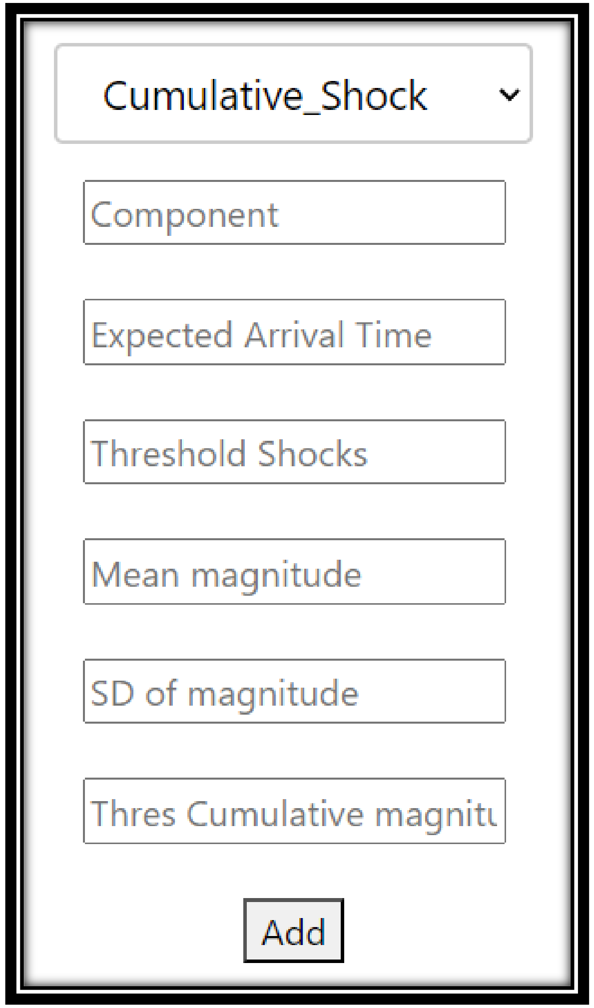
Parameters asked for Each Model



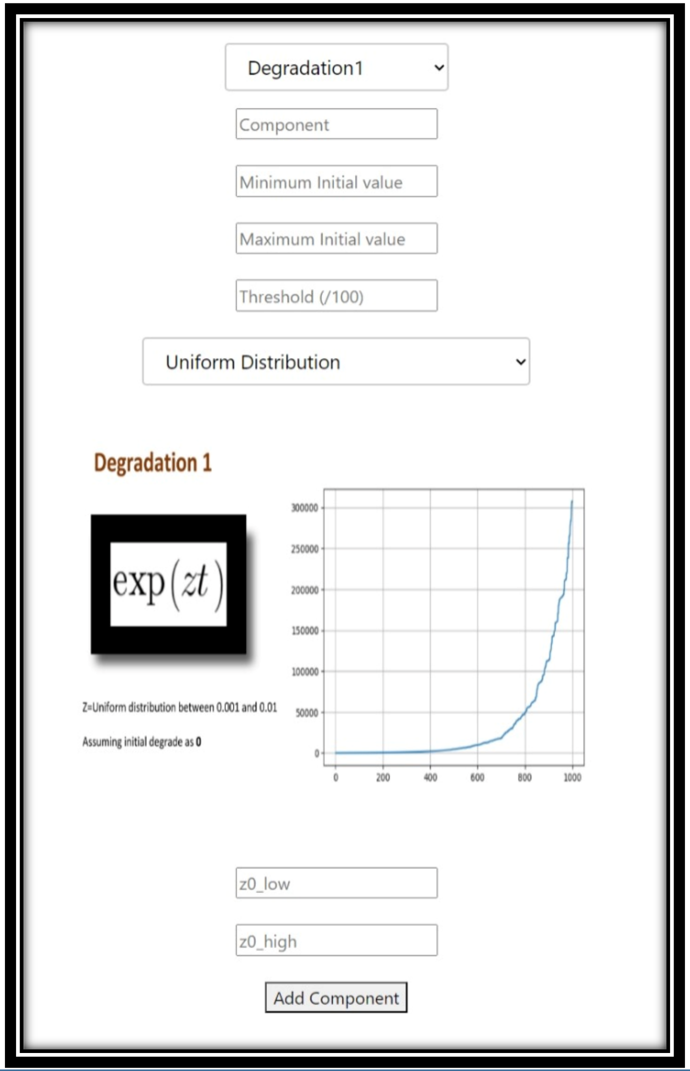


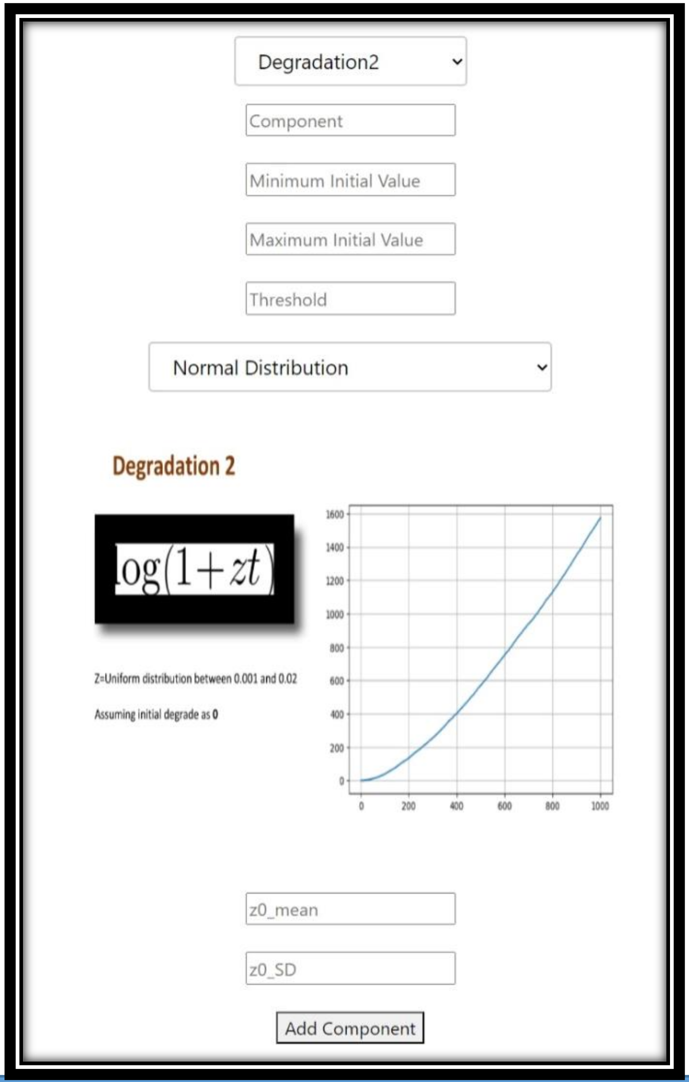
