



Norwegian University of
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A comparison study for bearing remaining useful life prediction by using standard stochastic approach and digital twin

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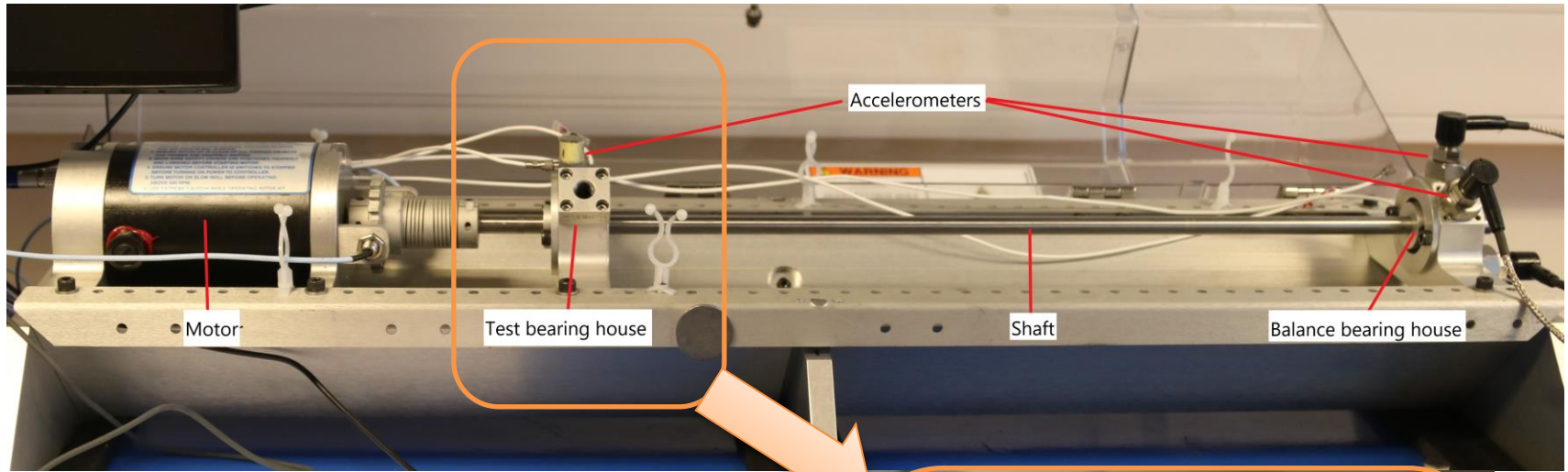
Prepared for RAMS seminar

Date: 10/03/22

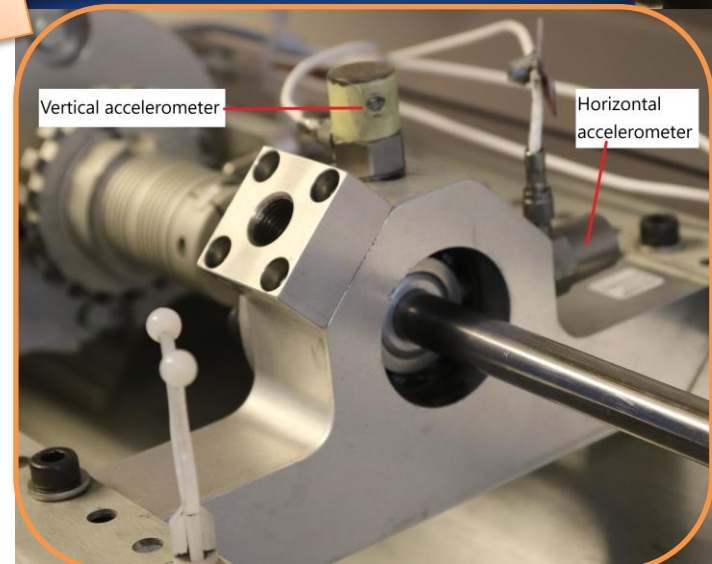
Comparison study for bearing remaining useful life prediction

- Authors: Jie Liu, Jørn Vatn, Viggo Gabriel Borg Pedersen, Shen Yin
- Journal: International Journal of Reliability and Safety
- Bearing experiment
- RUL prediction
 - Stochastic approach - Wiener process
 - Stochastic approach - GBM
 - Matlab digital twin

