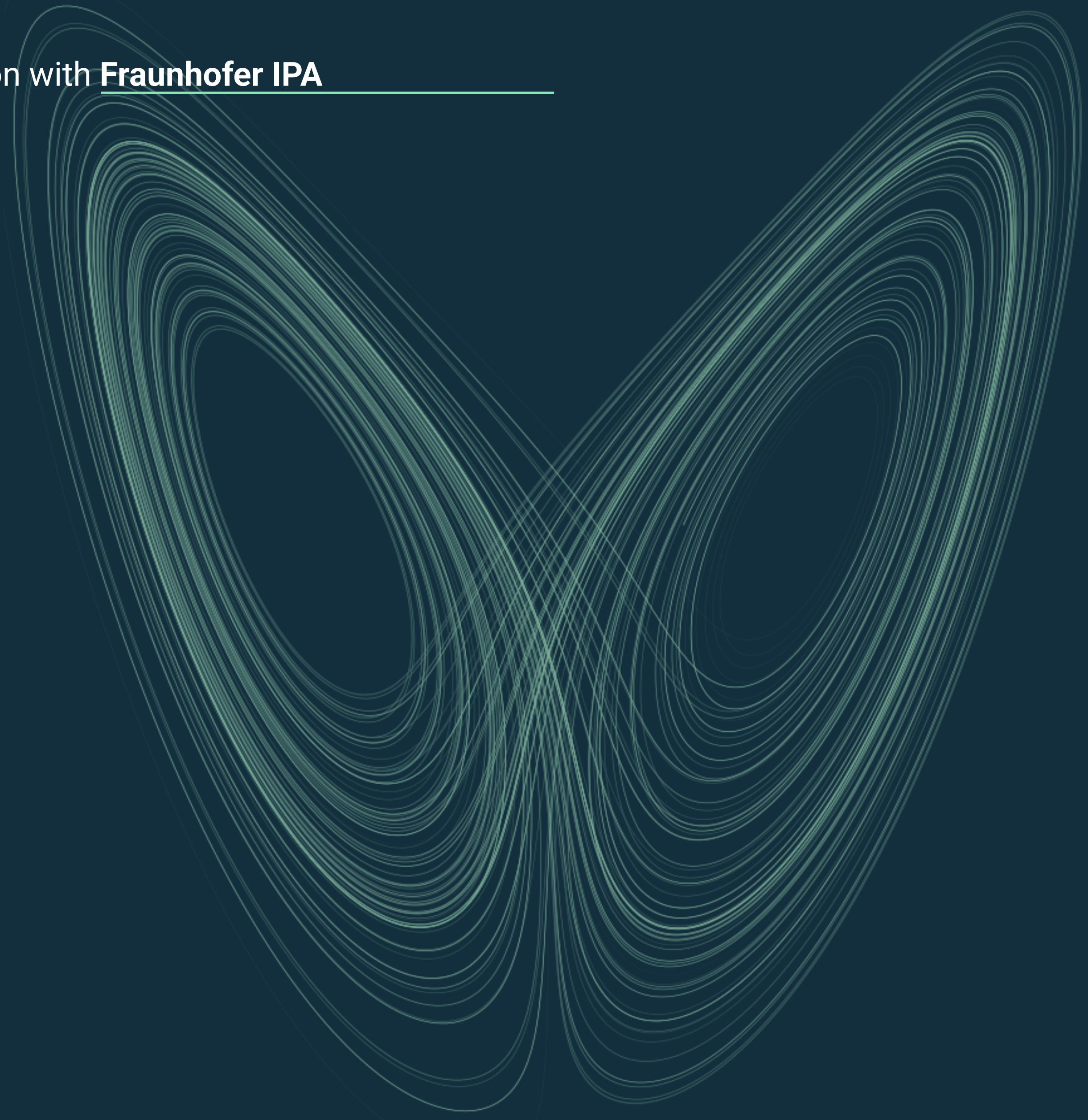
April 2026

Closing the loop in Battery Can Manufacturing

A Case Study on AI-Based Defect Prediction

In cooperation with **Fraunhofer IPA**



Prepared By :

AccelionTech

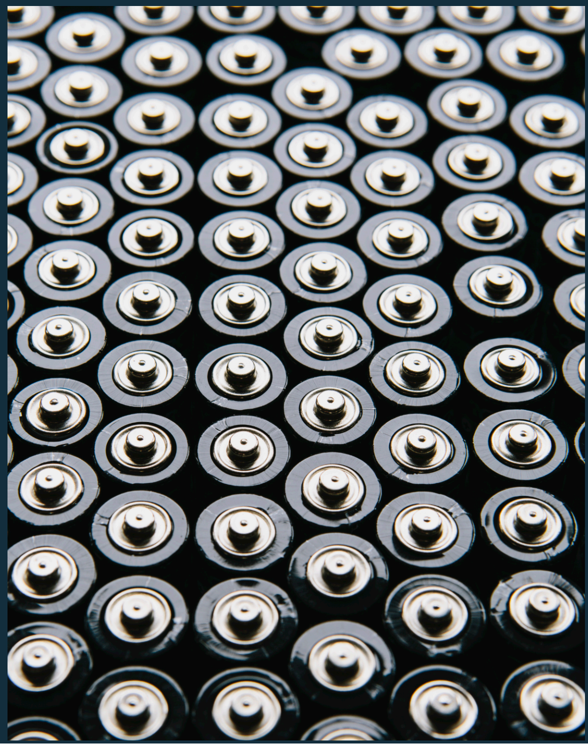
CONTENTS

EXECUTIVE SUMMARY

Manufacturing systems generate large volumes of process data, but quality decisions are often disconnected from the physical process behavior that drives defects. This disconnect limits interpretability, delays intervention, and constrains scalability in production environments.

