Estimation and Analysis of Remaining Useful Life (RUL) of Critical Mechanical Components in Tractor

Sahil Bhagat[1], Sanjeev Gupta[2], Pardeep Singh[3]

[1]Research Scholar, Mechanical Engineering Department, Government College of Engineering and Technology, Jammu, India
[2] Associate Professor and Head, Mechanical Engineering Department, Government College of Engineering and Technology, Jammu, India

Abstract
The proposed framework utilizes an evolutionary mathematical approach to optimize data-related parameters for estimating the Remaining Useful Life (RUL) of critical mechanical components. By integrating advanced time window techniques and considering factors like downtime and failure occurrences, it offers a comprehensive solution for RUL prediction across various industrial contexts. Continuous monitoring systems play a pivotal role by detecting component degradation early, allowing for proactive maintenance and minimizing catastrophic failures. Combining Mean Time to Repair (MTTR) and Mean Time Between Failures (MTBF) offers valuable insights into system performance, enabling proactive maintenance strategies. This review explores mathematical methodologies for predicting RUL in tractors, crucial for enhancing maintenance planning and remanufacturing engineering.

Keywords: Remaining Useful Life Prediction, MTTR, MTTF, MTBF, Failure analysis.

1. Introduction

The agricultural tractor belongs to the class of mobile machines designed for the traction process. The term "traction" and the name "tractor" are derived from the concept of "drawing" or "pulling," emphasizing the primary function of the tractor as a machine specifically built for pulling tasks [1]. This prediction is based on synthesizing observations, calibrated mathematical models to predict system behavior over time, facilitating proactive maintenance strategies. By integrating diverse data sources and advanced modeling techniques, it aims to forecast the remaining useful life (RUL) of engineering systems or components, crucial for informed decision-making in maintenance planning [2]. RUL, which stands for Remaining Useful Life, is also known as remaining service life or remnant life. This term refers to the time left before observing a failure, considering factors such as the current age of the machine, its condition, and the past operational profile. Essentially, RUL quantifies the remaining operational lifespan of a system or component before it is expected to fail or become non-functional [3]. In the agricultural tractor industry, the design of the components and systems adheres to predetermined specifications and requirements. The critical design criteria primarily revolve around strength considerations, given the substantial loads experienced by these components in the various applications of agricultural tractors. Among these primary components, the front axle and front axle support bear the most critical loading conditions, as they are directly subjected to the forces acting on the front axle during tractor operations [4]. Machinery, regardless of its cost, size, or complexity, is susceptible to breakdowns. Therefore, incorporating a well-defined maintenance schedule is crucial during capacity planning and activity scheduling in modern industries, spanning manufacturing [5]. The primary goal of maintenance is to enhance equipment performance by significantly reducing failures, faults, or breakdowns. This objective underscores the importance of implementing preventive and predictive maintenance strategies aimed at minimizing downtime, optimizing productivity, and extending the operational lifespan of machinery and critical components [6]. Remaining Useful Life (RUL) denotes the duration remaining for a component to fulfill its intended functional capabilities before encountering failure [7]. Remaining Useful Life (RUL) is pivotal for predictive maintenance, offering insights into equipment lifespan to optimize operations and minimize downtime. It informs proactive interventions for enhanced efficiency, guides decisions in remanufacturing engineering, and facilitates strategic resource allocation for maximizing equipment lifecycle across industries [8]. During literature surveys, numerous studies have been conducted to develop and implement various mathematical models for maintenance schedules. These studies explore diverse approaches to optimizing maintenance strategies, encompassing preventive, predictive, and corrective maintenance techniques [9]. The mathematical approach for evaluating the remaining useful life of the critical components is used to enhance equipment performance, minimize downtime, and maximize operational efficiency [10]. In industrial settings, machine maintenance is increasingly vital to boost availability and reduce production losses from breakdowns. Maintenance methods like replacement, repair, and servicing aim to sustain specified availability levels, with remaining useful life estimation pivotal. Analysis of critical component failure rates, along with parameters like MTBF, MTTR, and Availability, informs proactive maintenance strategies for enhanced operational efficiency [11]**.** Breakdowns result in increased downtime and reduced uptime, directly impacting the productivity of the unit. By adopting a suitable maintenance schedule, breakdowns can be effectively controlled. Implementing preventive and predictive maintenance practices can significantly reduce the likelihood of unexpected failures, thus minimizing downtime and maximizing uptime [12]**.** This study has the potential to provide significant value to numerous leading organizations, serving as a benchmark for them to enhance their maintenance practices. The outcomes of this research can inform decision-making processes related to maintenance planning, resource allocation, and operational strategies.