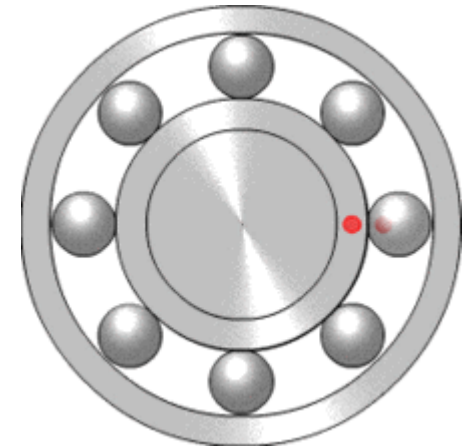
Experiment setup



**Amplifier:
coupler**



Bearings

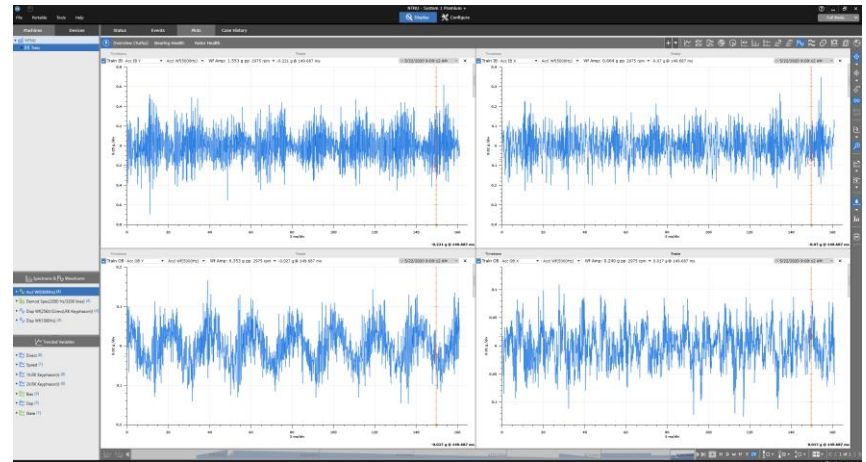


Type of Bearing	Open roller/ball bearings
Number of balls	10 Balls
Pitch diameter (B)	70 mm
Ball diameter	4.7 mm
Inner diameter(d)	15.9 mm
Outer diameter(D)	34.9 mm

