

The Impact of Mean Time to Repair on Overall Equipment Effectiveness: Evidence from a Food Manufacturing Facility

Tinashe Tendayi

Lecturer, Department of Industrial Engineering & Systems Engineering
Cape Peninsula University of Technology
Bellville, Cape Town, South Africa
tendayiit@cput.ac.za

Blessed Sarema

Lecturer, School of Mechanical, Industrial and Aeronautical Engineering
University of the Witwatersrand
Johannesburg, South Africa
blessed.sarema@wits.ac.za

Lucrecia Valentine

Programme Coordinator for Postgraduate Research, Department of Industrial Engineering & Systems Engineering
Cape Peninsula University of Technology
Bellville, Cape Town, South Africa
valentinel@cput.ac.za

Rumbidzai Muvunzi

School of Mechanical, Industrial and Aeronautical Engineering
University of the Witwatersrand
Johannesburg, South Africa
rumbidzai.muvunzi@wits.ac.za

Abstract

Unplanned equipment downtime remains one of the most persistent and costly challenges in food manufacturing, yet the metrics used to manage it are not always well understood in relation to broader production outcomes. Mean Time to Repair (MTTR) is a widely used maintenance indicator, but its specific influence on Overall Equipment Effectiveness (OEE), the composite measure of availability, performance, and quality, has received limited empirical attention, particularly in continuous food production settings. This paper examines that relationship using operational data from a food manufacturing facility in the Western Cape, South Africa. The facility runs eight machines on a 24-hour production schedule, and 91 days of maintenance and production records were analysed. Descriptive statistics and box-and-whisker plots were used to characterise breakdown frequency, machine availability, and OEE variability across the study period. Because the MTTR-OEE relationship showed a nonlinear pattern, Locally Weighted Scatterplot Smoothing (LOWESS) regression was applied to model it without imposing a fixed functional form. The findings confirm that repair duration exerts a measurable, nonlinear effect on OEE, with prolonged repair times disproportionately eroding availability and overall equipment performance. These results carry practical implications

for maintenance planning: reducing MTTR through faster diagnostics, better parts availability, or operator-level intervention offers a low-capital route to meaningful OEE gains. The study contributes empirical evidence to the lean manufacturing and Total Productive Maintenance literature, and provides a replicable analytical framework for facilities seeking to improve equipment effectiveness through targeted maintenance improvements.

Keywords

Lean manufacturing, Total Productive Maintenance (TPM), Overall Equipment Effectiveness, Meantime to Repair (MTTR) and Availability losses.

1. Introduction

In today's highly competitive global manufacturing environment, organisations face mounting pressure to ensure on-time and in-full delivery in order to meet increasingly demanding customer expectations. When production capacity constraints arise, managerial responses often include adding shifts, approving overtime, or acquiring additional machinery (Nallusamy et al., 2018). However, because machines form the backbone of production systems, contemporary operational excellence philosophy argues that improvements should prioritise maximising the utilisation of existing assets, eliminating bottlenecks, and reducing unplanned downtime before capital investment is considered (Nurprihatin et al., 2019). Lean manufacturing supports this perspective and is widely defined as a systematic approach aimed at delivering equal or greater customer value while using fewer resources (De Steur et al., 2016).

Central to lean thinking is the principle that new equipment should not be purchased unless the current machinery consistently achieves an Overall Equipment Effectiveness (OEE) score of at least 85%. An OEE level above this benchmark implies that combined losses related to availability, performance efficiency, and quality amount to less than 15% (Lakho et al., 2020). This threshold is particularly relevant for large-scale manufacturers such as PepsiCo, which operates more than 40 production facilities in South Africa and has recently invested R5.5 billion to modernise its operations in the country (PepsiCo, 2023).

1.1 Motivation for Research

This research is motivated by the need to demonstrate how productivity improvements can be achieved through efficient deployment of lean tools without relying on costly capital expenditure. The strategic use of Key Performance Indicators (KPIs) such as Mean Time to Repair (MTTR) enhances a maintenance department's ability to allocate labour, plan interventions, and manage assets effectively (Kedaria & Deshpande, 2014). Because MTTR measures the average time required to restore equipment to operational status, it directly influences machine availability and therefore forms a critical component of OEE performance (Tobe et al., 2018). A clearer understanding of this relationship enables organisations to drive targeted, data-driven improvements in maintenance practices and overall operational effectiveness.

1.2 Problem Statement

Productivity in food manufacturing is fundamentally dependent on the reliability and efficiency of production equipment. Yet, persistent downtime continues to erode operational performance, with Mean Time to Repair (MTTR) representing a critical determinant of equipment availability. Although MTTR is routinely monitored as part of maintenance practice, its precise impact on Overall Equipment Effectiveness (OEE)—the industry's principal metric for evaluating equipment performance—remains insufficiently theorised and empirically validated. Existing research tends to treat OEE as a holistic construct, rarely disaggregating the extent to which repair duration independently contributes to availability losses and, by extension, total productive output. This gap is particularly salient in food manufacturing, where process interdependencies magnify the consequences of even minor delays in equipment recovery. Without a clear understanding of how MTTR shapes OEE outcomes, maintenance strategies risk being misaligned with operational priorities, leading to suboptimal resource allocation and avoidable productivity losses. Accordingly, this study seeks to empirically examine the influence of MTTR on OEE within an operational food manufacturing context, thereby addressing a critical knowledge gap with direct implications for maintenance optimisation and operational excellence.

While these losses collectively impede production output, MTTR plays a pivotal role in measuring how effectively repair activities are performed once failures or stoppages occur. Reducing MTTR can therefore contribute significantly to improving machine availability and, by extension, total OEE performance. This study explores the relationship

between MTTR and OEE within a food manufacturing facility in the Western Cape, providing empirical evidence of how optimised repair times can enhance overall equipment effectiveness.

