Jurnal Teknologi dan Rekayasa Alat Berat

Jurnal Teknologi Rekayasa Alat Berat (JTRAB)
ISSN 3046-4773
Vol 2, pp. 36-46, 2025
published online on: 11, 08, 2025

ALIGNMENT MODEL OF EXPECTATIONS WITH ACTUAL LIFETIME OF MAINPUMP COMPONENTS ON HEAVY EQUIPMENT

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Received 16 November 2024, Revised 24 May 2025, Accepted 21 July 2025

ABSTRACT

This research focuses on the importance of optimal machine performance in various industrial sectors, emphasising the reliability of each component as a crucial factor in maintaining productivity and operational efficiency. In this context, specific research was conducted to analyse the difference between the expected life of components and the actual life achieved in the field. There is a significant knowledge gap associated with the mismatch between expected and actual component life, potentially leading to unexpected increases in operating costs and decreases in efficiency. This study used survey methodology and linear regression analysis to evaluate the relationship between the expected and actual age of mainpump components on Komatsu PC200 units. The main results showed that the actual life of the components tended to be lower than the expected life, with an average gap of 3,257 hours, indicating the need for adjustments to maintenance and replacement strategies. The analysis also revealed that factors such as severe operational conditions and suboptimal maintenance methods contributed to this mismatch. The implications of this study point to the importance of implementing a more adaptive and data-driven maintenance strategy to improve operational efficiency and minimise unexpected downtime.

Keywords: Heavy Equipment; Linear regression; Expected component life; Gap analysis; Actual component life.

1. INTRODUCTION

Heavy equipment is essential across various industrial sectors, including construction, mining, and forestry. The optimal performance of heavy equipment heavily relies on the reliability of each component, which plays a critical role in maintaining overall productivity and operational efficiency. In this context, the lifespan of components is a key consideration, particularly in the planning of maintenance and part replacements. Typically, machine owners establish a certain expected lifespan for each component based on their experience, manufacturer recommendations, and available historical data [1].

However, issues arise when there is a discrepancy between the expected lifespan of a component and its actual lifespan. This mismatch can lead to unexpected increases in operational costs, unplanned downtime, and a decline in operational efficiency. This phenomenon often goes unnoticed by machine owners until the component fails or requires earlier replacement than anticipated, potentially resulting in significant financial losses. Therefore, there is an urgent need for more in-depth research to identify the factors influencing the actual lifespan of components and to evaluate whether the expectations held by machine owners are based on accurate and relevant data.

From a theoretical standpoint, reliability theory suggests that the lifespan of components is influenced by various factors, including material quality, operational conditions, and maintenance procedures. Discrepancies between expected and actual component lifespans may result from differences in usage conditions and working environments that were not anticipated. Additionally, the concept of life cycle cost analysis (LCCA) is relevant in this context, as it emphasizes the importance of understanding and predicting the total cost of a component over its lifetime, including repair and replacement costs due to component failure [2].

This research is highly significant because its findings can provide machine owners with deeper insights into the alignment between expected and actual component lifespans. These insights will contribute to improved operational efficiency and reduced costs associated with component maintenance and replacement. Furthermore, the results of this study can be used to update maintenance guidelines and component replacement planning, as well as to assist in more data-driven decision-making [8]. As such, this research will not only offer practical

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DOI: 10.22146/jtrab.v2i2.17694

short-term benefits but will also contribute to the development of more reliable and durable components in the future.

The aim of this research is to determine whether the expected lifespan of components, as perceived by machine owners, aligns with the actual lifespan of those components. In this context, a key issue to investigate is the potential mismatch between the expected lifespan and the actual lifespan achieved by components under real operational conditions. This mismatch has the potential to cause various implications, both operational and financial, which negatively impact machine performance and resource use efficiency. Therefore, it is important to formulate the problems to be addressed by this research.

This research needs to answer the question: "What is the actual condition of machine component lifespans in various industrial sectors, and to what extent do these actual lifespans differ from the expectations of machine owners?" This question focuses on the objective reality of component lifespans in daily use and examines how closely this reality aligns with or differs from existing assumptions or expectations. The answer to this question will provide a clearer picture of the reality of component lifespans in the field.

This research has significant benefits from both theoretical and practical perspectives. Theoretically, this research will contribute to the body of knowledge on the reliability of heavy equipment components. By identifying and analyzing the expectations of component lifespans from machine owners against the actual lifespans, this research will enrich the literature on machine reliability and maintenance and provide new insights that can serve as a foundation for further research. The findings of this study are expected to bridge the gap between expectations and reality in component lifespans, a topic that has not been thoroughly explored in academic studies.

From a practical perspective, this research offers benefits that can be directly applied in the industry. With a better understanding of the mismatch between expected and actual component lifespans, machine owners and operators can make more informed decisions regarding component maintenance and replacement. This will not only help in reducing unexpected operational costs but also in enhancing overall machine efficiency and productivity. Additionally, the findings of this study can guide manufacturers in designing more durable components that are better suited to actual operating conditions.

