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Inventory Optimization and Just-in-Time Material Planning for Cost Reduction in EV Battery Pack Manufacturing: An Applied Study at Endurance Technologies Ltd., New Energy Plant

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Abstract - Electric-vehicle (EV) battery packs are costly, safety-critical products. Their manufacturers must keep assembly lines supplied without tying up working capital or floor space and without exposing stock to expiry, obsolescence, and customer rejection. This applied study, completed during on-the-job training at the Endurance Technologies Ltd. New Energy Plant in Pune, builds an integrated inventory and just-in-time (JIT) planning framework that connects demand, capacity, bill-of-materials (BOM) requirements, supplier ordering, production planning and control (PPC), and special-inventory handling. The evidence comprises a 10,000-pack monthly baseline, a four-hour line-side JIT model, illustrative cost scenarios, an import lead-time map, PPC records for 12 dates in July–August 2026, a 25 August 2026 stores snapshot, and plant counts of 400 obsolete and 250 customer-rejected packs. The baseline uses 55.56% of rated capacity, and stacked buffers inflate an 800,000-unit requirement to 906,576 units (+13.3%). PPC achievement was 50.82% in July and 69.64% in August on the recorded dates, and imported material carries a 10-day gap between 55-day lead time and 45-day coverage. The paper introduces an expiry-safe achievement threshold ($A^* = S \div [D \times u]$) and a JIT break-even carrying rate (27.2% per year in the base case). Simulation-calibrated regressions, reported as model-based evidence, show that plan adherence outweighs buffer size in explaining overstock and that blanket JIT is cost-negative in most scenarios. The study therefore recommends controlled JIT supported by first-expired-first-out (FEFO) issue, daily PPC–Stores feedback, engineering-change gates, and root-cause control of customer rejections.

Keywords: inventory optimization, just-in-time, bill of materials, FEFO, production planning and control, EV battery pack

1. INTRODUCTION

India's electric-vehicle market is expanding quickly. The India Brand Equity Foundation (IBEF, 2026) puts EV sales at roughly 2.66 million units in FY26 and notes continuing investment in batteries, components, and charging networks, while the PM E-DRIVE scheme, with an outlay of ₹10,900 crore, further encourages domestic EV manufacturing (Ministry of Heavy Industries [MHI], n.d.). Within this value chain the battery pack is among the hardest products to plan for. It is expensive, safety-critical, and fully traceable, and it is assembled from cells, electronics, enclosures, and sealants bought from many suppliers, several of them overseas. A plant therefore faces a two-sided risk. When material is missing, the line stops; when material is abundant, working capital and floor space are locked up and shelf-life-sensitive items drift toward expiry. Endurance Technologies Ltd. is an Indian automotive-component maker that has broadened its range from aluminium die casting, suspension, transmission, and braking products into lithium-ion battery packs (Endurance Technologies Ltd., n.d.). Inventory decisions at its New Energy Plant cut

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across Stores, PPC, Production, Quality, Purchase, Engineering, suppliers, and customers. Three problems surfaced repeatedly during the internship. Adhesives and sealants with limited shelf life came close to expiry whenever output fell short of plan. A batch of 400 packs built ahead of the start of production (SOP) became obsolete after the customer changed the design. And 250 packs were rejected by the customer and awaited controlled disposition. Behind all three lay the persistent gap between planned and actual output, which changes daily material consumption.

This paper responds with an integrated, data-driven framework built in three steps. The first converts the planning baseline into capacity utilisation, BOM-level requirements, and a JIT delivery schedule, and tests their cost consequences. The second examines PPC performance, imported-material lead time, and shelf-life exposure to show where the plan and the material position diverge. The third designs separate controls for obsolete and customer-rejected inventory. Beyond plant-level results, the paper adds four contributions: formal propositions on when JIT pays and when expiry bites, a set of new decision constructs (A*, c*, LCG, BSI, and SICR), a sampling and data-quality design suited to small industrial case studies, and simulation-calibrated regression models that turn each objective into a testable relationship.

Section 2 sets out the theory and its novelty, and Section 3 reviews the literature. Section 4 states the objectives, conceptual framework, and hypotheses. Section 5 explains the methodology, sampling, and data-quality safeguards. Section 6 analyses the plant data, Section 7 reports the regression analysis, Section 8 presents the contributions of the paper, and Section 9 concludes with findings, suggestions, and future scope.

2. THEORETICAL BACKGROUND

2.1 Core Concepts

Just-in-time (JIT) delivers material close to the time and in the quantity it is consumed, relying on pull signals, small lots, and close supplier coordination. It does not mean zero inventory: minimum (safety) stock still guards against variation in demand, lead time, and supplier quality (Gunasekaran et al., 1993; Heizer et al., 2017). A bill of materials (BOM) turns finished-product demand into component demand through BOM explosion, and once allowances for rejection and supplier-order adjustments are added, the result is the purchase quantity. Reorder logic sets an order as lead-time demand plus minimum stock less usable stock, subject to supplier minimum order quantities (MOQ).

For shelf-life-sensitive items, first-expired-first-out (FEFO) issues the batch with the earliest expiry first, so the value of stock depends on whether it can be consumed before it expires. PPC works as a feedback system in which actual output, and not only the plan, drives replenishment. Obsolescence arises when a change in design, technology, or demand leaves stock unusable, whereas customer rejection calls for a closed loop of segregation, root-cause analysis (RCA), rework and retest, and controlled disposition. Total-cost thinking weighs inventory value against transport, handling, floor space, obsolescence, and shortage risk. Finally, 5S (Sort, Set in order, Shine, Standardise, Sustain) provides the physical discipline of identification, fixed location, and cleanliness on which FEFO depends.

2.2 Theoretical Lenses

Four established theories frame the analysis. Toyota-style pull logic (Ohno, 1988; Womack & Jones, 1996) explains why small, frequent replenishment reduces waste. The theory of constraints (Goldratt & Cox, 1984) holds that system output is governed by its tightest constraint, which must be located rather than assumed. Perishable-inventory theory (Ghare & Schrader, 1963; Nahmias, 1982) treats stock as losing value with age. Little's (1961) law, which links average inventory, throughput, and time in the system, ties days of coverage to lead time. Resilience thinking (Christopher & Peck, 2004) adds that efficiency measures such as JIT must be weighed against exposure to disruption.

