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Evaluation of operational reliability and life cycle of key components of automotive equipment under conditions of intensive operation

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ABSTRACT

Herein, the reliability analysis of several critical automotive components operating under intensive conditions have been reported. Understanding failure mechanisms under high-stress environments compared to nomal operating conditions has been addressed. Real-world data failures have been collected. Weibull distribution of the failure data of several components where some are considered as wear sensitive components (like brake pads, tires and pistons) and fatigue-sensitive components like transmission and shock absorbers were modelled. Reliability quantification was based on incorporating Weibull parameters for shape (β) and characteristic life (η). The results showed a significant difference between normal and intensive regimes. Under intensive operational conditions, the characteristic life parameter eta decreased by 46% for brake pads, 44 % for tires, and 99% for piston engines. The failure modes classification indicated that wear was responsible of 52% of the failure cases. The main causes of failure were originating from intensive service, poor lubrication, and the non-respect of maintenance protocols, amplifying fatigue accumulation in key automotive components. These findings suggest incorporating predictive maintenance strategies based on Weibull parameters to mitigate such failures.

Keywords: Weibull distribution, Time to failure, Automotive, Intensive operation, Reliability

1. Introduction

Reliability in automotive industry is defined as the ability of a component to adequately perform its task without failure for a specified working period or mileage [1]. The concept of reliability does not concern only the period where the component is in service, but it is involved in the entire life cycle of a technical system, from design to under operation. Reliability studies are important because it directly impacts the safety and operational efficiency of a system or a component [2]. Accurate measurement and numerical modelling of the mechanical behavior of engineering systems under operational loading provide reliable information for reliability and structural integrity evaluation [3]–[5].

Specifically in automotive equipment, when subjected to high or intensive operational conditions could shorten the component's lifecycle by half [6]. In intensive conditions, vehicles are driven harder compared to normal conditions. This makes the components wearing out faster and breaking more often. In engineering reliability methods, measure and predict how long these parts will last. This helps predict future failures, planning maintenance, and increase safety [7]–[9].

Intensive operational use includes long working hours, frequent starts and stops, thermal and mechanical stresses [6]. Depending on which case, these factors accelerate the degradation mechanisms in automotive components. The main degradation mechanisms of automotive industry depend on the working condition of the components. The components may endure wear resulting from friction between two sliding components [10]. Fatigue, thermal softening, creep, cracking, and corrosion are all damage mechanisms in mechanical engineering, they might result from overloading (exceeding the materials resistance), or from fatigue (exceeding the safety zone of a material) [11]. As an example, if poor lubrication occurs, thermal stress and accelerated wear could cause the premature failure of the component [12]. Thermal loading can also arise from prolonged high-power output, and inadequate cooling conditions [13]. Long-term exposure to elevated temperatures has also been shown to reduce the durability and service life of engineering metallic structures through progressive material degradation [14]. Likewise, fracture mechanics analyses have demonstrated that crack initiation and propagation significantly accelerate structural failure under repeated loading conditions [15].

In reliability engineering, statistical methods have been extensively used both academically and industrially. These methods use empirical distribution of failure times to characterize component behavior over time. Good output comes from the quality and the quantity of available failure data [16]. A common approach to investigate a component reliability is using reliability metrics, such as Mean Time To Failure (MTTF) and Mean Time Between Failure (MTBF). They both represent the average lifetime of a component, where the first is for unrepairable and the second is repairable components.

Advanced statistical methods were used by several researchers in the automotive reliability engineering [17]. Kaplan-Meier estimator for instance is a powerful tool for accurate failures predictions. The Kaplan-Meier method helps estimate the probability that a component survives beyond a certain time. In mechanical engineering data contain both censored and uncensored data. Where uncensored data contain information on the failure event for a certain component, like time or mileage. On the other hand, censored data are observations taken at the time when the failure event did not yet occur. This is why the Kaplan-Meier method is preferred in this case, making it suitable for reliability analyses where not all components fail within the study period. [17].

The Weibull distribution is widely adopted method by engineers. It helps defining the probability of failure, from infant mortality and useful life, to wear-out phases. The most important parameter is the shape parameter β, which is sufficiently informative. If β is inferior than the value of 1, it indicates a decreasing failure rate (ie. infant mortality). If the β equals to 1, it represents a constant failure rate (referred to random failures), and if the beta is superior than 1 it signifies a failure phase (wear-out phase).