Furthermore, this research has the potential to have far-reaching impacts in the context of resource management and operational sustainability [3]. By improving component lifespan estimations, the industry can optimize resource usage, reduce waste, and enhance long-term operational sustainability. This research can also provide a basis for developing more efficient and effective maintenance policies, ultimately contributing to the industry's global competitiveness. Therefore, the benefits of this research extend beyond theoretical understanding to practical applications that have a direct impact on industrial operations.

A review of previous studies reveals various approaches that have been employed in assessing machine component lifespans and their operational reliability. For instance, Febrianto et al. [4] found that material quality and workingy1 environment conditions significantly influence component life. This finding aligns with the current study, as both emphasize the importance of external factors in determining component reliability. However, the current study specifically focuses on the gap between expected and actual component lifespans, while Smith's research focuses more broadly on component reliability analysis.

Moreover, relevant Scopus-indexed journals, such as those by Rychlik & Szymkowiak [5], highlight that predictive techniques can enhance the accuracy of component lifespan estimates. Their research used a data-driven predictive model approach, contributing significantly to understanding component life prediction. While this research offers valuable insights, the current study places greater emphasis on evaluating user expectations rather than solely relying on data-driven predictions, thus adding a different perspective to the discussion. Similarly, Bieniek et al. [6] employed both qualitative and quantitative methods to assess the lifecycle of machine components. Wang found notable differences in component lifespans depending on the maintenance methods applied. While these studies share similarities with the current research in their focus on component lifespan analysis, the current study introduces a new dimension by considering machine owners' expectations as a critical variable.

Additionally, Kulkarni & Rajarshi [7] conducted a quantitative study that demonstrated how environmental factors such as temperature and humidity significantly contribute to component life degradation. This research underscores the importance of environmental variables, which is also a consideration in the current study. However, the current research combines environmental analysis with user expectations to provide a more holistic understanding. Lastly, Almuhayfith et al. [8] used quantitative methods to optimize maintenance strategies based on component lifespan analysis, finding that appropriate maintenance strategies can significantly extend component life. While this research shares a focus on reliability and component lifespan, the current study offers a more focused perspective on how owner expectations compare with actual conditions, a topic not deeply explored in the previous study.

As a researcher, there is a perception that machine owners' expectations regarding component lifespans are often based on incomplete information or outdated historical data that may no longer be relevant to current operational conditions [6]. These expectations tend to be normative and may not fully consider variations in working conditions, types of loads, and the quality of maintenance performed. It is also argued that there is a significant gap between component life expectations and the actual lifespans experienced in the field. This gap could result from a lack of understanding of the variables that significantly impact component life, such as material quality, component design, and the effects of operational environmental conditions [9].

Therefore, there is a need for research that provides a deeper understanding of how factors influence the actual life of components and how these expectations can be adjusted to be more accurate and realistic. Reliability Theory serves as the primary theoretical foundation for understanding component life in an operational context. It posits that component life is influenced by various factors, including material quality, component design, and operational conditions [10]. The theory also introduces the concept of a "failure rate," which refers to the probability of a component failing within a certain period.

In this research, the application of reliability theory helps understand how these factors affect component life and how the ideal component life expectancy should be determined based on a comprehensive reliability analysis. The Component Life Cycle Theory, on the other hand, focuses on the entire lifespan of a component, from production to use, and eventually to its end-of-life. This theory considers all stages in the lifecycle, including design, manufacturing, operational use, and replacement or recycling phases [11].

This theory is relevant to the study as it allows researchers to analyze how each phase in the lifecycle impacts the overall lifespan of the component. It also helps identify critical points where lifespan expectations may not align with the realities observed in the field [12]. Condition-Based Maintenance Theory is another operational theory used to optimize maintenance strategies by monitoring the actual condition of components during use. This theory suggests that component life can be extended if maintenance is performed based on actual conditions rather than on a predetermined schedule [13].

In the context of this research, this theory helps understand how a more adaptive maintenance approach can help bridge the gap between expected and actual component lifespans. It also provides a framework for developing practical recommendations that can be implemented by machine owners [14].

Drawing from these three theories, this research paradigm is built on the premise that machine component life results from a complex interaction between component quality, operational conditions, and maintenance strategies. Component life expectations should not be solely based on historical data or manufacturer guidelines but must be verified and adjusted through an analysis that considers operational realities and specific field conditions [15].

This paradigm guides researchers to conduct an empirical evaluation of the component life expectations held by heavy equipment owners, aiming to provide recommendations that are more accurate and aligned with real-world conditions. Based on the theoretical framework previously described, as outlined in Table 1, this research hypothesis is formulated to examine the relationship between the expected component life as held by heavy equipment owners and the actual component life. The integration of Reliability Theory, Component Life Cycle Theory, and Condition-Based Maintenance Theory is expected to offer a more comprehensive understanding for heavy equipment owners in setting realistic component life expectations based on their experience and knowledge see Table 2.