2.3 Theoretical Novelty

A theoretical contribution is judged by the originality and utility it adds to an existing body of knowledge (Corley & Gioia, 2011; Whetten, 1989). The JIT, lean, and perishable-inventory streams rarely meet in one model. This paper joins them in battery-pack assembly and advances four propositions.

Proposition 1 (conditional value of JIT). JIT lowers total cost only when the annual carrying-cost rate exceeds a break-even rate, $c^* = 12 \times (\Delta T - \Delta F) \div \Delta I$, where ΔT is the monthly increase in transport cost, ΔF the monthly floor-space saving, and ΔI the reduction in inventory value.

Proposition 2 (adherence-coupled expiry). The expiry risk of a lot is a threshold function of plan adherence. A lot with stock S, planned daily use u, and D days to expiry is exposed whenever average PPC achievement A falls below $A^* = S \div (D \times u)$.

Proposition 3 (constraint migration). When utilisation of rated capacity is moderate (here 55.56%), the binding constraint migrates from capacity to material availability and plan adherence, so improvement effort should migrate with it.

Proposition 4 (plan-blind buffer inflation). When orders follow the plan without feedback from actual output, overstock approximates $(1 + BSI) \div A - 1$, where $BSI = (1 + r)(1 + m)(1 + s) - 1$ is the stacked-buffer inflation. At BSI = 13.3% and A = 0.62, overstock is about 83%.

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3. LITERATURE REVIEW

3.1 JIT and Lean Foundations

Early reviews framed JIT as a broad philosophy. Golhar and Stamm (1991) synthesised the JIT literature and singled out supplier participation, quality management, employee involvement, and waste elimination as the main implementation levers, while Gunasekaran et al. (1993) described JIT as a manufacturing-system approach that reaches across business functions. Shah and Ward (2003) showed that lean practices deliver results as bundles and not as isolated tools. In a meta-analysis, MacKelprang and Nair (2010) found a positive overall association between JIT practices and performance, although the strength varied from practice to practice. Yavuz and Akçali (2007) reviewed the production-smoothing models that support JIT, and Mahendran et al. (2018) documented a lean implementation in an automobile plant.

3.2 Integrated Planning and Battery Supply Chains

Xu and Song (2022) modelled raw-material ordering, production planning, and capacity together under uncertain lead times and quantities. For batteries specifically, Zou et al. (2025) optimised production and inventory capacities under demand uncertainty, Dhairiyasamy et al. (2024) identified import dependence, fragmented supply chains, production cost, quality control, and rapid technological change as the main barriers in India's EV-battery supply chain, and Yang et al. (2026) examined battery production decisions and supplier cooperation. Standard operations texts (Chopra, 2019; Christopher, 2016; Heizer et al., 2017; Slack et al., 2022) supply the BOM, capacity, and inventory-control foundations, and Silver et al. (2017) provide the inventory-control models on which reorder logic rests.

3.3 Perishability, Variability, and Resilience

Classical perishable-inventory work shows that ageing stock changes the optimal ordering policy (Ghare & Schrader, 1963; Nahmias, 1982). Research on the bullwhip effect shows that order variability is amplified as it moves upstream (Lee et al., 1997), and resilience studies caution that lean supply chains concentrate disruption risk (Christopher & Peck, 2004). Together these streams suggest that plan volatility, shelf life, and lead time should be analysed jointly, which the JIT literature seldom does.

3.4 Research Gap

The literature is strong on JIT, lean systems, and integrated planning, but it says little about shelf-life-sensitive adhesives, FEFO, design-change obsolescence, and customer-rejected packs in battery-pack assembly, and it rarely links daily PPC achievement to expiry exposure. Methodologically, few industrial case studies reconcile small, availability-limited samples with inferential modelling or report data-quality diagnostics. This study addresses both gaps.

4. RESEARCH OBJECTIVES, CONCEPTUAL FRAMEWORK, AND HYPOTHESES

4.1 Research Objectives

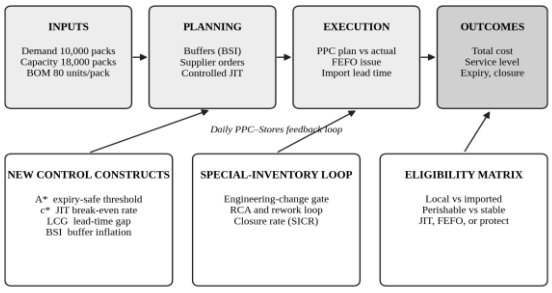
The study pursues four objectives. **O1:** to compute BOM-level material requirements for 10,000 battery packs per month from rated capacity and explicit planning assumptions. **O2:** to design supplier ordering and JIT delivery that reflect a 2% rejection allowance, 1% minimum stock, a 10% supplier-order increase, and supplier rejection. **O3:** to assess transport cost, floor utilisation, floor-space cost, and an illustrative reduction in inventory value. **O4:** to bring PPC performance, imported-material lead time, shelf-life exposure, and obsolete and customer-rejected inventory into one control framework.

4.2 Conceptual Framework and Conceptual Novelty

Figure 1 shows the framework. Demand, capacity, and the BOM feed a planning layer of buffers, supplier orders, and controlled JIT. Execution is governed by PPC plan-versus-actual feedback, FEFO issue, and import lead time. A special-inventory loop and a set of new decision constructs sit beneath this flow and discipline it. The conceptual novelty lies in these constructs (Table 1), which convert qualitative good practice into numbers that a planner can compute, monitor, and act upon.

Figure 1

Integrated Framework for Controlled JIT and Inventory Control



Note. Constructs in the lower row are original to this study. Arrows show the direction of influence.

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Table 1
Novel Decision Constructs Introduced in This Study

Construct	Definition and formula	Value in this study
Expiry-safe achievement threshold (A*)	Minimum average PPC achievement at which a lot is consumed before expiry: S ÷ (D × u)	3.8%–35.3% (Table 12)
Buffer-stacking inflation (BSI)	Compounded uplift from sequential buffers: (1 + r)(1 + m)(1 + s) − 1	13.3%
JIT break-even carrying rate (c*)	Annual carrying-cost rate at which JIT breaks even: 12 × (ΔT − ΔF) ÷ ΔI	27.2% (base case)
Lead-time coverage gap (LCG)	Total lead time minus days of coverage	10 days
Special-inventory closure rate (SICR)	Units dispositioned ÷ (obsolete + customer-rejected units)	650 units to close
Controlled JIT eligibility matrix	Classification of materials by source (local or import) and shelf-life sensitivity	Table 20

Note. S = stock; D = days to expiry; u = planned daily use; r, m, and s = rejection, minimum-stock, and supplier-order uplifts; ΔT, ΔF, and ΔI = monthly transport increase, monthly floor saving, and inventory-value reduction.