Experiment output

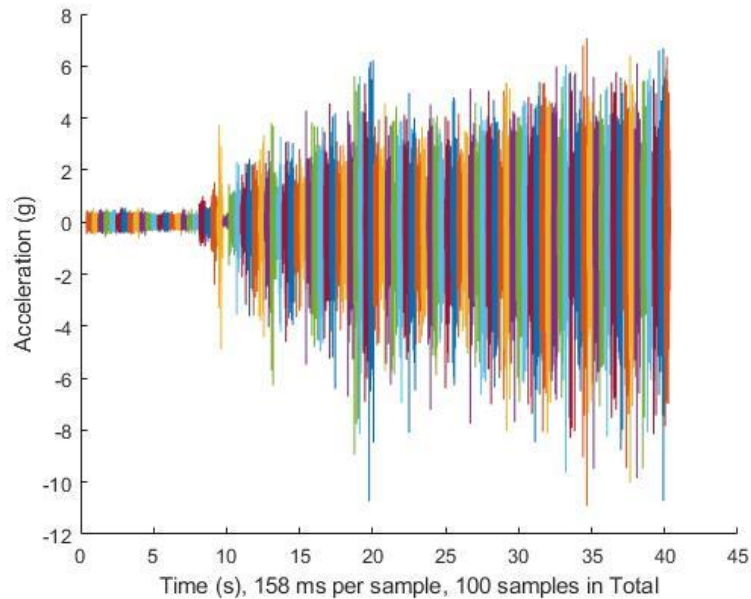
Experiment form

Bearing No.	5			Date	2020-05-22		
Activity	Start time	End time	Reason				
1	8:48	10:08	Compute required to restart.				
2	10:13	18:06	No stress between data 16 and 16-1, saved for comparing between stops.				
3							
4							
Data time interval	5mins						
Stress level (Target stress shall be marked)							
Speed		Size of silicon		Density of silicon			
3005rpm(input), 2975rpm(system)		M L		1 pour /time, 0.72 grams			
Stress change log							
	Time		Time		Time		Time
1	8:53	7	11:28	13	13:58	19	16:28
2	9:18	8	11:53	14	14:23	20	16:53
3	9:43	9	12:18	15	14:48	21	17:18
4	10:13	10	12:43	16	15:13	22	17:43
5	10:38	11	13:08	17	15:38	23	
6	11:03	12	13:33	18	16:03	24	
Summary							
Highest accelerate value	9.711 g (110b)			Lowest accelerate value	-10.162 g (110b)		
Note	Train IB ACC IBY ia.csv		Train IB ACC IBX ib.csv				
	Tested bearing, Vertical data		Tested bearing, Horizontal data				
	Train OB ACC OBY ic.csv		Train OB ACC OBX id.csv				
	Balance bearing, Vertical data		Balance bearing, Horizontal data				
No mixture left. To be changed next time.							
Number of data file	110-4		Prepared by	Jie Liu			



1	Machine Name	Train
2	Point Name	Acc IB Y
3	Wf Amp	0.006
4	Number of Revs	21.07337761
5	X-Axis Unit	ms
6	Y-Axis Unit	g
7	Sample Speed	1975 rpm
8	Sample Status	Valid
9	Timestamp	5/15/2020 10:06
10	Variable	AccI Wf(5000Hz)
11	X-Axis Value	Y-Axis Value
12		0 -0.001
13		0.078 0.001
14		0.156 0.001

Original data vs feature selection



Feature	Expression
Mean	$\frac{1}{N} \sum_{i=1}^N x_i$
Standard deviation (Std)	$\left(\frac{1}{N} \sum_{i=1}^N (x_i - \text{mean})^2 \right)^{\frac{1}{2}}$
Skewness	$\frac{1}{N} \cdot \sum_{i=1}^N \frac{(x_i - \bar{x})^3}{\rho^3}$
Kurtosis	$\frac{\frac{1}{N} \cdot \sum_{i=1}^N (x_i - \bar{x})^4}{\left(\frac{1}{N} \cdot \sum_{i=1}^N (x_i - \bar{x})^2 \right)^2}$
Peak to Peak	$x_{max} - x_{min}$
RMS (Root Mean Square)	$\left(\frac{1}{N} \sum_{i=1}^N x_i^2 \right)^{\frac{1}{2}}$
CrestFactor	$\frac{x_{max}}{RMS}$
ShapeFactor	$\frac{RMS}{\frac{1}{N} \sum_{i=1}^N x_i }$
ImpulseFactor	$\frac{x_{max}}{\frac{1}{N} \sum_{i=1}^N x_i }$
MarginFactor	$\frac{x_{max}}{\left(\frac{1}{N} \sum_{i=1}^N x_i \right)^2}$
Energy	$\sum_{i=1}^N x_i^2$
Absolute Maximum	$ x_{max} $

Stochastic approach I

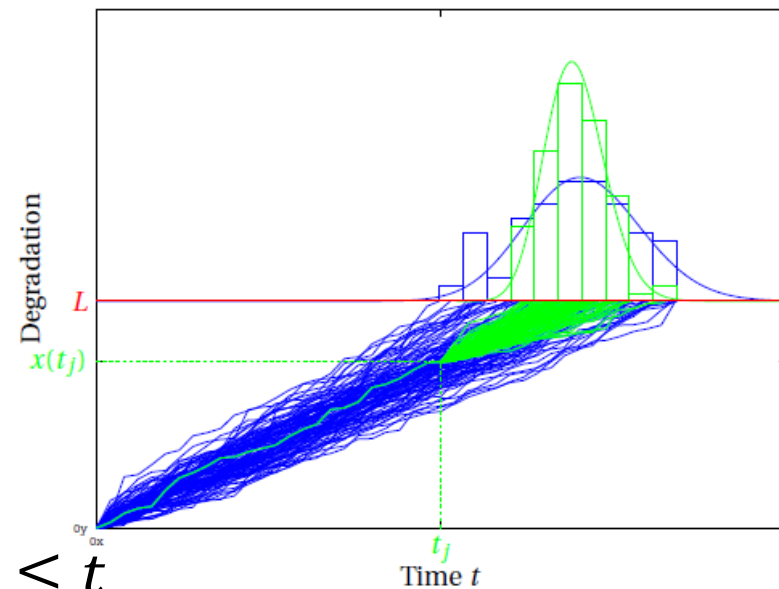
- Wiener process

- Degradation process
- $Y(t) = y_0 + \mu t + \sigma W(t)$
- $\Delta Y \sim N(\mu(t - s), \sigma^2(t - s)), 0 \leq s \leq t$
- Inverse Gaussian distribution method
- The CDF of first passage time