The hypothesis proposed in this study suggests a linear relationship between the expected component life, as estimated by the owner, and the actual component life. The basic assumption underlying this hypothesis is that machine owners, through their experience and knowledge derived from the application of reliability and maintenance theories, are capable of estimating component life with a high degree of accuracy. In this context, the expected component life is considered a reflection of the owner's practical and historical knowledge.

Thus, the hypothesis posits that when component life expectations are based on adequate analysis and the application of appropriate maintenance strategies, there will be a positive and linear correlation with the actual component life. Testing this hypothesis will provide insights into the reliability of the expectations held by machine owners in determining actual component life and how effectively the knowledge gained from related theories can be applied in industrial practice.

2. METHODOLOGY

This research begins with the data collection phase, which involves conducting a survey of the owners and operators of Komatsu PC200 units. The purpose of the survey is to gather information on the expected lifespan of main pump components, the actual lifespan achieved, and other variables that may influence component life, such as operational conditions, maintenance practices, and the work environment. Additionally, technical data from the manufacturer's manual and historical data related to the unit's operation are collected to establish a robust foundation for the subsequent analysis.

After data collection, the next step involves analyzing the data using linear regression methods. This analysis aims to evaluate the linear relationship between the expected lifespan of the component and the actual lifespan achieved [25]. Several key steps will be undertaken in this analysis to gain a comprehensive understanding of the discrepancy between expectations and reality see Figure 1. First, the average difference between expected and actual lifespans will be calculated to determine the overall trend of this difference. Then, the standard deviation of this difference will be calculated to assess the variation, providing insights into the extent of the variability. The analysis will also identify the minimum and maximum values of the difference to understand the extremes in the discrepancy between expectations and reality. The distribution of this difference will be visualized in a histogram, helping to identify the pattern of distribution.

Next, the coefficient of determination (R^2) from the linear regression will be calculated to evaluate how well the expected component life explains the variation in actual life. A high R^2 value would suggest that the machine owner's expectations have strong predictive power regarding the actual lifespan of the main pump component.

The analysis will also include the calculation of the Mean Squared Error (MSE), which provides a measure of the overall prediction error [26]. The Mean Absolute Percentage Error (MAPE) will be calculated as well, offering a measure of the prediction error in percentage terms, thereby indicating how much the expected component life deviates from reality on a relative scale [27]. The value of 1 - MAPE will be used as an indicator of prediction accuracy, with higher values signifying more accurate predictions.

