Leveraging Industry 4.0 and AI

To Extend Remaining Useful Life

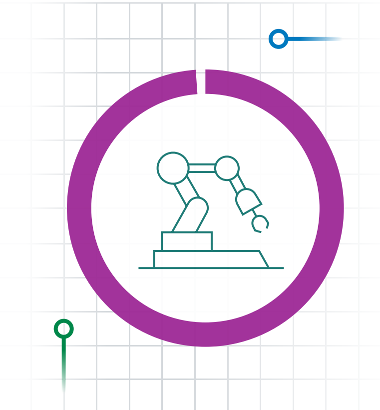
Bosch Software and Digital Solutions

Sreekanta Aradhya B,
Industry 4.0, Global Business Head

Rakesh Kumar Murugan,
Director – APAC Sales

Sathiya Singh V,
Strategy Consultant, Industry 4.0

Overview:



With the widespread adoption of revolutionary technologies such as **IoT, cloud computing, and AI** into production facilities, **smart factories** are now a reality. Asset productivity is a high priority for manufacturers across the globe, a recent McKinsey **survey** shows that **99% of leaders have undertaken** a maintenance transformation in their organizations in the past five years. As manufacturers strive to achieve unprecedented efficiency and economic progress, companies are increasingly recognizing the value of understanding and managing the Remaining Useful Life (RUL) of their assets.

Let's delve deeper into the value of accurately predicting RUL, taking a closer look at the **role of Industry 4.0** in extending RUL, the power of AI models in increasing the life expectancy of assets, and how enterprises have leveraged expertise and solutions from Bosch to **reduce costs and improve productivity.**

Understanding RUL: Why Does It Matter?

Defining RUL of an Asset

The Remaining Useful Life (RUL) of an asset refers to the estimated remaining operational time before it reaches a predefined threshold, indicating the need for **maintenance, replacement, or refurbishment.**

The Significance of RUL for Companies

Let us take the example of a major offshore oil and gas operator. Besides the challenges of managing heavy machinery with complex components, the smallest breakdown, downtime or disturbance could potentially disrupt the value chain of an entire ecosystem.

An RUL-informed predictive maintenance approach turned out to be the solution this enterprise needed. By analyzing data from the last 30 years of platform operations, this company managed to refine its **predictive maintenance approach, resulting** in an **average reduction in downtime of 20%.** This scenario is why accurately predicting and extending RUL is imperative for any manufacturing enterprise.

Across virtually every major manufacturing industry, predicted RUL values can play a monumental role in driving profits, enhancing safety, and minimizing risks.

For component manufacturers, the use of predicted RUL values can massively **reduce costs and improve productivity** through the use of predictive maintenance strategies to extend the lifespan of their tools.

For the mining industry, which deals with a myriad of heavy equipment, predicted RUL values can be used to **detect potential issues before they cause a breakdown.**

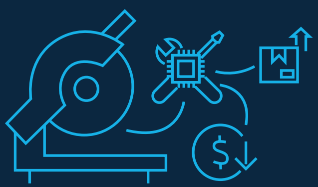
In the automotive and aerospace sectors, Industry 4.0-enabled RUL approaches can be leveraged to accurately monitor the state of health of equipment, preventing breakdowns and leading to **less downtime** and **improved safety.**

Our Success with Enhancing Asset RUL

At Bosch, we leveraged our deep engineering expertise to implement an RUL approach, resulting in significant business benefits for our partner.

Challenge:

Our partner had been facing a significant challenge with the **high cost of grinding** tool consumption due to the fixed interval at which they were replenished. The tools had a limited lifespan of only 800 cycles, which meant that they had to be frequently replaced, leading to high costs.



Result:

With the implementation of an **RUL approach,** the customer was able to move from schedule-based dressing to condition-based dressing. This led to a significant reduction in yearly grinding tool costs, with the **cost per tool reduced by about 20%.** There was also an **approximate 10% improvement in productivity** due to the reduction in the number of dressing cycles.

Developing a personalized RUL model

A series of essential steps:

1. **Understanding the problem statement** The first step is defining the problem statement with clear criteria for success. This includes determining ROI and project payback.

