Improving Production and Quality Control in Injection Moulding through Operational Optimization

A Final Term Submission Report for the BDM Capstone Project

Submitted by

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1. Executive Summary:

This project focuses on Ganes Metplast Pvt. Ltd., a Chennai-based manufacturer of precision plastic components serving the automotive and electrical industries since 2011. The company is currently facing key operational challenges, including elevated rejection rates due to moulding defects, inability to achieve actual vs. target production outputs and Inventory inefficiencies.

Data for this study, covering the period from June 2024 to May 2025 (12 months), focused on production output, rejection rates, downtime, lump generation, machine utilization, and inventory movement. Descriptive statistics revealed key trends in material losses, rejections, and inventory inefficiencies. Analytical tools like Excel, Python (via Google Colab), and Power BI were used to perform Pareto analysis, correlation studies etc. Visualizations included such as column, line, combo charts to highlight inventory trends, rejection causes, and output gaps.

The analysis uncovered a strong positive correlation ($r = 0.85$) between downtime and material wastage, with rejection peaking at 2.21% and lump generation exceeding 430 kg—indicating severe quality loss. February recorded the highest inefficiency, with 1211.9 hours of downtime and only 68.5% output efficiency. The analysis discovered severe fluctuations between excess and shortage, exposing unreliable forecasting and poor coordination between procurement and production. Pareto analysis revealed a few recurring causes behind 80% of losses.

The analysis revealed that actual vs. target output gaps were primarily driven by summer-season downtimes, with manpower shortages. Rejection patterns were strongly tied to quality inspection failures led by bubbles and dents, followed by dimensional issues, burn marks, etc. Additionally, Inventory inefficiencies worsened by material planning.

Notable, Improvements were observed between February and April, downtime reduced by 46.9%, improving machine availability; rejection rates dropped by 50.7% due to focused quality measures; and output efficiency increased by 14.7%, reflecting better planning and reduced disruptions.

2. Detailed Explanation of Analysis Process/Method:

Stage 1: Initial Phase of the Data Collection

Ganes Metplast Private Limited, a manufacturer of automobile and electrical plastic components, faces operational inefficiencies that impact profitability. High rework and rejection rates due to moulding defects such as short-fills, marks and dents, flash, and surface marks lead to cost escalation and customer dissatisfaction. Additional issues include production output gaps, untracked downtimes, and weak inventory planning caused by inefficient material planning and poor consumption tracking.

The study spanned 12 months (June 2024 – May 2025), collecting data from daily production logs, rejection summaries, downtime reports, inventory reconciliation, and OEE (Overall Equipment Effectiveness) sheets. A preliminary site visit provided operational context through shop floor observation and QC inspection reviews. This supported the interpretation of productivity, defect patterns, system gaps etc.

Nature and Complexity of the Data

The Excel-based dataset was complex, covering machine types, OEE metrics, downtime categories, rejection types, daily production logs, and inventory data. Managing it required version control, multiple copies and backups across my laptop, and phone, ensuring data safety during preprocessing and transformation.

Stage 2: Data Cleaning and Preprocessing

The data used in this project was primarily collected in Excel format, covering a comprehensive timeline from June 2024 to May 2025. A total of 14 datasets were compiled, including monthly production data files named systematically as “Production, Quality & Inventory Log <Month>” (e.g., “Production, Quality & Inventory Log February”), Inventory summary and Final analysis. Each dataset typically included key sheets such as OEE Summary, Downtime Summary, Daily Production Logs, Part List, Overall Part Stock, and Material Stock Details, offering a multidimensional view of the manufacturing performance.

During the initial data assessment, a few issues were identified, such as missing values, duplicate entries, and minor formatting misalignments. Fortunately, no merged column issues were observed, and the structure of the data was generally consistent. However, some months sheets protected with passwords; these were resolved by contacting the concerned team to gain access. Despite challenges like formula-based misalignments and unstandardized naming conventions, data labels such as “150 T” for machine tonnage and "OEE" for Overall Equipment Effectiveness were intuitive and retained in their original form for authenticity.

The data cleaning and preprocessing phase was executed using both Microsoft Excel and Python, leveraging the Pandas library within Google Colaboratory. Initially, Microsoft Excel was utilized to manually inspect the datasets, fix alignment issues, unlock frozen headers, and remove visible inconsistencies across files containing detailed sections like OEE Summary, Downtime Logs, Daily Production, Rejection Data, and Inventory Records. Excel also helped in generating early summaries and performing preliminary clean-ups. Following this, Python (Pandas) was used for more advanced operations such as merging datasets, filtering relevant variables, removing duplicates, handling missing values, and reshaping the data into analysis-ready formats. The structured data was then transformed into summary tables grouped by key dimensions like machine performance, rejection trends, material flow etc. This dual-tool approach ensured a thorough, accurate, and efficient preprocessing workflow that laid a strong foundation for deep-dive analysis.

To streamline the analysis, around 11 custom summary sheets were created, consolidating key insights from raw datasets. These sheets served as the foundation for trend analysis, rejection pattern tracking, efficiency evaluations, and correlation studies. Visualizations including charts and plots were generated using both Microsoft Excel and Google Colab to support analytical interpretation.

This genuine and hands-on approach to data preprocessing ensured that the insights derived from the data were reliable, actionable, and directly traceable to original manufacturing activities. The transparency and integrity maintained throughout the process significantly enhanced the quality and credibility of the final analysis.

Stage 3: Comprehensive Explanation of Methods and Analyses Used

1. Rejection and Lumps Analysis

Objective:

The rejection and lumps analysis were a crucial component in quantifying these losses both explicitly (through rejected products) and implicitly (via non-conforming residual material, i.e., lumps), which are often overlooked in conventional analysis.

