

# A Review of Modern Maintenance Techniques for Improving Mechanical System Reliability

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**Abstract**—The functional effectiveness of major components usually determines the operational reliability of large mechanical equipment. Therefore, to guarantee the dependability of mechanical equipment, timely maintenance is required before failure. This paper is a critical discussion of the reliable maintenance and care of mechanical systems to achieve the fullest life of equipment and efficiency. It discusses the shift in the past from reactive and preventative maintenance to smart, data-driven predictive and reliability-focused operations that Industry 4.0 technologies provide. The principles of reliability optimization design are discussed, which focus on combining the methods of probabilistic approach and dependability on a system level. Performance comparison is drawn between various maintenance strategies, and common mechanical failures of rotating machines, including bearing, gearbox, and misalignment faults, are discussed in terms of causes and consequences. Also, the paper addresses predictive maintenance and the significance of the Internet of Things (IoT)-based sensor technologies in real-time condition monitoring as part of lifecycle management. The literature review has indicated new trends related to machine learning (ML), deep reinforcement learning, and predictive maintenance optimization models. The paper ends with defining strategic research gaps and showing the necessity of a single, AI- and IoT-based maintenance system that will allow making the industry more reliable, cost-effective, and sustainable.

**Keywords**—*Mechanical System Reliability, Predictive Maintenance, Lifecycle Management, IoT Sensors, Equipment Lifespan, Fault Diagnosis.*

## I. INTRODUCTION

The swift advancement of the industrial sector, the complexity and reliability standards for mechanical apparatus are progressively rising [1]. Maintaining productivity and competitiveness has grown more dependent on the ongoing and efficient functioning of machinery as companies move toward intelligent production and automation [2]. Therefore, reliability engineering is a critical discipline that attempts to provide the assurance of the intended purpose of mechanical systems performing their intended duties over a specified duration and within specified conditions without breakdowns [3]. This is becoming an increasing concern in regard to dependability due to the need to minimize downtime, optimize performance, and put downward pressure on operating costs related to the unexpected failures of complex mechanical infrastructures [4]. This has led to increased reliance on reliability engineering in maintenance processes. Industries had been accustomed to reactive maintenance whereby they fixed the problems when they occurred. Such a strategy often resulted in costly downtimes and the reduction of equipment life. The time or usage-based scheduled interventions were introduced because the transition to preventive maintenance minimized the risk of unforeseen challenges. However, over time, maintenance has been transforming towards predictive and prescriptive maintenance, allowing the use of data to make decisions and monitor the conditions in real-time, and with the advent of Industry 4.0 and smart sensors, IoT gadgets, and AI [5]. Such a development is beneficial as it leads to increased reliability as well as long-term operating efficiency by enhancing maintenance schedules and resource utilization [6][7].

Further, to come up with systems that are robust and enduring, it is now important to comprehend the causes of mechanical failures [8]. In spite of the fact that large components such as motors, generators, and turbines are crucial components in the manufacturing processes, research indicates that small components such as bearings, gears and shafts are usually the reason why the entire system fails [9]. Factors that may lead to problems that are minor, such as maladjustment and total failures, may include poor alignment, absence of lubrication and material fatigue. Due to this fact, predictive maintenance paradigms are based on extremely accurate remaining useful life (RUL) prediction to contribute to enabling engineers to anticipate the alteration of the components and plan the intervention timeline [10].

Intelligent systems can now learn complex breakdown patterns from sensor data because of recent advances in AI, which have completely transformed RUL estimation [11]. These data-driven models can better identify and forecast faults than more traditional statistical methods due to the ability to adjust to the changing operating conditions [12]. To ensure the maximum equipment lifetime, cost savings, and industrial sustainability, a combined structure of reliability analysis and intelligent maintenance processes is required. In light of the importance of intelligent maintenance systems, predictive analytics, and reliability theory in enabling next-generation industrial resilience, this paper thoroughly analyzes the most recent advancements in mechanical system dependability and maintenance techniques.

### A. Structure of Paper

The following paper is organized as follows: Section II covers reliability optimization design. Section III reviews maintenance strategies and common mechanical faults.

Section IV discusses predictive maintenance and IoT-based monitoring. Section V presents recent studies and identifies research gaps toward integrated AI- and IoT-driven maintenance frameworks. Section VI concludes the paper with future scope.

