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IMPLEMENTATION AND OPTIMIZATION OF PREDICTIVE MAINTENANCE STRATEGIES THROUGH VIBRATION ANALYSIS IN MECHANICAL SYSTEMS

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ABSTRACT

Title of thesis: Implementation and optimization of predictive maintenance strategies through vibration analysis in mechanical systems

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Predictive maintenance (PdM) is transforming industrial maintenance by overcoming the disadvantages of traditional reactive and preventive techniques through real-time condition monitoring to enhance mechanical system efficiency and reliability. This study discusses crucial factors such as sensor selection, signal processing, and machine learning integration while focusing on getting the best out of PdM through vibration analysis in rotating machinery and SPM analysis.

By evaluating vibration sensors, advanced signal processing techniques (such as Fast Fourier Transform and Wavelet Transform), and an integrated monitoring solution platform (Condmaster) leveraging machine learning models (such as CNNs and LSTMs) for accurate fault detection, the study establishes a PdM framework. Optimizing sensor configurations, identifying fault features, and making the model interpretable with a focus on IoT and edge computing for real-time monitoring are key objectives to minimize false alarms.

Research was also carried out at the Arconic plant in Szekesfehervar, Hungary, where machine condition monitoring is done by the SPM method. The working principles of the leveler machine are discussed together with the setup and installation of the SPM control system as well as data analysis. It discusses how efficiently the monitoring method has been able to detect faults and possible future improvements and developments in enhancing better performance and reliability for the system.

The proposed framework can reduce costs, increase availability, and be compliant with Industry 4.0 by out-performing the conventional methods. The results provide useful insights for the industry as well as for future research in the development of intelligent maintenance systems.

Keywords: Industry 4.0, signal processing, machine learning, rotating machinery, vibration analysis, SPM, and predictive maintenance.

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1. Introduction

Machinery lies at the core of all production systems in industrialized settings. In manufacturing, energy production, or processing industries, in fact, all rely on mechanical systems such as motors, pumps, gearboxes, compressors, and turbines. These mechanical systems are pivotal elements that must run smoothly and breakdown whether anticipated or unanticipated can cause critical production downtime accompanied by high economic losses and compromise safety. Keeping these systems healthy is therefore a strategic imperative in organizations that strive for continuity at lower costs and competitiveness (Shtub 2014).

The traditional maintenance strategies were either reactive (run the equipment until it fails) or preventive (maintenance is scheduled without considering the actual state of the machine). Preventive maintenance slows breakdowns but results in unnecessary maintenance, high labor cost, and wasted component life. Reactive maintenance achieves maximum utilization of machines but sudden, drastic, or total failures may result. These two methods have deficiencies that present day industries can no longer tolerate, especially in lean operations, automation and Industry 4.0 philosophies (Mobley, 2002; Ahmad and Kamaruddin, 2012).

Predictive Maintenance (PdM) is a considerable advancement in maintenance philosophy. PdM differs from fixed schedules or breakdowns, as it involves determining the current condition of equipment in real-time or near real-time to initiate maintenance only as needed. PdM not only enhances equipment availability but also significantly slashes costs by making resources more efficient usage and increasing machinery longevity (Mobley, 2002).

Vibration analysis happens to be one of the most potent and widely used techniques under predictive maintenance. Mechanical systems in operation produce diagnostic vibrations; these vibrations subtly change as components degrade. For example, bearing faults, shaft misalignment, unbalanced rotors, and incorrect gear mesh adjustments each leave a particular signature within the vibration spectra. By monitoring or recording or otherwise acquiring such signals, it becomes possible to detect faults at an early stage-before they have even reached a critical level (Randall 2011; Jardine, Lin and Banjevic 2006).

With the advent of new technology, vibration-based maintenance systems have greatly improved. The advancements in high-sensitivity sensors, affordable data acquisition systems, and powerful signal processing methods enable detailed condition monitoring implementation in a wide range of industrial machines (Randall, 2011). Machine learning applications further support auto pattern recognition and anomaly detection besides automated fault categorization at high precision levels (Zhao, Yan, Wang and Mao, 2019).

In addition, the evolution to smart factories and cyber-physical systems in line with the Industry 4.0 vision places predictive maintenance as a core feature of intelligent production systems. Sensor networks, cloud computing, and artificial intelligence integration enable not only real-time diagnostics but decision making as well, boosting operational efficiency even more (Lee, Bagheri and Kao, 2015).

However, optimizing predictive maintenance systems through vibration analysis remains an extremely challenging task and a high level expert understanding is required in sensors, signal processing, machine learning as well as mechanical dynamics of the system under observation. Either most existing systems are highly unspecific or insufficiently optimized for the particular piece of equipment in which they find themselves effective only restricted by many false alarms or negatives or unaffordable deployment (Hosseini, 2024). This research addresses these challenges by designing and optimizing a predictive maintenance approach with vibration analysis for rotating mechanical systems. It discusses the proper choice of sensors, vibration feature extraction from vibration signals, and the deployment of machine learning models to reliably and efficaciously identify early indications of impending failure.

1.1 Problem Definition

While vibration analysis has huge potential for anticipatory maintenance, most industries are still struggling with:

- Choosing the most appropriate sensing technologies and data acquisition systems;
- Effective interpretation of large amounts of vibration data;
- Identifying early faults with high accuracy at low false alarm rates;
- Scaling predictive systems to different kinds of machinery that have different operational load levels.

Also, present approaches do not strongly support optimization strategies that integrate sensor configuration, feature selection, and algorithmic tuning within a comprehensive combined framework. Slightly less robust systems leave fault detection either as a conservative estimate high false positives or missing faint indications of impending failure. An exploration will therefore be undertaken on optimizing the whole vibration-based predictive maintenance pipeline right from sensor deployment up to fault prediction.

1.2 Significance of the Study

This research adds to the existing literature by presenting an integrated framework for the implementation and optimization of predictive maintenance via vibration analysis. This research is significant in the ways that:

- Mechanical failures are detected long before they actually occur, consequently increasing the reliability and uptime of critical equipment.
- Reduction can be achieved in unnecessary maintenance as well as reducing downtime; hence dual aspects of cost reduction.
- It is applicable to different rotating machines and various production setups.
- The study exploits recent advances in machine learning and sensing technologies, in line with Industry 4.0 and smart maintenance trends.
- It covers the research gap by combining signal processing, sensor assessment, and model optimization within one framework.

1.3 Research Objectives

The most efficient implementation of predictive maintenance by vibration analysis in mechanical systems and how best it can be optimized shall be discussed within this study. The system developed will present high fault detection accuracy and also ensure cost efficiency and scalability.

