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Review

Review on Digitalization and Industry 4.0: Maintenance and Repair Operations (M.R.O.) with Predictive Approaches

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Abstract. This article provides a comprehensive overview of the repair and maintenance operations in multiple modern industries. Accordingly, maintenance and repair approaches are problematical and overbearing issues. Scientific methodology involves in repair operation uses data to figure out repair ideas. Also, it develops and supports theories and facts over repair operation and procedures. Digital tools can enable lab managers and scientists to achieve their ideal vision for the laboratory and manage workloads. This article emphasizes the importance of systematic planning and prudent management to address the diverse and numerous risks associated with maintenance and repair strategies. It tells how to delves into the practical aspects of maintenance and repair operations, emphasizing the historical approach of reactive maintenance and the need for a more proactive and systematic strategy. It also defines key terms such as repair, fault and fault detection and diagnosis, providing a comprehensive understanding of the scientific methodology involved in the repair of machines, equipment and appliances. The importance of understanding and implementing effective maintenance and repair strategies are aligned with modern business goals and ensure efficient operations.

Today's, the era of fourth industrial revolution (Industry 4.0) is progressing due to the development of information and communications technologies (I.C.T.). The use of preventive/predictive maintenance (Pr./Pd.M.) approaches has become increasingly popular in recent years. The role of maintenance and repair operations/overhauls (M.R.O.) is very crucial and important aspect of intentional administration of assets/equipment and infrastructure. The aim is to optimize performance, minimize downtime and ensure operational excellence. Furthermore, it underscores the benefits of an effective M.R.O. program in enhancing efficiency, reducing costs and ensuring uninterrupted operations.

Keywords: fault and diagnosis, laboratory assets, equipment maintenance, repair, installations, preventive maintenance, predictive maintenance

Introduction

Maintenance and repair operations (M.R.O.) are vital for the proper functioning of laboratory and industry assets (machines, equipments, tools, etc.), while being a vital ways towards smooth running a laboratory/industry for all continuities in operations and operational effectiveness (Council *et al*., 2011). The challenge is that, the diverse and numerous risks of laboratory and industry work requires a systematic prudence and well performed planning to manage rapidly changing workload and the processes involved their (Lee *et al*., 2019). Maintenance and repair strategies are complicated matter. Most people agreed on types and categories of maintenance strategies that can exist for individuals, but this compromise ends up in recent years (Nota *et al*., 2021).

Reactive maintenance (R.M.) approaches are type of maintenance and repair operation (M.R.O.), where equipment is fixed after breakdown take place. Reactive approach can lead to higher maintenance costs, increased downtime and lower equipment lifespan (Venkataraman, 2007). Reactive maintenance (R.M.) relies on manual inspections and historic maintenance schedules. In reactive maintenance (R.M.), resources are allocated

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reactively, that is due to emergency repairs it relies on manual labour and expertise, with limited use of technology. Generally, it has unfixed maintenance schedules without considering actual or real performance record of equipment. The condition is monitored and conducted repair after break downs occurs, leading to higher costs of repair, production losses and inefficiencies of R.M.O. Because of unplanned downtime, it's commonly, leads to delay in production and thus lowered efficiency of laboratory/industry/plant etc.

Maintenance and repair, operations/overhaul (M.R.O.) offers an intentional administration of assets/equipment and infrastructure, including proactive and practical maintenance, timely repairs and efficient assets management. It aims at optimizing performance, minimizing downtime and ensuring operational excellence (Pesch-Cronin and Marion, 2024). Considering, the number of main factors that conceivably influence the maintenance fields (M.R.O.) could be as cost, staff size, geography, assets type, etc.

Maintenance and repair operations/overhaul is the strength of operational quality for organizations across industries. M.R.O. management program plays a vital role in enhancing efficiency, reducing costs and ensuring uninterrupted operations by optimizing maintenance processes, addressing repairs promptly and implementing effective asset management strategies (Moteff, 2007).

In this article, the delve into the world of M.R.O., explore key components for success and unveil innovative strategies and procedures to drive performance and productivity. An effective maintenance and repair operations/overhaul program offers several benefits that directly contribute to the success and profitability of an organization. Nevertheless, figuring out which strategy is best for an asset is essential for modern industries/organizations business goals. (Seneviratne *et al*., 2018).

In addition, it is infrequent to observe eye-to-eye on how and what those strategies look like in the practical field. Businesses/industries repaired or replaced an asset after it had broken down. In the past, laboratory enterprises/organizations maintained their assets reactively (Lees, 2012). Carrying maintenance and repair involve processes such as examination of assets, the location and identification of faults in asset/appliance, and rectification of these faults (Bloch and Geitner, 1997). In general, every person has to deal with classes of failures or malfunctions as and when happened. Malfunctioning or faulty machines, equipments, tools, etc. are most of time dumped into dustbin or abandoned in an unsecured area, which is an act of resources mismanagement and thereby caused environmental pollution (Rafael *et al*., 2023; Zakaria *et al.*, 2021).