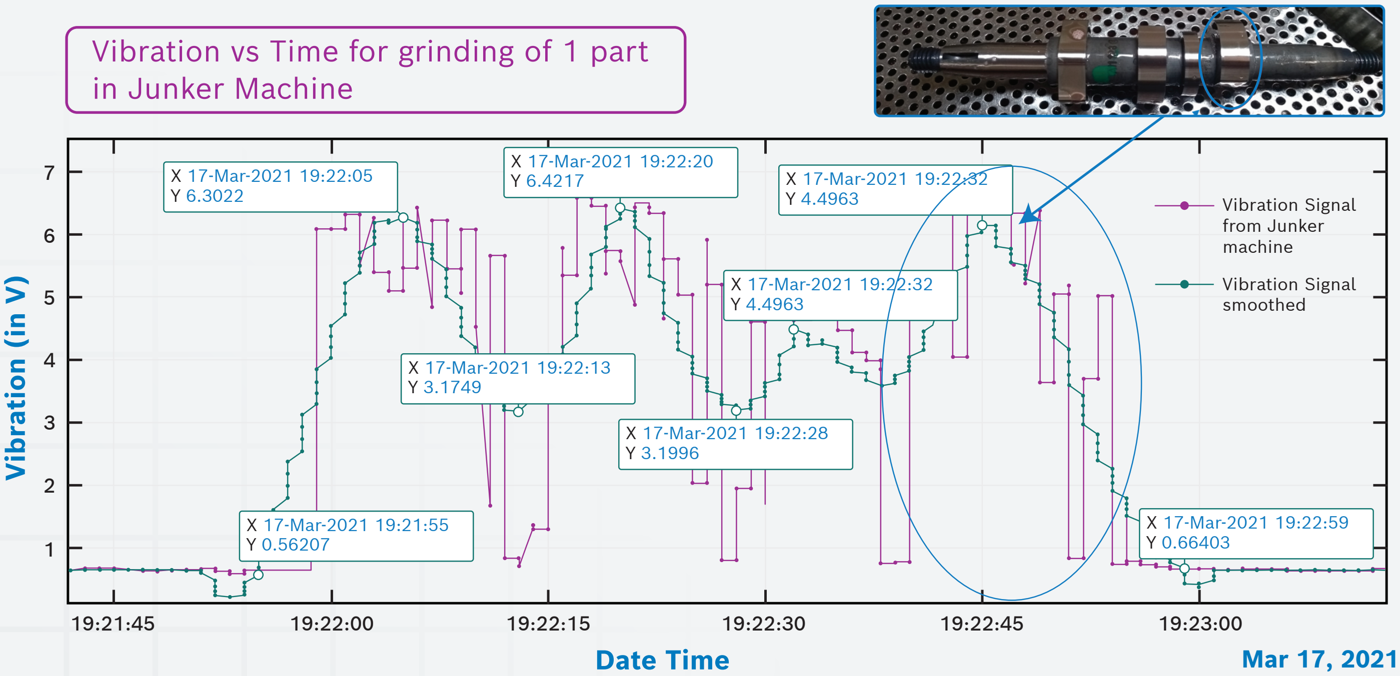
2. **Data collection from the system** Next, a list of necessary data is identified, a data acquisition strategy is created, and finally, the data is captured and stored on cloud servers.

3. **Exploratory data analysis (EDA)** EDA is performed on the collected data to identify patterns and perform trend and correlation analysis.