4.3 Hypotheses

Each objective is paired with at least one testable hypothesis (Table 2). Hypotheses H1–H4 are tested through the regression models in Section 7, H5 is tested descriptively, and H6 requires post-implementation data that do not yet exist.

Table 2
Research Hypotheses

ID	Obj.	Hypothesis	Test
H1	O1	Under plan-only ordering, overstock falls as PPC achievement rises, and achievement has a larger standardised effect than any buffer.	M1 (OLS)
H2	O2	The probability of a material shortfall rises with supplier rejection and demand volatility and falls with the supplier-order uplift.	M2 (logit)
H3	O3	Net monthly JIT benefit rises with the carrying-cost rate and inventory reduction and falls with delivery frequency and cost per trip.	M3 (OLS)
H4	O4	The probability of expiry risk falls as PPC achievement rises and rises with days of cover; a lot is safe only when A ≥ A*.	M4 (logit)
H5	O4	Imported-material lead time exceeds coverage (LCG > 0).	Descriptive
H6	O4	An engineering-change gate and an RCA loop raise SICR and lower repeat rejection.	Needs post-implementation data

5. METHODOLOGY

5.1 Research Design and Data Collection

An applied, descriptive and analytical single-case study was carried out during on-the-job training from 18 May to 31 August 2026 in Stores and PPC. The unit of analysis is one battery pack and its BOM components over a 26-working-day horizon. Five inputs were used: (a) the planning baseline of 10,000 packs per month, 26 working days, two shifts, 350 packs per shift, and 18,000 packs of rated monthly capacity; (b) PPC daily records for 24–30 July and 4–10 August 2026, twelve dates in all, with 31 July–3 August unavailable and deliberately not reconstructed; (c) a stores snapshot of shelf-life-sensitive materials dated 25 August 2026; (d) plant-supplied counts of 400 obsolete and 250 customer-rejected packs; and (e) hands-on exposure to ERP/SAP stock checks, goods receipt, material issue, and supplier follow-up (Endurance Technologies Ltd., New Energy Plant, 2026).

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5.2 Sampling Methodology

The population is every material-flow event of the battery-pack line during the training period, and the sampling frame is the set of PPC daily reports, stores records, and ERP transactions to which the author had approved access. Sampling was non-probability and purposive. A single plant was chosen as a critical case, because case logic aims at analytic rather than statistical generalisation (Flyvbjerg, 2006; Yin, 2018). Within the case, PPC dates were taken from two consecutive calendar weeks, each containing six working days, because these were the records available and verifiable. The shelf-life-sensitive materials and the special inventory were examined as complete censuses (Table 3).

Table 3

Sampling Design by Data Element

Element	Sampling design	Size
Plant	Purposive, single critical case	1 plant
PPC records	Availability-constrained, two consecutive-week blocks	12 working dates; 31 Jul–3 Aug missing, not imputed
Shelf-life materials	Census of the 25 August 2026 snapshot	6 material lines
Special inventory	Census	650 packs (400 + 250)
Regression inputs	Monte Carlo draws calibrated to observed parameters	5,000 monthly cycles; 4,998 lot draws

Note. Simulation draws are synthetic and are not field observations.

A sample of twelve dates cannot support multivariate regression. Green's (1991) rule of $N \geq 50 + 8k$ implies about 90 observations for five predictors. For this reason the regression models in Section 7 are calibrated by simulation, and the study specifies a field-collection protocol for later re-estimation: at least 90 consecutive production days and at least 30 shelf-life lots, each with a matched PPC date and stores snapshot.

5.3 Sampling Novelty

The study proposes **event-anchored, gap-aware, dual-ledger (EGD) sampling**, designed for small industrial cases in which records are patchy and disruptions drive outcomes. It has four features. First, **block sampling** keeps consecutive days together so that autocorrelation and disruption cascades are preserved, and uncertainty is expressed with a moving-block bootstrap (Künsch, 1989) rather than an independence assumption. Second, **gap awareness** treats missing dates as potentially informative (Rubin, 1976): they are logged, never imputed, and bounded through best-case and worst-case sensitivity checks. Third, **dual-ledger matching** links each production date to the stores snapshot and the expiry ledger, which is what makes A* computable. Fourth, **event anchoring** over-samples disruption days (power failure, PDI errors, clearance delays) and expiry-proximate lots, because these carry most of the managerial information. In this paper the first three features are applied in a limited form; the fourth is specified for the extension.

5.4 Data Bias and Genuineness

Because the paper rests on internal records gathered by a participant observer, bias and authenticity are treated explicitly. Table 4 lists the main biases, their likely effects, and the mitigations applied. In addition, the arithmetic of every plant table (Tables 6–14) was independently recomputed during this revision and reconciled with the stated inputs.

Table 4

Bias Register

Bias	Source in this study	Mitigation
Selection	Twelve dates in two blocks; June has no verified record; four dates missing	Report as sample, not month totals; no imputation; sensitivity bounds
Disruption-period	Sample window contains many power and machine disruptions	Event-anchored sampling; extend to 90+ days
Participant-observer	Intern embedded in Stores and PPC	Mentor review; triangulation with ERP/SAP records
Self-reported reasons	Gap reasons entered by shift staff; MES data sometimes not cleared	Cross-check with dispatch and MES; standard reason codes
Recording	Two expiry dates unverified, including one Henkel lot	Flag; verify against physical lot labels

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Bias	Source in this study	Mitigation
Anonymisation	Sensitive values anonymised, illustrative, or forecast	Label as directional; replace with actuals
Planning-rate mismatch	Daily PPC plans of 150–300 versus the 400-pack target	Recompute A* at actual plan; report both
Synthetic data	Regression inputs are simulated	Label as model-based; use wide ranges; re-estimate on field data
Confirmation	Prior preference for controlled JIT	Report null results (r and m); apply the c* break-even test
Single site	One plant	Analytic generalisation only (Yin, 2018)

Genuineness is assessed with a five-criterion **Data Genuineness Index** (DGI): provenance, verifiability, completeness, consistency, and timeliness, each scored 0 (poor), 1 (partial), or 2 (strong), for a maximum of 10. Table 5 gives a provisional rating derived solely from the limitations stated in this paper. Datasets scoring 7 or more are treated as decision-grade for the descriptive tables, and the cost scenario, at 4, is treated as directional only. The author should confirm these ratings against the source documents.

