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From Reactive Control to Autonomous Operations: Applying AI, Machine Learning and Digital Twins for Predictive Maintenance, Quality Stabilisation and Process Simulation in Paper Manufacturing

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Abstract: *Paper mills worldwide operate under relentless process variability - furnish shifts, felt degradation, moisture drift, and grade changes - that fixed setpoints and reactive control cannot adequately manage. This paper presents a framework for transitioning from reactive process control to AI-driven process steering using a continuously updated Process Digital Twin, a product-centric data structure (Product Clone), and a proprietary AI engine (CrossRank) that identifies optimal operating ranges from the mill's own production data. The methodology was applied across multiple industrial deployments. A corrugating medium mill achieved a 68% reduction in paper breaks and a 5% throughput gain within four months; a newsprint mill reduced sheet breaks from 7 per day to 0.5 per day, recovering USD 40 million in annual revenue. The applicability to Indian paper mills, including compliance with the Bureau of Energy Efficiency's PAT scheme, is discussed.*

Keywords: *Digital Twin, Artificial Intelligence, Process Optimisation, Break Reduction, Paper Machine.*

Introduction

The modern paper machine is one of industry's most complex continuous manufacturing systems, processing hundreds of interacting variables simultaneously: furnish freeness and consistency, headbox pressure, press nip loads, dryer steam pressures, and dozens of quality setpoints. Any one of these can drift; when several drift simultaneously - as occurs during grade changes, furnish switches, or seasonal humidity shifts - operators face a system too complex to steer optimally in real time through manual intervention.

For decades, the industry has responded with Distributed Control Systems (DCS), Quality Control Systems (QCS), and Statistical Process Control (SPC) [1]. These tools share a fundamental limitation: they are static in a dynamic world. A setpoint optimal at the start of a run is no longer optimal thirty minutes later when the recycled-fibre blend has shifted or the press felt has loaded up.

The financial consequences are substantial. Each paper break on a mid-size machine costs USD 3,000–10,000 in lost production, wasted fibre, and re-threading time. Quality-related losses account for 3–8% of production value. Steam and electricity - representing 25–35% of operating costs - are routinely consumed 10–20% above their technically achievable minimum.

This paper presents a framework for transitioning from reactive process control to AI-driven process steering [3], validated through documented industrial deployments, and evaluates its applicability to Indian paper mills.

Materials and Methods

Operating Context: Indian Paper Mills

The Indian paper industry presents a distinct operating environment that amplifies variability challenges [4]. Approximately 25–30% of India's paper production depends on imported wastepaper of variable quality. Agro-residue based mills (bagasse, wheat straw, rice straw) face inherently variable fibre morphology, ash content, and drainage characteristics - often shift-to-shift. Most mills have DCS and QCS infrastructure, but data is siloed, poorly time-stamped, and rarely integrated with laboratory, MES, and manual records into a unified analytical layer. The data exists; it is not yet systematically utilised.

This variability profile is precisely the condition Braincube's CrossRank – the intelligence layer in the solution – is designed to handle. Because the algorithm makes no assumption of normally distributed, single-cause relationships, it remains reliable when furnish composition, fibre source, or ash content shift from batch to batch — conditions under which classical regression-based control would need frequent recalibration. For agro-residue and mixed-recovered-fibre mills, this means the same Digital Twin and CrossRank approach validated on furnish and grade variability in the existing deployments [Section 3] is structurally suited to extend to Indian operating conditions, where the dominant source of variability is feedstock rather than grade changes alone. Realising the full benefit in an Indian mill would, however, require the same prerequisite step seen in every deployment to date: 12–24 months of time-stamped DCS, QCS, and laboratory data to build a mill-specific Digital Twin, since CrossRank learns operating ranges from each mill's own history rather than a generic model.

Process Intelligence Maturity Framework

The transition from traditional process control to AI-driven operations proceeds through five maturity levels (Figure 1). Each level builds upon the previous and delivers measurable value independently.

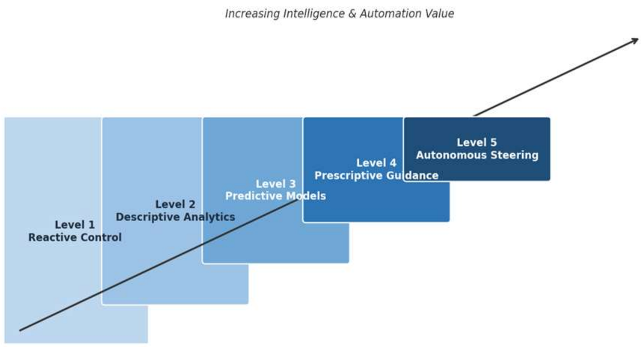

Figure 1: Five-level process intelligence maturity model

Data Sources and Integration

The analytical framework integrates data across all production systems. Table 1 summarises the principal data sources, variables captured, and key integration challenges.

