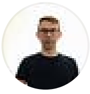
AI in Bearing Diagnostics: How We Learn to Predict Failures



Kirill | AI Solutions for High-Tech

8 min read · Mar 5, 2025

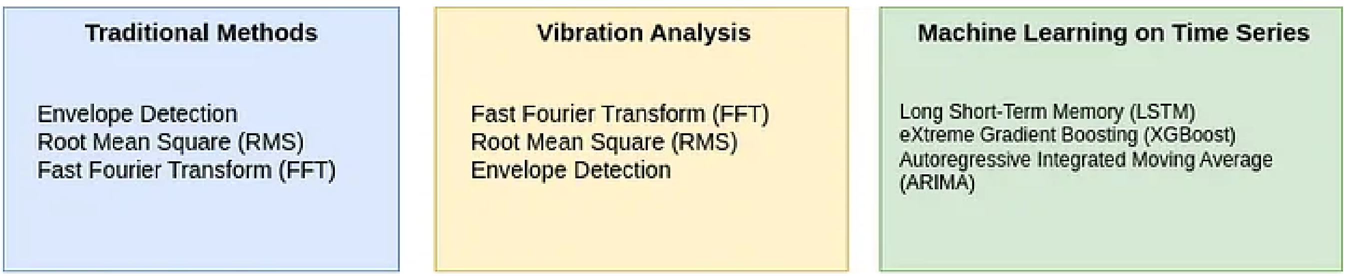
Imagine the complex mechanisms of industrial machines, aircraft engines, or turbines in power plants — wherever there is rotation and massive loads, bearings become one of the primary “bottlenecks.” The wear of a single bearing can bring an entire production line to a halt, cause power supply disruptions, or even affect flight safety. But what if we could “sense” a potential breakdown right at the onset of a defect, thus avoiding excessive effort (and cost) on critical repairs?

The Problem of Bearing Wear

Over time, a bearing inevitably faces friction, impact loads, temperature fluctuations, and other extreme conditions. With years of service or intensive use, damages appear — ranging from microcracks to deformation of rolling elements. A sudden failure can lead to unscheduled production downtime with serious financial losses, or even pose risks in transportation, aviation, and other critical industries.

Traditional Methods: Strengths and Limitations

Before diving into modern AI solutions, it’s worth looking at how engineers have been detecting bearing defects for decades. These traditional methods are time-tested but come with both advantages and limitations.



Vibration Analysis (Fast Fourier Transform (FFT), Root Mean Square (RMS), Envelope Detection)

In traditional bearing diagnostics, vibration analysis is frequently used, where:

> *Fast Fourier Transform (FFT) converts the signal from the time domain to the frequency domain, revealing characteristic peak frequencies if defects are present.*
>
> *Root Mean Square (RMS) calculates the mean square amplitude, reflecting the overall level of vibration activity.*
>
> *Envelope Detection helps highlight short, high-impact events and weak signals that may be "masked" in the main vibration profile.*

Advantages:

- **Fast computation:** Many algorithms (such as FFT) are easily implemented both on microcontrollers and on full-fledged server hardware.
- **Decades of practice:** A vast body of experience exists, with many proven solutions from different manufacturers.
- **Easy integration:** FFT and RMS vibration analysis is already part of the standard toolkit in industrial monitoring systems.

Disadvantages:

- **Late problem detection:** These methods typically flag issues only when the defect is already prominent in the frequency spectrum.
- **Fragmented coverage:** Each signal is considered separately, with no holistic view of the entire system.
- **Noise sensitivity:** In high-noise environments or with unstable equipment operation, thresholds often have to be set manually, complicating usage.

These approaches are quickly implemented on modern controllers and deliver results that have been validated by decades of practice. However, they primarily detect more "obvious" signals of problems and do not provide a system-wide perspective across all parameters.