As an example, in a diesel engine, Yao Ji et al. [18] have established a model-based reliability of a common rail fuel system. They showed that reliability analysis is a strong tool for predicting and identifying failure modes under various conditions. They found that increasing pressure increased wear rates of injectors, pumps and pressure regulators.

Another method using a one dimensional physical model, reported by Yao Ji et al. [18], have been used to evaluate the reliability of common rail fuel systems. Such models provide a mechanistic understanding of the underlaying damage mechanisms involved in mechanical engineering. Another statistical model extensively used in mechanical engineering is Condition-Based-Modeling (CBM). It is used when the degradation of one component leads to the failure of others. It has been shown that this model is effective to enhance reliability in such complex systems [19].

Because the Weibull distribution relies on extensive number of failure data, situations where the failure data is scarce or private make it hard to define accurately the shape parameter. Statistical and hybrid modelling approaches, including fuzzy-information-based models, have also been explored to improve engineering system analysis when uncertainty or incomplete information is present [20]. To address such limitations, recent research works have used advanced statistical and machine learning methods that can provide generative data sources. Techniques such as Relevance Vector Machine (RVM) and Principal Component Analysis (PCA) have been used to predict the reliability of automotive components [16], [21]–[23]. Both techniques use a generative data to assess the reliability analysis. Similarly, Shuzhi et al. [24] have developed a prediction method for rolling bearing reliability. They employed an isometric mapping and nonhomogeneous cuckoo search-least squares support vector machine (NoCuSa-LSSVM). Another deep learning model has been developed by Lanfei He et al. [25] addressing the life prediction of power transformers. Their model was capable to develop a DL of estimating transformer's life and linking it to diverse aging factors, including rated capacity, voltage level, environment, etc. They showed that their model outperforms traditional statistical models especially if sufficient operational data are available.

The ML and DL methods have shown to be effective in capturing complex and non-linear relationships between degradation mechanisms and operational parameters. Yet, the dynamic and complex nature of real operating conditions in automotive components, especially under intensive working conditions, limitates these models. Besides, the lack of fully integrated data, privacy and ethics concerns on data manipulation make it necessary to investigate failure modes of automotive components based on real data collection. Herein, real-life data, under normal and intensive conditions have been collected and studied to achieve accurate reliability management and predict failure of key automotive components.

The impetus of this study is to evaluate the operational reliability of various automotive components under intensive conditions, including brake pads, tires, piston engines, turbocharger, transmission, coil springs, and shock absorbers. Using real world data and Weibull analysis we have identified the most vulnerable key components in the automotive industry. Intensive conditions were chosen based on different intensive conditions such as high mileage, poor lubrication, road conditions etc…

2. Research method

2.1. Weibull failure probability analysis

Engineering reliability analyses rely on mathematical models of varying complexity to describe and predict the behaviour of physical systems [26]. In this paper, the two-parameter (β, η) based Weibull analysis was used. The shape parameter (β) describing the failure trend and the scale parameter (η) representing the characteristic life. The Cumulative Distribution Function (CDF) is defined as:

$$F(t) = 1 - e^{-(t/\eta)^{\beta}} \tag{1}$$

Where F(t) is the CDF, β the shape parameter, η the scale parameter, and t is the time to failure (hours).

This two-based model assumes the component may fail at any time, no minimum guaranteed life and no threshold before failures can occur.

2.2. Median Rank Regression (MRR) method and parameter estimation

In the dataset, several failure times of various components were collected. In order to define the two Weibull parameters Median Rank Regression (MRR) method has been used.

After sorting failures times from the smallest to the largest, the probability that each failure represents is calculated using the formula:

$$F_i = \frac{i}{n+1} \tag{2}$$

Where *i* represent the data rank in the dataset, and *n* the total number of failures. Fi is the function that converts the failure data into probabilities.

To identify the parameters of the Weibull distribution, linearization of the following formula (3) was used.

$$Ln[-\ln(1 - F_i)] = \beta \ln(t_i) - \beta \ln(\eta) \tag{3}$$

Turning it to a simple linear regression, the shape parameter β is defined as the slope. Where the function takes a linear form of:

$$y = \beta x + b \tag{4}$$

The intercept is calculated by :

$$b = \beta \ln(\eta) \tag{5}$$

And the scale parameter η could be calculatd using the formula defined in (6).

$$\eta = e^{-b/\beta} \tag{6}$$

2.3. Data classification and operating conditions

The dataset was classified by component according to vehicle usage. Two primary operating conditions were defined as shown in Table 1. The failure data was collected from several sources, including manufacturer warranty claims, and routine maintenance records. Data consistency was insured prior to statistical analysis.