2. Literature Review

Medjaher et al.(2012)[13] This paper examines RUL estimation methods, emphasizing a data-driven approach over model-based techniques, by assessing current health states and future operating conditions of physical systems. It outlines critical component identification, sensor deployment, and degradation modeling leveraging sensor data. Rigorous evaluation using prognostics metrics and application to real bearing data validate its effectiveness, with detailed experimental results discussed.**Salunkhe et al.(2014)**[3] Remaining Useful Life (RUL) is vital for dynamically controlled systems, crucial for meeting customer demands by minimizing sudden component failures. Continuous monitoring and fault propagation methods enable accurate RUL estimation across diverse applications like Automotive Components, Rotating Machinery, and Aero Engines, ensuring early fault detection and severity estimation.**Ali et al.(2015)**[14] This study introduces a novel method for accurately predicting Remaining Useful Life (RUL) of critical assets such as bearings, leveraging Prognostics and Health Management (PHM) techniques. By combining a Simplified Fuzzy Adaptive Resonance Theory Map (SFAM) neural network with Weibull distribution (WD) and a smoothing phase, the data-driven approach demonstrates reliability in RUL prediction based on vibration signals from rolling element bearings (REBs), applicable to diverse mechanical assets.**Laredo et al.(2019)**[15] This framework introduces a multi-layer perceptron and an evolutionary algorithm to optimize data parameters, integrating a piecewise linear model for estimating Remaining Useful Life (RUL) of mechanical systems. Evaluation on the C-MAPSS dataset highlights its superior accuracy compared to existing methods, offering a compact yet effective solution for RUL estimation.**Zhang et al.(2023)**[16]This paper introduces a two-stage machine learning approach for accurately predicting Remaining Useful Life (RUL) of industrial equipment, addressing diverse degradation rates and nuanced information accumulation. Through a rolling element bearing dataset case study, it demonstrates superior prediction accuracy and conservativeness, marking a significant advancement in RUL prediction efficacy for real-world applications.

3. Failure Analysis of Mechanical Components in Tractor

The first step is to identify the failed components. This may involve visual inspection of the tractor maintenance and repair workshop, examination of maintenance records, and discussions with operators or technicians who observed the failure. Collect relevant data about the failed component, including its operating conditions and maintenance history.

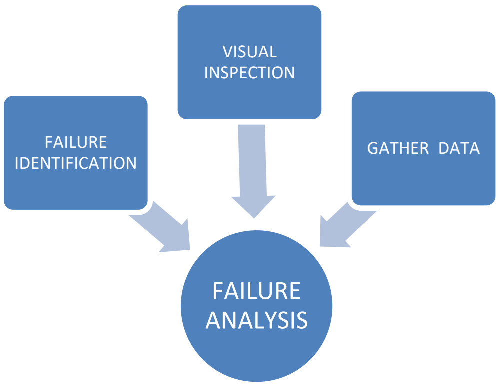


Figure 1: Failure Analysis of Mechanical Components

4. Data Collection

The availability of precise breakdown maintenance data is essential for RUL and failure analysis. For the current study, data from Tractor maintenance and repair workshop spanning three years (2020 January to December 2022) has been collected. This dataset encompasses information on machine breakdowns, causes of failures, machinery involved, and the remedial measures previously adopted by maintenance personnel. The failure data obtained from the Tractor Maintenance and Repair Workshop has been tabulated, detailing the number of failures and breakdowns corresponding to individual machinery. This comprehensive approach to data collection aims to provide a thorough understanding of the maintenance challenges faced by the unit and sets the foundation for a robust case study analysis.

5. Methodologies for Rul Estimation

The methodology followed to achieve this is as follows:

a. The collection of data includes historical failure data, downtime records, maintenance and repair record.

b. From the past failure data, downtime, and components Mean Time to Repair (MTTR), Mean Time To Failure (MTTF) and Mean Time Between Failure (MTBF) relevant calculations are performed.
c. The Mathematical Approach is used for the calculation of the Remaining Useful Life of the critical components of the Tractor.