Methodology:

i). Let R_t represent the rejection % then Monthly wise rejection percentage is defined as

$$R_t = \left(\frac{Rejected\ Quantity}{Actual\ Quantity\ Produced}\right) * 100\ \%$$

ii) For n days in a month the average percentage R_{av} is defined as

$$R_{av} = \frac{\sum_{i=1}^{n} R_t}{n}$$

ii). Let L_t represent the total lump weight (Kg):

$$L_t = \sum_{k=1}^{n} (Each\ months\ Lumps\ in\ kg)$$

Justification for Method Selection:

- **Rejection % (R_t):** This is a standard industry KPI to measure quality loss. However, its limitation lies in its inability to account for process waste like flashes, burrs, and trial overflows, which are captured as **lumps** in post-process scrap.
- **Lump Weight (L_t):** Including lump data provided a more complete view of wastage. Since lumps originate from setup trials, improper mould conditions, and inconsistent operations, they reflect systemic inefficiencies that are **not visible in product rejection counts**.
- **Trend Analysis across Months:** Using time-indexed analysis (June 2024 – May 2025) enabled pattern discovery, such as peak losses in August 2024 and anomaly detection in November. It also allowed correlation of trends with events like machine downtimes, labour issues, or raw material inconsistencies.

Tool Justification:

- **Microsoft Excel** was used for data validation, rejection-lump correlation graphs, and preliminary calculations due to its strong visualization and tabular summarization capabilities.
- **Python (Pandas)** was used for deeper processing, trend analysis, and automating calculations across months.

Analysis:

The analysis shows that focusing only on rejection rates overlooks significant hidden inefficiencies. Lumps, though not classified as defects, consume raw materials, time, and energy contributing to rising costs and stagnant profits. By integrating rejection rates (Rt) and lump generation (Lt), a more comprehensive loss framework emerges, enabling better identification of inefficiencies and improving operational efficiency in moulding processes.

2. Correlation Analysis

Objective:

To determine the relationships between rejection %, lump generation, and machine downtime, and to understand the hidden interdependencies that drive inefficiencies in production.

Methodology:

The statistical method used was **Pearson's correlation coefficient 'r'** defined by:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

- X: Variable 1 (e.g., Rejection %)
- Y: Variable 2 (e.g., Lumps or Downtime)

Justification for Method Selection:

- Pearson's correlation was chosen for its simplicity and effectiveness in identifying linear relationships.
- This statistical approach allowed quantification of interdependencies, supporting decisions on whether to prioritize quality improvement, machine uptime, or both.

Tool Justification:

- The correlation matrix was computed using Python in Google Colab and visualized with heatmap to show intensity and direction of relationships.

Analysis:

The correlation findings confirmed that machine downtime significantly contributes to material waste (lumps), whereas product rejections follow a separate pattern. This highlights that addressing root cause of downtime reasons and maintenance inefficiencies is crucial to minimizing material losses. These insights directly support the BDM project's problem statement by aligning with the goal of reducing waste and enhancing overall operational efficiency.

3. Downtime Trend and Root Cause Analysis

Objective: To study the monthly trend and root causes of downtime, identify high-impact categories, and recommend solutions for minimizing production disruptions.

Methodology: Let D_t be the total downtime in minutes at time t.
Downtime was broken down into classified categories, and total downtime was calculated using:

$$\mathrm{D_t} = \sum_{n=1}^{n} (\mathrm{d_n})$$

Where:

- d_n represents the downtime (in minutes) from cause at time.
- n is the total number of root cause categories identified.

Justification for Method Selection:

A quantitative approach was chosen for its objectivity and scalability. Categorizing and summing downtime by type revealed key contributors and trends across months. A mathematical model helped clearly show how each cause impacted total operational time

Tool Justification:

Microsoft Excel and Python (with Pandas and Matplotlib) were used for data cleaning, aggregation, and visualization. Excel facilitated quick downtime summaries using pivot tables, while Python enabled automated Pareto and trend analysis. These tools were selected for their efficiency, compatibility, and suitability for time-series production data.

Analysis:

The analysis directly addresses inefficiencies from untracked downtimes. Analysis further force to focus on the pareto analysis and helps maintenance supporting efforts to verify the gap between actual and planned output.

4. Pareto Analysis of Downtime Drivers

Objective:

To identify the vital few root causes that contribute to the majority of total downtime and prioritize them for corrective action.

Methodology:

The Pareto Principle (80/20 Rule) was employed to assess cumulative downtime contributions by category. The relative contribution of each cause was computed using the formula:

$$P_{ci} = \frac{d_{ci}}{\sum_{i=1}^{n} d_{ci)}}$$

Where:

- P(ci) is the percentage contribution of cause i.
- d_{ci} is the total downtime attributed to cause i.
- n is the number of total downtime categories.

Tool Justification:

The Pareto Chart was chosen for its ability to clearly visualize categorical downtime data in descending order of impact. It helps identify the "vital few" issues that significantly affect system performance. By displaying each category's contribution and cumulative effect, it simplifies prioritization and is ideal for actionable insights.

Justification for Method Selection:

The method uses the Pareto Principle (80/20 Rule), which reveals that a small number of causes often lead to most problems. In manufacturing downtime, this allows us to focus on the most critical issues. It's an efficient, data-driven approach for allocating limited resources effectively.

Analysis:

The project aims to reduce production inefficiencies from excessive and uneven downtimes. Pareto analysis pinpointed high-impact issues like manpower shortages and equipment delays, directly causing gaps between planned and actual output.

5. Overall Equipment Effectiveness (OEE) Analysis

Objective:

To evaluate machine-wise operational efficiency and identify opportunities for improvement by analysing the OEE metric across all production units on a monthly basis.

Methodology:

OEE is a comprehensive metric that combines three essential components of equipment effectiveness: Availability, Performance, and Quality. It was calculated using the standard formula:

$$OEE = Availability \times Plan\ Vs\ Actual\ \% \times Quality$$

Where:

$$Availability = \frac{Act\ hours}{Plan\ Time}, \quad Quality = \frac{Ok\ quantity}{Actual\ quantity}, \quad Performance \approx Plan\ Vs\ Actual\ in\ \%$$

Justification for Method Selection:

OEE was chosen for its comprehensive approach to measuring manufacturing efficiency by combining availability, performance, and quality into a single metric. Its breakdown helps pinpoint whether losses are due to poor effectiveness of machines or it directly indicates flag to the rejection causes as well lag in production target.

Tool Justification:

Excel structured the logs, while Python automated processing and created machine-wise comparisons for better insights and trends analysis of various machines effectiveness.

5. Inventory Analysis:

Objective:

To examine inventory fluctuations over time and identify key variables influencing, analysis of the Balance stock, total RM + RG (Raw Material + Regrind) input material, forecasting performed through statistically. The goal is to uncover patterns, inefficiencies, and root causes in inventory handling that affect material utilization and stock balance.