Parameters asked for Other Shock Models

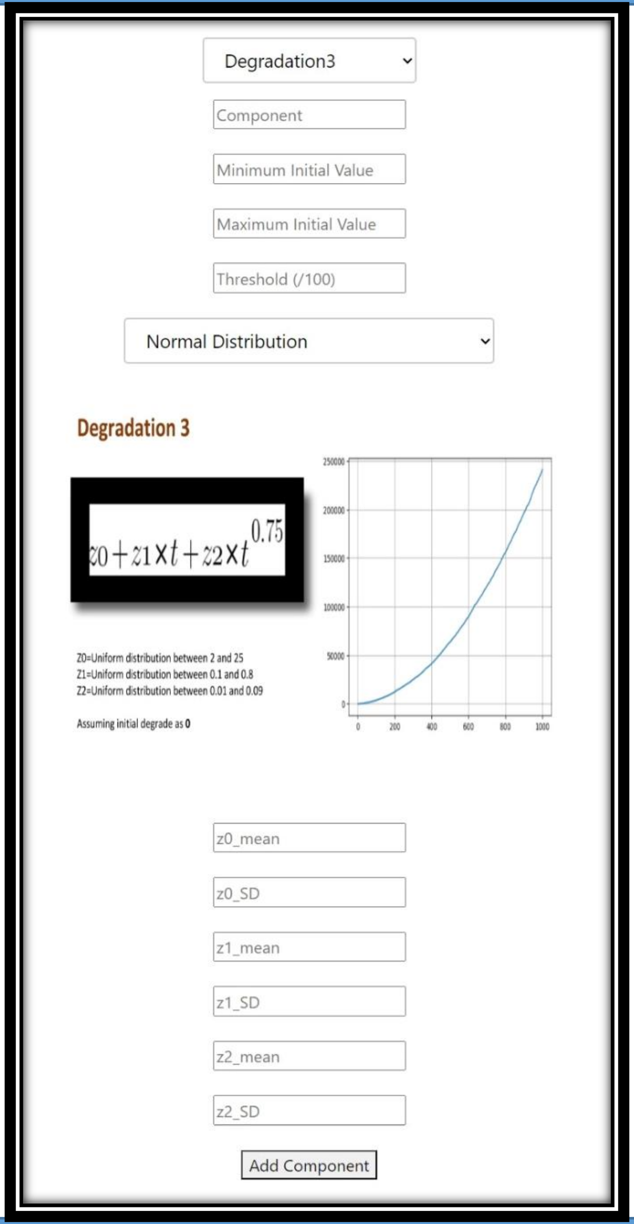




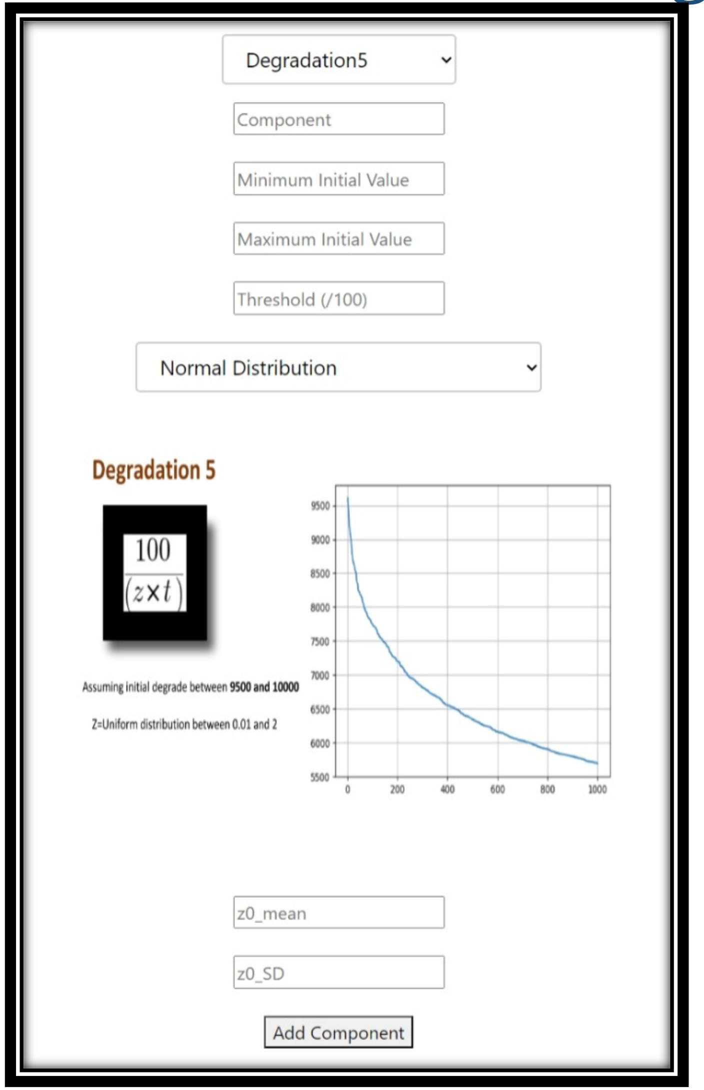
Parameters asked for Degradation Models



