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Leveraging industry 4.0 techniques for predictive equipment maintenance: from concept to commissioning

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Abstract. In recent decades, lean manufacturing has significantly impacted the manufacturing industry, gaining widespread adoption. Companies have increasingly recognised the competitive advantages of implementing flow-oriented production layouts, demand-flow technologies, and just-in-time production. This shift has also transformed the approach to maintenance, moving away from reactive strategies. With production cells becoming more susceptible to system disturbances, maintenance managers are now focused on strategic maintenance development to ensure reliable production equipment. The emergence of Industry 4.0 technologies has further reshaped plant maintenance, providing companies with accurate and dependable tools for proactive maintenance. This paper proposes a hypothesis of research conducted at the University of Malta, focusing on the potential application of predictive maintenance (PdM) in the upkeep of automation machinery. It suggests the use of a novel data management and acquisition system, grounded in simulation and deep learning modelling, to predict the remaining useful life (RUL) of machinery early during the design machine realisation. This exploration lays the groundwork for potential development of a comprehensive maintenance tool. Such a tool would optimise automation designs, estimate maintenance costs throughout the machine's lifecycle, and prevent machine breakdown through proactive interventions.

1 Introduction

The average manufacturing company typically allocates 12% to 18% of its annual revenue towards maintenance-related expenses [1]. This percentage reflects the belief of many operations managers that maintenance costs are inevitable and challenging to reduce significantly. However, as manufacturing practices have evolved, new strategies and approaches have emerged to optimise maintenance and reduce associated costs. In the past, manufacturing companies used to rely on buffering materials and built a surplus of finished goods, acting as Work-In-Progress (WIP) buffers between machinery, to compensate for unexpected downtimes and still meeting production demand [2]. While buffering materials provided a temporary solution, they introduced hidden costs, such as the risk of parts

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becoming obsolete and expenses related to storage space. As lean manufacturing principles gained traction, companies started realising the drawbacks of relying on material buffering.

Lean manufacturing aim to eliminate waste, increase efficiency, and improve overall production processes [2]. As a result, material buffering has gradually been phased out as a countermeasure for machine downtime in favour of more streamlined and efficient production processes. To ensure the effective implementation of lean manufacturing strategies, production assets must operate reliably and without interruptions [3]. By adopting PdM, companies can proactively identify and address potential issues, minimising unplanned downtime and optimising production efficiency. In recent decades, technology has significantly re-shaped PdM, from limited arithmetical methods to a more data-driven approach, utilising machine behaviour data, models, and domain knowledge for analysis.

While PdM offers a more efficient way of working, forecasting and benchmarking performance before the actual production line is built and functioning remains challenging. This is because common RUL models are typically set up to run on production data. As will be discussed further in the research, there are significant advantages, both from the perspectives of machine design and maintenance planning, in making RUL predictions based on machine design concepts.

The motivation behind this study is to propose a predictive maintenance tool that can be set up and utilised without requiring real-life production data. By developing a predictive maintenance tool that leverages alternative data sources or simulated data, this study aims to provide a flexible and accessible solution for maintenance planning and optimisation. This approach allows for the exploration of future implementation possibilities and the opportunity to benchmark such a system, ultimately validating the hypothesis that this maintenance tool can offer multiple dimensional advantages. The upcoming sections of this study presents critical research to reach this desired final goal.

2 Literature review

2.1 Review of current Pd

PdM is a maintenance strategy that has been in use since the early 1990s [5] . Numerical methods for estimating failure points have opened the door for Prognostics and Health Management (PHM). PHM refers to predicting the RUL of equipment and hence the most appropriate time to perform maintenance to prevent machine malfunction [6] . Therefore, the RUL value is the most sensitive and predominant parameter required for the correct creation and execution of any PdM plan. Accelerated Life-Time Testing (ALT) is a method that allows for predicting when components typically fail. During such a method, components are continuously subjected to adverse conditions to uncover and determine faults and failure points in a short period of time [7] .

Maddila et al. [7] investigated the RUL of a penumatic cylinder by analysing the forward thrust. They investigated the time between each cylinder stroke through an infrared (IR) presence sensor. Pneumatic cylinders are devices that convert compressed air pressure into mechanical energy. Due to their various operating advantages over electric and hydraulic actuators, pneumatic-based cylinders are the actuators of choice for designing automation systems. The IR sensor feeds into a microcontroller which analysed the time in between each stroke. In case that the cylinder seals wear out, and leakage of the internal pressure of the cylinder occurs, the time between each trust varies from the normal pre-set value. The micro controller then analyses and compares these readings to values of a properly functioning piston, indicating the deterioration state and rate of the tested cylinder [7] . Examples of ALT for predictive maintenance in literature are not limited only to pneumatic cylinders, Klausen et al.in [8] presented an ALT method to determine the onset of fault propagation in a bearing. Through calculations done such an ALT yielded that the earliest sign of bearing fault is identified after 5.37 million revolutions [8].

