Feasibility Study for the Development of a Diagnostic and Prognostic System on a High-Speed Rotating Cutter

Feasibility study for the development of a diagnostic and prognostic system on a high-speed rotating cutter

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Abstract. The integration of artificial intelligence and advanced machine learning techniques has radically changed the safety and reliability of industrial systems. This innovative paradigm led to the widespread adoption of condition-based maintenance strategies, with vibration monitoring emerging as a milestone technique. This study, conducted in collaboration with Tecnau SRL, investigates the feasibility of implementing a diagnostic and prognostic system for their "Revolution 50" series apparatus. This work explores machinery behaviour through endurance tests to lay the foundation for the future development of anomaly detection and machinery health classification. Experimental tests facilitate continuous monitoring under various operating conditions to potentially conceive real-time industrial diagnostic systems. Endurance tests reveal promising results, showing the potential for accurate recognition of the machine state of health. Multi-scale signal analysis highlights the significance and the detection of transient and steady-state phases, improving the effectiveness of potential real-time monitoring strategies. Future research directions include further industrial development of real-time monitoring systems, optimization of classification models, and exploration of cost-effective sensor selection and acquisition systems.

Keywords: machine diagnostics, machine prognostics, condition-based maintenance, vibration monitoring, signal processing, multi-scale analysis.

1 Introduction

Artificial Intelligence (AI) has transformed numerous scientific fields, including mechanical engineering, by offering innovative solutions to enhance the safety and reliability of industrial systems [1]. Through the application of advanced Machine Learning (ML) techniques, AI has laid the foundations for new frontiers in optimizing the safety and reliability of industrial systems. Predictive maintenance has rapidly developed thanks to the ability to monitor and predict the State Of Health (SOH) of machinery [2, 3]. This approach, known as Condition-Based Maintenance (CBM), aims to improve operational performance, reduce costs, and ensure a safer working environment, especially in complex industrial settings with high technological advancement [4, 5].

One of the key elements of CBM is represented by Vibration Monitoring (VM), a versatile, reliable, and cost-effective technique [6]. Accelerometric signals are processed for health classification using advanced methodologies [7–9]. Novelty Detection (ND) emerges as a highly effective anomaly detection technique [10]. This approach aims to identify significant deviations from reference data, enabling the prompt detection of abnormal operating conditions. The ND integration with optimization algorithms, such as heuristic techniques, has proven to be particularly promising in diagnosing complex machinery, contributing significantly to the definition of preventive and predictive maintenance strategies [11]. Managing the growing data volume from industrial systems requires robust Big Data strategies [12]. Approaches for data extraction, selection, and dimensionality reduction ensure accurate analysis for machinery monitoring [13, 14].

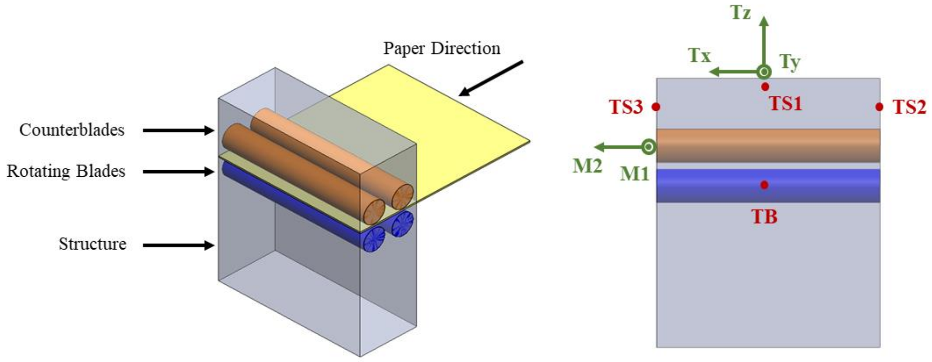
This work proposes a novel combination of techniques, facilitating the development of a diagnostic system for an application that has not been extensively explored in the existing literature. This collaboration with Tecnau SRL [15] aims at implementing a diagnostic and prognostic system in one of their machines, starting with a preliminary analysis to potentially use ML techniques such as classification. A similar study was conducted in [16] on another machine for paper processing and on-demand book production. Although the goal may seem similar from the perspective of predictive maintenance, the development of the two systems for recognizing the SOH of the machinery differs significantly. This difference is mainly due to the nature of the two machines. Indeed, in the present work, the machinery performs the cut activity using rotating blade systems mounted on cylinders. There exist specific studies about rotating machinery diagnostics and prognostics [17, 18]. CBM was investigated by implementing temperature sensors (infrared pyrometer and thermocouples) to the accelerometer system for VM, potentially integrated into a Supervisory Control And Data Acquisition (SCADA) system. The experimental campaign was initially set up using Design Of Experiments (DOE) techniques [19] and subsequently developed into endurance test acquisitions for continuous monitoring under different operating conditions. The analyzed features determined the feasibility of machinery condition monitoring, aiming for future industrial diagnostic system development.