Methodology:

➔ Trend Analysis of Balance over 12 Months.

$$\text{Balance}(\text{Opening Stock}) + (\text{Purchased}) - ((\text{Consumption/Dispatch}) \pm \text{Adjustments})$$

Justification for Method Selection:

- Trend analysis was used to detect long-term imbalance patterns, which can reflect inventory mismanagement, poor planning, or supply chain delays.

Tool Justification:

- Python (Pandas, Matplotlib, was used for trend analysis, forecasting etc.
- Excel aided quick inventory aggregations and balance checks.

Analysis Summary:

The trend analysis revealed months with consistent material shortages or excesses, indicating cyclical or planning-related inefficiencies. These insights are vital for demand forecasting and inventory optimization. Opening RM+RG, Rejection, Runner, and Shortage significantly affect total material levels. These variables act as key levers for reducing excess and preventing raw material stock-outs. Their influence guides strategic control of waste and quality improvements.

3. Results and Findings:

A) Primary Data Link: **Click Here**

B) Analysis Data Link: **Click Here**

C) Analysis Google Colab Link: **Click Here**

3.1 Operational Insights from Rejection Rates and Scrap Analysis

i) Line Chart Analysis:

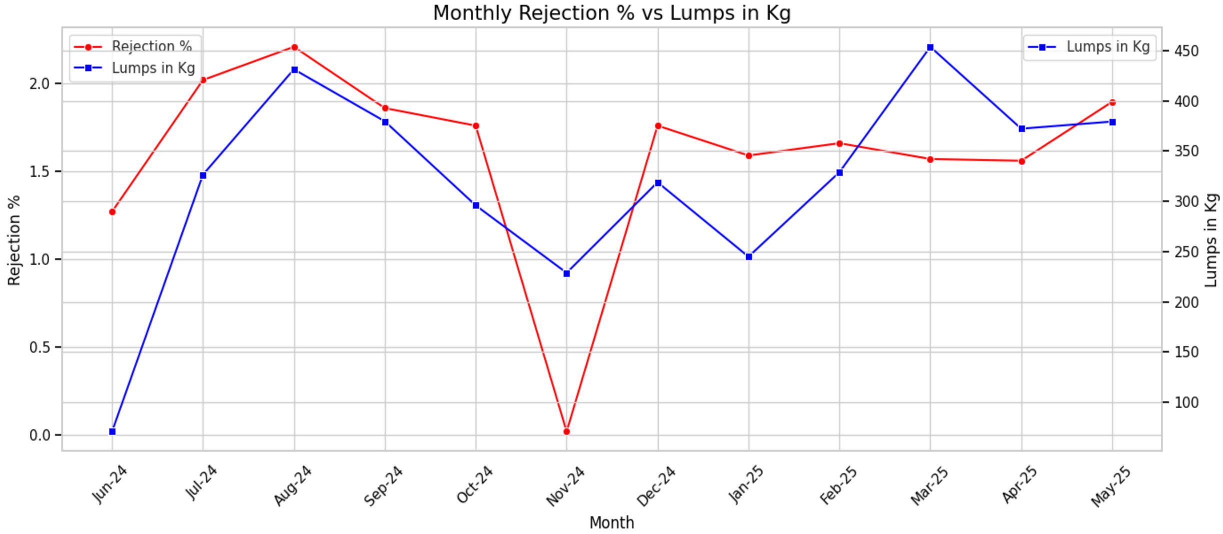


Chart 1: Analysis of Monthly rejections % and Lumps in Kg

Chart 1 presents two key quality indicators over a 12-month period (June 2024 – May 2025), offering insight into moulds rejections and material waste. The red line (left axis) shows the Rejection Percentage, representing defective moulds as an output, while the blue line (right axis) indicates Lumps in Kilograms, reflecting plastic waste from issues like flash, short fills, or purging. Together, these metrics provide a clear view of quality performance and material loss across the production cycle.

Surface level trends:

The rejection percentage and lump generation show a closely aligned trend across the production cycle, indicating strong correlation and pointing to systemic inefficiencies. Rejection rates peaked in August 2024 (2.21%), coinciding with the second-highest lump generation of 431.41 kg, implying significant process issues during that month. The highest lumps occurred in March 2025 (453.79 kg), despite a moderate rejection rate of 1.57%, suggesting underlying purging inefficiencies or unnoticed cycle losses. Anomalies were observed in November 2024, with an unusually low rejection rate of 0.017%, possibly due to shortened production cycles. The period from December 2024 to February 2025 showed stable rejection percentages (~1.6%) but consistently high lump weights (>300 kg), indicating hidden material wastage. Assuming ₹100/kg material cost, August alone incurred ₹43,141 in waste.

These patterns highlight that rejection percentage alone underestimates process inefficiencies, and material wastage through lumps represents a critical hidden cost factor.

Hidden Insights & Strategic Observation:

The data reveals subtle trends. The sharp drop in rejections and lumps in November 2024 may stem from festive season downtime or reporting gaps, not actual improvement. March 2025 mirrors August's spike, likely due to seasonal heat and year-end production pressure. While lumps and rejection rates usually align, anomalies in July and February suggest some lumps result from purging or trimming, highlighting distinct areas for process optimization.

Recurring spikes in August and March highlight a bi-modal instability in the production process, making these months critical for proactive quality checks and preventive maintenance. In contrast, the stable period from December to February offers a dependable baseline for benchmarking best practices. This suggests that a significant portion of material waste may arise from non-defective scrap such as purging, trimming, or mold changeovers. Therefore, reducing lump-related losses demands a distinct strategy focused on improving machine handling routines and operator practices, independent of defect-related quality controls.

ii) Correlation Analysis:

