AI-based Sensors for Predictive Maintenance

Pharmaceutical industry

Department of Mechanical and Materials Engineering
Bachelor's thesis

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The pharmaceutical industry requires a high level of reliability, compliance and efficiency, which creates increasing demands on maintenance strategies. Predictive maintenance (PdM), which relies on real-time data and advanced analytics to predict equipment failures, offers an alternative to traditional maintenance approaches. This thesis examines how AI-based sensors support the implementation of PdM in the pharmaceutical industry, focusing on both technical performance and industry-specific requirements.

The study presents an overview of various sensor types, including vibration, temperature, ultrasonic and acoustic sensors, examines their working principles, strengths, limitations, and suitability for pharmaceutical applications. Particular attention is given to how sensor data is processed and integrated with machine learning models to enable early fault detection and optimise maintenance planning. Through a literature review, the thesis highlights the importance of data quality, regulatory considerations in deploying effective PdM systems.

The findings show that while no single sensor type is universally sufficient, combining multiple sensors and integrating them with AI-based analytics can significantly improve equipment reliability and reduce unplanned downtime. Moreover, the adoption of PdM supports compliance with Good Manufacturing Practices (GMP) requirements by enabling better traceability and reducing the need for reactive interventions.

Keywords: Artificial Intelligence, Preventive Maintenance, Predictive Maintenance, Corrective Maintenance, Machine Learning

List of used abbreviations:

AI	Artificial Intelligence
PM	Preventive Maintenance
PdM	Predictive Maintenance
CM	Corrective Maintenance
OEE	Overall Equipment Effectiveness
GMP	Good Manufacturing Practises
FDA	Food and Drug Administration
DI	Data Integrity
MEMS	Micro-Electro-Mechanical Systems
RF	Random Forests
ANN	Artificial Neural Networks

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1 Introduction

In modern industrial settings, maintenance strategies have evolved from simple corrective actions to intelligent data-driven systems that support operational efficiency, product quality and regulatory compliance. This shift is especially valuable in the pharmaceutical industry, where the reliability of production equipment is critical and where unexpected downtime can lead to serious financial losses, product contamination or regulatory violations.

Predictive maintenance (PdM) represents the latest advancement in the field of maintenance. PdM relies on real-time data and condition monitoring to detect early signs of failure, allowing maintenance to be scheduled only when necessary. This approach minimises the unexpected disruptions and supports better planning across the entire production process.

At the core of predictive maintenance are sensors that measure operating parameters, such as vibration, temperature and acoustic emissions. When integrated with Artificial Intelligence (AI) and Machine Learning (ML) models, these sensors enable early detection of anomalies, helping predict system failures before they occur. In regulated environments such as pharmaceutical manufacturing, this approach is very valuable, as it reduces the risk of equipment-related deviations that could compromise product quality.

This thesis focuses on the role of sensors in enabling PdM within the pharmaceutical industry. It aims to identify the types of sensors used, evaluate their working principles, and explore how the data is transformed into maintenance insights through AI models. Additionally, the regulatory and operational challenges involved in applying PdM strategies in regulated pharmaceutical environments are considered.

The following research questions guide the thesis:

1. What type of sensors are suitable for predictive maintenance applications, especially in the pharmaceutical industry?
2. What complicates the implementation of predictive maintenance in the pharmaceutical manufacturing environment?

By addressing these questions, the thesis aims to provide a comprehensive overview of the technologies and practices involved in implementing an effective predictive maintenance strategy for pharmaceutical applications, highlighting both the opportunities and limitations of current approaches.

2 Maintenance

Maintenance is an essential activity in industrial operations, regardless of the sector. The standard NF EN 13306 [1] describes maintenance as a set of all technical, administrative and management actions during the lifecycle of an asset, intended to maintain or restore it to a state in which it can perform a required function. Maintenance ensures optimal performance, avoids downtime, and reduces costs. In some cases, an effective maintenance strategy may even extend the useful lifespan of industrial machines [2]. As industries continue to advance, the role of maintenance has evolved from simple corrective actions to data-driven strategies. To thrive in today’s competitive market, enterprises must adopt new technologies to satisfy customer needs and maintain market share. The integration of connectivity, data analytics, advanced devices, inventory optimisation, and controlled production has led to the rise of the fourth industrial revolution, also referred to as Industry 4.0 [3].

Industry 4.0 has transformed the industrial world by interconnected, smart factories that utilise the Industrial Internet of Things (IIoT), big data and Artificial Intelligence (AI) to improve manufacturing operations. In this digital landscape, machines can communicate with each other and make autonomous decisions, increasing flexibility and efficiency throughout the production chain [3].

2.1 Background

As mentioned, maintenance practices have progressed over the years from corrective maintenance (CM) to preventive maintenance (PM) and eventually to predictive maintenance (PdM) [4]. This section will discuss the different maintenance strategies, along with their advantages, limitations, and applications in industrial settings. The aim is to provide insight into how maintenance strategies contribute to Overall Equipment Effectiveness (OEE) and reduce costs while maintaining the safety of personnel and products. Figure 1 represents how the maintenance strategies can be divided into two main types: proactive and reactive. Proactive maintenance aims to prevent failures before they occur. Conversely, reactive maintenance involves taking action only after a failure has occurred [5].