- $$F_T(t) = \Phi\left(\frac{\sqrt{\lambda}}{v}\sqrt{t} - \frac{\sqrt{\lambda}}{\sqrt{t}}\right) + \Phi\left(-\frac{\sqrt{\lambda}}{v}\sqrt{t} - \frac{\sqrt{\lambda}}{\sqrt{t}}\right)e^{\frac{2\lambda}{v}}$$

- Where $v = L/\mu$ and $\lambda = L^2/\sigma^2$

- $$E(T) = \frac{L}{\mu} \quad \text{Var}(T) = \frac{L\sigma^2}{\mu^3}$$



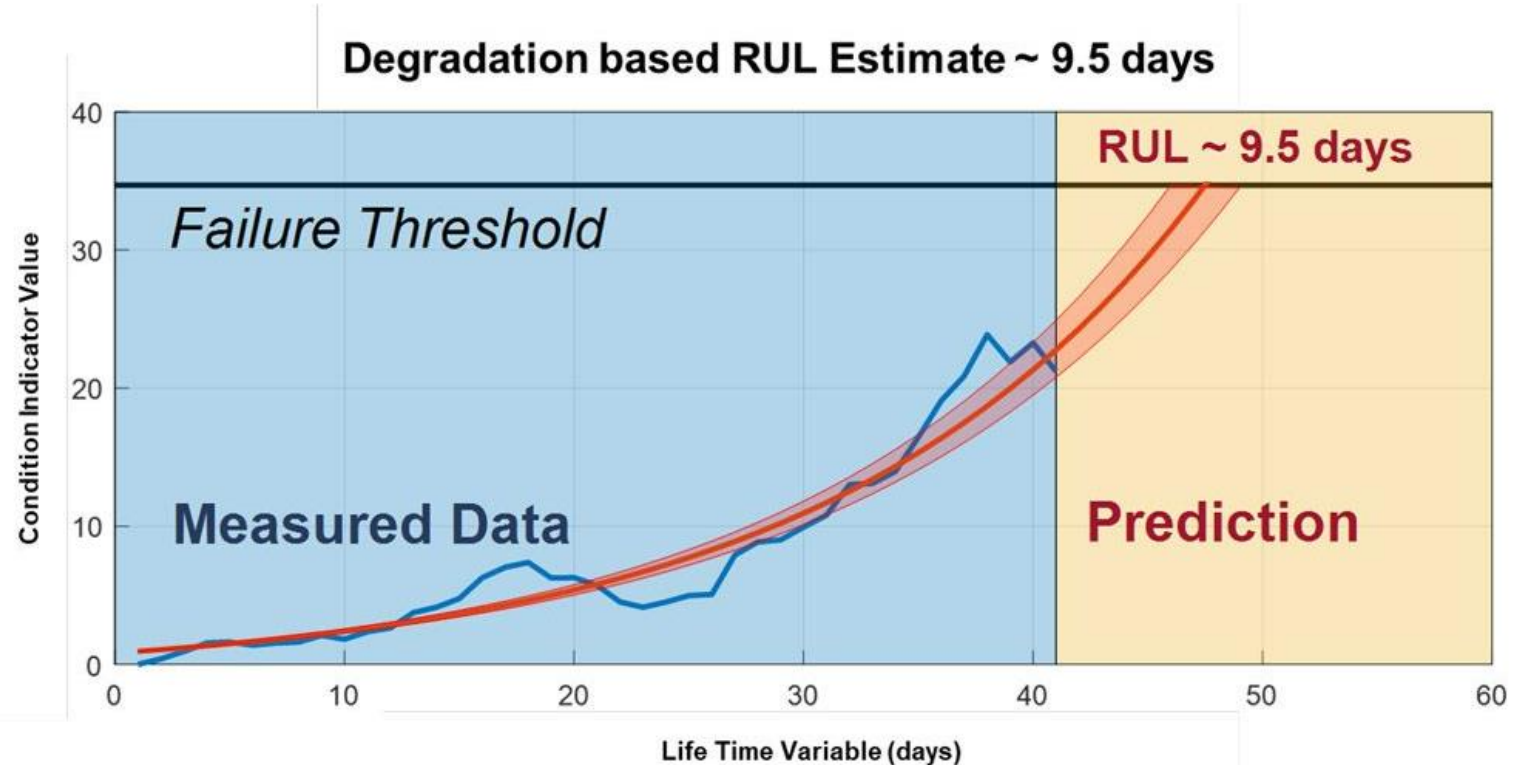
Stochastic approach II

- Geometric Brownian Motion

- Degradation process
- $dS(t) = \mu S(t)dt + \sigma S(t)dW(t)$
- $S_t = S_0 \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W(t)\right)$
- The CDF of first passage time
- $F_T(t) = \Phi\left(\frac{\sqrt{\lambda}}{v}\sqrt{t} - \frac{\sqrt{\lambda}}{\sqrt{t}}\right) + \Phi\left(-\frac{\sqrt{\lambda}}{v}\sqrt{t} - \frac{\sqrt{\lambda}}{\sqrt{t}}\right) e^{\frac{2\lambda}{v}}$
- Where $v = \frac{\ln L - \ln S_0}{\mu - \frac{1}{2}\sigma^2}$ and $\lambda = \frac{(\ln L - \ln S_0)^2}{\sigma^2}$
