When Predictive Signals Fail:
Why Some Time-Series Data Cannot Support Prediction

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Introduction

Predictive models are widely used in monitoring systems to anticipate failures and optimize maintenance.

In practice, however, many of these models fail.

Not because of noise.
Not because of insufficient data.
And not necessarily because of poor modeling choices.

But because the underlying signal does not contain usable predictive information.

This analysis is based on widely used benchmark datasets in predictive maintenance, including:
• the IMS bearing dataset (real-world vibration measurements)
• the C-MAPSS turbofan datasets (NASA simulation data)
• an independent vibration dataset sourced from GitHub (PredictiveMaintenance-and-Vibration-Resources)

Before building predictive models, a more fundamental question should be asked:

Can this signal support prediction at all?

Core Idea

Instead of directly training models, three observable properties are evaluated:

• Structural behavior — $M(t)$
• Cross-run consistency — C
• Prediction error — E

This leads to a simple decision framework:

Prediction is only feasible when all three conditions are satisfied simultaneously:
• structure is present ($M(t)$)
• structure is consistent across runs (C)
• the signal is learnable (low prediction error E)

If any of these conditions fail, predictive modeling will not be reliable.
Key Insight:
Predictability ≠ usefulness.
A signal can be highly predictable and still contain no meaningful information about system behavior.

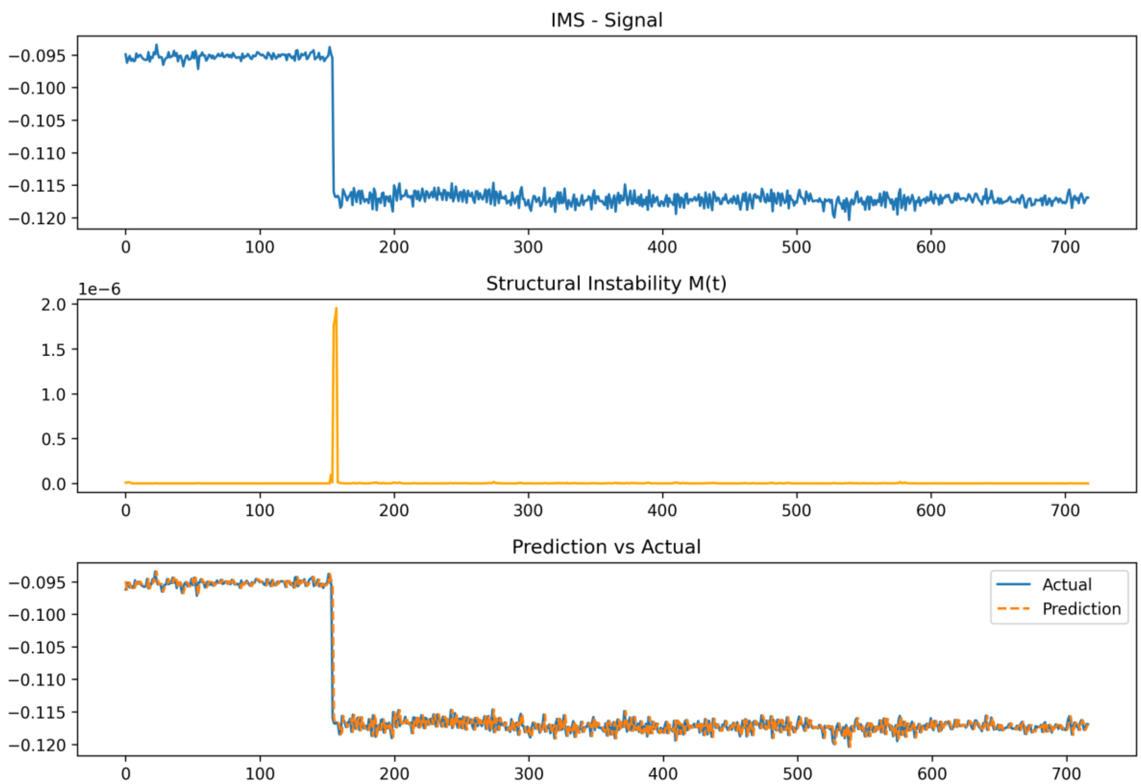
Case 1 — Predictable but Not Informative (IMS Dataset)

The IMS dataset is based on real vibration measurements from bearing systems.

The signal is stable and highly predictable over time.

However, it does not exhibit meaningful structural evolution associated with system degradation.

The signal appears suitable for modeling, but contains no predictive information.
Prediction is not supported by the signal.