The remaining useful life (RUL) can be calculated using the following formula, based on Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR):

RUL = MTTF - (t - MTBF)

Where:
- RUL, is the remaining useful life.
- MTTF, is the Mean Time to Failure.
- t, is the current time.
- MTBF, is the Mean Time Between Failures.

- **Mean Time Between Failures (MTBF):** MTBF is the average time between failures of a component. It is calculated as the total operational time divided by the number of failures. The formula for MTBF is :

$$MTBF = \frac{\text{Operating Time}}{\text{No. of Failures}} = \frac{\text{Running Time} - \text{Downtime}}{\text{No. of Failures}}$$

- **Mean Time to Repair (MTTR):** MTTR is the average time it takes to repair a failed component. It is calculated as the downtime due to failures divided by the number of failures. The formula for MTTR is :

$$MTTR = \frac{\text{Downtime}}{\text{No of Failures}}$$

- **Mean Time to Failure (MTTF):** The Mean Time to Failure (MTTF) is a measure used in remaining useful life to estimate the average time a system, component, or device operates before experiencing a failure.

6. Results And Analysis

After conducting a mathematical RUL approach using downtime and number of failure, it was determined that the MTBF and MTTF, indicating a high susceptibility to failure, which is deemed unacceptable. This evaluation extends to various components within the Tractor, specifically focusing on the performance of the Differential throughout the period from January 2020 to December 2022. This Mathematical RUL approach suggest a significant likelihood of breakdowns in these components, highlighting a critical need for remedial actions to enhance their maintenance and operational efficiency. The data obtained from the maintenance and repair workshop is used to evaluate MTBF, MTTF and MTTR for the Remaining Useful Life estimation and is tabulated in the table 6.1 to 6.3.

Table 6.1: Estimation of MTBF and MTTR For Differential For The Year 2020, 2021 and 2022.

S.No.	Month	Running Time (Hrs)	Down Time (Hrs)	No. of Failure	Operating Time (Hrs)	MTBF (Hrs)	MTTR (Hrs)
1	Jan. 20	372	0	0	372	0	0
2	Feb.	348	11	1	337	337	11
3	Mar.	372	16	1	356	356	16
4	April	360	0	0	360	0	0
5	May	558	38	3	520	173.33	12.66
6	June	540	27	2	513	256.5	13.5
7	July	372	0	0	372	0	0
8	Aug.	372	15	1	357	357	15
9	Sept.	360	8	1	352	352	8
10	Oct.	496	18	1	460	460	18
11	Nov.	480	0	0	480	0	0
12	Dec.	372	0	0	372	0	0
13	Jan. 21	372	0	0	336	0	0
14	Feb.	336	17	1	319	319	17
15	Mar.	372	0	0	372	0	0
16	April	360	0	0	360	0	0
17	May	558	32	4	526	131.5	8
18	June	540	28	3	512	170.66	9.33
19	July	372	13	1	359	359	13
20	Aug.	372	0	0	372	0	0
21	Sept.	360	0	0	360	0	0
22	Oct.	496	26	3	470	156.66	8.66
23	Nov.	480	23	3	457	152.33	7.66
24	Dec.	372	0	0	372	0	0
25	Jan. 22	372	12	1	360	360	12
26	Feb.	336	14	2	322	161	7
27	Mar.	372	0	0	372	0	0
28	April	360	0	0	360	0	0
29	May	558	35	5	523	104.6	7
30	June	540	30	3	520	173.33	10
31	July	372	0	0	372	0	0
32	Aug.	372	0	0	372	0	0
33	Sept.	360	0	0	360	0	0
34	Oct.	496	19	3	477	159	6.33
35	Nov.	480	17	2	463	231.5	8.5
36	Dec.	372	0	0	372	0	0

Table 6.2: Total sum of all listed values

Running Time (Hrs)	Down Time (Hrs)	No. of Failure	Operating Time (Hrs)	MTBF (Hrs)	Current Time (t)
14982	399	41	14539	4770.41	558