Table 1: Principal data sources and integration characteristics

Source	Variables	Key Challenge
DCS	Pressures, temps, flow rates, drive speeds (1–10 sec)	Volume; alignment with QCS timestamps
QCS	Basis weight, moisture, caliper, ash (30–60 sec)	Scanner lag; grade-change artefacts
MES	Grade, reel ID, order data, shift changes	Siloed from process historian
Laboratory	Freeness, tensile, tear, burst (1–4×/shift)	Infrequent; must be time-aligned
Operator Logs	Felt changes, broke additions, visual notes	Unstructured; requires standardisation

The Process Digital Twin and Product Clone

The Process Digital Twin is a continuously updated, contextualised replica of the machine built from the integrated data sources above [2]. It accounts for variable lag, grade-change contamination, sensor noise, and asset drift, serving as the single analytical source of truth. Three characteristics of real paper-machine data routinely defeat naive analysis:

- Time lags: The effect of a refiner setting change may not appear in sheet tensile strength for 20–40 minutes. The Digital Twin maps these lags so that learned relationships reflect true cause-and-effect.
- Grade transitions: The 30–60 minutes around a grade change represent a contaminated operating state. The Digital Twin tags these periods so that steady-state analysis is not polluted.
- Sensor noise and outliers: Traditional correlation methods are highly sensitive to outliers. The CrossRank engine (Section 2.5) uses a probabilistic approach that is inherently robust.

The Product Clone reorganises the same data around each unit of production - each reel or batch - and the complete set of process conditions that produced it. Rather than asking 'what was the temperature at 14:32?' the mill can ask 'what set of conditions consistently produces on-spec reels?' and receive a data-backed, actionable answer.

The CrossRank AI Engine

CrossRank is a proprietary data mining scoring methodology designed for real industrial data, which is inherently non-normal, contains outliers, and includes both continuous and discrete variable types - conditions that invalidate classical Pearson regression. Table 2 compares the two approaches.

Table 2: Pearson regression vs. CrossRank - comparative attributes

Attribute	Pearson R^2 → CrossRank
Output	Regression equation (no range) → Best impacting range of variable
Outlier sensitivity	Highly sensitive - one outlier destroys score → Inherently robust
Non-normal data	Unreliable → Fully reliable across all distributions
Discrete variables	Cannot handle → Native support for binary/categorical inputs
Threshold effects	Undetected → Accurately identifies threshold and sweetspot responses

A CrossRank score of 84 means the input variable correctly separates 84% of good output points from bad ones. The algorithm simultaneously identifies the specific input range $[x_1, x_2]$ where this separation is maximised - giving the operator a directly actionable setpoint target, not merely an alarm. Figure 2 illustrates how this output flows through the complete architecture, from raw shop-floor sensor data through the Digital Twin and CrossRank layers to the final operator-facing guidance.

From Shop Floor Data to Operator Guidance

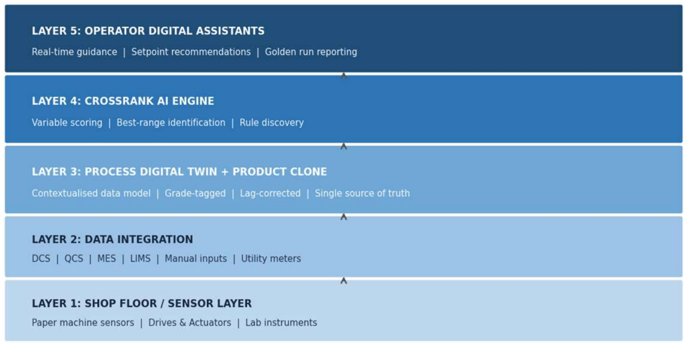

Figure 2: Five-layer architecture — from shop floor data to operator guidance

Results and Discussion

Break Reduction

Paper breaks are the single most visible and costly source of lost production on a paper machine. The AI approach identifies - from the mill's own historical data - the specific operating ranges across relevant variables associated with stable, break-free running, and guides operators back into those ranges as conditions drift.

Early warning signals span the entire machine: drainage variability and headbox consistency fluctuation at the wet end; nip load asymmetry and felt permeability decline at the press section; steam pressure hunting and hood humidity spikes at the dryer. Guidance is delivered as a clear, prioritised instruction: for example, 'Break risk elevated. Primary driver: headbox consistency 3.8% (recommended range: 3.2–3.5%). Secondary driver: press steam pressure 4.1 bar (recommended: 4.4-4.6 bar).'