Materials and Methods

Repair operations/overhaul work. Repair means the act of renewing, restoring, or reviving a damaged item to a performance oriented and sound condition. (Goetz and Jay, 1988), defined repair as "restoration or replacement of part or component of a material as necessitated by wear and tear, damage, failure or the like in order to maintain the specific item or material in efficient operating condition". In addition, repair involves the activities taken for the restoration of a broken, damaged or failed component, device, equipment, part or appliance to an acceptable operating or stable state. While, fault is a deviation between perfect performance and complete failure (Joseph, 2009). Also, fault in general, defined as "a departure of a calculated parameter in an observed variable, associated with a process, from its acceptable range" (Hadjadji *et al*., 2023; Venkat *et al*., 2003). If a machine reached to a no permitted deviation to any characteristics property, which leads to its inability for fulfillment towards the intended purpose of it, then it becomes faulty. A faulty or malfunctioning appliance occurs when the expected value of output is diminishing or equal to zero (Bloch and Geitner, 1997).

Scientific methodology, involves in repair operation by using data to form ideas and to develop and support theories and facts (Bousdekis *et al*., 2021). Thus, scientific repair of machines, equipments, appliances is termed fault detection and diagnosis (FDD) (Murtaza *et al.*, 2016; Chaing *et al.*, 2012). Fault detection and diagnosis means monitoring the machinery, equipment, appliance for detecting any failed or faulty components or part, then quantifying the fault and determining its causes, assessing its size and the impact on system performance and finally making decision on how to respond to the fault (Cinar *et al*., 2020; Venkat *et al*., 2003).

Understanding the root cause of a machine failure can be a challenging and complex task, but it is a vital step in developing effective strategies to prevent future failures. Appliances exist in different form with different performance, depending on their purpose of creation.

Exemplary, an operator guess a fault as a process abnormality or symptom, such as high temperature in a reactor resulting low product quality or elsewhere (Srinivas and Michael, 2005). The underlying cause(s) of this abnormality, such as a failed coolant pump or a controller, is (are) called the basic event or the root cause(s). The basic event is also referring as a malfunction or a failure.

A typical fault diagnosis (and identification) framework model has shown in Fig. 1. It illustrates the workings of an all-purpose fault diagnosis frame work. It shows a controlled system and the miscellaneous sources of failures in a process (gain through residual signals). Indeed, the fault information generated in the fault diagnosis procedures can be very useful for fault tolerant control. Since one can view the task of diagnosis as a classification of problems, the diagnostic system, works as a diagnostic classifier (Venkat *et al*., 2003). The fundamental problem of fault detection and isolation lies in the generation of indication signals, usually called "residuals", normally gives information and point out about the presence or absence of a fault in a process plant (Iqbal *et al*., 2007). Most of the model-based fault detection and isolation (FDI) techniques are based on the generation of residuals signals and their evaluation (Chetouani, 2014). The before time detection of faults may assist to avoid manufactured goods wear and tear, major damage to the machinery or plant or elsewhere.

Over the years, automated production systems have aided operators in controlling the process in order to improve the machine performance and final production quality, through the safety and the efficiency of industrial units. Detecting inconsistencies is an important problem and evaluation of residuals is based on many techniques ranging from observers methods (comparing the actual state of the system and possible inconsistencies), parity relations (input output relationship), directional residuals (specific faults or inconsistencies signals in the system) and stochastic methods such as sequential probability ratio tests (SPRT) and generalized likelihood ratio tests (GLRT) techniques used to detect changes in the statistical properties (Feras, 2015). In many cases, a combination of these methods can be used to achieve more robust and reliable results. Although, automated fault detection and isolation (F.D.I) algorithms are central components of an Abnormal Event Management (A.E.M.) system, which deals with the timely detection, diagnosis and correction of abnormal conditions in a process. (Wang *et al*., 2021)

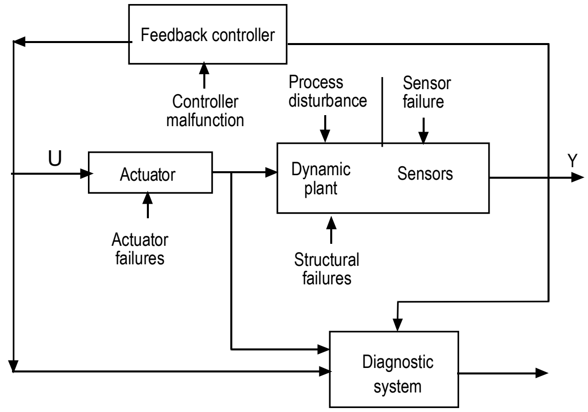

Fig. 1. A typical fault diagnosis frame work model. (Samantaray and Bouamama, 2008)

A broader class of fault detection and isolation methods makes explicit use of mathematical model of the dynamic system, which is referred to as model based fault detection and isolation. This approach is motivated by the fact that utilizing deeper knowledge of the system results in more reliable diagnostic decisions. One of the challenging tasks of residual evaluation is the threshold analysis (Iqbal *et al*., 2007). Thresholding techniques are based on fixed thresholding and adaptive thresholding. The fixed thresholding is simple and effective, it is adopted when the system's behavior is well-understood and the operating conditions are relatively stable, Fixed thresholding determined residuals based on the expected behavior of the system (in the absence of faults). In adaptive thresholding, adjust the threshold value based on the changing characteristics of the process or the residuals. The choice between fixed or adaptive thresholding should be made based on a careful analysis of the system's characteristics, their use in fault detection and isolation is based on the availability of a priori knowledge of the process/residuals (Minjae *et al.*, 2013).

