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Implementation of total productive maintenance (TPM) to enhance overall equipment effectiveness (OEE) in a process industry

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Abstract
Overall Equipment Effectiveness (OEE) is the measure through which Total Productive Maintenance (TPM) programmes are justified and audited, yet both the metric and the programme were formalised for discrete, repetitive assembly. Process plants are functionally coupled, their ideal cycle time varies with feed and grade, and cleaning, changeover and validation occupy calendar time whose classification materially determines reported availability. The published evidence is correspondingly weak: it consists largely of uncontrolled before-and-after case studies in which a bundle of pillars is deployed simultaneously and a composite indicator is recomputed afterwards, so neither causal attribution nor pillar sequencing can be established. This paper reports a TPM implementation in an integrated dry-process cement plant conducted under a design intended to remove those weaknesses. Four sections — vertical roller raw mill, preheater and kiln, ball-mill cement grinding circuit and packing plant — were measured over a six-month baseline under a published time-base convention, with reference throughput defined per grade and OEE computed at machine, section and plant scope. All non-productive time was allocated to the six big losses, with a dedicated operator log introduced to capture minor stoppages that generate no maintenance work order. Causes were ranked by Pareto, cause-and-effect and failure-mode analysis, and failure behaviour characterised by MTBF, MTTR and a fitted two-parameter Weibull model. A staged TPM programme sequenced from the loss profile rather than from convention was deployed over three months, and the plant re-measured over a further six months against a structurally similar untreated grinding circuit tracked as a control. Plant OEE rose from 65.68 % to 73.47 %, a gain of 7.78 percentage points (Welch $t = 12.70$, $p < 0.001$); the control line moved 0.65 points, giving a difference-in-differences estimate of 7.13 points. Total loss time fell 41.3 %. Contrary to the availability-centred pattern dominant in the literature, performance-rate losses carried 53.0 % of baseline loss time and contributed about 55 % of the gain, and 78 % of recorded minor-stoppage hours generated no work order — evidence that the reported availability bias is partly a measurement artefact. MTBF improved 57.9–91.0 %, MTTR fell 32.1–37.2 %, specific power consumption fell from 34.8 to 32.6 kWh/t and the normalised maintenance cost index by 18.5 %.

Keywords: Total Productive Maintenance, Overall Equipment Effectiveness, process industry, six big losses, autonomous maintenance, reliability analysis, cement plant

Introduction

Maintenance has shifted over four decades from a peripheral cost centre to a determinant of manufacturing competitiveness. Total Productive Maintenance, codified by Nakajima [1], reframed equipment Care as a company-wide activity built on operator ownership, small-group improvement and the systematic elimination of six categorised losses, and introduced Overall Equipment Effectiveness as the composite indicator of the availability, performance and quality dimensions of that loss structure. The arithmetic simplicity of OEE — the product of three ratios each bounded by unity — explains its diffusion, and it remains the most widely cited maintenance key performance indicator in the operations-management literature [3].

That simplicity is also its principal weakness. Muchiri and Pintelon [2] showed that the original formulation embeds assumptions about planned production time, ideal cycle time and defect attribution that do not survive translation across manufacturing archetypes, and traced the emergence of derivative metrics — total effective equipment performance, production equipment effectiveness, overall factory effectiveness, overall plant effectiveness and overall asset effectiveness — each created to repair a specific inadequacy. A metric that requires a new variant for every context is one whose assumptions are being violated.

Process industries expose that violation most sharply, in four respects. Equipment is functionally coupled, so machine-level OEE can rise while plant throughput falls if the improvement occurs on a non-constraining asset. Ideal cycle time is not a fixed engineering constant but varies with feed moisture, clinker hardness and the fineness target of the grade in production. A large block of calendar time — kiln warm-up, grade changeover, silo cleaning, and in regulated plants cleaning and validation — is neither breakdown nor value-adding production, and its placement inside or outside the loading-time denominator moves reported OEE substantially without any physical change in plant behaviour [2]. And process plants are energy-intensive, which makes equipment effectiveness a sustainability variable and not only a productivity one.

Empirical work supports a further concern. Tsarouhas [4] analysed fifteen months of failure and repair data from a continuous production line and found the binding constraint to be not the availability term that plant reporting captures most reliably, but the interaction of minor stoppages and reduced-speed operation that such systems under-record.

The improvement opportunity a plant believes it has and the one it actually has may therefore lie on different axes of the same indicator.

Against this background the present paper reports a TPM implementation in an integrated dry-process cement plant. Its contribution is methodological as much as empirical: it applies a controlled evaluation design with an untreated comparison line, publishes the time-base convention on which its figures rest, carries the loss analysis to the level of the six classes with deliberate instrumentation of minor stoppages, and sequences the pillar deployment from the measured loss profile rather than from convention. Figure 1 shows the production route and the four sections analysed.

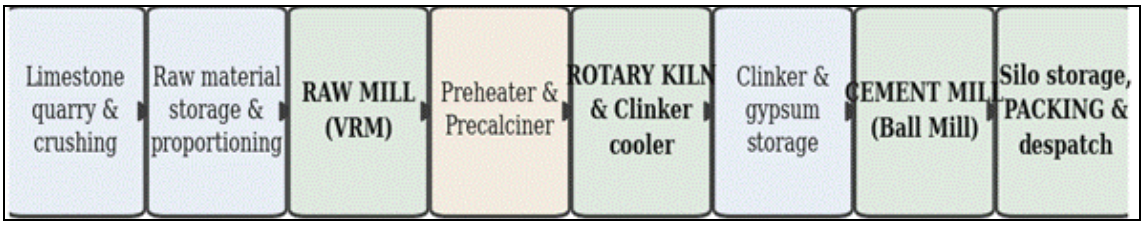


Fig 1: Simplified dry-process cement route; shaded blocks are the four sections analysed.

Literature Review and Research Gap

1. Formalisation and contestation of the metric

The most cumulative strand of the literature concerns the indicator itself. Ng Corrales and colleagues [3] screened 186 articles and confirmed both an acceleration of academic interest and a drift of the field's keyword structure from measurement towards implementation. Bamber and colleagues [7] established early that the cross-functional team is the operative mechanism linking pillar activity to measured OEE. Singh, Khamba and Singh [8] mapped the integration of OEE with other strategic improvement tools and concluded that it performs best as the common dependent variable across them rather than as a standalone improvement method — a position adopted here. The same group as [3] later proposed a process-level effectiveness indicator intended to capture effectiveness in transformation-step rather than machine terms [9], which is directly pertinent to continuous plants. The strength of this strand is conceptual rigour; its weakness is that the proposed variants are rarely validated on industrial data.