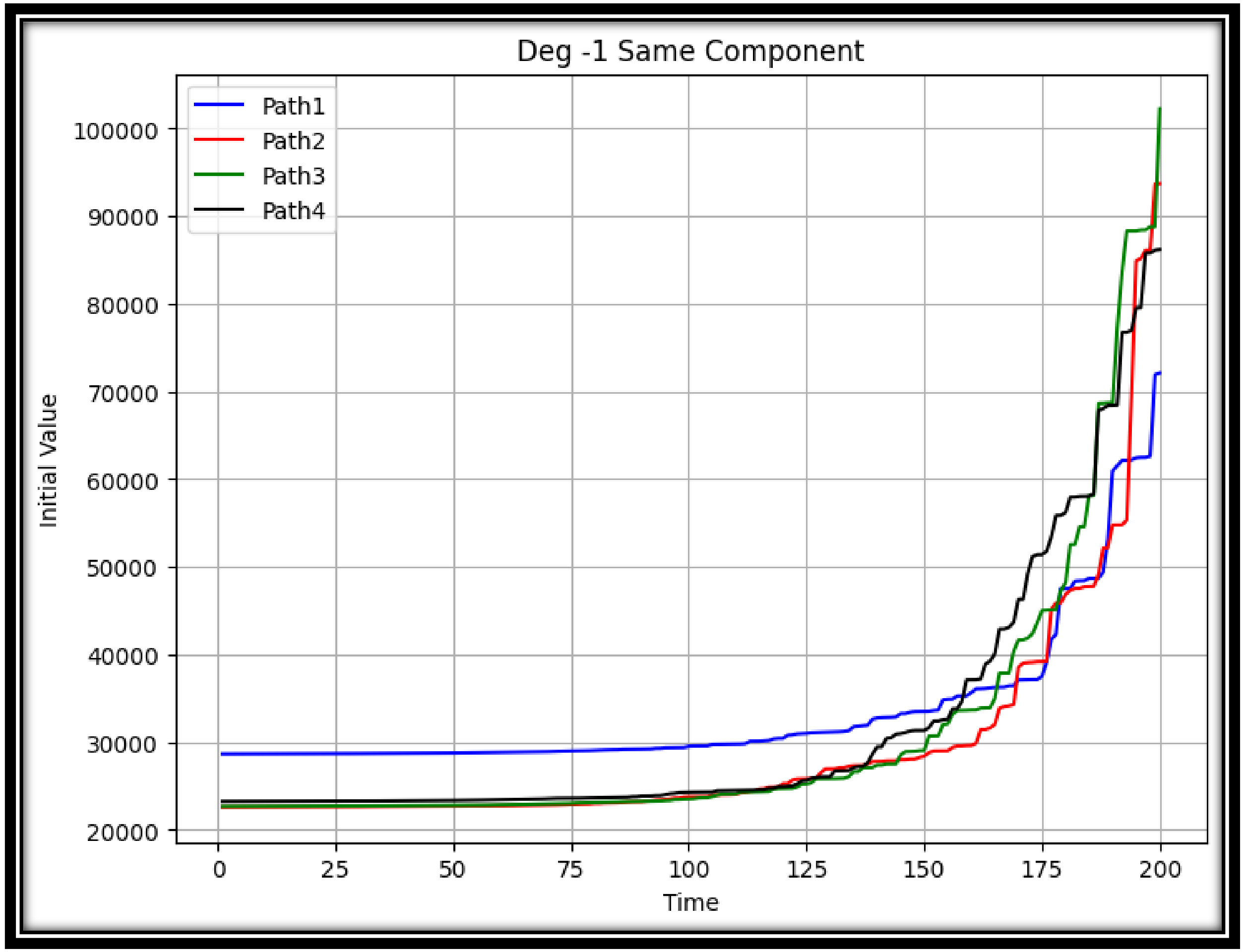


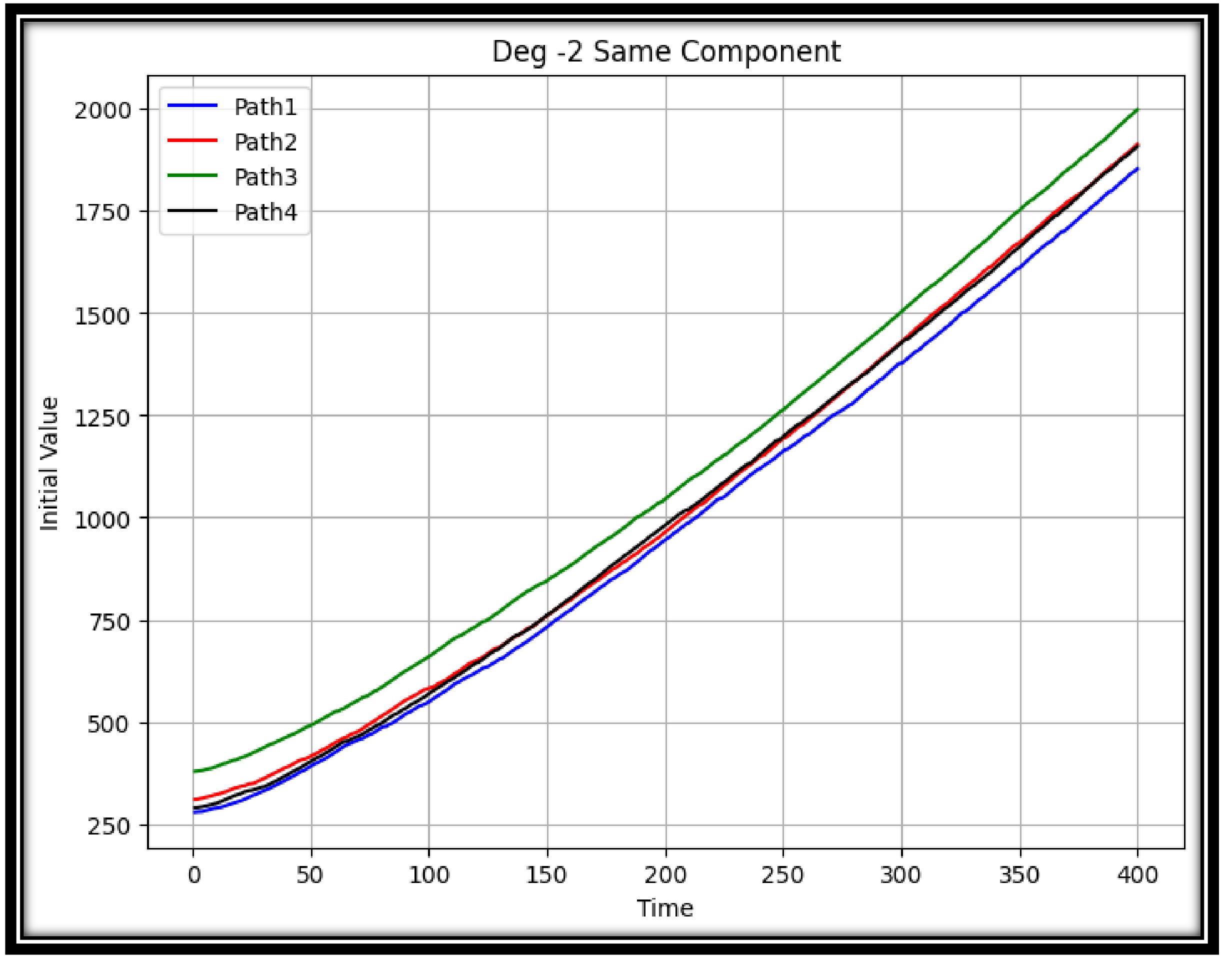


Parameters asked for Degradation Models

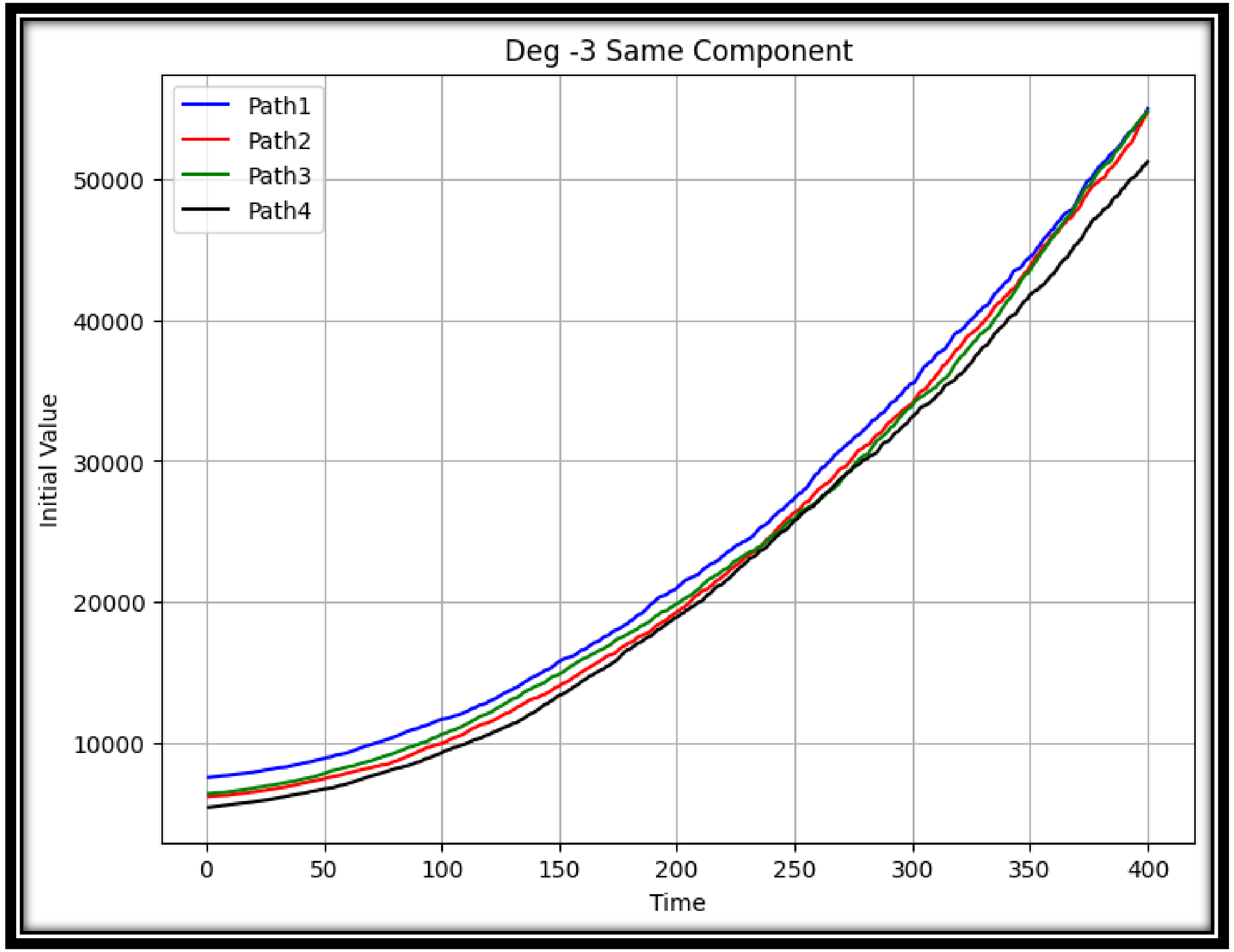