General Objective

Diagnosis of faults in rotating mechanical systems, design, and optimization of a predictive maintenance system with vibration analysis.

Specific Objectives:

- Identifying and classifying the different sensors to be used for predictive maintenance with special focus on vibration sensors.
- Study and pre-processing of vibration signals acquired from rotating machines to extract fault related features.
- Application of machine learning algorithms for mechanical fault prediction using vibration signals.
- Optimization of sensor selection, data processing technique and model accuracy through parameter tuning and algorithm comparison.
- Evaluation of optimized predictive maintenance solution on a real-world or benchmark test case Comparing how efficient it is with traditional or less optimized methods.

1.4 Research Questions

To answer the above research goals, the study will address the following research questions:

Technical Questions:

- What types of sensors (vibration and non-vibration) are most suitable for predictive maintenance in rotating mechanical systems?
- How can vibration signals be efficiently processed to extract features representing distinct fault modes such as imbalance, misalignment, or wear in a bearing?
- Which artificial intelligence algorithms offer the highest accuracy and reliability in making vibration-based mechanical failure predictions?

Implementation & Optimization Questions:

- Which strategies work best in optimizing the process of fault prediction? Feature selection, tuning parameter values, or enlarging the dataset.
- How does the optimized vibration-based predictive maintenance system perform relative to a traditional system in terms of accuracy for fault detection and cost efficiency?
- What are the practical challenges and constraints on vibration-based predictive maintenance systems when implemented in real industrial environments?

2. Overview of Predictive Maintenance

Predictive maintenance (PdM) is a proactive maintenance strategy that assures failures in equipment can be anticipated and detected by monitoring the operating condition of assets, most often implemented as continuous online asset condition monitoring. This is better than current reactive or preventive maintenance strategies, which are either inefficient or over-cautious. PdM enables organizations to carry out maintenance only when it is necessary as indicated by real-time or historical information on the state of a machine (Mobley, 2002).

Traditionally, reactive maintenance resulted in unplanned shutdowns and possible hazards to safety. Preventive maintenance was dependent on predicted intervals and could result in over-maintenance. PdM provides a cost-effective, knowledge based, optimized solution. It reduces unnecessary interventions and ensures that machines are maintained at a time corresponding to required conditions (Mobley, 2002; Ahmad and Kamaruddin, 2012).

The basic conditions of monitoring involve later physical data acquisition from machines containing vibration, temperature, sound signals, current, and lubrication characteristics. Of these most effective diagnostics used tools is vibration analysis particularly in rotating machinery (Randall 2011; Jardine Lin & Banjevic 2006). Slight variations either in the amplitude or frequency components of vibration can indicate incipient developments of mechanical faults such as an unbalanced condition misalignment wear in bearings or gear teeth.

PdM incorporates sensing, data acquisition, signal processing, and diagnostic modeling, Lin and Banjevic (2006) summarized. The functional components work together to detect anomalies as well as predicting a system or component Remaining Useful Life (RUL). With such information, maintenance teams can better improve the prioritization of task allocation and resource planning. PdM saves big on costs and adds productivity in industrial settings.

Results of estimates done by Mobley (Mobley, 2002) show that predictive maintenance programs can reduce maintenance expenditures as much as 30% while eliminating catastrophic failures by over 70% besides enhancing availability and reliability within the same system. Most urgently needed are such benefits in high risk manufacturing and electricity generation plus oil and gas together with aerospace.

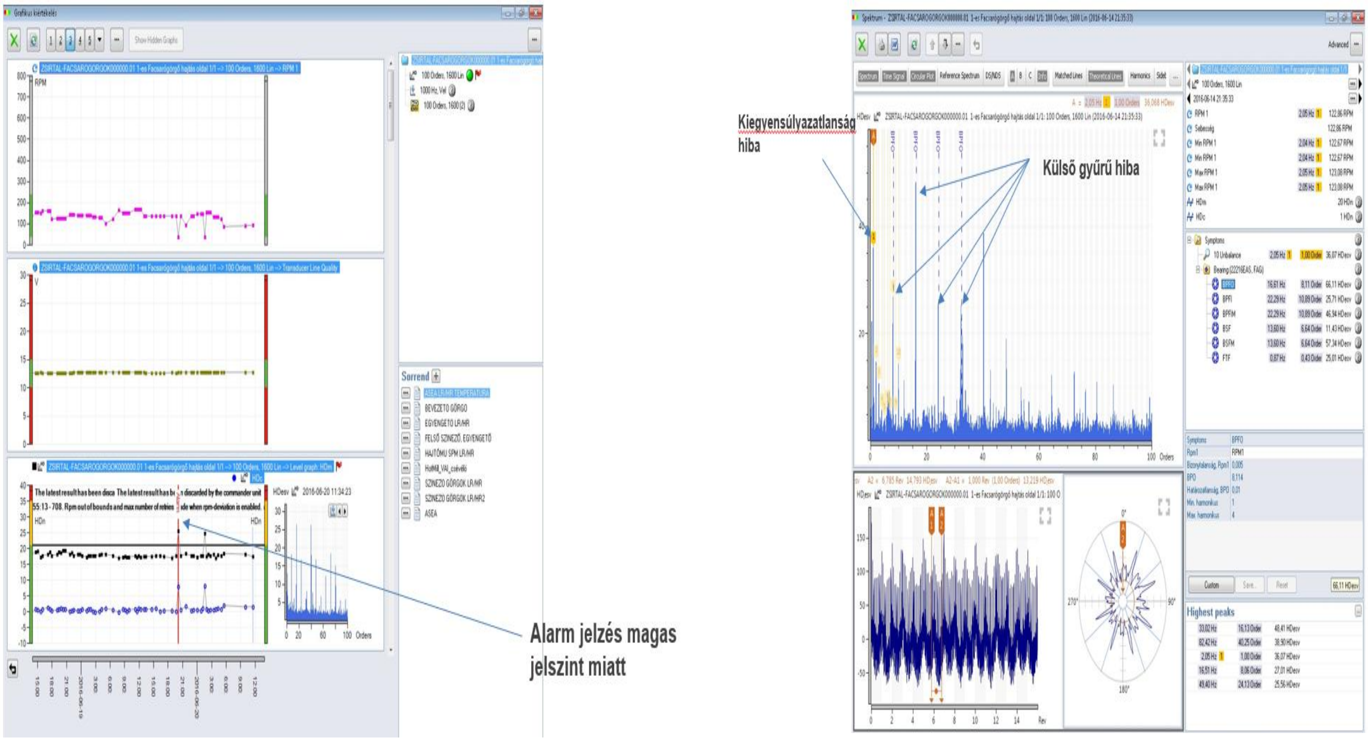
In addition, PdM has become this important under the Industry 4.0 paradigm with machines being connected through IoT and computations carried out by cloud computing as well as machine learning. Predictive maintenance in such a situation becomes not an auxiliary tool but a main feature of cyber-physical production systems (Lee, Bagheri and Kao, 2015). Finally, PdM supports the evolution of maintenance strategies from calendar based to condition based as well as risk based approaches thereby increasing transparency into asset health and supporting strategic decision making in complex operational environments.