Vibration Monitoring Project for Junker machines

Result 1: Automated Cam lobe and Eccentre detection

Successful detection of profile through vibration



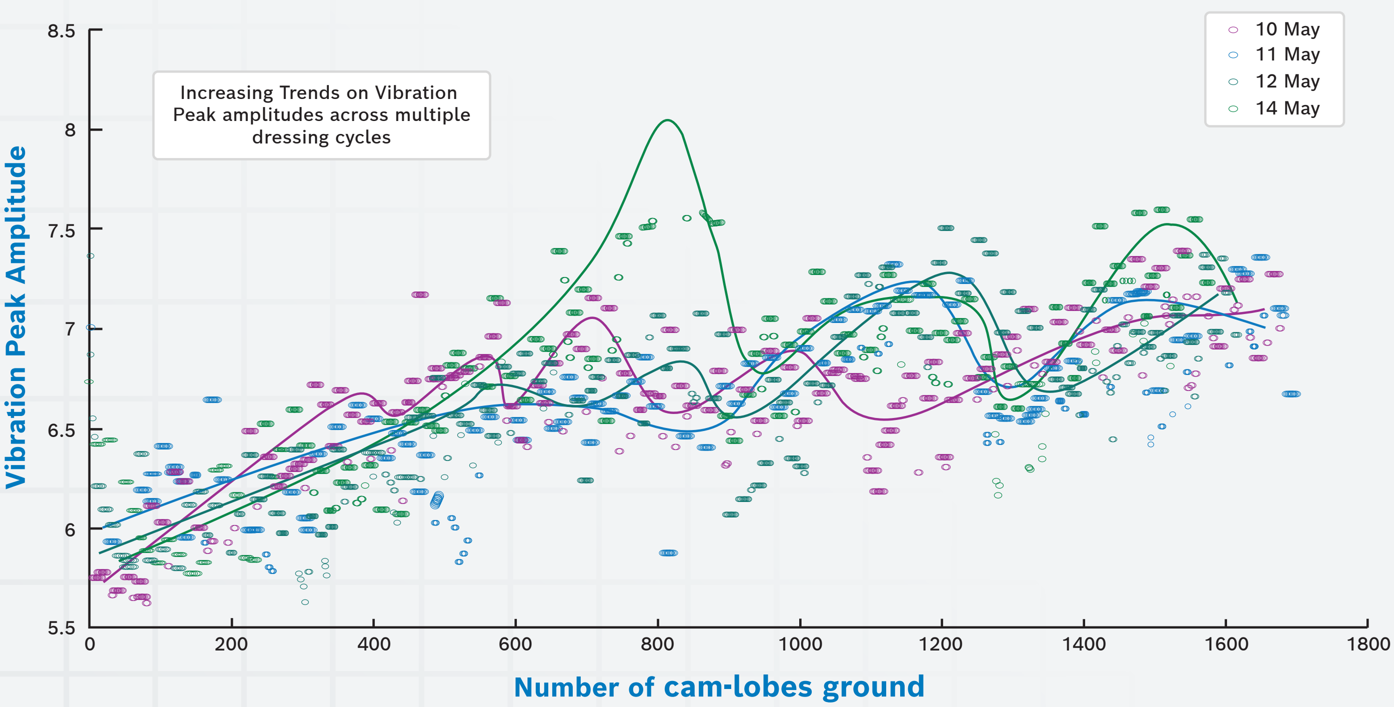
Sample image showing the mapping of vibration pattern with the profile of the part grounded

Identifying condition indicators Condition indicators are identified by performing feature extractions and creating a list of features based on the hypotheses built.

Feature Type	Feature
Time Domain	Clearance Factor
	Crest Factor
	Impulse Factor
	Kurtosis
	Mean
	Peak Value
	RMS
	Signal to Noise Ratio
	Shape Factor
	Skewness
	Standard Deviation
	Total Harmonic Ditortion
Frequency Domain	Power Spectrum Peak Amplitude
	Power Spectrum Peak Frequency
	Power Spectrum Band Power

Sample feature table with various time-domain and frequency-domain features derived from raw sensor data (in time-series)