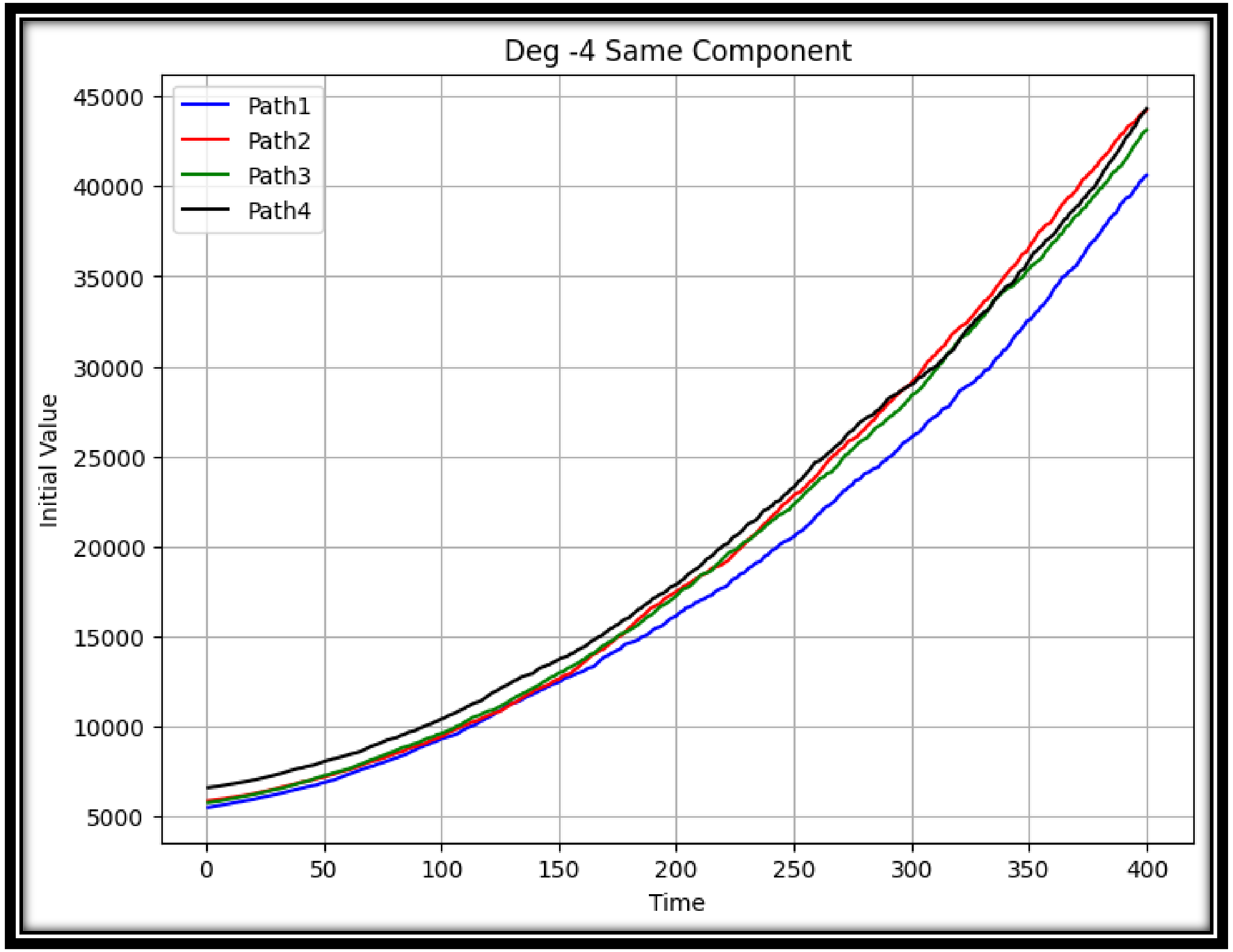
Degradation Paths for Same Component (D1 and D2)



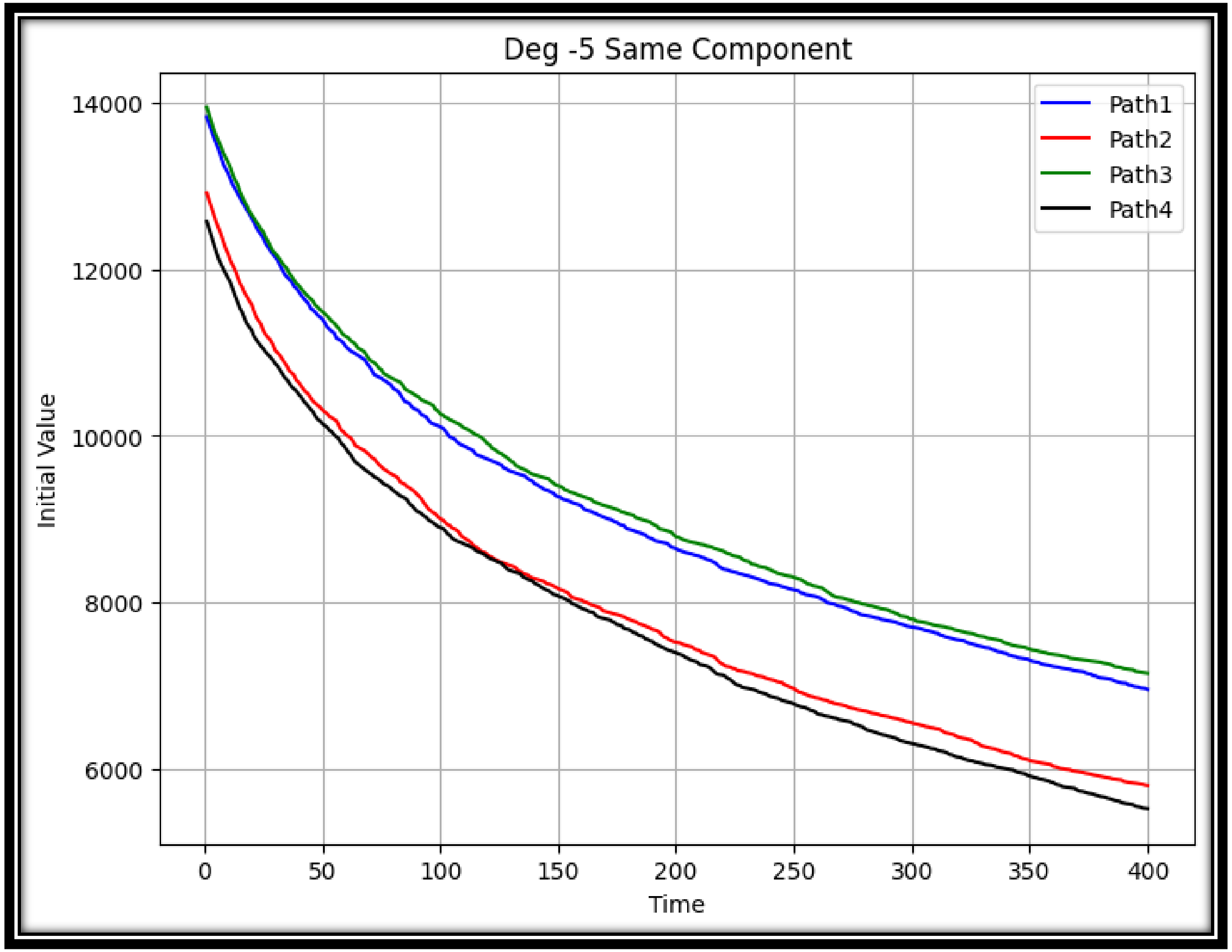


Degradation Paths for Same Component (D3 and D4)