In a joint study, **AccelionTech** developed for **Fraunhofer IPA** a physics-informed AI platform for the spin-grooving process in cylindrical battery can production that connects machine settings, predicted force behavior, and process quality. The approach identifies physical signatures of process quality; stable operation corresponds to strong, consistent measured process forces, whereas weaker and more variable signals reflect quality loss.

The system reasons in two directions: using standard inputs, the framework evaluates parameter configurations prior to production, attributes quality variation to individual variables, and expresses expected behavior through interpretable force characteristics. The model remains stable under previously unobserved conditions, with uncertainty explicitly quantified to support robust decision-making beyond the training domain. During validation this approach reduced the observed defect rate from **30% to less than 3%**.



Predictive Quality Control

This work shows how a **physics-informed AI** solution can make complex forming processes more predictable, less dependent on tacit expert knowledge, and more scalable across multiple processes and productions steps in **advanced manufacturing** environments.

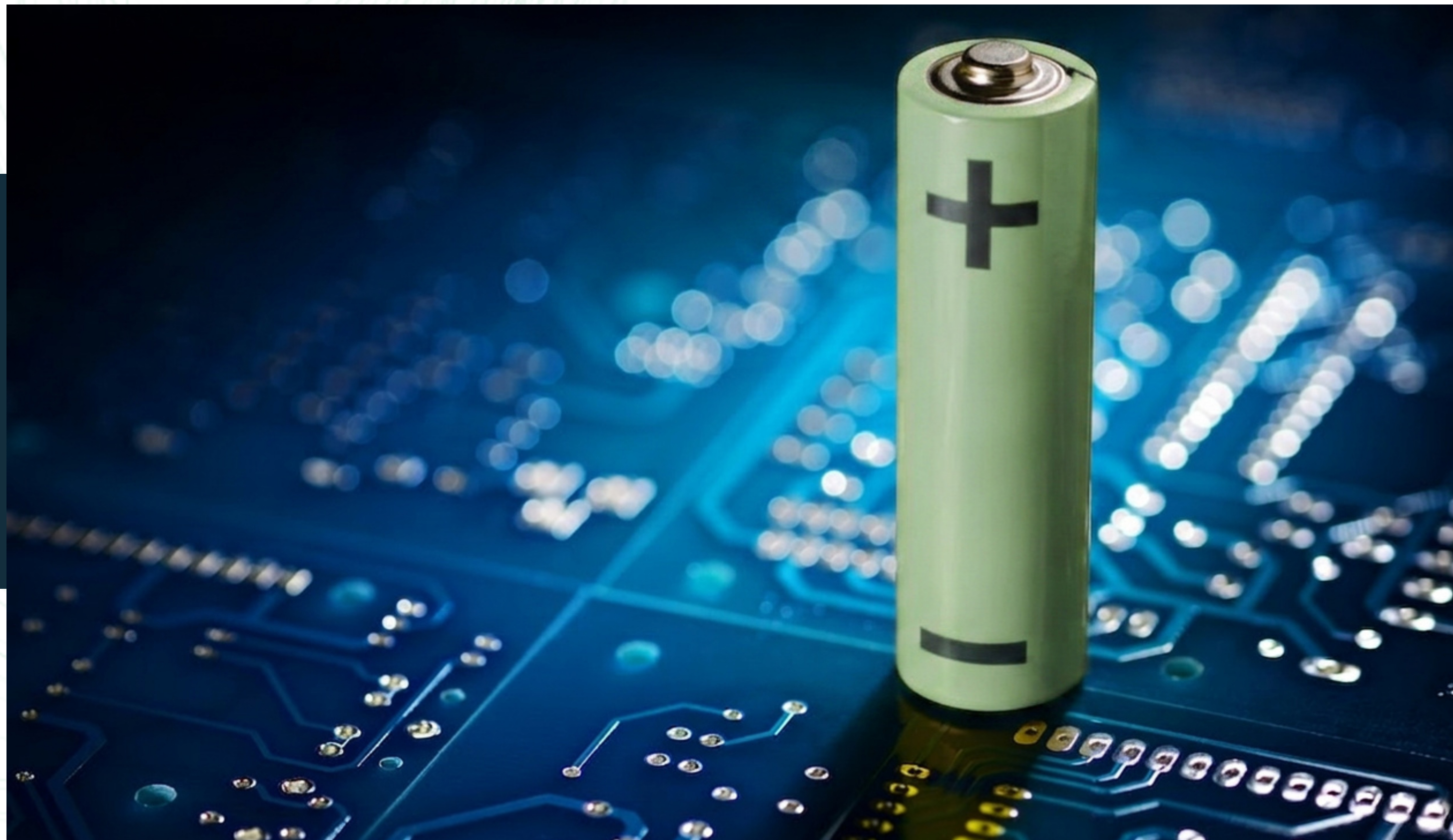
THE PROBLEM

In metal forming operations such as spin grooving, defects arise from multivariate, non-linear interactions between machine parameters, tool positioning, and material response. These interactions are reflected in process forces, which act as an intermediate state variable linking parameter configuration to final part quality. In industrial practice, this causal chain that covers parameter settings from force evolution to defect formation, is managed through iterative parameter adjustment and post-process inspection rather than structured evaluation during process setup.