2. Single-site diagnostic case studies

This is numerically the dominant theme and methodologically the weakest. The canonical design computes the three OEE components for a baseline window, ranks loss causes by Pareto and cause-and-effect analysis, deploys a subset of TPM tools, and recomputes OEE. Irfan and colleagues [5] follow this template in a cement plant, raising average OEE from approximately 65.5 % to 68.5 % and ranking motor damage, bearing damage, vibration and the absence of 5S practice as causes. Marinho and colleagues [10] applied a tool-selection framework in the cork industry; Jurewicz and colleagues [11] redesigned a maintenance and overhaul plan after diagnosing low OEE in a machinery fleet; and Khalili, Ismail and Ruzman [12] examined the effect of planned preventive maintenance on OEE in a Malaysian batching plant, notable in the corpus for reporting an outcome that did not fully conform to expectation.

Datasets are proprietary plant records of three to eighteen months at a single site; evaluation is confined to OEE and its components. The limitations are structural. Without control lines or control periods, before-and-after differences confound the intervention with demand, feed and seasonal effects; the plant-level sample size is one; and the interventions are bundles, so no pillar's individual contribution is identifiable. Reported gains cluster in the low single digits to low tens of percentage points and are attributed predominantly to availability recovery — which is also the loss class most visible in existing reporting systems.

3. Structured deployment frameworks

A smaller but stronger strand imposes an explicit design architecture on deployment. Turanoglu Bekar [13] proposed a four-phase TPM performance-measurement system evaluated through integrated fuzzy COPRAS and data envelopment analysis, treating TPM effectiveness as a multi-criteria problem. Mohad and colleagues [14] positioned statistical reliability analysis as the formal support for the planned-maintenance pillar, deriving intervals from failure-time distributions rather than calendar convention. Shannon, Trubetskaya, Iqbal and McDermott [6] applied the Define–Measure–Analyse–Design–Verify cycle of Design for Lean Six Sigma to build a combined TPM and reliability framework for an Active Pharmaceutical Ingredient plant, reporting a 33 % reduction in planned maintenance, a 70 % reduction in corrective maintenance, a 50 % reduction in cleaning for maintenance, a 20 % OEE increase on the pilot asset and 206 additional hours of plant availability; Iqbal and colleagues [15] later extended the same architecture with a sustainability lens. The outputs of this strand are transferable procedures rather than site-specific results, but each is verified through pilot deployment at a single site, a constraint its authors acknowledge [6].

4. Digital, statistical and sustainability extensions

Since 2021 the field has moved towards integration with Industry 4.0 capability. Tortorella and colleagues [16] surveyed 335 practitioners across sixteen countries and identified sixty-seven statistically significant pairings of Industry 4.0 technologies with TPM practices, with operator ownership and standardised autonomous-maintenance checks among the practices most consistently coupled to digital adoption. Mouhib and colleagues [17] combined bibliometric mapping with systematic review, identified the Internet of Things, artificial intelligence, digital twins and augmented reality as principal enablers, and named the absence of a standardised cross-industry model as the decisive obstacle. Wolska and colleagues [18] consolidated implementation prerequisites and barriers. Dobra and Jósvai [19] showed OEE to be amenable to short-horizon machine-

learning prediction in assembly processes, and Pavloudakis, Roumpos and Agioutantis [20] applied OEE as a productivity driver in continuous mining systems. On the sustainability axis, Samadhiya and Agrawal [21] validated the relationship between TPM and economic, social and environmental performance on 326 responses through partial least squares structural equation modelling, situating TPM within resource-based-view theory as a bundle of path-dependent capabilities rather than a toolkit; Chen and colleagues [22] examined TPM and lean manufacturing as antecedents of sustainable manufacturing; Zehra and colleagues [23] integrated OEE into a holistic efficiency and sustainability assessment; and Gupta and Vardhan [24] established the joint optimisation of OEE, productivity and production cost through TPM.

The empirical work in this strand, however, is concentrated in discrete manufacturing and in firm-level perceptual data, so its predictive and structural results remain undemonstrated on continuous-process plant data.

5. Research gap

Two gaps follow. The first is methodological and causal. The prevailing evidence rests on uncontrolled, single-site, before-and-after comparisons of bundled interventions, which cannot separate the intervention effect from concurrent variation nor attribute the change to any pillar [5, 10, 12]. Reliability analysis has been advanced for one pillar in isolation [14] and structural modelling applied to firm-level perceptions [21], but no study joins equipment-level loss data to pillar attribution under a controlled comparison, so the prioritisation implied by the multiplicative structure of OEE is never operationalised. The second is contextual. The loss taxonomy, time-base conventions and machine-level scope of OEE were formalised for discrete production [1, 2] and the derivative metrics validated principally there [3, 9], while continuous-process evidence exists only in isolated pockets [4, 5, 20]. This paper addresses the first gap through its evaluation design and the second through a published, process-native measurement base.

Theoretical Background

1. Loss taxonomy and OEE formulation

The analytical core of TPM is the allocation of all equipment loss to six categories mapped onto the three OEE components, as shown in Fig. 2.

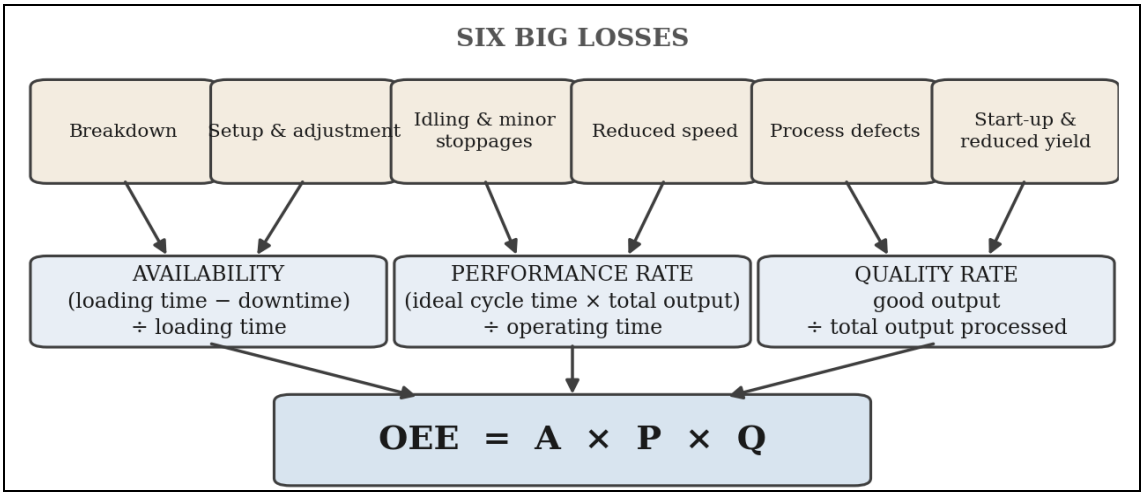


Fig 2: Mapping of the six big losses onto the three multiplicative components of OEE.