Specifically, Section 2 describes the machinery under analysis, the design of experiments, and the entire data acquisition system. Section 3 presents both the method and the corresponding results obtained. Finally, the conclusions are reported in Section 4.

2 System and Dataset Description

2.1 Test Bench

The machinery produced by Tecnau, belonging to the "Revolution 50" line, consists of an advanced cutting system designed to integrate with high-speed printing systems. The system is primarily equipped with single or double rotating cutters, which offer excellent performance at high operating speeds. The critical components of the machinery are the rotating blades. These cylindrical bodies enable the cutting of paper rolls into sheets of different sizes, thanks to their variable rotational speed. Each machine is primarily composed of two rotating blades and two respective counter-blades, which experience periodic impacts. Figure 1 shows a simplified description of the cutter machine and its main elements. For this reason, the analysis and the experimental campaign aim to measure and study the signals generated by these components, primarily transmitted vibrations and temperature.



(a) (b)

Figure 1. (a) Simplified description of the cutter machine. (b) Sensor positioning: thermocouples (TS), infrared pyrometer (TB), uniaxial (M) and triaxial (T) accelerometers.

2.2 Design of Experiments

Experimental tests were initially programmed via Design Of Experiments (DOE). The main aim is to ensure optimal paper cutting for high-quality final products and, consequently, to recognize machinery health, particularly the rotating blade, during non-operating cycles. Many factors could influence the measurements under canonical operating conditions: (1) the rotational speed of the blades, (2) the type of processed paper, (3) the room temperature, (4) the machine temperatures, and (5) the single or simultaneous activation of the blades.

However, the DOE scheduled tests have been simplified thanks to the following considerations. Given the functioning of the machinery, its diagnostics can be performed through some standardized non-operating cycles scheduled at the beginning of each production cycle. Indeed, it has been empirically demonstrated that performance degradation does not occur suddenly. Thus, a constant blade rotation speed and a single damaged machinery condition were simulated by adjusting the blade setting. This yields two levels of study on the blade adjustment factor representing machinery SOH (i.e., ideal and imperfect conditions) are obtained. Since the repeatability of these adjustments is crucial, the test execution order minimizes blade disassembly for feasible and repeatable comparison between conditions. Furthermore, since it is difficult to adjust the temperature to obtain comparable measurements, endurance tests were performed, considering continuous temperature levels rather than discrete ones.

The room temperature may initially be assumed negligible. Finally, to avoid confounding effects, the study of the blades was planned independently, decoupling them to prevent their interaction. The diagnostics is thus performed by repeating the same non-operating cycle, activating a single blade at a time.

In summary, at least two endurance tests are required (machinery in healthy and damaged conditions). Indeed, endurance tests allow the analysis of both transient and steady-state conditions as the temperature varies.

2.3 Data acquisition

The endurance tests were repeated to measure the signals related to the machinery in an ideal health state and including an anomaly (damaged condition). The tests were conducted maintaining a constant sampling frequency of 25.6 kHz, ensuring a sufficient test duration to reach a predetermined thermal excursion, and maintaining a constant rotating speed profile throughout the endurance test. It is important to note that environmental conditions (e.g., room temperature) may constitute confounding and uncontrollable factors in the analysis.