1.3 Objectives

The objectives of this research are as follows:

- Investigate the breakdown occurrences and availability of machinery at a food manufacturing facility in the Western Cape.
- Investigate the Overall Equipment Effectiveness of machinery at a food manufacturing facility in the Western Cape.
- Validate the relationship between MTTR and OEE of machinery at a food manufacturing facility in the Western Cape.

2. Literature Review

In an era of intensifying global competition and mounting pressure to reduce operational costs, manufacturing organisations continually seek approaches to improve productivity without significant capital investment. Lean manufacturing, rooted in the Toyota Production System (TPS), provides a systemic framework for the elimination of waste and the pursuit of operational excellence (Womack, Jones and Roos, 2008) (Liker and Morgan, 2006). A pillar of lean manufacturing is Total Productive Maintenance (TPM), a strategy aimed at maximising the effectiveness of equipment through the total involvement of all employees across the organisation (S.Nakajima, 1988) (Ahuja and Khamba, 2008).

A central metric associated with TPM is Overall Equipment Effectiveness (OEE), introduced by Nakajima (1988) as a measure of productive manufacturing time. OEE consolidates three dimensions of equipment performance, namely availability, performance, and quality, into a single composite indicator. The metric identifies the "six big losses" that erode manufacturing efficiency, grouped under availability losses, performance losses, and quality losses (Muchiri and Pintelon, 2008). Within the OEE framework, availability is directly impacted by unplanned downtime arising from equipment failures, and one of the key maintenance metrics for monitoring and reducing such downtime is Mean Time to Repair (MTTR). This literature review examines the theoretical underpinnings and empirical evidence related to lean manufacturing, TPM, OEE, and MTTR, with a particular focus on the food manufacturing context, and provides the conceptual foundation for empirical research conducted at a food manufacturing facility in the Western Cape, South Africa.

2.1 Lean Manufacturing and the Toyota Production System

Lean manufacturing is widely regarded as one of the most influential production paradigms of the twentieth century. Its origins lie in the Toyota Production System (TPS), developed by Taiichi Ohno and Shigeo Shingo in post-war Japan as a response to resource scarcity and the need to produce diverse products in small quantities at low cost. The term "lean" was subsequently coined by Krafcik (1988) and popularised in the seminal work *The Machine That Changed the World* (Womack, Jones and Roos, 2008), which demonstrated empirically that Toyota's methods produced significantly superior results compared to mass production in terms of quality, productivity, and time to market.

Womack and Jones further distilled lean into five core principles: defining value from the customer's perspective, mapping the value stream, enabling flow, establishing pull, and pursuing perfection (Womack and Jones, 1997). These principles collectively orient the organisation toward the systematic elimination of waste, activities that consume resources without adding value. The seven classical wastes (*muda*) of lean include overproduction, waiting, unnecessary transportation, over-processing, excess inventory, unnecessary motion, and defects (Liker and Morgan, 2006).

Lean principles have been adopted beyond automotive manufacturing into sectors including aerospace, healthcare, food processing, and services (Liker and Morgan, 2006). The overarching contribution of lean is to enable organisations to produce more with less. This means reducing lead times, inventory levels, and defects while increasing throughput and responsiveness.

2.2 Total Productive Maintenance (TPM)

Total Productive Maintenance is a manufacturing program designed primarily to maximise equipment effectiveness throughout its entire life through the participation and motivation of the entire workforce (Cua, McKone and Schroeder, 2001). The core premise of TPM is that maintenance is not solely the responsibility of a dedicated maintenance department but must be integrated into the daily activities of all employees, including machine operators.

Ahuja and Khamba (2008), in their comprehensive literature review of TPM, define it as a "continuous improvement" strategy that aims to maximise equipment effectiveness, eliminate failures and defects, and foster a culture of autonomous maintenance at the operator level. TPM has since matured into a broad, enterprise-wide framework that transcends traditional maintenance, embracing continuous improvement and total employee engagement as fundamental tenets (Agustiady, Cudney and Agustiady, 2018). Its eight foundational pillars include autonomous maintenance, focused improvement, planned maintenance, quality maintenance, early equipment management, training and education, safety and health, and TPM in administration.

A substantial body of empirical evidence documents the positive outcomes associated with TPM implementation. Chukwutoo and Chukwuebuka (2018) conducted a case study at a food processing facility and demonstrated that targeted TPM implementation on a packaging machine improved OEE from 48% to 74%, reduced downtime by 46.52%, and nearly doubled equipment reliability as measured by mean time between failures. Their findings underscore that TPM, applied systematically over a reasonable period, can yield substantial performance gains even in the absence of significant capital investment.

2.3 Overall Equipment Effectiveness (OEE)

OEE is defined by Nakajima (1988) and elaborated extensively in the subsequent literature as the product of three performance ratios: Availability, Performance, and Quality. Availability measures the proportion of planned production time during which equipment is actually operational, after accounting for downtime losses. Performance reflects the speed at which equipment runs relative to its designed maximum capacity, capturing speed losses and minor stoppages. Quality captures the proportion of output that meets required specifications on the first pass, without rework or scrap.

In a foundational review of OEE as a performance measurement tool published in the International Journal of Production Research, Muchiri and Pintelon (2008) describe OEE as one of the most comprehensive single-figure productivity metrics available. A key advantage is that it unifies multiple aspects of production efficiency, previously tracked as separate KPIs, into a single, actionable indicator. Their analysis of industrial applications also revealed meaningful gaps between the theoretical calculation of OEE and its practical implementation, underscoring the importance of contextualising the metric within the specific operational environment.

A core contribution of Nakajima's OEE framework is the identification of the "six big losses", which are the primary categories of production inefficiency. These losses are grouped by their impact on OEE's three components. Under availability losses: (1) equipment failures (unplanned breakdowns) and (2) setup and adjustment time. Under performance losses: (3) idling and minor stoppages, and (4) reduced speed operation. Under quality losses: (5) process defects (scrap and rework) and (6) startup/yield losses.