The maintenance team identifies the problem and determines that which components or parts need to be replaced. However, unlike the fault detection problems, the fault isolation problem has received less attention. Preferably, a fault identification scheme is used to observe the activities of the processes and would provide the entire information about any abnormality in the processes and comprises of three different tasks (Steven, 2008):

(i) Fault detection (F.D.): Confront for the occurrence of all or any fault in the system and determines, its time and frequency of occurrence; (ii) Fault isolation (F.I.): Find exactly or trace the component or subsystem that shows discrepancies or appeared malfunctioned in system behavior; (iii) Fault identification: Means to determine fault nature and form, magnitude and cause(s) of fault, previously detected and isolated.

Automation and digitalization are considered to be some of the most relevant industry and business topics today, as they bring about significant employment changes and the replacement of human work by robotics (Steven, 2008). Automated fault detection and isolation (F.D.I) procedures implemented in the supervision platform are meant to ensure safe operation of industrial processes because faults in a process will often cause an undesired sequence of events and the consequences could be, damaging to the plant, the personnels and the environment. Thus, for machines, equipments, appliances, tools, etc. maintenance and repair (M.R.O.) means all routine action performed through which damage part or component of these articles restored or replaced with the aim of restoring, reviving, renewing and maintaining such items in a good operating condition (Bloch and Geitner, 1997).

The components of maintenance and repair operations/overhaul strategy. ***(a) Autonomous maintenance (A.M.).*** It deals with small faults, abnormal operation of the machines/devices, minor errors related to the performance and operation of machines and devices. It deals throughout set of assets *via* the actions of the device's operator, in order to reduce the number of device failures and eliminate the anomalies associated with their mal-functions (Gajdzik, 2014).

(b) Time-based maintenance (T.B.M.). It is a traditional maintenance procedures and technique in which maintenance decision (e.g. preventive repair times/intervals) are determined based on breakdown and failure time analyses. (Ahmad and Kamaruddin, 2012).

(c) Preventive maintenance (Pr.M.). It consists of detection and diagnoses towards the state of assets and related resources based on monitored data, predict the abnormality of resources and perform appropriate maintenance actions. These performed actions are suitable for repair and replacement before any serious problems occurred. It is performed at the exact moment when measured parameters reach unacceptable levels (Shin and Jun, 2015).

(d) Predictive maintenance (Pd.M.). It concerns with the detection of unseen, concealed, hidden and potential faults and the prediction of equipment conditions. On this basis, predictive analytics can predict whether a failure event will happen, or when it is about to happen as well as the reason why it will happen. (Lepenioti *et al*., 2020). The predictive maintenance dissociated into two specific subcategories:

1) Predictive maintenance based on statistical analysis and machine learning techniques to predict when equipment is likely to fail or require maintenance. The goal of Pd.M. is to perform maintenance only when necessary, rather than following a fixed schedule (preventive maintenance) (Venkataraman, 2007). The use of statistics in predictive maintenance allows for more accurate and reliable predictions, leading to reduced maintenance costs, improved equipment reliability and increased operational efficiency.

2) Predictive condition-based maintenance (CBPM), through predictive condition-based maintenance framework, organizations can achieve more accurate failure predictions, optimize maintenance schedules and improve the overall reliability and availability of their equipment. Predictive maintenance refers to the activities required to identify and rectify the causes of failures or reduce these events (Susto *et al*., 2015).

These techniques are summarized for comparison in Table 1 for their compression and effectiveness. Although in order to address above techniques and challenges, organizations may need to invest in training and education for their maintenance and repair personnel. They develop comprehensive maintenance and repair plans and collaborate with suppliers and manufacturers to ensure the availability of compatible parts and components. Since with the progress of technology, older products or systems may become obsolete or discontinued, making it difficult to find replacement parts or components that comply with the relevant ISO and EU standards. This can lead to challenges in maintaining and repairing these older systems, potentially requiring costly and time-consuming retrofits or custom-made solutions.