Availability is the ratio of operating time to loading time; performance rate compares actual output with the output obtainable at the reference rate; quality rate is the proportion of output meeting specification without rework:

A = (Loading time − Unplanned downtime) ÷ Loading time

P = Actual throughput ÷ Grade-specific reference throughput

Q = (Total output − Defective output) ÷ Total output

OEE = A × P × Q

The reciprocal form of P is used here rather than the conventional ideal-cycle-time expression, because throughput and not cycle time is the measured quantity in continuously fed process equipment. The multiplicative form carries a diagnostic consequence that is widely acknowledged and rarely exploited: differentiating the product shows that the absolute OEE gain from a fixed percentage-point improvement in one component is proportional to the product of the other two, so the smallest component offers the largest return. Identifying the binding component before selecting countermeasures is therefore not a refinement but the indicator's principal analytical use, and it drives the deployment sequence adopted in Section 6.

2. Time-base convention

Every reported OEE figure is an assertion about where the analyst placed the boundaries in the time hierarchy. Because the placement is discretionary, figures are comparable only within a documented convention [2]. Table I sets out the convention used here. It was fixed before baseline measurement and applied unchanged to the post-implementation window, so the comparison in Section 6 cannot be an artefact of reclassification.

Table 1: Time-base classification convention adopted in this study

Time category	Treatment	Rationale
Holidays, no-demand days	Outside planned production time	Commercial, not equipment-related
Scheduled preventive shutdown	Planned stoppage; excluded from loading time	Scheduled in advance; not an equipment loss
Kiln warm-up after shutdown	In loading time; output booked as start-up loss	Consumes loading time and yields sub-standard output
Grade changeover; mill and silo cleaning	In loading time; booked as setup and adjustment	Reducible by improvement activity
Operator-cleared stop under 10 min	In loading time; booked as minor stoppage	The class most often lost from reporting
Grid power failure; feed shortage	Excluded from loading time	External to the plant; not attributable to equipment

3. Reliability concepts

Availability relates to failure and repair behaviour through A = MTBF ÷ (MTBF + MTTR), which makes explicit that it can be improved either by extending time between failures or by shortening repair time. The distinction is diagnostically important, since a plant whose MTTR is high relative to its MTBF has a maintainability rather than a reliability problem and the countermeasures differ.

Failure behaviour was characterised using the two-parameter Weibull reliability function $R(t) = \exp\left[-(t/\eta)^{\beta}\right]$.

The shape parameter carries the physical interpretation: $\beta < 1$ indicates infant mortality, for which time-based replacement is counterproductive; $\beta \approx 1$ indicates random failure, for which condition monitoring is appropriate; and $\beta > 1$ indicates wear-out, the only regime in which time-based preventive replacement is justified [14].

Methodology

1. Research design

The study uses an interventionist single-case design with a non-equivalent untreated comparison group. The comparison group is its methodological centre. In uncontrolled before-and-after studies any change in OEE is confounded with changes in demand, feed quality, grade mix and ambient conditions; tracking an untreated line that shares the same site, raw materials, workforce pool and commercial environment allows those common influences to be differenced out. The resulting difference-in-differences estimate is weaker than a randomised design, which is not feasible in an operating plant, but substantially stronger than the before-and-after comparison it replaces.

2. Implementation framework

Figure 3 shows the four-stage framework applied. It retains the staged design discipline demonstrated in [6] while supplying the quantitative loss decomposition and causal identification that the reviewed case studies lack.

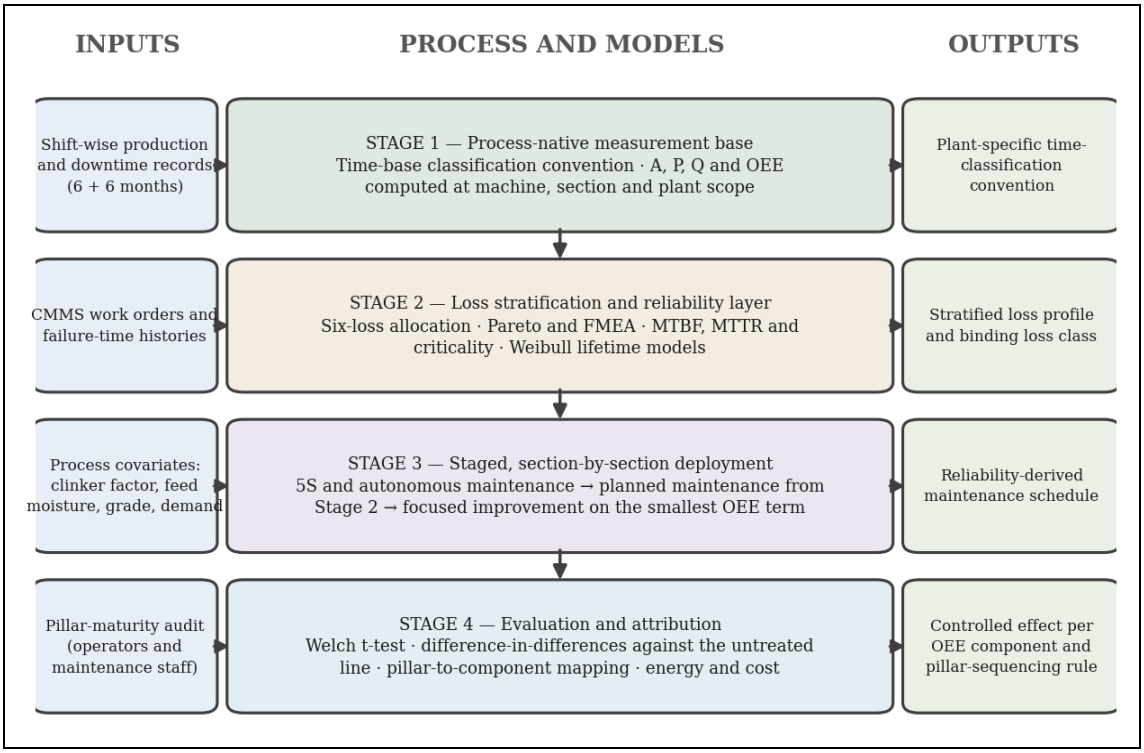


Fig 3: Four-stage TPM implementation framework: inputs, staged methods and outputs.