The employed acquisition system consists of a cDAQ-9185 chassis, three 4-channels NI-9234 modules (4 channel, sampling frequency f_s = 51.2 kS/s/channel, ±5 V), a NI 9203 module (provided with 8 current inputs ±20 mA), three PCB 355B03 monoaxial accelerometers, and a PCB 356A16 triaxial accelerometer with range equal to ±50 g. Temperature sensors, including the Optris CT4M fast temperature sensor (a high-speed pyrometer with an exposure time of 90 μs) for measuring the blade temperature and three thermocouples on the structure, were implemented alongside accelerometer measurements to monitor blade and structural temperatures. This setup facilitates studying temperature trends during operation and inferring machinery deformations. Indeed, preliminary tests suggest that variations in coupling tolerances and damages are the main causes of cutter malfunction. Since the structure temperature varies slowly, these measurements have been sampled at a lower frequency. This acquisition system has been exclusively used for an initial investigating phase aimed at understanding the cutter functioning, given its significant cost and ability to ensure high precision. Future developments foresee reducing the sensor specifications to find an optimal cost-performance trade-off.

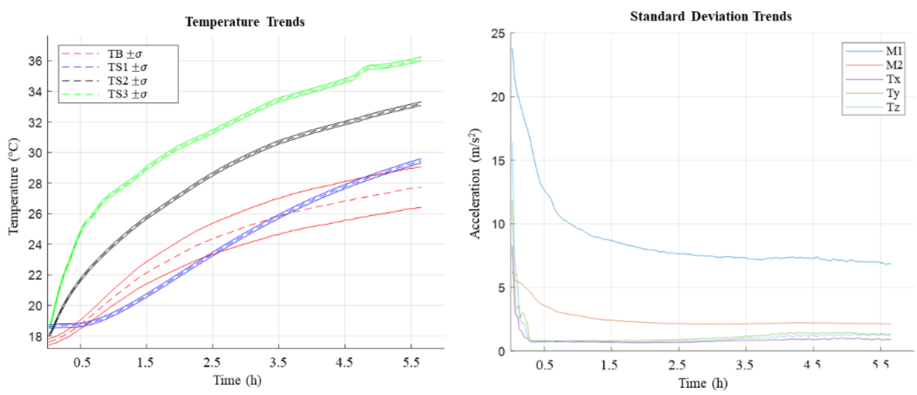
Figure 1 depicts the sensors positioning, determined based on the machinery functioning. For instance, the triaxial accelerometer has been placed in the proximity of the counterblade to minimize the transmission path from the phenomenon origin and, consequently, from the critical component under monitoring.

3 Methodology and Results

3.1 Preliminary Analysis

The preliminary study aims to understand the machinery functioning and, consequently, how its operational conditions vary during a working cycle. For this reason, an endurance test lasting approximately 6 hours was initially conducted. Due to the large amount of data to analyze, only a macro-scale analysis was performed at this stage.

Figure 2 depicts the trends of the average temperatures and their respective standard deviations, concerning the healthy condition. The extracted features were calculated over a 60-second time window. Trends show increasing patterns due to machinery operation, with similar trends for symmetrically positioned sensors TS2 and TS3, although TS2 exhibits lower temperatures possibly due to environmental and operational variability. Additionally, it is worth noting how the standard deviation ranges measured by the pyrometer (blade temperature) increase as the test progresses. Thus, as expected, the blade temperature increases more compared to its cylindric body, resulting in a higher temperature delta. Lastly, by examining the slopes of the four curves, it can be inferred that the main heat source is near the lateral sensors, as they exhibit a sudden temperature increase while the average temperatures of the rotating blade and sensor TS1 show a certain delay.



(a) (b)

Figure 2. (a) Temperature trends during the preliminary endurance test. Dashed lines represent the mean value, while the continuous lines the standard deviation, $\pm\sigma$. (b) Trends of standard deviations of accelerations during the entire preliminary endurance test.