Standardization for maintenance operation. According to the EN13306:2010* standard, maintenance is a "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function." (Rojek *et al.*, 2021). (*EU Standard for generic terms and definitions used in technical, administrative and managerial areas

Table 1. Autotest products, 2021

Comparison for performance of maintenance types							
Maintenance type (Characteristics and Objectives)	Preventive maintenance (before a failure occur)					Corrective maintenance (after a failure has occurred)	
	Time based	Failure finding	Conditioned based	Predictive	Risk based	Deferred	Emergency
Task type	Scheduled overhaul or replacement	Functional test	Measurement of condition	Calculation or extrapolation	Inspection or test	Repair or replace	Repair or replace
Objective	Repair or replace regardless of condition	Determine if hidden failure has occurred	Repair or replace based on a measurement of condition compared to a baseline		Determine condition and conduct a risk assessment to determine next course of action-test or repair	Repair or replace after failure	Repair or replace after following failure
Internal	Fixed time, for example 1000 hrs or 1 month	Fixed time interval, but set on particular criteria e.g. MTBF	Fixed time interval for inspection or measurement		Time based interval between tasks. Scope is based on risk assessment	None	None
Cost	Medium	Medium	Low	Lowest	Low	High	Highest

It's important to note that both preventive maintenance and corrective maintenance have their own advantages and should be included in maintenance plans. Preventive maintenance helps prevent unexpected failures and reduces overall productivity losses, while corrective maintenance addresses failures that have already occurred or are about to happen.

of maintenance and maintenance management irrespective of the type of item considered). Adhering to ISO and EU standards can sometimes increase the cost of maintenance and repair, as specialized tools, equipment, or training may be required.

Work group method (maintenance and repair operations/overhaul management). (Engineers Asset, 2021). Maintenance and repair operations (M.R.O.) group uses work orders (WO) to reorganize their assets functioning and organize responsibilities for maintenance work and to maintain organization operational work-flows. Work order management systems provide MRO group and maintenance manager's capabilities to simultaneously manage and administrate multiple work orders. It combines repair from base incident to task completion. A work order (WO) is a document containing details for conducting a maintenance task. There are two main types of work orders: paper work orders and ework orders (internet based) (Starr *et al.*, 2010).

The work order (WO) process typically begins with a maintenance request when a problem or fault is notice and reported through a working member or operator (Venkataraman, 2007). It mentioned with request to sort or identified that fault/problem, however different facilities have methodologies for evaluating work order/service requests and depending on this, a maintenance manager will either approve or deny a work request (IBM, 2024). Paper work order refers to the traditional method of creating and managing work orders using physical paper documents. These paper work orders can be easily damaged, misplaced, or lost, leading to communication delays and extra costs for data entry (Galar *et al.*, 2012).

Computerized maintenance management system (CMMS) software is a digital tool used by organizations to streamline maintenance operations, manage work orders, track assets, schedule preventive maintenance and optimize maintenance processes (Elizabeth, 2023).

CMMS software plays a crucial role in improving maintenance efficiency, reducing downtime and extending the lifespan of equipment. By leveraging the features of CMMS software effectively, companies can effectively manage repairs, reduce the impact of unplanned downtime and optimize maintenance operations in real-time (IBM, 2024).

Internet based e-mail or ework orders is a powerful computerized maintenance management system (CMMS). Work order management software designed to streamline processes and improve efficiency in managing maintenance tasks (Starr *et al*., 2010). It provides easy-to-use tools for defining processes and procedures, simplifying workflows, tracking tasks and documenting information. However, paper work orders are familiar and cost-effective and some organizations still rely on them.

The main difference between ework orders and paper work order lies in the medium used to create and manage work orders. In summary, ework orders is a digital CMMS work order. A management software provides streamlined processes with improved efficiency, while paper work order refers to the traditional method of creating and managing work orders using physical paper documents. The choice between the two depends on the organization's specific needs and preferences. (Lekan, 2024).

Accordingly, the assets with reactive maintenance strategy were problematic because it is associated with equipment breakdowns, which stop activities and lead to huge losses (Hildreth, 2020). To mitigate the inefficiencies of reactive maintenance, industrial organizations transitioned to the preventive maintenance (P.M.) model (Heinz and Fred, 2019). Preventive maintenance means businesses can schedule maintenance activities base on accurate predictions about an asset's lifetime (Nota *et al*., 2021). Planned corrective maintenance is a result of either a regular inspection or a prognostic equipment health management system. Preventive maintenance schedules repair and service operations at regular intervals to prevent equipment failures. Hence, preventive maintenance considers the assets' expected lifetime to inspect and maintain them proactively (Lee *et al*., 2019).

Modern maintenance. Machine failure is a major concern in the manufacturing industry, causing significant losses in terms of repair costs, production downtime and lost profits. Modern (preventive or predictive maintenance either or both) maintenance is currently the dominant laboratory or industry maintenance approach, as these typically maintains assets earlier than their end of life (EoL) (Lees, 2012). Therefore, it leads to a sub-optimal overall equipment efficiency (O.E.E.). To attain best possible overall equipment efficiency, laboratory enterprises/organizations have to plan maintenance activities based on "factual information" regarding the assets' condition rather than based on hypothetical end of life (EoL) assessment (Jeong-Gi *et al*., 2022).

With preventive or predictive maintenance, laboratory enterprises/organizations make the best possible use of their assets and improve their overall equipment efficiency (OEE). Modern (preventive or predictive maintenance) maintenance provides visibility on the actual condition of the assets, which minimizes possible unscheduled downtimes (Fauska and Kniezova, 2022).