2.1 Vibration Analysis in Rotating Machinery

Vibration analysis remains among the most popular approaches in predictive maintenance (PdM) for fault detection and diagnosis of mechanical defects within rotating machinery. Motion of internal components such as shafts, bearings, and gears is normally responsible for the vibration in machines. Therefore, a machine can operate successfully only if it passes through healthy vibrations that imply all its components are perfect or devoid of any kind of imperfection. In case these components become faulty due to unbalance, misalignment, wear or mechanical looseness then the imperfections develop into distinct variations in the vibration signal (Randall, 2011).

The theory is that all faults create unique signal signatures in a time, frequency, or time-frequency domain. For example, faulty bearings can display high frequency impulsive signals, while imbalance can manifest itself as high amplitudes at running frequencies. Therefore, not only fault detection but fault classification and estimation of severity as well (Zhao, Yan, Wang and Mao 2019).

1. Figure: Squeeze Roller Bearing Fault Detection – Symptom Analysis, Outer Bearing Ring and Unbalance and Trend Analysis
(Source: Zsolnai, A. (2016). NEZ SPM Diagnostic Report 20160620. [Internal company document]. Arconic.)



Mechanical movement is transformed into electrical signals by piezoelectric accelerometers normally mounted on the machine housings near important components. The signals can then be processed and examined for features such as RMS, kurtosis, crest factor, and harmonic frequencies (Randall, 2011; Suganya and Rajavel, 2025).

Advanced signal processing algorithms such as Fast Fourier Transform (FFT), Wavelet Transform (WT), and Hilbert Huang Transform (HHT) have made it possible to detect small fault features even under varying operating loads. The features include stationary and non-stationary components picked by these algorithms from the raw signals therefore enhancing the diagnosis performance as well as reducing false alarms (Kumar, Wyłomańska, Zimroz and Xiang, 2025).

Very recently it has been proven by experiment (Navarro-Navarro, Biot-Monterde and Ruiz-Sarrio, 2025) that vibration together with current signal analysis can detect synchronous reluctance motor misalignment faults because hybrid signal fusion is more sensitive to early failures. They have proposed an IoT-based deep learning model with vibration analysis to increase fault accuracy with a decrease in manual inspection time in rotating machines (Le, Tran, Wang, Pham and Dao, 2025). One of the most promising developments in this domain is digital twin (DT) and health indicator (HI) technology, which generates computerized replicas of rotating machines from vibration signals. The DTs enable continuous simulation as well as real-time fault prediction even in complicated machines that run in variable conditions (Bublil, Cohen, Kenett and Bortman, 2025).

Vibration analysis is a traditional monitoring tool. The integration of vibration signal processing with AI-based classification of faults and cloud systems redefines it as one of the main core pillars in predictive maintenance systems, thus keeping it aligned with Industry 4.0.

2.2 Types of Sensors in Predictive Maintenance

The implementation of predictive maintenance (PdM) depends on timely and accurate condition information. This information is typically collected by a group of sensors. Apart from acquiring physical parameters, sensors permit raw data to be transformed into helpful deductions. The share of every sensor type's contribution changes based on the machine type, environmental restrictions, and the type of failures expected.

2.2.1 Vibration Sensors

Vibration sensors are key in observing mechanical faults of rotating machinery such as motors, pumps, and turbines. A common high-bandwidth, low-noise MEMS accelerometer most suitable for monitoring high speed vibrations is the ADXL1004 (Panduru, Walsh and Hassan, 2024). Another is the piezoelectric accelerometer PCB Piezotronics 352C33; such type of sensors has been widely used in industrial monitoring due to their stability and accuracy (Panduru, Walsh and Hassan, 2024).

2. Figure: PCB Piezotronics 352C33 Accelerometer
(Source: ResearchGate (n.d.). PCB Piezotronics accelerometers, model: 352C33. Source: https://tinyurl.com/yc3hvp28

Most frequently they are installed on structural or bearing housings. They are used together with signal processing equipment, for example: FFT, envelope analysis; to detect imbalance, misalignment, and bearing faults (Randall, 2011; Panduru, Walsh and Hassan, 2024).

2.2.2 Temperature Sensors

Temperature is particularly suited to indication of overloading, inadequate lubrication or abnormally high friction. Resistance Temperature Detectors such as the PT100 offer very accurate and stable readings while, for high temperature applications, thermocouples may be used (Chen, Wei, Wang, Wang and Li, 2022). These sensors are used to monitor gearboxes, bearings and motor windings.

Temperature sensors can also be correlated with vibration sensors to enhance diagnosis by thermal vibration correlation (Chen, Wei, Wang, Wang and Li, 2022).

3. Figure: Temperature sensor on the leveler to improve vibration analysis
(Source: Own photo, Arconic Székesfehérvár plant (2025))

2.2.3 Acoustic Emission Sensors

The acoustic sensors pick up the high-frequency stress waves which result from incipient crack development, leaks, or cavitation. Microphone based sensors, for example, are used in gearbox diagnostic systems and ultrasound sensors such as the UE Systems Ultraprobe 9000 can detect steam leaks as well as valve fault signals (Chuang, Sahoo, Lin and Chang, 2019).

Such sensors are most useful in cases where internal components are not easily accessible or where it cannot utilize vibration sensors because of structural damping

2.2.4 Current and Voltage Sensors

These include electrical sensors, such as Hall-effect current transducers, which together with Rogowski coils make it possible to monitor motor health by Motor Current Signature Analysis (MCSA). The sensors can detect faults such as bad rotor bars, unbalanced phases or varying loads (Hashemian, 2011). The most common standard current sensor used in motor current analysis systems is the LEM LA 25-NP. When information from vibration or thermal sensors is combined with current sensors, there will be an increase in predictive accuracy.

