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Mill Roller Bearing Failure Prognosis, using Wireless Vibration Monitoring Systems, and Cloud Data Analysis, through the Application of Descriptive & Predictive Analytics Algorithms

Prepared by:

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Roller Bearing Failure Prognosis Predictive Analytics Algorithms

Case of Study

Ernesto Primera

Mechanical/Maintenance Engineer with 20 years of experience in Rotating Machinery, Condition Monitoring, Performance Analysis, and Reliability Evaluations. Experience in the Oil and Gas Industry, Power Plants and OEMs. A passionate about Data Analysis using technology platforms such as: R Studio, SAS, Minitab, SPSS Statistic & Modeler, Risk Simulator, @Risk, MS Power BI, and Tableau. Proven experience as employed for Chevron, Phillips-66, Williams, Flowserve and SKF. During the last 10 years Ernesto have worked in the Rotating Machinery Reliability Group at the Pascagoula Refinery in Mississippi (CHEVRON) and Lake Charles Refinery and Alliance Refinery in Louisiana (PHILLIPS-66). Global Instructor for the American Society of Mechanical Engineers (ASME), Industry Partner and Instructor for the Hydraulic Institute, certified Maintenance & Reliability Professional CMRP, Certified Vibration Analyst Category III by the Technical Associate of Charlotte. Bachelor’s Degree in Maintenance Engineering (University Complex AJS - Venezuela), Master’s degree in Predictive Maintenance & Diagnostics Technique (Sevilla University - Spain), Master’s degree in business Analytics (Grand Canyon University) and currently studying PhD in Applied Statistics in the University of Delaware. Ernesto is currently a member of the Non-Profit AFP Industrial Research Group (Advanced Failure Prognosis for Engineering Application), and SRE Lifetime National Member.

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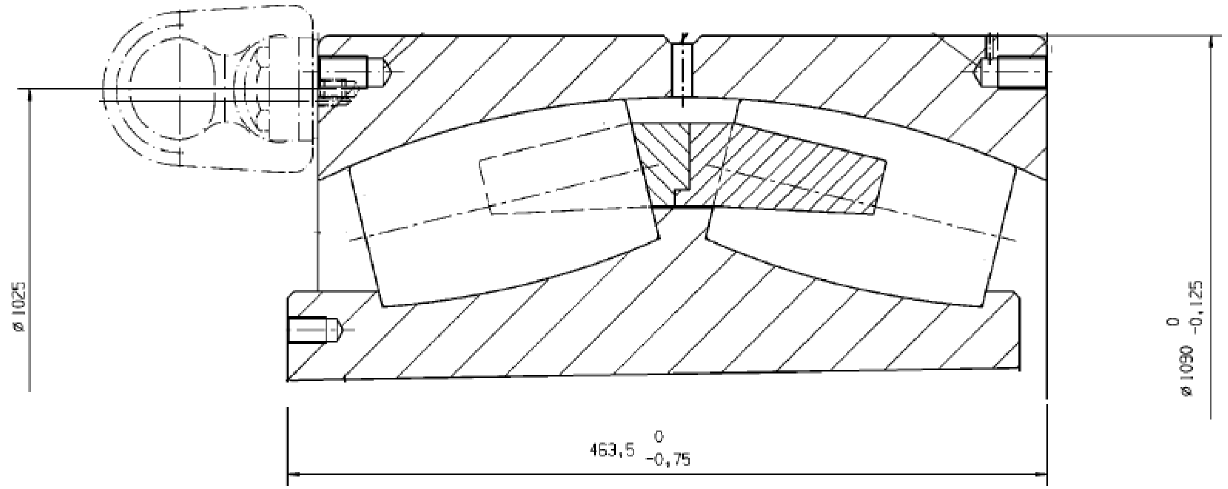
Background

- Roller mills are one of the main equipment to produce mining derivatives, since one of their objectives is to reduce the raw material to very small sizes and the combination of them.
- The roller mill has 4 rollers which are supported by two cylindrical roller bearings. The two bearings that support the roller are of a different size, one of them is larger and is the one that receives the greatest amount of operating load and is also subjected to vertical damping movements.
- Bearing weigh and dimensions:

  Roller Weigh = 1,759 Kg ≈ 3,878 Lb

  Outside Diameter = 1090 cm ≈ 43 Inches



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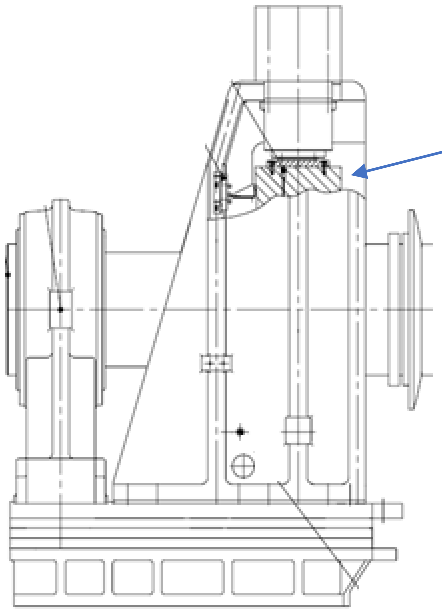
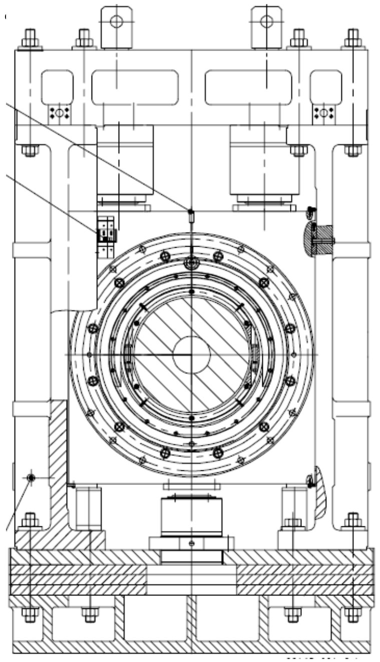
- The largest cylindrical roller bearings are our maintainable item of interest since it represents the highest equipment failure rate, (MTBF = 7 Months) with a very high dispersion (variability), whose failure mode is high vibrations due to excessive wear.
- Although a root cause failure analysis study determined that the main cause of the failure is mill overload, this is an operational condition that will not be possible to change during the next 10 years.

Small cylindrical roller bearings



largest cylindrical roller bearings



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Background

- The objective of the project was to make a prognosis to determine when the overall vibrations would reach a maximum allowed (2.5 IPS pK) , and thus be able to plan their replacement and get the maximum possible useful life in operation, without incurring an unscheduled corrective maintenance and an unexpected plant shutdown.
- The cost of each bearing plus replacement labor is approximately $ 350K USD. However, planning the activity avoids penalty costs for non-compliance with the production plan, and secondary effects on other equipment in the process due to unexpected shutdown are avoided.

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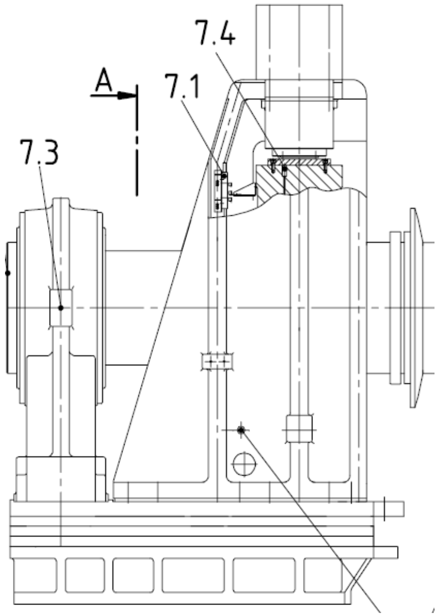
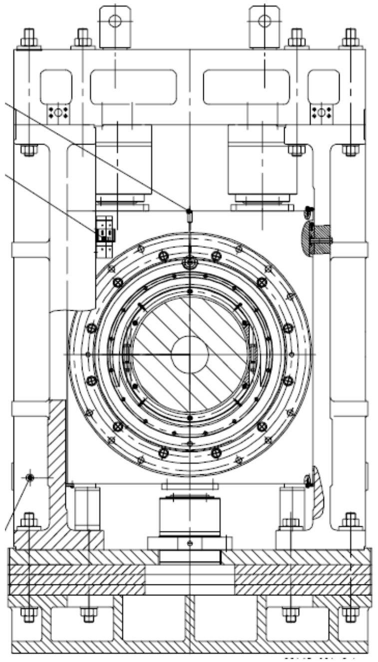
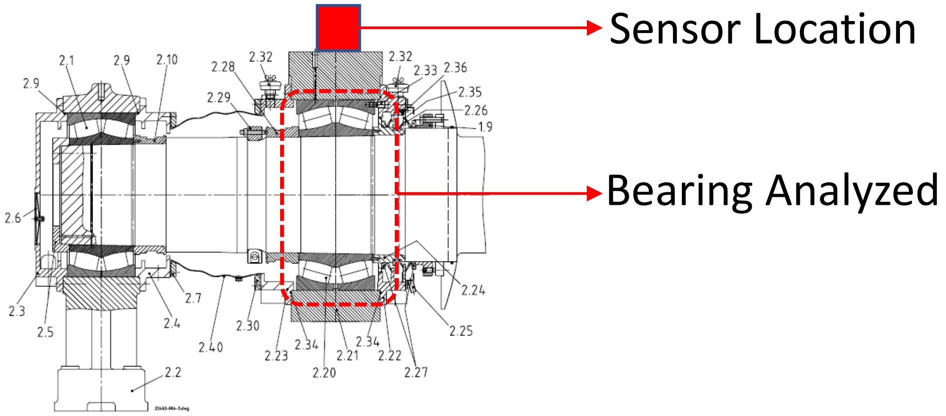
Roller Technical Information

Roller unit

- Four Units Analyzed, classified as: R1, R2, R3 and R4.
- Vibrations Measured in RMS Velocity (IPS) and Acceleration (g’s).
- Vibrations Captured in Radial Horizontal (H) and Vertical (V) Directions.
- Data Captured: every 5 minutes with Spectrums and Waveforms.
- Capture period between June 25th and October 25th of 2021 (Timeframe).