Preventive maintenance (Pr.M.) activities (optimal planning). Information about the asset's conditions and their anticipated end of life (EoL) can be combined with insights on business operations (e.g. production schedules, demand forecasts) towards maximizing revenues and minimizing M.R.O. costs (Nota *et al.*, 2021). The origin of preventive or predictive asset maintenance enables much value-added functionality to improve maintenance operation/repair processes and help professionals optimize their decisions regarding assets inspections, equipment repairs and field service engineering activities (Abdulrauf, 2012).

Preventive maintenance is an invaluable tool for maintenance professionals, designed to facilitate the scheduling of routine maintenance activities based on equipment usage, time intervals or specific parameters (Engineers Asset, 2021). This proactive tool enables maintenance teams to create detailed plans, generate work orders and maintain a systematic record of each asset's maintenance history. The automation of these processes ensures that equipment operates at peak performance, significantly reducing the likelihood of unexpected breakdowns (Esposito *et al*., 2019).

Preventive maintenance provides businesses with a robust platform to organize maintenance tasks, manage service dates, monitor financial performance metrics and ensure compliance with safety standards (Zuper Inc., 2024). The strategic adoption of preventive maintenance software is essential for companies looking to enhance their maintenance management practices, achieve cost savings and boost operational effectiveness. Maintenance actions are then scheduled based on the observed condition or predetermined thresholds.

A preventive/proactive approach to maintenance not only extends the life of assets but also aligns with the strategic goals of an organization, fostering long-term prosperity (Galar *et al*., 2012). The preventive maintenance work order gives users the ability to control, plan, schedule and identify the materials, parts and labor to do the work within a specific timeframe. The advantages of preventive maintenance are to keep existing equipment in good working condition, prevent equipment downtime, increase the life expectancy of assets, decrease the number of major repairs and control expenses (Shimon *et al*., 2015). A work orders can be generated through a service request form (work request form) that is submitted by a staff member, customer or tenant or automatically created through work order management software, such as a computerized maintenance management system (CMMS) (Reiss, 2023).

Among the range of alternatives in the market, e-work orders distinguishes itself as an award-winning platform, delivering a comprehensive array of tools (tracking, financial requirement, authorities approval, time schedule etc.) that are pivotal for fine-tuning maintenance operations (Alper *et al*., 2023; Venkataraman, 2007). e-work orders' robust feature set, industry recognition, and commitment to excellence position it as a leader in the field, enabling businesses across industries to proactively oversee their assets and avoid the disruptions of unforeseen equipment failures. Integrating e-work orders into a maintenance plan can unlock the full potential of operational capabilities, establishing a new benchmark for reliability and operational excellence. (Patrick *et al*., 2018).

Preventive maintenance tools and techniques. By using data set and CMMS, the visualization about the assets' conditions are made through dashboards and presented to maintenance personnel like maintenance engineers and technicians. A typical visualization solution for predictive maintenance presents information about each asset's health and condition, as well as information that commence maintenance professionals for best schedules about maintenance activities (Tania *et al*., 2021). In practice, maintenance engineers and service technicians relay on the information visualized from dashboards as part of their maintenance planning and decision-making methodologies, like: failure mode, effects and criticality analysis (FMECA); reliability centered maintenance (R.C.M) (Anderson and Neri, 2012; Venkataraman, 2007).

Predictive maintenance strategy (Pd.M. strategy). Predictive maintenance is an approach that can help prevent machine failure before it happens, significantly reducing these costs. An overview for the maintenance classifications is shown in Fig. 2. Predictive maintenance (Pd.M.) turned out to be one of the most promising strategies amongst other strategies of maintenance that has the ability of achieving those characteristics (Jezzini *et al*., 2013) thus the strategy has been applied recently in many fields of studies.

Predictive maintenance (Pd.M.) captivates the attention of the industries, hence it has been applied in the era of Industry 4.0 (I4.0) due to it is capability of optimizing the use and management of assets (Kumar *et al.*, 2019). In summary, predictive maintenance can help reduce the impact of machine failure in manufacturing, by anticipating and preventing issues before they occur. This technology allows users to plan maintenance in advance, preventing costly downtimes and repairs. As maintenance persons continue to explore the benefits and challenges of incorporating machine learning-based equipment failure prediction into maintenance practices, there is significant improvements in the reliability and efficiency of machinery across industries (Esposito *et al*., 2019). By staying ahead of equipment failures, operators can focus on assets core operations and achieve higher levels of productivity.