Table 1 Research related with lifetime components

Ref	Country	Industry	Research Objective	Methodology
[5]	Poland	Mathematics, Reliability Engineering	To determine sharp upper bounds for the expectations of the system lifetimes expressed in terms of the mean and various scale units based on absolute central moments of component lifetimes.	Theoretical analysis using probability and statistical tools, with focus on increasing failure rate (IFR) and increasing density (ID) functions.
[7]	India	Statistics, Reliability Engineering	To estimate the parameters of the lifetime distribution of components that form a coherent system using optimal estimating functions, specifically focusing on exponential and Weibull distributions.	Theoretical analysis using optimal estimating functions, Fisher's conditionality principle, and simulation-based approaches for constructing confidence intervals and testing hypotheses.
[8]	Saudi Arabia, Turkey, Egypt	Reliability Engineering	To introduce a versatile model, called α-monotone inverse Weibull distribution (αIW), for lifetime of a component under stress and to compare its performance with other models.	Theoretical modeling and analysis using the α-monotone concept, maximum likelihood, Monte Carlo simulation, and comparison with other distributions through goodness-of-fit tests.
[6]	Poland, Germany	Reliability Engineering	To evaluate tight lower and upper bounds on the expected differences between system and component lifetimes in the failure dependent proportional hazard model.	Theoretical modeling using failure dependent proportional hazard model, generalized order statistics, and Samaniego signatures.
[16]	Taiwan	Electronics, Reliability Engineering	To establish a fuzzy evaluation model for the lifetime performance index of electronic components using type-I right censoring data.	Theoretical modeling using type-I right censoring sample data, confidence intervals, and fuzzy testing methods to evaluate the lifetime performance index of electronic components.
[10]	Taiwan	Reliability Engineering	To extend the testing procedure for the lifetime performance index for products with a single component to the overall lifetime performance index for products with multiple components, where lifetimes follow the Chen distribution under progressive type I interval censoring.	Theoretical analysis using maximum likelihood estimation, progressive type I interval censoring, and hypothesis testing to evaluate the overall lifetime performance index of products with multiple components.
[17]	Greece	Reliability Engineering	To develop a signature-based framework for estimating the mean lifetime and variance of a coherent system with exchangeable components using Archimedean copulas.	Theoretical modeling using Archimedean copulas (Frank and Joe) for dependency modeling, followed by numerical experimentation and Monte Carlo simulations.
[18]	Poland	Molecular Sciences	To investigate the fluorescence properties of tryptophan-containing peptides in an AOT reverse micelle environment and understand the impact of micellar confinement on fluorescence characteristics.	Experimental study involving steady-state and time-resolved fluorescence spectroscopy to analyze tryptophan and its peptides in aqueous and micellar environments.
[19]	Iran, Spain	Reliability Engineering	To study the reliability of two coherent systems with shared heterogeneous components and to introduce the concept of joint survival signature for these systems.	Theoretical modeling using joint survival signature, survival signature, and various stochastic processes including non-homogeneous Poisson process (NHPP) and exchangeable distributions.
[9]	Palestine	Renewable Energy	To emphasize the importance of considering battery service lifetime when determining the optimal battery size in hybrid PV–diesel energy systems.	Simulation-based methodology using HOMER Pro software to assess different battery capacities in hybrid PV systems, considering battery cycling and service lifetime.
[20]	UK	Molecular Sciences, Cancer Research	To investigate the uptake, subcellular localization, and phototoxic mechanism of meso-tetraphenylporphine disulfonate (TPPS2a) in 2D and 3D ovarian cancer models, focusing on photodynamic therapy (PDT) and photochemical internalization (PCI).	Experimental study using fluorescence lifetime imaging microscopy (FLIM), confocal microscopy, and reactive oxygen species (ROS) detection probes in 2D and 3D cancer models.
[21]	Russia	Reliability Engineering	To propose a mathematical model of the k-out-of-n system to support Decision Makers (DM) about Preventive Maintenance (PM) under dependent failures.	Theoretical modeling using order statistics, sensitivity analysis, and regenerative process modeling to compare different PM strategies and optimize system availability.
[22]	Spain	Nanotechnology, Photonics	To explore the synergy of coupled gold nanoparticles and J-aggregates in plexcitonic systems to enhance photochemical applications.	Experimental study involving the synthesis of gold nanobipyramids, coupling with J-aggregates, and analysis of photophysical properties using spectroscopy and microscopy techniques.
[12]	South Korea, USA	Applied Statistics, Industrial Engineering	To develop an expectation-maximization (EM) algorithm for parameter estimation in the Birnbaum-Saunders distribution under competing risks, considering both masking and censoring effects.	Theoretical modeling using the quantile variant of the EM algorithm (QEM) to handle multimodal failures, masking, and censoring in the Birnbaum-Saunders distribution.
[23]	UK, Portugal	Psychology, Neuroscience	To investigate how expectations influence face perception and how this is modulated by individual expertise in face processing.	Experimental study involving behavioral tasks, EEG recordings, multivariate pattern analysis (MVPA), and statistical analysis to decode neural responses and measure behavioral impacts.
[24]	China	Applied Mathematics, Optimization	To propose a stochastic primal-dual adaptive method (SPDAM) for solving non-convex programs with expectation constraints, incorporating adaptive step size and momentum-based search directions to improve convergence.	Theoretical modeling using inexact augmented Lagrangian method, adaptive techniques, and momentum-based search directions, with convergence analysis and numerical experiments to validate the method.

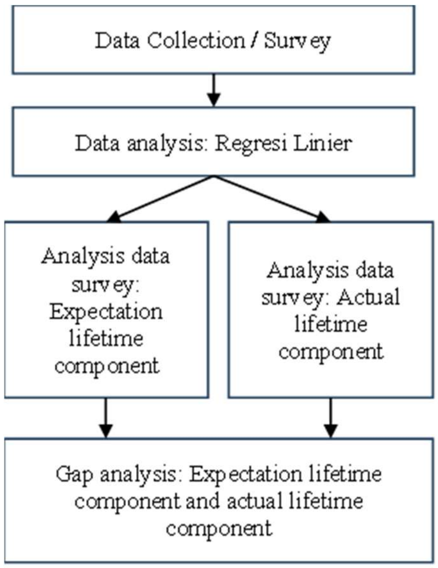

Figure 1 Conceptual framework

The final phase of this research involves conducting a gap analysis to identify and understand the discrepancies between the expected and actual lifespans of main pump components. The findings from this gap analysis will offer valuable insights into how closely the machine owners' expectations align with actual conditions. Based on these insights, the research will provide more accurate recommendations for component maintenance and replacement planning, as well as strategies for improving the accuracy of future component lifespan predictions. Ultimately, this research aims to make a significant contribution to the management of main pump component lifespans in Komatsu PC200 units, thereby enhancing the operational efficiency and effectiveness of these machines

3. RESULT AND DISCUSSION

3.1 Respondent demographics

This study involved respondents with various levels of work experience, positions within the company, and from the heavy equipment industry sector as shown in Table 3. Most of the respondents, 34 per cent, had work experience between 16 and 20 years. In addition, 22% of respondents have less than 10 years of experience, followed by 17% of respondents with work experience between 10 to 15 years. Meanwhile, only 14% of respondents have more than 21 years of work experience. This data shows that the majority of respondents have a significant level of work experience, especially in the 16 to 20 years range, which allows them to have a deep understanding of the industry they work in.