Since the mean values of accelerations should be zero (as accelerometers are not subject to displacement), Figure 2 displays the trend of standard deviations throughout the entire endurance test. As observed, the trend recorded by all sensors is decreasing and reaches a knee/minimum at different moments.

3.2 Macro-scale

The long-lasting duration of the endurance test (approximately 6 hours) resulted in a large volume of data to analyze. Therefore, shorter recordings (about an hour) have been measured, knowing a priori the machine behavior and its different phases. The first measurement regards the machine activation and the initial transient, and then another acquisition under approximately steady-state conditions, i.e., after hours of machinery operation. Hence, four endurance tests were conducted: two with the optimal blade (healthy conditions) and two with an irregular configuration (damaged conditions), performed under conditions as similar as possible.

Furthermore, a multi-scale analysis was performed to reduce the computational burden due to the large amount of data. Multi-scale analysis refers to the analysis of the cutter at multiple levels of temporal scales. The macro-scale analysis involved extracting features from each recording over relatively large time intervals. This approach allows observing the overall trend of the recorded physical quantities and subsequently isolating recordings of greater interest for a more detailed analysis in the different phases of machinery operation: activation, transient, and steady state. Indeed, systems often exhibit behaviors or properties that vary significantly across different scales. The temperature-related features were primarily used to compare the operational conditions of the four endurance tests and understand if a comparison between the different tests was reasonable.

The most commonly used features have been extracted from the signals and are reported in Table 1, where $y(t_k)$ represents the acceleration signal as a quantity discretized during the acquisition process, and N is the number of samples, variable according to the multi-scale analysis. To summarize, the following 44 features were extracted: mean value and variance (across all 10 channels), skewness, kurtosis, and positive/negative peaks (only for acceleration measurements). These features were converted into z-scores to standardize the magnitude orders of the different channels.

Table 1. List of extracted features.

Feature	Equation	
Mean value	$MEAN = \frac{\sum_{k=1}^{N} y(t_k)}{N}$	(1)
Variance	$VAR = E\left[\left(\frac{y(t_k) - \bar{y}(t_k)}{\sigma_y}\right)^2\right]$	(2)
Skewness	$SKEW = E\left[\left(\frac{y(t_k) - \bar{y}(t_k)}{\sigma_y}\right)^3\right]$	(3)
Kurtosis	$KURT = E\left[\left(\frac{y(t_k) - \bar{y}(t_k)}{\sigma_y}\right)^4\right]$	(4)
Positive peak	$PEAK^{+} = \max\big(y(t_k)\big)$	(5)
Negative peak	$PEAK^{-} = \min\big(y(t_k)\big)$	(6)

3.3 Micro-scale

The feature extraction at the micro-scale was performed by exploiting the infrared pyrometer signal, monitoring the rotating blade. Indeed, the features were calculated over time windows corresponding to a complete blade rotation. Figure 3 depicts the temperature trend measured by the pyrometer. In addition to highlighting the temperature difference between the blade and the rotating cylindric body, it allows the calculation of the rotation period, coinciding with the temporal window for feature extraction.

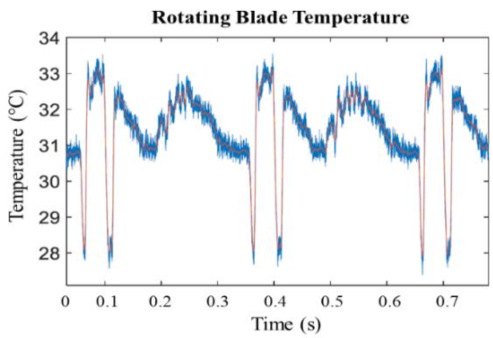


Figure 3. Example of a signal acquisition by the pyrometer to highlight the blade rotation.

Figure 4 illustrates the comparisons between the extracted features. For the sake of conciseness, only the comparison during the initial transient phase is presented, and the mean values are not considered as they are theoretically null and not relevant for the recognition of blade conditions.