Unplanned breakdowns that result in complete or partial production stoppages are among the most significant contributors to OEE losses, particularly availability losses. Minimising the frequency and duration of such failures is therefore a primary objective of TPM, and it is within this context that metrics such as Mean Time to Repair (MTTR) and Mean Time Between Failures (MTBF) assume critical importance (Ahmad, Hossen and Ali, 2018; Nurprihatin, Angely and Tannady, 2019).

2.4 OEE in the Food Manufacturing Context

The application of OEE to food manufacturing environments presents unique challenges and opportunities. (Soltanali, Khojastehpour and Torres Farinha, 2021) investigated production performance measurement in a food processing line and demonstrated that the uncertainty of OEE components, particularly measurement variance in production speed and stoppage duration, can obscure true performance estimates. Their work highlighted the need for rigorous data collection protocols in food processing contexts, where conditions such as frequent sanitation processes, complex changeovers, and perishable raw materials introduce additional sources of operational variability.

(Tonny et al., 2023) examined OEE factors in a vegetable oil manufacturing company and found that mean quality, availability, and performance rates were 96.9%, 63.4%, and 61.2%, respectively. This was an indication that

availability and performance were the primary drivers of the low OEE observed. Their results further identified equipment breakdown losses as a significant contributor to underperformance. (Worximity | The Truth Behind World-Class OEE Targets, 2022) notes that food and beverage manufacturers tend to achieve higher OEE levels than many other manufacturing sectors, with typical ranges of 70–80%, a reflection of the relatively standardised and high-volume nature of many food manufacturing processes.

A study at the University of Illinois at Chicago focused specifically on enhancing OEE in a food manufacturing process through lean management techniques combined with Industry 4.0 principles (Dossi, 2024). The research used gemba analysis, process mapping, bottleneck analysis, and a custom Stop Reason Application to capture micro-stoppage data previously overlooked. The outcomes underscored the value of granular data capture in understanding and addressing equipment-related losses in food production environments.

2.5 The Relationship Between MTTR, Availability, and OEE

Mean Time to Repair (MTTR) is defined as the time required to repair a component or a full system, or the duration of system stoppage. It is the time required to replace a faulty part with a new one, or the period needed to restore the manufacturing system to a satisfactory functional state (Kadir, 2025). The metric is calculated by dividing the total corrective maintenance time over a given period by the number of failures that occurred during that period. It is important to note that MTTR encompasses the entire repair cycle, including troubleshooting, parts retrieval, repair execution, testing, calibration, and documentation. It will, however, exclude scheduled or preventive maintenance activities.

The relationship between MTTR and OEE operates directly through the availability component. As a result, reducing MTTR, even without changing the frequency of breakdowns, directly increases availability and thereby improves OEE. The study by Y V S S S V (2025) provides evidence that reductions in MTTR are positively associated with improvements in OEE. Specifically, after implementing the data-driven framework, MTTR was reduced from 8.2 hours to 5.7 hours, a decrease of 30.5%, which contributed to a 6.1% increase in OEE (from 77.6% to 83.7%). The discussion explicitly links this reduction in MTTR to enhanced equipment uptime, which is a key component of OEE, indicating that faster repairs lead to higher operational efficiency. This was earlier shown by Nurprihatin, Angely and Tannady (2019), in a study of a manufacturing production line, whose findings confirmed that low availability, driven by high breakdown losses, was the primary reason OEE had not reached the ideal world-class value.

3. Methodology

This study adopted a quantitative empirical research design to analyse the operational performance of machinery at a food manufacturing facility located in the Western Cape. The research evaluated equipment reliability and production effectiveness using operational performance indicators derived from maintenance and production data. The analysis aimed to investigate breakdown behaviour, assess Overall Equipment Effectiveness (OEE), and validate the relationship between Mean Time to Repair (MTTR) and OEE. The methodology combined descriptive statistical analysis with non-parametric trend modelling to capture the operational dynamics of the manufacturing system.

3.1 Data Collection

Operational data were collected from a food manufacturing facility operating under a continuous production environment. The facility operates eight machines on a 24-hour production schedule and generates daily operational records of equipment performance. The dataset consisted of 91 observations representing machine operational performance over the study period. The variables extracted from maintenance and production records included: available production time, breakdown duration (minutes), breakdown occurrences, Mean Time to Repair (MTTR), availability (%), performance (%), Quality rate (%) and computing the Overall Equipment Effectiveness (OEE) (%). These variables provided the necessary information to evaluate machine reliability and operational efficiency.

3.2 Data analysis

The analytical framework was structured in two sequential phases, each aligned with the study's research objectives: descriptive statistical analysis and non-parametric regression modelling. To address the first two research objectives, descriptive statistical analysis was conducted to evaluate the frequency and impact of machine breakdowns on the Overall Equipment Effectiveness (OEE). Descriptive statistics such as mean, median, standard deviation, minimum and maximum values were calculated to understand the variability and distribution of the variables. In addition, box-

and-whisker plots were constructed to visualise variability and identify potential outliers in the variables. Lastly, the relationship between Mean Time to Repair (MTTR) and Overall Equipment Effectiveness (OEE) was validated. A scatter plot analysis was first constructed to visualise the relationship between the two variables. The initial inspection revealed a nonlinear relationship between MTTR and OEE, indicating that traditional linear regression models would not adequately capture the operational behaviour of the system. To address this, a Locally Weighted Scatterplot Smoothing (LOWESS) regression was applied. LOWESS is a non-parametric regression technique that estimates a smooth curve by fitting localised weighted regressions around each observation.