## II. RELIABILITY OPTIMIZATION DESIGN OF MECHANICAL PRODUCTS

In the field of optimization design, the significance of optimization design based on dependability has increased. used in two mechanical parts, the gear and the gear reducer. China has been at the forefront of designing planetary gear transmissions and gear transmissions with reliability-based optimization, among other things [13]. The ability of a system or component to operate flawlessly under particular circumstances for a predetermined amount of time is emphasised by mechanical dependability. The DRM discusses reliability in a number of chapters since a system component failure might lead to a utility service disruption or failure. Mechanical items have unique design and analysis methods and features when compared to electronic products [16]. In conclusion, mechanical product dependability design should adhere to the following guidelines:

### A. Combination of Reliability and Traditional Design

The dependability of mechanical parts may be guaranteed in the majority of situations using the conventional safety coefficient approach, which is straightforward, easy to understand, and requires little effort. However, it is now exceedingly challenging to implement classic dependability design for mechanical goods in certain situations [14]. Therefore, using probability design to refine and enhance the conventional approach appears both sensible and essential. Furthermore, it is possible to carry out the reliability probability design targeted at critical components progressively.

### B. Paralleling of Mechanical Reliability and Durability

In a broad sense, durability and dependability are components of mechanical product reliability. Thus, the two previously stated are part of mechanical dependability design. Reliability design specifically addresses sporadic errors, whereas durability addresses progressive defects. Therefore, their fault mechanisms differ [15].

### C. Paralleling of System and Parts Reliability

The designers must create a thorough system and part design since mechanical parts have a complicated functional status and structure, and are less standardized and universal.

The most basic building block of the entire system is its parts, and their strength is the fundamental assurance of systematic reliability. In this instance, the traditional dependability design should be enhanced by the parts' design.

## III. MAINTENANCE STRATEGIES FOR MECHANICAL SYSTEMS

Maintenance is essential to preserving every specific piece of machinery or facility's design life. Replacement of broken parts, adjustment of slack belts, and properly lubricating parts are basic maintenance practices to prolong the life of equipment. Machines that receive regular maintenance may better retain tolerances, produce more consistent and higher-quality parts, while producing less scrap [16]. The procedure of maintaining top-notch functioning gear and equipment to maintain efficiency and prolong their useful lives is referred to as maintenance. It includes various actions the company takes to maintain, replace, and repair the plant's equipment and components, ensuring continued operation within reasonable bounds.

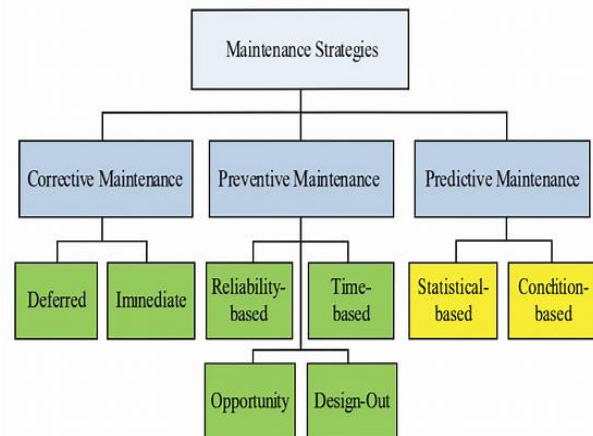


Fig. 1. Classes of maintenance strategies [17]

Maintenance management, which focuses on keeping machinery, equipment, and plant services in optimal operating condition at all times, may therefore be viewed as a restorative function of production management. Table I compares the various maintenance techniques with respect to different characteristics, and Figure 1 shows the maintenance strategy classification

