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Research Paper

Investigating Predictive Maintenance Strategies for CNC Machine Tools in the Industry 4.0 Era

Fionn Foley[1*]
[1]School of Science, Technology, Engineering and Mathematics, Munster Technological University, Clash, Tralee, Co. Kerry, Ireland, V92 CX88
[*]Email of Corresponding Author: Fionn.foley@mtu.ie
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Abstract
This research compares different approaches for achieving precise predictive maintenance (PdM) results from CNC machine tools. For smaller enterprises, it is crucial to be able to upgrade their existing industrial machines with industry 4.0 systems, as the global marketplace becomes more competitive. The evolution of the Internet of Things (IoT) and the creation of cyber-physical systems (CPS) in the industry has enabled big data generation. New maintenance methodologies have emerged where decisions are driven by mathematical models and data analysis. In this study, a low-cost strategy is used as a baseline to establish system accuracy. Results are then compared to a more comprehensive strategy outlining the potentials of these retrofit predictive maintenance (PdM) systems. Numerous data modeling techniques were employed to increase system accuracy while focusing on the remaining useful life (RUL) of the cutting tool. Through analysis of the selected strategies favorable correlation is evident between predicted results and physical tool wear, optimal accuracy of 95.68% is achieved by utilizing hybrid data modeling techniques. The study highlights the possibilities for enterprises looking to adopt PdM strategies and consequently capitalize on the potential of Industry 4.0.

Keywords
CNC Machine, Maintenance, Industry 4.0, Internet of Things, Predictive Maintenance, Retrofit

1. Introduction
The emergence of the Internet of Things (IoT) and Industry 4.0 have revolutionized industrial capabilities. Rapid advancement in a variety of processes is forcing enterprises to adapt to this new evolution by adopting the extensive use of sensors. Connectivity, big data, machine learning, and, controlled production have enabled the emergence of Industry 4.0. This term was first announced by the German government in 2011 at the Hannover fair and is an acronym for the Fourth Industrial Revolution [1]. The first three industrial revolutions came about as a result of mechanization, electricity, and IT. Now with Industry 4.0 the presence of these intelligent systems connected through the Internet of Things (IoT) can provide interaction in smart factories [2]. Industries are expected to have communication and intelligent capabilities throughout manufacturing, engineering, material

usage, supply chain, and, life cycle management [3]. The benefits are reflected in increased productivity, improved quality, efficiency, and mass customization [2].

Ruschel et al. [4] and Garg and Deshmukh [5] conducted maintenance management reviews and found that there are relatively few articles that focus on the cost of maintenance for management decision-making purposes.

According to the paper [6], unplanned downtime caused by a poor maintenance strategy reduces a plant’s overall productive capacity by up to 20 percent and costs around $50 Billion each year.

The earliest maintenance strategy is known as unplanned maintenance or run to failure. With this approach, no maintenance is performed until a machine breakdown occurs [7]. While this may increase the utilization of a machine component to some extent, it also results in unavoidable unplanned downtime. On the other hand, preventative maintenance is a widely used strategy in the industry. It involves inspecting and maintaining components at regular intervals to prevent unexpected machine failures. However, this practice can lead to long suspension times and high maintenance costs.

Maintenance engineers often face a tradeoff situation where they need to choose between maximizing the useful life of a component (unplanned maintenance) and maximizing uptime (preventative maintenance) [6].

Connected sensors in manufacturing equipment can generate the large volumes of data required and, careful analysis of this big data can optimize decision-making, identify improvement possibilities through machine learning (ML), or sense deviations from normal or expected operations throughout a facility. The data generation from connected sensors can be used to enable the management and optimization of predictive maintenance decisions. Previously maintenance decisions were based on operating hours and guidelines. Studies have shown that almost 60% of manufacturing equipment fails prematurely after the implementation of corrective maintenance [8]. The resultant downtime from machine failure can lead to significant financial losses, customer complaints, and supply chain issues. Additionally, large inventories of spare parts are an essential outlay for many manufacturing facilities.