> ***"The causal chain from parameter settings to force evolution to defect formation is managed through iterative adjustment and post-process inspection and not structured evaluation during process setup."***

THE APPROACH

The platform provides a unified decision environment that takes standard machine parameters as input and return defect probability, a decomposition of how individual parameters contribute to risk and expected process behavior in form of force characteristics. Each prediction is accompanied by a structured reasoning layer grounded in physical principles, where forces represent the process state linking parameters to quality and can be further explored through an interface that allows users to query and refine the interpretation. The same representation supports both forward and reverse use, from parameters to predicted quality and from process behavior to defect risk, enabling consistent interpretation across operating conditions. This approach is validated with Fraunhofer IPA to establish a deterministic basis for process decisions.

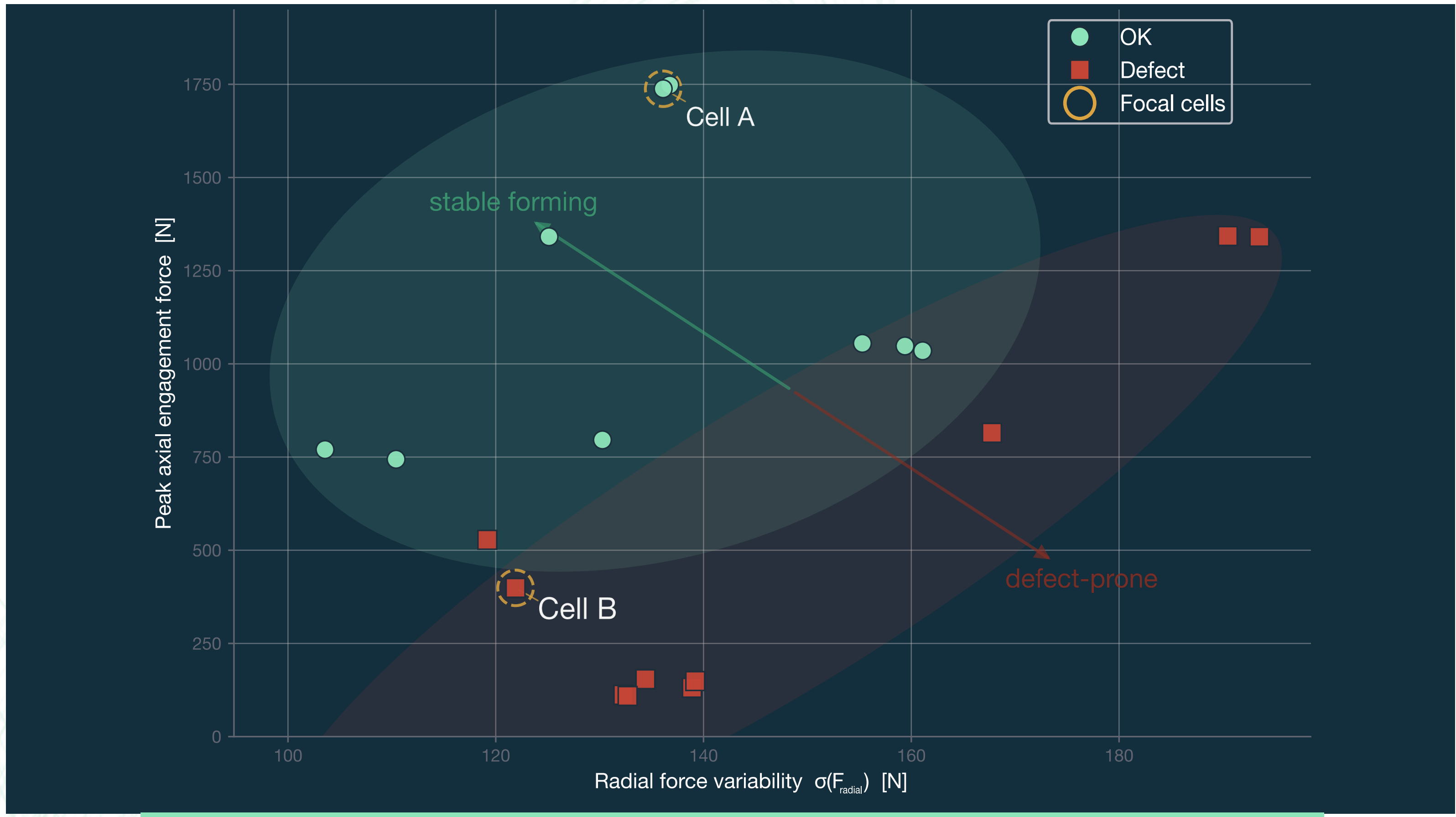


FORCE PROFILE CONSISTENCY AND DIAGNOSTIC INFERENCE

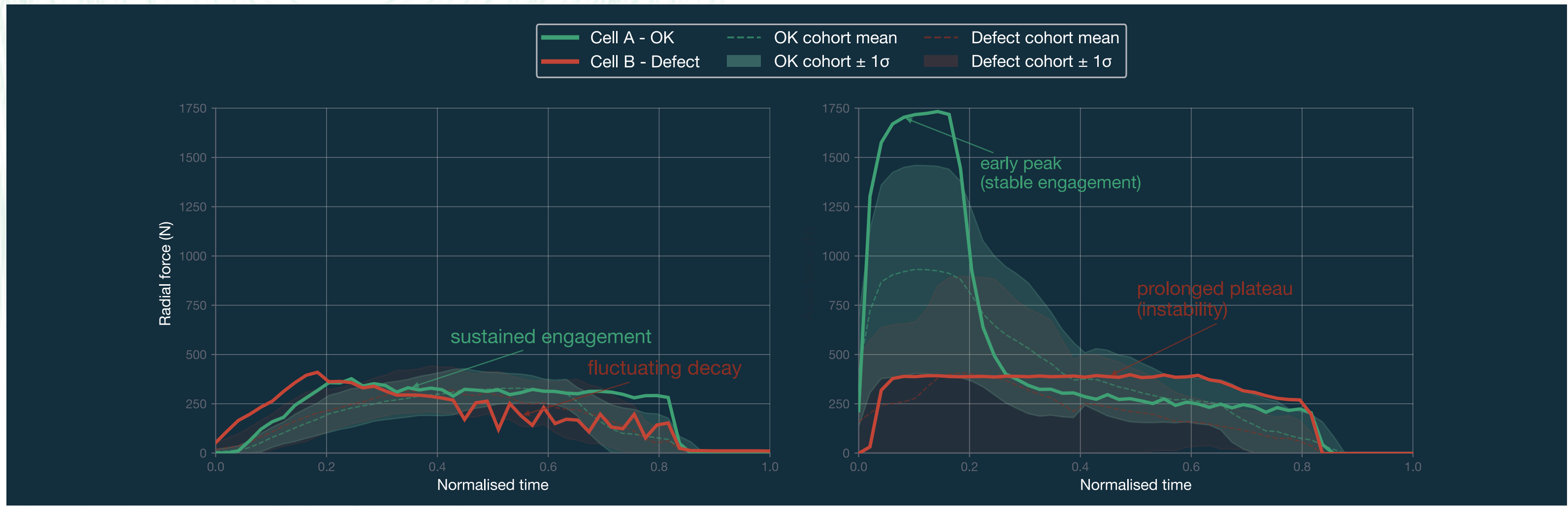
> *"Axial and radial force profiles contain enough information to distinguish stable forming from defect-prone forming."*

The platform establishes that measrured process forces are signatures of process quality, enabling direct inference of defect outcomes from force characteristics without parameter reconstruction. Across operating conditions, axial and radial force profiles exhibit structured