Machine Learning on Time Series (Long Short-Term Memory (LSTM), eXtreme Gradient Boosting (XGBoost), Autoregressive Integrated

Moving Average (ARIMA))

Machine Learning–based approaches can analyze historical data and identify relationships that simple statistical methods might miss. Specifically:

> ***Long Short-Term Memory (LSTM):*** *Capable of "remembering" long-term dependencies and detecting trends before the obvious symptoms of wear appear.*
>
> ***eXtreme Gradient Boosting (XGBoost):*** *Recognizes complex nonlinear relationships that can be overlooked by classic methods.*
>
> ***Autoregressive Integrated Moving Average (ARIMA):*** *A fundamental statistical approach well suited for time-series with seasonality and trends.*

Advantages:

- **Forecasting future states:** LSTM and other models use historical data to detect emerging issues early.
- **Nonlinear factor consideration:** XGBoost and similar algorithms capture complex patterns that simple linear regression might miss.
- **Flexibility:** With a large dataset, the model can be retrained regularly, adapting to new operating conditions.

Disadvantages:

- **Data-intensive:** A reliable model needs a large, well-labeled dataset, which is not always feasible.
- **High computational requirements:** Training complex neural networks (especially LSTM) demands significant computational power.
- **Interpretation complexity:** For a maintenance engineer, it may be difficult to understand why the model made a particular decision in a specific case.

If a company has enough historical data and the ability to invest in the necessary hardware and software, time-series machine learning enables earlier and more accurate wear detection. However, success depends on a robust data collection system and specialists able to interpret results and maintain/retrain the models as needed.

Anomaly Detection (Autoencoder, Isolation Forest, One-Class SVM)

For systems where failures are extremely rare or the specific failure scenario is almost nonexistent, anomaly detection algorithms are particularly useful. Instead of "learning" from breakdown examples, these methods build a model of the "normal" state of the equipment and then trigger an alert when deviations occur.

Main Algorithms:

> ***Autoencoder:*** *Uses a neural network trained to reconstruct ("rebuild") "healthy" input data. If reconstruction becomes inaccurate (high error), it indicates a possible failure.*
>
> ***Isolation Forest:*** *Randomly partitions the dataset; points that get "isolated" more quickly than others are considered anomalies.*
>
> ***One-Class SVM:*** *Constructs a hypersurface enclosing the "normal" data; anything falling outside this boundary is flagged as an anomaly.*

Advantages:

- **No need for failure examples:** Algorithms focus on what "healthy" operation looks like — ideal when failures are very rare and there is little historical failure data.
- **Versatility:** This approach suits various signal types and systems where even a single failure can cause critical losses.
- **Minimal labeling:** You only need sufficient "normal" data; you don't have to carefully label multiple failure scenarios.

Disadvantages:

- **Sensitivity to changing conditions:** If the equipment transitions to new settings or operating modes, the algorithm may treat it as an anomaly since it was not part of the "healthy" baseline.
- **Complex interpretation:** In case of an alarm, it's clear that there is a deviation from the norm, but not necessarily which parameters caused it.
- **Risk of false positives:** Poor signal quality, unstable sensor behavior, or abrupt load changes can lead to an overload of false alarms.

If a company has no substantial failure history but knows well what "proper" operation looks like, anomaly detection methods can deliver quick and effective results. However, adjustments are needed when operating conditions change; otherwise, the system may generate many false alarms.

A New AI Approach: A Comprehensive "Snapshot" of the System

To analyze a bearing not in isolation but in conjunction with numerous other parameters, we employ techniques inspired by natural language processing (NLP). We utilize a specially designed LLM model adapted for industrial signals and analyze sensor readings (vibrations, temperature, RPM, load, and other indicators). This approach offers a holistic view of the system rather than focusing on just one sensor. In other words, instead of a traditional "per-sensor" method, we get an extensive "map" of the system's state — a map that reflects numerous, interrelated parameters. This approach enables us to:

- **Assess Degradation:** Track how the "matrix" representation of the entire system changes over time and how far it is from the reference "healthy" state.
- **Detect Anomalies:** Sharp, atypical spikes in this "matrix" signal that something is off, prompting immediate equipment checks.
- **Go from General to Specific:** Start with a system-wide analysis and then drill down to an individual sensor.