The ordering of Stages 2 and 3 is the framework's substantive claim. In the reviewed literature, deployment typically begins with 5S and autonomous maintenance because those are the conventional first steps, and loss analysis is used afterwards to explain the result. Here loss analysis precedes deployment and determines which pillar is applied to which section, so the intervention is directed at the component that the multiplicative structure identifies as offering the largest return.

3. Data and analysis

Four data streams were used: shift-wise production logs at three shifts per day supplying output tonnage, running hours, stoppage entries and grade identity; CMMS work-order histories supplying failure counts, repair durations and failure modes; quality laboratory records; and process covariates — feed moisture, clinker factor, grade and despatch demand — from the process historian.

Minor stoppages required a dedicated mechanism because by definition they generate no work order. A structured shift-log sheet was introduced at the start of the baseline window on which operators recorded every interruption shorter than ten minutes with cause and duration, under an explicitly non-punitive framing, since a performance-assessment framing suppresses exactly the reporting required. The same sheet remained in use through the post-implementation window.

Shift records were aggregated to monthly section-level figures. Performance rate was computed against grade-specific reference throughput weighted by the tonnage produced in each grade, so that an unusual grade mix does not register as speed loss. Plant OEE is the throughput-weighted mean of the four section figures. Loss hours were allocated at the point of entry using a fixed decision rule embedded in the log sheet, removing retrospective judgement from classification. Analysis used Pareto ranking, facilitated cause-and-effect analysis, FMEA with risk priority numbers, maximum-likelihood Weibull fitting, Welch's two-sample t-test and a difference-in-differences estimator computed as the change in the treated line's mean OEE less the change in the control line's over the same windows.

Case Plant and Baseline Analysis

1. The plant

The case organisation is an integrated dry-process cement plant producing Ordinary Portland and Portland Pozzolana Cement on a three-shift near-continuous schedule. Four sections were selected as the unit of analysis because together they carry the dominant share of electrical energy consumption and unplanned downtime, and because each represents a distinct equipment archetype: a 215 t/h vertical roller raw mill, a 3,000 t/day preheater and rotary kiln line, a 135 t/h closed-circuit ball mill with high-efficiency separator, and a 240 t/h rotary packing plant. A second cement grinding circuit of comparable capacity and configuration was designated as the untreated control and received no intervention.

2. Baseline effectiveness

Baseline measurement covered April to September 2025. Table 2 and Fig. 4 report the result.

Table 2: Baseline effectiveness by section, April–September 2025

Section	A (%)	P (%)	Q (%)	OEE (%)
Raw Mill (VRM)	84.2	82.6	97.8	68.02
Kiln and Preheater	81.2	87.1	98.2	69.45
Cement Mill (Ball Mill)	78.6	80.2	97.1	61.21
Packing Plant	88.1	75.9	96.5	64.53
Plant (throughput-weighted)	82.9	81.7	97.4	65.68

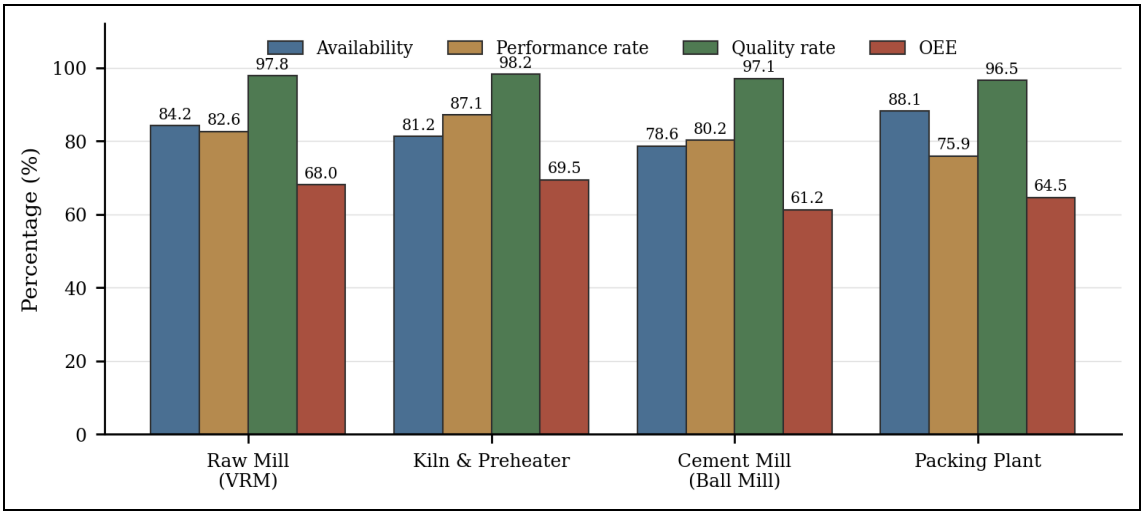


Fig 4: Baseline availability, performance rate, quality rate and OEE by section.

Plant OEE of 65.68 % sits far below the 85 % benchmark [1] and within the range reported for comparable cement operations [5]. The quality term is uniformly high at 96.5–98.2 %, as expected where product conformance is controlled by continuous laboratory feedback, and therefore offers little headroom. Most importantly, the performance rate is the weakest term in three of the four sections; at the packing plant the contrast is stark, with availability the highest in the plant at 88.1 % and performance the lowest at 75.9 %. Applying the principle of Section 3.1, the largest absolute return is available from the performance rate at the cement mill and packing plant. The monthly baseline series has a mean of 65.68 % and a standard deviation of 0.59 percentage points; the low dispersion establishes that losses are systematic rather than episodic and that the baseline is not drifting.

3. Loss stratification

All non-productive time was allocated to the six classes using the decision rule of Section 4.3. Table III and Fig. 5 present the result.