Vibration Peak vs No. of cam-lobes ground

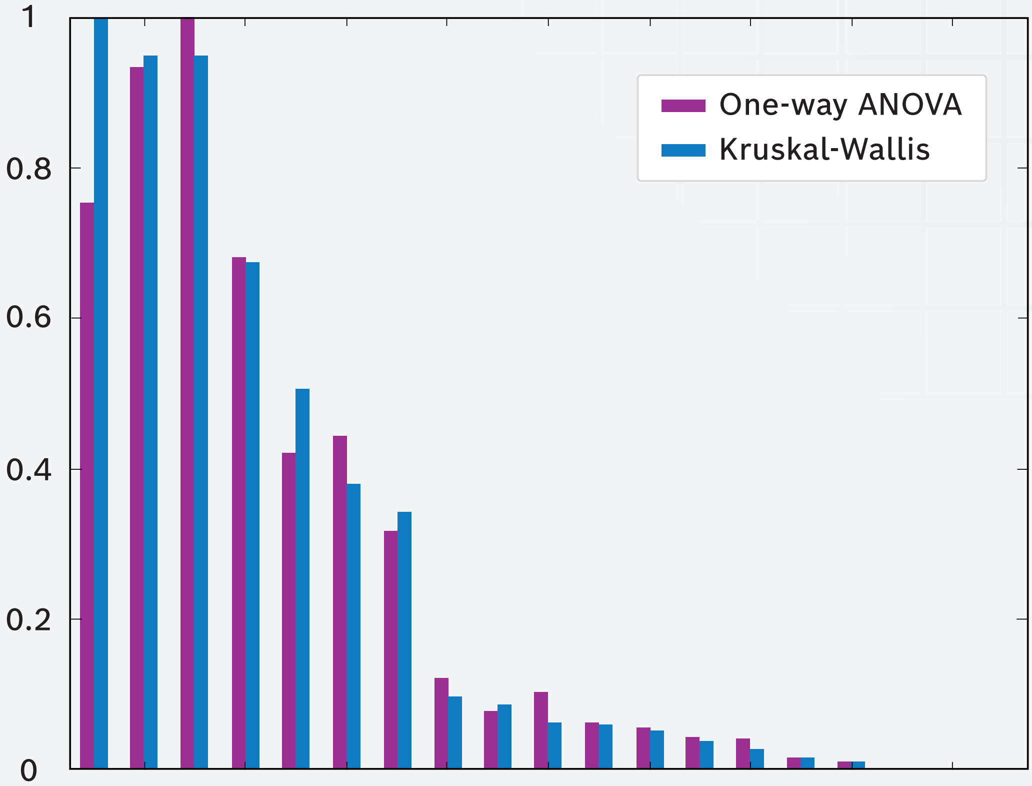


Sample trend analysis for extracted features vs life of grinding wheel (i.e., no of parts grounded)

5

Ranking of condition indicators to determine the Health Indicator To identify the top features with a high impact on machine health/condition, we use ranking algorithms like ANOVA and feature importance matrix. The health indicator is derived by combining various condition indicators based on PCA analysis.