Literature has demonstrated that ALT is a reliable approach for predicting the RUL of components. This methodology ensures precise results by replicating machine conditions in a physical manner, thus accounting for all stochastic requirements. However, it is important to note that ALT modelling can be costly, time-consuming, and constrained by the availability of a specific dataset [9].

2.2 Cyber physical systems

With the advent of Industry 4.0, companies must now look towards more effective ways of PdM. Through digitalisation tools maintenance can be performed through self-aware machinery. The idea of replicating physical machinery through simulation and reacting in real-time is a concept commonly referred to as an Intelligent Cyber-Physical System (ICPS) [10]. By utilising advanced sensors, networking, and embedded systems, data is extracted from running physical objects and relayed to a decision-making body in real-time [11]. The control loop shown in Fig.1 represents a typical ICPS where real-time sensing of the physical world occurs and is transmitted into cyberspace. Cyberspace consists of a control centre and a data centre. The data transmitted from the physical artefact is first sent to the data centre and analysed [12]. Once the data is processed and analysed, instructions are then sent to the control centre. Subsequently, actuation instructions are fed to the physical artefact to regulate its operations. Therefore, this concept revolves around the intersection of physical and cyber elements rather than their union [12]. The convergence between the physical and cyber space holds significant potential for improving asset management, product quality, and optimising production [12].

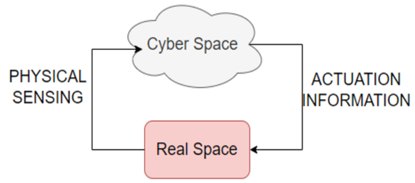

Fig.1. A Cyber Physical System

2.3 Gap analysis

Undoubtedly, Lean Manufacturing and PdM hold tremendous promise for revolutionising operational efficiency. However, companies often grapple with substantial limitations during the conceptual stage of the automation system. Although Lean Manufacturing principles promote efficiency, accurately forecasting and benchmarking performance before the production line is constructed and operational remains challenging. As a result, process engineers must rely on rough estimates to anticipate potential production bottlenecks and critical parameters such as OEE levels and cycle times [4].

In addition, while PdM has gained popularity as a maintenance strategy, it requires data from machines already in production to start performing RUL predictions. Without a comprehensive understanding of component life spans, companies may face challenges in selecting appropriate components, optimising system dynamics, and ensuring long-term reliability. The study will focus on presenting a case for the critical aspect of collecting and utilising accurate failure data to inform RUL calculations during the design stage of automation.

3 Methodology – proposed framework

The proposed RUL data management and acquisition framework in this study aims to enable accurate RUL predictions before production. This can be achieved through an AI blended modelling approach. The framework involves collecting data from two simulation modes.

The first simulation mode is based on physical modelling, which entails developing a digital replica of the physical automation machinery. This digital replica needs to take into account various stochastic real-life conditions to create high-fidelity representations. Whereby the fidelity level that such a digital replica is developed directly impacts the accuracy of RUL results. By using this simulation modelling approach, RUL calculations can be performed on a substantial dataset, resulting in more accurate results. This eliminates the need for costly physical replicas and enables the acquisition of larger sample sizes for analysis. The study also proposes the integration of physical modelling data into RUL predictions, complementing simulation-based models. This combined approach leverages the strengths of both modelling techniques. While simulation-based modelling may face limitations in accurately replicating physical artifacts, physical modelling ensures a comprehensive consideration of the physical environment and its dynamic factors. However, a purely physical approach to RUL prediction can be costly and may not always yield a substantial dataset. This challenge is addressed via simulation modelling that can generate a larger sample size, enabling more robust analysis and accurate RUL predictions. By combining the benefits of physical modelling and simulation-based modelling, a more effective approach to RUL prediction can be achieved, considering both the physical aspects and the advantages of simulation modelling.