Generally, predictive maintenance applications are command and control by modern networks of sensors,

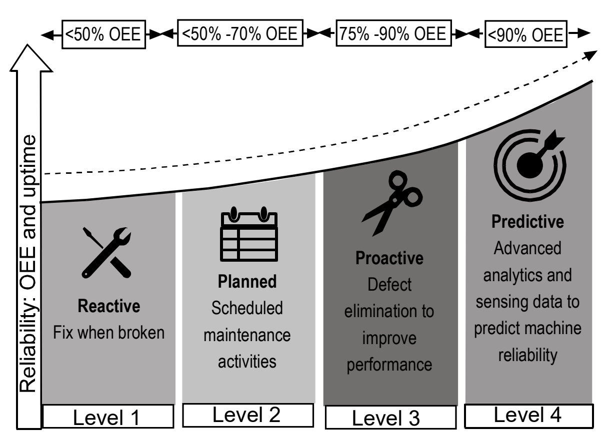

Fig. 2. Preventive maintenance tools and techniques. (Cinar *et al.*, 2020)

which gathers and collects a large amount of data about asset conditions. Industrial organizations deploy complex sensor data collection infrastructures consisting of wired or wireless sensors (Seneviratne *et al*., 2018). These infrastructures are digital networks and by using communication network attached with assets, can cope out performance record with different rates and formats of the data streams from the various sensors at special points (Fauska and Kniezova, 2022; Nota *et al*., 2021). In most cases, data from sensor networks are usually persisted and managed within scalable cloud computing infrastructures (Nota *et al*., 2021). Maintenance datasets leads to the extraction of insights about asset conditions and the parameter calculations like EoL and remaining useful life (RUL) (Fauska and Kniezova, 2022). The availability of rich sets of digital data for the assets' condition provides a sound basis for determining key maintenance parameters such as an asset's remaining useful life (R.U.L.) (Ning *et al*., 2020).

The planning and execution of maintenance and repair operations/overhaul (MRO) activities require considerable human resources and represent a noteworthy line in laboratory/industrial organizations' budgets. This is why laboratory enterprises/organizations are constantly seeking ways to improve the efficiency and cost of their maintenance activities (Lee and Lim, 2018). While there isn't a one-size-fits-all approach, each predictive maintenance method offers distinct benefits depending on the circumstances.

Critical assets typically undergo closer monitoring, employing more sensitive testing methods like vibration sensors or frequent monitoring. The core objectives of predictive maintenance (Pd.M.) revolves around minimizing maintenance intervals, effectively preventing unplanned downtime and curbing avoidable expenses associated with routine preventive maintenance measures (Venkataraman, 2007). By directly monitoring equipment performance and condition during regular operations, predictive maintenance (Pd.M.) empowers maintenance teams with real-time insights, significantly decreasing the likelihood of unexpected breakdowns. This approach enables the identification and prevention of predicted failures before they occur.

Traditionally, maintenance strategies primarily encompassed reactive or preventive methods, where repairs were conducted post-failure or scheduled based on manufacturer guidelines. However, with the advent of new software and technologies, many organizations are transitioning towards predictive maintenance approaches (Reiss, 2023). Various testing methods such as infrared testing, vibration analysis and oil analysis are employed based on asset requirements.

Predictive maintenance applications. Assets fitness ranks are controlled by information technology (IT) enabled predictive maintenance applications by providing a variety of intelligent applications such as (Boris *et al*., 2022):

- Intelligent control (asset management). Intelligent control encompasses the utilization of advanced technologies such as robotics, artificial intelligence (AI), machine learning and the internet of things (IoT) to optimize asset management. Intelligent control for optimizing asset utilization encompasses the integration of advanced technologies and cost-effective IT asset management practices to enhance overall operational efficiency and value creation. It relies on the power of data and digital tools to make informed decisions regarding asset utilization. The data analytics predictive insights, about optimize of physical assets of organizations and mitigate labor shortages (Mobasshir, 2021).
- Optimization of maintenance schedules. The optimization of maintenance schedules is a critical practice for ensuring efficient and cost-effective facility management
- Future condition of the asset. It is predictable from simulation (software developments or from graph model). This predictive modeling technique involves analyzing historical and current data to generate a model that aids in forecasting future outcomes (Cavalieri and Marco, 2020). The predictability of the future condition of assets from simulation involves leveraging predictive modeling techniques, software developments, graph models and simulation methods to analyze historical and current data for forecasting future outcomes.
- Root cause analysis (RCA). Root cause analysis is an important component in any maintenance department, aiming to eliminate the source of equipment failures rather than just addressing the symptoms, in order to prevent recurring issues (Jonathan, 2022). Root cause analysis (RCA) is a systematic method used to identify and solve the underlying factors that lead to defects, errors or failures in assets. By effectively utilizing RCA, organizations can save significant amounts of downtime and costs associated with equipment failures, while also improving overall operational efficiency.
- Leveraging remote maintenance. Remote maintenance technology offers various features that enhance

maintenance, such as scene recognition to track industrial sites and machines, instant tracking for remote guidance. Remote maintenance enables real-time remote maintenance support by establishing live connections with remote maintenance experts to receive step-by-step instructions, accessing online catalogues for spare parts, and facilitating troubleshooting and on-site problem resolution. Remote maintenance experiences with persistent instant targets, allowing staff to leave important messages directly on the machinery itself (Farhad *et al*., 2020). This ensures that technicians have all the tools they need to be efficient and effective, ultimately reducing machine downtime and improving service quality and speed.