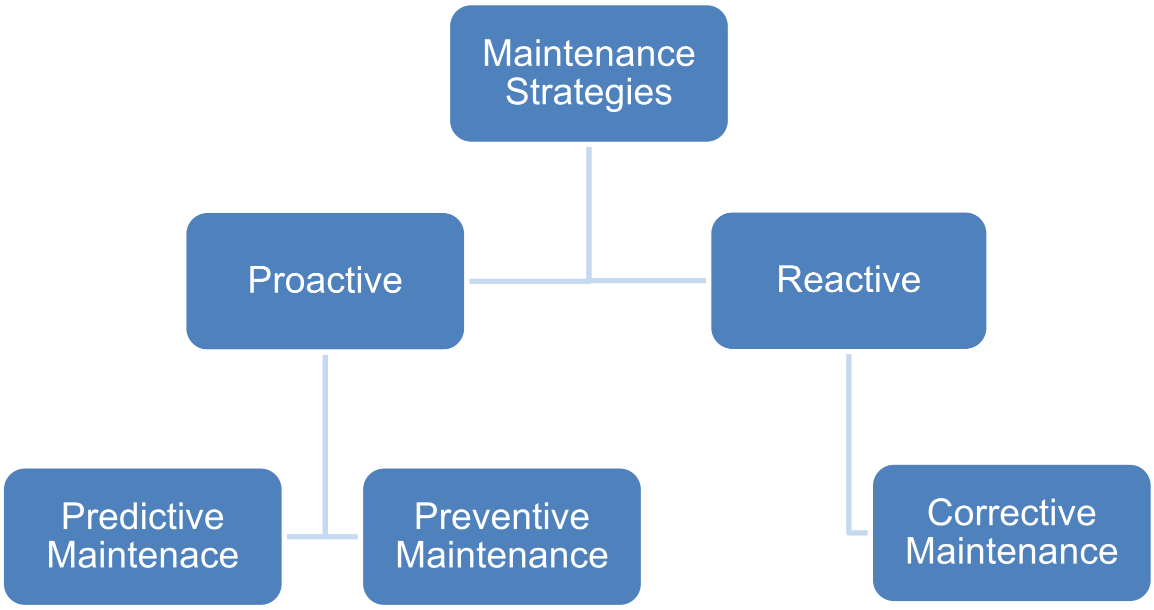

Figure 1. Overview of maintenance strategies.

2.1.1 Corrective Maintenance

Corrective maintenance, also known as Run-To-Failure (RTF), is a reactive maintenance strategy. It refers to a process of repairing equipment after a failure or malfunction has occurred. It plays a vital role in non-critical assets, where unplanned downtime is acceptable. As it does not require complex monitoring systems or scheduled interventions, the initial costs are lower compared to other maintenance strategies. However, when applied to critical systems, CM might lead to safety risks and higher costs for parts and labour. This approach should only be used when the cost of unexpected failures is low and when failures do not compromise safety or compliance [6].

2.1.2 Preventive Maintenance

Preventive maintenance, also known as time-based maintenance, is a proactive maintenance strategy. It includes planned inspections, service and repairs prevent equipment failures before they occur. Unlike corrective maintenance, preventive maintenance aims to minimise unexpected downtime and enhance operational efficiency.

In PM, maintenance tasks are scheduled, typically based on either calendar time or the equipment's operational hours, with the frequency generally established by the manufacturer. This approach is widely used in various industries and offers advantages such as an extended lifespan for equipment, along with improved safety and compliance. However, there are also some disadvantages to consider. If maintenance intervals are too long, it may overlook the equipment’s deterioration, potentially leading to faults or even breakdowns. Conversely, if the intervals are too short, it can result in additional costs, excessive material consumption, and the use of unnecessary organisational resources [7].

2.1.3 Predictive Maintenance

Predictive maintenance is a proactive strategy to anticipate system failures by continuously collecting data [7]. The equipment’s condition is monitored, and if deviant trends are detected, maintenance is scheduled. This means that the maintenance work can be performed at the most convenient times, minimising unplanned downtime and thereby increasing production capacity. This approach allows for the timely purchase of needed parts, reducing the necessity for a large inventory of spare parts. Thus, it can be said that PdM offers various advantages, including enhanced reliability and availability, optimised maintenance planning, and lower costs for parts and labour.

PdM is based on advanced sensor technology; sensors continuously monitor system conditions, collecting real-time data that is transmitted to cloud-based systems and analysed to predict when maintenance is needed. This reduces the need for manual inspections and human intervention. It is crucial to acquire the right tools for monitoring and to provide training for the personnel performing the maintenance work. If the equipment's deterioration is incorrectly assessed, it could lead to unnecessary maintenance work.

2.2 PdM in the Pharmaceutical Industry

Implementing PdM in the pharmaceutical industry presents challenges and considerations not typically encountered in other sectors. While the core principle of PdM, using sensor data to predict system failures, remains consistent, the strict requirements for product quality, hygiene, and equipment control influence its applications in pharmaceutical environments.

Pharmaceutical manufacturing involves complex machinery operating under regulated environmental controls. Production equipment such as tablet pressers, granulators, coating machines, and HVAC (Heating, Ventilation and Air Conditioning) systems are not only critical to production but also subject to validation requirements and hygienic standards [8].

Even minor deviations in equipment performance can lead to the rejection of entire product batches [9].

PdM strategies rely on continuous monitoring and analysis of sensor data to detect early signs of degradation. Sensors typically track parameters such as vibration, electrical current, and temperature [2]. PdM reduces unnecessary preventive maintenance tasks and instead triggers actions only when they are truly needed – improving OEE. In pharmaceutical settings, minimising unplanned maintenance is especially important in order to maintain documented performance records and ensure regulatory compliance [8].

Unlike in other industries, where maintenance interruptions typically cause only temporary production delays, maintenance in pharmaceutical facilities may carry additional consequences. For instance, maintenance tasks performed in cleanrooms may require environmental cleaning or even revalidation of equipment – resulting in extended downtime and operational costs. This makes the timing and accuracy of PdM predictions particularly valuable in pharmaceutical applications. Additionally, the wide variety of equipment and processes used often demand highly customised PdM models. The behaviour of a single machine type can vary significantly depending on factors like product formulation, batch size, or environmental conditions. This complicates the development of generalised models and increases the need for high-quality sensor data [2,10]

Despite these challenges, the pharmaceutical industry stands to gain significantly from PdM. When successfully implemented, it can increase equipment availability, reduce unexpected downtime, and improve production reliability. Perhaps most importantly, PdM supports better planning by enabling maintenance during scheduled downtimes, which reduces the operational and regulatory burden associated with unplanned repairs [2,10].