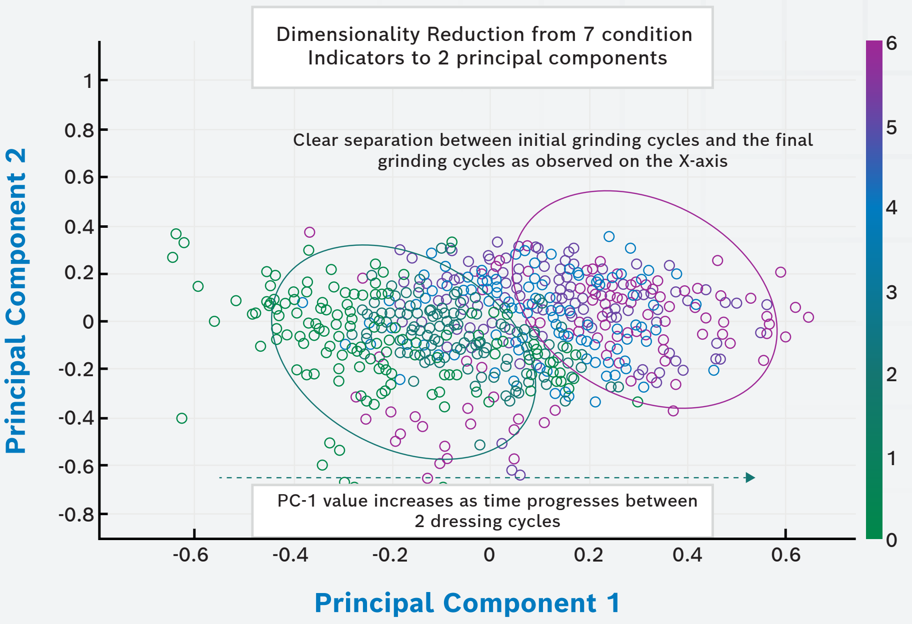
Feature Sorted by Importance



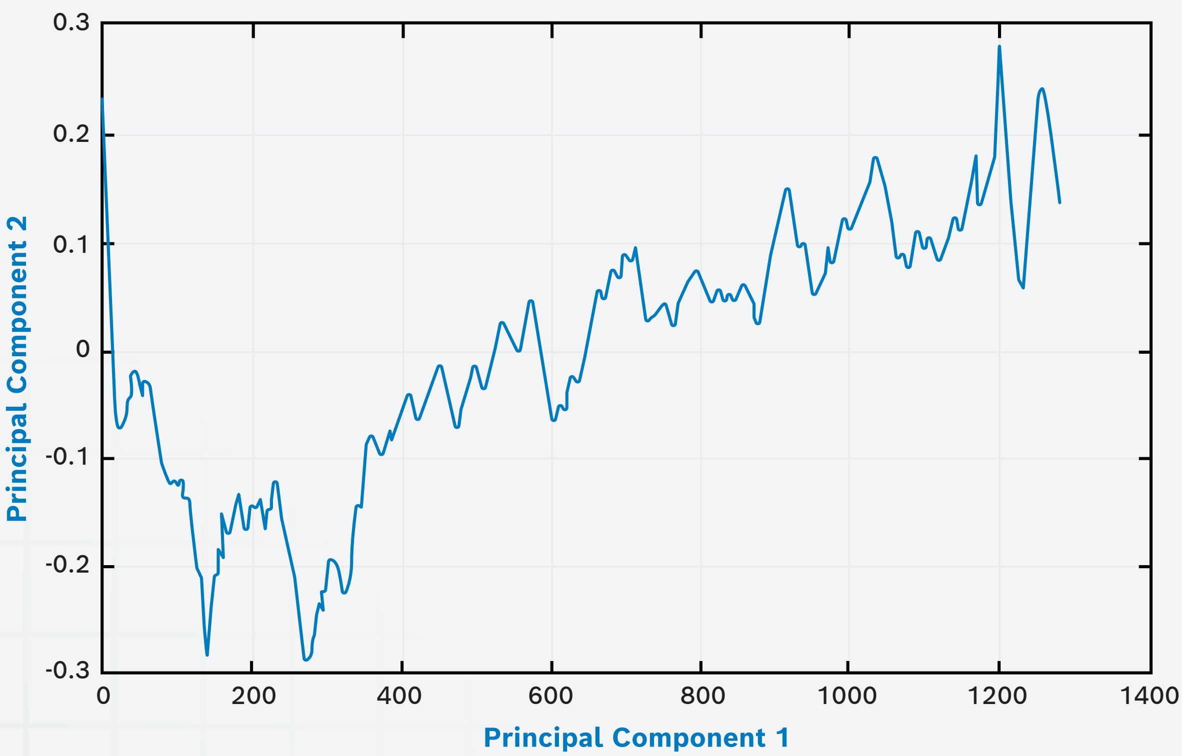
Feature	One-way..	Kruskal-Wallis
spe...ec/Junker1_Vibration_PealAmp1	102.3343	439.8404
spe...ec/Junker1_Vibration_RMS	97.0236	545.6888
spe...ec/Junker1_Vibration_PeakValue	91.2724	583.3194
spe...ec/Junker1_Vibration_Mean	69.0003	396.6535
spe...ec/Junker1_Vibration_BandPower	51.7505	245.1732
spe...ts/Junker1_Vibration_Std	38.8812	258.4519
spe...ec/Junker1_Vibration_BandPower	35.0432	184.4951
spe...ts/Junker1_Vibration_Skewness	9.7604	70.3011
spe...ts/Junker1_Vibration_CrestFactor	8.6726	44.7239
spe...ec/Junker1_Vibration_PeakFreq1	6.4091	60.4659
spe...ts/Junker1_Vibration_Kurtosis	6.1371	36.6779
spe...ts/Junker1_Vibration_ImpulseFactor	5.4020	31.1875
spe...ts/Junker1_Vibration_ClearanceFactor	3.7624	25.3697
spe...ts/Junker1_Vibration_ShapeFactor	2.7889	24.5793
spe...ec/Junker1_Vibration_PeakFreq1	1.5785	9.1891
spe...ec/Junker1_Vibration_PeakAmp1	0.9063	5.6614
spe...ts/Junker1_Vibration_SINAD	0	0
spe...ts/Junker1_Vibration_SNR	0	0
spe...ts/Junker1_Vibration_THD	0	0

Sample feature ranking table where the feature list is ranked in the descending order of their importance (impact on condition indicator)

Dimensionality Reduction



Color Label	Time Duration (after the firstdressing cycle)
0	0 - 3 hours
1	3 - 6 hours
2	6 - 9 hours
3	9 - 12 hours
4	12 - 15 hours
5	15 - 18 hours
6	18 hours and above



Sample of Principal component analysis (PCA) results where top-ranked features are grouped into principal components