Degradation Paths for Same Component (D5)



Display the system after adding Components

COMPONENTS LIST

Weibull

id	component_w	eta	beta
1	Cw	1900	1.2

BasicShock

id	component_bs	expected_arrival	threshold_shocks
2	C_bs	700	3

ExtremeShock

id	component_es	expected_arrival	threshold_shocks	mean_magnitude	std_magnitude	threshold_magnitude
4	C_es	500	5	10	2	12.8

CumulativeShock

id	component_cs	expected_arrival	threshold_shocks	mean_magnitude	std_magnitude	threshold_magnitude
2	C_cs	300	5	15	2	60

Degradation1

id	component_d1	low_in	high_in	threshold	p1	p2	dist
3	CD1	10000.0	22000.0	3000.0	0.005	0.02	Uniform

Degradation2

id	component_d2	low_in	high_in	threshold	p1	p2	dist
3	CD2	300.0	500.0	3500.0	0.02	0.005	Normal

Degradation3

id	component_d3	low_in	high_in	threshold	p1	p2	p3	p4	p5	p6	dist
2	CD3	5000.0	8000.0	2450.0	2.0	25.0	0.1	0.85	0.01	0.1	Uniform

Degradation4

id	component_d4	low_in	high_in	threshold	p1	p2	p3	p4	dist
2	CD4	5000.0	8000.0	4700.0	12.0	2.0	0.5	0.12	Normal

Degradation5

id	component_d5	low_in	high_in	threshold	p1	p2	dist
4	CD55	10000.0	15000.0	150.0	0.01	0.04	Uniform