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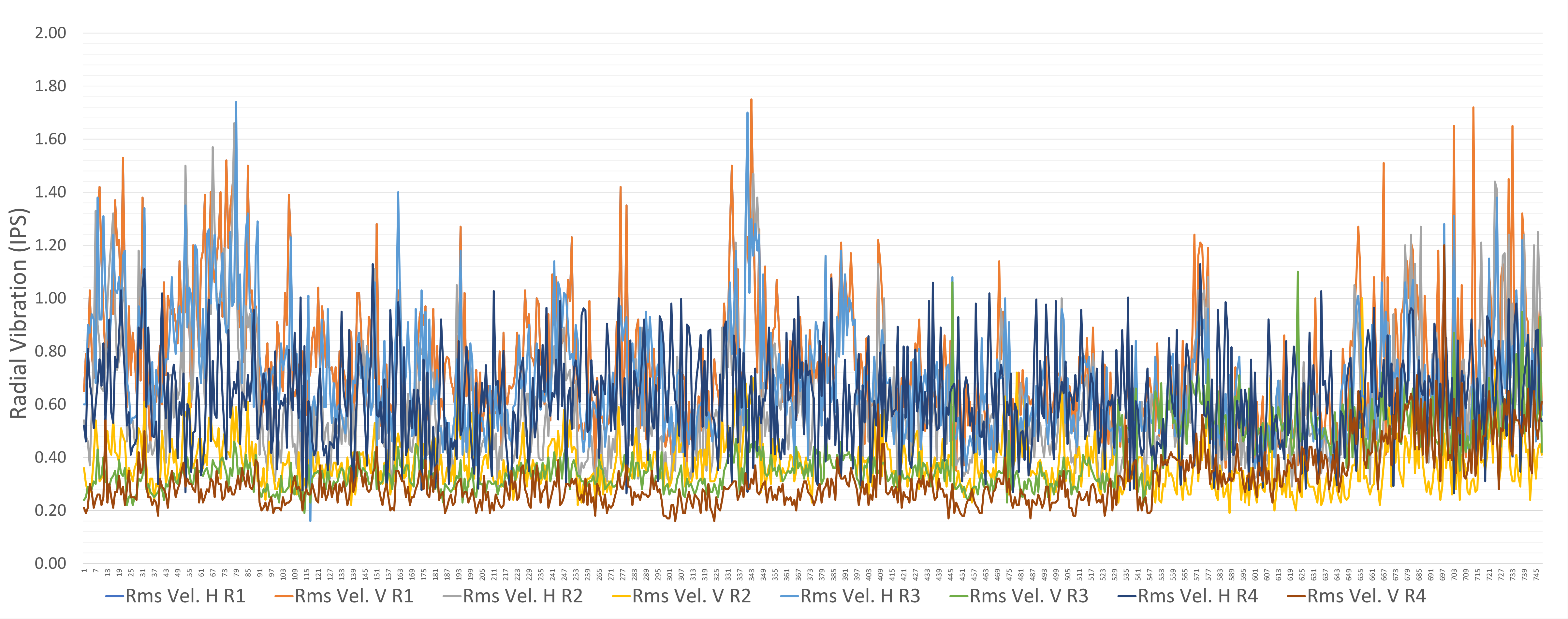
Rollers Overall Radial Vibration Trend
Timeframe: June 25th – October 25th @ 2021



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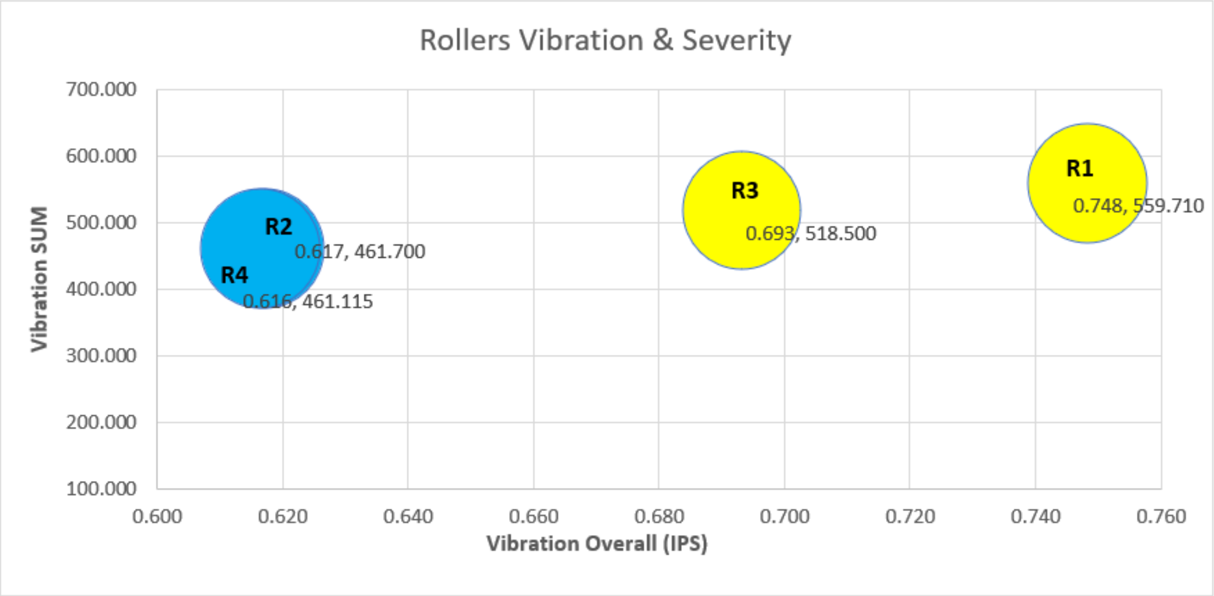
Rollers - Overall Vibration vs Accumulated Vibration

Timeframe: June 25th – October 25th @ 2021

The data analysis shows a summary table of overall vibration values whose distribution is Gaussian for each Roll, this indicates that the behavior pattern can be analyzed and projected with the overall vibration values.

We construct the severity chart with the overall vibration mean value and the sum of the accumulated overall vibrations, which we call the exposure time to high vibrations, as a result we get a clear correlation that shows that **Roller # 1** has the highest level of overall vibrations and the greatest time to exposure. **However, Rollers #3** are very close to this in amplitude values.



	Rms Vel. H R1	Rms Vel. H R2	Rms Vel. H R3	Rms Vel. H R4
Mean	0.748	0.617	0.693	0.616
Variance	0.060	0.064	0.046	0.033
Std. Dev.	0.245	0.252	0.215	0.183
Median	0.690	0.560	0.660	0.610
Mode	0.192	0.186	0.167	0.148
Minimum	0.600	0.570	0.520	0.890
Maximum	0.350	0.250	0.040	0.265
Count	748.000	748.000	748.000	748.000
Sum	559.710	461.700	518.500	461.115