In terms of job titles, respondents are spread across various positions in the company's organisational structure. Most respondents, 31 per cent, work as staff, followed by 28 per cent who occupy supervisory positions. Manager positions were filled by 17% of respondents, while director positions were held by 12% of respondents see Table 1. This shows that the survey

Table 2 Data expectation age vs actual age of engine components

No	Expectation Age	Actual Age	No	Expectation Age	Actual Age
1	30000	28252	27	12000	9479
2	30000	25248	28	12000	9211
3	30000	20891	29	12000	9128
4	24000	19366	30	12000	9058
5	20000	18448	31	12000	8926
6	20000	17025	32	12000	8765
7	20000	16213	33	12000	8748
8	20000	15258	34	12000	8657
9	20000	15180	35	12000	8640
10	20000	15048	36	12000	8561
11	20000	14672	37	12000	7996
12	18000	14399	38	11000	7854
13	18000	13489	39	10000	7477
14	18000	12561	40	10000	7420
15	18000	12345	41	10000	7135
16	18000	12000	42	10000	7091
17	18000	11767	43	10000	7074
18	18000	11625	44	8000	6708
19	18000	11540	45	8000	6453
20	16000	11267	46	8000	6428
21	15000	10524	47	8000	6359
22	14000	10161	48	8000	6280
23	14000	10083	49	8000	6219
24	14000	9889	50	6000	6218
25	12000	9674	51	6000	6170
26	12000	9564			

includes views from different levels of management, providing a more comprehensive perspective on the issues faced in the heavy equipment industry. All respondents in this study were from heavy equipment companies, demonstrating a specific and relevant focus on the topic at hand. The diversity of experience and working positions amongst the respondents lends depth and credibility to the results, as the feedback comes from individuals with different backgrounds and responsibilities within the industry.

3.2 Descriptive statistics

Descriptive analysis of the expected and actual life data of mainpump components on Komatsu PC200 units showed a significant difference between expectations and reality in the field. The average expected life of the component is around 15,686 hours, reflecting the owner's or operator's expectation of the durability of the component see Figure 2. However, the data shows that the actual life of these components tends to be shorter, averaging only 12,429 hours. This discrepancy suggests that mainpump components often fail earlier than expected, which can result in increased operational costs and higher maintenance frequency see Figure 3.

Table 3. Respondents demograpic characteristics

Experience	N
Below 10 year	13
10 - 15 year	10
16 - 20 year	20
Above 21 year	8
Position	
Director	7
Manager	10
Staff	18
Supervisor	16
Company	
Heavy Equipment Company	28

The variation in expected and actual life is also significant, with a standard deviation of 6,688 hours for expected life and 5,461 hours for actual life, respectively. This indicates that not all components performed consistently, both in terms of durability and realised lifespan. Some components did manage to approach or even exceed their expected life, but most others performed significantly lower. This could be due to a variety of factors, such as different operating conditions, material quality, or maintenance methods applied.

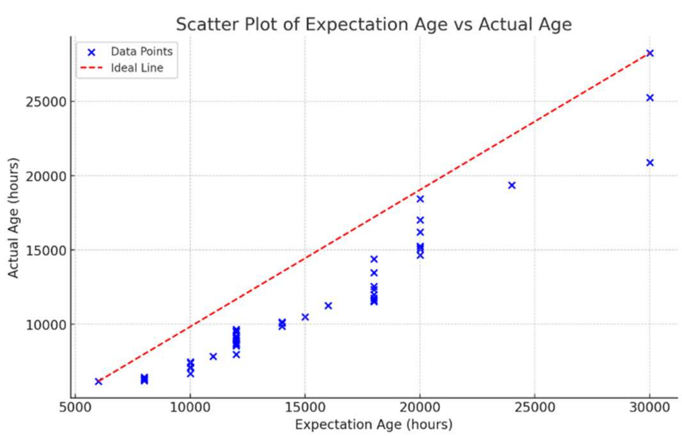

Figure 2 Scatter plot of expectation age vs actual age

From the results of this analysis, it can be concluded that maintenance and component replacement strategies need to be evaluated and possibly adjusted to better match actual operational conditions. With a better understanding of the factors that influence the difference between expected and actual life, machine owners and operators can make more informed decisions to improve the operational efficiency and effectiveness of Komatsu PC200 units, as well as minimise unexpected costs due to premature component failure.