2.2.1 Regulatory and Compliance Considerations

The pharmaceutical industry is highly regulated. Compliance is mandatory not only to ensure legal operation but also to uphold the highest standards of product quality and patient safety. Regulations such as Good Manufacturing Practise (GMP) dictate every stage of the manufacturing lifecycle, from raw material sourcing to equipment design, personnel hygiene and environmental control [10].

A critical regulatory expectation in pharmaceutical operations is equipment validation. Validation ensures that production equipment operates consistently and reliably within defined parameters. According to U.S Food and Drug Administration (FDA) requirements and GMP guidelines, validation is performed in three stages [11]. The first part is Installation Qualification (IQ), which verifies the correct installation of the equipment according to the company's standards and manufacturer's specifications. A part of IQ testing is the installation inspection of all components, which includes all sensors and digital components. The second step is Operational Qualification (OQ), which confirms that the equipment and associated systems perform as intended across all operating conditions. The third and final step is Performance Qualification (PQ), which demonstrates consistent performance in real-world production [11].

In the context of PdM, these validation principles apply to both hardware and software. This means that IQ tests are performed to ensure the sensors and monitoring systems are installed correctly. With OQ tests, AI-based systems are evaluated to ensure accurate failure detection, and with PQ tests, it is validated that predictive models consistently identify maintenance needs [12]. When installing a new machine, these tests are carried out along with all other necessary tests. However, if tailored sensors are installed for existing production equipment, this creates a need for revalidation, which can be very expensive and time-consuming, especially in cleanroom environments.

Good Automated Manufacturing Practice (GAMP) is a framework that guides the development, validation and management of computerised systems used in the pharmaceutical industry. GAMP was created to ensure automation and digital technologies used in GMP environments are robust, traceable and consistently capable of supporting product quality. The most recent version, GAMP 5, developed by the International Society for Pharmaceutical Engineering (ISPE), introduces a risk-based lifecycle-oriented approach for system validation. Instead of treating all systems the same, it promotes scalable validation. This means that the more a system can impact product quality, the more accurately it should be documented, tested and controlled. A key part of the GAMP framework is its focus on Data Integrity (DI). DI ensures that all collected and processed data are complete, consistent and accurate. Regarding PdM, this means all data used for maintenance decisions must be attributable, legible, contemporaneous, original and accurate [13].

Maintenance performed inside cleanrooms adds another regulatory dimension. Cleanrooms in pharmaceutical manufacturing are critical environments designed to maintain precise air quality, temperature, humidity, pressure differentials, and contamination controls. These conditions are governed by international standards such as ISO 14644-1, which classifies cleanrooms based on allowable particle concentration, as well as by GMP grades A through D, which define additional controls for manufacturing processes [14]. Cleanrooms undergo initial validation and routine revalidation to confirm compliance with these classifications. Maintenance work performed in cleanrooms may also necessitate revalidation. When maintenance introduces tools, external personnel, or airflow disruption into cleanroom environments, the controlled environment might be compromised. Regulatory frameworks ISO 14644-1 and GMP guidelines require the cleanroom to be revalidated after such interventions to ensure it continues to meet the original qualification criteria [14].

Ultimately, regulatory compliance does not conflict with PdM; rather, it defines the framework we must operate within. When implemented in validated systems and supported by traceable data handling, PdM provides an effective strategy that reduces documentation burdens and improves overall quality assurance [12]. For PdM, regulatory compliance introduces some constraints: maintenance activities must be clearly defined, documented, and traceable. GMP requires that all processes affecting product quality are followed and verifiable, which means PdM systems must integrate with formal maintenance documentation systems [8].

2.3 Challenges and Limitations of PdM

As already discussed, the implementation of PdM is not without challenges. One of the most fundamental problems is data quality. For a PdM system to be effective, it requires large amounts of accurate real-time sensor data. Collected data is used to train machine learning models and to support reliable predictions. Most of the time industrial data can be noisy, incomplete or inconsistent due to harsh operating conditions, sensor faults or incomplete data logging infrastructure. Poor quality data directly impacts model performance and can lead to misclassification or missed failure predictions [2]. This issue becomes particularly evident when considering that PdM systems are based on detecting anomalies from collected data. Abnormal behaviour may result from an actual degradation of the equipment, which is valuable and should trigger maintenance. Conversely, sensor malfunctions, battery problems or external disturbances might cause abnormalities. These so-called false positives introduce further noise into the dataset, potentially leading to incorrect diagnostics, unnecessary maintenance interventions or general mistrust in the PdM system [2,12]

Another challenge is the complexity of industrial environments and equipment. Factories are usually a mix of old and new machines, each with different types of control systems and sensors. Creating a predictive model that would generalise across each equipment type and operating condition, is very challenging, if not impossible. Even for identical machines, slight differences in usage profiles or environmental factors can lead to deviant behaviour, which is difficult to model with uniform accuracy. In addition to the diversity of equipment, the behaviour of an individual machine is not stable over its lifespan. As machines age, are updated or operate under changing conditions, the data patterns used to train the original models may not reflect the current behaviour. Predictive models may become outdated and unreliable without continuous monitoring and periodic detraining [12].

In an ideal situation, implementing a PdM system reduces costs by minimising downtime, optimising performance and preventing equipment failures. However, especially for small or medium-sized enterprises the initial costs can be a major barrier. Investments include sensors, data infrastructure, integration with existing systems and staff training. PdM systems based on machine learning often also require ongoing costs for data management, system updates and model retraining. For that reason, it is important to carefully evaluate the cost and expected benefits to determine whether the investment is justified [12].

Finally, even with the technical systems in place, organisational and cultural challenges may complicate the successful implementation of PdM. Transitioning from preventive or corrective maintenance to predictive maintenance requires a shift not only in workflow but also in mindset. Maintenance technicians and plant operators may initially resist relying on automated systems, especially if these systems are difficult to understand or do not demonstrate how decisions are made. This requires clear communication, system transparency, and the inclusion of operational staff in both the implementation and evaluation phases [12].

3 Sensors

Predictive maintenance is a data-driven maintenance strategy. Sensors collect data, which is then analysed to predict issues and maintenance needs.