patterns that reflect the underlying deformation mechanics. Stable forming is characterized by strong axial engagement, a rapid rise to a high peak force followed by controlled decay, together with a smooth, sustained radial response indicative of stable material flow. In contrast, defect-prone conditions manifest as reduced axial engagement, prolonged low-force plateaus, and increased radial variability, reflecting insufficient constraint and unstable flow. These signatures arise from first principles: support pressure governs contact force and boundary constraint, which determines whether deformation remains stable or transitions into instability.

This evidence demonstrates that force is a diagnostic variable that encodes process stability. As a result, the platform operates directly on measured physical signals, detecting defects and attributing them to their underlying causes. This supports real-time quality assurance and closed-loop control: corrective actions can be guided by interpretable force signatures rather than empirical tuning.



Force-derived feature space. *Stable runs cluster at high axial engagement and low radial variability; defect-prone runs cluster at reduced engagement and higher variability. The separation demonstrates that measured process forces enable direct inference of process stability.*



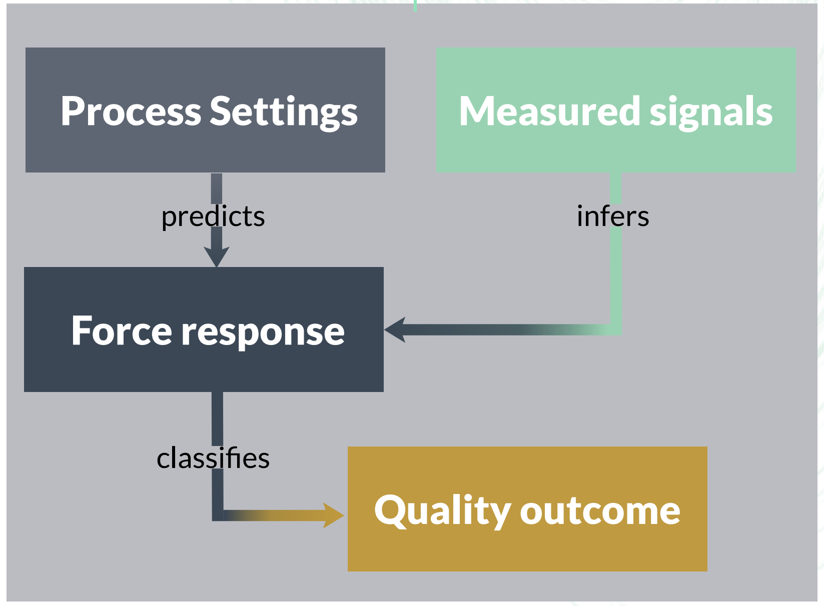
Force profiles. *Stable forming show strong axial engagement (early peak, controlled decay)and a smooth radial response. Defect-prone runs show reduced axial engagement and increased radial variability. Patterns hold across the*