The data were obtained from automotive maintenance garages in California City, USA [27]. The records taken in this study were from a period ranging from 2023 to 2025. The car models that the study was based on were: a pick-up Ford F-150-V6 (for tires), Toyota Camry 2.5L 4-Cyl Hybrid (for brake pads), and different models of Honda and Toyota brands for the other components.

Table 1. Failure mileage data from 8 automotive components

Automotive component	Normal condition	Intensive condition	Total failures
Brake pads	14	13	27
Tires	13	11	24
Engine pistons	11	9	20
Turbocharger	8	6	14
Auto transmission	10	8	18
Manual transmission	6	5	11
Coil springs	5	7	16
Shock absorbers	8	7	15

2.4. Reliability function

R(t), which is the reliability function, is defined as the probability of component survival beyond time. This function is the complement of the CDF function and calculated using the formula:

$$R(t) = e^{[-(\frac{t}{\eta})^{\beta}]} \tag{7}$$

The parameter estimation was conducted by python coding using the reliability library in Anaconda framework. Using MMR, the function allows getting the shape and scale parameters, and the associated probability plot.

3. Results and discussion

Table 2 shows how the dataset was refined to meet our criteria of intensive conditions. The data of each component studied herein was chosen based on two conditions. The first defined as normal conditions, which aligns with different warranty claims manuals. Whereas the intensive conditions are detailed in Table 2 and explained in the following. Based on mileage, a stress multiplier of 3.3 was chosen according to NYC taxi fleets. The criteria was to choose only vehicles that exceeds this minimal threshold, defined as 40000 miles. The normal annual mileage was defined as 12000 miles/year, according to the Federal Highway Administration (FHWA). A second criterion was based on the vehicle usage purpose, private cars (personal use cars) versus commercial vehicles. The data was further refined where a range of 8-12 hours daily usage as intensive compared to 1-2 hours range in normal conditions. At last, load capacity (how much weight the vehicle carries generally, defined approximately) and the braking frequency which was chosen based on the road-type (if the vehicle often used in urban, rural, or highways).

Table 2. Operating conditions and load characteristics of key automotive components under intensive operation

Parameter	Normal (warranty)	Intensive (real-data)	Stress multiplier
Annual mileage	12000 miles/year	<40000 miles/year	3.3×
Vehicle usage	Private cars	Taxi, delivery, commercial uses	-
Daily operation	1-2 hours	8-12 hours	6×
Load	50-70% capacity	90-100% capacity	1.4×
Braking frequency	Normal stops	Frequent hard stops	4×

All components have been modeled using a two-parameter Weibull distribution. Note that only three components are shown in Figure 1, brake pads, tires, and engine pistons. In every case, the failure data (black dots) are well fitted with the Weibull regression line (in blue). The plots show a sufficiently adequate model fit across the entire dataset. The calculated shape parameters under normal and intensive conditions are calculated from these plots and summarized in Table 3.