The next chapters will introduce different types of sensors, their working principles, pros and cons, and discuss their suitability in the pharmaceutical industry. In a later chapter, the contribution of AI will be noted.

3.1 Vibration Sensors

Vibration monitoring is commonly employed in PdM, especially for rotating machinery. To evaluate vibrations in equipment, a vibration sensor is used. This device detects mechanical changes and converts them into a measurable output, usually in the form of an electrical signal [15].

Vibration sensors measure the intensity and frequency of mechanical vibrations to detect faults such as unbalance, misalignment, looseness, and bearing wear. These defects typically produce deviant vibration patterns that can be identified early, before they develop into serious failures [16]. In addition to mechanical applications, vibration can negatively impact electronic devices. Common vibration-related faults in electronics are severed cable connections, faulty solder joints, broken output terminals, short circuits, functional failure of components and misalignment in optical circuits [17].

Vibration can be measured with different types of sensors. Some require direct attachment to the monitored equipment, while others can detect vibrations remotely through free space. The most common vibration sensor types are acceleration, velocity, and displacement [15].

3.1.1 Accelerometers

An accelerometer is a sensor that measures acceleration. They are the most used vibration sensors due to their superior accuracy, broad measurement range, straightforward installation and cost-effectiveness. They operate based on the principle of inertia and are fundamentally grounded in Newton’s second law of motion, which states that force is a product of mass and acceleration ($F=ma$). Inside an accelerometer, a small internal mass resists a change in motion. When the sensor is subjected to acceleration, the inertia of this mass generates a pseudoforce with a magnitude proportional to the applied acceleration [16]. Accelerometers are popular because they can measure low to very high frequencies and because they are available for application-specific systems. Different types of accelerometers exist, such as piezoelectric accelerometers and Micro-Electro-Mechanical Systems (MEMS) [17]. These sensors can be uniaxial, which means that they detect acceleration only in one axis, or triaxial, detecting motion in all three dimensions [15].

Piezoelectric accelerometers are the most popular sensors used in industrial devices. They function on the principle of the piezoelectric effect, which occurs when specific crystalline materials produce an electrical charge in response to mechanical stress – vibration. Inside the sensor, a seismic mass is mounted on a piezoelectric material. As the system experiences vibration, the mass resists acceleration due to inertia, applying force to the material, which generates an electrical signal [16,18]. The produced electrical charge is measured and is directly proportional to the applied force. Because the electrical signal produced has a very high impedance, the sensor includes an internal electronic circuit that converts the impedance, making the signal suitable for transmission to downstream systems. Piezoelectric accelerometers are valued for their high sensitivity, wide frequency range (1Hz to 30kHz) and durability in harsh environments [16].

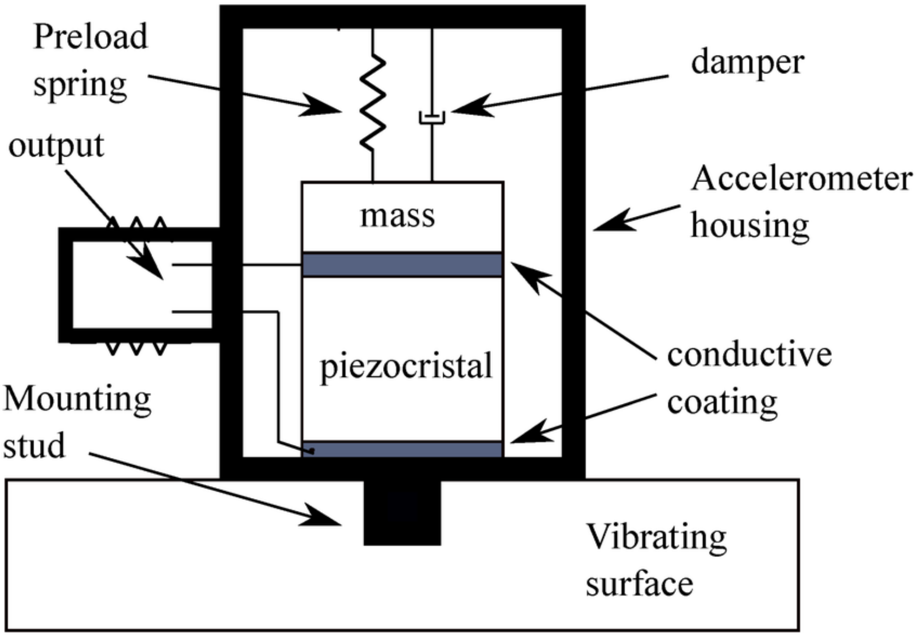

Figure 2. Elements of piezoelectric sensor. Source: M. Romanssini, P.C.C. De Aguirre, L. Compassi-Severo, A.G. Girardi (2023), published under Creative Commons Attribution (CC BY) license [15].

The recent developments in semiconductor microfabrication technology have led to the development of devices containing mechanical components on the micrometre scale. This development has led to the emergence of MEMS accelerometers, which are known for their compact size and cost-efficiency compared to piezoelectric accelerometers [15]. MEMS accelerometers can operate either on piezoresistive or capacitive principles [15].

Piezoresistive accelerometer structure typically consists of two strain gauges configured within a wheatstone circuit. When the sensor is subjected to mechanical movement – vibration, the attached seismic mass causes alternating compression and tension in the strain gauges, producing a change in resistance. This results in a voltage input, directly proportional to the applied acceleration [17,18].

Capacitive MEMS accelerometers consist of three key components: a movable proof mass, a suspension system, and fixed electrodes known as capacitive fingers. The fingers are situated on either side of the proof mass. This design enables the mass to shift sideways in response to acceleration. In Figure 3, the elements of the capacitive MEMS accelerometer are presented.

