International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 10 Issue 4, Jul-Aug 2026 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Preventive Maintenance as a Driver of World-Class Overall Equipment Effectiveness (OEE): Evidence from a Grease Manufacturing Case Study in India

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ABSTRACT

Background: Overall Equipment Effectiveness (OEE) is an internationally accepted metric for quantifying manufacturing productivity, which combines Availability, Performance, and Quality into a single composite score. Despite extensive literature on OEE in automotive and food manufacturing, empirical studies on grease and lubricant manufacturing, particularly in developing economies, remain scarce.

Methods: This study presents a primary data case study of Siddharth Grease & Lubes Pvt. Ltd. (SGLPL), a contract grease manufacturer at IMT Manesar, Haryana, India. Twelve months of production records (April 2024–March 2025), First Time Right (FTR) quality data, formal preventive maintenance (PM) documentation (MM-F-003, MM-F-007), and daily machine check sheets were analyzed. The OEE components were calculated using the ISO 22400-2 (2014) formulas. Plan deviations were categorized using Pareto analysis, and the PM system was evaluated against Total Productive Maintenance (TPM) best practice criteria.

Results: Across 3,134 grease batches produced during the study period, the FTR Quality Rate was 100% (zero reworks, zero rejections), against an internal target of >95%. Of the 41 documented production plan deviations, none were attributable to machine breakdowns. All deviations were supply chain-related: Holding Tank unavailability (53.7%) and raw/packaging material shortages (46.3%). The estimated OEE was 95.6% (availability 97.8%, performance 97.8%, quality 100.0%), exceeding the internationally recognized world-class threshold of 85% for all three components.

Conclusion: The findings empirically demonstrate that a comprehensively implemented PM regime encompassing 68 assets across four maintenance frequency tiers, supported by shift-level daily check sheets, can sustain world-class OEE in a high-complexity batch manufacturing environment. The residual OEE improvement frontier in a PM-mature facility shifts from maintenance to production scheduling and supply chain management. This study provides original primary evidence from the underrepresented grease manufacturing sector and offers a replicable PM effectiveness evaluation framework for similar process manufacturers.

How to cite this paper: Shiv Ahuja "Preventive Maintenance as a Driver of World-Class Overall Equipment Effectiveness (OEE): Evidence from a Grease Manufacturing Case Study in India" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-10 | Issue-4, August 2026, pp.1041-1052, URL: www.ijtsrd.com/papers/ijtsrd141979.pdf

IJTSRD141979

KEYWORDS: *Overall Equipment Effectiveness (OEE); Preventive Maintenance; Grease Manufacturing; First Time Right (FTR); Total Productive Maintenance (TPM); Batch Processing; Production Schedule Adherence; India; Case Study.*

1. INTRODUCTION

The lubricant and grease manufacturing industry operates under significant competitive pressure, where production efficiency, product consistency, and asset reliability are strategic imperatives. Grease, a semi-solid lubricant composed of base oil, soap or non-soap thickener, and performance additives, is manufactured through thermally intensive batch processes. Disruptions in critical process equipment, such as cooking kettles, homogenizers, and filling machines, can cascade into significant productivity losses, batch failures, and customer delivery delays.

Overall Equipment Effectiveness (OEE), introduced by Nakajima (1988) within the Total Productive Maintenance (TPM) framework, is the most widely adopted metric for quantifying manufacturing productivity. OEE integrates three components: availability (the fraction of planned production time during which equipment is operational), performance (the ratio of actual to ideal throughput), and quality (the proportion of output meeting specifications on the first production run) into a single composite score. International benchmarks define world-class OEE at ≥85%, with individual component targets of availability ≥90%, performance ≥95%, and quality ≥99% (Dal et al., 2000).

The relationship between preventive maintenance (PM) and OEE is well established theoretically: PM reduces unplanned stoppages (improving availability), prevents degraded operating conditions that slow throughput (improving performance), and maintains process stability that supports consistent product quality (improving quality). Quantitative empirical evidence of this relationship from live manufacturing environments, particularly in process industries in developing economies, remains comparatively sparse in the literature.

This study addresses this gap through a primary data case study of Siddharth Grease & Lubes Pvt. Ltd. (SGLPL), an operational grease contract manufacturer at IMT Manesar, Haryana, India. Twelve months of production and quality records, formal PM documentation, and daily machine check sheet data were analyzed to calculate the real OEE, characterize the causes of production disruptions, and evaluate the plant's PM system against TPM best practices. The findings yield an empirically grounded answer to the research question: To what extent can a comprehensively implemented PM regime sustain world-class OEE in a high-complexity batch grease manufacturing environment?

1.1. Research Contribution

This paper makes three contributions to the manufacturing management literature:

- To the best of our knowledge, it provides the first published OEE case study based on primary data from a grease manufacturing facility in India, addressing a documented gap in the literature (see Section 2.4).
- It presents an empirical finding: that in a PM-mature batch manufacturing facility, 100% of production disruptions are attributable to supply chain and scheduling factors rather than equipment failures, which has practical implications for understanding where the OEE improvement frontier lies once PM is effectively implemented.
- This demonstrates a replicable methodology for OEE evaluation in batch process manufacturing environments where digital downtime logging is absent, which characterizes a large segment of small-to-medium process manufacturers in developing economies.