2.2.5 Oil Condition Sensors

Oil condition monitors check lubricant viscosity, contamination, water, and wear metal particles. Hydac Contamination Sensors and Parker Kittiwake Ferrous Wear Meter are used to detect metal debris in gear cases and hydraulic systems (Hong, 2020; Duchowski and Mannebach, 2006; Hong and Jeon, 2022). The sensors function mainly in identifying the patterns of wear and oil deterioration before actual mechanical failure.

2.2.6 Pressure Sensors

Pressure sensors play a critical role in hydraulic and pneumatic systems. Honeywell's PX2 Series transducers, Bosch Rexroth pressure transducers, these give real-time feedback on the integrity of a system. A drop in pressure anomaly could be indicative that there is a leak somewhere within the system; probably just blocked filters or maybe even pump failure (Shanbhag, Meyer, Caspers and Storti 2021).

4. Figure: Sensor used for Hydraulic system of Ungerer line 3
(Source: Own photo , Arconic Székesfehérvár plant (2025))

2.2.7 Smart and Wireless Sensors

Smart sensors perform several measuring functions within one single product. In most cases, wireless communication is present between smart sensors and the IoT platform to which it connects for example, SKF Enlight sensor that monitors vibration together with temperature; ABB Ability™ Smart Sensors (Pech, Vrchota and Bednář 2021). This therefore supports remote monitoring automatically logged into cloud based analytical software.

5. Figure: SKF Enlight sensor
(Source: SKF (n.d.). Source: https://share.google/images/w5kXqr8MMBvJMtTAK)

1. Table: Sensor types used in condition monitoring and predictive maintenance, their applications, and advantages
(Source: Own work)

Sensor Type	Example Models	Measured Parameter	Typical Applications	Advantages	Reference
Vibration Sensor	ADXL1004, PCB 352C33	Acceleration / Velocity / Displacement	Rotating machinery (motors, bearings, pumps)	Early fault detection (imbalance, misalignment, wear)	(Panduru, Walsh and Hassan, 2024)
Temperature Sensor	PT100 (RTD), Type-K Thermocoupe	Temperature	Motors, bearings, gearboxes	Detects overheating, lubrication issues	(Chen, Wei, Wang, Wang and Li, 2022)
Acoustic Sensor	Ultraprobe 9000 (Ultrasound)	Acoustic emissions / sound waves	Gearboxes, valves, pressure vessels	Leak and crack detection, non-contact	(Chuang, Sahoo,Lin and Chang, 2019)
Current Sensor	LEM LA 25-NP, Hall-effect sensor	Current, voltage	Motors, transformers	Detects electrical imbalances, rotor faults	(Hashemian, 2011)
Oil Condition Sensor	Hydac CS 1000, Parker Ferrous Wear Meter	Particulate, moisture, viscosity	Gearboxes, hydraulics	Predicts wear, lubrication degradation	(Hong, 2020; Hong and Jeon, 2022)
Pressure Sensor	Honeywell PX2, Bosch Rexroth	Hydraulic/pneumatic pressure	Hydraulic systems, cylinders, pumps	Detects leaks, clogs, pressure drops	(Shanbhag, Meyer, Caspers and Storti, 2021)
Smart/IoT Sensor	SKF Enlight, ABB Ability	Multi-sensor (vibration, temp., accel.)	General PdM (Industry 4.0 environments)	Wireless, remote access, integrated analytics	(Pech, Vrchota and Bednář, 2021)

2.3 Signal Processing Techniques in Predictive Maintenance

Signal processing is key to implementing efficient predictive maintenance (PdM) mainly in vibration based applications. The primary data collected from sensors, more so vibration sensors, is always noisy and complex. Signal processing enables engineers to derive such structured information out of the raw data that can easily be interpreted and associated with features representative of different machine faults. There are basically three categories under which signal processing methods applied for PdM can be broadly classified: time domain, frequency domain, and time frequency domain methods. All methods have their advantages; hence, the selection depends on the type of fault signals as well as real-time requirements.

2.3.1 Time-Domain Techniques

These deal with vibration amplitude directly as a function of time. They are being widely used in real-time threshold monitoring. Most frequently used parameters are:

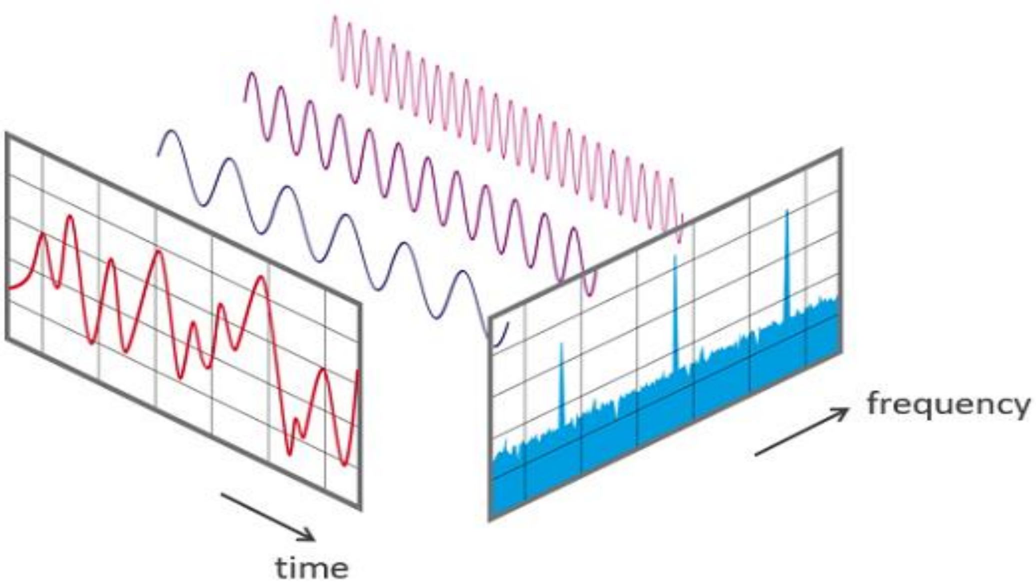
- Root Mean Square (RMS)
- Kurtosis
- Crest Factor
- Peak-to-Peak Amplitude

Very easily computed and highly interpretable, they more often fail to display fault frequency components, especially when an incipient defect is present (Randall, 2011).

2.3.2 Frequency-Domain Techniques (FFT-Based)

The Fast Fourier Transform (FFT) is the tool which takes time domain information and transforms it into the frequency domain, hence making possible fault pattern identification by frequencies such as unbalanced shaft rotation frequency, gear meshing harmonics or bearing defect frequencies. FFT is particularly effective in identifying periodic faults within stationary signals.