BIDIRECTIONAL CONSISTENCY BETWEEN PARAMETERS, FORCE, AND QUALITY

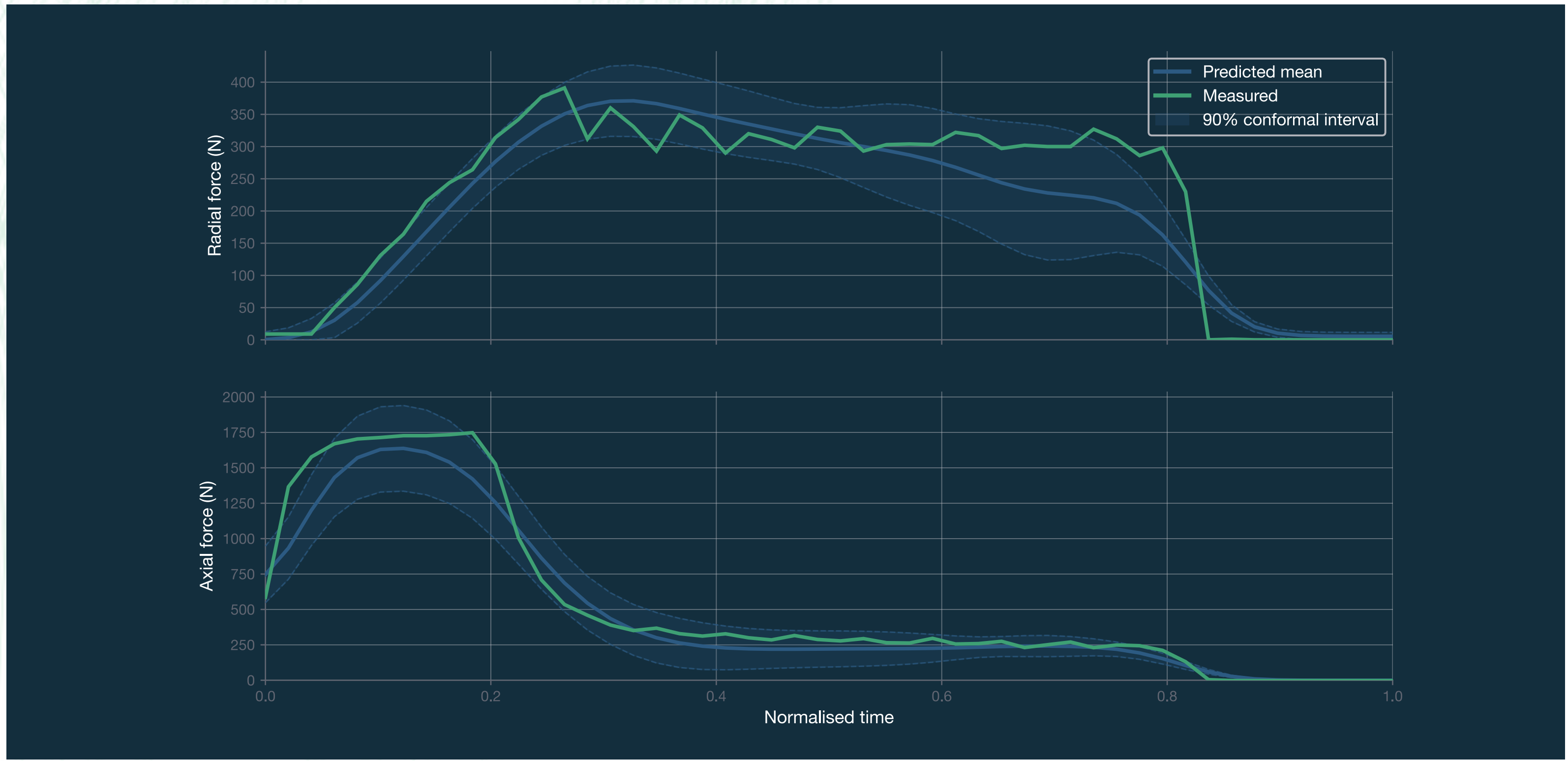
> *"The same force signature can be predicted forward from settings or read backward from sensors, and both routes give the same quality verdict."*

The platform demonstrates bidirectional consistency between process parameters, force response, and quality outcome which establish force as a physically grounded intermediary representation of the manufacturing process. From forward simulation, machine parameters generate predicted force profile that reproduce signal with high fidelity, capturing both the magnitude and temporal structure of tool-material interaction. These predicted force signatures lead to the same quality classification as the measured process, which confirms that the model encodes the correct physical dependencies.

Crucially, the same consistency holds in reverse; measured process forces alone are sufficient to infer process outcome, enabling diagnosis directly from in-situ data without access to machine setting. This enables inversion of the process, where force signatures can be used not only to assess quality but to reconstruct and reason about the underlying operating conditions.



In industrial terms, this established a unified, physics-aligned representation that supports both predictive process design and real-time quality assurance, that transforms Measured process forces into a direct and actionable measure of process stability