TABLE I. THE PROS AND CONS OF MAINTENANCE MANAGEMENT STRATEGIES

Maintenance strategy	Advantages	Disadvantages
Breakdown/Reactive (Run-to-Failure)	<ul style="list-style-type: none"> <li>• Quite simple and easy to understand</li> <li>• Minimal planning required</li> <li>• Fewer people/resources are required</li> </ul>	<ul style="list-style-type: none"> <li>• Highly unpredictable</li> <li>• Expensive in certain cases</li> <li>• Scheduling/planning for staff is complicated</li> <li>• Involves some safety risk.</li> </ul>
Preventive	<ul style="list-style-type: none"> <li>• Minimized asset breakdowns</li> <li>• Reduced downtime</li> <li>• Safer work environment</li> <li>• Increases asset's productive life</li> <li>• Improves production quality</li> </ul>	<ul style="list-style-type: none"> <li>• More labour-intensive</li> <li>• Unnecessary equipment maintenance (loss of income and man hours)</li> <li>• Can cause early deterioration of equipment</li> </ul>
Predictive [18]	<ul style="list-style-type: none"> <li>• Decreased maintenance costs</li> <li>• Reduced unexpected failures and repair time</li> </ul>	<ul style="list-style-type: none"> <li>• High start-up costs</li> <li>• Limitations of some equipment</li> </ul>

	<ul style="list-style-type: none"> <li>• Increased production efficiency</li> <li>• Extends component availability and operating life.</li> <li>• Permits preventative remedial measures.</li> </ul>	<ul style="list-style-type: none"> <li>• False maintenance requests resulting from misinterpreted data</li> <li>• Difficult to install, configure, and run.</li> </ul>
Reliability-centred maintenance	<ul style="list-style-type: none"> <li>• Increases equipment availability and reliability</li> <li>• Reduces maintenance costs</li> <li>• Lowers staff costs</li> <li>• The prevention of fatalities, destruction of property, and environmental degradation</li> <li>• Incorporates root cause analysis.</li> </ul>	<ul style="list-style-type: none"> <li>• Rather significant initial expenditures for equipment and training</li> <li>• Savings potential not evident to management</li> <li>• A certain degree of maintenance maturity is necessary to provide accurate and comprehensive asset data.</li> </ul>

### A. Mechanical Faults in Rotating Machines (RMs)

RMs are crucial in a variety of industrial domains, including power generation, transportation, and manufacturing. To convert mechanical energy into useful work, spinning machinery such as turbines, motors, and generators is required [19]. Such machines are effective, dependable, and diverse, but prone to a number of undesirable failures because of their complex mechanical and electrical

parts. The mechanical and electrical components of most of these IMs are the windings, bearings, stator, shaft, and rotor. Gearboxes and rolling element bearings, which are used to make the machinery run more smoothly, are the fundamental components of RMs [20]. Mechanical faults are the most widespread failures in such kinds of machines, and these faults include gearbox faults, misalignment faults, and bearing faults [21]. A summary of some mechanical flaws, their sources, and their effects is provided in Table II.

TABLE II. SUMMARY OF MECHANICAL FAULTS, THEIR CAUSES, AND THE CONSEQUENCES OF THESE FAULTS [22]

Fault	Causes	Consequences
<b>Bearing fault</b>	<ul style="list-style-type: none"> <li>• A rise in shaft voltage over the bearing grease's insulating capacity</li> <li>• Shaft misalignment/imbalance</li> <li>• Overload</li> <li>• Loss/contamination of lubricants</li> <li>• Manufacturing flaws</li> <li>• Increased temperatures</li> </ul>	<ul style="list-style-type: none"> <li>• Excessive vibration and eventual bearing failure</li> <li>• Accelerated wear on rotating components</li> <li>• Ripple in output torque</li> <li>• A current harmonic spectrum ripple at a specific frequency</li> <li>• Eccentricity faults</li> </ul>
<b>Gearbox fault</b>	<ul style="list-style-type: none"> <li>• Overload</li> <li>• Improper lubrication</li> <li>• Misalignment</li> <li>• Frosting</li> <li>• Surface contamination</li> <li>• Manufacturing flaws</li> </ul>	<ul style="list-style-type: none"> <li>• Dynamic Instabilities (vibrations)</li> <li>• Fluctuations in load that are transmitted to the driving equipment</li> <li>• The power transmission system's mechanical losses</li> <li>• Structural Fatigue</li> </ul>
<b>Misalignment fault</b>	<ul style="list-style-type: none"> <li>• Incorrect alignment of drive shaft with load</li> <li>• A heavy spot-on rotor has a center of mass that is not on the axis of rotation.</li> <li>• Installation errors</li> <li>• Failure in bearings</li> </ul>	<ul style="list-style-type: none"> <li>• Premature wear to mechanical drive components</li> <li>• The motor driving shaft and the load are both receiving vibration.</li> <li>• Eccentricity faults</li> <li>• Gear and bearing damage</li> </ul>

It describes the specific impacts of all types of defects on the mechanical parts of RMs and discusses the different sources of bearing, gearbox, and misalignment faults [23]. Furthermore, the detailed discussion of the causes and effects of each type of fault is presented in the subsequent subsections, beginning with an in-depth examination of rolling bearing flaws, which are followed by gear faults and misalignment faults.