Severity Scale →	Very Low	Low	Medium Low	Medium High	High

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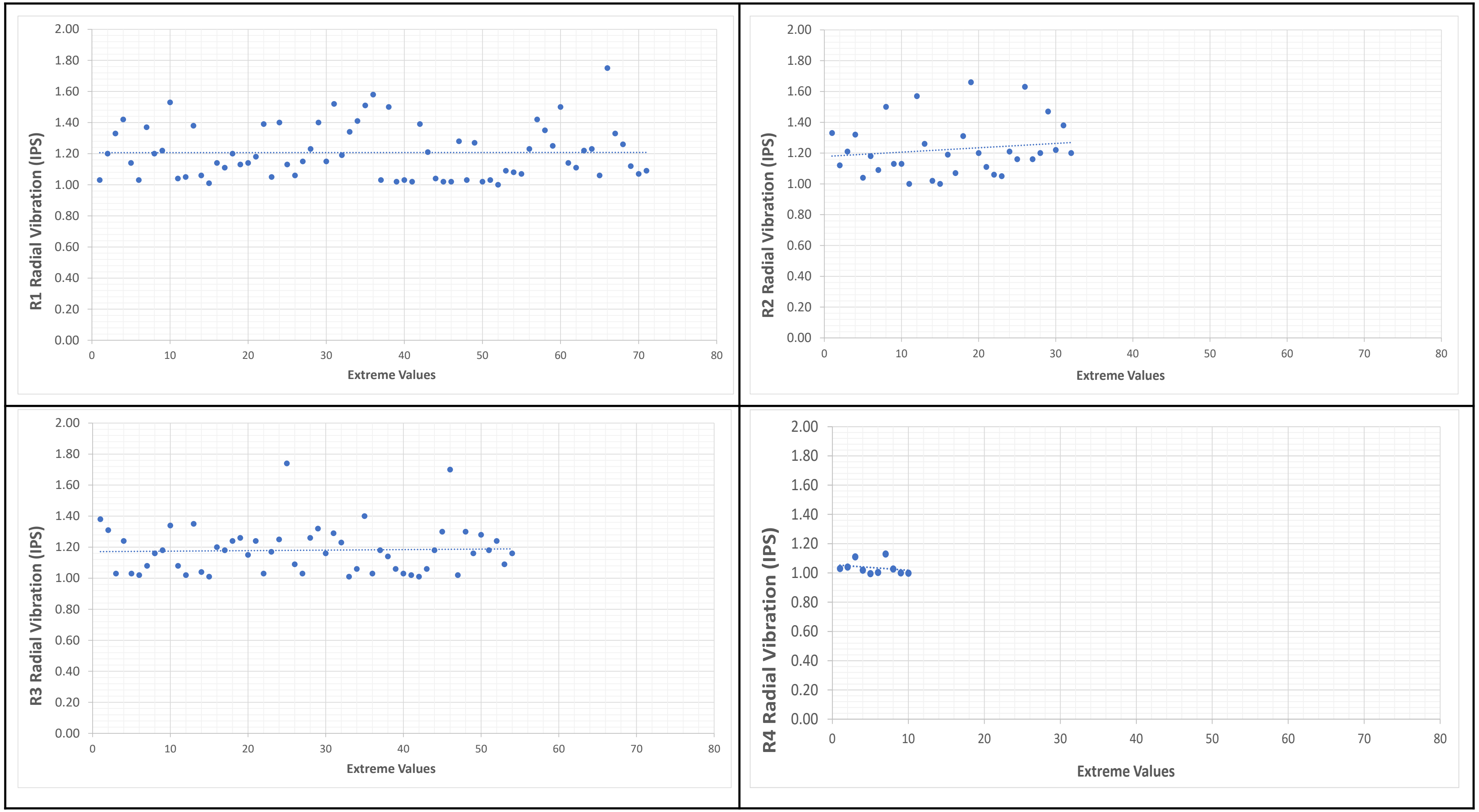
Rollers - Overall Vibration Extreme Value Analysis

Timeframe: June 25th – October 25th @ 2021



For the analysis of extreme values, we only capture the values greater than 1 Inch/s (IPS).

It can be clearly seen that **Roller # 1 Roller #3** are the ones that have been most exposed to extreme values, with this we validated the severity shown in the previous slide.

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Roll/Race Bearing Failure Frequencies

n (min^{-1})	T_{kr} (mm)	d_w (mm)	Z	β Degrees	β Minutes	β Seconds	β Decimal
60	885.548	103.000	24	13	50	0	13.8333

BPFFI (hz)	BPFFI (cpm)	BPFFO (hz)	BPFFO (cpm)	BSFF (hz)	BSFF (cpm)	RPFFB (hz)	RPFFB (cpm)
13.3553	801.3	10.6447	638.7	4.2439	254.6	8.4879	509.3

FTFF_i (Inner Ring Rotation) (hz)	FTFF_i (Inner Ring Rotation) (cpm)	FTFF_o (Outer Ring Rotation) (hz)	FTFF_o (Outer Ring Rotation) (cpm)
0.4435	26.6	0.5565	33.4

SG SRB p/n: **F-562181.02.PRL**

n: Shaft Speed
T_{kr}: Pitch Circle Diameter
d_w: Rolling Element Diameter
Z: Rolling Elements / Row
β: Contact Angle

BPFFI: Overrolling frequency factor (I.R. defect)
BPFFO: Overrolling frequency factor (O.R. defect)
BSFF: Overrolling frequency factor (rolling element defect)
RPFFB: Ring pass frequency (rolling element)
FTFF_i: Speed factor of rolling element set (inner Ring Rotation)
FTFF_o: Speed factor of rolling element set (outer Ring Rotation)

Source: FAG

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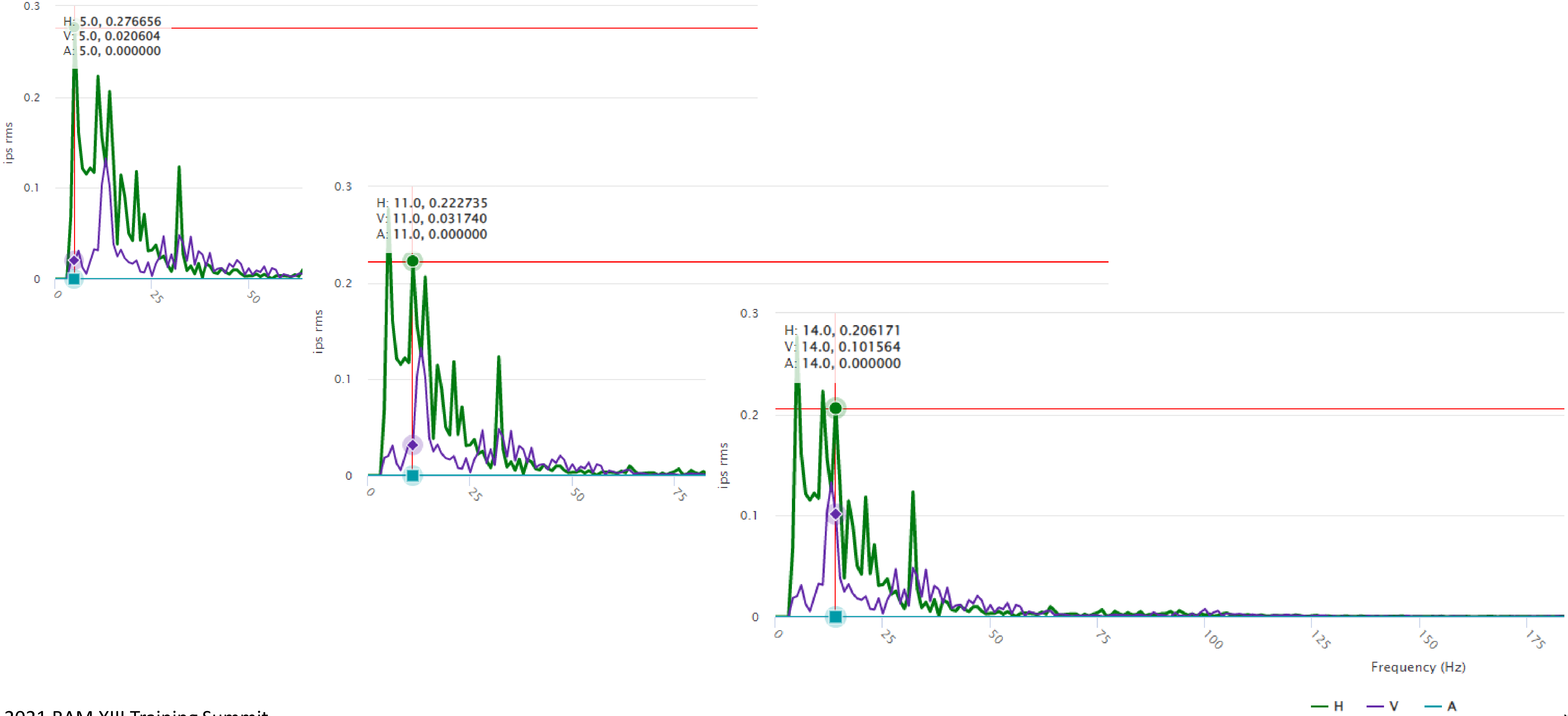
Roller #1 Spectrums