Table 5
Data Genuineness Index (Provisional)

Dataset	Prov.	Verif.	Compl.	Consist.	Timely	Total
PPC daily records	2	1	1	1	2	7
Stores snapshot (25 Aug 2026)	2	1	1	2	2	8
Special-inventory counts	2	1	1	2	2	8
Import lead-time map	1	1	2	2	1	7
Cost, transport, and floor scenarios	0	0	1	2	1	4

Note. Prov. = provenance; Verif. = verifiability; Compl. = completeness; Consist. = consistency; Timely = timeliness. Scores are 0–2 per criterion.

5.5 Analytical Framework and Limitations

Material requirements follow a fixed sequence. The basic requirement is monthly volume × BOM quantity per pack; this is then multiplied by 1.02 for rejection, 1.01 for minimum stock, and 1.10 for the supplier-order increase, and a separate supplier-rejection adjustment follows. For shelf-life items, daily consumption = daily plan × quantity per pack; coverage days = stock ÷ daily consumption; days to expiry = expiry date − planning date; and expiry-risk quantity = max(0, stock − days to expiry × daily consumption). Production achievement = actual ÷ plan × 100. The expiry-safe threshold follows directly: a lot is consumed in time when achievement is at least $A^* = S \div (D \times u)$. Regression strategy is described in Section 7.

Several limitations apply. The cost, transport, and floor-space figures are illustrative. Actual supplier-rejection rates, MOQ, and adhesive lead times were not supplied. The PPC sample covers only twelve dates, and its daily plans (150–300 packs) differ from the 400-pack operational target. Two expiry dates are unverified (one Henkel glue lot and one 40 kg sealant lot). No post-implementation trial was measured, so results are model-based. Finally, the regression coefficients reflect the assumed simulation ranges and must not be read as field estimates.

6. DATA ANALYSIS AND DISCUSSION

6.1 Converting Demand into Capacity and Material Requirements

Table 6
Planning Baseline and Capacity

Parameter	Basis	Value
Monthly demand	Given	10,000 packs
Average daily demand	10,000 ÷ 26	384.6 packs

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Parameter	Basis	Value
Operational daily target	Rounded	400 packs
Plan per shift (2 shifts)	400 ÷ 2	200 packs
Theoretical capacity per day	350 × 2	700 packs
Rated monthly capacity	Given	18,000 packs
Monthly demand utilisation	10,000 ÷ 18,000	55.56%
Target utilisation	400 ÷ 700	57.14%
Rated monthly headroom	18,000 − 10,000	8,000 packs

Table 6 keeps the 10,000-pack monthly baseline separate from the 400-pack shop-floor target, so that a demand assumption is not confused with a rounded operating figure. The plant uses just over half of its rated monthly capacity, so capacity is not the binding constraint; material availability and plan adherence are (Proposition 3).

Table 7

Illustrative BOM Calculation (80 Units per Pack)

Step	Calculation	Quantity
Basic requirement	10,000 × 80	800,000
After 2% rejection	800,000 × 1.02	816,000
After 1% minimum stock	816,000 × 1.01	824,160
Supplier order (+10%)	824,160 × 1.10	906,576
Per delivery (52 per month)	906,576 ÷ 52	≈17,434

The three buffers lift the supplier order 13.3% above basic need (BSI = 13.3%). The 10% supplier-order increase is applied after the rejection and minimum-stock steps, and supplier rejection is a separate quality adjustment whose actual percentage must come from approved supplier data. A uniform 13.3% uplift sits uneasily beside an inventory-reduction goal, so buffers should be justified by material class, lead time, and supplier performance and not applied to every part.

6.2 Controlled JIT and Total Cost

At 200 packs per eight-hour shift the line consumes 25 packs per hour, so four-hour line-side coverage equals 100 packs, or 8,000 units for the 80-unit example BOM. The delivery model assumes two deliveries per day, or 52 per month. Four-hour coverage across two eight-hour shifts would strictly imply four deliveries per day; with two, each delivery covers a full shift of about 16,000 basic units. Four daily deliveries would double the trip count to 104, or ₹5.2 lakh per month at the assumed ₹5,000 per trip. Delivery frequency is therefore a logistics assumption to be tested against MOQ and vehicle capacity.

Table 8

Illustrative Transport, Floor-Space, and Inventory Scenarios

Measure	Before	After	Change
Trips per month	4	52	+48
Transport cost per month	₹20,000	₹2,60,000	+₹2.40 lakh
Inventory equivalent	5,000 packs	1,500 packs	−70%
Floor area (0.5 sq ft per pack)	2,500 sq ft	750 sq ft	−1,750 sq ft
Floor cost (₹40 per sq ft)	₹1,00,000	₹30,000	−₹70,000
Inventory value	₹4.00 Cr	₹3.25 Cr	−18.75%

Note. All figures are illustrative scenarios supplied for planning.

Table 8 shows the central trade-off. JIT releases 1,750 sq ft and saves ₹70,000 per month in floor cost (₹8.40 lakh annually) and ₹0.75 crore of inventory value, but adds ₹2.40 lakh per month in transport. The scenarios do not complete the total-cost comparison, so the break-even rate c* is derived here (Proposition 1). After netting the floor saving, the carrying saving on ₹0.75 crore must exceed ₹1.70 lakh per month, equivalent to c* = 27.2% per year. At ordinary carrying-cost rates the scenario is cost-negative, which supports controlled JIT for suitable local materials with consolidated deliveries where MOQ and vehicle capacity allow.

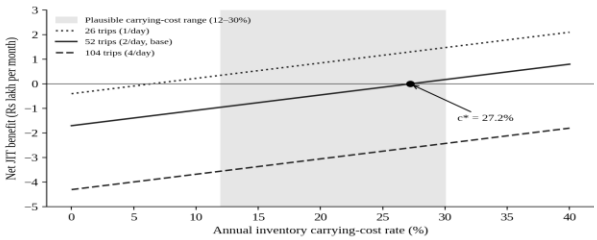
Delivery frequency changes the answer sharply. Holding all other inputs constant, c* is 6.4% per year at 26 trips per month (one delivery a day), 27.2% at 52 trips (two a day), and 68.8% at 104 trips (four a day). A four-delivery-a-day regime would therefore be uneconomic at any realistic carrying-cost rate, whereas a daily-delivery regime pays for itself at a modest rate (Figure 2). The 70% unit reduction and the 18.75% value reduction are separate illustrations and should be reconciled with plant data.