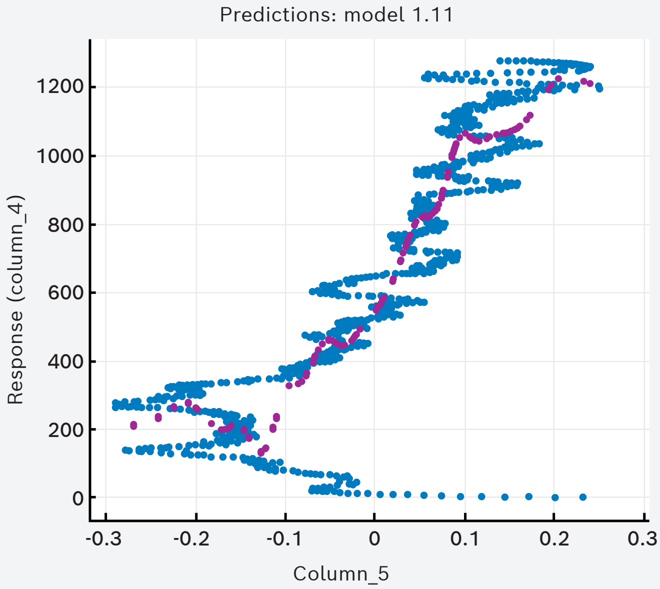
6

ML model training for RUL prediction Next, the training of the ML model for RUL prediction is done by performing experiments to push beyond the manual safety threshold for failures, training the RUL model as a regression model, and iterating through different model types and hyperparameters.

Regression Model

Models Tested
Linear Regression
Decision Trees
Ensemble Boosted Trees
Ensemble Bagged Trees
Support Vector Machines

Out of the above types of models tested, Support Vector machines had the highest accuracy of R - squared value less than 0.8 and RMSE less than 190 (RMSE in this case is the error in the actual parts predicted)

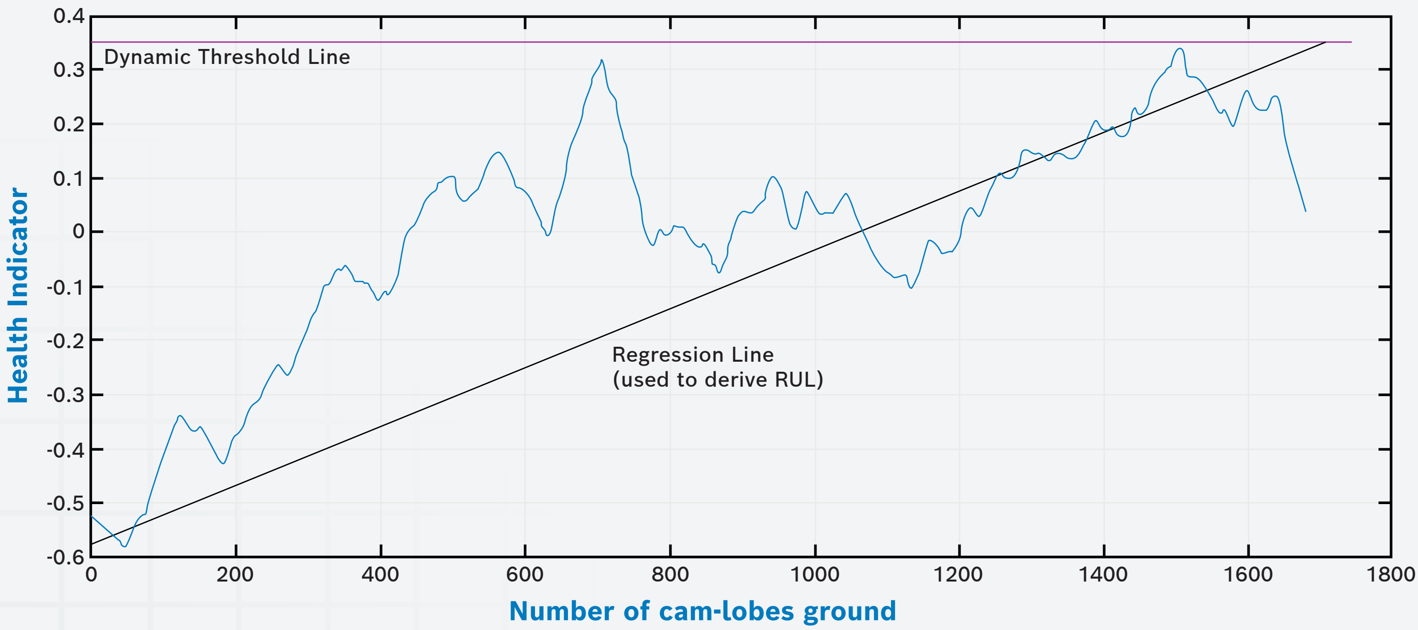


SVM Type	R-squared	RMSE (Error)
Linear SVM	0.72	188
Quadratic SVM	0.72	187.14
Cubic SVM	0.78	166.08
Fine Gaussian SVM	0.78	165.84
Ensemble Boosted Trees	0.77	169.36

* Model with R-squared value close to 0.4 is said to have a good fit

Sample prediction model output depicting the trend of RUL from a cohort of results obtained from various model types

Regression model is trained with Health Indicator values. The point of intersection of regression line with dynamic threshold line is the predicted failure point



Sample snapshot of RUL prediction model in action, displaying the predictions for the remaining life of a machine based on previous health indicator trends

7

Model testing and validation The testing and validation of the model is conducted by developing a model test strategy and identifying the model evaluation KPIs.