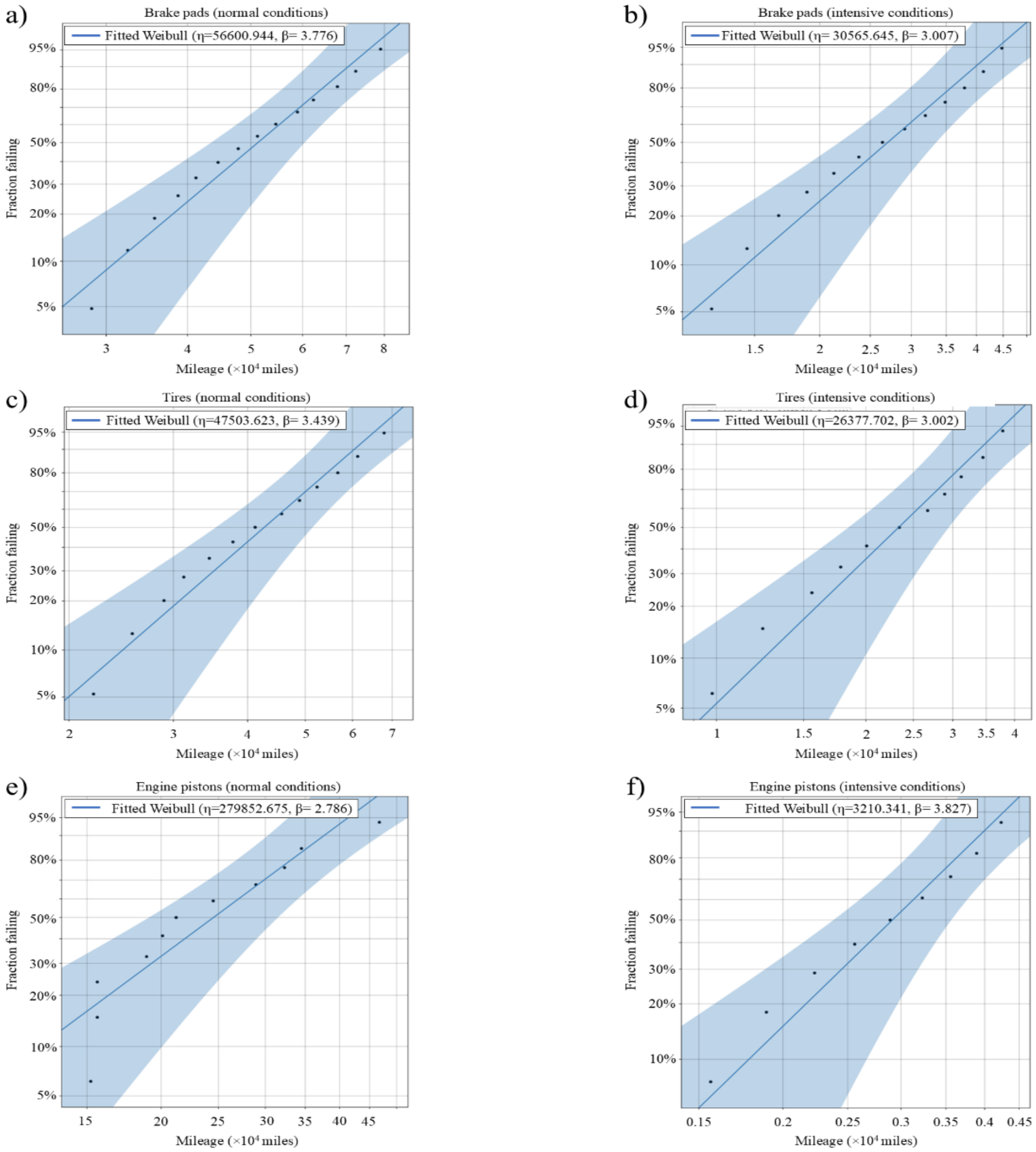

Figure 1. Weibull CDF probability plots of the different automotive components' failure mileage for: brake pads under a) normal and b) intensive conditions; tires under c) normal and d) intensive conditions; and engine pistons under e) normal and f) intensive conditions.

Table **3**. Estimated reliability indicators and life cycle parameters of key automotive components

Automotive component	η (normal conditions)	η (intensive conditions)	β (normal conditions)	β (intensive conditions)	MTTF (normal conditions)	MTTF (intensive conditions)
Brake pads	56600	30565	3.77	3.007	51132	27295
Tires	47503	26377	3.4	3.002	42676	23555
Pistons	279852	3210	2.786	3.827	249147	2902
Turbocharger	23547	14946	5.44	4.35	21725	13613
Fuel injectors	34413	19376	6.12	5.37	31961	17864
Auto-transmission	262981	175392	4.4	3.64	239677	158142

Automotive component	η (normal conditions)	η (intensive conditions)	β (normal conditions)	β (intensive conditions)	MTTF (normal conditions)	MTTF (intensive conditions)
Manual transmission	324845	180315	7.1	6.08	304096	167404
Coil springs	296823	207062	4.89	4.88	272183	189851
Shock absorbers	175392	69127	3.64	5.87	158142	64052

In all automotive components analyzed, the shape parameter beta showed values superior than 1, indicating a wear-out dominated failure mode. Another observation made is that the intensive conditions used in the present dataset showed it to have an impact on the characteristic life parameter η. In all cases, the η parameter decreased under intensive conditions compared to the normal conditions. The most striking reduction is recorded for brake pads, it decreased from 56601 to 30565 miles, representing a 46% reduction.