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Figure 2

Net Monthly JIT Benefit by Carrying-Cost Rate and Delivery Frequency



Note. Drawn from the inputs in Table 8 at ₹5,000 per trip. Lines cross zero at c* = 6.4%, 27.2%, and 68.8%.

6.3 Imported-Material Lead-Time Exposure

Table 9

Import Lead-Time Map

Element	Days	Element	Days
Shipping China to India	21	Plant movement	5
China customs	7	Quality clearance	5
India customs	7	**Total lead time**	**55**
Truck movement	10	Project coverage / gap	45 / 10

Table 9 shows a 55-day end-to-end lead time against a 45-day coverage assumption, a lead-time coverage gap of 10 days (H5 supported). Imported and long-lead materials therefore fall outside the four-hour JIT window and need lead-time-based protection: a shorter lead time, supplier-held stock, or a revised safety stock. The exposure is consistent with the import dependence reported for India's EV-battery supply chain (Dhairiyasamy et al., 2024).

6.4 Plan-versus-Actual Performance through PPC

Table 10

Observed PPC Achievement on Recorded Dates

Month	Dates	Plan	Actual	Achievement
July 2026	6	972	494	50.82%
August 2026	6	1,650	1,149	69.64%

Note. Dates: 24–30 July and 4–10 August 2026. These are sample totals, not complete-month totals; June has no verified record.

Achievement rose by 18.82 percentage points between the two samples. The improvement is real for the recorded dates but cannot be read as a complete-month result. Daily achievement ranged from 0% on 25 July to 169.8% on 27 July, and fell to 13.6% and 11.1% on 29 and 30 July. Dispatch was zero on 24, 29, and 30 July against a daily plan of 162, because of pending customer quality clearance and data not cleared in the manufacturing execution system (MES).

The recorded reasons for gaps are varied: casting and rework availability, an ALT machine or PLC breakdown, high delta-voltage failures at the CDC stage, a power failure and a transformer fault at the CDC area, repeated power cuts, bootloader errors at pre-delivery inspection (PDI), and clearance delays. The PPC report is therefore a cross-functional control document linking Production, Quality, PDI, Dispatch, Engineering, and the customer. It also feeds inventory: when output falls below plan, consumption falls and shelf-life exposure rises, and when output recovers, short-coverage materials need faster replenishment. A daily PPC–Stores review of actual output, coverage days, lead time, and FEFO status is the recommended control.

6.5 Shelf-Life-Based Control of Cell Glue and Sealants

The earlier approach ordered adhesives by quantity, without linking orders to the latest PPC plan or to remaining shelf life. The redesigned method converts stock into pack coverage and coverage days, checks days to expiry before any purchase order, issues the earliest-expiry batch first, plans Cell Glue Part A and Part B together because both are needed, and sets the next order from lead-time demand plus minimum stock less usable stock.

Table 11

Shelf-Life Coverage at 400 Packs per Day (25 August 2026)

Material	Stock	Daily use	Cover (days)	Earliest expiry
Cell glue, Henkel	72 L	4 L	18.00	15-Oct-26*
Cell glue, Part A	45 L	4 L	11.25	15-Oct-26
Cell glue, Part B	45 L	4 L	11.25	15-Oct-26
Loctite (screws)	77,750 mL	4,000 mL	19.44	24-Oct-26
Sealing sealant	820 kg	18.4 kg	44.57	10-Feb-27†
Connector silicon sealant	64,800 mL	6,800 mL	9.53	30-Apr-27

Note. *Henkel expiry is not recorded in the source sheet and must be verified. †One 40 kg lot has no expiry recorded. Expiry-risk quantity is 0 for all dated lots at this rate.

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At 400 packs per day no dated lot carries a positive expiry-risk quantity, because each lot is consumed well before expiry. The result is rate-dependent, however: PPC achievement was at or below 92.3% of plan on eleven of the twelve recorded dates, and the same stock would then take longer to consume. The redesigned system therefore recalculates risk from actual output each cycle. The comparison with the earlier scrap-quantity field is a model-based comparison at the stated planning rate, not a measured post-implementation wastage trial.

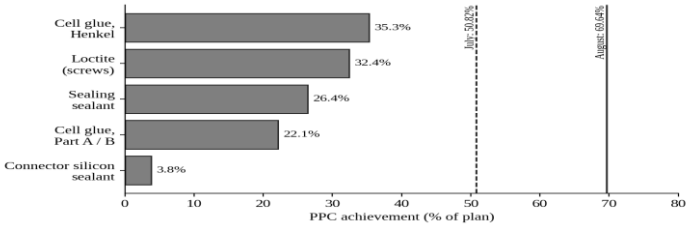
The expiry-safe threshold A* makes this rate-dependence explicit (Proposition 2). Table 12 shows that A* ranges from 3.8% for connector silicon sealant to 35.3% for Henkel glue. Every threshold lies far below the observed 50.82% and 69.64% (Figure 3), which explains why no expiry-risk quantity appears. The binding materials are Henkel glue and Loctite: if average achievement over the remaining shelf life stayed below about one-third of plan, stock would be stranded. Single-day dips to 0%, 13.6%, and 11.1% matter far less for expiry than for line stoppage, because lots are consumed cumulatively and only the horizon average must clear A*.

Table 12
Expiry-Safe Achievement Thresholds

Material	Cover (days)	Days to expiry	A* (%)	Model P(A < A*) (%)
Cell glue, Henkel	18.00	51	35.3	4.7
Cell glue, Part A	11.25	51	22.1	0.4
Cell glue, Part B	11.25	51	22.1	0.4
Loctite (screws)	19.44	60	32.4	3.1
Sealing sealant	44.57	169	26.4	1.1
Connector silicon sealant	9.53	248	3.8	< 0.1

Note. Days to expiry are counted from 25 August 2026. A* = S ÷ (D × u) at a 400-pack daily plan. Model probabilities assume achievement follows a Beta distribution with mean 0.62 and SD 0.15 (Table 16). The Henkel expiry date is unverified.

Figure 3
Expiry-Safe Achievement Thresholds Compared With Observed PPC Achievement



Note. Bars show A*. Vertical lines show observed achievement on the recorded July and August dates.