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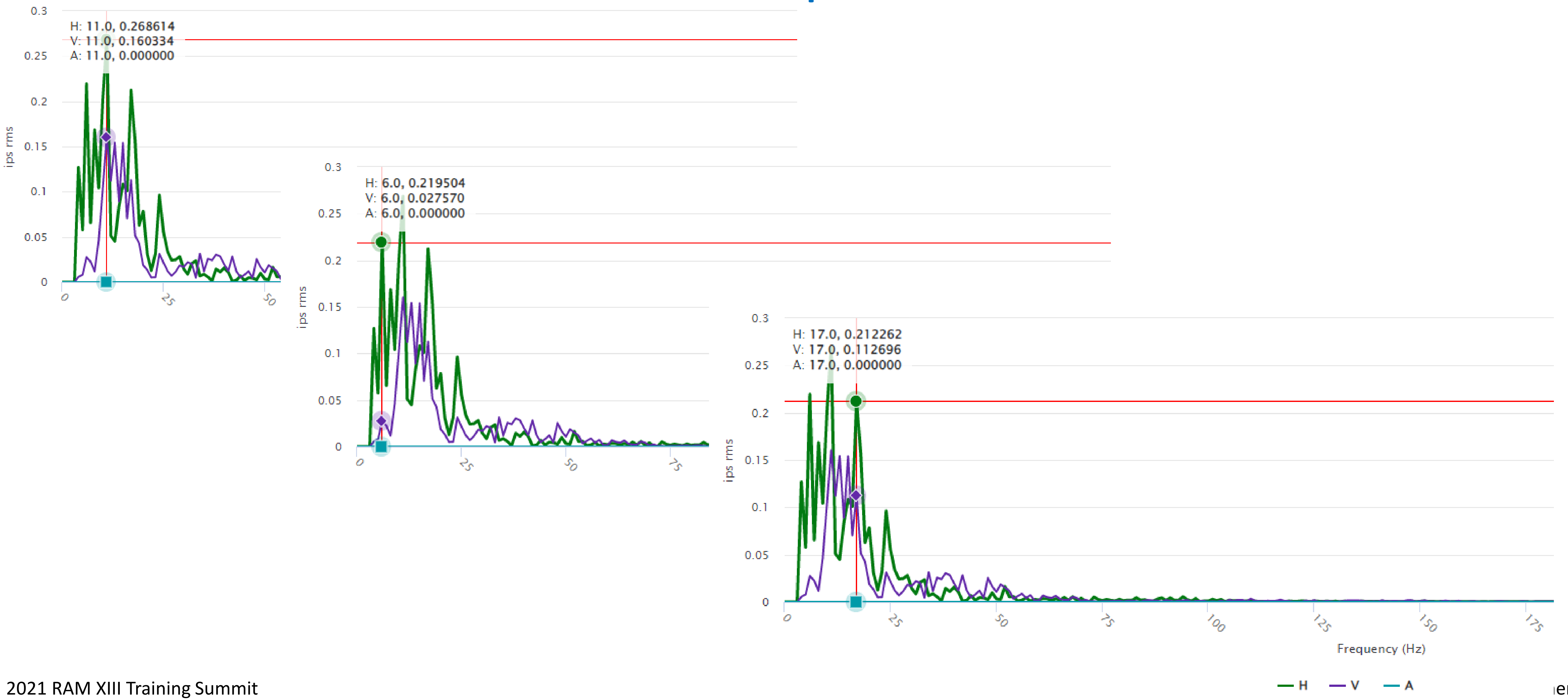
Roller #2 Spectrums



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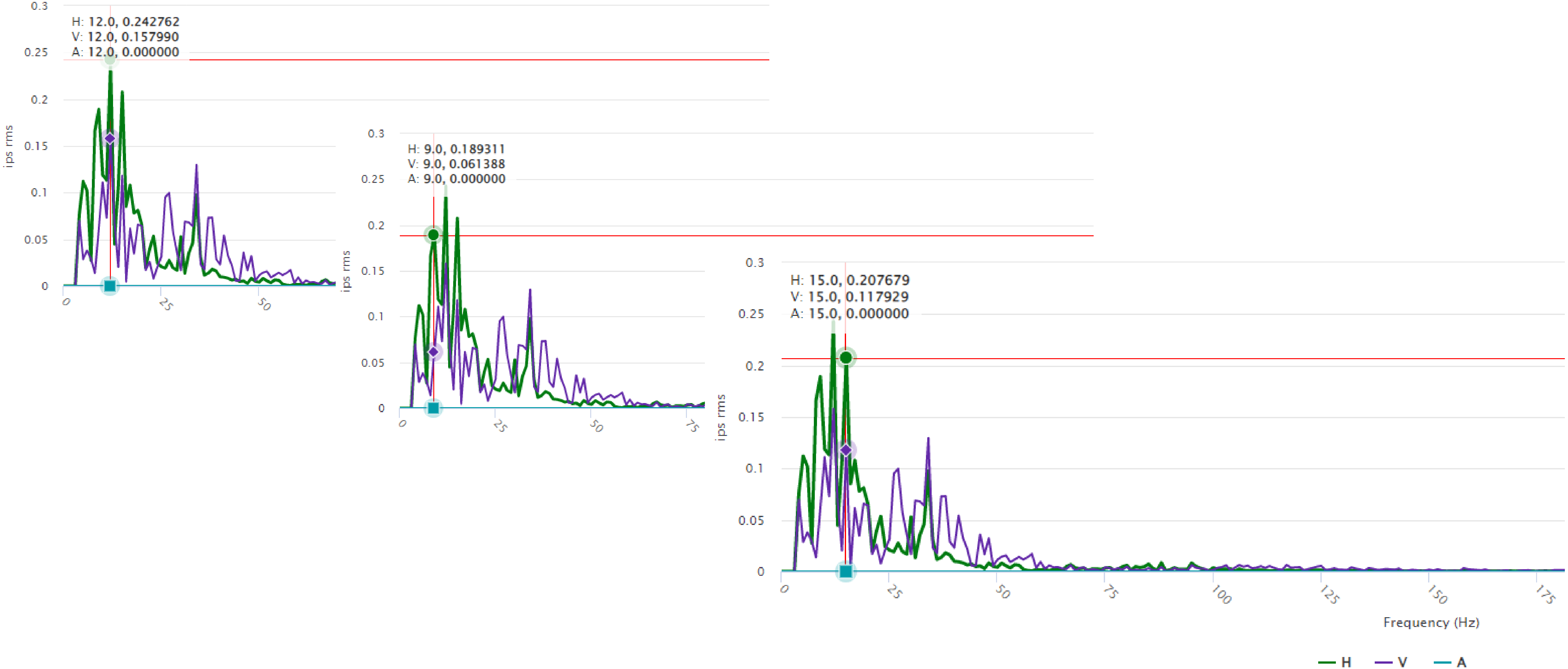
Roller #3 Spectrums



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Bearing Failure Frequencies – Roller #1, 2 & 3 Assessment

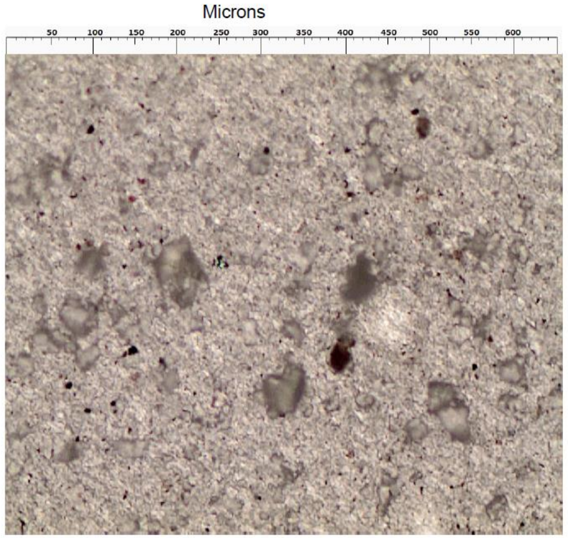
In the frequency analysis, it can be observed that the BSFF is predominant. These will be the frequencies to observe as a function of the change in magnitude (amplitude).

		BPFFI (Hz)	BPFFO (Hz)	BSFF (Hz)	RPFFB (Hz)	FTFF_i (Hz)	FTFF_o (Hz)	Speed (RPM)	Speed (Hz)
	1x	13.36	10.64	4.24	8.49	0.44	0.56	60.00	1.00
2	2x	26.71	21.29	R3 8.49	R2 16.98	0.89	1.11	120.00	2.00
3	3x	40.07	31.93	R3 12.73	25.46	1.33	1.67	180.00	3.00
4	4x	53.42	42.58	R2 16.98	33.95	1.77	2.23	240.00	4.00
5	5x	66.78	53.22	21.22	42.44	2.22	2.78	300.00	R1 5.00
6	6x	80.13	63.87	25.46	50.93	2.66	3.34	360.00	R2 6.00
7	7x	93.49	74.51	29.71	59.42	3.10	3.90	420.00	7.00
8	8x	106.84	85.16	33.95	67.90	3.55	4.45	480.00	8.00
9	9x	120.20	95.80	38.20	76.39	3.99	R1 5.01	540.00	R3 9.00
10	10x	133.55	106.45	42.44	84.88	4.44	5.57	600.00	10.00

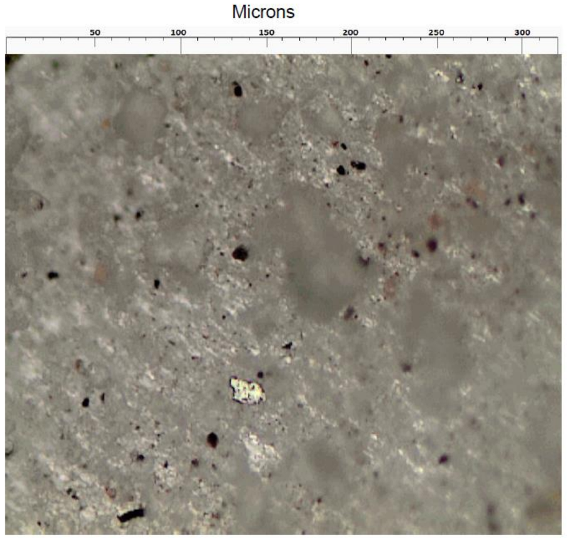
Severity Scale →	Very Low	Low	Medium Low	Medium High	High

BSFF: Overrolling frequency factor (rolling element defect)

Lube Oil Analysis– Roller #3

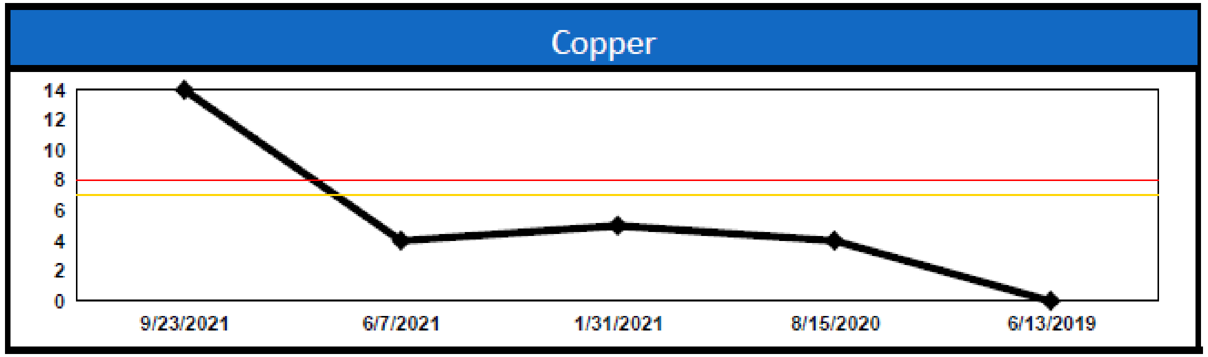


100x Rubbing wear & dust/dirt.