2. Literature Review

2.1. Overall Equipment Effectiveness: Origins and Framework

OEE was introduced by Nakajima (1988) as the primary performance metric within the TPM framework, enabling plant managers to quantify all productivity losses attributable to equipment. The metric is calculated as OEE = A×P×Q, where Availability, Performance, and Quality each correspond to specific loss categories. Dal et al. (2000) demonstrated OEE's value as both a performance indicator and a diagnostic tool, showing that most manufacturing plants operate at 40–60% OEE, with world-class performance defined at ≥85%. ISO 22400-2 (2014) subsequently standardized OEE calculation terminology for manufacturing operations management, providing the definitional basis used in this study.

Muchiri and Pintelon (2008) refined the theoretical basis of OEE, distinguishing it from Total Effective Equipment Performance (TEEP), which accounts for all calendar time. Their work established that OEE is most actionable at the individual equipment level. Braglia et al. (2008) extended the OEE framework to multi-machine production lines, introducing Overall Line Effectiveness (OLE), a consideration relevant to sequential batch processes such as grease manufacturing, where cooking, holding, and filling stages are operationally interdependent.

2.2. Total Productive Maintenance and the Planned Maintenance Pillar

TPM, operationalized through Nakajima (1988) and the Japan Institute of Plant Maintenance, comprises eight pillars. The Planned Maintenance pillar (Pillar 4) is the most directly relevant to OEE improvement through downtime reduction. It encompasses time-based maintenance (TBM), condition-based maintenance (CBM), and predictive maintenance (PdM), which are escalating in sophistication and data requirements. Eti et al. (2004) reported OEE improvements of 20–35 pp following TPM implementation in Nigerian manufacturing firms. Chan et al. (2005) demonstrated that PM combined with Autonomous Maintenance (Pillar 2-operators performing basic machine care) produced the strongest OEE gains, consistent with the multi-tier check sheet approach observed at SGLPL.

Smith and Hinchcliffe (2004) established through reliability-centered maintenance (RCM) analysis that planned PM costs three to five times less than emergency corrective maintenance for equivalent component interventions. Alsyouf (2007) quantified that PM implementation reduces unplanned downtime by 25–40% and maintenance costs by 12–18% compared with reactive maintenance regimes. Campbell and Reyes-Picknell (2015) documented 15–25% higher OEE in plants using computerized maintenance management systems (CMMS) versus paper-based systems, underscoring the role of data infrastructure in maintenance effectiveness.

2.3. OEE in Batch Process Manufacturing

The application of OEE to batch manufacturing differs from that in discrete manufacturing in methodologically important ways. In batch processes, the Performance Rate is calculated relative to the planned batch count rather than a continuous cycle rate, and quality losses manifest as batch-level failures (rework or disposal) rather than unit-level defects (Braglia et al., 2008). Availability losses in batch manufacturing carry higher per-event costs than in discrete manufacturing because an unplanned stoppage mid-batch may render the entire partially processed batch unrecoverable, a consequence of particular significance in grease manufacturing, where saponification reactions cannot be interrupted without product degradation.

Prajogo and Sohal (2006) established that high first-time-right (FTR) rates, the batch manufacturing equivalent of the Quality Rate component of OEE, are correlated with equipment reliability and maintenance maturity. This relationship contextualizes the importance of PM for Quality OEE in grease manufacturing, where process deviations caused by equipment malfunction (temperature sensor drift, mixing speed variation, and seal failure) directly manifest as batch quality failures.

2.4. Gap in the Literature: Grease Manufacturing

A systematic review of the OEE and TPM literature reveals that peer-reviewed empirical studies of OEE in grease and lubricant manufacturing are essentially absent. The majority of published OEE case studies are drawn from automotive assembly (e.g., Chan et al., 2005), food processing (e.g., Hedman et al., 2016), pharmaceuticals, and electronics. The closest domain - bulk chemical processing - has limited representation (Braglia et al., 2008). Grease manufacturing presents distinctive equipment characteristics (high-viscosity process fluids, temperature-sensitive reactions, abrasive thickener compounds) that accelerate wear differently from liquid chemical or discrete part processes. This paper directly addresses the identified gap.

3. Methodology

3.1. Research Design

This study adopts a single embedded case study design (Yin, 2018), with the case being SGLPL's Manesar grease manufacturing plant and the embedded units of analysis being the three critical equipment categories: cooking kettles, homogenizers/milling machines, and filling machines. A deductive approach is employed: established OEE and TPM frameworks are applied to primary plant data to evaluate performance and identify the structure of the remaining improvement opportunities. Both quantitative and qualitative data were used, consistent with the mixed-methods paradigm (Creswell, 2014).

The case study strategy is appropriate here because the research question is as follows: To what extent can PM sustain world-class OEE in a batch grease manufacturing environment? It requires contextual depth rather than statistical breadth. Single-case studies are particularly suited to confirming, challenging, or extending established theoretical propositions (Yin, 2018), which is the function performed here relative to the PM-OEE relationship established in the literature.