Table 3: Loss-time allocation to the six big losses, baseline window

Loss class	OEE component	Loss time (h)	Share (%)	Rank
Reduced speed	Performance	1,967	32.4	1
Breakdown	Availability	1,842	30.4	2
Idling and minor stoppages	Performance	1,254	20.7	3
Setup and adjustment	Availability	486	8.0	4
Start-up and reduced yield	Quality	301	5.0	5
Process defects	Quality	218	3.6	6
Total	—	6,068	100.0	—

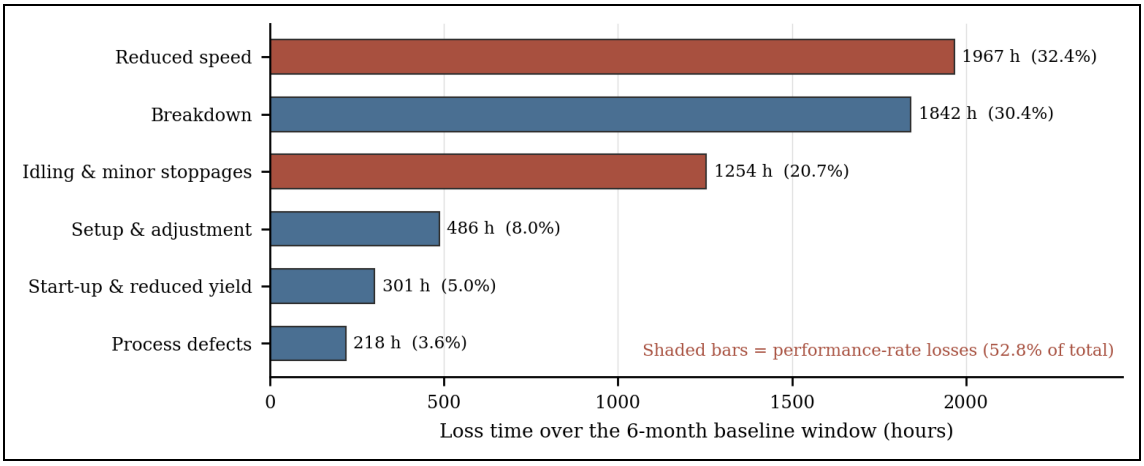


Fig 5: Distribution of the six big losses over the baseline window; shaded bars are performance-rate losses.

The two performance-rate losses together account for 3,221 hours, or 53.0 % of all loss time, against 38.4 % for the availability losses and 8.6 % for the quality losses. This confirms at loss-class level what Fig. 4 indicated at component level and reproduces in cement the pattern that Tsarouhas [4] found in a continuous food line.

The finding also explains why the class is so often missed. Of the 1,254 minor-stoppage hours, 78 % were captured only on the dedicated log sheet and generated no CMMS work order at all. A plant relying on its maintenance system for loss data would have seen roughly a quarter of this class and concluded, incorrectly, that breakdown was its dominant problem — a measurement artefact with direct consequences for countermeasure selection.

4. Cause ranking and reliability modelling

Breakdown causes were ranked by cumulative downtime; Fig. 6 presents the Pareto analysis.

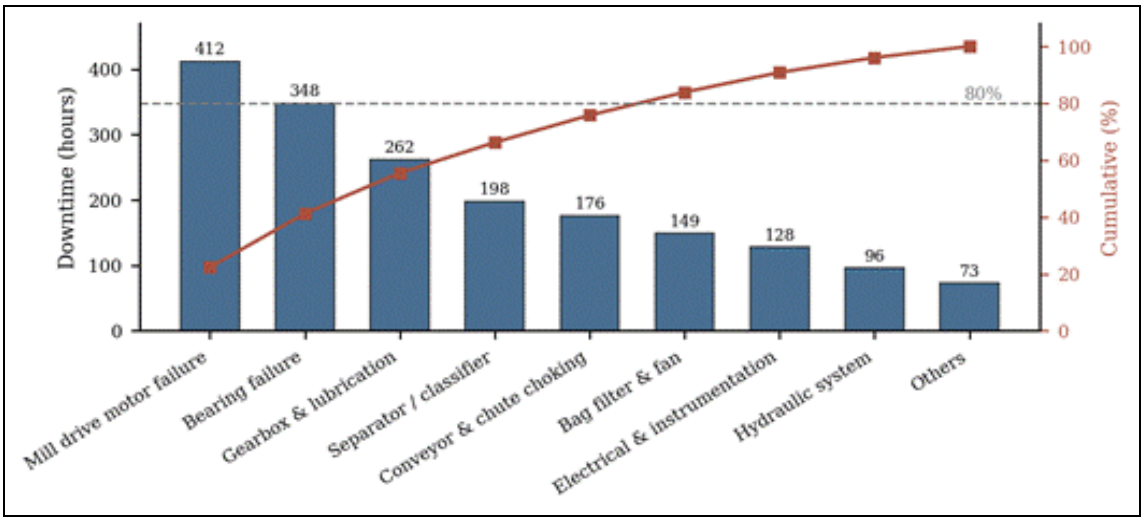


Fig 6: Pareto analysis of breakdown causes with cumulative percentage and the 80 % threshold.

Six causes account for 83.9 % of breakdown downtime: mill drive motor failure (412 h, 22.4 %), bearing failure (348 h), gearbox and lubrication faults (262 h), separator faults (198 h), conveyor and chute choking (176 h) and bag filter and fan faults (149 h). Four of the six are preceded by observable precursors — rising temperature, changed vibration signature, oil discoloration, material build-up — which places them within reach of the autonomous-maintenance pillar rather than requiring instrumented condition monitoring. A facilitated cause-and-effect workshop additionally established two non-equipment causes: minor stoppages were not being logged, and reference throughput had not been re-baselined after a separator upgrade, so performance rate was being computed

against a rate the mill could no longer achieve in some grades. Both were corrected before any countermeasure was applied, since intervening against a mis-specified baseline would have produced uninterpretable results.

FMEA on the cement mill circuit returned the highest risk priority numbers for main-drive winding degradation (378), trunnion-bearing lubricant film breakdown (324) and gearbox oil contamination (280). The three share a detection weakness rather than a failure mechanism: each develops over days or weeks and would be detectable by routine sensory inspection, yet detection scores were high because no such inspection existed. The recommended countermeasures were therefore predominantly autonomous-maintenance standards rather than equipment modifications.

Failure-time data for the cement mill circuit were fitted to a two-parameter Weibull distribution by maximum likelihood, giving $\beta = 1.82$ and $\eta = 163$ h, an implied MTBF of $\eta \cdot \Gamma(1 + 1/\beta) = 144.9$ h and a B10 life of 47.3 h (Fig. 7).