## IV. PREDICTIVE MAINTENANCE IN LIFECYCLE MANAGEMENT

Predictive maintenance is an important part of lifecycle management. Predictive maintenance is able to optimize system performance by monitoring in real-time and data analytics to avoid sudden failures [24]. It assists in making wise decisions regarding when repairs, replacements, and even upgrades of the system should be done to facilitate the efficient operation of the system as long as possible at a reduced cost. Planning, creating, running, maintaining, and discarding a system are all included in lifecycle management [25]. It is the management of the life cycle of the system, from creation to decommissioning [26][27]. With the help of proper lifecycle management, the systems are made to optimize their

performance and cost-efficiency to strike a balance between operational readiness and resource limitation, budget and time.

### Stages of Lifecycle Management:

- **Design and Development:** The whole system's lifespan is predetermined at the design phase. Careful consideration must be given to performance standards, failure mechanisms, maintenance requirements, and operating circumstances that might eventually impact the system.
- **Operational Use:** This phase involves monitoring the system's health continuously, generally with the use of sensors and diagnostic tools. To make judgments about how to perform repairs, replacements, and upgrades, real-time information is collected and used.
- **Maintenance and Upgrades:** To ensure the system's dependability and extend its lifespan, maintenance is necessary [28]. In terms of modular designs, straightforward diagnostics, and simple repair, the systems must be made to be simply maintained.

Additionally, it can be necessary to address unforeseen difficulties or upgrade and introduce new technologies.

- **Decommissioning and Disposal:** The issue of decommissioning and disposal emerges when the system's useful life is coming to an end. Good lifecycle management ensures that this phase is handled with the least amount of negative environmental effects and recovery costs.

#### A. IoT Technologies in Industrial Predictive Maintenance

The industrial IoT systems of today use a wide variety of sensor technologies (see Table III) to measure detailed machine health indicators [29]. Vibration analysis is still an essential part of rotating machinery, where accelerometers and velocity sensors identify imbalance, misalignment, and bearing failures, as well as other mechanical anomalies [30]. The thermal states are observed with the help of thermal sensors such as thermocouples, RTDs, and infrared sensors that indicate thermal anomalies which could be the result of friction, electrical problems, or cooling failures

TABLE III. IOT SENSOR TECHNOLOGIES FOR INDUSTRIAL PREDICTIVE MAINTENANCE [31]

Sensor Type	Parameters	Measurement	Fault Detection Capability	Typical Equipment
Accelerometer	Vibration (acceleration)	±2g to ±200g	Bearing defects, imbalance, misalignment, looseness, gear faults	Motors, pumps, gearboxes, turbines
Infrared Thermal Camera	Surface temperature distribution	-20°C to +2000°C	Hot spots, electrical connections, insulation defects	Electrical panels, motors, process lines
Velocity Sensor	Vibration (velocity)	0.1-100 mm/s RMS	Overall machinery health, resonance detection	Rotating machinery, fans, compressors
Thermocouple	Temperature	-200 °C to +1800 °C	Overheating, thermal degradation, cooling failures	Motors, bearings, transformers, furnaces
RTD (Resistance Temperature Detector)	Temperature	-200 °C to +850 °C	Precise temperature trends, thermal abnormalities	Critical bearings, windings, process equipment
Current Sensor (CT)	Electrical current	0-1000 A+	Motor degradation, phase imbalance, rotor bar faults	Electric motors, generators, transformers
Voltage Sensor	Electrical voltage	0-690 V AC/DC	Power quality issues, insulation breakdown, loose connections	Electrical systems, motor drives
Acoustic Emission Sensor	Ultrasonic waves	20 kHz - 1 MHz	Crack propagation, friction, wear, leakage	Pressure vessels, bearings, valves, pipelines
Pressure Sensor	Fluid/gas pressure	0-10,000 psi	Leak detection, blockages, pump degradation	Hydraulic systems, pneumatic systems, pipelines
Ultrasonic Sensor	Ultrasonic sound waves	20 kHz-100 kHz	Air/gas leakage, bearing lubrication issues, electrical arcing	Compressed air systems, steam traps, electrical equipment
Oil Quality Sensor	Viscosity, moisture, contamination	Varies by parameter	Lubricant degradation, wear particles, contamination	Gearboxes, engines, hydraulic systems
Flow Meter	Fluid flow rate	.01-10,000 L/min	Pump efficiency, blockages, system leaks	Cooling systems, hydraulic circuits, process equipment