A* guards only the lower side of a **shelf-life corridor**. Connector silicon sealant has the lowest A* but also the shortest cover, 9.53 days, so its exposure is to shortage and not to expiry. The upper side of the corridor is the achievement level at which stock runs out before the next delivery arrives, S ÷ (u × L) for supplier lead time L, which cannot be computed here because adhesive lead times were not supplied. Collecting those lead times would complete the corridor for every material.

Table 13
No-Replenishment Shortage Risk, September–November 2026

Material	Monthly demand	Sep deficit	3-month deficit
Cell glue, Henkel	100 L	28 L	228 L
Cell glue, Part A / B	100 L each	55 L	255 L each
Loctite	100,000 mL	22,250 mL	222,250 mL
Sealing sealant	460 kg	0 kg	560 kg
Connector silicon sealant	170,000 mL	105,200 mL	445,200 mL

Note. Theoretical deficits if no inward supply is received and 10,000 packs per month is maintained. These are risk indicators, not forecasts of actual shortage.

Table 13 sizes the replenishment task. Opening stock covers September demand for sealing sealant but falls short for the other families from the first month, so ordering must continue under the lead-time-demand rule, with FEFO and shelf-life checks, rather than move toward zero-inventory purchasing.

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6.6 Obsolete and Customer-Rejected Inventory

Table 14
Special Inventory Categories and Controls

Category	Qty	Driver	Control sequence
Obsolete	400	Customer design change at SOP	Segregate; verify approved design; controlled dismantling; recover approved cells and components after inspection; powder-coat approved covers; scrap the rest under authority; retest; close in ERP
Customer rejected	250	Customer quality rejection	Segregate; defect analysis; RCA; rework feasibility; rework and retest; customer approval and re-dispatch, or recovery or scrap
Total	**650**		Controlled closure

The two categories need different controls because their causes differ. Obsolescence is an engineering-change failure, so the preventive control is an inventory gate before SOP: when a customer design change is approved, PPC, Engineering, Stores, Production, and Quality jointly identify and freeze pre-change finished goods, work in process, and critical components. Customer rejection is a quality failure, so the control is a closed loop that prevents repeat defects. Progress can be tracked through obsolete quantity, recovery rate, and SICR for the first category, and rejection rate, repeat-rejection rate, rework recovery rate, and SICR for the second. Defect-wise data for the 250 rejected packs were not supplied, so root-cause categories could not be analysed.

6.7 Recommended Improvements

Table 15
Recommendations, Expected Outcomes, and KPIs

Recommendation	Expected outcome	KPI
Controlled JIT for suitable local parts, with c* test	Lower line-side excess stock	Delivery-frequency adherence; c* versus actual carrying rate
Supplier monitoring	Lower shortage risk	Supplier rejection %; on-time delivery
Inventory and floor dashboard	Lower capital blockage; space release	Inventory value; floor utilisation
Import lead-time review	Protection against supply interruption	LCG (days)
Daily PPC–Stores feedback with A* alert	Faster corrective action	Coverage days; A*; expiry-risk quantity
Engineering-change gate	Lower obsolete inventory	Obsolete quantity; SICR
Rejection RCA dashboard	Lower repeat rejection	Repeat-rejection rate
5S and FEFO discipline	Lower expiry and identification risk	Expiry scrap quantity; audit score

7. REGRESSION ANALYSIS

7.1 Rationale and Simulation Design

Twelve PPC dates and six material lines cannot support inferential regression, and several drivers (supplier rejection, carrying cost, adhesive lead time) were not supplied. Each objective is therefore expressed as a regression on a calibrated Monte Carlo process (Table 16). Inputs are anchored to observed plant values where these exist and otherwise take wide, plausible ranges, in the spirit of global sensitivity analysis (Saltelli et al., 2008). The resulting data are **synthetic**. The regressions recover the relationships implied by the planning logic and show which inputs dominate; they are not field evidence, and their coefficients depend on the assumed ranges. Their value is to prioritise what to measure and to fix an analysis plan before real data arrive.

Table 16
Simulation Parameters

Variable	Distribution	Anchor
Monthly demand, V	Normal (10,000; 1,000), truncated to 6,000–14,000	Planning baseline

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Variable	Distribution	Anchor
PPC achievement, A	Beta, mean 0.62, SD 0.15	Observed 0.508 (July) and 0.696 (August)
Rejection allowance, r	Uniform 1%–3%	2% in Table 7
Minimum stock, m	Uniform 0.5%–1.5%	1% in Table 7
Supplier-order uplift, s	Uniform 5%–15%	10% in Table 7
Supplier rejection, ρ	Uniform 0%–12%	Assumed (not supplied)
Demand volatility, CV	Uniform 5%–25%	Assumed
Carrying-cost rate, c	Uniform 12%–30% per year	Assumed
Cost per trip, t	Uniform ₹3,500–₹6,500	₹5,000 in Table 8
Trips per month, n	26, 52, or 104 with equal probability	Daily, twice daily, four times daily
Floor rate, f	Uniform ₹30–₹50 per sq ft	₹40 in Table 8
Inventory reduction, ΔI	Uniform 50%–100% of ₹0.75 crore	Table 8
Lot stock (M4)	Observed stock × Uniform (0.6, 1.6)	Table 11

Note. Seed = 2026; 5,000 monthly cycles for M1–M3 and 4,998 lot draws for M4.

7.2 Model Specification

M1 (O1, requirement planning). $\ln(1 + OS) = \beta 0 + \beta 1A + \beta 2r + \beta 3m + \beta 4s + \beta 5 \ln V + \varepsilon$, where overstock $OS = Q \div (80 \times V \times A) - 1$ and $Q = 80 \times V \times (1 + r)(1 + m)(1 + s)$ is the plan-based order.

M2 (O2, supply continuity). logit $P(\text{Shortfall} = 1) = \gamma 0 + \gamma 1\rho + \gamma 2CV + \gamma 3r + \gamma 4m + \gamma 5s$, where shortfall occurs when $Q \times (1 - \rho)$ is less than the actual need $80 \times V^* \times (1 + r^*)$, with V^* drawn from Normal(V, CV × V) and r^* from Uniform(0.5r, 1.5r).

M3 (O3, total cost). $\Delta\text{Net} = \delta 0 + \delta 1c + \delta 2t + \delta 3n + \delta 4f + \delta 5\Delta I + \varepsilon$, where ΔNet is the floor saving plus the carrying-cost saving less the added transport cost (₹ lakh per month).