With the evolution of these connected sensors and the use of the data generated, maintenance teams can now make smart maintenance decisions by mathematical and computational models [1] and communicate via IIoT. Production systems are evolving into cyber-physical-production systems (CPS) and machine tools are now becoming smart machining centers [9] supporting the implementation of condition-based maintenance (CBM). The physical is machines and sensors and the cyber is modeling, data storage, and mining. CBM has become feasible for a large range of applications where detecting the degradation of machine components by data collected from carefully positioned sensors is the pillar of this framework. Predictive maintenance (PdM) strategies similarly monitor the current state of equipment and additionally compile it with historical data, relevant user knowledge, and data modeling. This enables the prediction of trends, behavior patterns, and correlations through statistics or machine learning models.

Machine tools are crucial elements of manufacturing systems. They have undergone a significant evolution, from manually operated machines to computer numerical control (CNC) machine tools, with the introduction of computers during the third industrial revolution (3IR) [10].

The CNC machine is a significant pillar of modern manufacturing systems across a broad and diverse range of industries.

As small and medium-sized enterprises (SMEs) increasingly adopt 'Industry 4.0' principles and leverage disruptive digital technologies such as cloud computing, artificial intelligence, and big data, a new generation of machines is emerging. These machines are advancing the concept of distributed numerically controlled (DNC) machines, which originated in the 1980s [11]. Despite the ongoing transformations, SMEs are often overlooked when discussing advanced technologies, as many implementation methods are deemed too complex and capital-intensive for them to adopt.

The reliability and performance of these machines determine the quality of the product it processes [12]. In another study [10], authors affirmed PdM's tangible value creation for SME CNC machine shops with predicted positive impacts on their MT cost and performance drivers. The research results supported SMEs in considering exploring the path to adapting PdM, and it is anticipated that maintenance managers, business executives, and researchers will benefit from this research.

Predictive maintenance (PdM) is a promising technique that aims to break this tradeoff. It involves monitoring the condition of in-service equipment and predicting when equipment will fail. By approximating the future behavior and condition of machine components, maintenance tasks can be optimized, leading to significant reductions in machine downtime and maintenance costs while minimizing the frequency of maintenance. This is achieved through techniques such as prognostic health monitoring.

It is a complex system with mechanical, electronic, and hydraulic components all interdependent while interacting with each other. Due to this complexity, a large variety of faults can occur and, the performance degradation is non-linear. Additionally, extreme acoustic emissions are generated during running, making PdM on these systems extremely difficult. However due to the direct relationship between machine condition and product quality, there is a significant need for PdM on CNC machines, studies have focused on the cutting tool to enable PdM. Degradation of the CNC cutting tool can be observed in Figure 1.

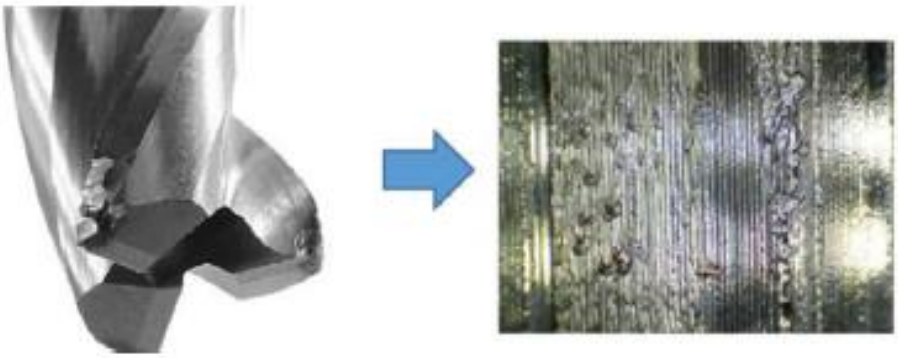

Figure 1. Cutting tool wear leads to an increase in surface roughness and quality rejections