Dependency

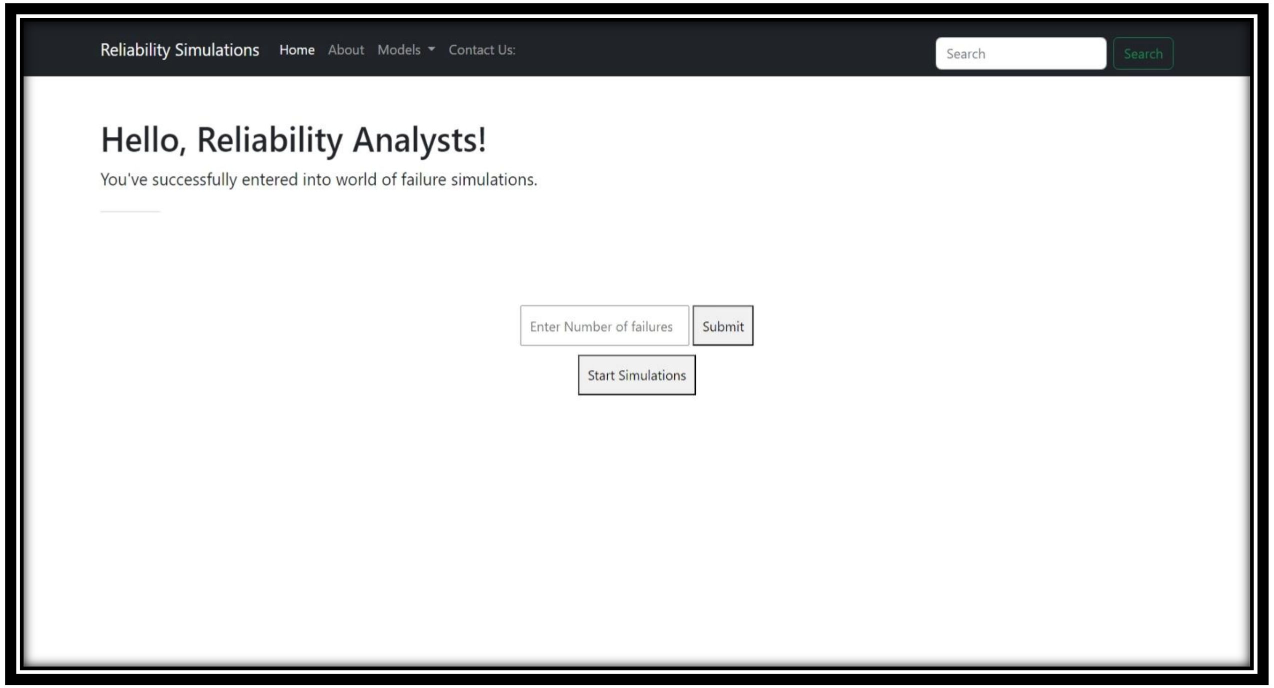
No_Dependency

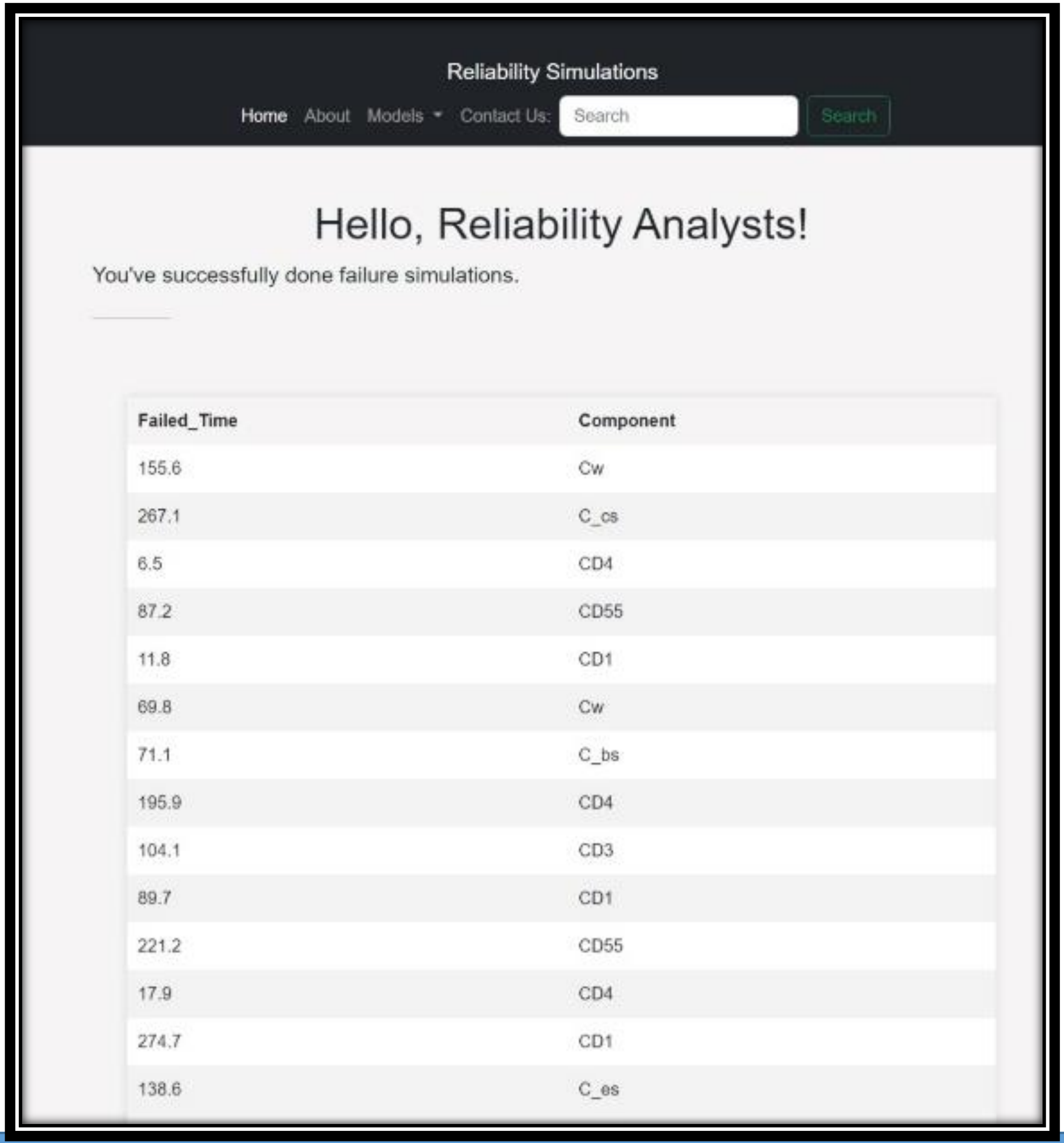
If Dependency is applicable

	Cw	C_bs	C_es	C_cs	CD1	CD3	CD4	CD55
Cw	1							
C_bs		1						
C_es			1		2			
C_cs				1				
CD1					1			
CD3						1		
CD4							1	
CD55								1

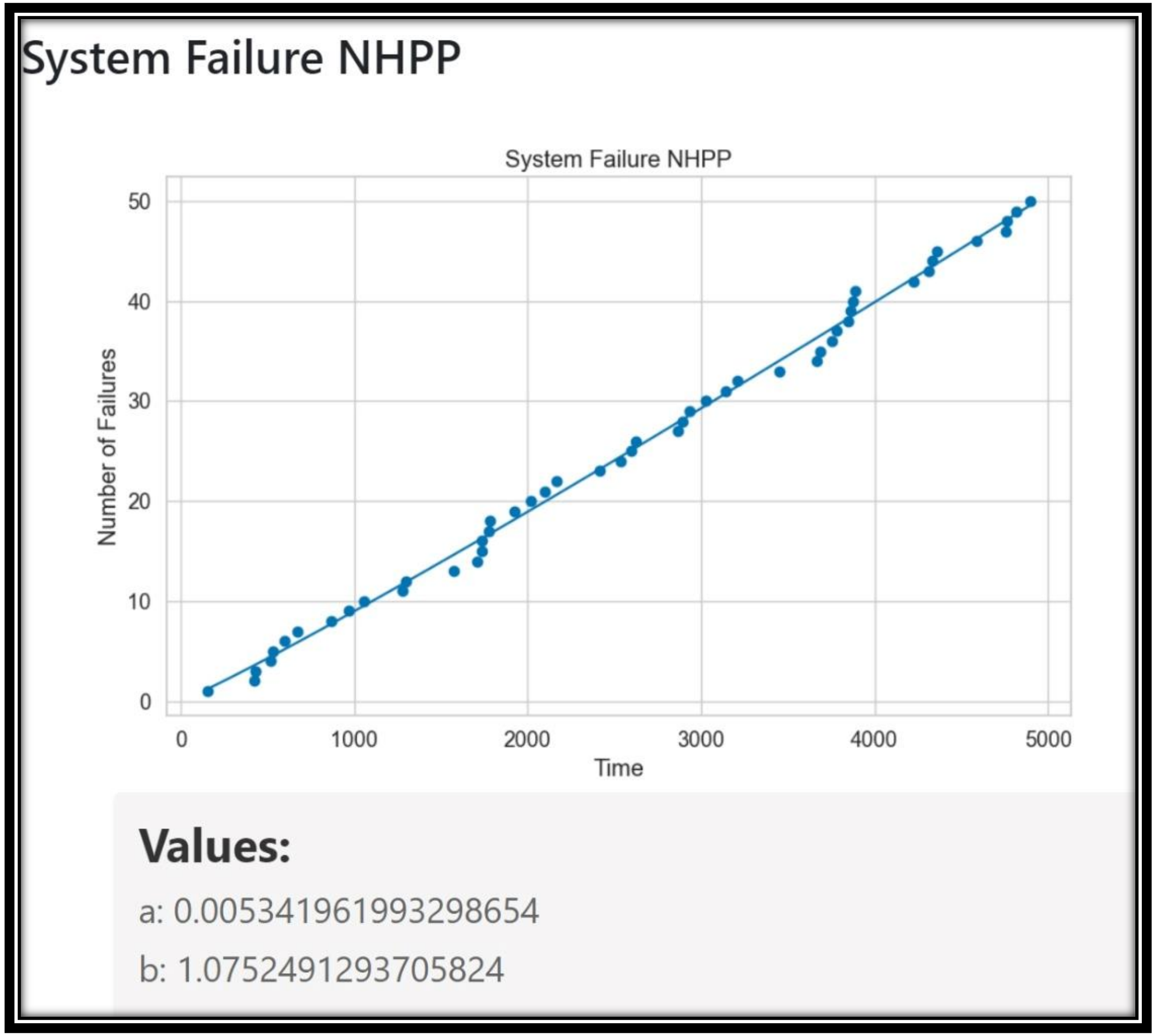
! Value must be less than or equal to 0.99.