Industry 4.0 is a smart industry synonymous which is the realization of the digital transformation of the field, delivering real-time decision making, enhanced productivity, flexibility and agility. These digital technologies lead to increased automation, predictive maintenance, self-optimization of process improvements and a new level of efficiencies and responsiveness to customers that are not previously possible (Joel, 1998).

Industry 4.0 (Digitalization and predictive maintenance). The period of fourth industrial revolution (Industry 4.0) has triggered by the development of information and communications technologies (ICT) and employed technological basis on digitalization (Rojko, 2017). Industry 4.0 is a strategic initiative of the German government, which heavily and traditionally supports development of the industrial sector.

The basic concept about Industry 4.0 was first presented at the Hannover fair in the year 2011. The main idea is to exploit the potentials of new technologies and concepts such as: Availability and use of the internet and internet of things (IoT); Integration of technical processes and business processes in companies; Digital illustrations and virtualization of the real world; 'Smart' factory including 'smart' means of industrial production and 'smart' products. (Shirowzhan, 2020).

The deployment of these technologies forms parts of the so-called fourth industrial revolution (Industry 4.0). In recent years, this is gradually changing by deployment of sensing systems and advanced digital technologies (e.g. internet of things, big data, artificial intelligence) in large organizations' planning and production facilities (Reiss, 2023). Many industrial automation systems would redesigned to accommodate the new digital transformation paradigms, including the need to consider what industry 4.0 means for such environments. Figure 3 gives ideas for a useful method to classify the types of maintenance strategies applied at organization end.

The rise of industry 4.0 leads to a proliferation of such applications in settings like smart buildings, production plants, manufacturing floors and oil refineries (Nota *et al*., 2021; Omar, 2018). Digital transformation and predictive maintenance considered as applications of industry 4.0 for a variety of reasons. It applies to most organizations, including those that manage industrial, business, governmental and residential installations in many sectors like manufacturing, energy, oil and gas, mining, construction, smart buildings and smart cities (Fauska and Kniezova, 2022).

It has effectively combine with other industry 4.0 applications like digital automation and digital twins to enable value-added laboratory/industry maintenance functionalities (e.g. remote maintenance and optimal maintenance planning) (Zuper Inc., 2024). In Fig. 3 a direction to modified direction for M.R.O. is presented. It is to almost all laboratory/industry assets, if they were equipped with proper digital platforms and electronics of sensors platforms.

Nevertheless, predictive maintenance is still not widely deployed, given that getting access to timely and detailed information about the assets' condition is quite challenging. The benefits of predictive maintenance translate to significant cost savings and increased revenue for business and laboratory enterprises/organizations that manage large installations (Seneviratne *et al*., 2018).

Generally, predictive maintenance considered as one of the "killer" applications of industry 4.0 for a variety of reasons; laboratory/industry maintenance are facilitated from the collection of large volumes of digital data about the condition of machinery and equipment through bluetooth etc., that are utilizes by industry 4.0. This data collection is empowered by deploying different types of sensors, like vibration sensors, acoustic sensors, temperature sensors, power consumption sensors and thermal cameras etc. (Fig. 1) (Fauska and Kniezova, 2022; Nota *et al*., 2021).

The key tools and methods that plant/lab managers could use in order to prevent and respond to unexpected events in their work environment before a catastrophe, is to recognize any plant/laboratory hazards that can create a disaster and develop a plan that would be helpful for avoiding them (He *et al*., 2017). Laboratory/plant safety begins before a lab accident occurs. A work place