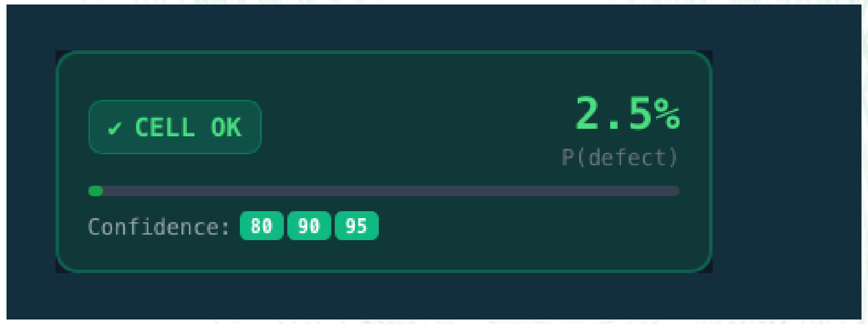


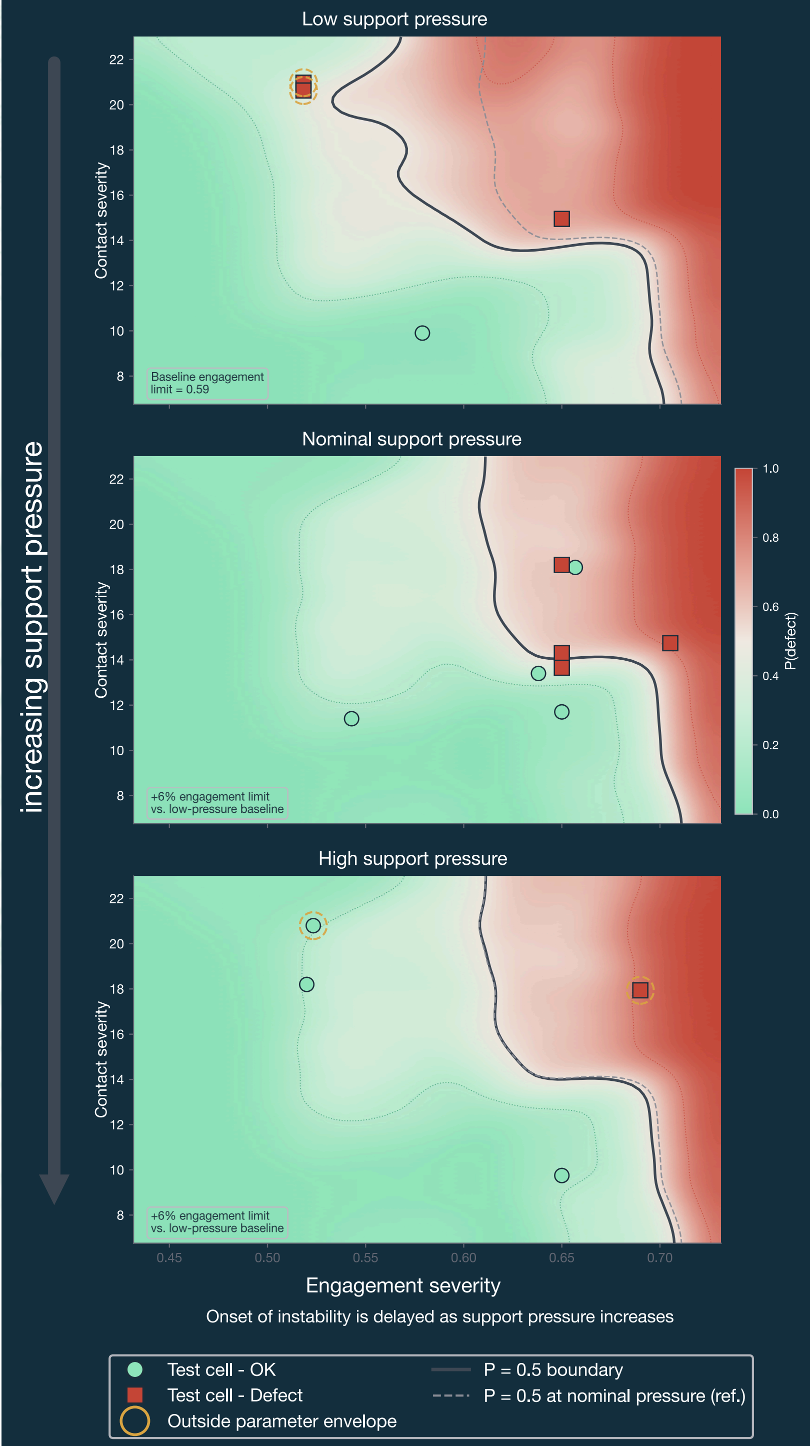
Predicted vs measured force. *Force profiles predicted from machine parameters closely match measured signals, and both yield the same quality classification: forward (parameters → force → outcome) and reverse (measured force → outcome) providing a unified basis for simulation and real-time process diagnosis.*

INTERPRETABLE DECISION SUPPORT

> *"Every flagged defect carries a deformation mechanism and a direction for correciton."*

The platform supports process operators by presenting predicted process quality through underlying physical drivers and their interactions. Process behavior is represented through two derived quantities: engagement severity (feed stroke relative to tool position) and contact severity (combined effect of feed stroke and process duration), which together describe the intensity and duration of material deformation. Defect risk increases as process loads approaches the stability limit. Increasing air pressure shifts this limit, enabling higher load operation while maintaining stability. The reasoning output makes each decision traceable from parameter setting to process behaviors to quality outcome. A predicted defect is causally explained through its underlying physical drivers, enabling corrective action to be based on cause rather than trial-and-error. In practice, this means that each operating condition is mapped into a process-state space where the source of instability is directly observable, and the direction for correction, such as reducing engagement or increasing support pressure, is defined. This establishes a direct connection between model output and process physics and enable transparent and explainable decision-making in industrial operation.