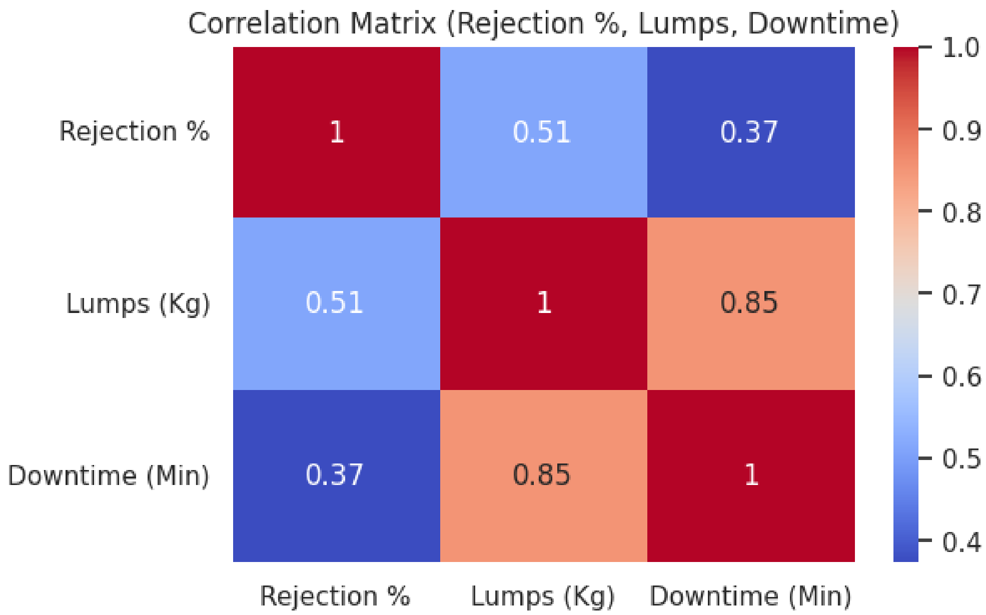


Chart 2: Correlation Analysis Between Rejection, lumps and downtime

After closely examining the monthly trend line chart, which highlighted fluctuations in rejection percentages and lump generation over the year, it became essential to determine whether these patterns were statistically related or simply coincidental. To uncover this, a correlation matrix was visualized, revealing critical relationships between Rejection %, Lump Generation, and Machine Downtime. A moderate positive correlation (r = 0.51) was found between Rejection % and Lumps, indicating that higher material wastage generally coincides with increased product rejections suggesting shared root causes like poor mould conditions or unstable purging. However, Downtime showed only a weak correlation (r = 0.37) with Rejection %, implying that equipment stoppages are not the primary reason for product defects. In contrast, Lumps and Downtime showed a strong correlation (r = 0.85), highlighting that frequent machine interruptions contribute significantly to material wastage. These findings suggest rejections may stem more from inspection-related factors, mould wear, or material inconsistencies than from direct downtime events.

iii) Quality Testing Analysis of Rejection Categories:

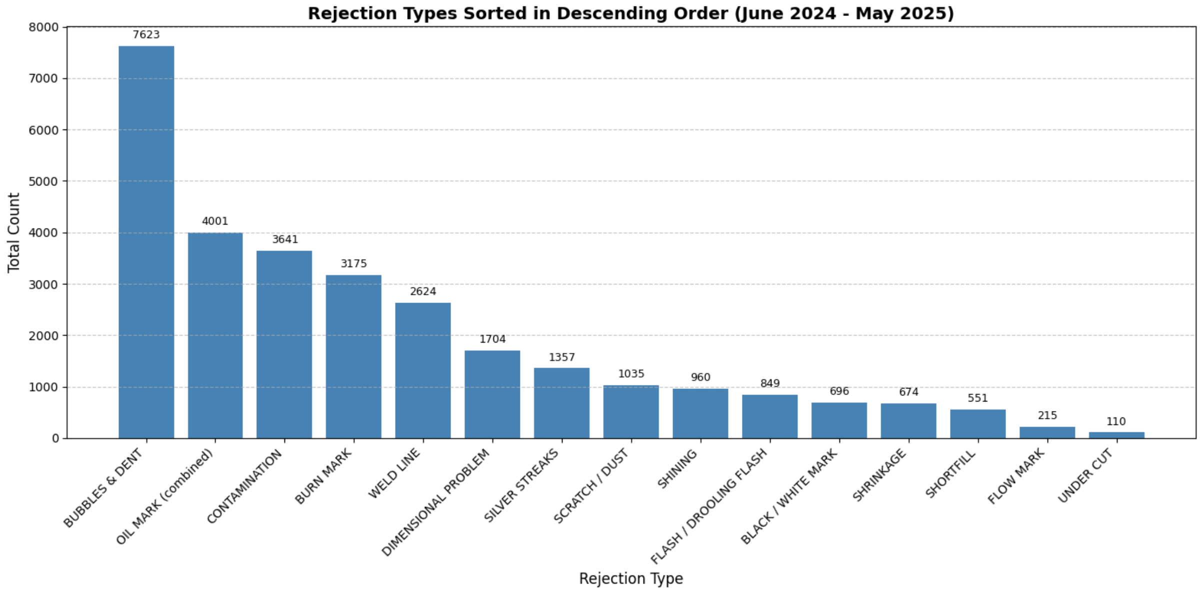


Chart 3: Rejection types analysis over 12 months (June-24 to May-25)

Following the correlation analysis, which revealed significant associations between Rejection %, Lump Generation, and Machine Downtime, it became necessary to dissect the issue further by delving into the specific types of defects contributing to the total rejection volume. While the earlier line chart and correlation matrix provided macro-level insights into when and how severely rejections occurred, this breakdown helps answer the more critical question—why. As visualized in the rejection-type bar chart, the top contributors are Bubbles & Dents (7,623 rejections), Oil Marks (4,001), and Contamination (3,641)—together accounting for over half of the total defects. These categories strongly point to material handling flaws, moisture issues, or process contamination, likely aggravated by inconsistent pre-drying, hopper maintenance lapses, or excessive purging. Notably, Burn Marks (3,175) and Weld Lines (2,624) are also prominent, suggesting mould overheating, poor venting, or uneven flow fronts—issues that align with earlier observations from the March and August quality dips. Meanwhile, Dimensional Problems (1,704) and Silver Streaks (1,357) hint at process instability or thermal fluctuations, which may stem from machine age or inconsistent cycle setups. Although defects like Flow Marks (215) and Undercuts (110) appear less frequently, they can still cause functional or cosmetic rejections, especially in critical parts.

This rejection-type insight builds directly upon the foundations laid by the trend and correlation analyses. It not only clarifies the sources of the spikes observed in key months but also enables root-cause-based targeting where interventions can be prioritized based on the dominant defect types rather than general assumptions. Moving from when problems happen to what causes them, this layer strengthens the roadmap for focused quality improvements.