200x Rubbing wear & dust/dirt.

Machine Condition	MARGINAL
Lubricant Condition	CRITICAL



Wear Particle Analysis Report

	Trace	Light	Moderate	Heavy	Max. Size	Particle Composition
Rubbing Wear					15-30	Ferrous,White Non-Ferrous

The high level of wear (copper, aluminum) suggests that an abnormal wear mode exists.

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Mechanical Condition Severity Analysis Summary

Mechanical Condition Severity Analysis	Roller 1	Roller 2	Roller 3	Roller 4
Overall Vibration (IPS)	MH	M	MH	M
Overall Vibration (g's)	L	L	L	L
Extreme Values	MH	M	MH	L
Bearing Failure Frequencies	M	L	M	L
Wear Particle	L	L	MH	L

Severity Scale →	Very Low	Low	Medium Low	Medium High	High

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Roller #1 & 3 Vibration Prognostics

Descriptive Analytics, which use data aggregation and data mining to provide insight into the past and answer: “What has happened?”

Predictive Analytics, which use statistical models and forecasts techniques to understand the future and answer: “What could happen?”

Prescriptive Analytics, which use optimization and simulation algorithms to advice on possible outcomes and answer: “What should we do?”

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Data Mining Process

CRISP-DM: The Cross-Industry Standard Process for Data Mining.

1. Business Understanding: Get a clear understanding of the problem you're out to solve, how it impacts your organization, and your goals for addressing it

2. Data Understanding: Inspect, describe and evaluate the available data.

3. Data Preparation: Take data from the state it's into the state needed for analysis.

4. Modeling: Use mathematical techniques to make models (equations or other logic) you can use to support business decisions.

5. Evaluation: Figure out whether your models are any good.

6. Deployment: Integrate models into everyday business.

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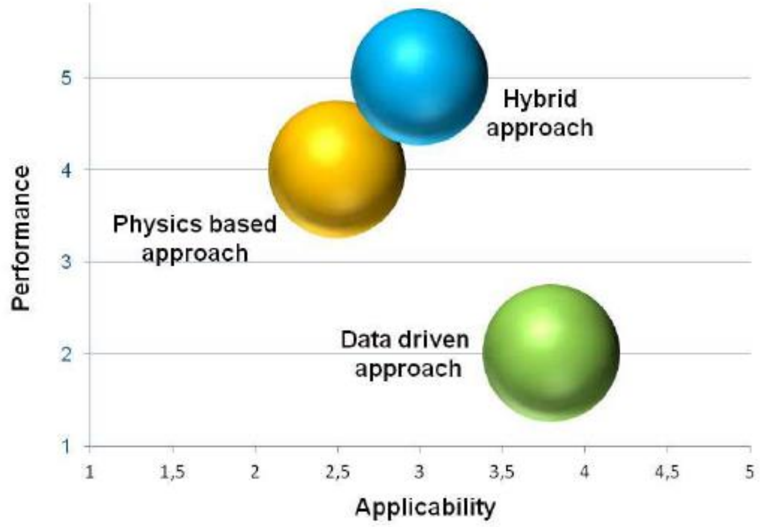
Modeling

Time Series Prognosis Models

- **Data Driven**
  - Machine Learning
    - Neural networks
    - SVM
    - CART
    - Fuzzy Logic
    - Required Robust Historical Data
  - **Numerical-Based Methods**
    - **Regression-Based** ✓
    - **Smoothing Methods** ✓
    - Required Moderated Historical Data
    - Bayesian
    - Gaussians
- **Expert-Driven**
- Hybrid Models
- Physics Models
  - Wavelet Transform
  - Hilbert-Huang Transform
  - Entropy Degradation



Source: **Enrico Zio.** Politecnico Di Milano. Italy.

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Modeling

Numerical-Based Methods

- Regression-Based
  - Linear Regression
  - **ARIMA** ✓ Univariate Dataset
- Smoothing Methods
  - Moving Average
  - **Holt-Winters** ✓ Univariate Dataset

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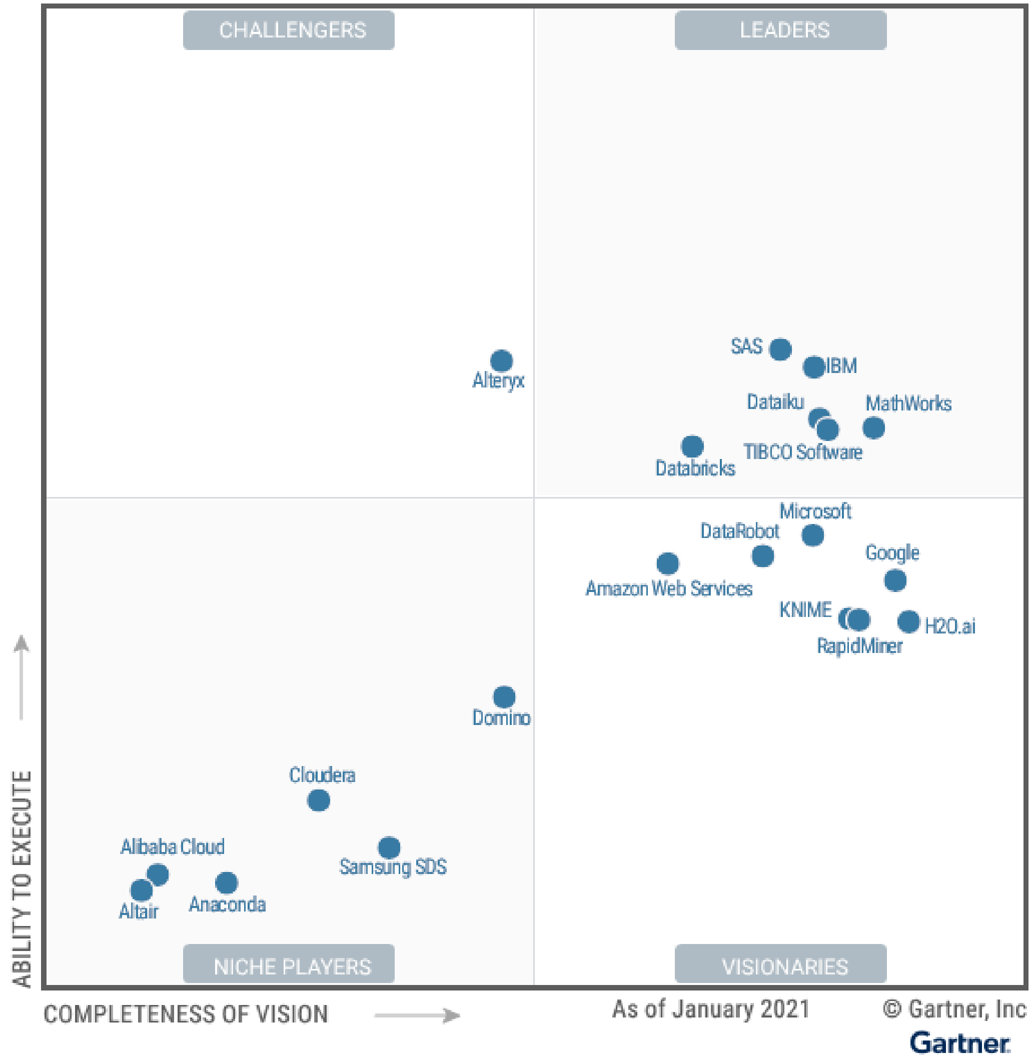
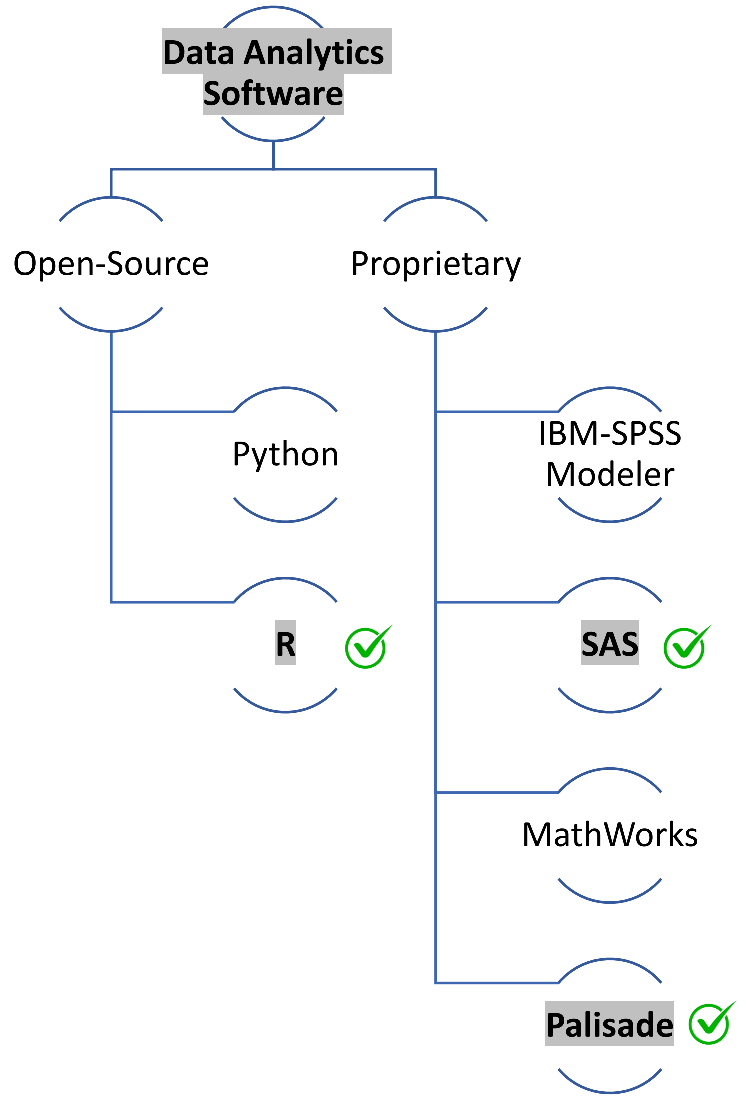
Modeling