3.2. Data Sources and Collection

Primary data were collected from SGLPL with the written permission of its owner. Six document categories were obtained (Table 1), all relating to the twelve-month period April 2024–March 2025 (or the 2025–26 plan year for forward-looking documents):

Document	Content	Period	OEE Component
Plan vs. Actual Records	Daily planned vs. actual batch production with deviation remarks	Jan–Dec 2025	Performance (P)
FTR Records	Batch-level First Time Right vs. rework data	Apr 2024–Mar 2025	Quality (Q)
MM-F-003 PM Plan	Annual PM schedule: 68 machines, M/Q/HY/Y frequencies	2025–26 plan	Availability (A)
MM-F-007 Checklists	Per-machine PM inspection checklists	Current	Availability (A)
SGLPL-DMC-01	Daily shift-by-shift machine check sheets	Current	Availability (A)
Plant & Machinery Register	Equipment inventory: 57+ assets with specs and purchase data	Current	Context

Table 1: Primary Data Sources-SGLPL Case Study

3.3. Analytical Methods

3.3.1. *OEE Calculation*

The OEE components were calculated using the ISO 22400-2 (2014) formulas. The Quality Rate (Q) was computed directly from the FTR records as Good Batches÷Total Batches. The performance Rate (P) was calculated as Actual Batches÷Planned Batches from the Plan vs. actual records. Availability (A) was estimated from the deviation event counts and stated MTTR, following the approach described in Section 4.3 and discussed as a study limitation in Section 3.5.

3.3.2. *Pareto Analysis of Plan Deviations*

All deviation remarks in the plan vs. actual records were extracted and categorized into mutually exclusive cause categories. Events were ranked by frequency, and cumulative percentages were computed, enabling the identification of the dominant causes of production disruption consistent with the Pareto principle (Juran, 1954). A Pareto diagram is presented in Figure 2.

3.3.3. *Failure Mode and Effects Analysis (FMEA)*

FMEA was conducted for three critical equipment categories (cooking kettles, homogenizers, and filling machines) following IEC 60812 (2018). Severity (S), occurrence (O), and detectability (D) were rated on a 1–10 scale. Risk Priority Numbers (RPN = S×O×D) were computed to prioritize PM attention. Occurrence ratings were calibrated against the actual twelve-month operational record to ensure that they reflected the plant's PM-influenced failure environment rather than the theoretical component failure rates.

3.3.4. *PM System Evaluation*

The documented PM system of the plant was evaluated against the criteria of the TPM's Planned Maintenance pillar (Nakajima, 1988; Wireman, 2003) using a structured gap analysis. Each best-practice criterion was assessed as Present, Partial, or Absent, with supporting evidence cited from the primary documents.

3.4. Data Triangulation

The findings were triangulated across three independent sources: (1) production records (Plan vs. Actual), (2) quality records (FTR), and (3) maintenance documentation (MM-F-003, MM-F-007, DMC-01). The plant management's written statement, '*No Breakdown, All Covered in Preventive and Predictive Maintenance*', is treated as a claim requiring evidential corroboration, which the production and quality records independently provide.

3.5. Limitations

Three limitations are acknowledged. First, the plant maintains maintenance records in hard copy, so precise stoppage timestamps are unavailable, requiring Availability to be estimated rather than precisely calculated. Second, as a single case study, statistical generalizability is limited, though analytical transferability to comparable contract grease manufacturers is claimed. Third, the student-researcher's family relationship with the plant owner may introduce social desirability bias in interview-based data; this is mitigated by relying primarily on documentary evidence rather than interview responses for quantitative findings.

4. Case Study Context: SGLPL, Manesar

4.1. Plant Overview

Siddharth Grease & Lubes Pvt. Ltd. (SGLPL) is a grease and lubricant contract manufacturer located at Plot No. 13, IMT Manesar, Sector 3, Gurgaon, Haryana, India. The plant produces greases across all principal chemistries

- lithium, lithium complex, calcium sulfonate, polyurea, aluminum complex, clay-based (non-soap), and silicone-for more than 50 national and international client brands, including Shell, SKF, JCB, Castrol, Gulf, Petronas, Timken, and MAK. The plant operates 24 hours per day, six days per week (26 days per month) across two 12-hour shifts.

SGLPL represents an appropriate and methodologically valuable case for OEE research for several reasons: (a) it operates at an industrial scale with a documented 57-asset plant register; (b) it produces over 200 distinct formulations on shared equipment, creating a high-complexity scheduling and quality management environment; (c) it maintains formal PM documentation to ISO-style document control standards; and (d) 12 months of operational data are available for analysis.

4.2. Production Equipment

The critical production assets are summarized in Table 2. Equipment ages range from 2007 to 2025, reflecting ongoing capital investment alongside legacy infrastructure, a configuration common in growing process manufacturers and one that creates a mixed maintenance management challenge.

Code	Equipment	Capacity	Make / Origin	Process Stage
CK-01/02/03	Grease Cooking Kettle (Open)	9 MT×3	Ajax Mixing, India	Saponification / cooking
CK-04	Counter-Rotating Cooking Kettle	10 MT	PUNJA, India (2025)	Advanced cooking
ST-01 / ST-02	Saponator / Patterson Autoclave	5.5 MT / 5 MT	Std. Engineers / Patterson, Canada	Closed saponification
HT-01 to HT-11	Holding Kettles	3–12.5 MT	Ajax Mixing	Post-cooking buffer storage
CO-01 to CO-06	Cooling Kettles	12.5 MT×6	Ajax Mixing	Batch cooling
HOM-01/02 /03	Homogenizers (incl. 2×Gaulin)	8–10 MT/h	SPX Flow (USA) / Indigenous	Texture homogenization
MIL-01 to 04	Milling Machines	4.5–5 MT/h	Charlotte (USA) / Frigmaires	Fine milling
GF-01	Twin-Head Grease Filling Machine	20 MT/8h	Cadetronics, India	Primary filling
POU-01/02/ 03/04	Pouch Filling Machines	200 kg/h×4	Amson Engineering (2024–25)	Pouch packaging

Table 2: Critical Production Equipment-SGLPL Manesar Plant

4.3. OEE Calculation Approach

Quality Rate (Q): Calculated directly from FTR records as Q = Good Batches÷Total Batches. **Performance Rate (P):** Calculated from Plan vs. actual records as P = Actual Batches÷Planned Batches, consistent with the batch-process OEE convention (Braglia et al., 2008).