In summary, the methodology integrates descriptive statistics and non-parametric regression to evaluate the operational reliability and effectiveness of machinery in a food manufacturing facility. By analysing breakdown occurrences, machine availability, and OEE performance, and validating the relationship between MTTR and OEE, the study provides a comprehensive data-driven framework for assessing maintenance performance and production efficiency.

4. Results and Discussion

The plant under study operates 24 hours a day. To determine the available time for Availability and Overall Equipment Effectiveness (OEE) calculations, the scheduled production time, in minutes, for the eight production lines was considered. The planned production time considered did not consist of planned stops, for example, breaks, changeovers, cleaning, meetings, and planned maintenance, and therefore varies from day-to-day in order to evaluate the impact of Mean Time To Repair on the Overall Equipment Effectiveness.

4.1 Planned Production Time

The Available Time or Planned Production Time (PPT) for the day, summed across eight production lines, was calculated using Equation 1.

$$PPT_{day,total} = \sum_{i=1}^8 PPT_{day,i}$$

Equation 1

Since each production line is nominally 24h/day (1440 min), the maximum time would be $8 \times 1440 = 11,520$ min/day. Accounting for planned stops such as comfort breaks, cleaning, changeovers, and maintenance reduces the available time to less than 11,520 min/day. Figure 1 shows a box-and-whisker plot of the planned production time in minutes observed during the study. The observed data during the 3-month period showed that the available time varied from 7200 to 10080 min/day.

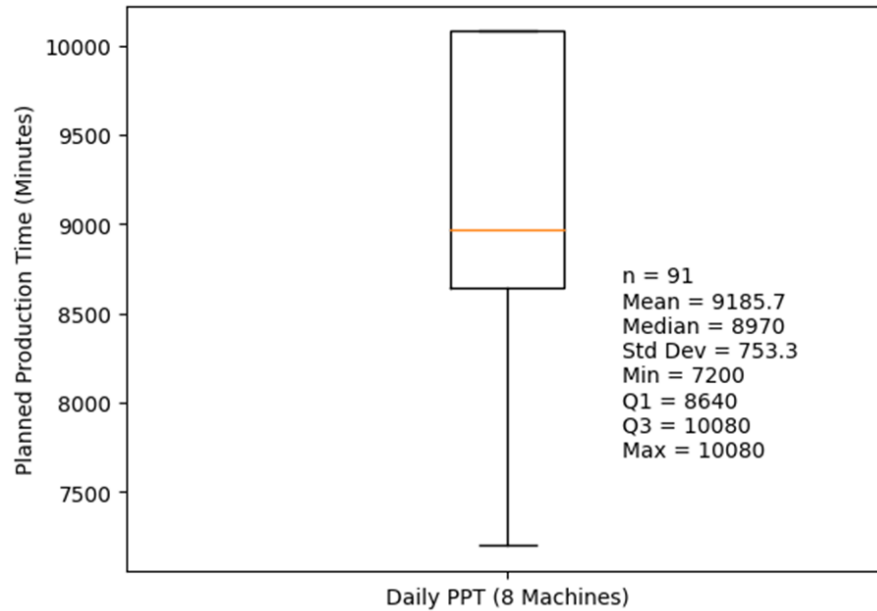


Figure1. Box and whisker plot of planned production time

The distribution of Planned Production Time exhibits moderate variability with a standard deviation of 753 minutes, a median of 8,970 minutes and an interquartile range of 1,440 minutes. The absence of statistical outliers suggests stable scheduling patterns across the observation period. The upper quartile at 10,080 minutes indicates that a substantial portion of the dataset reflects near-maximum scheduled operating time, while the lower bound of 7,200 minutes represents reduced-schedule days. The distribution demonstrates controlled operational variability rather than extreme disruptions.

4.2 Breakdown Analysis

The breakdown minutes plot in Figure 2 shows the distribution of total daily downtime attributed to equipment failures. The median breakdown time is 747 minutes, while the mean of 831.7 minutes indicates a right-skewed distribution influenced by days with unusually high breakdown durations. The interquartile range (Q1 = 572.5 minutes, Q3 = 1,059 minutes) reflects substantial variability in breakdown severity across days. The minimum breakdown duration of 214 minutes represents highly stable operating days, whereas the maximum of 1,799 minutes highlights rare but severe downtime events. The presence of upper-range values suggests episodic breakdowns that significantly impact maintenance workload and operational continuity.