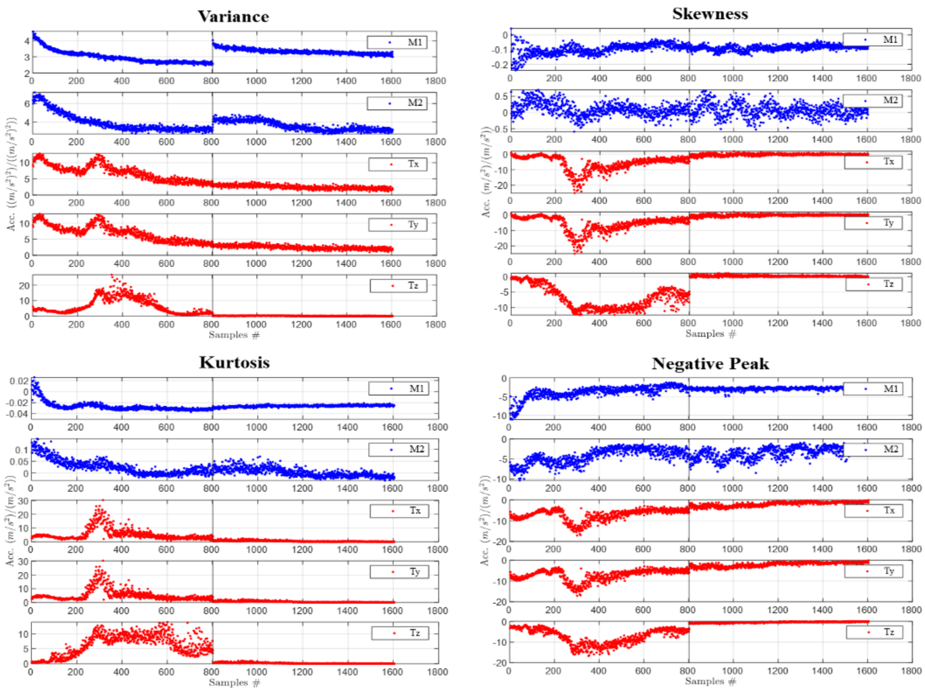


Figure 4. Feature comparison inherent to the transient phase to highlight the differences between the two SOH (Features n. 1-800: healthy blade; features n. 801-1600: damaged blade).

The results demonstrate a visible and objective difference in the trends of the features between the two machine SOH, providing a solid foundation for the development of an accurate classification model. By reproducing the statistical analysis conducted in

[16], a significant deviation between the two distributions (correctly and not adjusted blade) was verified through a simple Student's T-test at a 5% confidence interval. With only two distributions, conducting a one-way ANOVA is unnecessary, as the focus is solely on identifying the blade effect. Post-hoc ANOVA analyses (i.e., multivariate comparison techniques) are also unnecessary, as any deviation would only be detected between the two distributions being analyzed if the null hypothesis is rejected. To properly assess these results, the normality and homoscedasticity assumptions were checked using Q-Q plots, Jarque-Bera, Lilliepots test for the former, and Bartlett's test for the latter.

4 Conclusions

Endurance tests were performed and analyzed to compare different machine SOH under analogous operating conditions. A multi-scale analysis enabled observing signal trends, understanding machinery behavior, and identifying critical phases. Attention was given to both transient and steady states to accurately recognize the blade conditions across operational phases. The damage detection was prearranged through an initial non-operating cycle when the machinery starts from a standstill. However, the steady-state phase could lead to further exploring possible real-time monitoring strategies.

The obtained results proved to be promising, indicating feasibility for developing a diagnostic and prognostic system to accurately assess machinery health. Future work should focus on further system development, involving real-time monitoring, classification models, ML algorithms, and including analyses (such as the principal component analysis) to decorrelate the trends due to temperature effects. Additionally, exploring system downgrade possibilities, such as reducing sampling frequency and the number of sensors, could significantly reduce diagnostic system costs and facilitate industrial implementation. Finally, the proposed method holds potential for adaptation and application across various machinery types, validating its ability to generalize effectively.