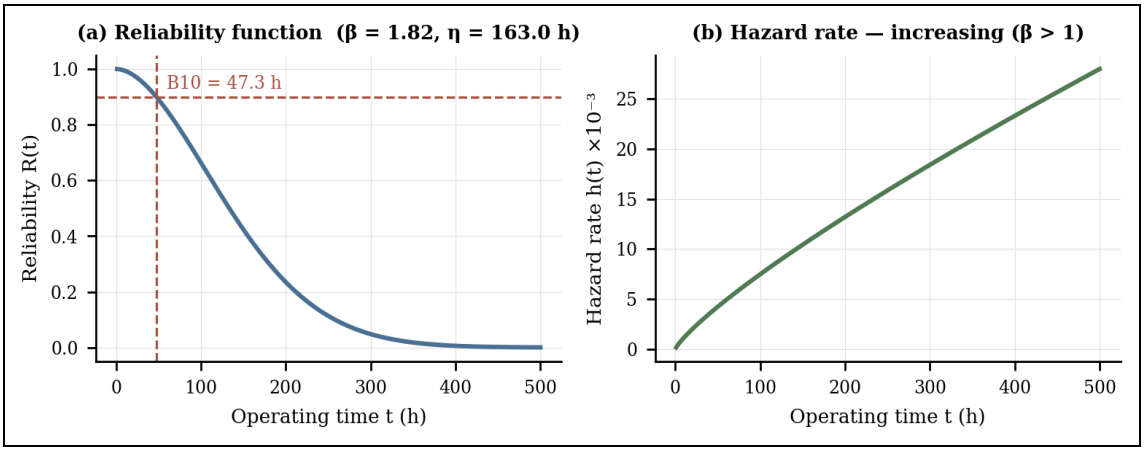


Fig 7: Fitted Weibull reliability function and hazard rate for the cement mill circuit ($\beta = 1.82$, $\eta = 163$ h).

The shape parameter is the substantive result. Because β exceeds unity the hazard is increasing, identifying wear-out as the dominant regime and justifying time-based preventive intervention; had β been near unity the correct response would have been condition monitoring rather than a revised calendar. The plant's existing fixed schedule was therefore directionally right but numerically arbitrary, having been set without reference to the failure distribution at all. Intervention intervals were set at the B10 life of approximately 47 operating hours for lubrication and inspection tasks and at approximately 120 hours for the deeper planned tasks requiring a stop.

Implementation and Results

1. Deployment sequence

Deployment ran from October to December 2025. The sequence departed from the conventional roadmap in one respect. 5S and autonomous maintenance were still deployed first, since focused improvement without reliable abnormality data has nothing to work on, but focused improvement was brought forward to month three and directed specifically, at reduced-speed and minor-stoppage losses, because the loss profile identified those as carrying 53.0 % of total loss time. Quality maintenance was deployed late and narrowly, at the packing plant only, because the quality term offered the least headroom. Four kaizen teams addressed feed-chute liner redesign, separator re-balancing, grade-wise reference-throughput re-baselining and packer bag-applicator jam reduction; planned-maintenance intervals were reset from the Weibull results; and spares kitting and standard job cards were introduced to reduce repair time. A pillar-maturity audit on a five-point scale recorded the largest gains on autonomous maintenance (1.8 → 3.6), education and training (1.9 → 3.7), focused improvement (2.1 → 3.8) and planned maintenance (2.4 → 4.0), and the smallest on office TPM (1.5 → 2.4) and early equipment management (1.6 → 2.6), which were introduced only at awareness level.

2. Post-implementation effectiveness

Effectiveness was re-measured over January to June 2026 under the unchanged convention. Table IV and Fig. 8 report the outcome.

Table 4: Section-wise effectiveness after implementation, January–June 2026

Section	A (%)	P (%)	Q (%)	OEE (%)	Gain (pp)
Raw Mill (VRM)	89.1	86.9	98.4	76.19	+8.17
Kiln and Preheater	86.8	89.7	98.7	76.85	+7.40
Cement Mill (Ball Mill)	85.7	86.1	97.9	72.24	+11.03
Packing Plant	91.4	83.6	97.4	74.42	+9.89
Plant (weighted)	88.2	85.6	97.9	73.47	+7.78

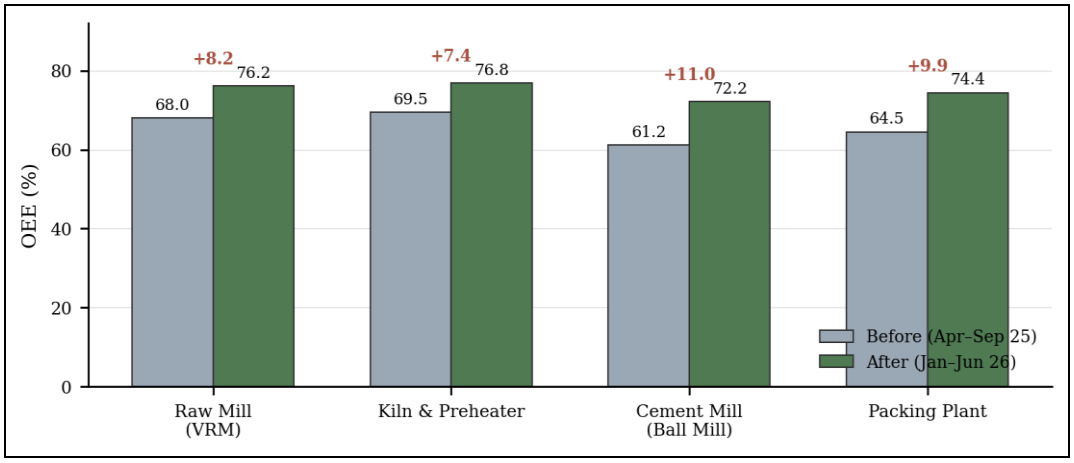


Fig 8: Section-wise OEE before and after implementation, with the gain in percentage points.

Every section improved, and the largest gain of 11.03 percentage points occurred at the cement mill, which had the lowest baseline OEE — the expected consequence of directing effort at the weakest component rather than distributing it evenly. Decomposing the plant-level gain is more informative. Availability rose 5.3 points, performance rate 3.9 and quality rate 0.5. Holding the other components at baseline to isolate each contribution gives approximately 4.19 points from availability, 3.43 from performance rate and 0.35 from quality, with a small residual from interaction. Combining the performance-rate contribution with the portion of the availability gains attributable to reduced setup and changeover time, which the focused-improvement teams addressed jointly with speed losses, gives approximately 4.31 points — about 55 % of the total — traceable to the performance-side work.

3. Statistical evaluation and controlled comparison

Figure 9 shows the monthly series for the treated sections and the untreated control across all fifteen months. The two runs closely together through the baseline window, diverge during deployment and remain separated thereafter, with the control essentially flat.