- $E(T) = \frac{\ln L - \ln S_0}{\mu - \frac{1}{2}\sigma^2}$ $Var(T) = \frac{\sigma^2 (\ln L - \ln S_0)}{(\mu - \frac{1}{2}\sigma^2)^3}$

Matlab Digital twin

- $$h(t) = \phi + \theta * \exp(\beta t + \epsilon - \frac{\sigma^2}{2})$$



Results

Status	Standard Deviation	Peak to Peak	RMS	Energy
Initial status	3.49E-01	2.53E+00	3.49E-01	1.71E+01
Threshold	2.15E+00	1.65E+01	2.15E+00	9.54E+03
Lifetime	500 minutes			

Comparison of stochastic approaches

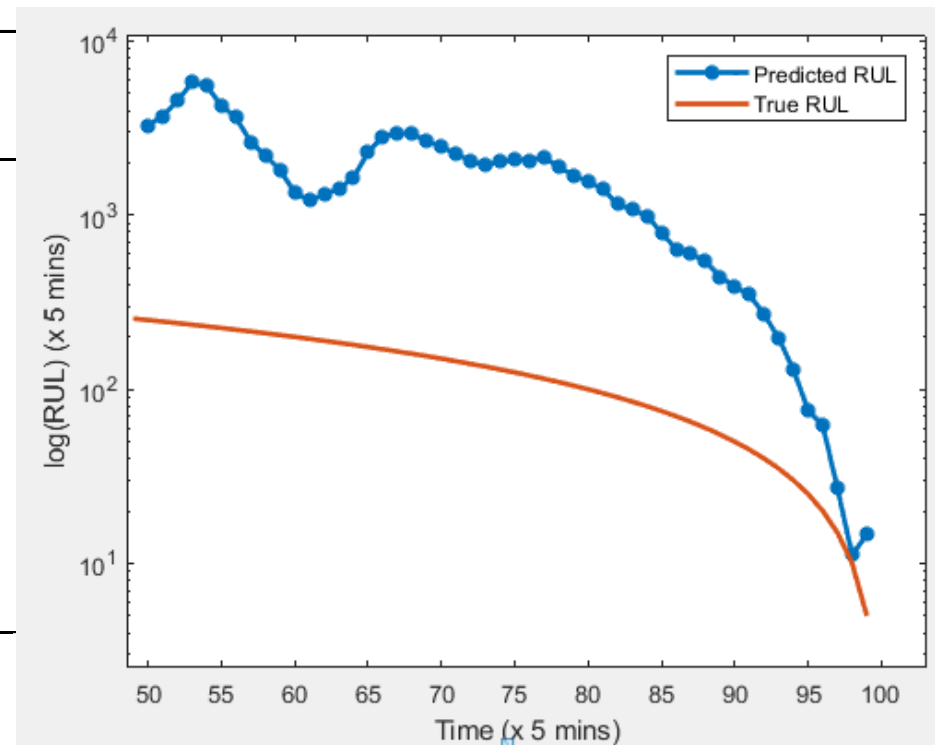
Stochastic Process	Parameter	Standard Deviation	Peak to Peak	RMS	Energy
Wiener process	$\hat{\mu}_{50}$	1.57E-03	1.63E-02	1.57E-03	2.70E+00
	$\hat{\sigma}_{50}$	8.44E-03	2.63E-01	8.43E-03	1.46E+01
	$\hat{\mu}_{99}$	3.84E-03	3.00E-02	3.84E-03	1.87E+01
	$\hat{\sigma}_{99}$	1.65E-02	3.10E-01	1.65E-02	8.74E+01
GBM	$\hat{\mu}_{50}$	3.88E-03	4.48E-03	3.88E-03	8.56E-03
	$\hat{\sigma}_{50}$	5.28E-02	4.41E-01	5.28E-02	2.89E+00
	$\hat{\mu}_{99}$	5.23E-03	4.45E-03	5.23E-03	1.21E-02
	$\hat{\sigma}_{99}$	5.37E-02	4.07E-01	5.37E-02	4.11E+00