6. Figure: Fast Fourier Transform (FFT) plot used for vibration signal processing (Source: Nti Audio (n.d). Source: https://share.google/images/93u6gAbxYeUauIJBv)



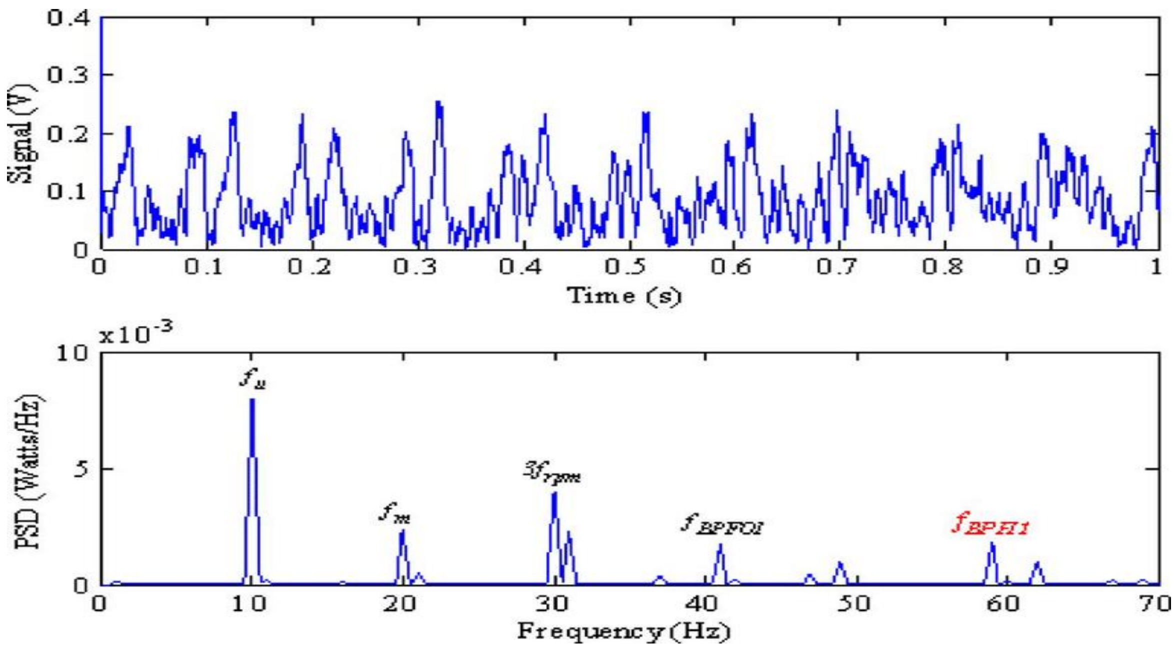
For instance, FFT was used by Mohd. Ghazali and Rahiman to detect shaft misalignment and gear wear with high accuracy in rotary machines (Mohd Ghazali and Rahiman, 2021). However, FFT is limited in non-stationary signals, where fault frequencies vary with time.

2.3.3 Impulse-Based Analysis: Envelope Detection and Shock Pulse Measurement (SPM)

Envelope analysis

Envelope detection is one of the frequently applied demodulation methods in bearing diagnostics. It analyzes high frequency signals modulated by low frequency fault impulses. Normally, a certain range of frequencies containing the bearing resonances is isolated by bandpass filtering; then, the Hilbert transform is applied to obtain the envelope of the signal. The envelope reveals periodic impacts corresponding to specific defect frequencies such as ball spin frequency (BSF), inner race (BPFI), and outer race (BPFO) frequencies (Randall, 2011; Incandela, 2018).

7. Figure: Envelope analysis of the vibration signal from a defective bearing
(Source: ResearchGate (n.d.). Source: https://share.google/images/QYp4TFot4tohP1cm8)



Shock Pulse Measurement (SPM)

Shock Pulse Measurement (SPM) is a unique vibration based technique developed particularly for monitoring rolling element bearing health. It is designed to detect shock pulses, short-duration, high frequency pressure waves generated when defects or imperfections on the bearing surfaces pass through the load zone. These shock pulses carry crucial information regarding the condition of bearing surfaces and are directly initiated by metal to metal contact or failure of lubrication. SPM isolates these transient signals and measures them to obtain an extremely sensitive and repeatable indication of bearing health useful especially in early fault detection (Randall, 2011; Lindh, 2018). General vibration analysis, however, records a broad spectrum of machine dynamics.

Operational Principles

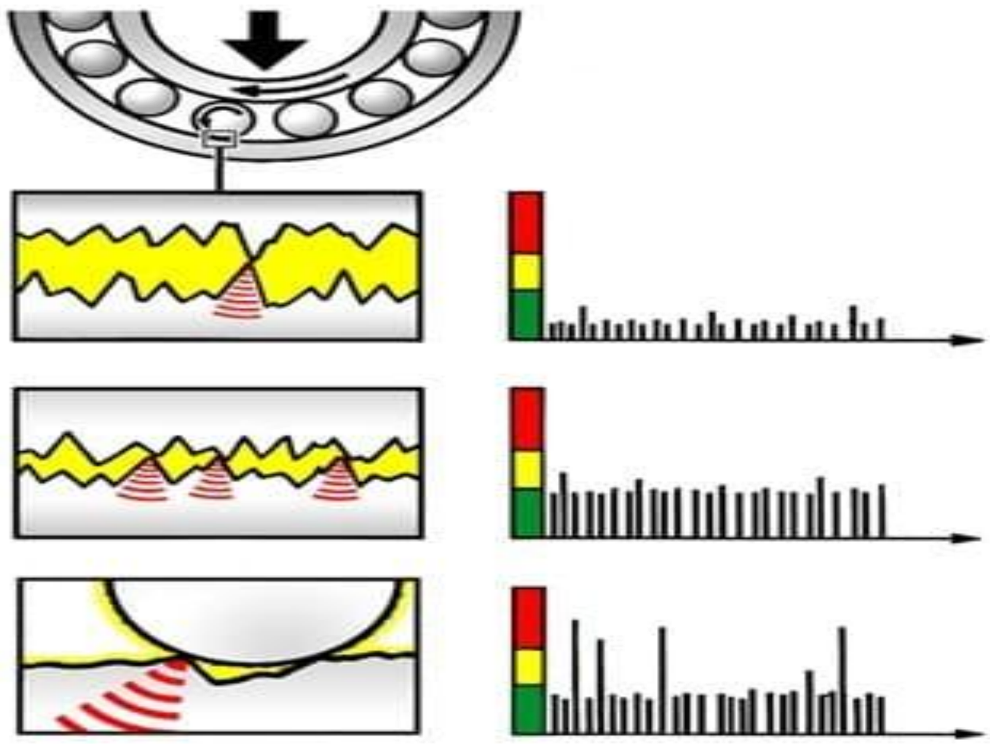
A vibration transducer signal is taken from a low narrow band resonant type transducer usually mounted on the bearing housing. The shock component of the signal is separated by filtering and then processed into two basic overall values:

- The decibel shock value, dBsv, measures the amplitude of the peak shock pulse. This indicates how strong the impacts were.
- The decibel carpet value, or dBc, is defined as the underlying background noise or carpet level created by normal surface roughness and lubrication film.