Availability (A): Estimated as A = (Planned Hours−Estimated Lost Hours)÷Planned Hours. The planned hours were 26 days×12 months×24 hours = 7,488 hours. Estimated lost hours = 41 deviation events × 4 hours average scheduling delay = 164 hours. The 4-hour average is a conservative estimate; actual delays may be shorter than this. The plant's stated MTTR for equipment faults is1–2h, but deviation events are predominantly scheduling delays rather than equipment repairs.

5. Results

5.1. Production Schedule Adherence

Table 3 and Figure 1 present the monthly plan versus actual batch production data for the full study period. Across 309 recorded production days, 2,804 batch-slots were planned and 2,743 were executed, yielding an annual schedule adherence rate of 97.8%. Eleven of twelve months achieved adherence between 97.8% and 99.3%. December 2024 recorded lower adherence (84.1%) attributable to only 19 active production days, consistent with a planned partial shutdown period. Excluding December, the eleven-month average is 98.7%.

Month	Days	Planned	Actual	Deviations	HT Issue	Mat. N/A	Adherence %
January	27	230	226	3	1	0	98.3%
February	28	242	238	5	4	0	98.3%
March	29	257	252	5	3	2	98.1%
April	27	263	260	3	2	1	98.9%
May	31	314	308	6	3	3	98.1%
June	29	269	267	2	1	1	99.3%
July	29	253	251	2	1	1	99.2%
August	26	193	191	2	1	1	99.0%
September	30	211	209	2	1	1	99.1%
October	26	200	197	3	1	2	98.5%
November	29	227	222	5	3	2	97.8%
December	19	145	122	3	1	2	84.1%
Annual Total	**309**	**2,804**	**2,743**	**41**	**22**	**16**	**97.8%**

Table 3: Monthly Production Schedule Adherence-SGLPL (Jan–Dec 2025) HT Issue = Holding Tank occupancy conflict; Mat. N/A = raw or packaging material unavailable

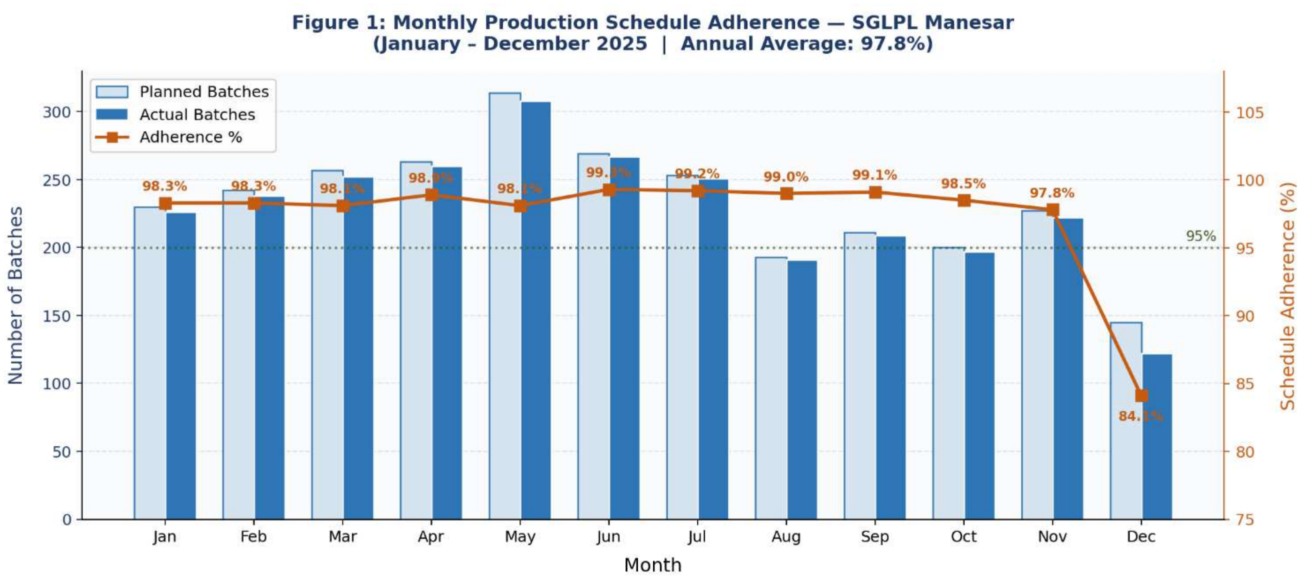

Figure 1: Monthly Plan vs. Actual Batch Production and Schedule Adherence Rate

5.2. Pareto Analysis of Production Plan Deviations

All 41 plan deviation remarks were extracted from the monthly production records and categorized accordingly. Table 4 and Figure 2 present the results of the Pareto analysis. The most significant finding is categorical: zero deviations were attributable to machine breakdowns or equipment failures. The two root causes accounted for 100% of all deviations.