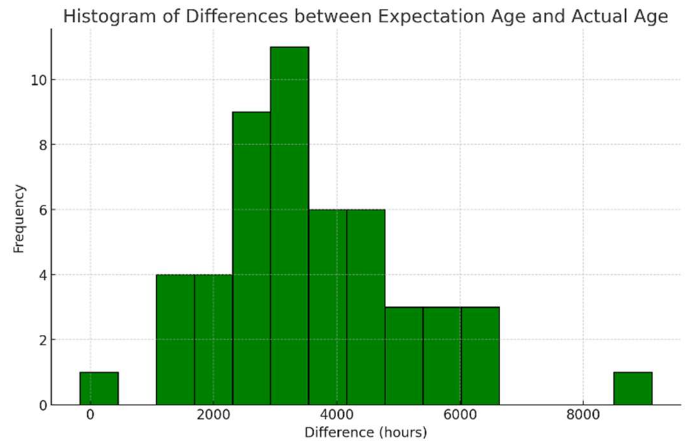

Figure 3 Histogram of differences of expectation age vs actual age

3.3 Linier regression analysis

The results of statistical analyses using linear regression models on the expected and actual ages of mainpump components on Komatsu PC200 units provide a strong picture of the relationship between expectations and reality of component performance. With a Coefficient of Determination (R^2) value of 0.933, it can be concluded that approximately 93.3% of the variability in the actual age of the component can be explained by the previously defined expected age. This indicates that the predicted expected life made by the owner or operator has a significant influence on the actual life achieved by the component. However, although this relationship is strong, further results show that there are differences that need to be considered.

The Mean Squared Error (MSE) value of 1,560,109.81 indicates the average of the squared difference between the predicted and actual values. While this value is relatively large, it is understandable given the scale and variation present in the data. This MSE provides an overview of how far away the model predictions are from the actual values, highlighting that there is a margin of error that needs to be considered, especially in an operational context where the accuracy of component life prediction is critical for maintenance and replacement planning.

Furthermore, the Mean Absolute Percentage Error (MAPE) of 7.6% indicates that on average, the model predictions deviate about 7.6% from the actual values. MAPE provides a measure of prediction error in percentage terms, which is easier to interpret in an operational context. With a fairly low MAPE, the model can be said to be fairly accurate in predicting the actual age of components based on the expected age, but there is still room for improvement.

The MAPE value of 92.4% further confirms that the model has a high level of prediction accuracy. With this level of accuracy, the model can be considered a reliable tool to assist in the decision-making process regarding component maintenance and replacement. However, it is important to note that despite the high accuracy of the model, the lower than expected actual life of the components indicates the presence of other external or internal factors that may not be fully accommodated in the model.

Overall, this analysis revealed that while the linear regression model was able to explain most of the variability in actual component life, there were indications that expectations of component life were often higher than what could actually be achieved in the field. This highlights the importance of further evaluation of other factors that may affect component performance, such as severe operational conditions, variations in maintenance quality, and component material quality. With a deeper understanding of these factors, machine owners and operators can develop more effective strategies to maximise component life and improve overall operational efficiency.

3.4 ANOVA analysis

To address the primary research question regarding the alignment between heavy equipment owners' expectations and the actual lifespan of machine components under real operational conditions, a one-way analysis of variance (ANOVA) was conducted. This statistical method aimed to determine whether a significant difference exists between the expected component lifespan and the actual lifespan, based on data from 51 observations.

The ANOVA results yielded an F-statistic of 11.57 with a p-value of 0.00096, indicating a statistically significant difference between the expected and actual lifespans of the components ($p < 0.05$). Consequently, the null hypothesis (H_0)—which posited no difference between the two lifespan groups—is rejected.

This finding substantiates the assertion presented in the literature review that equipment owners' expectations are frequently based on incomplete or outdated information, such as legacy data or generalized manufacturer recommendations. These expectations often do not account for the variability of real-world operating conditions. The observed disparity aligns with the principles of Reliability Theory and Component Life Cycle Theory, both of which highlight the critical influence of material quality, environmental conditions, and maintenance practices on component longevity.

Moreover, the results reinforce the relevance of Condition-Based Maintenance Theory, which advocates for maintenance interventions based on actual equipment conditions rather than fixed schedules. Inaccurate expectations can result in premature or delayed replacements, leading to increased operational costs, unexpected downtime, and reduced overall efficiency.

Thus, the findings of this analysis provide empirical support for the hypothesis that a significant mismatch exists between expected and actual component lifespans. Addressing this gap requires recalibrating expectations using empirical field data and adopting more comprehensive analytical frameworks. Such an approach will enable equipment owners to make more informed, data-driven decisions, ultimately improving asset reliability, operational performance, and cost efficiency.

3.5 Model testing

The results of testing the linear regression model against the expected and actual age data of mainpump components on Komatsu PC200 units provide an in-depth picture of the model's predictive effectiveness in explaining the relationship between these variables. The Coefficient of Determination (R^2) value of 0.933 indicates that the model is able to explain 93.3% of the variability in the actual age of components based on the specified expected age. This is a strong indication that expected life is a very good predictor for estimating the actual life of components. However, there is still 6.7% of variability that cannot be explained by the model, which may be influenced by factors other than expected life.

Furthermore, the Mean Squared Error (MSE) value of 1,560,109.81 reveals the margin of error in the model prediction, where the average squared error between the predicted and actual values is quite large. While the R^2 indicates that the model is good at explaining relationships, the MSE value indicates that there is still a significant difference between the model's predictions and the actual data. This means that, in practical applications, decisions made based on these predictions should consider the potential margin of error.