For all nine automotive components, the MTTF has been derived and calculated from the Weibull parameters and compiled in Table 3. The recorded values further show how intensive operational conditions reduce the characteristic life for all components. The reduction percentage varies from 30.2% for coil springs to 98.9% for pistons. These results show how accelerated degradation could happen if intensive conditions such as high speed, thermal stresses, and poor maintenance are present. The shape parameter in reliability engineering is very informative, from the results presented in Table 3, all components have shown a β value superior than 1 in both cases (normal and intensive conditions). This falls within the wear-out regime indicating that the failure mode is predominantly material fatigue and wear degradation mechanisms.

For most components working under intesive use, the β decreased slightly compared to normal condition. Interestingly, two components showed an exception, the β parameter for pistons increased from 2.79 to 3.83, and shock absorbers from 3.64 to 5.87. These results probably indicate that the two components are sensitive to the intensified operating regime.

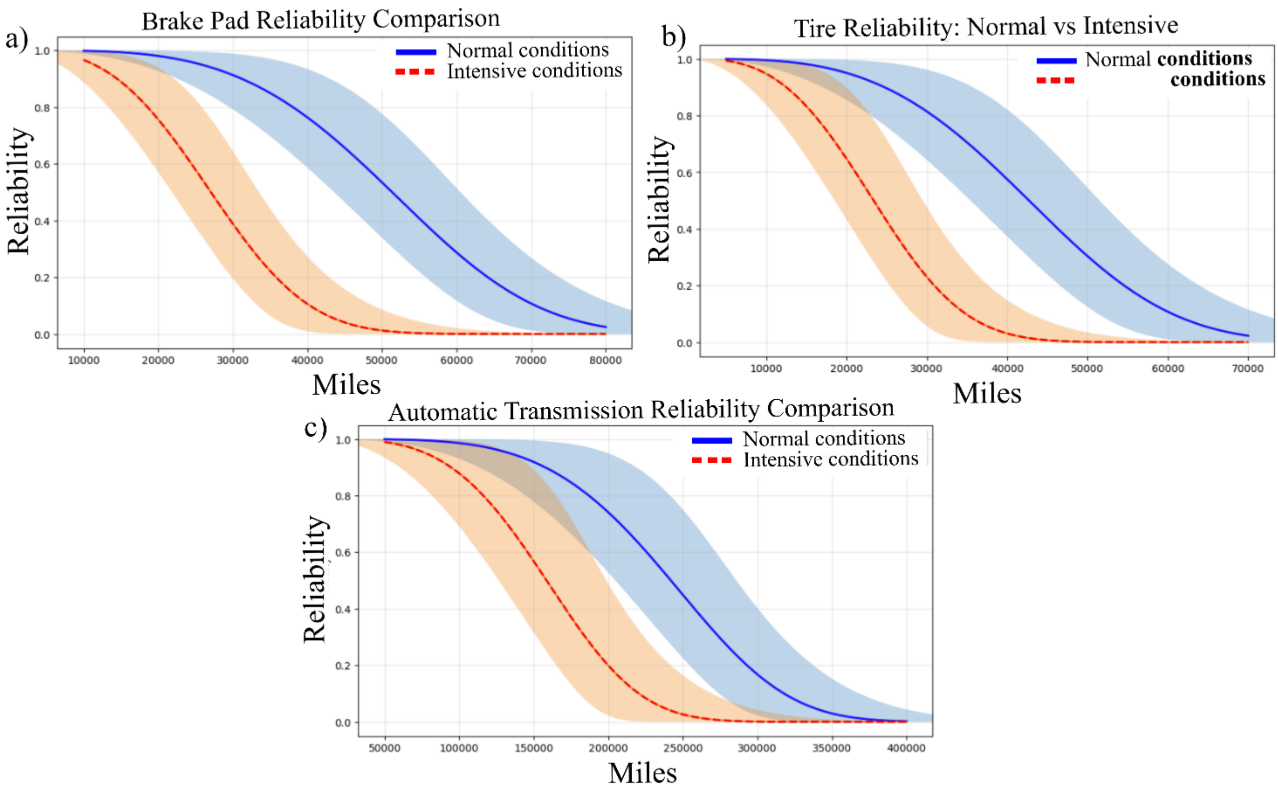

Figure 2. Comparative reliability curves of a) brake pads, b) tires, and c) automatic transmission; under normal conditions (in blue) and intensive conditions (in red).