Rank	Cause of Deviation	n	% of Total	Cumulative %	Root Category
1	Holding Tank unavailability (occupied by prior batch)	22	53.7%	53.7%	Scheduling
2	Raw material / packaging material unavailable	16	39.0%	92.7%	Supply Chain
3	Packaging material unavailable (containers/cartons)	3	7.3%	100.0%	Supply Chain
4	Machine breakdown / equipment failure	0	0.0%	100.0%	Maintenance
	Total	**41**	**100%**	-	-

Table 4: Pareto Analysis of Production Plan Deviations-All Causes (12 Months)

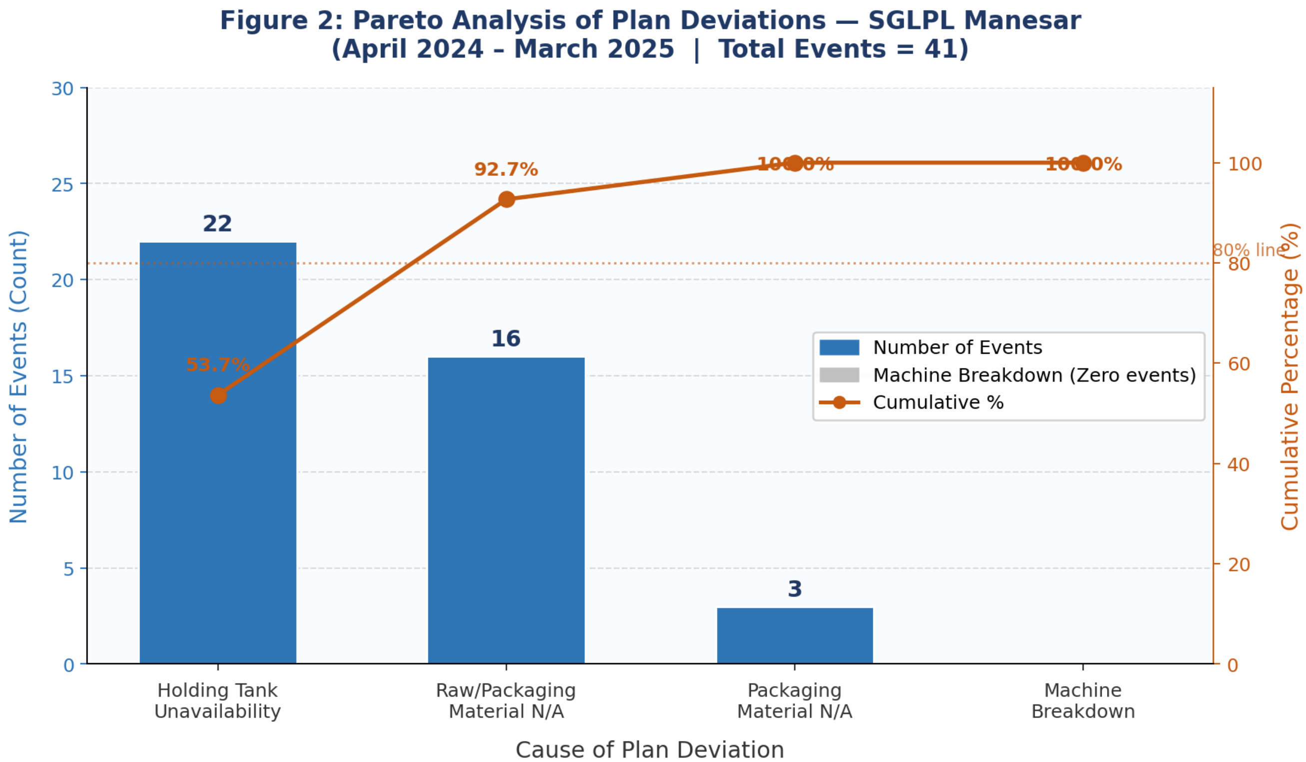

Figure 2: Pareto Chart-Causes of Production Plan Deviations, SGLPL (n=41) Note: Machine Breakdown = 0 events across 12 months of production

5.3. Quality Performance: First Time Right (FTR)

The FTR records for the twelve-month period of April 2024 to March 2025 document 3,134 batches produced across all grease types and client formulations. Table 5 and Figure 3 present a monthly summary. The annual FTR rate is 100%, with zero rework events recorded in any month, against an internal target of >95%.

Month	Period	Total Batches	Rework	FTR Count	FTR Rate
April	Apr-2024	244	0	244	100.0%
May	May-2024	269	0	269	100.0%
June	Jun-2024	266	0	266	100.0%
July	Jul-2024	270	0	270	100.0%
August	Aug-2024	251	0	251	100.0%
September	Sep-2024	241	0	241	100.0%
October	Oct-2024	242	0	242	100.0%
November	Nov-2024	246	0	246	100.0%
December	Dec-2024	256	0	256	100.0%
January	Jan-2025	269	0	269	100.0%
February	Feb-2025	298	0	298	100.0%
March	Mar-2025	282	0	282	100.0%
Annual Total	**Apr 2024–Mar 2025**	**3,134**	**0**	**3,134**	**100.0%**

Table 5: Monthly FTR Quality Performance-SGLPL (April 2024–March 2025)