#### V. LITERATURE REVIEW

The reliability of the mechanical system has been highlighted here, and the method that optimizes the life of the equipment is highlighted in Table IV below:

Rathore (2025) discusses such new technologies as 3D printing, environmentally friendly energy systems, robotics, and the IoT. These technologies contribute to productivity and error reduction as well as compliance of the mechanical engineering with the global environmental approaches, like reducing carbon emissions, improving resource utilization, and adherence to the principles of a circular economy. The study comes to the conclusion that creative strategies that integrate environmental responsibility with industrial expansion are essential to the future of mechanical engineering [32].

Yuan et al. (2025) provide a novel reliability reconstruction approach that instructs the DRL agent to more effectively balance between cost and reliability by reforming the reliability measure in training. Unlike traditional maintenance policies, which base maintenance decisions on periodicity or pre-defined thresholds, DRL-based agents are

always learning and adapting to the equipment's condition, negating the need for pre-established maintenance thresholds. Unlike existing reinforcement learning approaches that often merely optimise cost or make simplistic assumptions about degradation, this framework integrates a multi-objective reward with a realistic reliability model, resulting in safer and more robust judgements. The framework is confirmed by case studies on aviation engines and CNC machine tools, where the taught principles retain good dependability while drastically lowering maintenance costs. In terms of dependability trade-offs and cost savings, the suggested approach performs better than baseline alternatives, proving its exceptional efficacy and versatility for intelligent maintenance planning [33].

Liu et al. (2024) The reliability-centered maintenance (RCM) concept is proposed to identify the essential components for implementing preventive maintenance with a focus on single-unit mechanical equipment, and PM models are developed to provide a more realistic PM plan. There are two PM optimization models that take time-varying failure rates into account: one that tries to maximize availability and the other that tries to minimize costs. A six-part tire-building machine component is used to illustrate a PM plan example, demonstrating the models' validity. According to the

availability maximization model, two components that match the maintenance plan have availability results that are higher than 0.99, while the cost minimization model yielded results of the other four parts' total costs per unit of time that were below 5.69 [34].

Vincent et al. (2024) explain the compatibility of modern industrial models with predictive maintenance. The study assessed how effectively five popular forecasting models predicted the need for repair on industrial equipment: RF, LR, Exponential Smoothing, ARIMA, and LSTM. Several performance criteria were used to assess each model's efficacy. The R-squared number indicates the proportion of the model's ability to account for the variance in the real-time data, a model's accuracy is shown by its lowest MSE, RMSE, and largest R-squared values [35].

Ji (2023) The recovery and forecast accuracy of reliability assessment models for mechanical systems can be enhanced by applying ML techniques, according to research on the impact of ML technologies on reliability evaluation and prediction. With the dependability evaluation model of

mechanical systems based on metal learning approaches, users are quite happy, and the accuracy rate and recall rate have risen by around 8% and 10%, respectively. The findings of this study demonstrate the practical importance and wide range of applications of ML technology in the assessment and forecasting of mechanical system dependability [36].