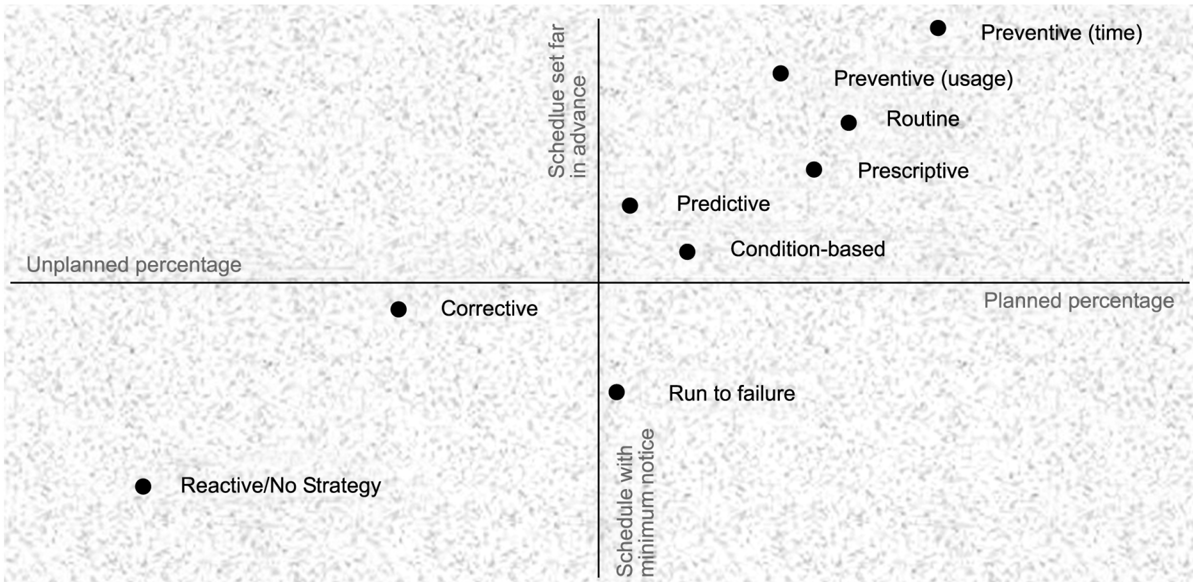

Fig. 3. Maintenance strategies and advance digital technology (Elizabeth, 2023).

safety plan protects both the people who work in and around the lab., as well as provide work and investment safety in laboratory/plant (Chepkemei *et al*., 2012). In addition, M.R.O. plan protects samples, equipment and scientific data. For these reasons, effective safety planning is a valuable tool in maintaining a productive workplace. In order to determine the most effective ways to respond to a lab accident prior to an accident advances. Digitalization and industry 4.0 have also been studied in the context of intelligent financial system and accounting with the development of digitalization through software, which has proven successful in saving time and efforts thus improving efficiency.

Maintenance and repair operations/overhauls (M.R.O.), for safeguarding the workers/peoples/scientist in companies are most effective and vital for functioning of laboratory/industry and safe guarding of assets and involves activities, including as (Qu *et al*., 2016):

Scrutinizing and inspecting laboratory/industrial equipment installations to ensure proper setup and functioning; Executing and performing functional/practical checks on devices and equipment to verify their operational status; Replacing malfunctioning component/parts before they fail in order to maintain equipment reliability and uptime; Properly repairing any damaged or out-of-order machines and parts to restore them to working condition; Repairing equipment and machinery, then re-checking and test running them to verify successful repairs; Performing and executing on-site assignments related to the maintenance and technical management of equipment and infrastructure assets; Scheduled maintenance is any work that has been put on the calendar, given a deadline and assigned to a specific technician for completion; The task's assignee and deadline, whether that has done a day or a year in advance; Planned maintenance is the what, where, why and how of a task. It does not always establish the exact date and time of work but you know how to execute the work when the time comes. (Zennaro *et al*., 2019)

Conclusion

As the use of electronics across industries like transportation, medical devices and communications (IT), is increasing, the importance of product reliability has become increasingly significant. Although product reliability has always been a crucial consideration in various industries and organizations, the growing use of electronics has led to a significant reliance on semiconductors, solid-state devices and integrated circuits (ICs) for improved performance and product life cycle design. To meet these demands, businesses must prioritize maintenance operations that emphasize the necessary level of machine and device reliability, availability, efficiency, safety and environmental sustainability. From the perspective view of a business and industries, maintenance operations focused on, e.g.:

Ensuring the required level of efficiency, reliability and availability of machines and devices; Best use of the capital invested; Ensuring the required level of safety for users and technical operators; Monitoring the environmental aspects of machine operation and operation processes; Modernizations ensuring the economic efficiency of the objects used; Machine providers should collaborate in replacement of parts.

Transitioning from conventional repair (reactive maintenance etc.) practices to industry 4.0 repair practices involves a strategic shift in mindset, processes and technologies. Industry 4.0 repair practices revolutionize maintenance operations by leveraging advanced technologies to shift from reactive to proactive strategies, ultimately optimizing equipment performance, reducing downtime and enhancing overall operational efficiency.

Preventive/proactive approaches improve equipment reliability, reduce maintenance costs, enhance production efficiency and extend equipment lifespan. Preventive and predictive maintenance approaches uses real-time data and analytics to anticipate and prevent unwanted breakdowns. It commencing with the use of IoT sensors and data analytics to monitor equipment health in real-time, enabling preventive and predictive maintenance based on actual condition of equipment from data records. It integrates IoT, machine learning (AI) and big data analytics for automated monitoring, predictive maintenance and intelligent decision-making. It dynamically planned maintenance operation that truly based on real-time equipment data and predictive analytics.

Lower maintenance costs due to predictive maintenance, optimized scheduling and reduced unplanned downtime. Also, preventive and predictive maintenance allocates insight resources efficiently, optimizing workforce and spare parts usage. These minimize downtime through planned and predictive maintenance reducing the impact of repair on production schedules.

Industry 4.0 is set to have a significant impact on two critical areas within organizations - operational technology (OT) and information technology (IT). OT refers to systems that operate in environments like factory floors or oil/gas pipelines, while IT includes systems that manage and deliver data. These areas traditionally have had limited synergy, but the convergence of IT and OT is changing this landscape. The progress in industrial internet of things (IIoT) and edge computing is playing a crucial role in bridging the gap between IT and OT. With everything connected in this new paradigm, sensors that gather vast amounts of data hold the promise of improving efficiency, performance and ultimately, profits across various industries.

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