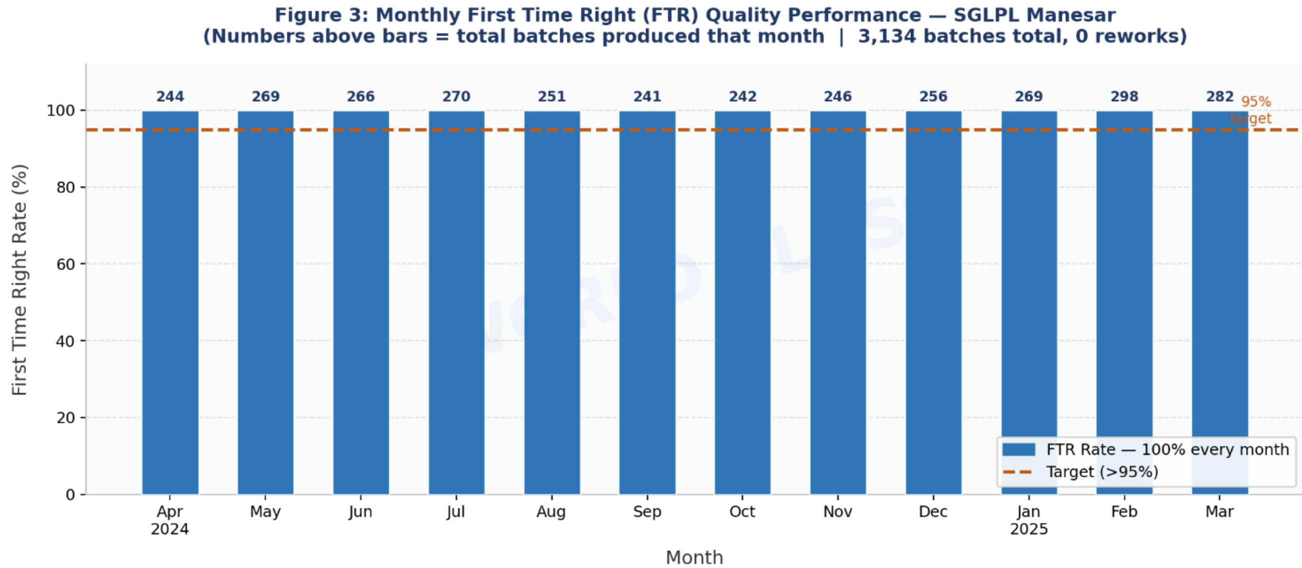

Figure 3: Monthly FTR Rate vs. Internal Target (>95%)-3,134 batches, 0 reworks Numbers above bars indicate total batches produced per month

5.4. FMEA for Critical Equipment

The FMEA results for the three critical equipment categories are presented in Table 6. Occurrence ratings were calibrated against the twelve-month operational record. All Occurrence values are low (2–4), reflecting active PM suppression of failure rates rather than inherent component reliability.

This distinction is methodologically important because low Occurrence scores are not a property of the equipment but of the maintenance regime that manages it.

Machine	Failure Mode	Potential Effect	S	O	D	RPN
Cooking Kettle	Agitator bearing failure	Production stop; batch loss	9	3	4	108
Cooking Kettle	Gearbox oil seal leakage	Contamination; speed loss	7	3	3	63
Cooking Kettle	Heating jacket fouling	Temperature deviation; batch OOS	8	2	4	64
Homogenizer (Gaulin)	Homogenizing valve wear	Consistency deviation; FTR risk	8	3	3	72
Homogenizer (Gaulin)	High-pressure seal failure	Unplanned stop; leakage	7	2	4	56
Filling Machine	Nozzle blockage	Minor stop; dosing accuracy	5	4	2	40
Filling Machine	Pump seal degradation	Leakage; contamination risk	7	3	3	63

Table 6: FMEA for Critical Equipment (S=Severity, O=Occurrence, D=Detectability, scale 1–10) Low Occurrence scores reflect PM-suppressed failure rates, not inherent component reliability

5.5. OEE Calculation and Benchmarking

OEE components (Figure 4 and Table 7) are calculated as follows:

Q = Good Batches÷Total Batches = 3,134÷3,134 = 1.000 (100.0%)

P = Actual Batches÷Planned Batches = 2,743÷2,804 = 0.978 (97.8%)

A = (7,488−164)÷7,488 = 7,324÷7,488 = 0.978 (97.8%) *[estimated]*

OEE = A×P×Q = 0.978×0.978×1.000 = 0.956 (95.6%)