Stochastic Process	Data sets No.	Method	Parameter	Standard Deviation	Peak to Peak	RMS	Energy
WP	First 50	Inverse Gaussian distribution	E(T)	1370	1011	1370	3530
			Var(T)	3.97E+04	2.62E+05	3.97E+04	1.03E+05
			Prediction error	174%	102%	174%	606%
		Monte Carlo simulation	E(T)	1371	1017	1371	3531
			Var(T)	3.96E+04	2.65E+05	3.93E+04	1.02E+05
			Prediction error	174%	103%	174%	606%
	First 99	Inverse Gaussian distribution	E(T)	559	550	559	510
			Var(T)	1.03E+04	5.86E+04	1.03E+04	1.11E+04
			Prediction error	12%	10%	12%	2%
		Monte Carlo simulation	E(T)	561	552	560	511
			Var(T)	1.04E+04	5.92E+04	1.04E+04	1.12E+04
			Prediction error	12%	10%	12%	2%
GBM	First 50	Inverse Gaussian distribution	E(T)	730	NA	730	NA
			Var(T)	3.29E+05	NA	3.29E+05	NA
			Prediction error	46%	NA	46%	NA
		Monte Carlo simulation	E(T)	729	NA	734	NA
			Var(T)	3.09E+05	NA	3.11E+05	NA
			Prediction error	46%	NA	47%	NA
	First 99	Inverse Gaussian distribution	E(T)	479	NA	479	NA
			Var(T)	9.58E+04	NA	9.58E+04	NA
			Prediction error	-4%	NA	-4%	NA
		Monte Carlo simulation	E(T)	484	NA	481	NA
			Var(T)	9.68E+04	NA	9.42E+04	NA
			Prediction error	-3%	NA	-4%	NA

There are some limitation to use GBM. GBM follows log-normally distribution. The mean value is $\ln S_0 + (\mu - \frac{\sigma^2}{2}) * t$ and variance is $\sigma^2 t$. If $\mu - \frac{\sigma^2}{2} \leq 0$, the process might go backwards and being absorbed at zero. Therefore, the drift parameter μ shall always be larger than $\frac{\sigma^2}{2}$, otherwise there is no result for prediction.