Figure 2 shows the reliability function R(t) as a function of accumulated mileage of brake pads, tires and automatic transmission. Normal conditions are plotted by a solid blue curve and the dashed red curves for intensive conditions. One can notice that a shifting towards lower mileage is discernible in all automotive components. Both brake and tires show reliability to fall below 50%, as shown in Figure 2a and 2b. On the other hand, in the case of the automatic transmission component, reliability percentage is closer at low mileage and tend to get separated further at higher absolute mileages (Figure 2c). This indicate that transmission has a longer nominal service life compared to the other two. These reliability shifts have been reported by C. Luo et al. [21] where they reported that dynamic variations in braking intensity and road conditions produce a clear contraction of the survival function, with front pads consistently exhibiting shorter lives due to elevated mechanical loading. Besides, Wu and Bai [22] have shown that intensified thermal and mechanical stresses causes the shift in the entire reliability curve toward lower mileages. The three automotive components, form a survival perspective, show clearly that transition from normal to intensive cycles have an impact even at the early mileage. This underscores why preventive maintenance schedules and spare-part provisioning must be envisaged in engineering.

Figure 3 identifies the failure mechanisms for the automotive components analyzed. Piston engines, tires, and brake pads, have all a dominant failure degradation mode, which is wear. It is by far the dominant failure mode responsible for 52% of all recorded failures. followed by thermal degradation at 23%, fatigue at 14% and overload at 7%. Adhesive and abrasive wear, tribo-corrosion, and excessive heat generated by friction under poor lubricated conditions worsen the life cycle of the automotive components. This intensive service explains the wear-out behavior captured in the Weibull analyses where the shape parameter always exceeded 2.7 value.

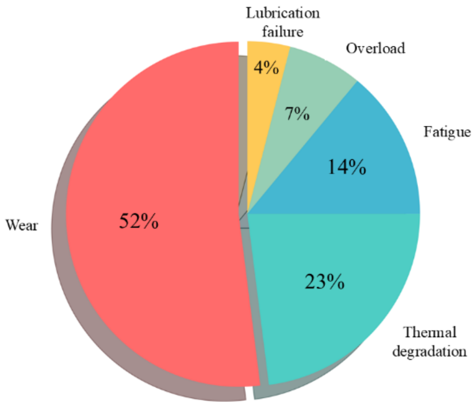

Figure 3. Classification of failures of key components under intensive operation

This classification on failure mode distribution identifies the priority for the design and maintenance interventions, and emphasizes on the importance of lubrication and cooling, specifically in automotive components. Comparable failure modes distribution have been reported by Heyes et al. [23]. They analyzed 70 failure cases in automotive components and found that wear was the dominant degradation mechanism. Besides, manufacturing issues have amplified failure and was identified as the primary root causes. Our observations had similar trend with this previous study, yet, our current data do not show any observations on manufacturing issues. Thus, manufacturing issues might be one of the causes that could have a direct effect on the wear of the studied automotive components.

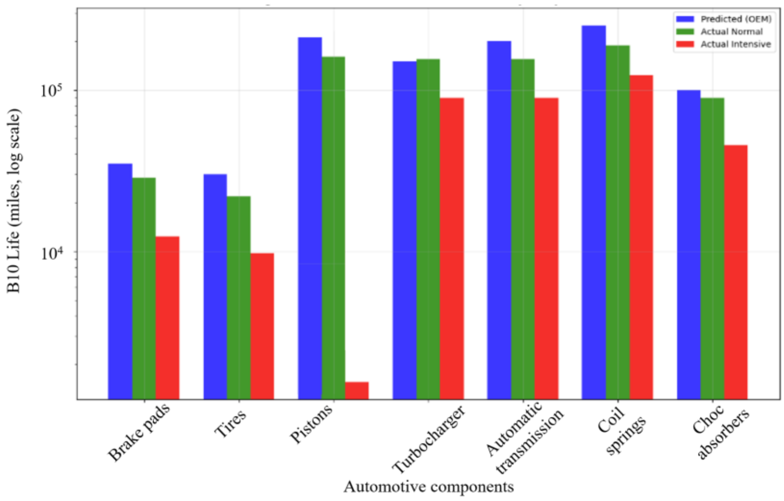

Figure 4. Predicted vs actual resource of key automotive components.