M4 (O4, shelf-life control). logit $P(\text{Expiry risk} = 1) = \theta 0 + \theta 1A + \theta 2\text{Cover} + \theta 3D$, where expiry risk occurs when $S - D \times u \times A > 0$.

Linear models were estimated by ordinary least squares with HC3 heteroskedasticity-robust standard errors (White, 1980; Wooldridge, 2020), and logit models by maximum likelihood. A bootstrap interval (Efron, 1979; 300 resamples) was computed for the carrying-rate coefficient in M3. Inputs were drawn independently, so multicollinearity is absent by construction.

7.3 Results

Table 17
OLS Regression Results (HC3 Robust Standard Errors)

Predictor	b	SE	β	p
Panel A. M1: ln(1 + overstock ratio); N = 5,000; R^2 = .966				
Intercept	1.651	0.063	—	< .001
PPC achievement, A (0–1)	−1.776	0.010	−.978	< .001
Rejection allowance, r	0.865	0.115	.019	< .001
Minimum stock, m	1.187	0.242	.013	< .001
Supplier-order uplift, s	0.882	0.025	.094	< .001
ln(Monthly demand)	−0.003	0.007	−.001	.622
Panel B. M3: net monthly JIT benefit (₹ lakh); N = 5,000; R^2 = .974				
Intercept	2.0604	0.0518	—	< .001
Carrying-cost rate (percentage points)	0.0465	0.0008	.137	< .001
Cost per trip (₹ thousand)	−0.5722	0.0062	−.284	< .001
Trips per month	−0.0500	0.0002	−.921	< .001
Floor rate (₹ per sq ft)	0.0175	0.0007	.058	< .001
Inventory reduction (₹ crore)	1.7898	0.0379	.110	< .001

Note. b = unstandardised coefficient; β = standardised coefficient. Results are simulation-based.

Model M1. Plan adherence dominates. A ten-point rise in PPC achievement lowers the log overstock ratio by 0.178, roughly a 16% lower ratio, and its standardised effect (β = −.978) is about ten times that of the largest buffer (supplier-order uplift, β = .094). Under plan-only ordering at the assumed achievement distribution, mean overstock is 96.6% and median overstock is 81.1%, consistent with

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Proposition 4. Monthly demand has no independent effect (p = .622). H1 is supported within the model.

Model M3. Mean net JIT benefit across scenarios is −₹1.15 lakh per month, and only 35.1% of scenarios are positive. Each additional percentage point of carrying cost adds ₹0.047 lakh per month (95% bootstrap interval 0.045 to 0.048), but delivery frequency dominates (β = −.921): every extra monthly trip costs ₹0.05 lakh. H3 is supported within the model, and the finding matches the analytical break-even in Section 6.2.

Table 18
Logistic Regression Results

Predictor	b	SE	Odds ratio	p
Panel C. M2: material shortfall (1 = yes); N = 5,000; prevalence = 36.7%; McFadden R² = .064				
Intercept	−1.066	0.209	0.345	< .001
Supplier rejection, ρ (pp)	0.139	0.009	1.149	< .001
Demand volatility, CV (pp)	0.045	0.005	1.046	< .001
Rejection allowance, r (pp)	0.056	0.053	1.057	.293
Minimum stock, m (pp)	−0.046	0.106	0.955	.663
Supplier-order uplift, s (pp)	−0.110	0.011	0.896	< .001
Panel D. M4: expiry risk (1 = yes); N = 4,998; prevalence = 3.8%; McFadden R² = .895				
Intercept	28.799	3.272	—	< .001
PPC achievement, A (pp)	−0.748	0.083	0.473	< .001
Days of cover	1.247	0.146	3.480	< .001
Days to expiry	−0.483	0.057	0.617	< .001

Note. pp = percentage points. Odds ratios in Panel D are inflated by near-perfect separation and should be read for direction and threshold behaviour only.

Model M2. Shortfall occurs in 36.7% of cycles when orders are sized to plan. Each percentage point of supplier rejection raises the odds of a shortfall by 14.9%, each point of demand volatility by 4.6%, and each point of supplier-order uplift lowers them by 10.4%. The 2% rejection allowance and 1% minimum stock are not significant (p = .293 and .663), which suggests that, within the sampled ranges, they add little protection on their own; the 10% uplift is the effective shock absorber. H2 is therefore partly supported. The low pseudo-R^2 (.064) reflects the large random component in demand and rejection.

Model M4. Expiry risk is a threshold phenomenon. Higher achievement lowers its odds (odds ratio 0.473 per point), whereas more days of cover raise them (3.48 per day) and longer remaining shelf life lowers them (0.617 per day), as Proposition 2 implies. The very high pseudo-R^2 (.895) shows the near-deterministic nature of the threshold and not a rich behavioural fit. Using Table 12, the model probability that average achievement falls below A* is 4.7% for Henkel glue, 3.1% for Loctite, 1.1% for sealing sealant, 0.4% for Part A and Part B, and below 0.1% for connector silicon sealant. H4 is supported within the model.

7.4 Hypothesis Verdicts

Table 19
Summary of Hypothesis Tests

ID	Verdict	Key evidence
H1	Supported (model-based)	β for A = −.978 versus β for s = .094 (Table 17)
H2	Partly supported (model-based)	ρ, CV, and s significant; r (p = .293) and m (p = .663) not
H3	Supported (model-based)	Mean net benefit −₹1.15 lakh; 35.1% of scenarios positive; c* = 27.2% in the base case
H4	Supported (model-based)	A and D lower the odds of expiry risk; cover raises them; P(A < A*) = 0.0%–4.7%
H5	Supported (descriptive)	LCG = 10 days (Table 9)
H6	Not yet testable	Needs post-implementation SICR and rejection data

7.5 Robustness and Caveats

Signs and relative magnitudes follow from the planning logic and are therefore stable, but the coefficient sizes depend on the assumed ranges, and no further robustness variants were run. The simulation should be re-estimated on field data collected under the protocol in Section 5.2, and the departure of the field estimates from these model-based values would itself be informative about hidden frictions in the plant.

8. CONTRIBUTIONS OF THE STUDY

8.1 Theoretical Contributions

The paper moves beyond the claim that JIT is beneficial by stating the conditions under which it is not. Proposition 1 gives an explicit economic threshold for JIT (c*), Proposition 2 turns expiry

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from an inventory-age problem into a plan-adherence problem, Proposition 3 applies the theory of constraints to show that, at moderate utilisation, the constraint moves from capacity to material and plan reliability, and Proposition 4 quantifies how plan-blind buffers become overstock. Together they link pull logic, perishable-inventory theory, and constraint thinking in one analytical frame, which the existing literature treats separately.