Machine learning is a tool of artificial intelligence (AI) and it provides a machine with the ability to learn without being specifically programmed [9]. A machine can therefore change or adapt when new data is introduced as it constantly searches for patterns in data provided by the connected sensors [12]. Numerous methodologies have been used to apply machine learning models in efforts to reduce

error and complexity while still maintaining accuracy.
Data features that reflect the health and condition of a machine or component can be extracted to construct a data-driven model for PdM purposes. However, strictly focusing on a data-driven model has been proven to produce some error percentages as the equipment's physical characteristics are often complex and difficult to fully capture. An alternative model is based on a physical model which reflects the performance degradation of the system over time but, it relies on the support of experts and therefore can become unattainable for a smaller enterprise. This physical model may typically be generated by computational simulation techniques that can accurately depict degradation, a reliability statistics method uses historic fault data for fault prediction, and this does not rely on expert analysis. These methods are typically focused on singular large batch products and are not ideally suited to complex systems. The significant drawbacks of each model highlighted are particularly relevant in the case of the CNC machine. The complexity of the system involved makes it a difficult use case and therefore many enterprises feel adopting PdM techniques for their CNC machine may not be possible. The focus of the presented work outlines the accuracy of two PdM strategies, a low-cost entry-level system creates the baseline, and a more comprehensive industry-focused strategy details the greater possibilities of PdM.

2. Methods

A review of two PdM strategies for CNC machine tools was conducted to establish the accuracy of this industry 4.0-enabled approach. The CNC machine is a complex system, however, the cutting tool itself directly affects the accuracy and quality of the parts once processed. Therefore, this is the primary focus area. While a newly purchased CNC machine may have industry 4.0 capability, a substantial cost outlay is associated with machine purchase and many SMEs may not be in a position to outlay this type of revenue. Consequently, an alternative industry 4.0 approach is investigated. Related literature was compared focusing on the accuracy of retrofit approaches to establish whether these methods can provide a sufficient approach to understanding the remaining useful life (RUL) of the cutting tool and therefore, the final quality of parts produced.

3. Results and discussion

Both studies positioned sensors on the spindle and tests were conducted in several steps, running the cutting tool-to-failure. The primary machine parameters of both studies included spindle speed, feed rate, and depth of cut and all tests used aluminum sample pieces for analysis. Analysis of the data sets enabled the plotting of increased vibration and temperature which correlated to a negative trend in tool wear. A major difference between the two studies was the introduction of cutting-head computational simulation. This was used to refocus the Machine learning model by referencing several set points and proved extremely beneficial in achieving optimized accuracy. Once the system models were created an alert would be sent to warn the user of impending failure ultimately guiding the intervention of PdM in advance of a machine breakdown. An overview of the results is provided in Figure 2.

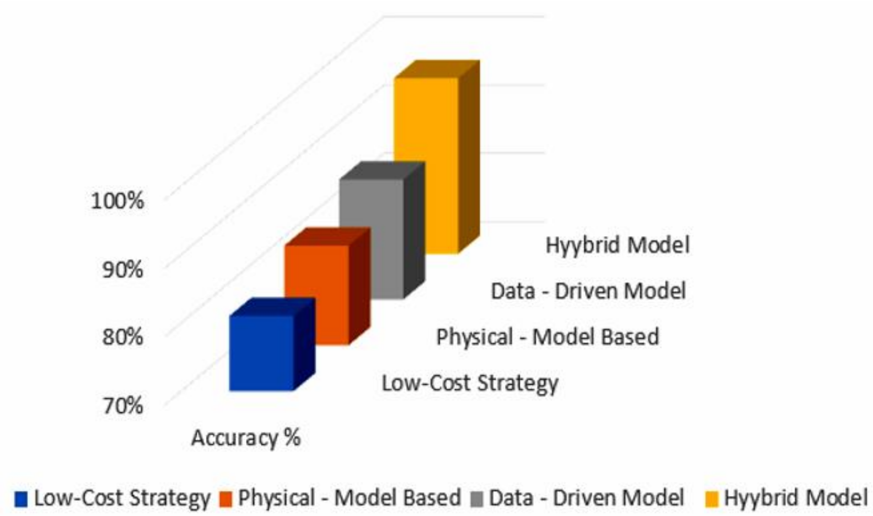

Figure 2. Accuracy of the various PdM strategies investigated, the industry-focused hybrid model returned highest accuracy of 95.68%

The relationship between vibration, temperature, and sample surface roughness was the primary baseline used to establish the accuracy of the low-cost PdM approach. Here an average accuracy of 81% was achieved. The PdM framework used by the low-cost model correlated tool wear to surface roughness coupled with selected data features to model the RUL of the cutting tool. The data modeling approach used here involved recursive partitioning and regression tree techniques to create a decision tree that can be used to classify the regression problems [9]. Analysis of the surface roughness was conducted after each test run and the resultant figures guided the tool wear prediction. This was then incorporated into the algorithm for increased accuracy.