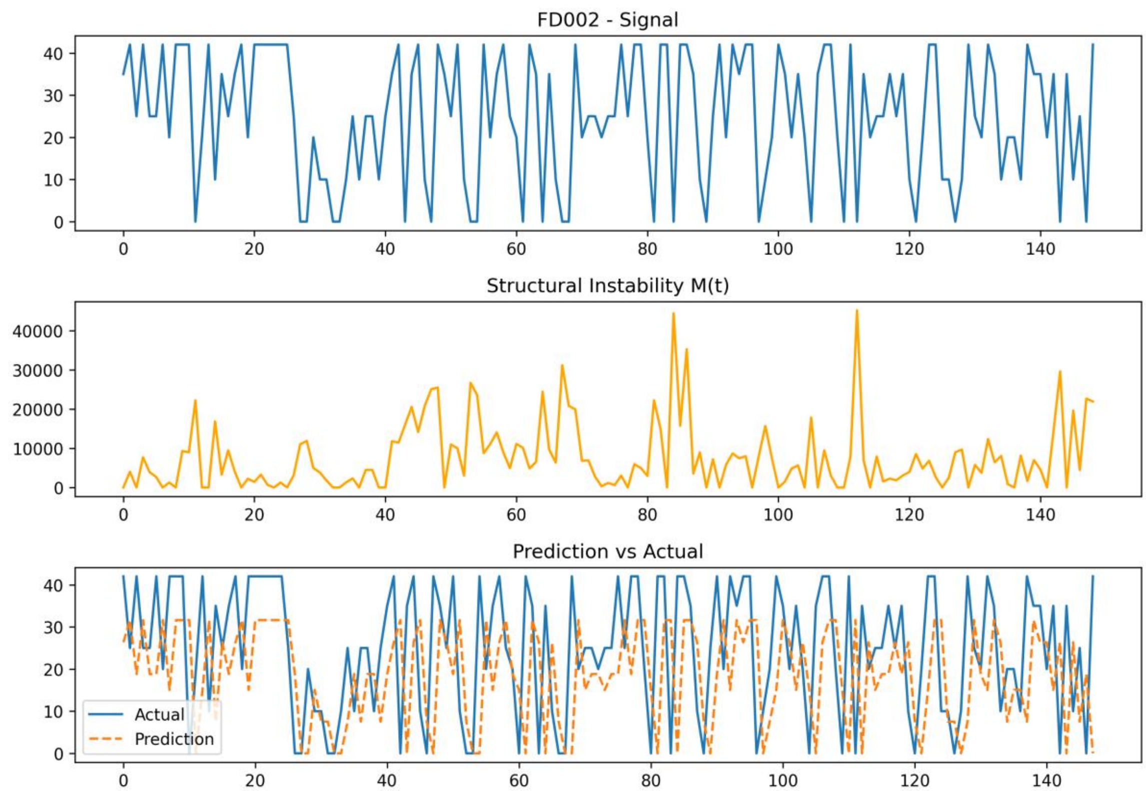


Case 2 — Inconsistent Structure (FD002 Dataset)

The FD002 dataset (NASA C-MAPSS) shows strong activity and structural variation.

However, patterns are not consistent across runs.

Prediction is unreliable because the underlying structure is not reproducible.

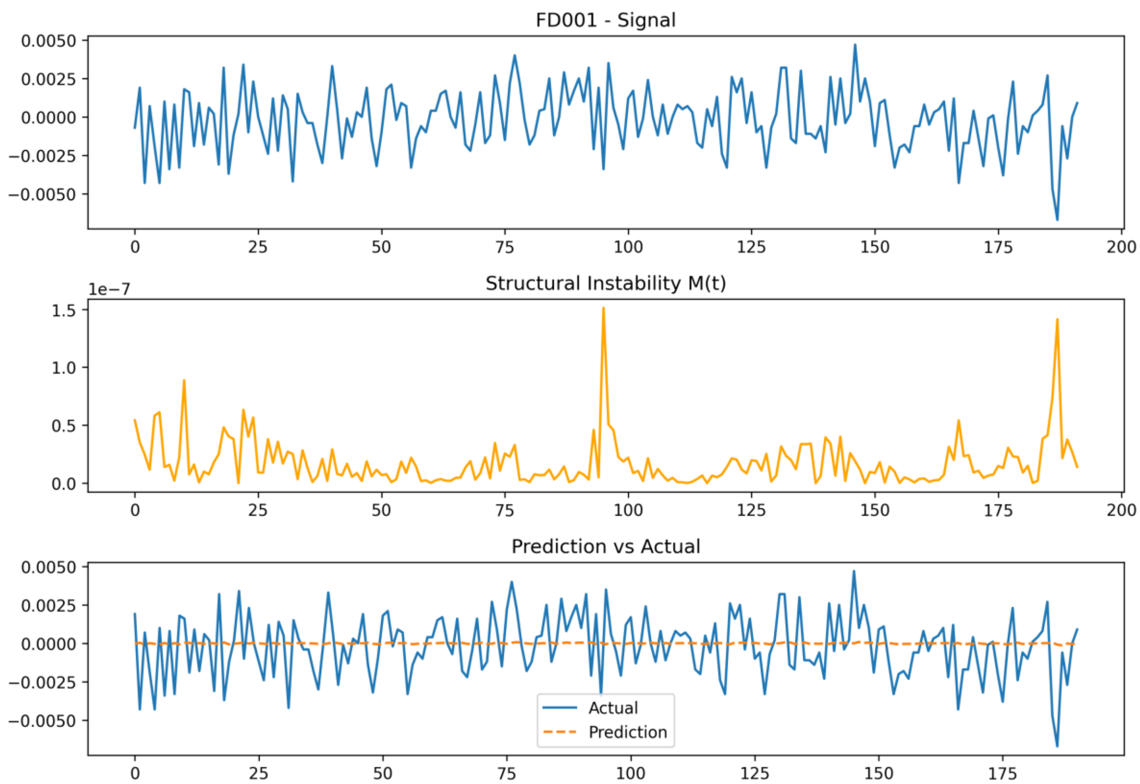


Case 3 — Consistent and Predictable Structure (FD001 Dataset)