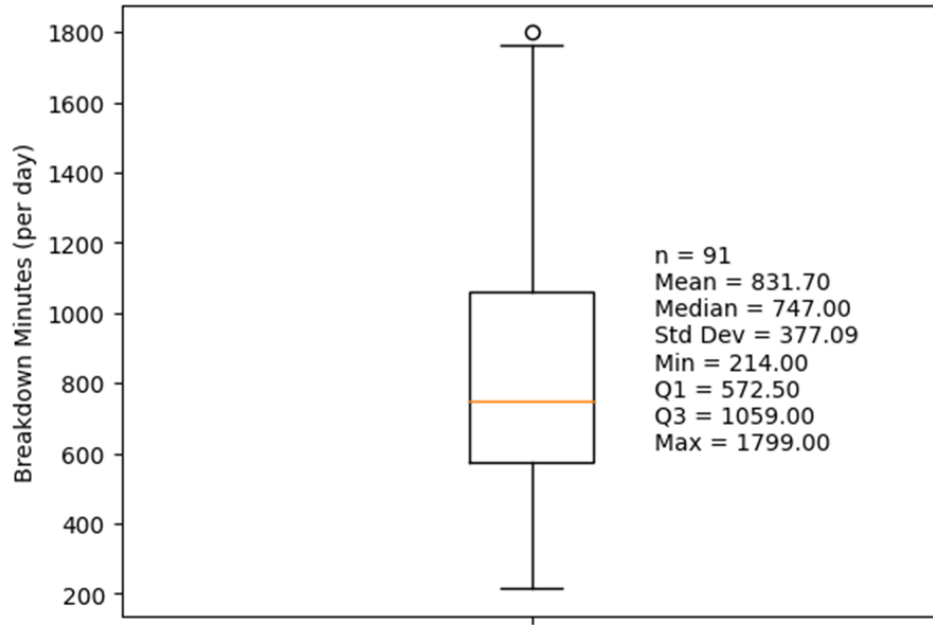


Figure 2. Box and whisker plot of breakdown duration in minutes

4.3 Mean Time To Repair

The MTTR plot in Figure 3 reveals the distribution of average repair times per day. The median MTTR is 23.51 minutes, while the mean of 26.87 minutes indicates right skewness due to several high-duration repair events. The interquartile range spans from 19.89 minutes (Q1) to 30.55 minutes (Q3), reflecting generally efficient maintenance response times. The minimum MTTR of 6.11 minutes corresponds to rapid corrective interventions, whereas the maximum value of 81.45 minutes represents infrequent but prolonged repairs. These extreme values highlight the presence of complex failures that require extended diagnostic and corrective actions.

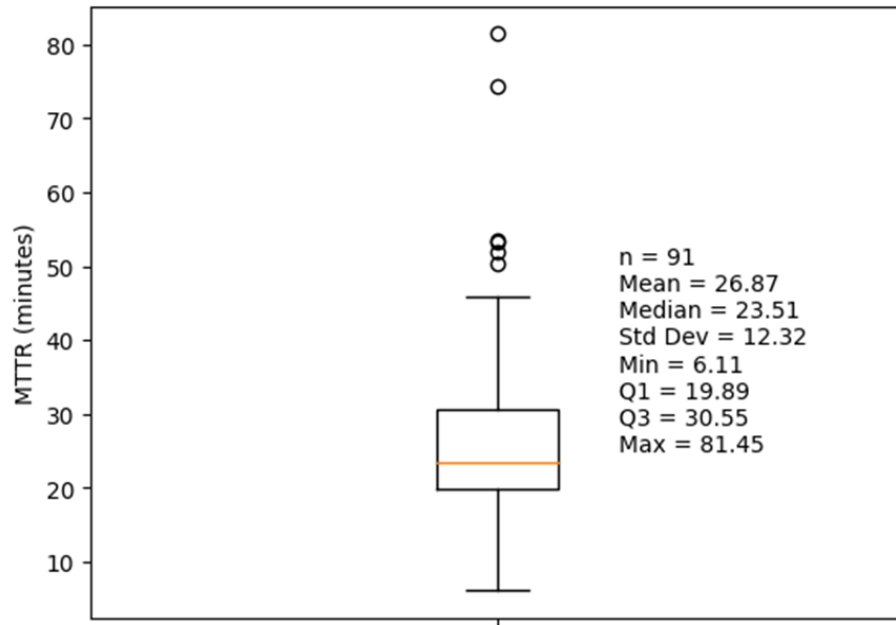


Figure 3. Box and whisker plot of Mean Time To Repair in minutes

4.4 Breakdown Occurrences

The plot of breakdown occurrences in presents the frequency of equipment failures per day as shown in Figure 4. The median number of breakdowns is 33, with an interquartile range between 26 (Q1) and 38 (Q3) occurrences. This suggests a relatively stable frequency of breakdown events across the production system. The minimum value of 9 occurrences reflects exceptionally stable days, while the maximum of 63 occurrences indicates periods of heightened equipment instability. The spread of the data suggests that while breakdown frequency fluctuates, it remains within predictable operational limits for most of the observation period.

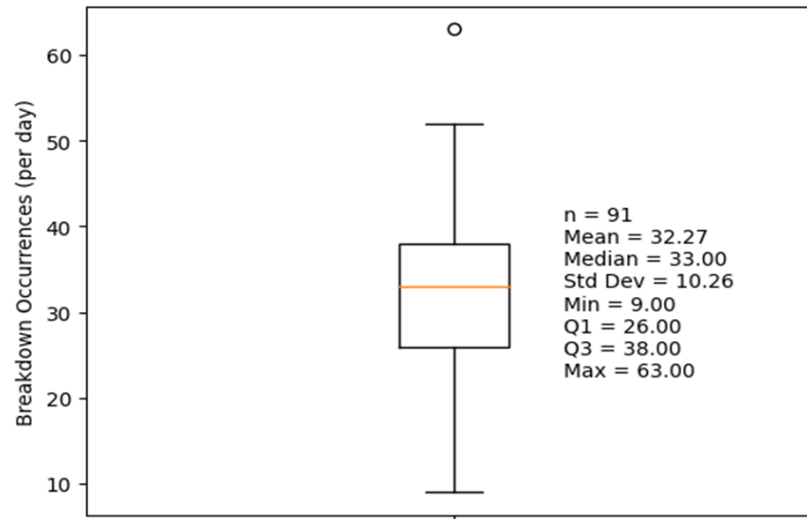


Figure 4. Box and whisker plot of Breakdown Occurrences

4.5 Availability

Figure 5 shows a box and whisker plot of availability. As shown, the availability distribution demonstrates consistently high equipment availability throughout the study period. The median availability is 92%, with a mean of 90.87%, confirming strong maintenance performance overall. The interquartile range from 88% (Q1) to 94% (Q3) indicates that most days operated within a narrow and controlled availability band. Lower values down to 75% represent days affected by extensive breakdowns, while the maximum availability of 98% reflects near-optimal operating conditions. The limited spread and clustering around high availability values indicate effective maintenance strategies in mitigating downtime.