Mathematically,

$$MTBF = \frac{RN-DN}{N}$$

Where, MTBF- Mean Time Between Failure

RN- Running Time

DN- Down Time

N- Number of Failure

Running Time, RN =14982 Hrs

Number of Failure, N =41

$$\text{Mean Time Between Failure, } MTBF = \frac{RN-DN}{N}$$

$$= 4770.41 \text{ Hrs}$$

$$\text{Mean Time To Failure, } MTTF = \frac{\text{Total operating Time}}{\text{No. of Failures}}$$

$$= \frac{14539}{41}$$

$$= 354.60 \text{ Hrs}$$

$$(RUL)_{Differential} = MTTF - (t - MTBF)$$

$$= 354.60 - (558 - 4770.41)$$

$$= 354.60 - (-4212.41)$$

$$= 354.60 + 4212.41$$

$$= 4567.01 \text{ Hrs}$$

Table 6.3: Estimation of Remaining Useful Life for Differential

MTBF(Hrs)	MTTF(Hrs)	T(Current Time)	RUL(Hrs)
4770.41	354.60	558	4567.01

Figure 2: Graph showing variation of downtime and Number of failures

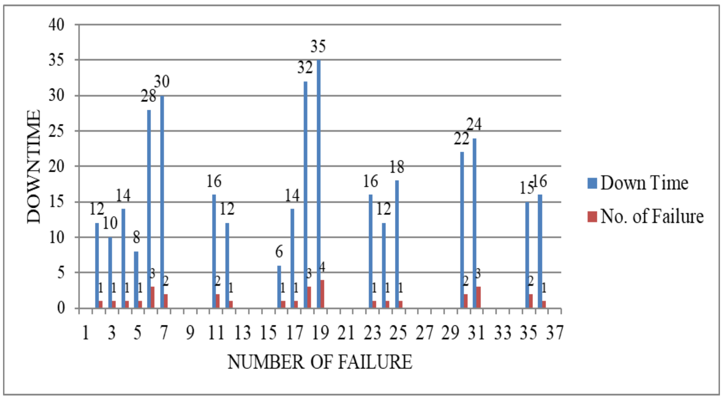
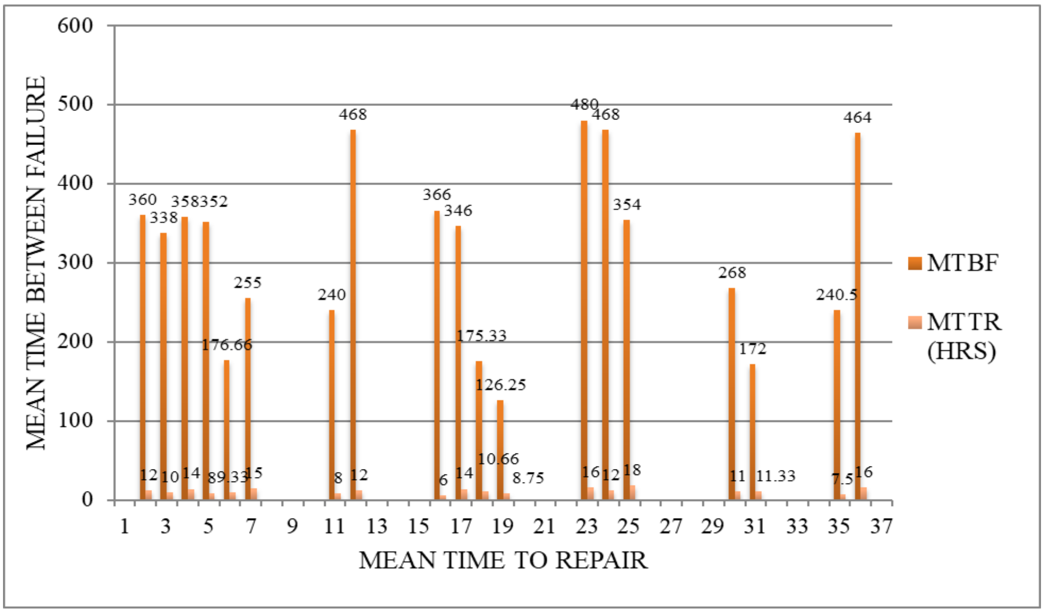


Figure 3: Graph showing variation of MTBF with MTTR (in hrs)



7. Conclusion

In conclusion, the mathematical approach for remaining useful life estimation of mechanical components is contributing to improved Remaining Useful Life, reduced downtime, number of failures and optimized resource utilization in mechanical systems. The analysis focused on past breakdown data of critical components, including the Diesel pump, Cooling System, Clutch, Gearbox and Differential. The most critical component is found to be Differential as compared to other components. By employing Mathematical approach, it is possible to accurately predict the RUL of these components. This enables proactive maintenance strategies, minimizing downtime and preventing unexpected failures. Overall, RUL estimation is a pivotal aspect of modern agricultural machinery management, contributing to improved operational efficiency and longevity of critical tractor components. This deliberate focus on historical breakdown information serves as a foundational step in developing insights that will contribute to the creation of an effective maintenance strategy.