The FD001 dataset represents a stable system regime.

This signal exhibits consistent and reproducible structural behavior across runs.

This represents a regime where prediction is feasible because structural behavior is consistent and reproducible.



Case 4 — Independent Industrial Vibration Data (GitHub Dataset)

This dataset is sourced from the GitHub repository:
Predictive-Maintenance-and-Vibration-Resources.

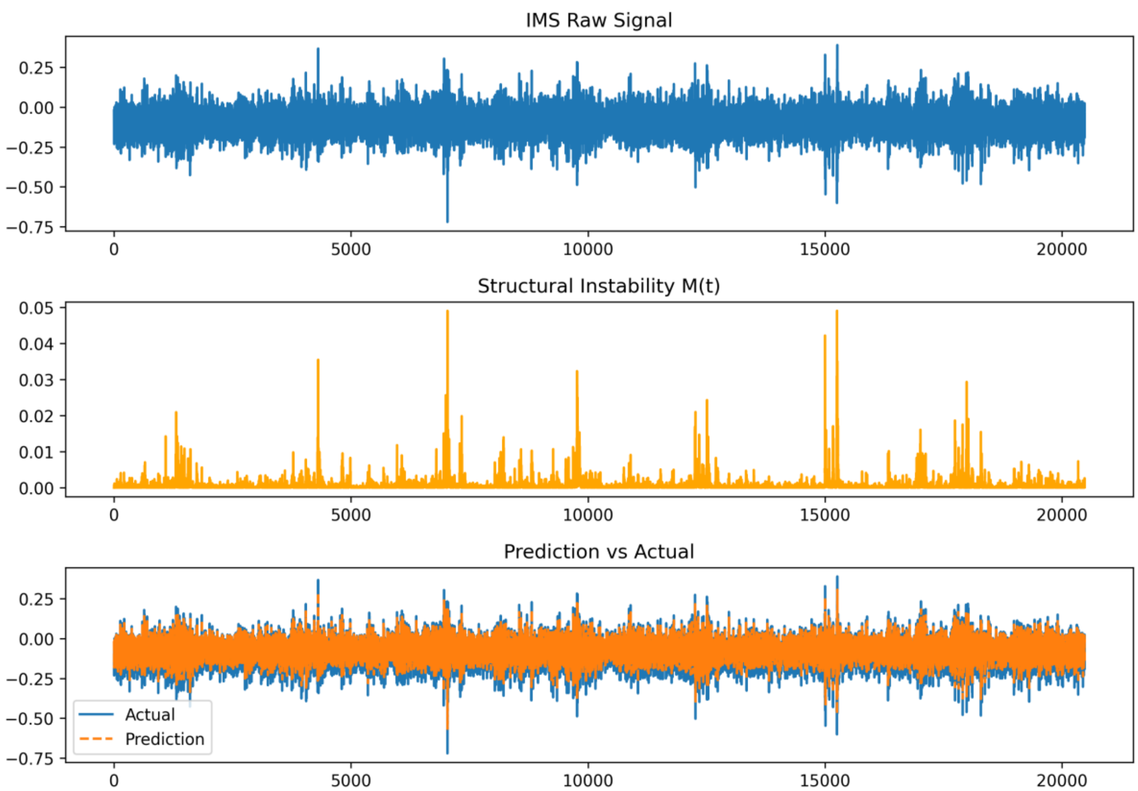
The analysis is based on multiple independent signal recordings, including:
• 2003.10.22.12.06.24
• 2003.10.22.12.09.13
• 2003.10.22.12.14.13
• 2003.10.22.12.19.13

These recordings are treated as separate observations of the same system.

The signal appears stable and predictable when analyzed individually.

However, when compared across multiple recordings, structural behavior is not reproducible. Patterns observed in one run do not persist in others, indicating the absence of a consistent underlying structure.

Conclusion:
The signal does not contain usable predictive information.



Across these cases, the difference is not how much change is present, but whether that change is consistent and interpretable across observations.

Conclusion

The main limitation in predictive systems is not modeling.

It is the signal itself.
Detecting change is easy.
Interpreting change is not.

Predictive modeling should not start with models, but with a simple question:
Does this signal contain meaningful predictive structure

If not, prediction is not a modeling problem — it is a limitation of the signal itself.