Predicted RUL by Wiener process feature: Energy

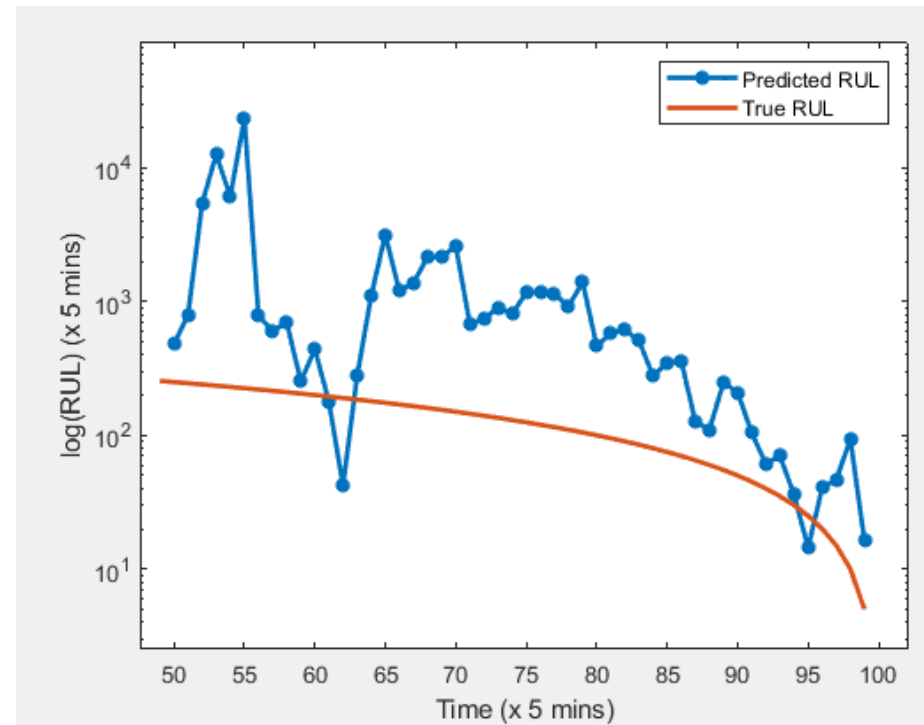
Samle No.	Current Time	Predicted Lifetime	True RUL	Predicate RUL	Variance	Predict error
50	250	3530	250	3280	1.03E+05	606%
55	275	4542	225	4267	3.68E+05	808%
60	300	1654	200	1354	6.14E+04	231%
65	325	2624	175	2299	3.84E+05	425%
70	350	2807	150	2457	4.78E+05	461%
75	375	2468	125	2093	3.17E+05	394%
80	400	1954	100	1554	1.63E+05	291%
85	425	1218	75	793	5.56E+04	144%
90	450	840	50	390	2.54E+04	68%
95	475	551	25	76	1.33E+04	10%
99	495	510	5	15	1.11E+04	2%