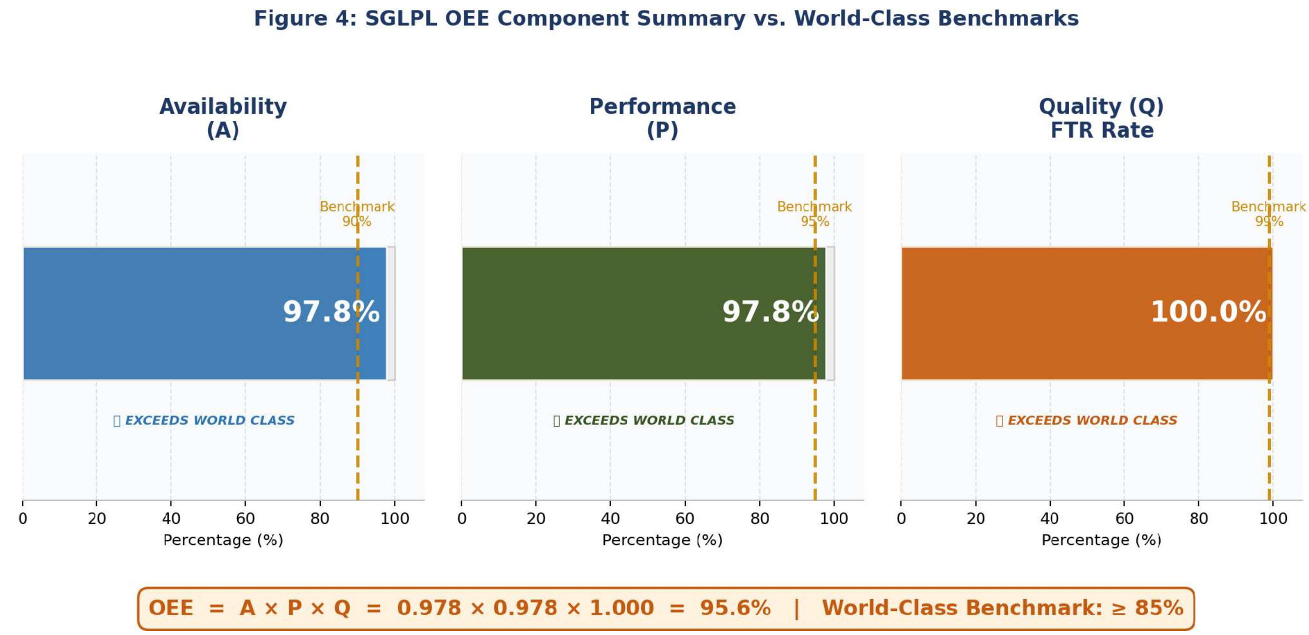

Figure 4: OEE Component Summary-SGLPL vs. World-Class Benchmarks

OEE Component	SGLPL Result	World-Class Target	Margin	Status
Quality Rate (Q)	100.0%	≥99.0%	+1.0 pp	Exceeds
Performance Rate (P)	97.8%	≥95.0%	+2.8 pp	Exceeds
Availability (A)-est.	97.8%	≥90.0%	+7.8 pp	Exceeds
Overall OEE	**95.6%**	**≥85.0%**	**+10.6 pp**	**WORLD CLASS**

Table 7: SGLPL OEE Summary vs. World-Class Benchmarks (pp = percentage points)

6. Discussion

6.1. The PM–OEE Relationship: Confirming Theory with Evidence

The primary findings of this study empirically confirm and extend the theoretical PM–OEE relationship established in the literature. Alsyouf (2007) predicted that PM implementation reduces unplanned downtime by 25–40%; the present study documents a more complete outcome-the effective elimination of equipment-caused production disruptions. All 41 plan deviations over 12 months were attributable to supply chain and scheduling constraints, not equipment failure. This represents a qualitative, not merely quantitative, difference from the literature baseline: not a reduction in maintenance-related downtime but its complete removal from the deviation record.

This finding is consistent with the upper bound of Chan et al.'s (2005) PM effectiveness evidence, while extending it to a domain, Indian grease contract manufacturing, not previously represented in the peer-reviewed literature. The result also corroborates Smith and Hinchcliffe's (2004) RCM proposition that the most effective PM systems do not merely reduce failure rates but redefine the dominant source of operational loss, shifting management attention from maintenance to the next constraining factor in the production system.

6.2. The Residual OEE Improvement Frontier

A significant theoretical implication of this study concerns the nature of OEE improvement in PM-mature facilities. The conventional OEE improvement narrative-implementing PM, reducing breakdowns, and improving availability - assumes that maintenance-induced downtime is the dominant suppressor of OEE. The present evidence challenges this assumption for the case of a PM-mature facility: once maintenance-induced downtime is effectively eliminated, the residual OEE improvement frontier is determined by factors outside the maintenance domain.

At the SGLPL, the residual frontier has two components. The first is the Holding Tank throughput scheduling: the eleven holding kettles create a queuing bottleneck between cooking and filling that accounts for 53.7% of all plan deviations. This is a production scheduling optimization problem that can be addressed through capacity sequencing logic, not maintenance. The second is the supply chain reliability of raw and packaging materials, which accounted for 46.3% of the deviations. This is a procurement and inventory-management problem. Neither is resolvable through further PM investment, suggesting that PM resource allocation in PM-mature facilities should be redirected toward operational system optimization.

This finding has practical relevance beyond SGLPL, suggesting that the standard recommendation of 'implement PM to improve OEE' requires qualification. The OEE improvement leverage of PM investment is highest in reactive-maintenance environments and diminishes as PM maturity increases. At the upper end of PM maturity, the OEE improvement frontier migrates upstream to scheduling and the supply chain, a pattern not clearly articulated in the existing OEE literature.

6.3. Quality Rate as a PM Outcome Indicator

The 100% FTR rate, sustained across 12 months, 200+ formulations, and 50+ client quality standards, provides strong evidence for Prajogo and Sohal's (2006) proposition that equipment reliability and maintenance maturity are correlated with high FTR rates in process manufacturing. In grease manufacturing, the mechanisms are direct: a well-maintained agitator delivers consistent mixing energy throughout the batch cycle, a calibrated temperature sensor provides accurate process control, and a clean homogenizer produces a consistent grease texture. The elimination of these equipment-condition sources of quality variance through PM is the proximate cause of the 100% FTR outcome.

The significance of this Quality Rate finding extends beyond the OEE calculation. A 100% FTR rate across 3,134 batches for 50+ clients in a contract manufacturing environment is an exceptional commercial outcome directly attributable to the stability of well-maintained production equipment. This operational-commercial link-PM → equipment stability → FTR → client satisfaction → commercial competitiveness - is the ultimate business case for preventive maintenance investment.