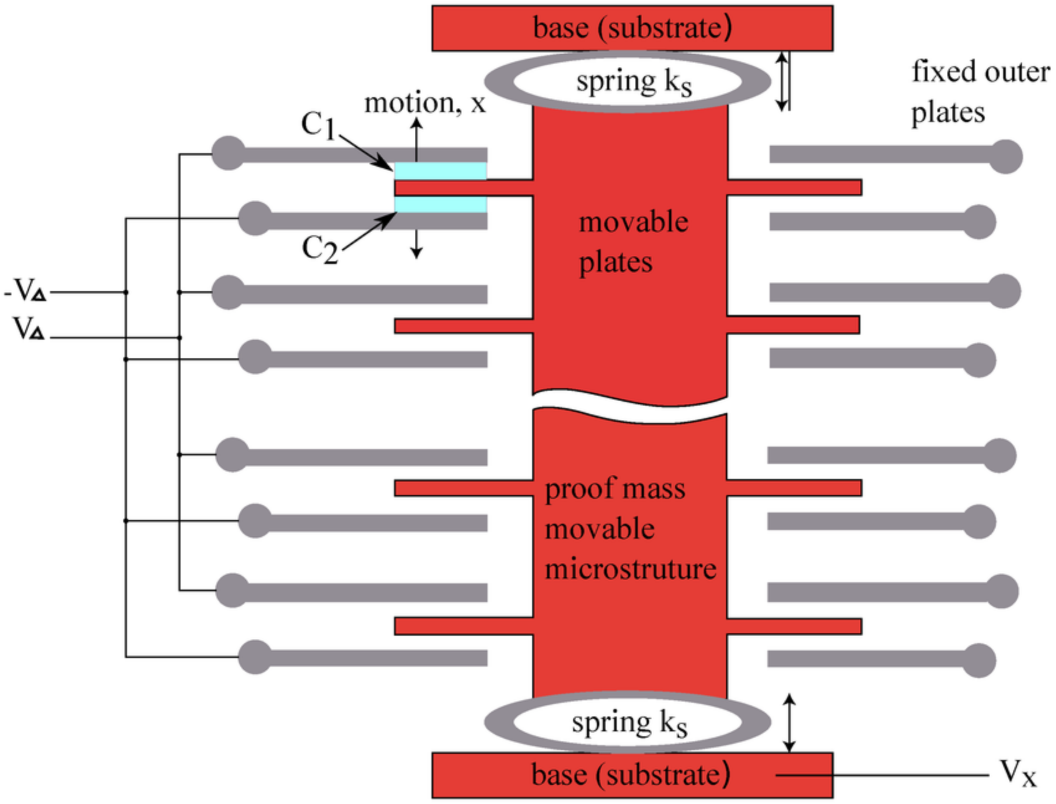

Figure 3. The elements of capacitive MEMS accelerometer. Source: M. Romanssini, P.C.C. De Aguirre, L. Compassi-Severo, A.G. Girardi (2023), published under Creative Commons Attribution (CC BY) license [15].

When the sensor is stationary, the proof mass stays in the middle, resulting in equal capacitance on both sides. When the sensor is subjected to acceleration, the mass is displaced, causing an imbalance in capacitance between the two sides. This change in differential capacitance is then used to calculate the acceleration [15,19].

Compared to piezoelectric accelerometers, MEMS accelerometers have a narrower bandwidth and higher noise floor, which can limit their sensitivity in fault detection, particularly in high-frequency vibration analysis. They are also more limited in operating temperature, with a maximum temperature of 105°C, whereas piezoelectric commonly rated to 120°C [18]. MEMS accelerometers are a great choice for applications that do not require extremely high accuracy but benefit from small size, low cost and ease of integration [15].

3.1.2 Displacement Sensors

Displacement sensors are used to measure the relative movement of machine components with respect to a reference point. They rely on various physical principles, including capacitive, optical, and ultrasonic methods, to sense changes in position caused by vibrations. These sensors are particularly effective at detecting low-frequency vibrations under 10 Hz, making them well-suited for equipment that rotates slowly [15].

In PdM applications, sensors called eddy current sensors, also known as gap current sensors, are typically used. They operate based on induced current principles. A coil inside the sensors produces a high-frequency magnetic field, which interacts with a nearby conductive surface, such as a rotating shaft. This interaction induces eddy currents on the surface, altering the coil’s impedance. The resulting change in impedance corresponds directly to the distance between the sensor and the target surface, allowing for accurate measurement of displacement [15].

Displacement sensors are highly stable across temperature variations and offer high reliability, even in harsh industrial conditions. They are widely used for misalignment, imbalance and shaft displacement in motors and turbines. The simplicity of signal processing is another advantage, it can deliver displacement readings with minimal computational effort. They, however, have some limitations as well. Their installation is more complex compared for example to MEMS sensors, requiring precise alignment and secure mounting. They are also sensitive to mechanical shocks and require material-specific calibration [15].

3.1.3 Velocity Sensors

Velocity sensors measure the speed at which the vibrating object moves. They are used to detect faults in machinery operating within frequencies from 10Hz to 1000Hz, making them suitable for rotating machines like motors, fans and pumps. Velocity sensors operate on the electromagnetic induction principle, where a coil moves relative to a magnetic field in response to vibration. This motion induces a voltage that is directly proportional to the velocity of the vibration. The result is a signal that reflects the vibration velocity, which can be interpreted directly by most monitoring systems without requiring extensive signal processing [15,17].

The advantage of the velocity sensors is that they do not require an external power supply. They are also easy to install and less costly compared for example to piezoelectric accelerometers. Velocity sensors have some limitations as well. They are relatively bulkier and more fragile than modern accelerometers. They have inconsistent sensitivity across different input frequencies and have a limited frequency range. The internal moving parts can wear out over time, especially in conditions of high mechanical stress [15].

3.2 Temperature Sensors

Temperature sensors detect thermal energy, or in other words, measure the temperature of components or the environment. Temperature sensors work and obtain information on two principles, directly or indirectly. Direct contact sensors include thermocouples, Resistance Temperature Detectors (RTD) and thermal resistors. These sensors physically attach to the surface of the machine to measure the temperature directly. Infrared sensors are indirect temperature sensors [20].