Deployment at a corrugating medium and kraft liner mill demonstrates the achievable outcomes (Table 3).

Table 3: Break reduction outcomes - corrugating medium mill

Problem	Recurrent breaks averaging 5–7/day; root causes dispersed across wet end, press, and dryer; manual analysis unable to isolate primary drivers
Method	Process Digital Twin built from historical DCS and QCS data; CrossRank identified operating ranges for stable running; delivered to operators as updated production standards
Results	68% reduction in paper breaks within 4 months; 5% throughput increase (~1,850 additional break-free production hours/year)
Key Finding	Most impactful break drivers were cross-sectional variable combinations - relationships that CrossRank surfaces from data but are extremely difficult to isolate manually

Quality Stabilisation

Quality stabilisation focuses on holding finished paper properties within customer specification throughout the run, across grade changes, and under varying input conditions. Working from the Product Clone, CrossRank identifies which process conditions separate on-spec product from off-spec product for parameters including basis weight (GSM), moisture profile, caliper, tensile/tear strength, and ash content. In one documented deployment, isolating the two process temperatures most strongly influencing quality raised good-batch incidence from 32% to over 50%, even at high line speeds.

Operator Empowerment and Dynamic Standards

A global packaging and pulp manufacturer connected 25+ facilities using dashboards integrating DCS, QCS, MES, and laboratory data. A Trouble-Cause-Correct methodology was embedded directly in dashboards so operators see both the deviation and the corrective action simultaneously. Production standard limits became dynamic - when a standard changes, dashboards update automatically without IT involvement. Approximately 80% of global facilities expressed interest in adoption after seeing pilot results.

Runnability Recovery at Scale

A newsprint mill averaging 7 sheet breaks per day and running below design speed demonstrates the phased value model (Table 4).

Table 4: Phased runnability recovery - newsprint mill

Phase	Intervention
Phase 1: Optimised	CrossRank identified new setpoints for the highest-impact variables
Phase 2: Amplified	Expanded model coverage across additional process sections
Phase 3: Transformed	Machine speed ramped 12% to meet demand without additional capital expenditure

Value Identification Framework

Pre-qualifying business value before deployment is a significant barrier to digital adoption. A structured data audit - using 12–24 months of DCS, QCS, break logs, and production records - can pre-quantify potential gains. Table 5 presents an illustrative calculation for an Indian writing and printing paper mill producing 200 tonnes/day.

Table 5: Illustrative annual value potential - 200 TPD writing and printing paper mill, India

Value Dimension	Indicative Annual Impact (₹)
Break reduction (50–68%)	₹3.5–6.0 Cr
Throughput gain (3–8%)	₹4.0–10.0 Cr
Energy saving (8–15%)	₹2.5–5.0 Cr
Chemical / fibre saving (5–10%)	₹1.5–3.0 Cr
Maintenance optimisation	₹1.0–2.5 Cr
Total (illustrative)	**₹12.5–26.5 Cr / year**

Sustainability Impact

Every operational improvement translates directly into reduced resource consumption, supporting compliance with environmental discharge and emissions standards for the pulp and paper sector [5]. Break reduction cuts specific fibre consumption by 3–8% and specific energy consumption by 4–10% (GJ/tonne). Dryer optimisation reduces steam consumption by 8–15% and direct CO_2 emissions by 6–12%. Refiner optimisation reduces electrical energy by 5–12%.

For Indian mills, these gains are increasingly mandated. The Bureau of Energy Efficiency's Perform-Achieve-Trade (PAT) scheme sets gate-to-gate Specific Energy Consumption (SEC) targets for designated paper mills, with penalties for non-compliance and tradeable energy-saving certificates for over-achievement [6]. AI-driven process optimisation is among the most cost-effective pathways to PAT compliance and to meeting India's updated Nationally Determined Contribution (NDC) commitments on emissions intensity [7].

Conclusion

The paper industry has operated on the same fundamental control paradigm for decades: set targets, measure deviations, correct manually. This approach has reached its ceiling. The variability of modern paper machines - in furnishing composition, equipment condition, and operating environment - exceeds the capacity of static setpoints and human reaction times to manage optimally.

The Process Digital Twin and Product Clone, combined with Cross Rank AI analysis, provides a technically validated means to transition from reactive control to AI-driven process steering using data that mills already generate. Documented evidence confirms that break frequencies can be reduced by 50–68%, throughput increased by 5–12%, and significant energy and material savings achieved within months of deployment.

For Indian paper mills - operating with structurally more challenging input variability from agro-residue and imported recovered-fibre furnishes - the framework is particularly applicable. The integrated approach also supports compliance with PAT scheme SEC targets and contributes measurably to India's NDC commitments, making the sustainability and operational business cases mutually reinforcing.

Acknowledgements

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