3.2. Performance Gap Analysis Between Targeted and Actual Output

i) Downtime Trend Analysis & Root Cause Interpretation:

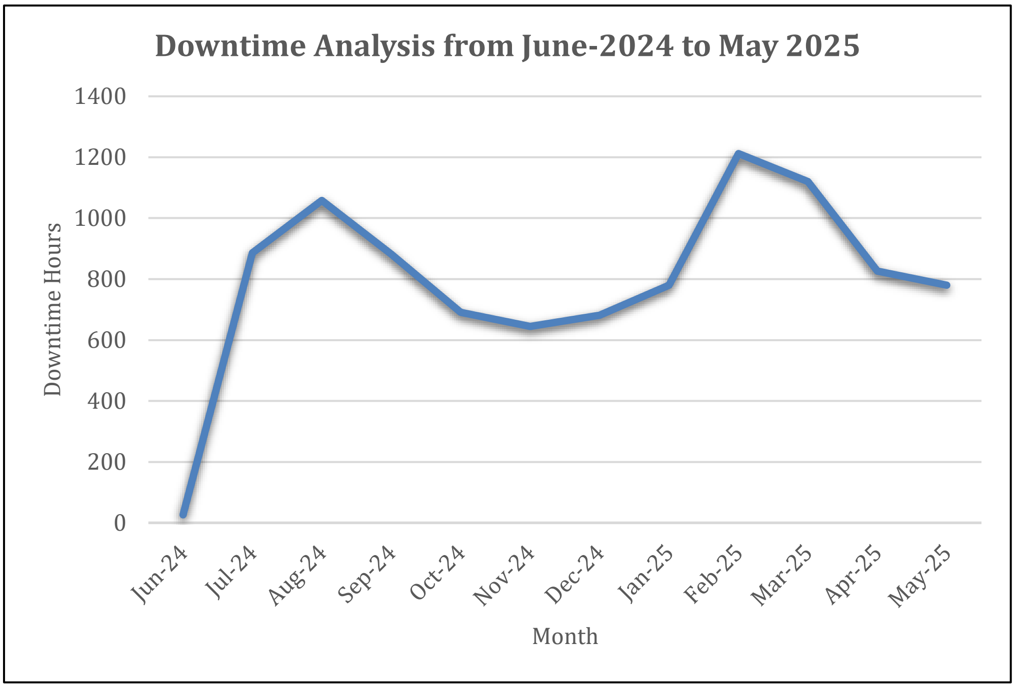


Chart 4: Downtime Analysis over 12 months June 2024-May-2025

The downtime trend across June 2024 to May 2025 reveals cyclical spikes aligned with seasonal, fiscal, and operational factors. A steep rise in downtime from June to August peaking at over 1,050 hours likely stems from delayed preventive maintenance, extreme summer heat, and temporary workforce gaps during holidays. In plastic moulding, overheating impacts machine calibration and mould performance, particularly in automotive-grade precision parts. From September to November, downtime declined steadily, suggesting process stabilization and lower production loads during festive months. However, another surge from December to February, culminating in a record 1,200+ hours in February, points to pre-fiscal year-end pressures, under-maintained tooling, and operator fatigue. These months also coincide with a spike in electrical part demand, often requiring stricter quality control, slowing production.
The gradual decline post-March reflects corrective maintenance, budget resets, and reduced OEM activity. Overall, downtime is not random. It's deeply tied to equipment fatigue, human factors, and production stress cycles, highlighting the need for season-aware preventive strategies and shift-wise efficiency tracking.

ii) Downtime Analysis with respect to Actual Vs Target:

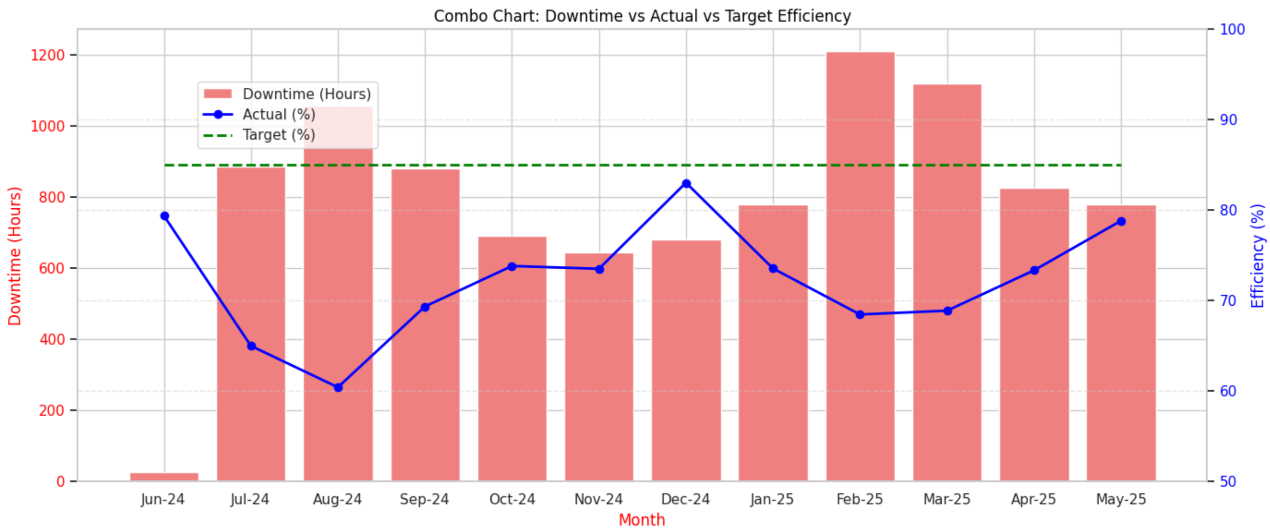
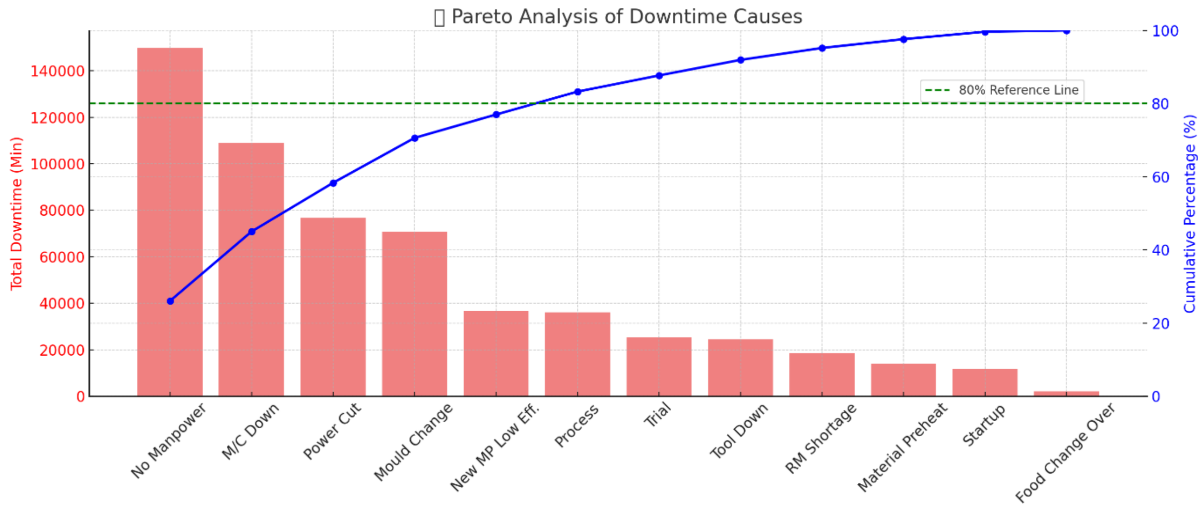