A very powerful diagnostic indicator is the difference between these two values (dBsv - dBc):

- A small gap indicates healthy bearings with adequate lubrication.
- A wide gap indicates wear or lubrication failure or bearing defects (Lindh, 2018).

8. Figure: Shock Pulse Measurement principle
(Source: MarineInsight (n.d.). Source: https://share.google/images/AeS2wlYUDLi5cSLZb)



SPM is typically suitable in applications that are online and real-time while the asset is operating because it is normally non invasive, it does not require a shutdown of the machine to perform.

Advantages of SPM

- SPM has some very obvious advantages even over conventional vibration analysis or, for that matter, envelope detection.
- It becomes highly sensitive to incipient faults, particularly in machinery operating over a wide range and low speeds.
- The general construction of the machine does not affect it since it focuses on high frequency shock energy rather than low frequency vibrations.
- It makes the diagnosis easier since standardized thresholds can be used (for instance, severity scales based on ISO 2372).
- Quantitative trend analysis: SPM values are good for watching the growth of faults because they can be trended. Lubrication monitoring effectively is difficult with conventional vibration techniques (Randall, 2011; Lindh, 2018).

Practical Applications

- Such industries have adopted SPM for condition based critical bearing monitoring
- Pulp and paper: SPM is used on calendar roll and large dryer bearings where it has to pick up loss of lubrication at an early stage.
- Mining and minerals: In difficult, dusty environments, SPM benefits both fixed and mobile equipment (conveyors, crushers, etc.).
- Wind and hydropower: SPM performs nicely within slow turning machines in which conventional vibration features are extremely weak or seem to be completely masked by noise (Lindh, 2018; SPM Instrument, 2012).

Through the use of digital signal processing, automatic fault frequency tracking and integration with online monitoring systems (for instance, Condmaster Ruby), modern implementations such as SPM HD® enhance the original technique.

2. Table: Comparative overview of SPM, Envelope Analysis, and FFT-based vibration analysis techniques
(Source: Own work adapt from Randall (2011))

Feature	SPM	Envelope Analysis	FFT-Based Analysis
Target Faults	Bearings, Lubrication	Bearings	Gears, Misalignment, Imbalance
Signal Focus	High-frequency shock pulses	Demodulated impact modulations	Harmonic frequencies
Sensitivity to Early Defects	Very High	Moderate	Low to Moderate
Suitability for Low Speeds	Excellent	Limited	Poor
Ease of Interpretation	High (dB scale)	Medium	Requires expert analysis

2.3.4 Time-Frequency Techniques

Time-frequency techniques better suit non stationary situations where machine conditions change with time. A few of them are:

Short-Time Fourier Transform (STFT): Produces time localized spectra from fixed sized windows. Helpful in identifying faults with slowly changing properties.

Wavelet Transform (WT): Uses variable window sizes to provide multiresolution analysis. The forms of WT more useful in denoising and separation of transient faults are Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) (Soualhi, Medjaher, Hawwari and Clerc, 2018).

Hilbert-Huang Transform (HHT) and Empirical Mode Decomposition (EMD): EMD is defined as an adaptive decomposition method which breaks the signal down into IMFs. The application of the Hilbert transform on each IMF will give a set of instantaneous frequencies at every time sample, suitable for non stationary and non linear signals such as those modeled for incipient fault development and propagation (Bagri, Tahiry, Hraiba, Touil and Mousrij, 2024; Pavithra and Ramachandran, 2025).

The combination of wavelet features with statistical and HHT greatly improve the accuracy of bearing fault classification. This was demonstrated by Soualhi, Medjaher, Hawwari and Clerc (2018).

2.3.5 Intelligent and Hybrid Signal Processing

New and emerging systems automatically set up PdM by fusing machine learning with signal processing. Deep learning architectures feed on raw time series data, thus skipping manual feature extraction. However, traditional signal processing is still very much handy in the course of getting features pre-processing, enhancing, and reducing dimensions before feeding into learning models (Zhao, Yan, Wang and Mao, 2019; Pavithra and Ramachandran, 2025).

2.4 Machine Learning in Predictive Maintenance

Machine learning has redefined predictive maintenance in environments where mechanical systems can continuously acquire massive amounts of sensor data, such as vibration signals. The pattern recognition models trained to detect patterns associated with degradation and impending failure provide a powerful alternative approach to traditional threshold based condition monitoring.

2.4.1 Role of Machine Learning in PdM

The main applications of machine learning in PdM for diagnostic and prognostic purposes are classification, regression, and clustering methods. Prognostics concentrates on the prediction of the remaining useful life (RUL) of components while diagnostics applies ML models which classify the state of equipment for example healthy, degraded, or faulty (Jardine, Lin and Banjevic, 2006; Zhao, Yan, Wang and Mao, 2019; Hashemian, 2011).

Machine learning models are good at dealing with nonlinear and multivariate data relations which mostly exist between vibration signals and other sensor readings (Bagri, Tahiry, Hraiba, Touil and Mousrij 2024).

Support Vector Machines (SVM), k-Nearest neighbors (k-NN), Random Forests (RF) and Artificial Neural Networks (ANN) based techniques have been reported widely used in PdM due to their high accuracies in type of fault classification supervised learning techniques (Zhao, Yan, Wang and Mao 2019; Bublil, Cohen, Kenett and Bortman 2025; Pavithra and Ramachandran 2025). However when labelled failure data is less available unsupervised methods autoencoders k means clustering used anomaly detection (Zhao, Yan, Wang and Mao 2019; Bagri, Tahiry, Hraiba, Touil and Mousrij, 2024).