In terms of prediction accuracy, the Mean Absolute Percentage Error (MAPE) value of 7.6% indicates that, on average, the model predictions deviate by 7.6% from the actual values. This relatively low MAPE indicates that the model is quite accurate in providing predictions, although such small errors are still important to consider in an operational context, especially in critical component maintenance planning. In addition, the 1 - MAPE value of 92.4% provides confidence that the model has an excellent level of accuracy, meaning that the model's predictions are reliable in the majority of cases. However, it is important to remain aware of possible prediction errors that may arise due to variability that is not fully captured by the model.

Overall, the results of testing this linear regression model reveal that while expected life is a strong predictive tool for actual life of components, there are indications that actual life is often lower than expected. This highlights the importance of continuously monitoring and adjusting component maintenance and replacement strategies based on actual conditions in the field, as well as considering other factors that may affect component performance to achieve higher operational efficiency.

3.6 Gap Analysis

This gap analysis began by identifying a significant difference between the expected and actual life of the mainpump components. From the available data, it was found that the average expected life of the components was 15,686 hours, while the average actual life achieved was only 12,429 hours. This indicates an average gap of 3,257 hours, where components tend to fail or require replacement sooner than expected. This gap reveals a gap between expectation and reality in the field that needs special attention.

The variability of this gap is also significant, with a standard deviation of expected age of 6,688 hours and a standard deviation of actual age of 5,461 hours. This shows that there is not only a difference between the expected and actual ages, but also a large variation between the different components. Some components may be close to or even exceed their expected age, while others fail much earlier, which suggests that certain factors may play a role in widening or narrowing this gap.

Factors that could potentially cause this gap include operational conditions that may be more severe than anticipated, sub-optimal maintenance methods, and variations in the quality of materials or parts used. For example, harsh working environments or higher than normal workloads can accelerate component wear. Similarly, maintenance that is inconsistent or not in accordance with the manufacturer's standards can reduce component life, and differences in material quality can be another significant factor.

The implications of this gap are very important for machine owners and operators to consider. These gaps can lead to increased operational costs as components need to be replaced more frequently than expected. In addition, unexpected component failures can lead to unplanned machine downtime, which negatively impacts productivity and operational efficiency. Therefore, expectations of component life may need to be revised and maintenance strategies should be adjusted to better match actual operational conditions.

3.7 Finding and discussion

From the results of the research on the gap between expected and actual life of mainpump components on Komatsu PC200 units, there are several important findings that are worth noting. The main finding shows that there is a significant gap between the expected and actual life, where the average expected life of the components is 15,686 hours, while the average actual life only reaches 12,429 hours. With a gap of 3,257 hours, this indicates that these components are likely to fail or require replacement sooner than expected. In addition, the high variability in this gap indicates that not all components are performing consistently, and some components are failing much earlier than expected.

This finding is in line with Reliability Theory, which states that component life is influenced by various factors, including material quality, component design, and operational conditions. The mismatch between expected and actual life can be caused by differences in usage conditions and working environments that do not match the initial prediction. This theory also reminds us of the concept of "failure rate", which suggests that component failure may occur sooner than anticipated if operational conditions do not match expectations.

In addition, Life Cycle Cost Analysis (LCCA) theory supports these findings by emphasising the importance of understanding and predicting the total cost of a component over its lifetime, including repair and replacement costs due to failure. In this context, overly optimistic component life expectations can lead to increased operational costs and unexpected downtime, negatively impacting efficiency and productivity. This research reinforces the importance of LCCA in helping machine operators and managers to set more realistic expectations regarding component life and manage costs more effectively.

Another significant finding is the influence of operational and maintenance factors on the actual life of components. Condition-Based Maintenance Theory offers a relevant view here, stating that monitoring the actual condition of components during their use can help extend component life if maintenance is performed based on real conditions rather than a predetermined fixed schedule. The findings suggest that the implementation of technology-based condition monitoring and a more proactive maintenance approach can be an effective solution to reduce the gap between expected and actual life.

Overall, the findings of this study not only confirm existing theories but also highlight the importance of implementing more adaptive and data-driven practices in machine component management. Adjusting maintenance strategies and expectations based on real-world conditions is essential to maximise component life and improve overall operational efficiency. As such, this study provides valuable insights for machine operators and managers in managing expectations and realities regarding mainpump component life on Komatsu PC200 units.

The results of this study confirm that there is a statistically significant difference between the expected and actual lifespans of heavy equipment components, as perceived by equipment owners. The ANOVA analysis revealed a clear misalignment between what owners anticipate and what occurs in real operational environments. This gap reflects a deeper issue in how component life is estimated and managed in the field.

Expectations regarding component lifespan are often built upon generalized manufacturer recommendations, legacy operational knowledge, or anecdotal experience. These sources, while useful, may no longer fully represent the complexities of modern working conditions. As a result, operators frequently overestimate the durability of components, leading to unanticipated failures. This misalignment has practical consequences. It increases operational costs due to premature replacements, causes unplanned downtime, and undermines the overall efficiency of equipment fleets.