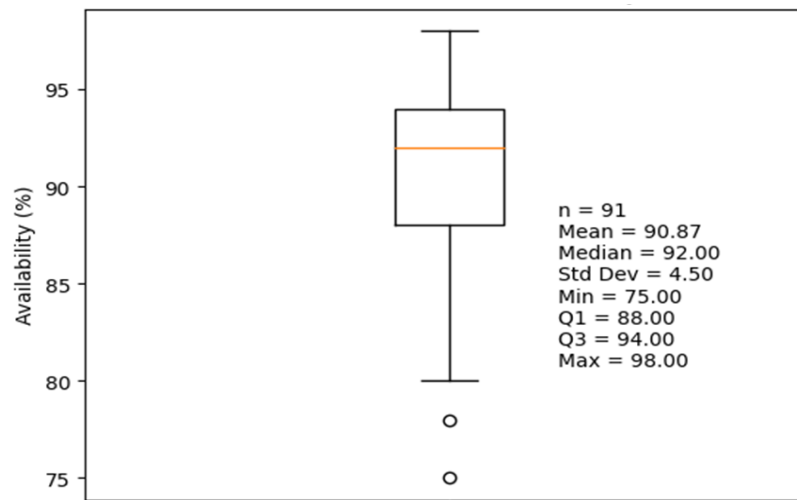


Figure 5. Box and whisker plot of Availability

Collectively, the box-and-whisker plots demonstrate that while planned production time and availability remain consistently high, variability in breakdown minutes and MTTR introduces operational risk. The skewed distributions in breakdown minutes and MTTR indicate that a small number of severe events disproportionately affect maintenance performance. These findings support the need for targeted reliability improvement initiatives to reduce the frequency and duration of high-impact breakdowns.

4.6 Availability Against Mean Time To Repair

Figure 6 shows a plot of Availability (%) against Mean Time to Repair (MTTR) using the observed daily dataset for 3 months. The plot represents the actual data sequence after sorting observations by MTTR and connecting them with a continuous line. This shows the raw day-to-day variability in Availability associated with different MTTR values. Because multiple days can share similar MTTR values but have different availability outcomes due to differences in breakdown frequency, breakdown severity, and production conditions, the connected line exhibits fluctuations rather than a perfectly monotonic trend.

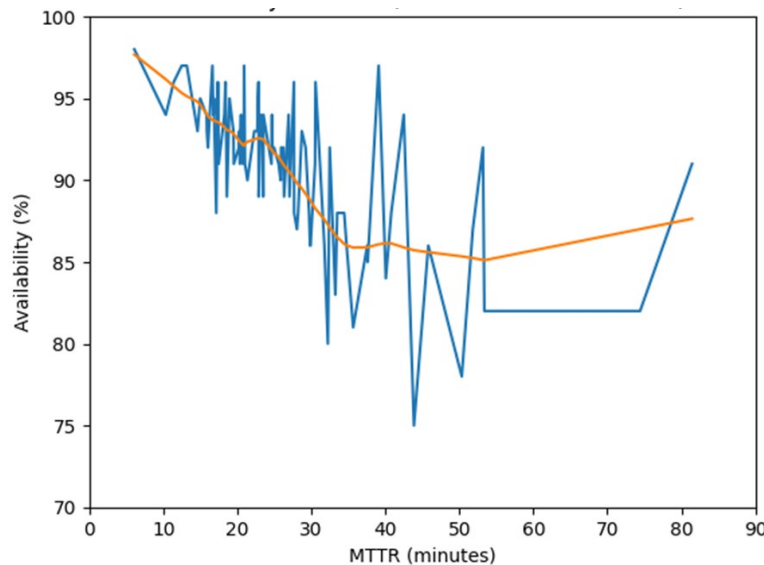


Figure 6. Availability Against Mean Time to Repair

To reveal the underlying relationship, a smooth fitted curve is overlaid using a non-parametric Locally Weighted Scatterplot Smoothing (LOWESS) approach. This smooth curve reduces the influence of short-term noise and highlights the overall trend. The smoothed relationship indicates a generally inverse association between MTTR and Availability, as MTTR increases, Availability tends to decrease. This is consistent with the definition of availability in maintenance performance measurement, where higher repair times increase downtime and reduce the proportion of time equipment is available for production, but the relationship is complex to model using predictor variables. The curve shows the steepest decline in Availability at lower-to-moderate MTTR values, approximately 10–35 minutes, suggesting that incremental increases in repair time in this range have a noticeable effect on availability. Beyond this region, the curve flattens, which may reflect fewer observations at very high MTTR values and the influence of other factors such as planned production time variations and breakdown frequency. Overall, the plot provides visual evidence that reducing MTTR is a practical way to improve equipment availability and operational continuity.

4.7 Overall Equipment Effectiveness and Associated Metrics

It is also necessary to evaluate the impact of MTTR on the overall equipment effectiveness. The performance rate and quality rate were also analysed during the study to get a clearer picture of the OEE during this study. Figure 7 shows the box-and-whisker plot the availability, performance rate, quality rate as well as the resultant OEE computed as a product of the three metrics. The performance rate indicated a relatively stable and well-controlled process. The mean performance rate was approximately 87.7%, closely aligned with the median of 88.0%, suggesting a fairly symmetrical distribution with minimal skewness. The standard deviation of 3.32% is the lowest among the OEE components, reflecting limited variability in operational speed losses. The interquartile range, from Q1 of 86.0% to Q3 of 90.0%, is narrow, indicating that most observations cluster tightly around the central tendency. Although the overall range

spans from 78% to 96%, extreme values are limited and do not significantly distort the distribution. This consistency suggests that production speed and cycle-time adherence are largely controlled and predictable. From a managerial perspective, performance is not the primary driver of OEE variability; rather, it represents a comparatively stable component within the production system.