Thermocouples are devices operating on the principle of the Seebeck effect to covert temperature differences into electrical voltage. At their core, they consist of two different metals joined at a junction. When there is a temperature difference between that junction and the other ends of the metals, a voltage knows ad Seebeck voltage is produced. This voltage is directly proportional to the temperature difference. Thermocouples are used to measure temperature in HVAC systems, which are essential in the pharmaceutical industry. They offer a wide temperature range from -200°C up to 1800°C but are not as accurate as RTD sensors.

RTDs are well known for their high precision. They determine temperature by measuring the change in electrical resistance of metal, as it responds to temperature variations. They are usually constructed from pure metals, like platinum, as it has a predictable and linear resistance change with temperature. As the surrounding temperature varies, the resistance of the metal element also changes proportionally. Due to their excellent accuracy and long-term stability, they are suitable for applications where precise and reliable temperature monitoring is essential. Compared to thermocouples, the temperature range is narrower, from -200°C to 500°C [21].

Thermal resistors, also known as thermistors, operate on two principles: Negative Temperature Coefficient (NTC), where the resistance drops as temperature rises, and Positive Temperature Coefficient (PTC), where resistance rises with increasing temperature. Their electrical resistance varies significantly with temperature changes, making them very accurate over a limited range from 0°C to 100°C. Similar to thermocouples, thermistors are commonly used for monitoring and regulating temperature in HVAC systems [21].

Indirect infrared (IR) sensors operate based on the principle of black body radiation and Stefan-Boltzmann's law. The law indicates that any object with a temperature above absolute zero emits infrared radiation, with the intensity of this emission corresponding directly to the object's temperature. The radiation is focused onto a detector with a lens, which then converts the emitted radiation into an electric signal [21]. Infrared sensors are effective for measuring the temperature of moving objects and in environments where non-contact sensors are essential.

3.3 Acoustic Sensors

An acoustic sensor is a device that detects both audible and ultrasonic sound waves and converts them into electrical signals. Acoustic sensors often operate based on the time-of-flight principle, where a sound wave is transmitted and the time taken for the reflected signal to return is measured. This enables the calculation of distances, such as the location of a gas leak, by applying the speed of sound in air [22].

In the context of PdM, acoustic sensors are used to detect anomalies that emit characteristic acoustic signatures, like gas leaks, friction, or mechanical impacts. Since the signal amplitude is highest near the source of the disturbance, acoustic sensors can be used to accurately localise faults along the equipment. However, the performance of acoustic sensors can be affected by external factors. These include temperature and humidity, which influence the propagation speed and attenuation of sound; background noise, which may mask relevant signals; and signal frequency, which determines both detection range and resolution. Due to these sensitivities, acoustic sensors are often more effective when deployed in combination with other sensor technologies [22].

3.4 Ultrasonic Sensors

Ultrasound is described as a sound wave with a frequency higher than 20 kHz, which exceeds the upper limit of human hearing. Ultrasonic sensors detect high-frequency sound waves caused by friction, turbulence or impact. It is effective for both low- and high-speed mechanical applications, as well as for equipment operating under high-pressure fluid conditions [23]. Ultrasound has a short wavelength, which makes it directional. This makes it easy to pinpoint the exact location of a fault, even in noisy industrial environments. For example, when searching for compressed air or vacuum leaks, the ultrasonic signal grows stronger as the sensor approaches the source of the fault [23]. The working principle is the same as acoustic sensors. A wave is transmitted, and the time for it to return is measured. The working principle is illustrated in Figure 4.

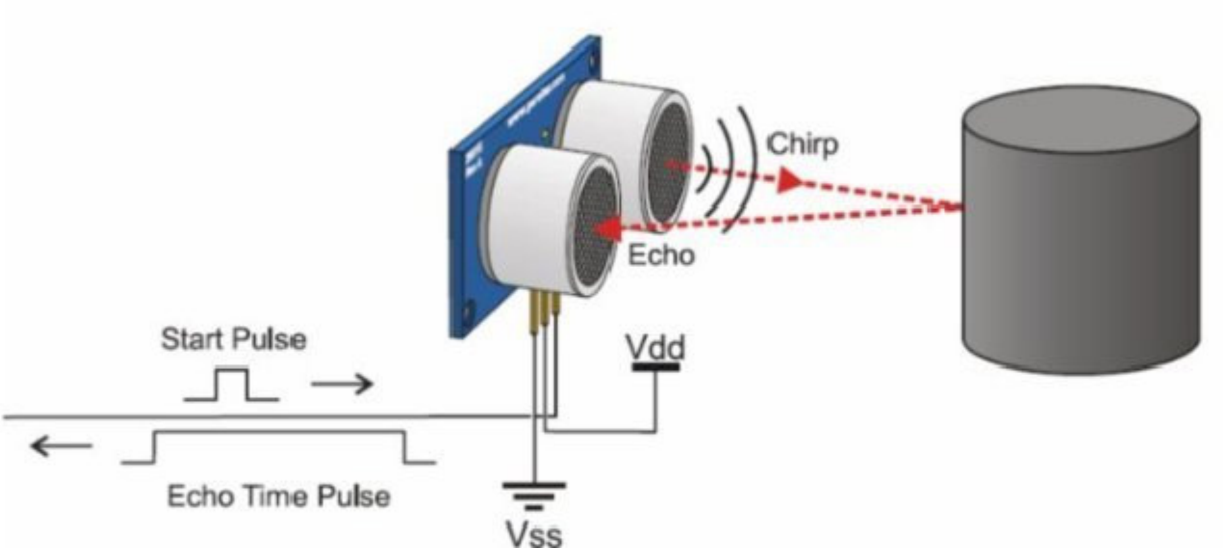

Figure 4. The working principle of acoustic and ultrasonic sensors. Source: Engiz, Begum & Bashir, Rakan. (2019). Implementation of a Speed Control System Using Arduino [24].

The advantage of ultrasonic sensors is that they provide early-warning capability and complement other earlier introduced sensor technologies, such as accelerometers and thermal sensors. They are very useful sensors for PdM, particularly in detecting faults that do not produce noticeable vibration or temperature changes. They are commonly used to monitor bearing health, detect compressed air or gas leaks, and identify vacuum system faults. They are also used to estimate lubrication quality in rotating elements and evaluate mechanical wear in components like valves and pumps [25,26].