Chart 5: Analysis of Downtime with Actual vs Target

Based on the detailed downtime chart from July 2024 to May 2025, the plant consistently faced chronic downtime exceeding 40,000 minutes each month, with a critical peak in February (72,719 minutes) and March (67,221 minutes) equating to over 1,200 hours of lost production time monthly. This extended disruption had a severe impact on target achievement and overall operational efficiency. The leading contributor was the "No Manpower" category, responsible for over 155,000 minutes across the period, including approximately 630 idle hours in February alone. Other substantial causes such as machine breakdowns (over 99,000 minutes), power outages (86,000+ minutes), and excessive mould changeovers (85,000+ minutes) highlight not just technical shortcomings but deeper managerial and systemic inefficiencies. These trends align with notable production dips and increased rejection rates, especially in February and March 2025, when compounded effects of staff shortages, equipment wear, and unstable processes created a perfect storm. The downtime data therefore reveals more than operational lapses—it points to the need for synchronized manpower planning, robust preventive maintenance, and smarter resource allocation to avoid cascading production failures.

iii) Pareto Analysis:



<u>**Chart 6: Pareto Analysis to perform major downtime reasons**</u>

Pareto analysis reveals that five key causes contribute over 80% of total downtime, with "No Manpower" alone accounting for ~150,000 minutes. This single issue reflects chronic staffing inefficiencies, likely due to shift absenteeism, weak planning, or low retention. Machine breakdowns (~109000 mins) and power cuts (~77000 mins) follow closely, highlighting both mechanical and infrastructural vulnerabilities. Mould changeovers (~71000 mins) also rank high, indicating batch planning inefficiencies and the need for SMED implementation.

Another major contributor is "New Manpower Low Efficiency" (~37000 mins), suggesting that untrained operators or improper onboarding are inflating setup times and rejections. This confirms that downtime isn't just a technical issue. It is deeply rooted in workforce management, training, and process standardization.

3.3. OEE Performance (Overall Equipment Effectiveness) Analysis:

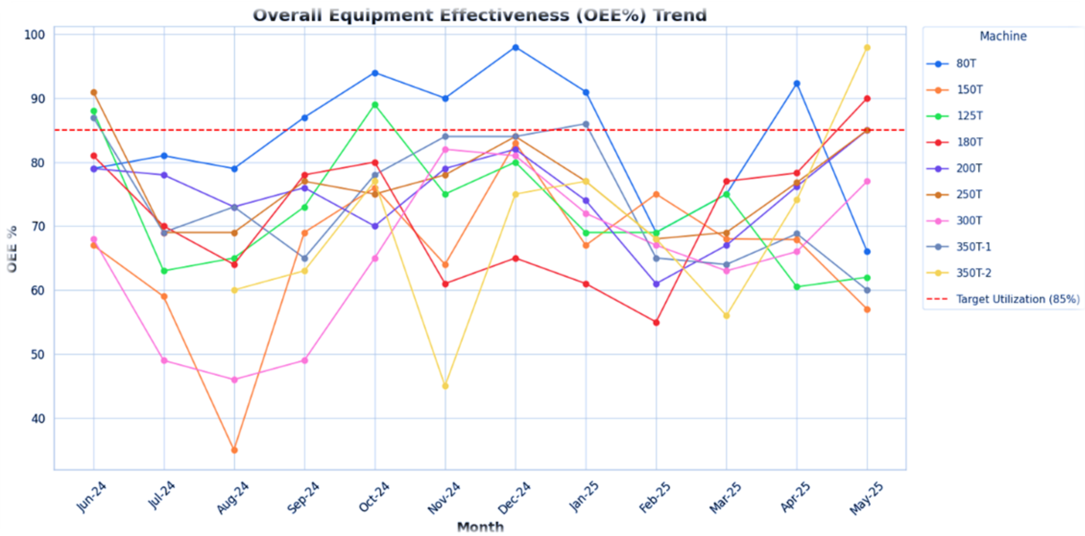


Chart 7: Overall equipment effectiveness %

The 12-month line chart highlights key utilization gaps linked to production shortfalls and inefficiencies. While machines like 80T, 250T, and 200T consistently met targets, 150T and 300T underperformed, often staying below 60%, contributing to output deficits. Machines 125T, 180T, and 350T-1 showed erratic usage, hinting at planning and manpower issues. The newly added 350T-2 is heavily loaded, risking overuse. Dips in Feb–Apr and August suggest reactive scheduling. These patterns confirm earlier concerns about poor planning, misallocated resources, and high rejection rates, underscoring the need for strategic load balancing and preventive maintenance.