6.4. PM System Structural Assessment

The gap analysis of SGLPL's PM system against TPM best practices (Table 8) reveals a system with high structural maturity in scheduled maintenance execution and moderate maturity in data infrastructure and predictive maintenance formalization.

TPM Best Practice Element	Status	Evidence	Development Priority
Formal PM plan covering all assets	Present	MM-F-003: 68 machines, M/Q/HY/Y	None
Criticality-differentiated PM frequency	Present	High-criticality assets on full M+Q+HY+Y	None
Equipment-specific PM checklists	Present	MM-F-007 series: per-machine	None
Operator-level daily autonomous checks	Present	DMC-01: Day and Night shift checks	None
In-house + specialist contractor execution	Present	Both, per requirement	None
MTTR target and performance tracking	Partial	Stated:1–2hrs max; not digitally logged	Digital logging required
CMMS / digital downtime logging	Absent	Hard copy records only	High priority
Formal CBM / predictive maintenance	Partial	Referenced; not formally documented	Medium priority-esp. new assets
Formal FMEA-driven task selection	Partial	Tasks align with failure modes; FMEA undocumented	Medium priority
OEE measurement and display	Absent	Not currently calculated or tracked	High priority

Table 8: SGLPL PM System Gap Analysis Against TPM Best Practice

The two highest-priority gaps, digital downtime logging and formal OEE tracking, are particularly consequential given the plant's recent capital investment in high-value assets (Patterson Autoclave: INR 2.5 crore; Punja Kettle: INR 80 lakh; two Gaulin Homogenizers). Protecting this investment through data-driven predictive maintenance and demonstrating continued OEE performance through formal tracking represent the most strategically important near-term maintenance development opportunities for SGLPL.

7. Recommendations

7.1. For SGLPL

Three recommendations are prioritized based on impact and implementation feasibility:

1. **Implement digital downtime logging:** The transition from paper-based to digital maintenance records, achievable through a low-cost CMMS or structured digital form, would

enable precise OEE calculation, MTBF/MTTR trend tracking, and data-driven PM interval optimization. Campbell and Reyes-Picknell (2015) documented a 15–25% OEE improvement in comparable transitions.

2. **Introduce a Holding Tank scheduling system:** Given that Holding Tank occupancy conflicts represent the dominant (53.7%) production disruption cause, a visual real-time tank status board or simple scheduling logic would directly address the primary residual OEE loss driver.
3. **Formalize predictive maintenance for new high-value assets:** Vibration analysis for cooking kettle agitator bearings (highest FMEA RPN: 108) and oil analysis for gearbox lubrication systems, together with pressure trend monitoring for Gaulin homogenizers, would extend the PM system's coverage to condition-based monitoring-the next tier of maintenance maturity beyond time-based scheduling.

7.2. For the Field

This study offers two broader recommendations for maintenance management researchers and practitioners. First, OEE improvement frameworks should incorporate a maturity-conditional model: the marginal OEE value of additional PM investment decreases as PM maturity increases, and at high PM maturity levels, the dominant OEE improvement levers shift to scheduling and the supply chain. Second, OEE measurement programs in process manufacturing should explicitly capture the cause categories of production deviations, not merely their frequency, to distinguish maintenance-driven losses from scheduling-driven losses, enabling more targeted improvement prioritization.

8. Conclusion

This study presents primary evidence from a twelve-month analysis of an operational grease manufacturing plant, Siddharth Grease & Lubes Pvt. Ltd., Manesar, India, demonstrating that a comprehensively implemented preventive maintenance system can sustain world-class Overall Equipment Effectiveness in a high-complexity batch manufacturing environment.

The core empirical findings are as follows: (1) a 100% First Time Right quality rate across 3,134 batches, with zero reworks or rejections; (2) zero equipment-failure-related production disruptions across all 41 documented plan deviations over 12 months; and (3) an estimated OEE of 95.6% (A: 97.8%, P: 97.8%, Q: 100.0%), exceeding the internationally recognized world-class benchmark of 85% on all three components. These findings were corroborated across three independent data sources, production records, quality records, and maintenance documentation, providing robust triangulated evidence.

The theoretical contribution of this study lies in its characterization of the residual OEE improvement frontier in a PM-mature facility. Once PM eliminates equipment failures as a source of production loss, the remaining improvement levers: Holding Tank scheduling and supply chain reliability, are outside the maintenance domain. This finding suggests that OEE improvement frameworks should be PM-maturity-conditional, that is, the appropriate intervention depends on where the plant currently sits on the PM maturity curve, not solely on its current OEE score.

To the best of our knowledge, this study contributes the first published OEE case study based on primary data from a grease manufacturing facility in India and provides a replicable evaluation methodology applicable to PM-mature batch process manufacturers in developing economies. Future research should extend this work through multi-plant comparative studies within the grease manufacturing sector and through longitudinal analysis examining whether CMMS adoption at PM-mature plants produces the OEE gains observed in less mature facilities.

Declarations

Conflict of Interest: The lead author has a familial relationship with the management of the study site (SGLPL). All findings were derived from documentary primary data and independently verified through triangulation across multiple data sources. No financial relationship exists between the authors and study site.

Data Availability: The primary datasets (production records, FTR records, PM documents) are proprietary to SGLPL. Aggregated data sufficient to verify the study's findings are presented in full in the tables and figures of this paper. Requests for access to underlying data should be directed to SGLPL's management.

Acknowledgements: The authors thank the management and staff of Siddharth Grease & Lubes Pvt. Ltd. for their openness in sharing operational data and their time in supporting this research.

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