Gartner Magic Quadrant for Data Science and Machine Learning Platforms





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Evaluation

Scale Dependent Errors

Scale-dependent errors, such as mean error (**ME**) mean percentage error (**MPE**), mean absolute error (**MAE**) and root mean squared error (**RMSE**), are based on a set scale, which for us is our time series.

Lower values of RMSE indicate better fit. RMSE is one of the good measure of how accurately the model predicts the response, and it is the one of the most important criterion for fit if the main purpose of the model is prediction, and It has the benefit of penalizing large errors.

The mean absolute error (MAE) is a quantity used to measure how close predictions are to the outcomes, It refers to the results of measuring the difference between two continuous variables, in our case assuming that TRAINING and TEST represent the same phenomenon but have recorded different observations.

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Evaluation

Although both models show acceptable accuracy when compared, Holt Winter's method was the best fit, so we chose it to make the prognosis. The graphic result can be seen in the following slide.

Roller #1 Overall Vibration	ME	MAPE	MAE	RMSE
ARIMA	-0.079	0.212	0.088	15.394
HOLT WINTERS	-0.050	0.197	0.085	14.210
Roller #3 Overall Vibration	**ME**	**MAPE**	**MAE**	**RMSE**
ARIMA	-0.007	0.138	0.055	7.850
HOLT WINTERS	-0.006	0.100	0.036	4.850
Green: Best Fit or Result.				

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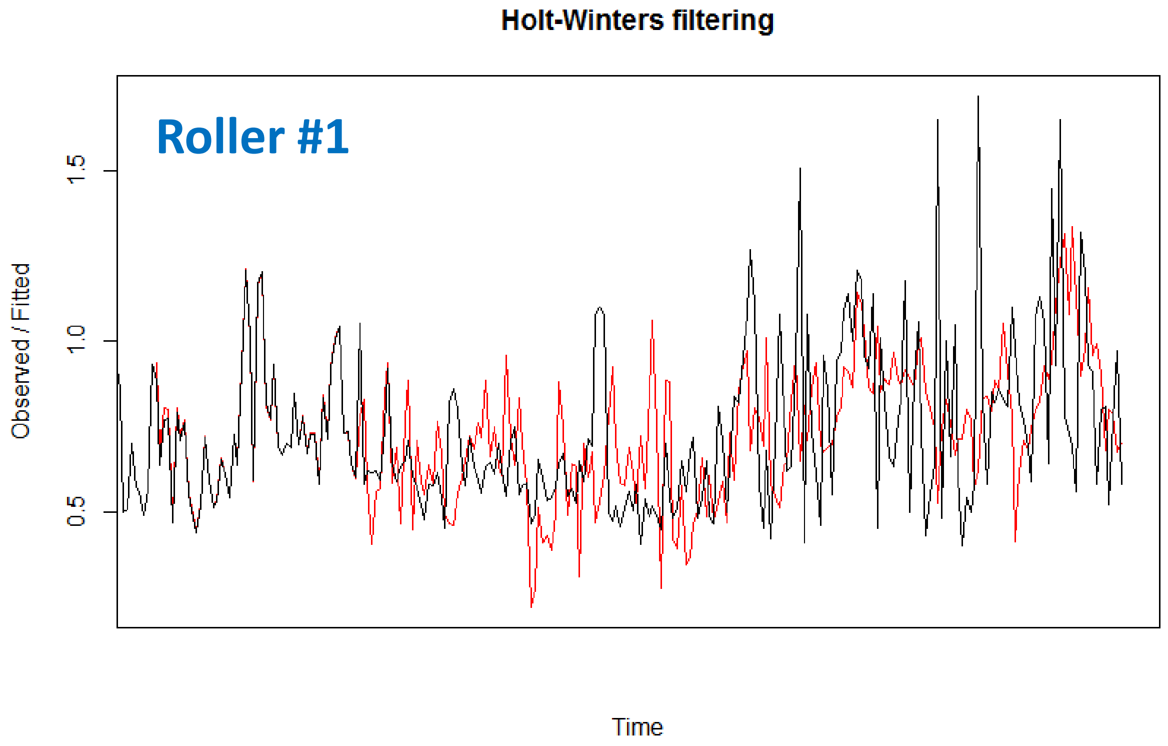
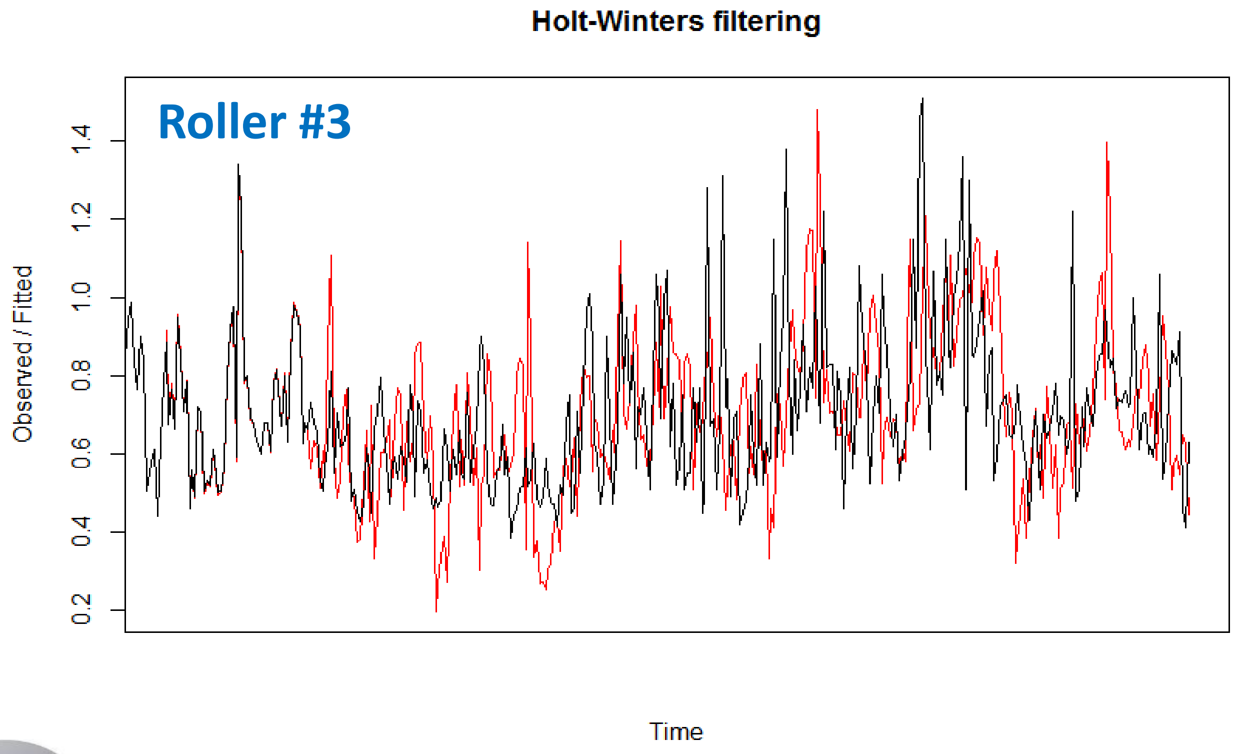
Evaluation

Holt-Winters Model: Training Set (Black Line) versus Test Set (Red Line)