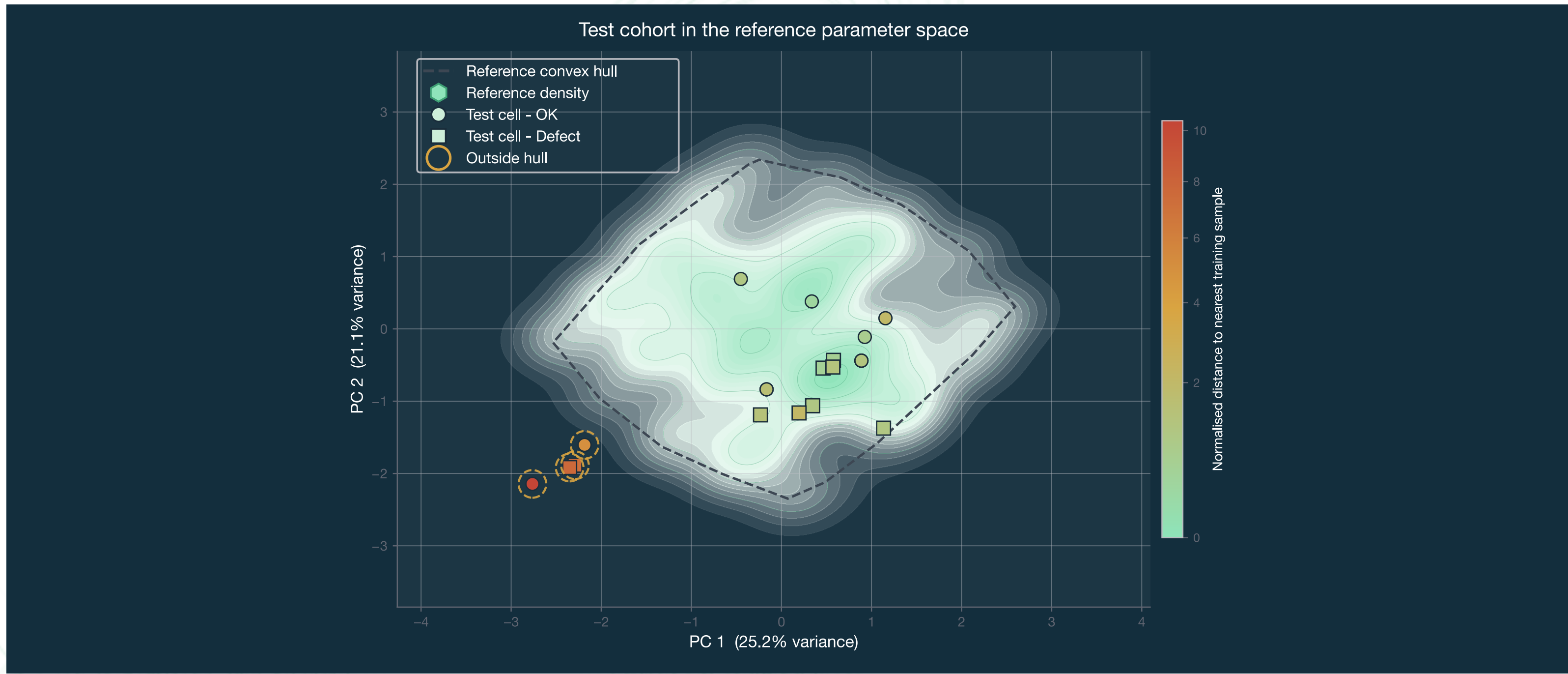


Pressure-sliced process-state maps. *Process quality risk is visualized as a function of engagement severity and contact severity, with separate panel for low, nominal, and high-pressure conditions. The transition from stable (low risk) to unstable (high risk) operating states is defined by a learned decision boundary, which shifts with increasing pressure. The visualization shows that instability is governed by the interaction of deformation intensity and support conditions.*

