

# PREDICTIVE FEASIBILITY

PFA

## Real-World Validation Case 01

### FD001 vs FD002

#### Question

Can two similar datasets produce completely different predictive feasibility outcomes?

#### Result

FD001 → GO

FD002 → NO-GO

#### Key Insight

Signal structure matters more than dataset category.

## Same Benchmark. Completely Different Outcome.

#### Question

Can two datasets from the same benchmark family produce fundamentally different predictive feasibility outcomes?

This question was investigated using two of the most widely used turbofan degradation datasets from the NASA C-MAPSS benchmark:

- FD001
- FD002

At first glance, both datasets appear suitable for predictive modeling. Both contain degradation trajectories, multiple operating cycles, and are commonly used in Remaining Useful Life (RUL) research.

However, the Predictive Feasibility Assessment (PFA) framework revealed a fundamental difference.

## **What Was Evaluated?**

The analysis focused on:

- structural reproducibility
- cross-run consistency
- predictive stability
- long-range deployment viability

The objective was not to determine whether a model could be trained, but whether the signal itself contained stable and reproducible predictive structure.

## **Result**

The two datasets produced fundamentally different outcomes.

### **FD001**

- Stable degradation trajectories
- High structural consistency
- Reproducible behavior across runs
- Persistent predictive regime

### **Classification: GO**

Predictive modeling is structurally justified.

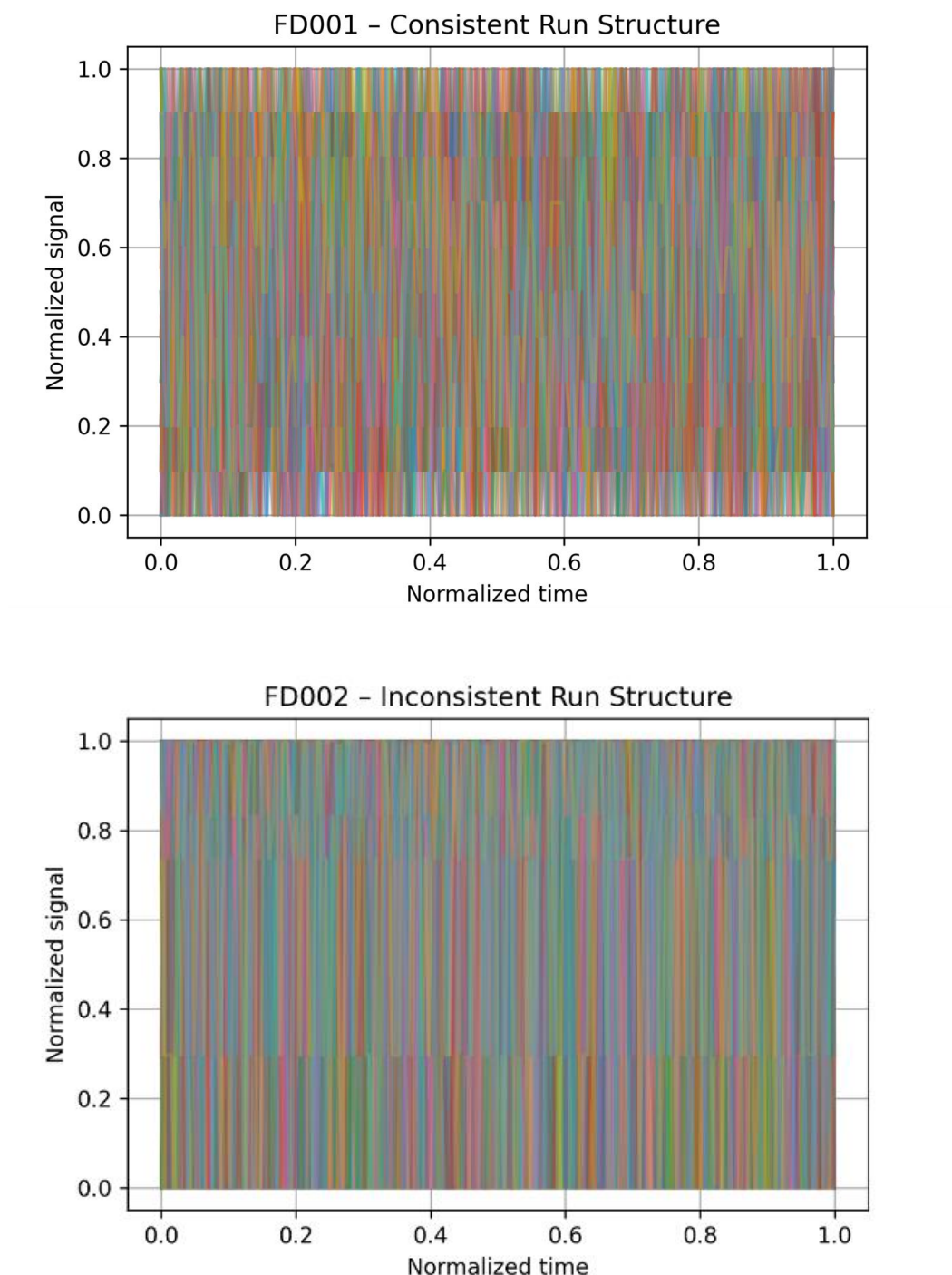
### **FD002**

- Strong operational variability
- Inconsistent trajectory behavior
- Reduced cross-run reproducibility
- Persistent instability across runs

### **Classification: NO-GO**

Predictive modeling is structurally constrained by the signal itself.

**Figure 1 — FD001 versus FD002**



**Caption**

Comparison of predictive feasibility behavior across the NASA C-MAPSS FD001 and FD002 datasets.

Although both datasets belong to the same benchmark family and are frequently used for predictive modeling research, the underlying signal structure behaves fundamentally differently.

FD001 exhibits stable and reproducible degradation behavior, supporting reliable predictive modeling. FD002 exhibits persistent structural inconsistency and instability across runs, resulting in substantially lower predictive feasibility.

The figure illustrates that predictive success depends not only on the dataset category, but on the reproducibility of the underlying signal structure.

## Why This Matters


Many predictive AI projects begin with the assumption that prediction is possible because data exists.

This case demonstrates that:

- similar datasets can produce different predictive outcomes
- model complexity cannot compensate for missing reproducible structure
- predictive feasibility should be evaluated before model development begins


The limitation is often not the model.

The limitation already exists within the signal.




## INDUSTRIAL IMPLICATION

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Two datasets may appear similar.

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**FD001** → Stable Deployment Potential


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**FD002** → Structural Deployment Risk



**The difference is *not* the model.**  
The difference is the reproducibility of the underlying signal structure.



Evaluating predictive feasibility **before** model development can **prevent months** of unnecessary engineering effort and **reduce deployment risk** before resources are committed.

## **Key Takeaway**

The FD001 versus FD002 comparison represents one of the clearest examples of why predictive feasibility must be evaluated before substantial modeling effort is invested.

Two datasets.

One benchmark family.

Completely different predictive feasibility outcomes.

The difference is not model choice.

The difference is signal structure.