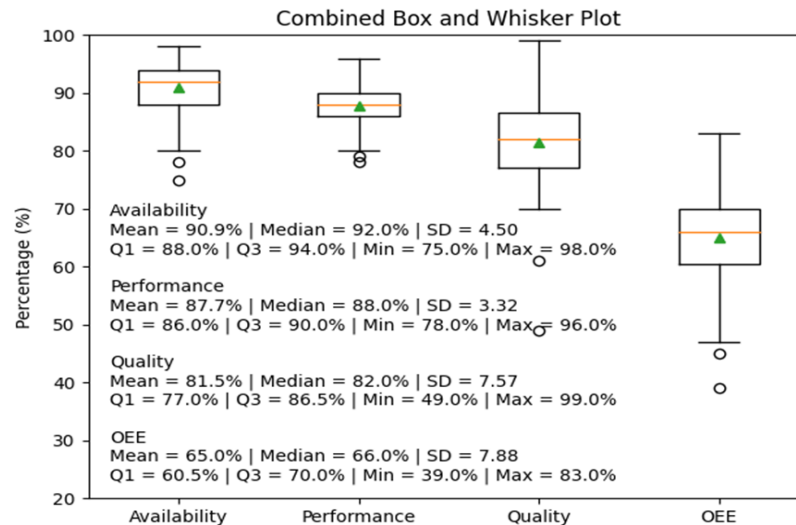


Figure 7. Availability, Performance rate, Quality rate and OEE

The box-and-whisker plot for quality shows greater variability than for availability and performance. The mean quality rate is approximately 81.5%, closely aligned with the median of 82.0%, indicating a fairly balanced distribution overall. However, the standard deviation of 7.57% is substantially higher than that of the other primary components, reflecting notable dispersion in quality performance. The interquartile range Q1 of 77.0% to Q3 of 86.5% shows that most observations fall within a moderate band, yet the full range extends from 49% to 99%, indicating the presence of significant outliers and occasional severe quality losses. These lower-end deviations suggest sporadic process instability or spikes in defects. From an operational standpoint, quality appears to be the most volatile of the three OEE components and likely contributes materially to fluctuations in overall OEE performance. Consequently, improvement efforts targeting defect reduction and process consistency would be expected to yield meaningful gains in overall equipment effectiveness.

4.8 Overall Equipment Effectiveness Against Mean Time To Repair

The box-and-whisker plot for Overall Equipment Effectiveness (OEE) demonstrates moderate central performance with relatively high variability. The mean OEE is approximately 65.0%, closely aligned with the median of 66.0%, indicating a reasonably symmetrical distribution without strong skewness. However, the standard deviation of 7.88% is the highest among the four metrics, reflecting considerable dispersion in overall system effectiveness. The interquartile range Q1 of 60.5% to Q3 of 70.0% suggests that most observations cluster within a 10-percentage-point band, yet the total range spans from 39% to 83%, indicating substantial performance swings. The lower tail of the distribution reflects periods of compounded losses across availability, performance, and particularly quality. Given that OEE is multiplicative, small fluctuations in individual components can significantly amplify overall variability.

From a managerial perspective, an average OEE of 65% indicates room for structured improvement, with stability likely achievable through targeted interventions in quality control and loss-reduction strategies.

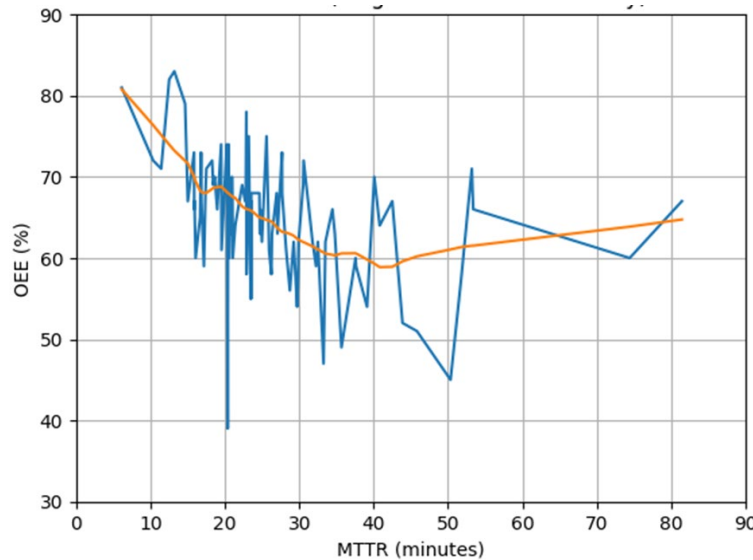


Figure 8. OEE Vs MTTR

Figure 8 presents the relationship between Overall Equipment Effectiveness (OEE) and Mean Time to Repair (MTTR) using both the original observed values and Locally Weighted Scatterplot Smoothing (LOWESS) trend line. The actual recorded OEE values are ordered by increasing MTTR, while the trend line illustrates the underlying trend after removing short-term fluctuations and noise. The original data exhibit considerable variability, particularly in the MTTR range of approximately 15–35 minutes, where OEE fluctuates significantly between roughly 55% and 75%. This variability reflects day-to-day operational influences such as quality deviations, performance losses, and unplanned disturbances beyond maintenance duration alone. The smoothed trend reveals a moderate inverse relationship between MTTR and OEE. As MTTR increases from low levels of 6 to 25 minutes, OEE generally declines, indicating that longer repair times directly reduce productive availability. Around the 30- to 40-minute range, OEE reaches its lowest average levels. Beyond approximately 40 minutes, the curve begins to flatten, suggesting diminishing marginal impact of further MTTR increases, likely due to fewer observations in this range and the increasing influence of other OEE components. Overall, the overlay demonstrates that while MTTR is an important contributor to OEE performance, it is not the sole determinant. The spread in the original values confirms that additional factors, particularly quality and performance losses, also materially influence overall equipment effectiveness.