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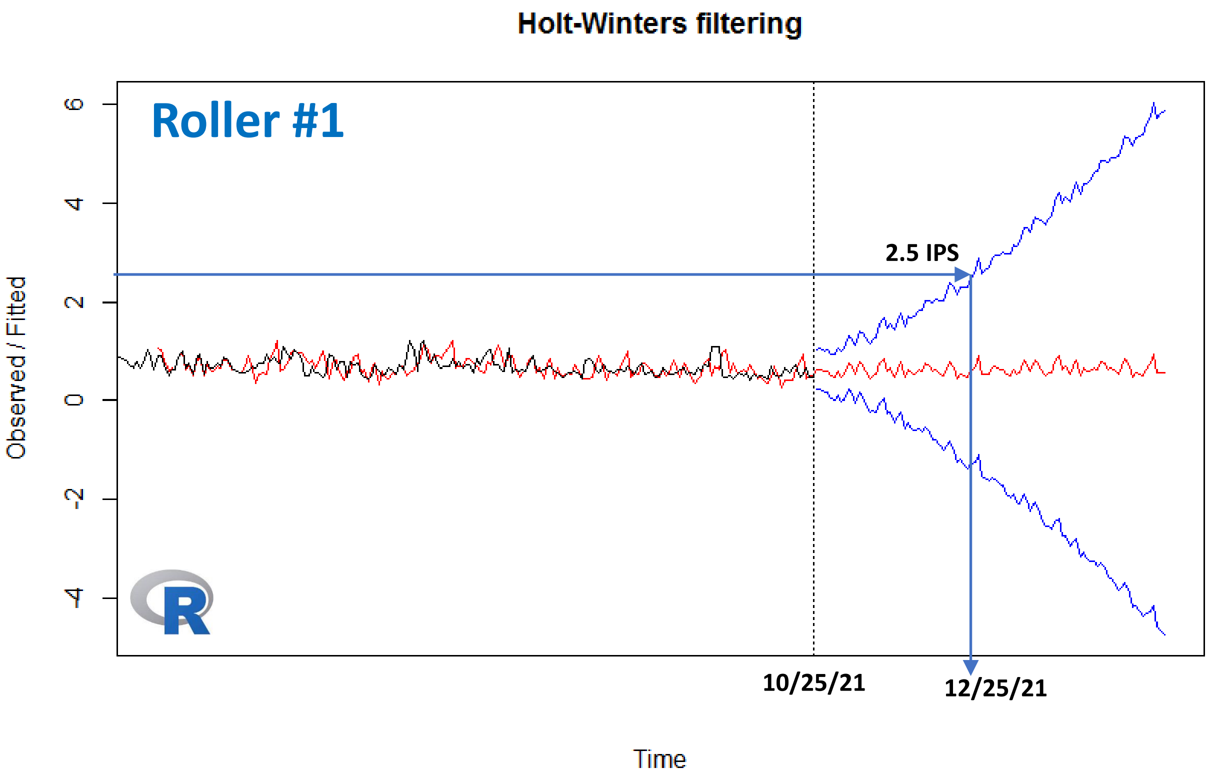
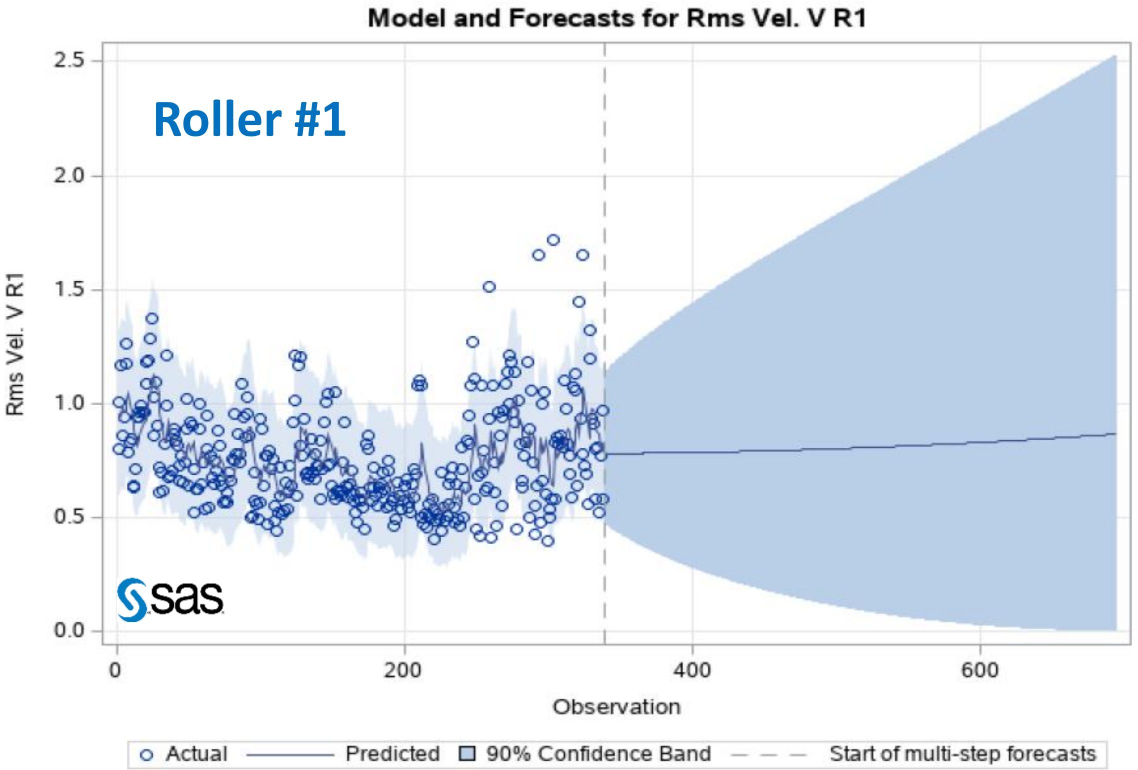
Roller #1 Overall Vibration Prognosis

The evaluation time period was approximately 4 months, and we made a prognosis of 3 months for both Rollers in R, and 4 months with SAS with a confidence interval of 90%. **Roller #1** shows in R Prognosis a stable and linear trend with a slight positive slope; however, the uncertainty level exceeds 2.5 IPS at 2 months, but in SAS the Prognosis confidence band rise the limit of 2.5 IPS at 4 months, with this we apply the principle of, based on the confidence interval, we can conclude that the model is accurate for a 3-months prognosis without taking risks that vibrations may exceed the unacceptable limit of 2.5 IPS.





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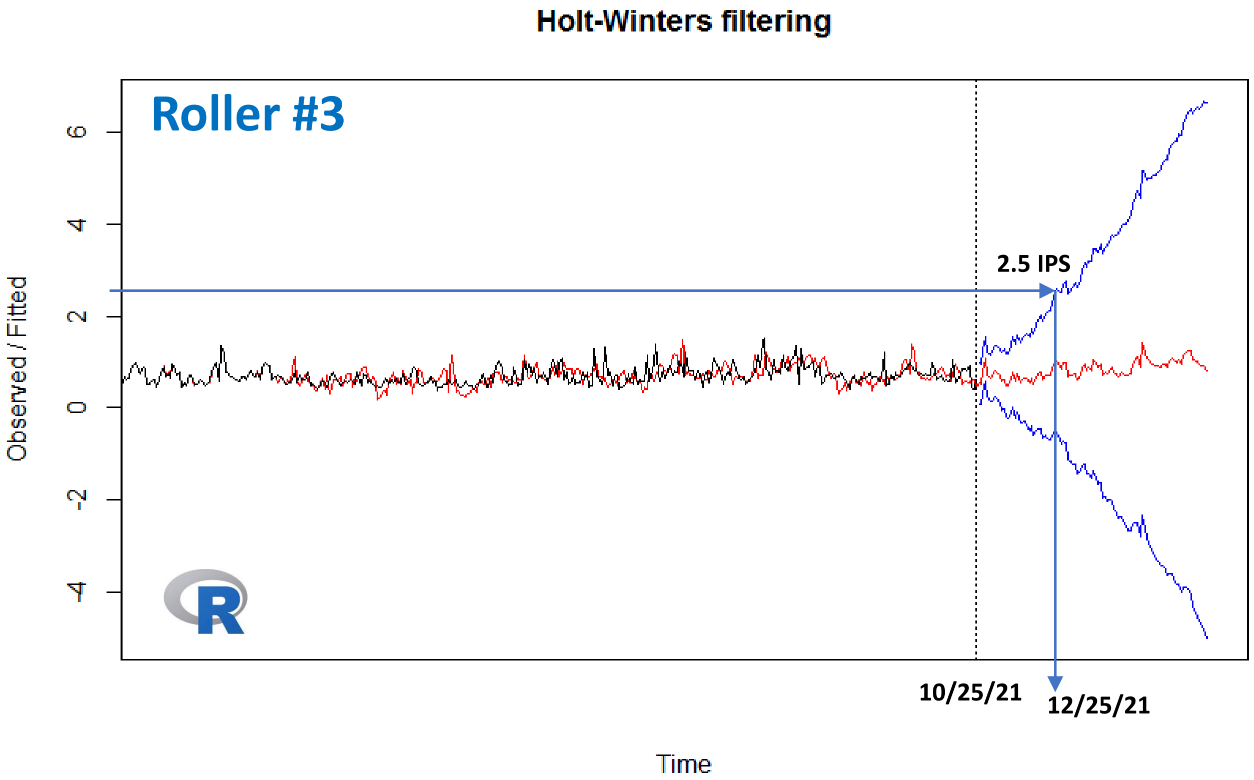
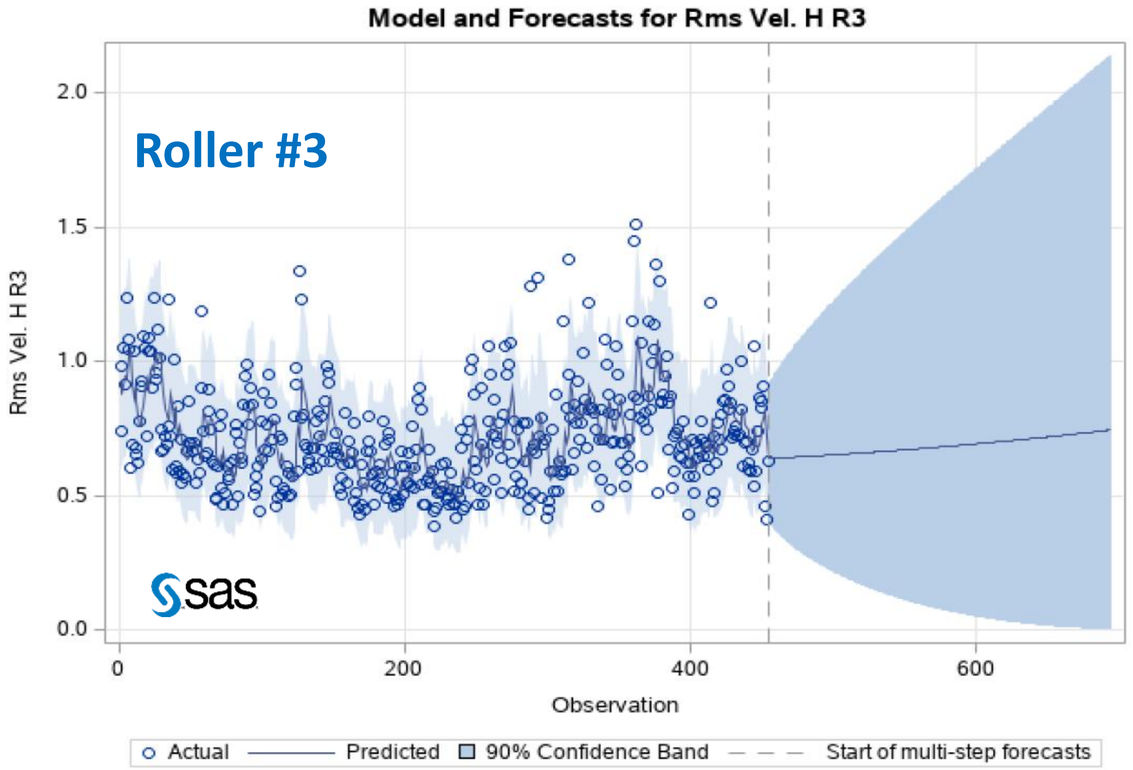
Roller #3 Overall Vibration Prognosis