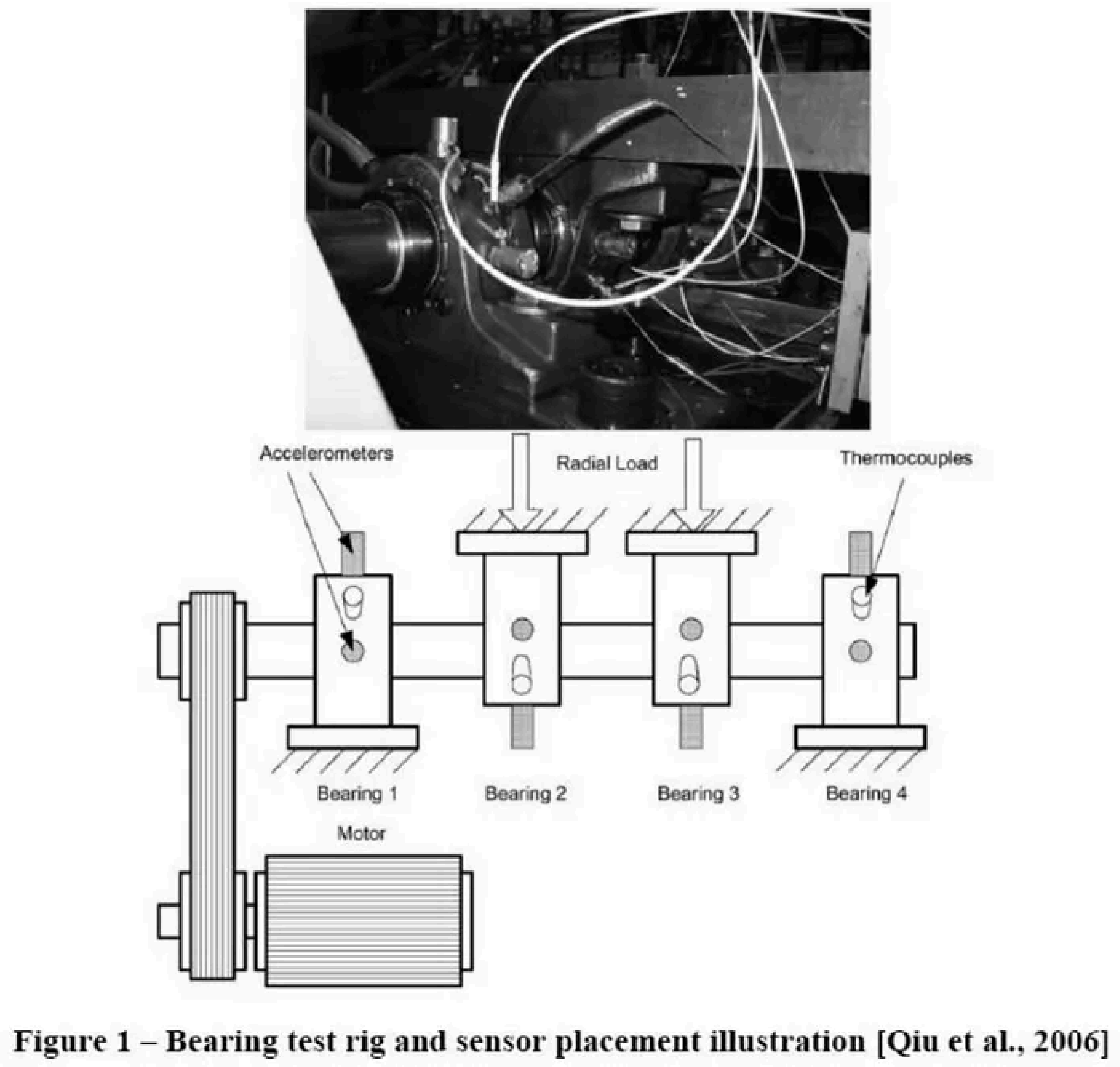
Why It Works

- **Deep context:** Instead of a single "channel" (e.g., a vibration signal), it looks at a combination of measurements from different sensors, catching subtle changes invisible when viewed separately.
- **Adaptability:** The system adjusts to changing conditions (operating modes, new sensor settings), minimizing false alarms.
- **Combining various features:** If one method is "silent" (due to noise), another can highlight the problem.