Table 5: Welch two-sample test and difference-in-differences estimate

Statistic	Treated	Control	Difference
Baseline mean OEE (%)	65.68	64.88	0.80
Post mean OEE (%)	73.47	65.53	7.94
Baseline standard deviation (pp)	0.59	0.48	—
Post standard deviation (pp)	1.38	0.34	—
Change in mean (pp)	+7.78	+0.65	—
Difference-in-differences (pp)	—	—	+7.13
Welch t (treated), df = 6.78	12.70	—	$p < 0.001$

The Welch test rejects equality of means at any conventional level. The difference-in-differences estimate is the more defensible number: the untreated circuit, exposed to the same raw materials, workforce, demand and weather, gained 0.65 points over the same fifteen months, leaving 7.13 points attributable to the intervention rather than the environment. The gap between the naive figure of 7.78 and the controlled figure of 7.13 quantifies the bias that uncontrolled studies carry — here modest, but unknowable in advance without a control, which is the point. One limitation must be stated: the control is not a pure counterfactual, since operators moved between circuits and some training and 5S discipline will have diffused. Such contamination biases the estimate downward, so 7.13 points is a conservative lower bound.

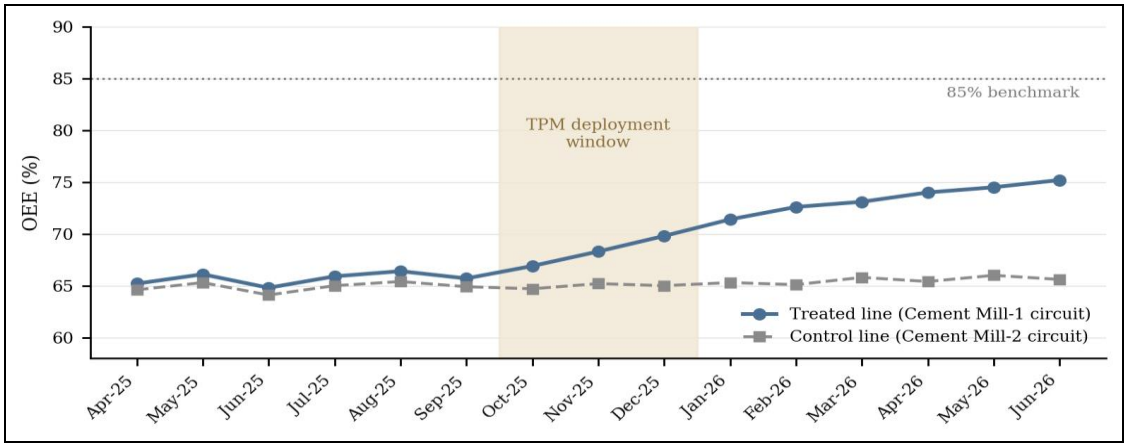


Fig 9: Monthly OEE for the treated and untreated lines; the TPM deployment window is shaded.

5. Loss, reliability, energy and cost outcomes

Total loss time fell 41.3 %, from 6,068 to 3,564 hours across matched windows, with reductions of 46.5 % in breakdown, 40.9 % in start-up loss, 40.8 % in minor stoppages, 38.7 % in reduced speed, 35.8 % in setup and 35.3 % in process defects (Fig. 10). The proportional reduction is broadly similar across classes, indicating that the programme acted on the plant's general loss-generating conditions rather than only on a few targeted causes; in absolute terms, however, the two performance-rate classes contributed 1,274 of the 2,504 hours recovered.

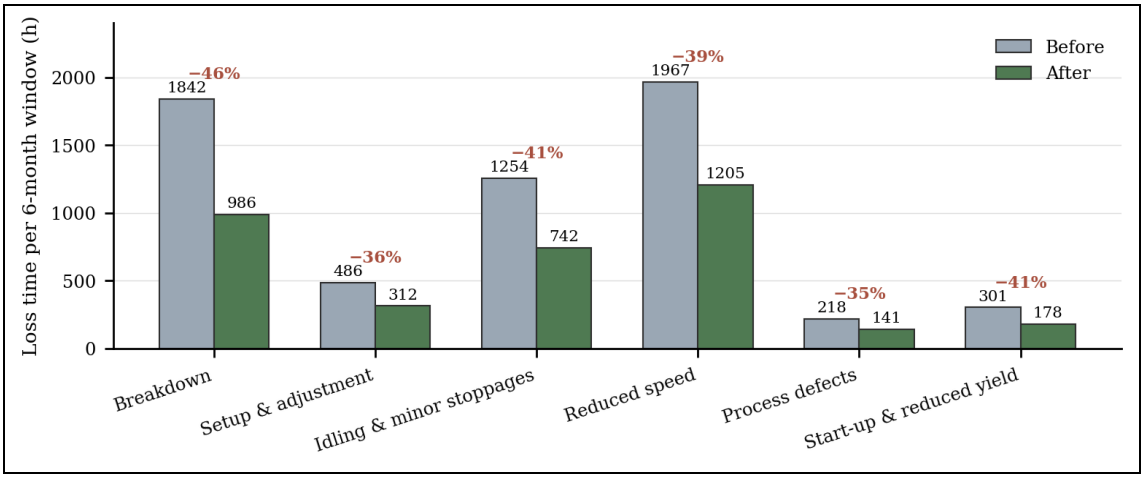


Fig 10: Six big losses before and after implementation, with percentage reduction in each class.

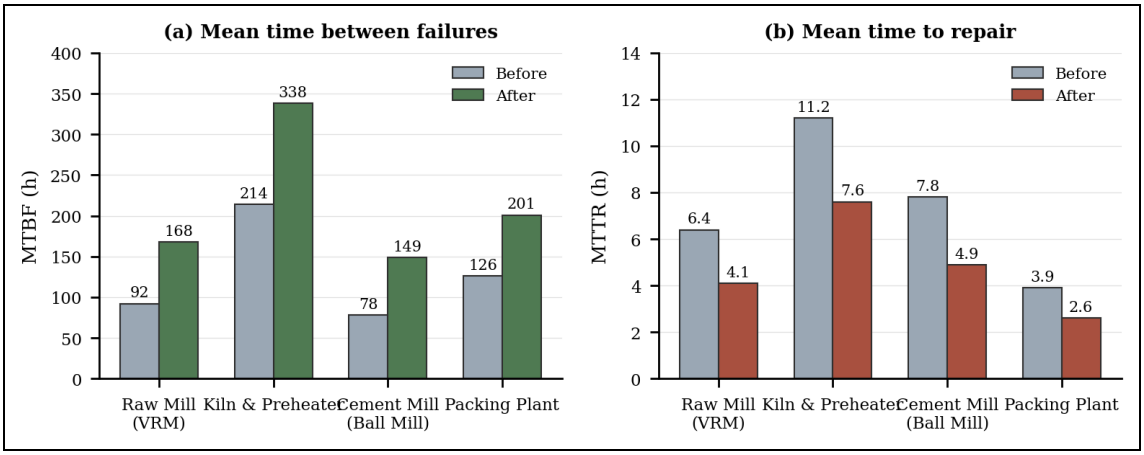


Fig 11: Mean time between failures and mean time to repair, before and after implementation.