Roller #3 shows in R Prognosis a stable and linear trend with a positive slope; however, the uncertainty level exceeds 2.5 IPS at 2 months, but in SAS the Prognosis confidence band rise the limit of 2.5 IPS at 3 months, with this we apply the principle of, based on the confidence interval, we can conclude that the model is accurate for a 2.5-months prognosis without taking risks that vibrations may exceed the unacceptable limit of 2.5 IPS.





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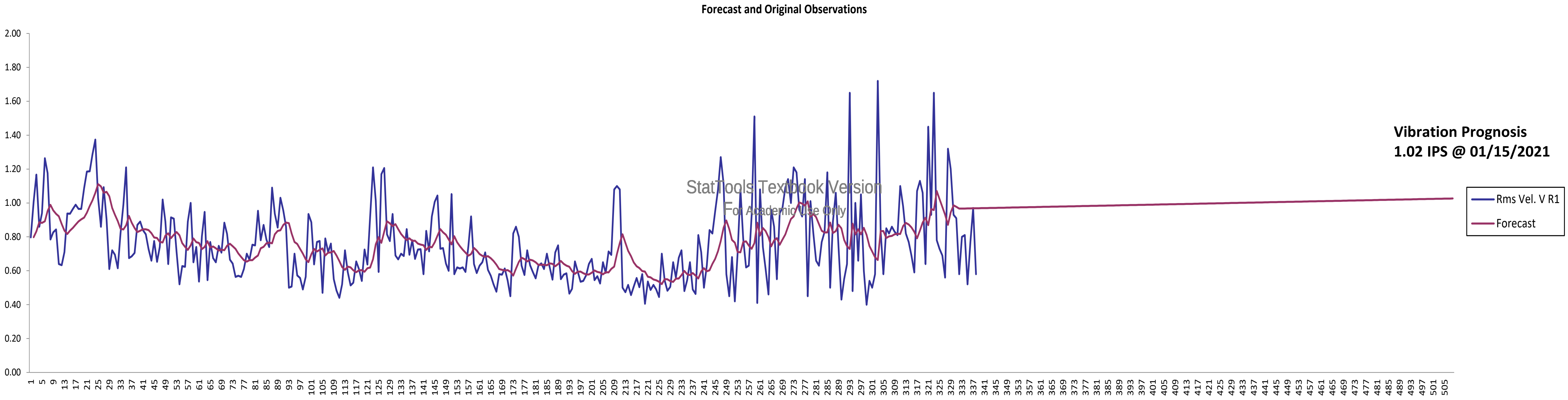
Roller #1 Vibration Prognostics

Making a projection until January 15th, 2022, the vibration value will be at an average of 1.02 IPS



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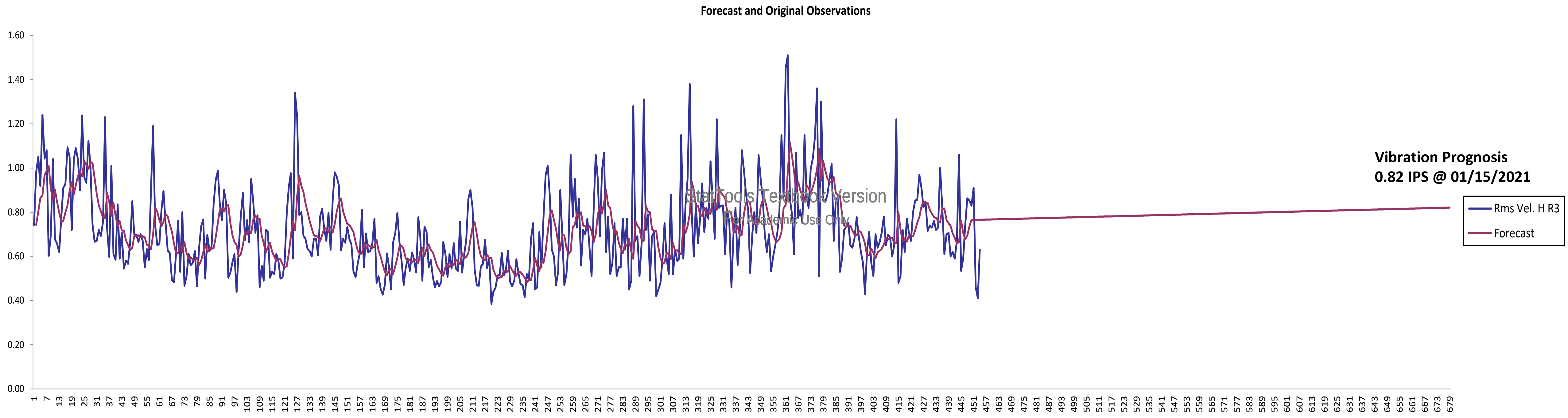
Roller #3 Vibration Prognostics

Making a projection until January 15th, 2022, the vibration value will be at an average of 0.82 IPS



Palisade

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Observations and Conclusions

1. There is no reliability threat that represents a potential unexpected bearing failure for the next 3 months.
2. Based on the condition pattern of the 4 rollers, we can see that Rollers # 1 and # 3 have the highest level of severity.
3. Although we do not have the vibration severity levels established by the manufacturer, the levels we defined were based on the current condition of the 4 rollers.
4. The Prognosis Analysis of Roller # 1 & #3 shows a growing trend, however with a slope that does not represent a predictable reliability threat in the short term (3 months).

Recommendations

1. Keep monitoring mechanical condition of the 4 Rollers.
2. Make a prognosis update for February 2022.
3. Include a Remaining Useful Life Analysis for the next prognosis analysis, and thus estimate with greater accuracy when any of the rolls could reach the unacceptable vibration amplitude (>2.5 IPS).

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Lessons Learned

1. The prognosis of univariate time series represents a great challenge for predictive analytics models, because the most robust models are multivariate and include predictor variables, such as multiple regression, Support Vector Machine (SVM), and COX model.
2. The data extraction and cleaning phase is the hardest phase, and which requires more time, additionally working with the Heavy-Industry, which generated many outliers due to the equipment operating conditions. The management of outliers, although they have several methods to be treated, in our experience the opinion of experts was required to validate the treatment process.
3. Although the models were evaluated through the measurement of errors, the participation of experts (SME) was also necessary to carry out a results sensitivity analysis.
4. To use open resource software such as Python and R it is necessary to have a professional with experience in programming language, and specifically in the scripts of these software, however we learned that proprietary software such as SAS and IBM-SPSS Modeler can do the same, in an interactive and user-friendly environment with no programming experience.
5. For a proper understanding of the prognosis models and the parameters of each algorithms, it is necessary to have deep and advanced knowledge in applied statistics.