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5 References

1. Liu, R., Yang, B., Zio, E., Chen, X.: Artificial intelligence for fault diagnosis of rotating machinery: A review. Mech. Syst. Signal Process. 108, 33–47 (2018)
2. Viale, L., Daga, A.P., Fasana, A., Garibaldi, L.: Least squares smoothed k-nearest neighbors online prediction of the remaining useful life of a NASA turbofan. Mech. Syst. Signal Process. 190, 110154 (2023). https://doi.org/10.1016/j.ymssp.2023.110154

3. Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., Nandi, A.K.: Applications of machine learning to machine fault diagnosis: A review and roadmap. Mech. Syst. Signal Process. 138, 106587 (2020)
4. Jardine, A.K.S., Lin, D., Banjevic, D.: A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech. Syst. Signal Process. 20, 1483–1510 (2006). https://doi.org/10.1016/j.ymssp.2005.09.012
5. Worden, K., Dulieu-Barton, J.M.: An Overview of Intelligent Fault Detection in Systems and Structures. Struct. Health Monit. 3, 85–98 (2004). https://doi.org/10.1177/1475921704041866
6. Randall, R.B.: Vibration-based condition monitoring: industrial, automotive and aerospace applications. John Wiley & Sons (2021)
7. Daga, A.P., Garibaldi, L.: Machine vibration monitoring for diagnostics through hypothesis testing. Information. 10, 204 (2019)
8. Tiboni, M., Remino, C., Bussola, R., Amici, C.: A review on vibration-based condition monitoring of rotating machinery. Appl. Sci. 12, 972 (2022)
9. Daga, A.P., Garibaldi, L., He, C., Antoni, J.: Key-Phase-Free Blade Tip-Timing for Nonstationary Test Conditions: An Improved Algorithm for the Vibration Monitoring of a SAFRAN Turbomachine from the Surveillance 9 International Conference Contest. Machines. 9, 235 (2021)
10. Pimentel, M.A., Clifton, D.A., Clifton, L., Tarassenko, L.: A review of novelty detection. Signal Process. 99, 215–249 (2014)
11. Viale, L., Daga, A.P., Fasana, A., Garibaldi, L.: From Novelty Detection to a Genetic Algorithm Optimized Classification for the Diagnosis of a SCADA-Equipped Complex Machine. Machines. 10, 270 (2022). https://doi.org/10.3390/machines10040270
12. Daga, A.P., Fasana, A., Garibaldi, L., Marchesiello, S.: Big Data management: A Vibration Monitoring point of view. In: 2020 IEEE International Workshop on Metrology for Industry 4.0 & IoT. pp. 548–553. IEEE (2020)
13. Viale, L., Daga, A.P., Fasana, A., Garibaldi, L.: Dimensionality Reduction Methods of a Clustered Dataset for the Diagnosis of a SCADA-Equipped Complex Machine. Machines. 11, 36 (2023). https://doi.org/10.3390/machines11010036
14. Carreira-Perpinán, M.A.: A review of dimension reduction techniques. Dep. Comput. Sci. Univ. Sheff. Tech Rep CS-96-09. 9, 1–69 (1997)
15. Tecnau SRL, https://www.tecnau.com/
16. Viale, L., Daga, A.P., Garibaldi, L., Caronia, S., Ronchi, I.: Books Trimmer Industrial Machine Knives Diagnosis: A Condition-Based Maintenance Strategy Through Vibration Monitoring via Novelty Detection. Presented at the ASME 2022 International Mechanical Engineering Congress and Exposition February 8 (2023)
17. Heng, A., Zhang, S., Tan, A.C.C., Mathew, J.: Rotating machinery prognostics: State of the art, challenges and opportunities. Mech. Syst. Signal Process. 23, 724–739 (2009). https://doi.org/10.1016/j.ymssp.2008.06.009
18. Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., Siegel, D.: Prognostics and health management design for rotary machinery systems-Reviews, methodology and applications. Mech. Syst. Signal Process. 42, 314–334 (2014). https://doi.org/10.1016/j.ymssp.2013.06.004
19. Antony, J.: Design of experiments for engineers and scientists. Elsevier (2014)