2.4.2 Deep Learning Approaches

Deep Learning (DL) is a branch of machine learning which has gained much attention because of its remarkable capabilities towards raw time series data such as vibration signals hence eliminating any intensive feature engineering requirements (Zhao, Yan, Wang and Mao, 2019; Suganya and Rajavel, 2025; Pavithra and Ramachandran, 2025). Convolutional Neural Networks (CNNs) are particularly suitable for rotating machinery health monitoring due to their ability to extract both spatial and temporal features from vibration signals (Suganya and Rajavel, 2025; Pavithra and Ramachandran, 2025). Suganya and Rajavel (2025) proposed a 1D CNN model that attained high accuracy with low preprocessing for predictive health monitoring of an induction motor.

More accurate prediction of machine degradation becomes possible through the very widely applied Recurrent Neural Networks (RNN) involving Long Short Term Memory (LSTM) networks to capture sequential dependencies within time series sensor data (Zhao, Yan, Wang and Mao 2019). The application of deep architectures such as deep belief networks and stacked autoencoders for hierarchical representation learning which has shown great potential in PdM applications was summarized by Zhao, Yan, Wang and Mao (2019) in their review.

2.4.3 Data Preprocessing and Feature Engineering

This is one of the important aspects in implementing ML models for PdM, more specifically on vibration data which are mostly noisy and non stationary signals. Useful features could be extracted from raw signals using WT, EMD, and FFT (Kumar, Wyłomańska, Zimroz and Xiang, 2025; Incandela, 2018; Pavithra and Ramachandran, 2025). Such a method has been adopted wherein fault classification is improved; CNNs combined with EMD have been used to denoise as well as enhance the quality of input vibration signals (Pavithra and Ramachandran 2025).

To reduce computational complexity and to avoid overfitting, usually, the best features are selected or dimensionality reduction techniques like Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE) are applied (Kumar, Wyłomańska, Zimroz and Xiang, 2025; Soualhi, Medjaher, Hawwari and Clerc, 2018).

2.4.4 Integration with IoT and Edge Computing

IoT platforms integrate ML based PdM systems to support real-time monitoring and instant decision making. Edge computing solutions based on Raspberry Pi allow local processing of data thereby reducing latency as well as bandwidth requirements. For example, (Chuang, Sahoo, Lin and Chang, 2019; Le, Tran, Wang, Pham and Dao, 2025) developed an IoT integrated DL model for rotating machinery fault diagnosis and demonstrated its effectiveness under real-time industrial environments.

Cloud based platforms also enable cross facility learning and continued model updates as they provide scalable computation and storage resources (Lee, Bagheri and Kao, 2015; Bublil, Cohen, Kenett and Bortman, 2025).

2.4.5 Challenges and Future Directions

Many challenges remain despite the very promising potential that ML has shown towards PdM. They include:

Data imbalance and scarcity: The performance of supervised models is constrained by the rarity and underrepresentation of fault data (Zhao, Yan, Wang and Mao, 2019; Bagri, Tahiry, Hraiba, Touil and Mousrij, 2024).

Interpretability of the models: Most ML/DL models work in a black box mode as their decisions are difficult to interpret. In industrial environments this is needed (Bublil, Cohen, Kenett and Bortman, 2025).

Generalizability: In the absence of transfer learning or domain adaptation, models developed under a specific machine or operational condition fail when applied to other machines or conditions (Bagri, Tahiry, Hraiba, Touil and Mousrij, 2024).

Most probably, future research will focus on explainable AI methods for better interpretability, transfer learning to address the paucity of data, and hybrid models incorporating physics based and data-driven approaches (Zhao, Yan, Wang and Mao, 2019; Bublil, Cohen, Kenett and Bortman, 2025; Soualhi, Medjaher, Hawwari and Clerc, 2018).

3. Case Study: Application of SPM in Arconic's Leveler Machine

A guided tour at Arconic's Székesfehérvár plant and a follow-up interview with Mr. András Zsolnai, Process Control IT Engineer, made available the practical data to this case study. In August and October 2025, the engineer replied in written form to a pre-prepared set of structured questions. The answers gave detailed explanations of the business's predictive maintenance practices, particularly installation and operation of the SPM system in vital machinery such as the Leveler machine. This thesis treats these materials as unpublished personal communication since they are not accessible to the general public. Every source that uses this information is properly cited.

The author keeps the transcript of the answers and provides it on demand. Also, production lines, monitoring procedures, and machine functions were described using internal documents that Arconic provided. These are referred to as internal company documents (for example, "Arconic, 2025, internal report").

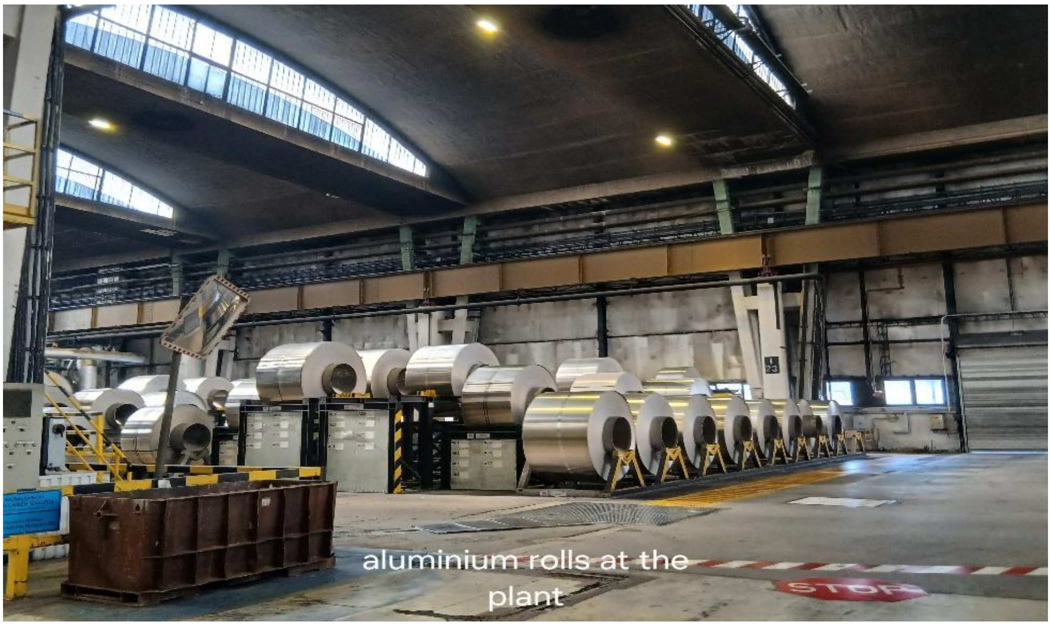
3.1 Company Overview

The plant in Székesfehérvár is the largest establishment of Arconic Corporation within Europe, producers of semi-finished aluminum products for both European and international markets. Its goods apparatus heating pipes, utensil bases, and heat exchanger elements are used mainly by construction, automotive, and home goods industries (Zsolnai, personal communication, August 2025).