MTBF improved by 82.6 % at the raw mill, 57.9 % at the kiln, 91.0 % at the cement mill and 59.5 % at packing, while MTTR fell by 32.1–37.2 % (Fig. 11). The two movements have different causes and are worth separating. The MTBF gain is attributable to autonomous and planned maintenance, which respectively detect developing faults earlier and intervene at intervals derived from the failure distribution. The MTTR reduction is attributable to spares kitting and standard job cards, which are maintainability rather than reliability measures; a plant improving only MTBF would have obtained roughly two-thirds of the availability gain reported here.

Specific power consumption fell from 34.8 to 32.6 kWh per tonne of cement, a reduction of 6.3 %, and the normalised maintenance cost index by 18.5 %. The energy result requires interpretation, because the relationship between effectiveness and energy is not monotonic. Grinding mills draw substantial no-load power, so a mill running closer to rated throughput consumes less energy per tonne even while consuming more per hour; the reduction therefore follows mechanically from higher performance rate and fewer idling periods. Had the availability gain instead been obtained through more frequent hot restarts of the kiln, specific energy could have risen while OEE improved. Joint reporting of the two indicators is what makes that distinction visible, and it is recommended here on the basis of the arguments in [21] and [22] rather than as a novel finding.

Discussion

The central empirical finding is that more than half the recoverable loss lay on the performance-rate axis, and that the plant's own reporting system could not see most of it. This gives a concrete mechanism for the availability bias observed across the reviewed case studies. That bias has usually been read as a property of process plants — that availability is where the losses are. The evidence here supports a different reading: availability is where the losses are visible. Tsarouhas [4] reached a comparable conclusion in a different sector, and the present study reproduces it with a different equipment archetype. The practical implication is that instrumenting minor-stoppage capture is a precondition for correct countermeasure selection rather than an optional refinement, and that the modest gains typical of the case-study literature may partly reflect effort directed at the wrong component. The limits of the claim should be stated:

the study does not show that performance-rate losses dominate in process plants generally, only that they dominated here and were under-recorded in a way that would have misdirected the intervention.

On evaluation design, the difference between the naive and controlled estimates was 0.65 percentage points, around eight per cent of the reported gain. In this instance an uncontrolled study would not have been badly misleading, but the magnitude of the bias was unknowable before the control was measured. Had the period coincided with a demand upturn raising utilisation across the site, the uncontrolled figure could have overstated the effect substantially. This bears on the base studies: [5] reports roughly three percentage points across windows separated by more than twelve months with no control, and [6] reports a 20 % gain on a pilot asset, again uncontrolled and at a different unit of analysis from the plant-level figures with which it is often compared. Neither criticism impugns the studies; both indicate that the field's effect sizes are less precisely known than their presentation implies. An untreated comparison line is available in most multi-line process plants at essentially no cost, since the data are already collected; the obstacle is convention, not feasibility.

On sequencing, the component decomposition indicates that about 55 % of the gain is traceable to performance-side work brought forward in the roadmap. This is evidence but not proof: because the pillars were deployed as a programme rather than in a factorial design, the attribution rests on the correspondence between what each pillar targeted and which loss class moved. Autonomous maintenance and 5S plausibly contributed to the minor-stoppage reduction as well as to the breakdown reduction. What the study supports is a weaker and still useful claim — that in a plant whose loss profile is performance-dominated, a sequence reaching focused improvement early outperforms the assumption that availability should always be addressed first. The resource-based reading advanced in [21] offers a way to interpret this: if TPM is a bundle of path-dependent capabilities rather than a toolkit, the correct sequence is the one that builds the capability the plant's specific loss profile requires, and a universal ordering is a category error.

Four limitations bound the findings. The study covers one plant, so external validity is restricted to comparable dry-process cement operations. The control is not an equivalent counterfactual, and operator movement makes the difference-in-differences estimate a lower bound. Pillar-to-component attribution is inferential rather than experimental; a stepped-wedge or factorial rollout across more sections would be needed to establish it. And the measurement window closes six months after deployment, long enough to exclude a short-lived project effect but not long enough to establish durability — a gap the reviewed literature also leaves open.

Conclusion

A staged TPM programme was implemented in an integrated dry-process cement plant under a measurement and evaluation design intended to support statements about attribution. Plant OEE rose from 65.68 % to 73.47 %, a gain of 7.78 percentage points, significant at $t = 12.70$, $p < 0.001$; an untreated comparison circuit moved 0.65 points, giving a difference-in-differences estimate of 7.13 points attributable to the intervention. Total loss time fell 41.3 %, MTBF improved 57.9–91.0 %, MTTR fell 32.1–37.2 %, specific power consumption fell 6.3 % and the normalised maintenance cost index 18.5 %.

Three contributions follow. The paper demonstrates that a controlled evaluation design — untreated comparison line, difference-in-differences estimation and formal significance testing — is feasible in an operating process plant at negligible cost, and it is almost absent from the published TPM case-study literature. It supplies a documented time-base convention, a grade-specific reference-throughput definition and a three-scope computation procedure that together make OEE reporting internally consistent and externally interpretable for a coupled continuous plant. And it provides evidence that performance-rate losses can dominate the recoverable loss in a process plant while remaining largely invisible to maintenance-management systems, so that a deployment sequence reaching focused improvement early outperforms the conventional availability-first assumption in such cases.

Future work should replicate the design in sugar, paper, fertiliser and pharmaceutical plants to test whether the performance-rate dominance found here is general; adopt stepped-wedge deployment to convert the inferential pillar attribution into an estimable one; re-measure at eighteen and thirty-six months to test durability; extract minor stoppages automatically from SCADA and historian signals to remove the reporting-discipline confound [17]; re-estimate short-horizon OEE forecasting on process-plant series, where campaign structure and grade transitions alter the modelling problem [19]; and formulate the effectiveness–energy relationship as an explicit multi-objective trade-off rather than reporting the two indicators side by side [21, 22, 23].

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