Predicted RUL by GBM

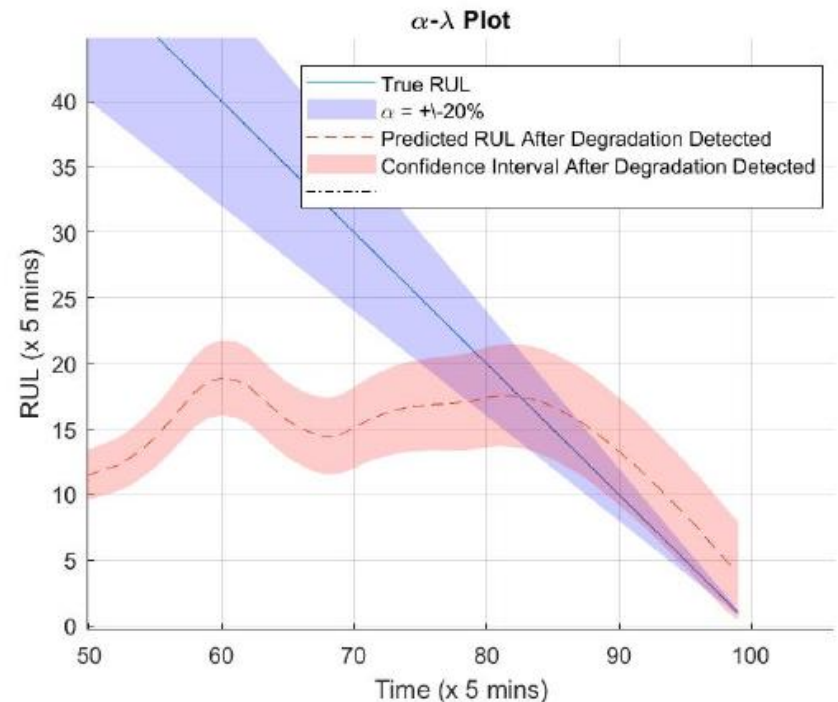
feature: standard deviation vs RMS

Samle No.	Current Time	Predicted Lifetime	True RUL	Predicate RUL	Variance	Predict error
50	250	730	250	480	3.29E+05	46%
55	275	-23227	225	-23502	-1.09E+10	-4745%
60	300	739	200	439	3.62E+05	48%
65	325	3495	175	3170	4.39E+07	599%
70	350	2965	150	2615	2.53E+07	493%
75	375	1543	125	1168	3.48E+06	209%
80	400	864	100	464	6.01E+05	73%
85	425	773	75	348	4.13E+05	55%
90	450	660	50	210	2.54E+05	32%
95	475	489	25	14	9.95E+04	-2%
99	495	479	5	-16	9.58E+04	-4%



Predicted RUL by Matlab digital twin

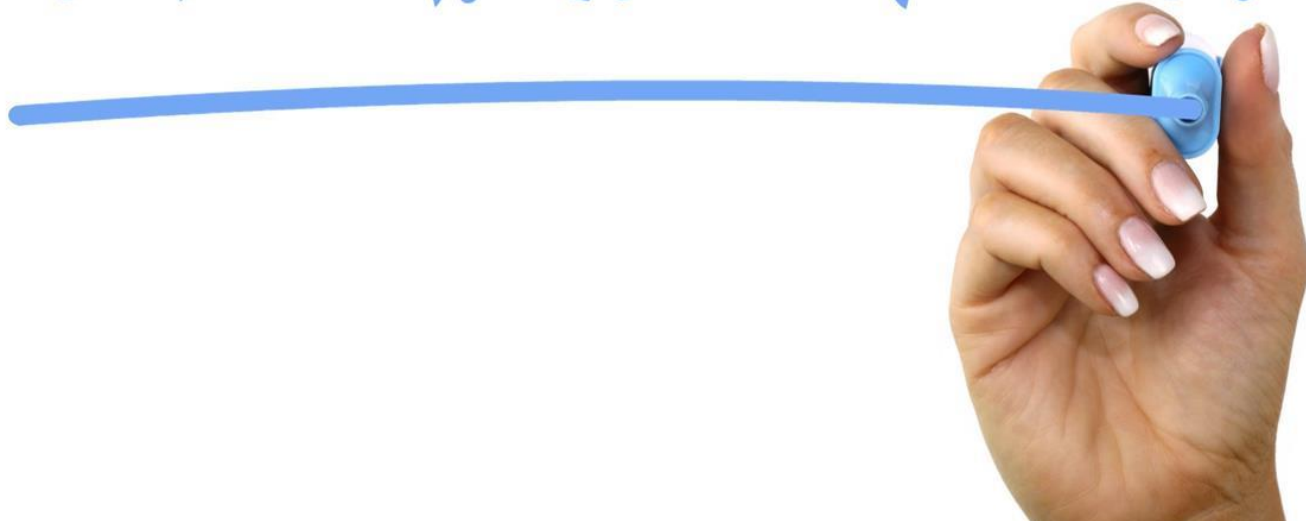
Sample No.	Current Time	Predicted RUL	Predicted lifetime	Variance	Prediction error
50	250	57.45	307.45	2.60	-39%
55	275	71.69	346.59	3.51	-31%
60	300	94.34	394.34	5.25	-21%
65	325	78.22	403.22	5.13	-19%
70	350	75.34	425.34	6.14	-15%
75	375	83.84	458.84	6.11	-8%
80	400	86.98	486.98	6.41	-3%
85	425	83.61	508.61	5.76	2%
90	450	66.39	516.39	12.37	3%
95	475	42.32	517.32	12.17	3%
99	495	19.83	514.83	11.92	3%



Conclusions

- All model's prediction results are improved when there are more information about the bearing's status. Number of required data sets: Matlab digital twin < GBM < Wiener process.
- When there is enough information, stochastic models have lower prediction error than the Matlab digital twin.
- After dataset 80, the prediction error of Matlab digital twin is around 3%.
- For stochastic approaches, single feature is used for prediction. While for Matlab digital twin, it used fusion features for prediction.
- Digital twin is that it takes longer time to run the model than stochastic approaches.

THANK YOU



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