The data generated from these modelling techniques, as shown in Fig.2, are then passed to a machine learning algorithm, where through deep learning, degradation data can be interpreted and analysed. This is done through multilayers of artificial neural networks, that enable such algorithms to learn complex representations of the data. The training process of such model involves providing labelled simulation and physical modelling data to the neural networks, allowing them to automatically learn and make accurate predictions or decisions [13]. By utilising these proposed methods, the machine learning algorithm is trained to effectively differentiate between data patterns that indicate component health condition. In this study, it is recommended to incorporate recurrent neural networks (RNNs) within any machine learning algorithm used for predicting RUL. This is since RNNs are particularly suitable for time-series data and sequence prediction due to their ability to utilise internal state memory when processing sequential inputs [14]. Once the RNN is configured and trained to analyse data, manufacturing companies have a tool to predict when the first maintenance intervention is required on a design concept.

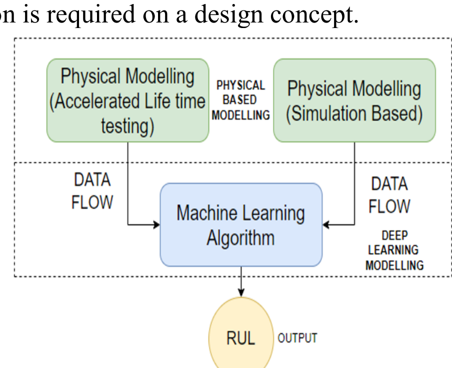

Fig.2. Proposed Data Management System

4 Discussion

Developing and incorporating PdM plans within plant maintenance settings is indeed an investment. Like any other investment, the expectation is that the money and resources invested will yield significant benefits. PdM leads to enhanced safety, efficient utilisation of maintenance resources, flexible and optimised process planning, as well as reduced overall downtime [15].

The proposed PdM setup in this study offers significant advantages. By creating a digital twin during the design phase, engineers can simulate the machine's behaviour and performance, enabling them to identify potential weak points in the design that are more prone to failure. This understanding of maintenance requirements allows for performance optimisation, taking advantage of the design phase where modifications are less costly. Consequently, costs associated with unreliable initial predictive maintenance can be minimised, reducing the risk of unexpected machine failures and resulting downtime until a robust predictive maintenance tool is established. Additionally, designers can determine the necessary preventive safety measures based on the criticality of potential component failures. In summary, the use of a digital twin during the design phase provides the means to simulate machine behaviour, optimise performance, reduce costs associated with unreliable maintenance, and make informed decisions regarding preventive safety measures.

The successful implementation of any PdM technology relies on the knowledge and skills available within a manufacturing company. However, the majority of companies currently do not have reliability engineers or data scientists on their staff [15]. This creates a barrier for these companies to effectively develop and implement PdM technologies. As a result, there are limitations associated with implementing PdM systems in real-life industrial settings. Due to the lack of expertise within companies, they may need to incur high consulting fees for quick implementation of such technologies. However, through the presented explained concept, which includes a valid data management structure and a simplified setup process, there is potential to address these challenges and make the situation better for companies. The described data management structure ensures that relevant data can be collected, integrated, and analysed effectively for PdM purposes. Additionally, the simplified setup process reduces the complexity and technical requirements, making it more accessible for companies without extensive expertise to adopt and implement PdM technologies.

As a future direction, this study will focus on the implementation of the proposed system, as well as validation of its accuracy, assessment of cost implications, and establishing benchmarks for its effectiveness. This would involve setting up and acquiring data from both simulation and physical modelling, which will be used to train the developed deep learning algorithm. Once the algorithm is established, tests will be conducted to validate its accuracy in predicting the RUL of machinery. This will help validate the hypothesis regarding the significant advantages of having such a system in place prior to machinery assembly. These efforts will contribute to the ongoing research aimed at exploring the potential application of PdM in maintaining machinery.

5 Conclusion

The transformation of maintenance strategies in the manufacturing industry has been a focus of extensive research. With the adoption of lean manufacturing principles and the integration of Industry 4.0 technologies, maintenance practices have shifted from reactive to proactive approaches. The implementation of PdM using data-driven techniques and advanced technologies has become essential for ensuring reliable production equipment. This research highlights the significance of proactive maintenance strategies and demonstrates the potential benefits of integrating PdM into the design phase of machinery. More importantly, however, it presents a compelling case for the adoption of PdM and proposes a methodology to set up a PdM tool during the design phase of machinery. By utilising the proposed data management and acquisition system based on simulation and deep learning modelling, the RUL of machinery can be calculated early in the machine lifecycle. This proactive approach to maintenance enables improved design concepts, optimised maintenance planning, and efficient resource allocation enhancing equipment reliability, optimising maintenance processes, and driving operational efficiency.

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