3.4. Inventory Analysis:

i) Trend Analysis of balance over months:

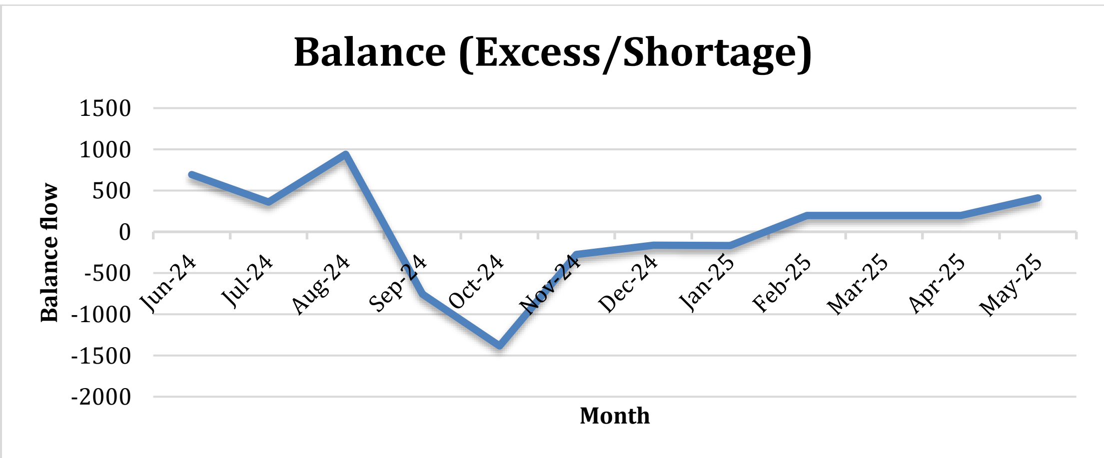


Chart8: Balance trend analysis over the months

The inventory balance data reveals a highly unstable material planning system, marked by significant fluctuations between excess and shortage. From June to August 2024, the company maintained excess stock, peaking at +940 units, which suggests either over-purchasing or underutilization of materials. However, this was followed by a critical downturn, with sharp shortages in September and October (dropping to -1384 units), indicating a breakdown in forecasting, procurement timing, or coordination between production and supply chain teams. This sudden reversal likely disrupted operations, caused delays, and forced reactive, high-cost corrections is a sign of fragmented planning processes lacking real-time integration.
Recovery from Nov 2024 to Jan 2025 was slow and manual, lacking a strong strategic response. From Feb 2025, inventory levels stabilized in the positive range, but this posed a risk of excess if demand didn't rise. The trend reflects reactive inventory management with missed chances for predictive planning. A shift to proactive, data-driven strategies aligning demand, procurement, and production is essential for long-term resilience.

ii) Inventory Component Forecast Analysis.

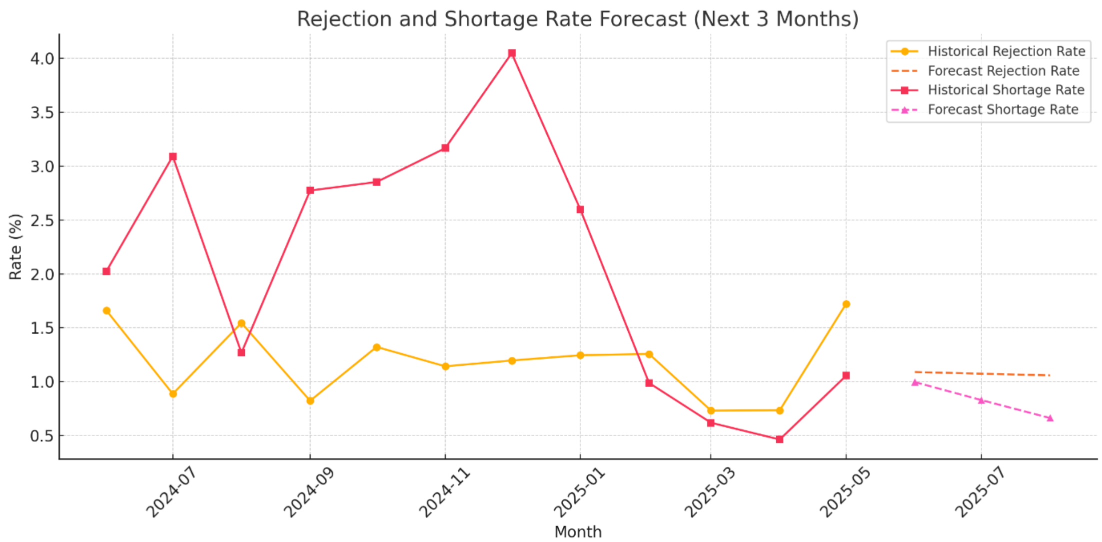
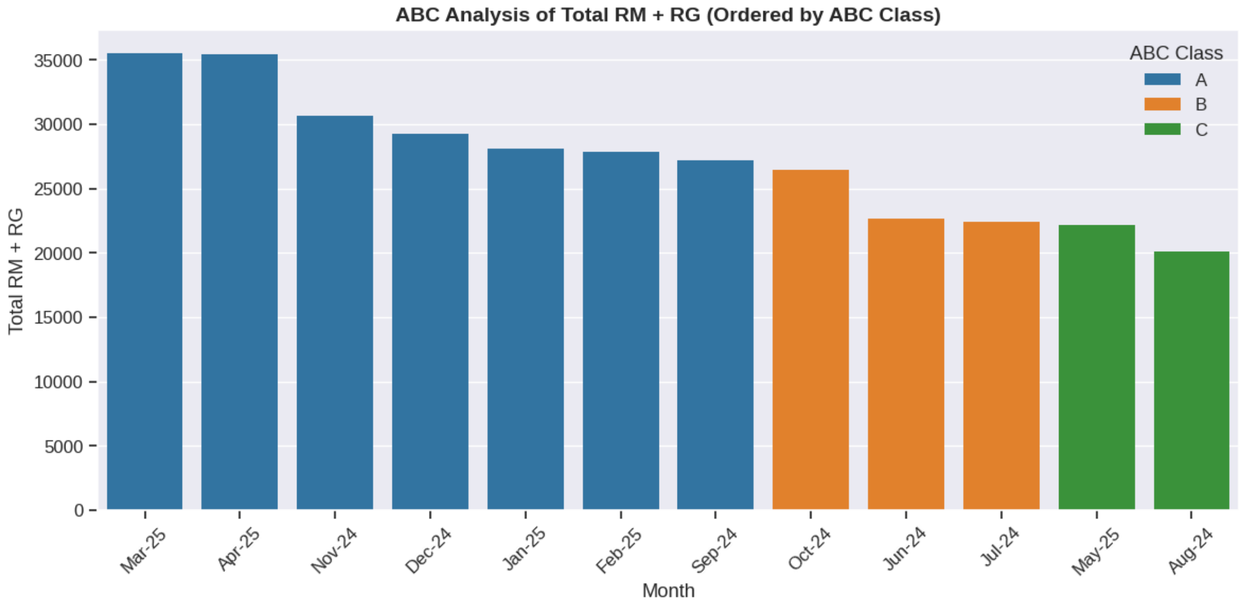