Miraje et al. (2022) Among other ML algorithms commonly used for predictive maintenance, take into consideration supervised and unsupervised learning techniques, DL models, and ensemble methods. Examine actual case studies that demonstrate how ML has been successfully applied to predictive maintenance across a number of sectors, including aerospace, automotive, energy, and manufacturing. Discuss performance evaluation metrics and methods, considering account variables like accuracy, precision, recall, and F1-score that are used to evaluate the efficacy and dependability of predictive maintenance models. This comprehensive study aims to clarify the practical use of ML for predictive maintenance and its potential impact on extending the lifespan and functionality of mechanical systems [37]

TABLE IV. SUMMARY OF RECENT STUDY ON MECHANICAL SYSTEM RELIABILITY AND PREDICTIVE MAINTENANCE

Author	Focus/Objective	Techniques/Methods	Key Findings/Outcomes	Limitations / Recommendations
Rathore (2025)	Trends in mechanical engineering for efficiency & sustainability	3D printing, IoT, AI, robotics, eco-friendly energy systems	Enhances productivity and accuracy while supporting environmental sustainability and circular economy principles	Focuses on broad technological trends; lacks detailed case studies or quantitative evaluation of performance gains
Yuan et al. (2025)	Reliability reconstruction and adaptive maintenance	DRL-based framework with multi-objective reward	Reduces maintenance cost while maintaining high reliability; outperforms conventional and prior RL approaches	Applied to limited case studies (CNC tools, aircraft engines); needs validation on diverse equipment and larger-scale industrial settings
Liu et al. (2024)	Preventive care for individual pieces of equipment	Reliability-Centered Maintenance (RCM), PM optimization models	Availability >0.99 for critical parts; cost per unit time <5.69 for other components; validates PM optimization models	Limited to single-unit or component-level analysis; scalability and integration with IoT/real-time monitoring not addressed
Vincent et al. (2024)	Forecasting for predictive maintenance	Random Forest, Linear Regression, ARIMA, Exponential Smoothing, LSTM	Accuracy measured via R <sup>2</sup> , MSE, RMSE; identifies best-performing forecasting models for equipment maintenance	Focused on model comparison; lacks integration with adaptive maintenance strategies and real-time data streams
Ji (2023)	Machine learning for reliability evaluation	ML-based reliability prediction models	Increases prediction accuracy (~8%) and recall (~10%), improving user satisfaction and model effectiveness	Mostly theoretical evaluation; limited practical implementation and cross-equipment validation
Miraje et al. (2022)	Machine learning for predictive maintenance	Deep learning, ensemble approaches, and supervised/unsupervised learning	Enhances operational effectiveness, lowers maintenance expenses and downtime, and illustrates useful machine learning applications in a variety of sectors	General overview; lacks detailed framework for deployment and multi-objective optimization including cost, reliability, and sustainability

**Research Gap:** Recent studies on predictive maintenance and mechanical system reliability have developed using DRL, ML, and optimization models; however, the vast majority of studies examine individual equipment or particular cases, which makes them less generalizable. There is still no integration of emerging technologies into a single, real-time, and sustainable maintenance framework, including the IoT, AI, and digital twins. Additionally, there are not many methods to maintain the balance between cost, reliability and environmental goals, and a holistic, adaptive, and scalable maintenance solution is needed.

## VI. CONCLUSION AND FUTURE WORK

The growing sophistication of the contemporary industrial practice has augmented the necessity of reliability-focused technologies to guarantee ongoing functioning and reduce the quantity of unplanned terminations in the industrial setup. In the current study, reliability-based technologies in industrial systems and maintenance are considered to be important in terms of guaranteeing long-term efficiency of operational activities and decreasing unexpected interruptions in the industrial systems. The paper highlights the shift toward more intelligent processes of relying on data and AI technologies to

optimize the reliability of various systems, instead of the traditional reactive ones, by providing a detailed analysis of reliability optimization design, maintenance methods, and predictive maintenance incorporation. Supported by sensor-based monitoring and advanced data analytics, predictive maintenance has shown itself to be a highly effective way of improving the availability of equipment, the accuracy of fault detection, and cost-effectiveness throughout the lifecycle of machinery. The literature review indicates that there has been significant advancement in ML and reinforcement learning-based reliability models, but it also shows that there is a gap in scalable frameworks to incorporate real-time monitoring, cost optimization and sustainability. The next-generation industrial architectures must be holistic, AI-driven, and IoT-driven maintenance architectures, which are able to make adaptive decisions, guaranteeing greater reliability, longer equipment life, and a sustainable industrial future.

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