Asking number of failures and showing Results

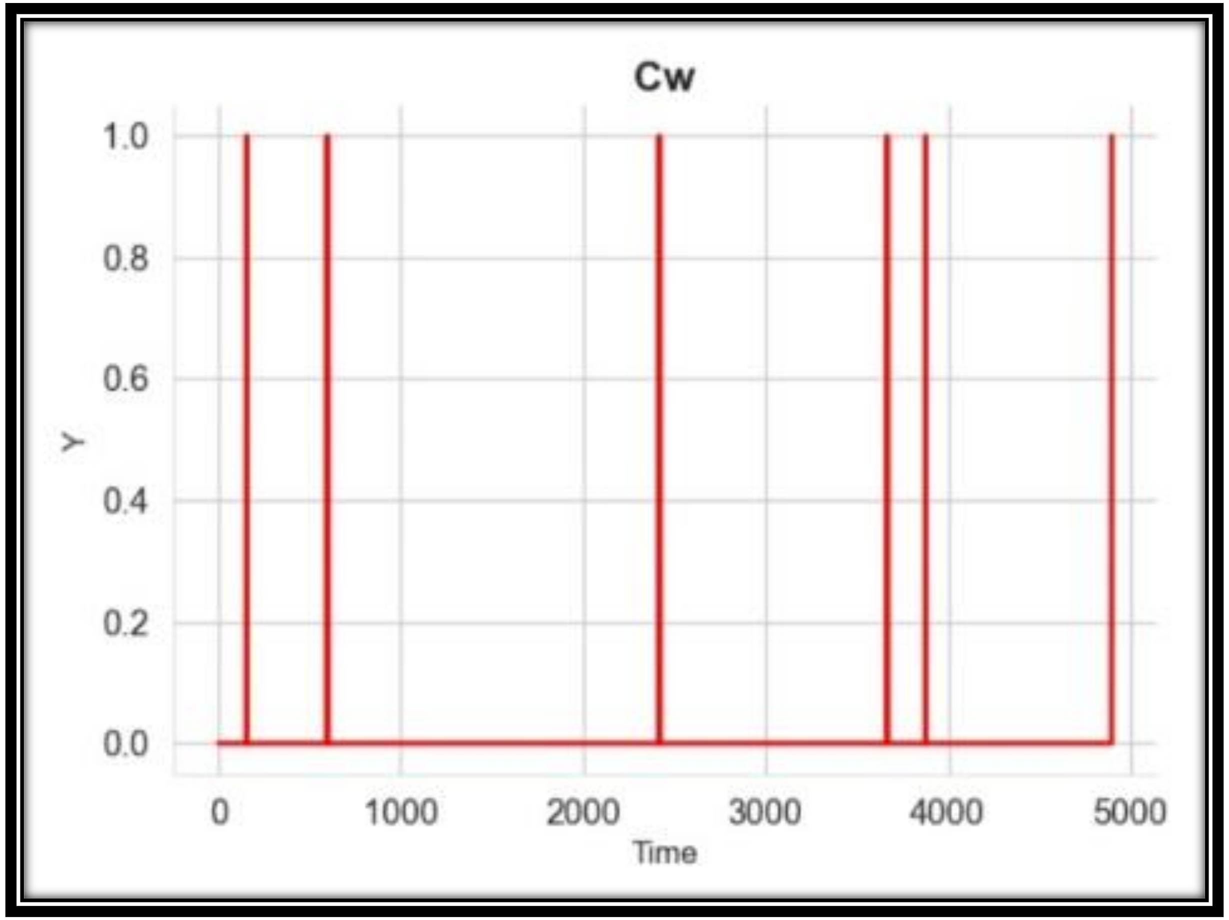




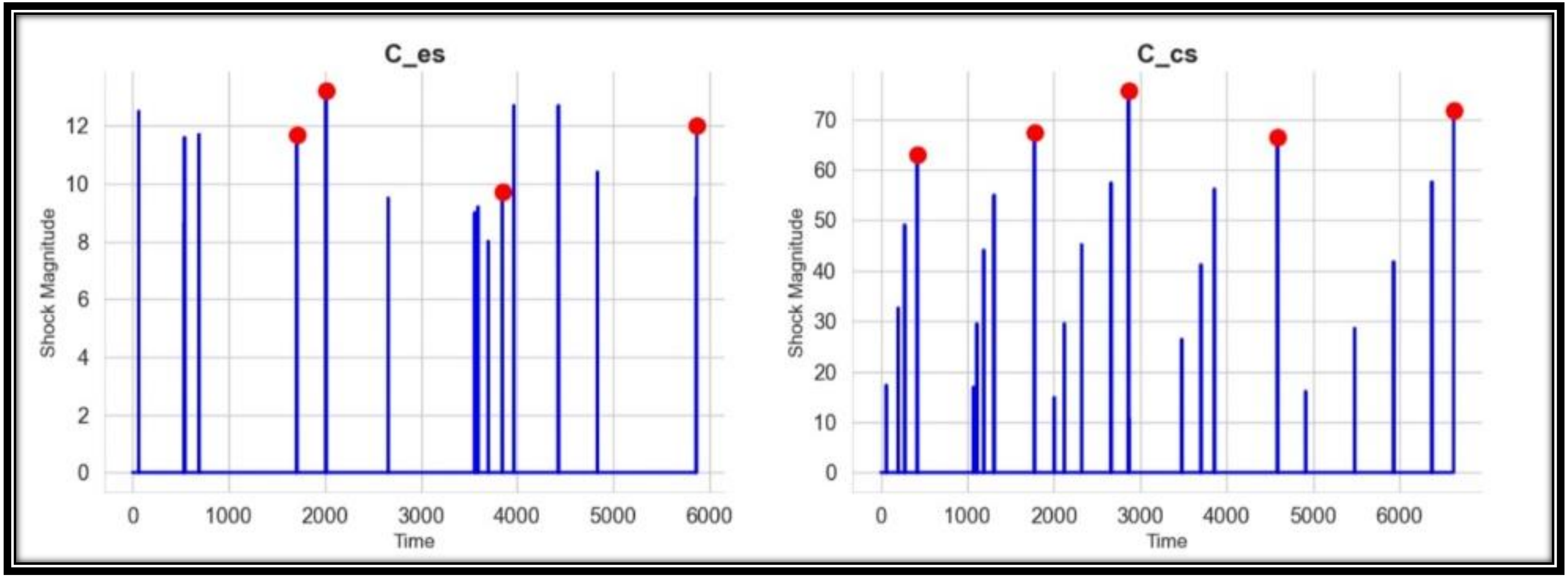
System Behaviour



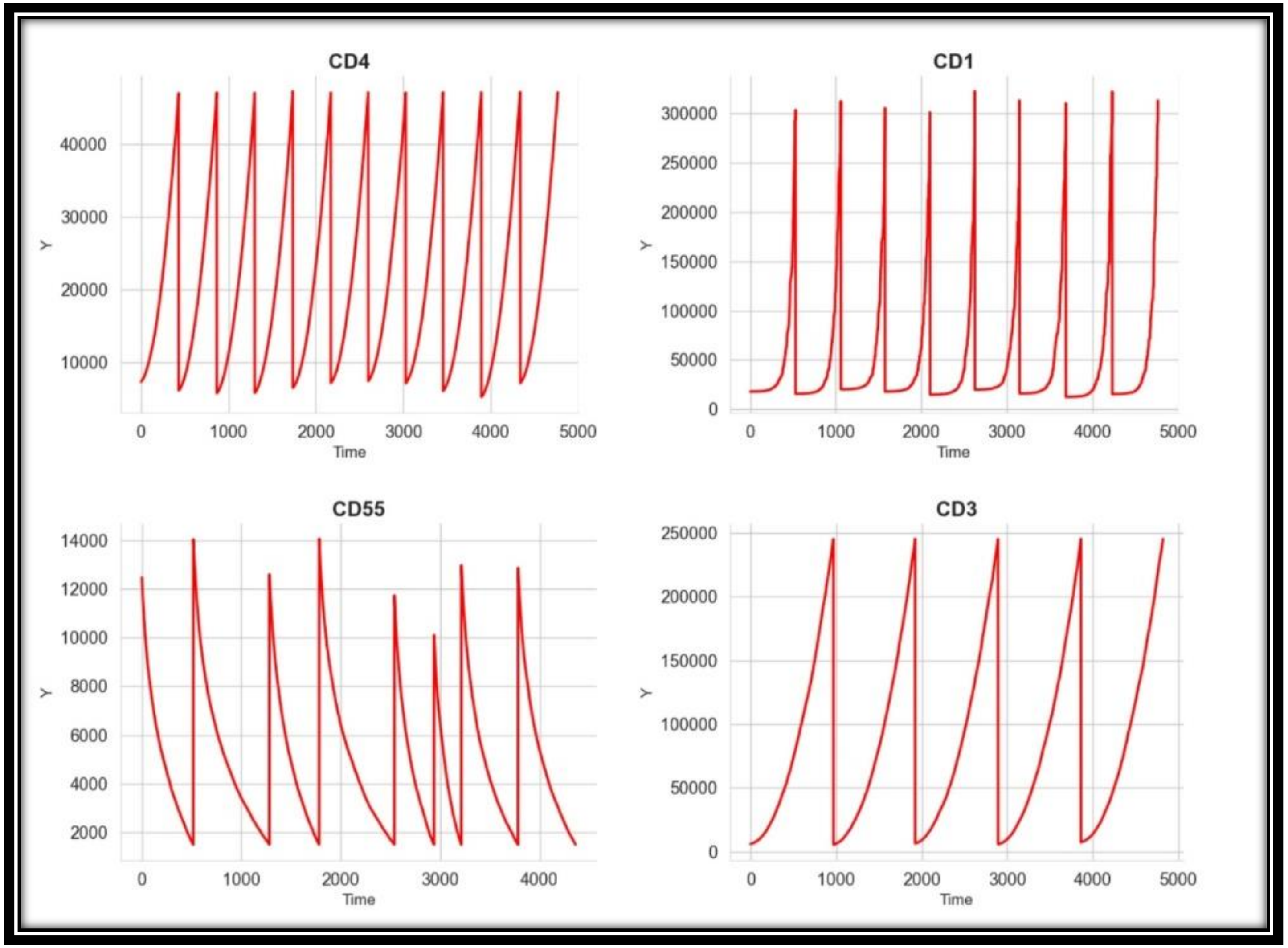
Weibull Model Components



Shock Model Components



Degradation Model Components



Saving the Data

1	Failure Time
2	155.5881319
3	598.0222621
4	2417.956628
5	3666.30741
6	3876.206503
7	4896.16215

Weibull

Time	Magnitude	State
204	1	0
665	1	0
669	1	1
708	1	0
1235	1	0
1733	1	1
2195	1	0
2821	1	0
3756	1	1
3814	1	0
4240	1	0
4311	1	1
4345	1	0
4781	1	0
5113	1	1

Basic Shock

Time	Magnitude	State
65	12.5	0
537	8.6	0
542	11.6	0
694	11.7	0
1711	11.7	1
2014	13.2	1
2660	9.5	0
3560	9	0
3595	9.2	0
3700	8	0
3846	9.7	1
3967	12.7	0
4430	12.7	0
4835	10.4	0
5860	9.5	0

Extreme Shock

Time	Magnitude	State
63	17.3	0
202	32.6	0
276	49.1	0
422	62.9	1
1071	16.9	0
1110	29.5	0
1190	44.1	0
1309	55	0
1778	67.4	1
2006	14.9	0
2121	29.5	0
2322	45.2	0
2664	57.4	0
2866	75.6	1
2870	10.6	0
3482	26.4	0
3702	41.2	0
3859	56.2	0
4587	66.5	1
4912	16.1	0
5481	28.6	0

Cumulative Shock

Saving the Data
(Degradation Models)

Increasing Degradation Model

Magnitude	State	time
17937.58	0	1
17960.68	0	21
17990.93	0	41
18030.32	0	61
18085.22	0	81
18153.18	0	101
18243.41	0	121
18388.43	0	141
18578.2	0	161
18857.74	0	181
19199.46	0	201
19639.7	0	221
20375.42	0	241
21302.1	0	261
22645.35	0	281
24007.95	0	301
25968.87	0	321
30145.84	0	341
33402.57	0	361
40629.24	0	381
50286.29	0	401
62560.53	0	421
80077.13	0	441
102300.5	0	461
135757.6	0	481
186721.4	0	501
291958.8	0	521
15683.87	1	541
15710.61	0	561

Decreasing Degradation Model

Magnitude	State	time
12474.57	0	1
10854.48	0	21
9748.735	0	41
8797.443	0	61
8104.294	0	81
7495.675	0	101
6934.339	0	121
6410.853	0	141
6016.355	0	161
5607.69	0	181
5251.186	0	201
4932.723	0	221
4627.128	0	241
4323.033	0	261
4029.65	0	281
3723.668	0	301
3475.465	0	321
3260.799	0	341
3013.468	0	361
2800.499	0	381
2587.221	0	401
2380.67	0	421
2169.068	0	441
1958.957	0	461
1793.843	0	481
1612.469	0	501
13764.28	1	521
12243.03	0	541
11088.22	0	561

Analysis on Dependency (using n-gram):

	cw	cd4	cd3	c_es	c_cs	c_bs	cd55
cw	0.037037	0.518519	0.074074	0.037037	0.074074	0.111111	0.148148
cd4	0.076923	0.064103	0.230769	0.089744	0.115385	0.083333	0.339744
cd3	0.014286	0.342857		0.085714	0.142857	0.114286	0.3
c_es	0.027778	0.388889	0.111111		0.055556	0.055556	0.361111
c_cs	0.102041	0.265306	0.142857	0.061224	0.020408	0.020408	0.387755
c_bs	0.028571	0.285714	0.142857	0.114286	0.114286		0.314286