8

RUL model deployment Finally, the deployment of the model is done by preparing the deployment code, developing a deployment strategy, and deploying the final model in the actual environment.

Calculating RUL of an Asset

How exactly is RUL calculated for the modern manufacturing industry?

Since a number of factors play a role in estimating the RUL of an asset, a single strategy for calculation cannot be relied upon. Moreover, since different assets degrade at different rates, calculating RUL can be extremely specific.

Harnessing the power of data and AI models:

The extensive use of sensors across modern smart factories has enabled the collection of large pools of real-time asset performance data. AI/ML models can be utilized to estimate RUL values based on such data sets. Some popular models include **similarity models, survival models, and degradation models.** Recent case studies show how ML models were used to **accurately predict almost 45%** of failures for the transmission transformers asset class.

Considering all the factors:

As we mentioned earlier, a number of factors play a critical role in calculating RUL. These can include environmental factors, historical data, past experiences, usage patterns, maintenance history, and so on.

Analyzing degradation mechanisms:

Understanding the degradation mechanisms of a component can aid in the calculation of RUL and in developing maintenance plans. General degradation mechanisms include wear, corrosion, fracture, and deformation.

Leveraging RUL for Life Extension of Assets

Accurately predicting RUL can be **useful in extending the life of any asset.**

Industrial assets are generally designed to have long service lives. For example, wind turbines tend to have a life expectancy of about **20–25 years;** the same goes for aircraft in the aviation sector, depending on flight hours and cycles. When expensive assets near the end of their design lives, replacing them becomes both costly and time-consuming, which makes a Life Extension (LE) strategy essential.

Key Focus on Life Extension

Life Extension (LE) is an EoL strategy based on extending the operational life of an asset beyond the original design life to extract the most value from it. For modern manufacturing industries that wish to reap the most benefits, a smart LE strategy can be a gamechanger.

According to the condition of the asset, LE strategies can vary based on a number of technical and economic factors. Suitable LE strategies for an individual asset or component can often include replacement, reconditioning, repair, use-up, and refurbishment, to name a few.

Utilizing RUL for Personalized LE Strategies

A one-size-fits-all LE strategy **cannot adequately cover the individual requirement of each machine.** By leveraging RUL values predicted on a real -time basis, personalized LE strategies can be formulated for maximum benefits.

Customized Maintenance Plans:
To maximize the longevity of assets, it is crucial to develop tailored maintenance schedules based on RUL insights. These customized plans contribute to greater LE of assets.

Improved Safety and Risk Mitigation:
Implementing personalized LE strategies based on RUL insights contributes to improved safety and risk mitigation. By proactively addressing maintenance needs and potential failure points, companies can minimize the risk of accidents and equipment malfunctions.

Data-driven Optimization:
By carefully analyzing RUL values, organizations can identify patterns, risks, and areas for improvement.

The Issues With Assets

In a highly volatile ecosystem, a plethora of challenges regularly hinder operations. What are the most prevalent issues with asset management and **how can an RUL-informed approach solve these challenges?**

Soaring Costs

Maintenance costs roughly range between 20–60% of all opex spend in a manufacturing industry. The traditional reactive maintenance approach, without a clear picture of RUL, often leads to increased costs as organizations face the burden of sudden breakdowns, emergency repairs, and expensive impromptu replacements.

By adopting a proactive maintenance approach based on accurate RUL insights, manufacturers can **effectively manage assets** and **prevent costly breakdowns.** Accurate RUL estimations enable timely maintenance interventions as well, reducing the likelihood of unexpected failures, emergency repairs, and associated expenses.

Losses Due to Downtime

Unexpected downtimes from unforeseen asset failures massively disrupt production schedules, resulting in production delays and significant financial losses.

By leveraging RUL estimates, manufacturing companies can **implement proactive maintenance strategies to minimize downtime.** Timely predictive maintenance interventions based on RUL insights help avoid costly unplanned downtime, maximize asset availability, and ensure uninterrupted production. Predictive maintenance is so effective that companies with the most mature RCM (reliability-centered maintenance) **capabilities spend approximately 70–85% of technician hours on it.**

Unavailability of Critical Parts for Assembly Lines and Value Chains

Unpredictable demand for vital parts is often a result of insufficient visibility into RUL and inaccurate asset health assessments. Due to disruptions caused by the lack of essential components, **manufacturing is delayed, delivery dates are missed, and consumers are dissatisfied.**

Data-driven digital maintenance transformations in heavy industries have the potential to **increase asset availability by 5 to 15%.** RUL optimization encompasses proactive management of the supply chain in addition to asset maintenance. Organizations can predict the need for crucial components and proactively control their supply by successfully estimating RUL.