NASA Bearing Data Set: Putting Theory to the Test

To illustrate how the AI algorithm works, we used a public dataset from NASA **"4. Bearings,"** created by the Center for Intelligent Maintenance Systems (IMS) at the University of Cincinnati. It includes vibration measurements and other parameters of several bearings throughout their "lifespan". The dataset documentation describes the test stand and sensor placement.

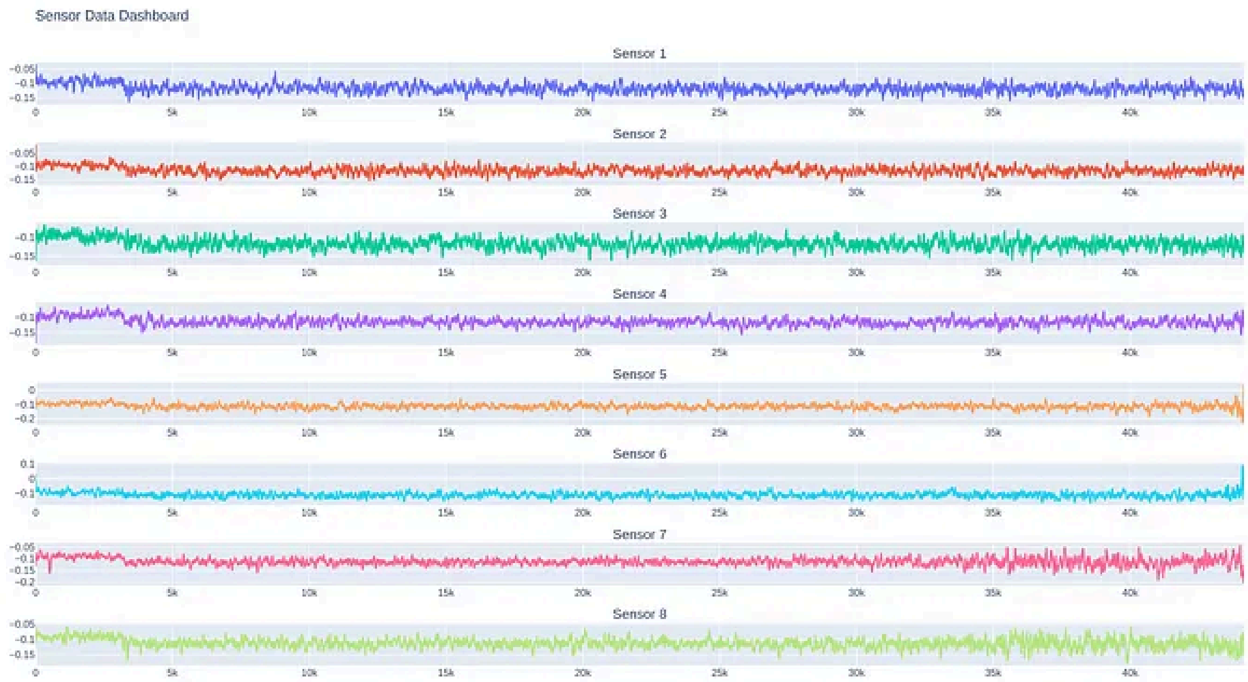
Sample Photograph from the Dataset



Sample Photograph from the Dataset

Experiment Overview

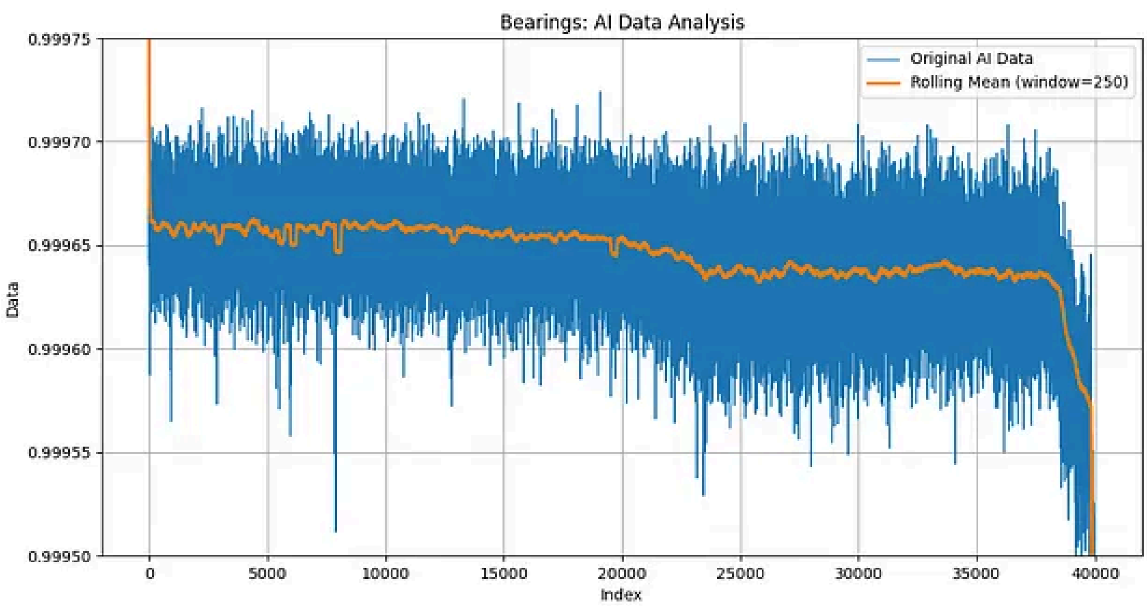
Initially, we examine the provided data. The first dataset includes information on four bearings and eight sensors. A graph of the sensor data is shown below.