3.5 Summary of Sensors

All the main sensor types relevant to PdM have now been introduced. Table 1 below provides an overview of the sensors introduced in this chapter. While each sensor operates based on a different measuring principle and offers unique advantages, they also have limitations that must be considered when designing a PdM system. In most industrial settings, no single type of sensor is sufficient on its own. The most reliable outcome is received when multiple sensors are used together.

Table 1. Sensors

Summary of introduced sensors, their working principles, pros and cons and their suitability for the pharmaceutical industry.

Measured parameter / Sensor type	Measuring principle	Pros	Cons	Suitability for the pharmaceutical industry
Vibration				
Piezoelectric accelerometer	Electric charge generated by crystal under mechanical stress	Wide frequency range, robust, accurate	More expensive, requires protection as sensitive to shocks	Excellent, widely used in critical equipment
MEMS	Micro-electromechanical structure	Compact, low cost, easy to integrate	Less accurate, limited temperature resistance	Good, especially for non-critical applications and wireless setups
Displacement	Magnetic field variation in conductive material	Accurate at low frequencies, stable	Complex installation, sensitive to impacts	Good, but validation requirements may complicate
Velocity	Voltage generated by moving magnetic field	Direct velocity output, simple use	Limited frequency range, bulky	Limited use, may serve as a supporting sensor

Measured parameter / Sensor type	Measuring principle	Pros	Cons	Suitability for the pharmaceutical industry
Temperature				
Thermocouples	Seebeck effect between two metals	Wide temperature range	Less accurate, requires compensation	Good, useful in high temperature equipment
RTD	Linear change in resistance with temperature	Accurate, stable	More expensive	Excellent, well accepted and easy to validate
Thermistors	Resistance changes with temperature (NTC/PTC)	Very accurate, low cost	Narrow temperature range	Good for local monitoring, not commonly used as a main process sensor
Infrared	Black body radiation and Stefan Boltzmann's law	Non-contact, very fast	Sensitive to reflections and dirt	Excellent, ideal for moving object and cleanrooms
Acoustic				
	Sound wave detection	Non-invasive, complement other data	Sensitive to interference	Moderate, best used in combination with other sensors
Ultrasonic				
	High frequency sound detection	Great for detecting leaks and lubrication issues	Affected by noise, requires training	Very good, especially as a supplementary sensor in cleanrooms

4 Sensor Integration with AI Models

The effectiveness of the PdM process is based on more than just sensor deployment. Sensors act as the functional layer, collecting real-time operational data. The full value of this data is revealed when it is systematically processed and analysed through AI models, which are capable of learning and adapting over time [27]. AI models can identify complex patterns in high volumes of sensor data, detect anomalies and support decisions about equipment condition and maintenance timing. They rely on live inputs and on large volumes of historical data, which is used as the training ground for understanding what “normal” is and what deviates from expected performance [27,28].

The pharmaceutical industry produces large amounts of process and equipment data as a part of GMP requirements. This historical data provides an ideal foundation for AI-based analysis. When properly cleaned and aligned, this data can reveal equipment degradation trends or shifts in operational baselines that would be difficult to detect manually.

4.1 Predictive Maintenance Workflow

As illustrated in Figure 5, the PdM workflow typically involves four stages: data collection, data processing, prediction and modelling and maintenance scheduling.

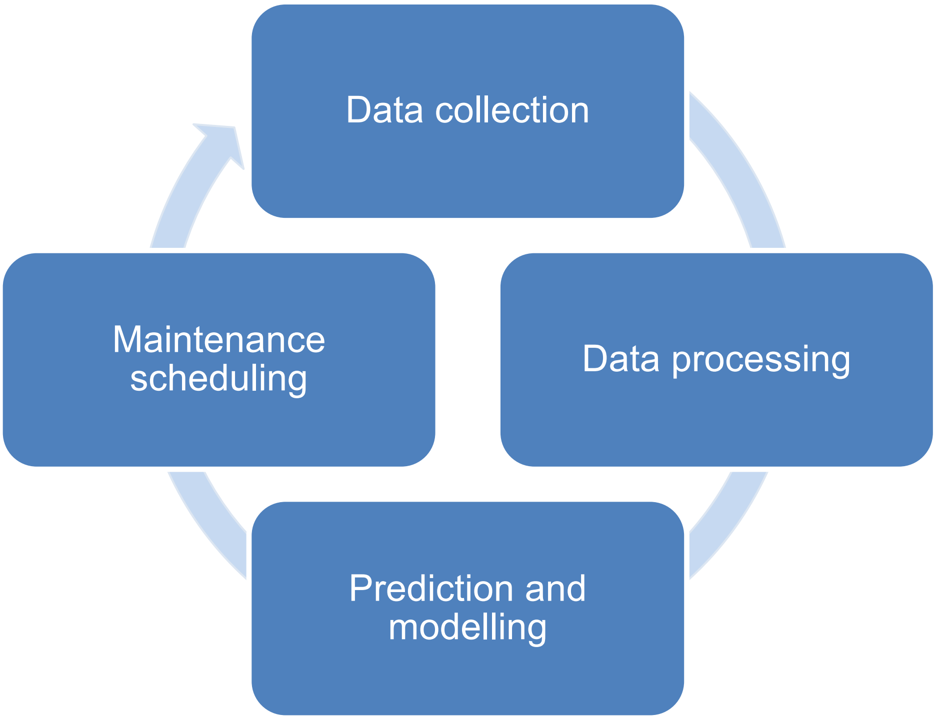

Figure 5. Typical workflow of data-driven predictive maintenance.

The workflow begins with data collection, where sensors monitor equipment and process conditions in real time. These sensors capture a wide range of parameters, depending on the equipped sensors, providing a continuous stream of raw operational data [29]. The reliability of this phase is dependent on proper installation and calibration of sensors, as well as the data acquisition infrastructure that transmits the data, usually to cloud based storage systems [28].