A three-dimensional accelerometer, dynamometer, and acoustic emissions (AE) sensor were installed by [12] in the industry-focused study, the highest accuracy returned increased to 95.68%. This figure was achieved using a hybrid model that incorporated an advanced computational simulation model of the cutting head in combination with a data-driven model. This is a highly accurate result and reflects the true benefits of this PdM technique. In addition to the hybrid model, two slightly less favorable results were returned by moving to both data-driven modeling and a model-based approach. The lowest accuracy model-based solution is derived from the physical wear modeling of the cutting tool. The cutting speed is the primary input parameter, and it does not account for the large number of variables influencing tool wear, linking the result to a lower accuracy of 84.58%. Anomalies include inconsistent strain on the cutting tool as this force is far greater in the cutting speed direction than in any other direction. Additionally, variations in operational temperatures and product geometries may lead to further complications with this approach. A slight increase in accuracy is achieved by using the data-driven model which returned 87.56%. Here the sensor data is collected, and carefully reprocessed to reduce noise or drift over time, and relevant features are selected for analysis through algorithms. In a highly complex system selecting the most suitable algorithm can be challenging and numerous experiments may need to be run. The reduced accuracy of both singular approaches highlights the need to use a hybrid approach to take maximum advantage of the PdM technique.

4. Conclusions

In the presented paper several results were put forward detailing the accuracy of varied industry 4.0 retrofit PdM systems. A significant advantage is available by adopting a PdM approach in CNC machining operations. Evidence points to inherent weaknesses in single-strategy approaches where sensor data alone can be compromised due to the harsh operating environments of industrial machines. However, the inclusion of physical models that reflect the real-time wear can guide the decision-making and increase overall accuracy. This hybrid approach can therefore be used to accurately predict RUL, returning less error and a superior accuracy than singular strategies. A baseline low-cost study returned an accuracy of 81%, and a more comprehensive investigation achieved numbers as high as 95.68%. The increased accuracy was heavily linked to detailed feature extraction and algorithms, coupled with extensive physical modeling of the cutting tool. It must be noted that this accuracy increase would require expert consultation so can be perceived as a significant drawback for many SMEs. However, the resultant benefits can help to ensure unnecessary maintenance tasks are eliminated and costly downtime can be avoided as the RUL is precisely mapped. Superior quality can be achieved by taking action when a machine alerts the user of an approaching quality setpoint. As a result, the adoption of industry 4.0 standard machine capabilities should be of high focus for SMEs seeking accurate PdM techniques.

5. Conclusion

The laboratory tests conducted yielded the following general results:

- As compared to other methods, the force required for assembling parts in cryogenic and thermal assembly (using a torch) methods was minimal, almost zero, making the assembly easy.
- The cryogenic assembly method was found to be cleaner, with no environmental pollution, than other methods.
- Disassembly force was also found to be lower in the cryogenic method, at 25.7 kN, as compared to other methods.
- After disassembling using the cryogenic method, the parts had a high surface quality, with a surface roughness of 0.8 microns. Therefore, these parts can be reused as new material, with uniform stress distribution in contact surfaces sufficient to prevent relative movement and fretting fatigue.
- For subsequent assembly, the pressing method with interference fit was recommended over thermal methods due to less force required for disassembly and better surface quality, although the uniform distribution of radial forces between mated surfaces was not expected.
- The cryogenic assembly method did not alter the parts' energy-absorbing ability or hardness, indicating that it did not change the microstructure and properties of the parts.
- Although expansion fit of parts at high temperatures resulted in easy assembly, uniform radial forces, and high disassembly force, non-uniform heating, and oxidation had side effects. Therefore, uniform heating at a furnace with controlled atmosphere is recommended in this method.
- Compared to thermal assembly, the cryogenic assembly method has the added advantage of being a cleaner and safer process, resulting in cost savings.

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