Key Benefits of an RUL-Informed Approach

Enhanced Asset Reliability:
Accurate RUL estimations enable proactive maintenance strategies, reducing the likelihood of unexpected breakdowns and minimizing detrimental downtime to **improve asset reliability.**

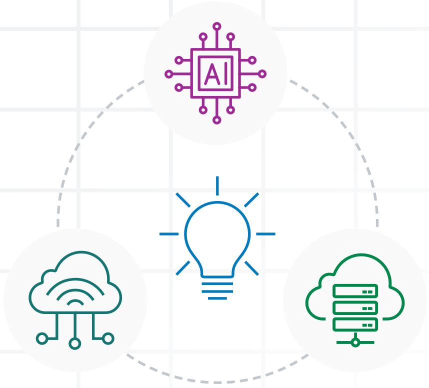
Cost Savings:
Adopting an RUL-informed approach allows companies to optimize their maintenance and asset replacement strategies, resulting in substantial cost savings. For heavy industries, leveraging digital maintenance transformations can **reduce maintenance costs by 18 to 25%.**

Data-Driven Decision-Making:
An RUL-informed approach empowers companies to make informed decisions regarding asset management.
A recent industry case study shows that using data-driven analytics in asset management can help companies save **20-25% in operating costs and 40-60% in capital expenditures.**

Enables Predictive Maintenance:
Leveraging Industry 4.0 technologies, **companies can analyze real-time asset data** and historical trends to predict when maintenance interventions will be required. In fact, recent case studies have shown that manufacturing companies that enable predictive maintenance.

Strategic Resource Allocation:
By identifying assets with **shorter RULs,** organizations can allocate resources where they are most needed, ensuring that the unavailability of critical components never causes an issue by disrupting the value chain.

The Bosch Standard: Our Expertise and Solutions to Extend RUL



Bosch stands as one of the global leaders with expertise in Asset Life and Asset Management by leveraging state-of-the -art solutions and **modern technologies such as AI, IoT, cloud computing,** and so much more.

Embracing Industry 4.0

According to a survey conducted among a group of **maintenance managers, only 50%** believed their current IT/OT architecture could sufficiently support their maintenance and reliability processes. This shows an evident lack of a strong technological backbone.

At Bosch, we have spent years perfecting our Industry 4.0 services, many of which are regarded as staples for the modern, smart factory today. By embracing connectivity and data-driven decision-making, we ensure our partners reap the benefits of RUL-driven asset management made possible by Industry 4.0 solutions.

Companies that adopt the latest technologies into their maintenance processes have successfully **reduced their maintenance costs by up to 30%.** The comprehensive solutions provided by Bosch include IoT services powered by complex sensors, resilient cloud-computing capabilities, sophisticated AI models for RUL predictions, and much more.

The Power of AI-Based Models

AI lies at the very core of Bosch's RUL prediction and extension endeavors. By harnessing the capabilities of AI/ML algorithms, companies can analyze the vast amounts of data collected by their sensors to enable predictive maintenance.
In fact, certain case studies have shown that companies that take a data-driven approach and adapt their maintenance schedules accordingly see **cost reductions of up to 46%.**

At Bosch, we leverage mathematical models that capture relevant information and identify the optimal settings. Currently supporting over 30 asset models, our digitalization offering DEEPSights can be deployed on any customer site with ease, only requiring minimal tuning based on the contextual data collected from the new components and machines.

Meeting Essential Business KPIs

Significant cost reductions

Utilization of sophisticated predictive maintenance

Improved productivity and efficiency

Enabling process optimization through prescriptive process insights

Maximize the productivity, efficiency and profitability of your enterprise

Leverage the power of Industry 4.0 and AI to extend the life and value of your assets. We bring our expertise and solutions to help you get the most out of your assets. To learn more about how to strategize an RUL approach for your organization, get in touch with us today.

Contact Us

Bosch Software and Digital Solutions

India | USA | Europe | UK | Japan | Middle East | China | Vietnam

www.bosch-softwaretechnologies.com

connect.bgsw@in.bosch.com