Chart 9: Rejection and Shortage Forecast

The forecasted rejection and shortage rates for the upcoming three months (June to August 2025) reveal early warning signs of emerging operational inefficiencies. The rejection rate shows a gradual upward trend, suggesting a possible decline in manufacturing consistency that could stem from mold wear, machine inefficiencies, or gaps in quality control. This increase, though seemingly moderate, could lead to significant hidden costs through material waste, rework, and reduced production yield. Simultaneously, the projected shortage rate exhibits fluctuation rather than stability, indicating inconsistencies in raw material planning and possible delays in procurement or dispatch alignment. These two trends, when combined, point to a compounding effect are rising rejection consumes more material while shortages delay production is contributing to widened gaps between planned and actual output.

iii) ABC Analysis on Total RM (Raw Material) **+ RG** (Regrind):



<u>Chart 10: ABC Analysis on total RM+ RG monthly</u>

The ABC classification shows that a significant portion of material flow is concentrated in just a few months—most notably March, April, and November, which dominate the annual usage volume. These months fall into Class A, indicating extremely high input or dispatch activity during those periods. In contrast, months like May, August, and July are in Class C, contributing minimally to the overall total. The classification implies that inventory demand is highly uneven across the year, with sporadic spikes rather than a consistent flow. This uneven distribution signals a potentially unstable inventory environment where the system cycles through phases of intense material movement followed by relative dormancy. Such a trend may indicate bottlenecks or unbalanced procurement-production cycles, possibly tied to seasonal orders or ad-hoc planning. The dominance of a few months in material activity could also mask systemic inefficiencies—such as overstocking in anticipation of demand or delayed consumption patterns. Moreover, the inconsistency in Class B and Class C months suggests that the organization might not have a strong predictive mechanism to regulate flow across the year, increasing the likelihood of surplus or shortage risks during non-peak periods

4. Interpretation of Results and Recommendations:

4.1 Interpretation of Results

The comprehensive analysis reveals systemic inefficiencies across rejection handling, downtime management, machine utilization, and inventory control, each directly impacting operational consistency and cost-effectiveness. Rejection percentages alone fail to capture the full extent of material loss, as significant lump generation, particularly during peak months like August 2024 and March 2025, indicates hidden wastage costing tens of thousands in raw material. The moderate-to-strong correlation between downtime and lump generation ($r = 0.85$) emphasizes that interruptions in production, especially those tied to manpower shortages and power cuts, contribute significantly to material inefficiencies. Additionally, machine utilization trends expose imbalanced deployment, with chronic underperformance in units like 150T and 300T, while others face overuse, confirming poor planning and reactive maintenance cycles. Inventory patterns reflect similar volatility—cycling from excessive surplus to acute shortages due to fragmented forecasting and coordination lapses. Forecast models project further risks in rejection and shortage rates, which if left unchecked, could amplify quality issues and output shortfalls.

Overall, the results confirm the original business problem: the organization is losing value due to inefficiencies embedded in people, process, and planning systems. **The issues are interlinked** to downtime impacts inventory accuracy; inventory shortages increase rejection risks; unbalanced machine loads cause inefficiencies in both quality and throughput. Without strategic interventions, these patterns will persist, hampering both scalability and profitability.

4.2 SMART Recommendations and Implementation

Short-Term Recommendations (0–3 months)

1. **Initiate Shift-Wise Rejection Audits**: Implement mandatory end-of-shift rejection tracking by defect type, with supervisor-level RCA reviews.
   - Measurable: Reduce rejection percentage to below 1.2% within 90 days.
   - Benefit: Improved traceability and early detection of mould or operator-related quality issues.
2. **Manpower Planning Revamp**: Introduce attendance-linked resource allocation tools to address “No Manpower” and “Low Efficiency” issues.
   - Measurable: Cut manpower-related downtime by 25% in 3 months.
   - Benefit: Smoother shift transitions and increased machine uptime.

3. **SMED Pilot on High-Downtime Machines**: Launch Single-Minute Exchange of Die (SMED) procedures on machines with high mould changeover time.
    - Measurable: Reduce mould change downtime by 40% in pilot areas.
    - Benefit: Improved batch switching efficiency and lower production delays.

 # SMED stands for Single-Minute Exchange of Dies. It is a Lean Manufacturing technique used to reduce the time it takes to change a production process.

Long-Term Recommendations (4–12 months)

4. **Downtime Analytics Dashboard**: Deploy a real-time digital dashboard integrating downtime categories, shift data, and machine-level insights.
    - Measurable: Achieve 15% overall reduction in total monthly downtime within one year.
    - Benefit: Enhanced decision-making through visibility and accountability.
5. **Preventive Maintenance and Condition Monitoring**: Integrate seasonal triggers and thermal load thresholds into maintenance planning.
    - Measurable: Stabilize peak-season downtime to below 900 hours.
    - Benefit: Reduced heat-related breakdowns and smoother summer operations.
6. **Inventory Planning with Predictive Models**: Shift from reactive ordering to forecast-driven procurement using historical usage and ABC demand patterns.
    - Measurable: Maintain stock balance within ±300 units margin for 9 months straight.
    - Benefit: Minimized stockouts and overstocking, improved production continuity.

4.3 Impact of Implementation

By acting on these recommendations, the organization stands to significantly improve production stability, quality outcomes, and cost efficiency. In the short term, enhanced rejection tracking and manpower stabilization will restore baseline performance. Over time, digital tools and predictive strategies will enable proactive control over downtime, inventory, and machine allocation which can operations from reactive to resilient. The cumulative effect will be improved profitability, increased customer confidence, and readiness for higher production volumes without scaling inefficiencies.