8.2 Conceptual Contributions

Five measurable constructs (A*, BSI, c*, LCG, and SICR) and a classification device, the controlled JIT eligibility matrix (Table 20), convert qualitative good practice into numbers a planner can compute from existing Stores and PPC data. The matrix replaces the all-or-nothing question of whether to adopt JIT with a material-by-material decision.

Table 20
Controlled JIT Eligibility Matrix

Material class	Local (short lead time)	Imported (long lead time)
Shelf-life-insensitive	**Pull JIT.** Frequent small deliveries, with the delivery frequency chosen so that c* stays below the actual carrying rate.	**Lead-time protection.** Coverage at least equal to lead time; supplier-held stock; work to close LCG.
Shelf-life-sensitive	**FEFO-pulled JIT.** Order against actual output; monitor A*; plan paired lots (Part A and Part B) together.	**Dual protection.** Smaller, staggered shipments; FEFO; monitor both A* and LCG.

8.3 Methodological Contributions

Three methodological contributions are offered. EGD sampling gives small, patchy industrial case studies a principled way to handle blocks, gaps, and disruption days. Simulation-calibrated regression shows how a case with too few observations can still state pre-specified, falsifiable models and identify the variables worth measuring. The Data Genuineness Index gives practitioners a short, auditable scorecard that makes data quality visible alongside results.

8.4 Managerial and Practical Contributions

For the plant, the paper offers a decision toolkit that can be run from existing records: an A* alert in the daily PPC–Stores review, a c* test before any increase in delivery frequency, a buffer budget by material class in place of a uniform 13.3% uplift, and an engineering-change inventory gate before SOP. A phased roll-out is feasible. In the first 30 days, compute A*, LCG, and coverage for all shelf-life and imported materials and fix the data gaps in Section 5.4. In days 31 to 60, launch the daily PPC–Stores loop and the rejection RCA dashboard. In days 61 to 90, apply the eligibility matrix, pilot controlled JIT on two or three local parts, and begin collecting the field data needed to re-estimate the regressions. Taken together these elements form a **plant control tower** in which four dashboards (coverage and expiry, lead time, cost, and special-inventory closure) share one daily data feed.

8.5 Industry, Policy, and Sustainability Contributions

The study supports the localisation goals behind PM E-DRIVE (MHI, n.d.) by showing how a domestic assembler can protect continuity without bloating inventory. Its recovery-focused handling of 650 obsolete and rejected packs, which recovers approved cells and components instead of defaulting to scrap, aligns with the extended-producer-responsibility logic of the Battery Waste Management Rules, 2022 (Ministry of Environment, Forest and Climate Change, 2022). Lower expiry scrap and lower blocked floor space also reduce material waste and the physical footprint of the plant.

9. FINDINGS, CONCLUSIONS, AND SUGGESTIONS

9.1 Findings

The baseline uses 55.56% of the 18,000-pack rated monthly capacity, and the 400-pack operational target uses 57.14% of theoretical daily capacity. A four-hour JIT window equals 100 packs. Stacked buffers raise the illustrative supplier order from 800,000 to 906,576 units. In the illustrative scenario JIT releases 1,750 sq ft and ₹70,000 per month of floor cost and lowers inventory value by 18.75%, but adds ₹2.40 lakh per month in transport; the break-even carrying rate is 27.2% at two deliveries a day and ranges from 6.4% to 68.8% across delivery frequencies. Imported material shows a 10-day exposure. Observed PPC achievement was 50.82% in July and 69.64% in August across the recorded dates, held back by power, machine, PDI, and clearance disruptions. At 400 packs per day no dated adhesive lot carries expiry risk, coverage ranges from 9.5 to 44.6 days, and expiry-safe thresholds range from 3.8% to 35.3% of plan. In the simulation-calibrated models, plan adherence outweighs buffer size as a driver of overstock, delivery frequency dominates JIT economics, and only the supplier-order uplift gives measurable protection against shortfall. In all, 650 packs (400 obsolete and 250 customer-rejected) require controlled disposition.

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9.2 Conclusions

Inventory optimisation in an EV battery-pack plant is a cross-functional activity and not a Stores task. The answer is neither minimum nor maximum stock but the right stock for each material class, lead time, and consumption pattern. Local, reliable materials can be replenished frequently provided delivery frequency passes the c* test. Imported materials need lead-time-based protection. Shelf-life-sensitive items need FEFO and production-linked ordering monitored through A*. Obsolete and rejected packs need separate engineering and quality controls. The study met its four objectives at the level of a planning model, and the cost, floor-space, and regression results remain illustrative until validated with plant data.

9.3 Suggestions

For PPC, Stores, and Purchase: run a daily PPC–Stores feedback loop so that the next material requirement reflects actual production; make FEFO, remaining shelf life, and A* mandatory inputs before purchase-order release; keep Cell Glue Part A and Part B balanced; and use controlled JIT for local, reliable materials while protecting long-lead imports. **For Engineering and Quality:** introduce an engineering-change inventory gate before SOP and maintain a customer-rejection RCA and closure dashboard with an owner and target date for each item. **For Plant Management:** review inventory, transport, and floor-space cost together, because lower stock is beneficial only when it does not create a larger shortage, transport, or line-stoppage cost, and sustain the controls with periodic 5S and expiry audits.

9.4 Implications

Plant management: controlled JIT and FEFO protect continuity while reducing blocked capital, floor occupancy, and expiry losses. **PPC and Stores:** actual-output feedback replaces plan-only ordering, so replenishment follows real consumption. **Quality and Engineering:** the gate and the RCA dashboard turn one-off clean-ups into preventive controls. **Suppliers:** early visibility of schedules and rejection feedback supports delivery and quality reliability.

9.5 Future Scope

Future work can re-estimate the regressions on at least 90 days of field data, complete the shelf-life corridor with adhesive lead times, and add ABC–XYZ classification, statistical safety stock, e-Kanban, supplier scorecards, and milk-run delivery optimisation once reliable history exists. Digital dashboards and predictive rejection analytics could replace manual tracking, and a study of battery recovery economics would value the recovered cells and components. A full financial model covering carrying cost, transport, shortage, and obsolescence would quantify the return on the proposed controls, and post-implementation measurement over complete months would validate the results.

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