Graph with sensor data from Dataset 1

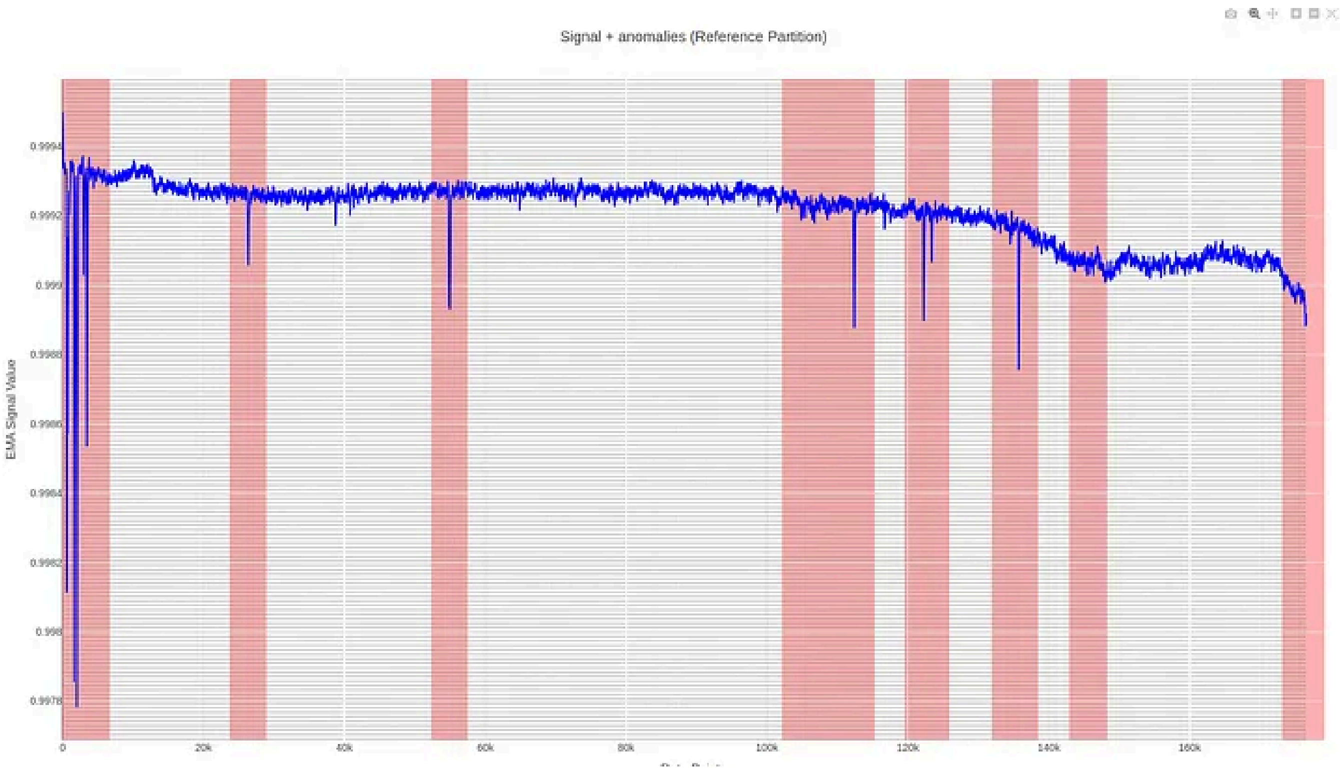
The previously mentioned methods alone would struggle to identify which bearing is failing. We do not have a large dataset for training models, nor do we have data from similar bearings for comparison. Essentially, aside from eight plots, there is nothing else.