5. Future Research

Further research could expand the scope of this study by incorporating additional reliability and maintenance performance metrics to provide a more comprehensive understanding of machinery performance at the facility. While this study focused primarily on the relationship between Mean Time to Repair (MTTR) and Overall Equipment Effectiveness (OEE), future investigations could include metrics such as Mean Time Between Failures (MTBF), failure rate, Mean Time to Failure (MTTF), maintenance costs, spare parts consumption, and planned maintenance compliance. The inclusion of these indicators would allow for a deeper evaluation of both equipment reliability and the economic impact of maintenance strategies. Additionally, distinguishing between different types of downtime, such as planned maintenance, corrective maintenance, and operational stoppages, could improve the identification of root causes of production losses. Future research could also explore advanced analytical approaches such as predictive maintenance models, machine learning techniques, and digital twin simulations to forecast breakdowns and optimise maintenance scheduling. From an operational perspective, improvements at the facility could include reducing repair response times through improved maintenance planning, optimising spare parts inventory management, implementing condition-based monitoring technologies to detect early equipment deterioration, and strengthening maintenance personnel training to improve diagnostic and repair efficiency. The adoption of structured maintenance frameworks

such as Total Productive Maintenance (TPM) may further enhance collaboration between operators and maintenance teams, reduce downtime, and improve overall production performance. Collectively, these approaches could support more effective maintenance strategies and contribute to sustained improvements in equipment reliability, operational efficiency, and overall manufacturing productivity.

6. Conclusion

This study investigated the reliability and operational effectiveness of machinery at a food manufacturing facility in the Western Cape province in South Africa by examining breakdown occurrences, machine availability, and Overall Equipment Effectiveness (OEE). The analysis of operational data from eight production lines operating under a continuous production environment provided insight into the variability of maintenance performance and its influence on production efficiency. Descriptive statistical analysis revealed notable variation in breakdown occurrences and repair durations, which, in turn, affected machine availability and overall production performance. The evaluation of OEE components indicated that availability losses associated with equipment breakdowns and repair times contribute significantly to reductions in overall equipment effectiveness. Using a non-parametric LOWESS regression, the relationship between Mean Time to Repair (MTTR) and OEE was analysed and found to be nonlinear, indicating that increases in repair time are generally associated with declines in equipment effectiveness. The findings of this study emphasise the importance of effective maintenance management, timely repair interventions, and continuous monitoring of key reliability indicators in improving equipment performance. By understanding the relationship between maintenance response time and operational effectiveness, manufacturing facilities can implement targeted maintenance strategies to reduce downtime, improve availability, and enhance overall productivity.

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Biographies

Tinashe Tendayi is a lecturer in industrial engineering in the Faculty of Engineering and the Built Environment at the Cape Peninsula University of Technology (CPUT), South Africa. He holds a master's degree in industrial engineering and brings a balanced combination of academic and industry experience to his teaching and research. His academic interests are centred on operations and production management, project management, engineering economics, and process improvement. He has been actively involved in curriculum development and the facilitation of undergraduate and postgraduate programmes, with a focus on strengthening the integration between theoretical foundations and practical application. Tinashe's research focuses on maintenance management, life cycle costing, and lean systems within asset-intensive environments. He has published in the South African Journal of Industrial Engineering and presented at national and international conferences on maintenance frameworks, decision-support methods, Industry 4.0, and the renewal of the engineering education curricula in response to technological changes. In addition to his teaching and research responsibilities, he contributes to academic quality assurance processes and supervises postgraduate research projects. He is committed to advancing industrial engineering as a discipline that serves both industry and society through disciplined analysis, structured problem-solving, and continuous improvement.

Blessed Sarema is a professional engineer with experience spanning industry and academia. He has held leadership and technical roles in manufacturing, mining, construction, and service industries, with expertise in production management, systems optimisation, process improvement, and engineering design. He has led projects involving ISO 9001 implementation, ERP systems, Lean transformation, plant installations, and renewable energy solutions. He currently serves as a lecturer at the University of Witwatersrand, Johannesburg, in the School of Mechanical, Industrial and Aeronautical Engineering. As a Lecturer and researcher, his work focuses on advanced manufacturing, industrial systems, and sustainable engineering innovation. He holds a PhD in Industrial Engineering and is committed to developing practical engineering solutions with measurable industrial impact.

Lucrecia Valentine is the Programme Coordinator for Postgraduate Research Studies in the Department of Industrial and Systems Engineering at the Cape Peninsula University of Technology. She holds qualifications in Food Technology and Quality and completed her PhD in Commerce and Administration at Cranefield College. Dr Valentine brings 12 years of experience from various sectors of the food industry, where she developed deep expertise in quality control, quality assurance, and quality management. Her experience as a lead auditor for a certification body expanded her insight into manufacturing environments beyond the food sector, including the automotive, clothing, and construction industries. Her research interests include **systems management, operational optimisation, quality, and food safety**, with a growing emphasis on the research supervision and development of postgraduate research.

Rumbidzai Muvunzi is a Senior Lecturer in the School of Mechanical, Industrial & Aeronautical Engineering at the University of the Witwatersrand (WITS), Johannesburg, South Africa. She holds a PhD in Industrial Engineering from Stellenbosch University, where her doctoral research focused on the application of additive manufacturing to improve the efficiency of hot forming tools. She also holds a Master's degree and Bachelor's degree in Engineering Sciences. She is a registered Professional Engineer (PrEng) with the Engineering Council of South Africa and a member of the Southern African Institute of Industrial Engineers (OMSIE). Dr. Muvunzi's research interests span advanced manufacturing technologies, additive manufacturing, simulation and modelling, artificial intelligence and robotics in predictive maintenance, and sustainable manufacturing systems. She has been involved in international research collaborations and has published her work in accredited journals and conference proceedings. She was a recipient of the OWSD PhD Fellowship (2014-2019) and recently received the prestigious Thuthuka research grant (Post-PhD track) from the National Research Foundation (NRF).