A comparison of predicted data (by the Original Equipment Manufacturer ”OEM”) and actual resource of automotive components under normal and intensive conditions is shown in Figure 4. Under normal services, the actual dataset aligns well with OEM predictions, however, a drastic failure drop is apparent for the engine piston component. This is most likely because of the intensive conditions chosen for data selection in this study. For piston engine component, the selection of the data failure was based on insufficient lubrication and non-adherence to recommended oil change. Which might explain this drastic failure within this specific component.

The Weibull analyses (Figures 1 and 2) for the automotive components studied herein showed a rection of 30-99% of characteristic life parameter under intensive service. Where β showed accelerated and unchanged wear-out mode compared to normal operating conditions. Our findings correlate well with previous studies on automotive parts and components [23]. A recent study on copper brake pads under repeated cycles of stops and runs, induced an oxidation driven failure leading to accelerated wear of the component. They reported a comparable drop in eta values of 44-46%, similarly as reported in our study [24]. The drastic failure of piston was attributed to poor lubrication and missed oil-change intervals in the real-life dataset. Transmission components showed 44-47% life reduction. This is consistent with gearbox and clutch studies in heavy-duty fleets [25]–[27].

It must be noted that the automotive components rely on each other, and further analysis should take in consideration other factors that could intensify the failure rates of the components. The synergistic amplification of corrosion and wear mechanisms caused by other factors such as poor lubrication or cooling could worsen failure and false engineering predictions [28]. From a material science point of view, if poor cooling is endured, microstructural softening and oxidation enhances fatigue and lead to an early degradation of the automotive component. When irregular oil changes occurs or bad oil filtering, debris comping from the sliding metals in contact will play an abrasive third body wear and oil-film rupture causing an exponential wear rate [29] –[30].

Hence, reliability-centered maintenance strategies and good quality data collection are mandatory for reliability prediction in automotive industry [31]. Furthermore, the effective implementation of maintenance strategies also requires efficient organization of maintenance services and resource allocation, where mathematical service models can support decision-making and operational efficiency [35]. Real-time telemetry should focus on different aspects including service temperature, vibration degrees, and oil condition. Similar monitoring approaches are widely adopted in other engineering infrastructures to evaluate operational conditions and support system assessment [36]. This study showed that some components need preventor actions such as spare-parts inventory for high sensitive components like pistons and shock absorbers, especially under intensive conditions of usage.

4. Conclusions

Reliability and service life of critical automotive components under intensive operational conditions have been analyzed. Various components including brake pads, tires, pistons, turbocharger, and transmissions has been studied, the main conclusions can be drawn as follows.

Our results confirm that intensive regimes such as frequent braking and elevated mechanical loads accelerate the automotive's components degradation. The Weibull analysis revealed characteristic life drop ranging from 30% for coil springs t nearly 99% for piston engines. Reliability functions shifted towards lower mileage under intensive use. Non-optimal maintenance has been identified as the most driven-failure cause of degradation of automotive components. Amplified wear, thermal effects, extensive non-stop hourly usage, and poor lubrication are the driving forces for premature failures in automotive components. The difference between OEM-predicted lives calibrated from normal conditions and actual intensive service conditions showcases the limitation of life-cycle prediction methods. Models often fail to predict failure especially when synergistic and dynamic stresses are dominant within the service life of the component. This study showed the importance to improve prediction approaches and the necessity of using hybrid methods that take into account diverse duty cycles and conditions. Our results also emphasize on the need of recalibration of preventing maintenance schedules, and prioritizing wear-resistant materials and designs especially for high-sensitivity components. The most vulnerable components identified within this study are piston engine, tires, and brake pads, which all components undergo wear as the main degradation mechanism.

Declaration of competing interests

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: S. Pernebekov, A. Junusbekov: study conception and design A. Junusbekov: data collection; S. Pernebekov, A. Madiyarova, A. Junusbekov, A. Kartashova: analysis and interpretation of results; A. Madiyarova, S. Pernebekov, U. Kokayev: draft preparation. All authors approved the final version of the manuscript.

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