To solve this problem, we employ the AI approach described above. We build a "system state" matrix and observe how it changes over time. Below is a graph of the analysis results.



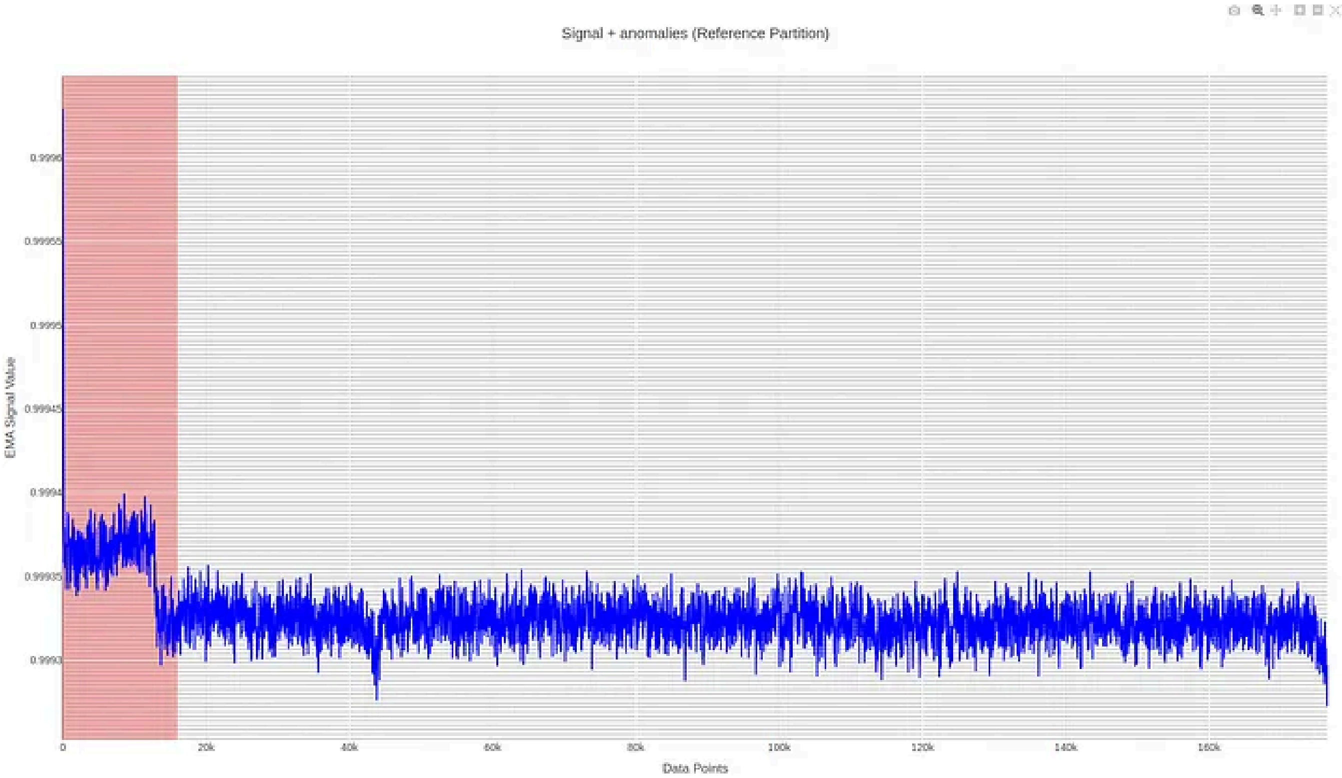
Graph showing AI-based degradation analysis of Bearing from Dataset 1. We can see that after the point at 20,000, the system's state starts to change.