From a cost and planning perspective, the consequences are significant. When component lifespans fall short of expectations, maintenance schedules become reactive rather than proactive. This reduces control over inventory, leads to emergency procurement, and disrupts workflows. Moreover, these events contribute to a higher total cost of ownership, especially when multiplied across a fleet of machines over extended operational periods. The findings, therefore, reinforce the importance of aligning expectations with empirical data to support more precise and economically sound decision-making.

Beyond the statistical result, a deeper technical understanding is also essential. Many premature component failures can be traced back to physical degradation mechanisms that are often overlooked during expectation setting. These include fatigue, corrosion, and thermal stress—each of which has a specific influence on component longevity.

Fatigue occurs through the accumulation of stress over time, particularly in high-load or repetitive-use environments. This is common in rotating parts or hydraulic components subjected to cyclic forces. Corrosion, meanwhile, accelerates in high-humidity or chemically exposed environments, silently weakening structural integrity. Thermal stress—resulting from fluctuations in operating temperatures—causes expansion and contraction that gradually damages seals, gaskets, and sensitive materials. These mechanisms do not always manifest visibly until a component fails, which contributes to the false perception of reliability during much of the component's service life.

Understanding these mechanisms highlights the importance of moving beyond purely time-based maintenance strategies. The adoption of condition-based or predictive maintenance strategies—grounded in actual operational data and supported by monitoring technology—can dramatically improve the accuracy of lifespan forecasting. It also allows for tailored maintenance interventions that prevent early failure while minimizing unnecessary replacements.

4. CONCLUSION

While this study employs established methodologies such as ANOVA and draws upon foundational theories like Reliability Theory and Life Cycle Cost Analysis, its core novelty lies in reframing component lifespan not solely as a technical parameter, but as a comparative construct between expectation and reality. Unlike prior studies that focus predominantly on engineering-based predictions or failure modeling, this research introduces a unique perspective by treating owner-perceived lifespan as a measurable and analyzable variable. By statistically examining the gap between expected and actual component life, the study reveals a critical disconnect that has practical consequences in terms of cost overruns, unplanned downtime, and maintenance inefficiencies—dimensions often overlooked in conventional reliability research.

In addition to this conceptual contribution, the study integrates practical insights with technical reasoning by connecting field data to the physics of failure mechanisms such as fatigue, corrosion, and thermal stress—factors that directly affect component longevity in real-world settings. This integration not only validates the significance of the expectation-reality gap but also leads to actionable recommendations for condition-based maintenance, data-driven planning, and customized lifecycle management. Therefore, while the statistical tools used are well-established, the novelty of this research lies in its focus, framing, and applied implications, offering both theoretical enrichment and tangible value to industry practitioners.This study revealed a significant gap between the expected and actual life of mainpump components on Komatsu PC200 units, with actual life consistently lower than expected. This gap averaged 3,257 hours indicating that many components failed or required replacement earlier than predicted. Factors such as severe operating conditions, sub-optimal maintenance methods, and varying material quality contribute to this mismatch. This finding confirms that expectations of component life need to be matched with actual operational conditions to minimise the gap between expectation and reality.

This research makes an important contribution by providing an in-depth analysis of the difference between expectation and reality in machine component life. Using a gap analysis approach, this research identifies the factors that cause the mismatch between expected and actual life. In addition, this research strengthens existing theories such as Reliability Theory, Life Cycle Cost Analysis (LCCA), and Condition-Based Maintenance Theory, by providing relevant empirical evidence in the context of the heavy equipment industry. The results also provide insights for practitioners in setting more realistic expectations regarding component life.

The findings of this study have important implications for machine managers and operators in managing component maintenance and replacement. Firstly, managers should consider adopting a more proactive and data-driven condition-based maintenance approach to reduce the gap between expected and actual life. Secondly, managers should conduct periodic evaluations of component life expectations, using historical data from component performance in the field to adjust these expectations. This will help in making more informed decisions regarding maintenance and replacement planning, which in turn can improve operational efficiency and reduce unexpected downtime.

For future research development, there are several areas that need to be further explored. Firstly, future research could focus on identifying in more detail the specific factors that influence the difference between expected and actual age, such as in-depth analyses of working environmental conditions and variations in maintenance methods. Secondly, the study could be extended by considering other types of components or other types of machines to see if similar findings occur in different contexts. In addition, experimental research that tests the effectiveness of condition-based maintenance approaches or sensor-based monitoring technologies may also provide additional insights for improving component reliability and durability in the heavy equipment industry. As such, future research can contribute to the development of best practices in maintenance management and component replacement, and improve overall operational efficiency.

ACKNOWLEDGMENTS

The author sincerely appreciates the editor for their ongoing support and guidance, and the reviewers for their valuable and constructive feedback in improving the quality of this manuscript. We also extend our gratitude to all those involved in this research for their participation.

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