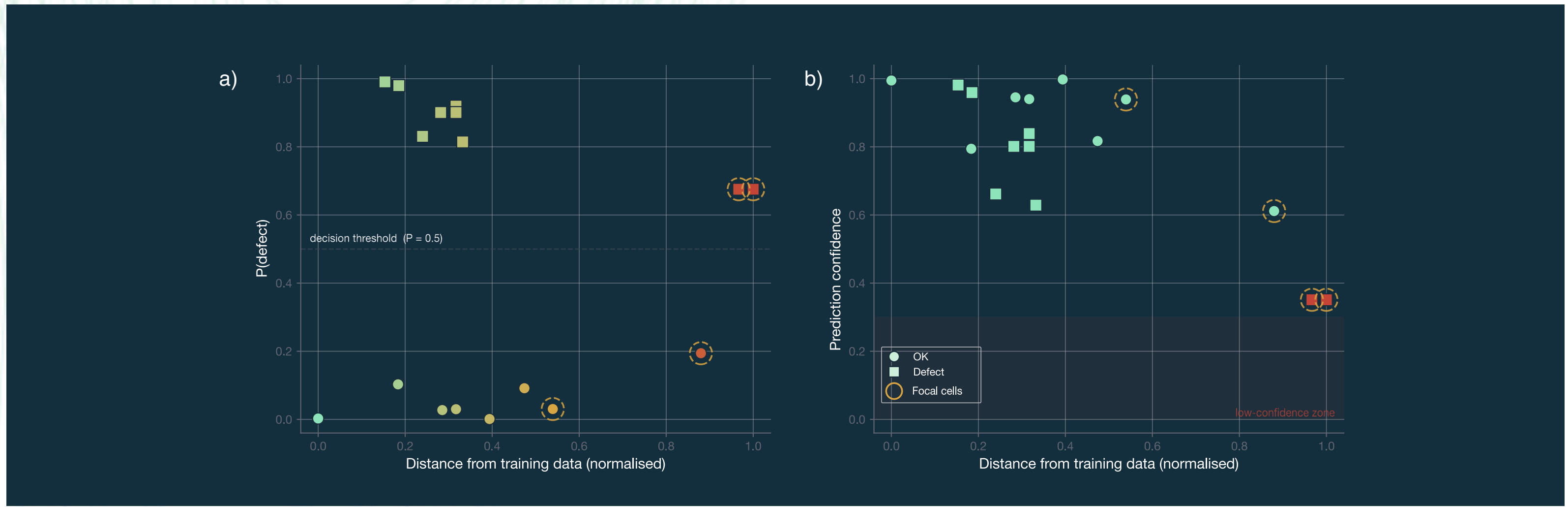
RELIABLE DECISION SUPPORT BEYOND OPERATING RANGE

> *"For settings outside the historical data, the platform returns both a prediction and a calibrated measure of its own confidence."*

The platform provides consistent decision support when applied to configurations beyond the observed range. As illustrated in the Figure 1, selected configurations lie outside the distribution defined by historical data. In these regions, the platform delivers probabilistic defect estimates together with calibrated uncertainty, enabling decisions to be made with an explicit measure of reliability rather than a single-point prediction (Figure 2). The relationship between distance from the training distribution and prediction behavior shows a response, where uncertainty adapts with operating conditions while prediction trends remain aligned with observed outcomes. This behavior, demonstrated in our collaboration, enables evaluation of new settings with quantified risk and supports controlled expansion of process windows in production environment.



1. Projection of the high-dimensional parameter space onto principal components (PC1, PC2). *Projection showing the distribution of historical operating conditions and validation configurations. The convex hull defines the observed parameters space, while highlighted points indicate configurations outside this region. Density contours represent the concentration of historical data. Validation points located beyond the hull correspond to previously unobserved operating states where the platform continues to provide prediction and uncertainty estimates."*



2. Relationship between distance to the historical data and model outputs for validation configurations. *a) predicted defect probability relative to decision threshold. b) prediction confidence with indication of uncertainty, showcasing the reliability of platform for decisions under extrapolated conditions.*

SCIENTIFIC FUNDATIONS

The relationship between process forces and part quality in metal forming is well established. Tekkaya et al. [1] showed that forming forces encode information about material state and process conditions beyond what parameter settings alone describe forces act as a physical mediator [4] between machine configuration and product properties [5]. Allwood et al. [2] demonstrated that closed-loop control using in-process force signals can improve dimensional accuracy and reduce defect rates, but noted that the mapping from parameters to forces to quality remains difficult to operationalize without process-specific models. He et al. [3] reviewed in-process monitoring in metal forming and identified force-based monitoring as a primary signal source, while highlighting the persistent gap between signal acquisition and actionable process control [6].

KEY REFERENCES

[1] Tekkaya et al. (2015)
Metal forming beyond shaping: Predicting and setting product properties. *CIRP Annals*, 64(2), 629–653.
DOI: 10.1016/j.cirp.2015.05.001

[2] Allwood et al. (2016)
Closed-loop control of product properties in metal forming. *CIRP Annals*, 65(2), 573–596.
DOI: 10.1016/j.cirp.2016.06.002

[3] He et al. (2025)
In-process monitoring strategies and methods in metal forming: A selective review. *Journal of Manufacturing Processes*, 138, 100–128.
DOI: 10.1016/j.jmapro.2025.02.011

[4] Karniadakis et al. (2021)
Physics-informed machine learning. *Nature Reviews Physics*, 3(6), 422–440.
DOI: 10.1038/s42254-021-00314-5

[5] Kolade et al. (2026)
The Future of AI for Knowledge Production. In: Generative AI in Research. Palgrave Macmillan, Cham.
DOI: 10.1007/978-3-032-02440-4_8

[6] Senorer et al. (2022)
Using Explainable Artificial Intelligence to Improve Process Quality: Evidence from Semiconductor Manufacturing. *Management Science*, 68(8), 5704–5723.
DOI: 10.1287/mnsc.2021.4190

> ***"Specific literature on spin grooving is scares or non existent."***

IMPLICATIONS FOR INDUSTRY

Traditional manufacturing workflows address quality primarily through post-process inspection, with corrective action guided largely by operator experience. This makes it difficult to link defects back to the parameter combinations that caused them and creates a strong dependence on specialized operators, whose absence can lead to production delays or downtime.

This approach moves quality assessment upstream. By evaluating parameter configurations before forming begins, the system identifies defect risk in advance and highlights the variables driving that risk, giving engineers a structured basis for adjustment. Three characteristics make this relevant beyond the specific grooving process studied. First, it works with limited data, second, it expresses uncertainty explicitly, distinguishing between confident predictions and borderline cases that require closer attention and third, it provides interpretable root-cause attribution, allowing engineers to understand, audit, and act on the reasoning behind each prediction.

Success on scarce data

Confident predictions

Understand, Audit, Act

The broader implication is a shift from reactive quality control to predictive process control. Most production lines already have the required sensors, data acquisition, and computing infrastructure. What is often missing is a reasoning layer that links process settings, physical behavior, and quality outcome. This collaboration demonstrates how that layer can be implemented in practice, with principles that extend to other multivariate manufacturing processes where defects emerge from interacting parameters.

> ***"What is often missing is reasoning"***

AccelionTech

April 2026

Contact us

info@acceliontech.com

Website

www.acceliontech.com