The next step is data processing. The collected raw sensor data undergoes cleaning, filtering and normalisation. This is a crucial step, as the collected data is often noisy and incomplete. During this step, noise is eliminated, missing values are corrected, and consistency across datasets is ensured [27,28]. Without robust preprocessing, data-fed models are prone to misinterpretation, leading to inaccurate predictions and diagnostics.

In the prediction and modelling stage, the processed data is used as an input for AI models that assess equipment condition and predict future failures. These models are trained on historical data to detect anomalies and assess degradation trends. Rather than relying on fixed thresholds, the models use machine learning approaches to continuously evaluate new data against established baselines. This allows for early detection of anomalies that would otherwise go unnoticed. A big advantage of AI-based modelling is its ability to adapt over time. The more data is collected, the models can be retrained to reflect equipment behaviour, ensuring that predictions remain accurate even as equipment ages or operating conditions shift [27,28]. In the next chapter, some machine learning algorithms are introduced.

The final stage, maintenance scheduling, uses the model outputs to inform proactive interventions. Rather than relying on fixed intervals, the system recommends maintenance actions based on the condition of the equipment. The model monitors the sensor data in real-time and triggers interventions if it identifies any anomalies, like changes in temperature or deviant vibration patterns [27].

4.2 Machine Learning Algorithms

Several machine learning approaches have emerged as effective for PdM. Machine learning methods can be categorised into supervised and unsupervised reinforcement learning. Supervised learning involves training models using data that includes known outputs, whereas unsupervised learning analyses data without predefined labels to uncover hidden patterns. Among the most widely used supervised learning models are Random Forests (RF), which are especially suitable when dealing with high-dimensional data sets. RFs generate multiple decision trees using randomised feature subsets and then average their output to produce more stable and generalised predictions. This model is especially effective when the number of input variables exceeds the number of observations. RFs are employed for both failure classification and regression-based prediction of degradation. These models can update predictions based on new operational data, allowing real-time adaptation to changing conditions [30].

Another widely used supervised learning algorithm for PdM is Artificial Neural Networks (ANN). The working principle is inspired by a simplification of the structure and functioning of the human brain. One of the most significant advantages of ANN is that they function without relying on expert knowledge. Instead, they learn patterns directly from historical datasets, making them highly adaptable. ANNs are known for their robustness as they can maintain accuracy even when the data is noisy or inconsistent. Once trained, a well-designed ANN model can operate in real-time without requiring adjustments with every new input or update. These benefits are, however, accompanied by certain limitations. ANNs can sometimes generate results that are inconsistent with domain knowledge. They also demand a large volume of data to produce accurate results [30].

The K-means model is an unsupervised learning algorithm for clustering tasks. The goal is to divide a dataset into k distinct clusters based on feature similarity, ensuring that data points within clusters are as close as possible to each other, while points from different clusters are far apart. It is known for being simple to implement and efficient in handling large datasets. It adapts well when data is introduced, as it can re-train and adjust the cluster centers accordingly [30].

5 Discussion

This thesis has explored AI-driven predictive maintenance with a focus on the pharmaceutical industry. The working principle and practical relevance of various sensor types were discussed, alongside their integration with AI models. As no practical work was performed to establish the best sensor, this part will summarise the discussed topics in a general form.

The implementation of predictive maintenance in the pharmaceutical industry is a big step towards achieving a smarter, more reliable and compliant manufacturing environment. By integrating sensor technologies with AI, PdM enables early detection of equipment degradation, minimising unplanned downtime and supporting data-driven maintenance planning. Transitioning from time-based to condition-based maintenance strategies is particularly valuable in GMP critical systems, where equipment failures may lead to environmental deviations, batch losses or costly revalidation processes. When effective, PdM enhances regulatory compliance by providing detailed records of equipment conditions and maintenance activities. These records support traceability, which is a core requirement of GMP. Even with the clear benefits, the successful implementation of PdM in the pharmaceutical industry is complex. It requires not only significant upfront investments in sensors and data infrastructure, but also careful consideration of several technical, regulatory and operational factors. In particular, the selection and deployment of sensors is central to the reliability.

Several types of sensors were introduced in this thesis, including vibration, temperature, ultrasonic and acoustic sensors. Each sensor type operates based on a different physical principle and has distinct advantages and limitations. Piezoelectric accelerometers, for example, offer high accuracy over a wide frequency range, but are more expensive and require robust signal conditioning. MEMS accelerometers are compact and affordable, making them suitable for distributed monitoring, though they are less accurate in high-precision applications. Temperature sensors offer varying degrees of accuracy, response time and suitability depending on the environment and target application. Ultrasonic sensors are effective for detecting leaks and lubrication issues, especially in cleanroom environments. It is important to note that no single sensor type is universally optimal. Sensor selection must be tailored to the specific application, equipment and environment. In many cases, a combination of different sensors provides a more comprehensive understanding of equipment condition.

When selecting a sensor for a pharmaceutical environment, some critical factors must be considered to ensure both operational effectiveness and regulatory compliance. Sensors used in a GMP critical environment must support traceability, calibration and data integrity. The chosen sensors must also function reliably in cleanroom settings, withstand frequent cleaning with chemical substances and comply with hygienic standards. Maintenance and calibration needs must also be evaluated, as the sensors themselves also require maintenance. Limited access in sterile areas makes low-maintenance and long calibration interval sensors more desirable. Overall, sensor selection must balance between performance, compliance and practicality in the regulated environment of pharmaceutical manufacturing.

In summary, the integration of sensors with AI models transforms passive condition monitoring into intelligent proactive maintenance. When properly designed, PdM systems can reduce unplanned downtime, extend equipment lifespan and increase the overall reliability of critical systems. This is especially valuable in the pharmaceutical industry, where equipment failures might lead to high operational and regulatory costs. While technical and organisational challenges remain, the continuous development of sensor technologies and AI models indicates that PdM will play a growing role in the future of pharmaceutical operations.

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