Once we detect a system change, the same algorithm is applied to all sensors, revealing that the problem lies in Sensor 7. We also identify anomalies that appeared. We do not analyze the physical meaning of an anomaly, but we do observe it.



Graph showing AI-based degradation analysis for Bearing #7 from Dataset 1

For comparison, below is a graph for Bearing #1, which has no defects.



Graph showing AI-based degradation analysis for Bearing #1 from Dataset 1

In both graphs, some transient processes are visible at the very beginning, but then the system operates steadily.

How the AI Approach Overcomes Limitations and Provides Advantages

1. **Holistic Perspective and Quick Problem Identification**
Instead of monitoring individual sensors independently, the AI method immediately displays a "map" of the entire system, then allows you to drill down to the specific node (or sensor) where a fault may lie.

2. **Early Diagnostics**
The system detects signs of degradation long before they escalate to critical levels. This gives you time to carry out maintenance when it is still cost-effective and avoid emergency downtime.

3. **No Need for Large Fault Datasets**
The model evaluates the current state of the equipment and does not require extensive breakdown histories, greatly simplifying implementation.

4. **Versatility**
This approach detects both gradual wear and sudden spikes. Its "matrix" core can be easily adapted to a variety of signals (vibration, temperature, load, etc.).

5. **Cost-Effectiveness**
   By catching failures early, companies reduce expenses on emergency repairs and equipment downtime. In addition, timely diagnostics enhance safety in critical industries.

By integrating a system-wide analysis, adaptive capabilities, and minimal requirements for failure data, AI solutions deliver detailed and timely detection of bearing issues, driving down costs and increasing the reliability of production infrastructure.

Where Is This Approach Useful?

- **Aviation and Transportation,** where reliability saves lives.
- **Mechanical Engineering,** where every second of downtime equals financial losses.
- **Energy Sector,** where a turbine or generator failure can trigger a “domino effect” in the grid.
- **Other Industries** with harsh operating conditions and high safety standards.

Conclusion

We’ve demonstrated that innovative AI technologies can be used not only for everyday tasks or creating chatbots but also to analyze critical systems. By employing holistic analysis, flexible adaptation, and minimal data on failures, AI provides powerful, early, and cost-saving diagnostics for bearings, enhancing reliability across vital industrial sectors.

AI High Tech Predictions Bearings Artificial Intelligence