8. Conflict of Interest

It is declared that the research work performed was independent and unaided by any other external funding agencies or sponsors. There is no conflict of interest of any type with any of the author whosoever is involved in this research work.

9. Acknowledgement

I am very thankful to Mr. Sanjeev Gupta, Associate Professor and Head, Mechanical Engineering Department, Government College of Engineering and Technology, Chak Bhalwal Jammu, for giving permission to carry out my research work at industrial site and completing my thesis work under the guidance of Dr. Pardeep Singh, Assistant Professor (A.A),Mechanical Engineering Department ,Chak Bhalwal, Jammu in stipulated time.

10. References

1. R.H. Macmillan, “The Mechanics of Tractor-Implement Performance”, Senior Academic Associate, Agricultural Engineering International Technologies Development Center, University of Melbourne, October 2002.
2. P. E. Leser, “Probabilistic Prognostics and Health Management for Fatigue-critical Components using High-fidelity Models,” 2017.
3. T. Salunkhe, N. I. Jamadar, and S. B. Kivade, “Prediction of Remaining Useful Life of Mechanical Components-A Review,” vol. 3, no. 6, pp. 125–135, 2014.
4. Dilip K. Mahanty, Vikas Manohar, Bhushan S Khomane, Swarnendu Nayak, “Analysis and Weight Reduction of a Tractor’s Front Axle”, Tata Consultancy Service, India, 1995.
5. Wild, R., *“Production and Operations Management",* 5th Edition, Cassell Educational Limited, New York, 1987.
6. Tanwari, A.D., Abbasi, A.A., and Rashdi, R.S., *"Preventive Maintenance as a Productivity Improvement Strategy",* Journal of Engineering and Applied Sciences, University of Engineering & Technology, Volume 19, No. 2, pp. 36-42, Peshawar, Pakistan, 2000.
7. Lei, Lei, et al. "Deep reinforcement learning for autonomous internet of things: Model, applications and challenges." *IEEE Communications Surveys & Tutorials* 22.3 (2020): 1722-1760.
8. Yawei Hu, Shujie Liu, Huitian Lu and Hongchao Zhang, "Remaining useful life assessment and its application in the decision for remanufacturing", 21st CIRP Conference on Life Cycle Engineering, Vol. 15, pp. 212-217, 2014.
9. Gits, C.W., *"On the Maintenance Concept for a Technical System*: A Framework for Design", Ph.D. Thesis, Eindhoven University of Technology, 1984.
10. Flores, V., and Feldman, R.M., *"A Survey of Preventive Maintenance Models for Stochastically Deteriorating Single-Unit Systems"*, Naval Research Logistics Quarterly, Volume 36, No. 4, pp. 419-446, 1989.
11. I,Ushakov, Reliability : past, present, future, Recent advances in Reliability theory, Methodology, practice and interface, Birkhauser, Boston,2000, pp 3-14.
12. Barlow, R., and Hunter, L.C., *"Optimum Preventive Maintenance Policies"*, Operations Research, Volume 8, pp. 90-100, 1960.
13. K. Medjaher, D.A. Tobon-Mejia and N. Zerhouni, "Remaining useful life estimation of critical components with application to bearings", IEEE Transactions on Reliability, Vol. 61, pp. 292-302, 2012.
14. Ali, Jaouher Ben, et al. "Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network." Mechanical Systems and Signal Processing 56 (2015): 150-172.
15. Laredo, David, et al. "A neural network-evolutionary computational framework for remaining useful life estimation of mechanical systems." Neural networks 116 (2019): 178-187.
16. Zhang, Huixin, Xiaopeng Xi, and Rong Pan. "A two-stage data-driven approach to remaining useful life prediction via long short-term memory networks." Reliability Engineering & System Safety 237 (2023): 109332.