cd55	0.047244	0.551181	0.125984	0.062992	0.094488	0.062992	0.047244

No DEPENDENCY

	cw	cd4	cd3	c_es	c_cs	c_bs	cd55
cw	0.033898	0.288136	0.169492	0.135593	0.067797	0.016949	0.288136
cd4	0.126667	0.066667	0.186667	0.046667	0.14	0.086667	0.34
cd3	0.029851	0.41791		0.029851	0.074627	0.074627	0.373134
c_es	0.153846	0.423077	0.115385		0.076923		0.230769
c_cs	0.133333	0.422222	0.088889	0.044444		0.088889	0.222222
c_bs	0.5	0.1875	0.0625	0.03125	0.0625		0.15625
cd55	0.082645	0.487603	0.165289	0.049587	0.090909	0.07438	0.049587

C_w dependent on C_bs

Conclusion:

- ❖ Next time to failure was almost correctly predicted through LSTM networks.
- ❖ Next component failure gave terrible results. The RNN approach where there was no information regarding the age gave better results than the classification results.
- ❖ A simulator tool was developed for those analysts who have no idea of coding and want to do failure simulations.
- ❖ A different variety of models were included in the tool with functionality of creating dependency.
- ❖ Simulated data were plotted and saved for future use of analysts until component level.
- ❖ N-gram couldn’t conclusively prove that dependencies exists among components or not.

References:

[1] Ech-chhibat, M.E., Bahatti, L., Raihani, A. and Fentis, A., 2018, April. Estimation of a repairable system reliability. In 2018 4th International Conference on Optimization and Applications (ICOA) (pp. 1-5). IEEE.

[2] Alsina, E.F., Chica, M., Trawiński, K. and Regattieri, A., 2018. On the use of machine learning methods to predict component reliability from data-driven industrial case studies. The International Journal of Advanced Manufacturing Technology, 94(5), pp.2419-2433.

[3] Rafiee, K., Feng, Q. and Coit, D.W., 2014. Reliability modeling for dependent competing failure processes with changing degradation rate. IIE transactions, 46(5), pp.483-496.

[4] Olteanu, D. and Freeman, L., 2010. The evaluation of median-rank regression and maximum likelihood estimation techniques for a two-parameter Weibull distribution. Quality Engineering, 22(4), pp.256-272.

[5] Yousefi, N., Tsianikas, S. and Coit, D.W., 2022. Dynamic maintenance model for a repairable multi-component system using deep reinforcement learning. Quality Engineering, 34(1), pp.16-35.

[6] Yousefi, N., Tsianikas, S., Zhou, J. and Coit, D.W., 2020. Inspection plan prediction for multi-repairable component systems using neural network. arXiv preprint arXiv:2001.09015.

[7] https://www.reliawiki.com

[8] https://chat.openai.com/

THANK YOU