9. Figure: Arconic Plant
(Source: Own photo, Arconic Székesfehérvár plant (2025))

Production is organized between two complementary plants. The Casthouse produces raw materials such as rolling billets, later processed in the Flat Roll Product (FRP) line. Products in FRP receive surface preparation, heat treatment, rolling, and slitting or size cutting. Maintenance activities are managed by Total Productive Maintenance (TPM) in tandem with planned preventive measures across these facilities (Arconic, 2025, internal company document).

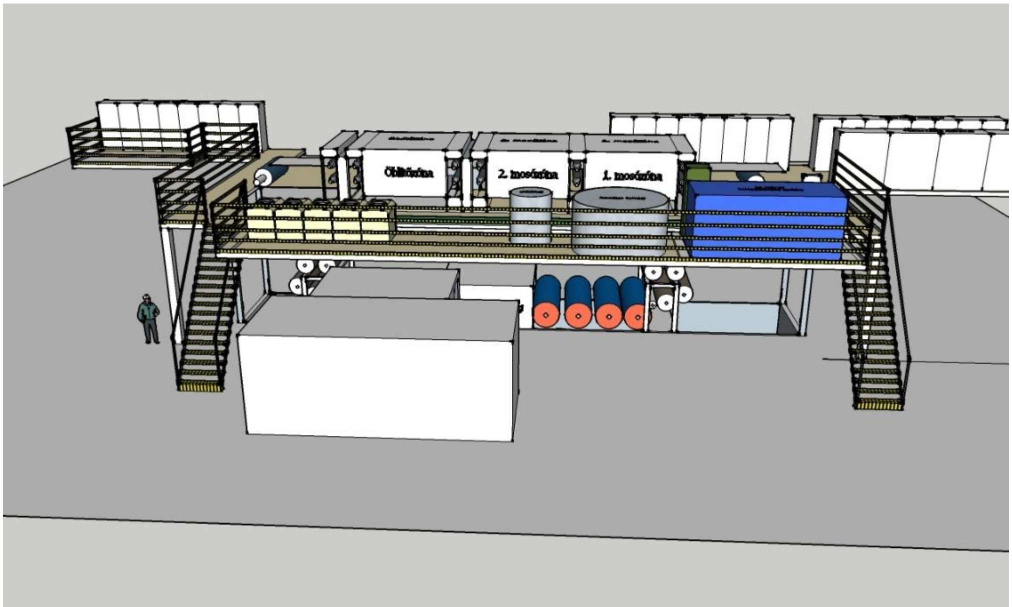
10. Figure: Aluminium rolls at Arconic
(Source: Own photo, Arconic Székesfehérvár plant (2025))



3.2 Overview of the Leveler Machine

This is a stretch leveler machine made by Ungerer in their Székesfehérvár plant, now part of the Arconic line. It operates very closely downstream with a degreaser section that has its own dedicated SPM monitoring system installed (Arconic, 2023; Arconic-Köfém Mill Products Hungary Kft., n.d.).

11. Figure: Stretch leveler and degreaser unit- line 3
(Source: Arconic (2017). Internal document NEZ. [Internal technical document])

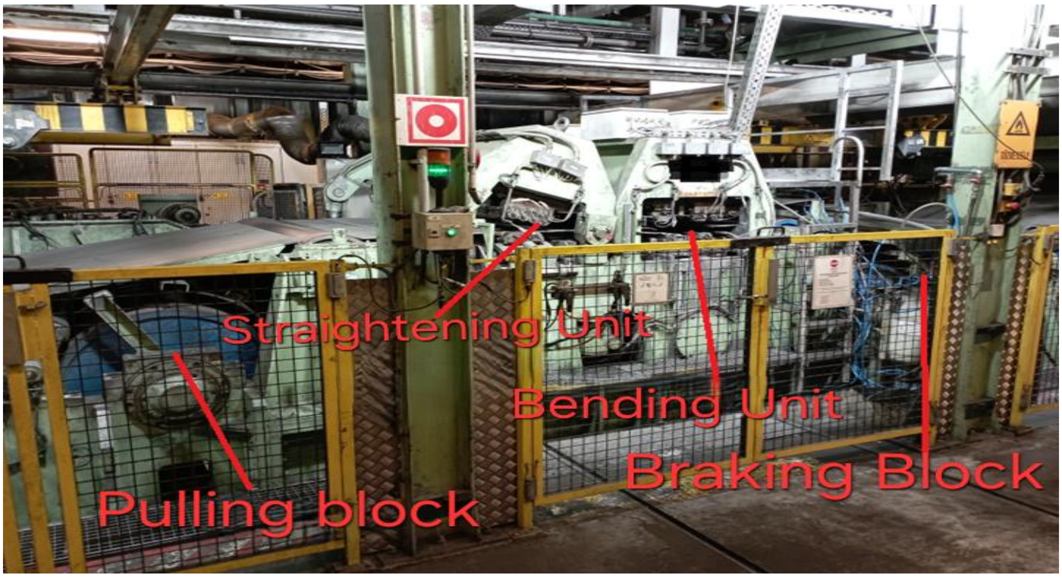


Essential pieces of equipment in the FRP plant include the Scalper and Hot Mill, besides intermediate equipment like the Stretch Leveler and the Degreaser (Zsolnai, personal communication, August 2025). In particular, the Leveler is very important to ensure structural integrity and flatness of the final product. For this reason, it is included in the company's predictive maintenance program and regularly monitored through the SPM system. (Arconic, 2025, internal company document).

At Arconic's facility in Székesfehérvár, Ungerer line 3 hosts a stretch-leveler that is basically a combined stretch-leveling and degreasing unit playing a central role in strip preparation just before recoiling. Decoilers, guiding rolls, the stretch leveling unit, and recoilers are some of the subsystems making up this aluminum coil processing line. In such an installation the Leveler passes the strip through its series of rolls under controlled tension to ensure flatness as well as to remove any residual stresses in the material. The system eliminates residual stresses and corrects flatness by creating controlled speed differentials between a braking block and pulling block hence the resultant tension plus a special bending-leveling unit. Rolling oil can be continuously removed before any heat treatment thanks to the plant's multi-zone degreasing module comprising two high pressure washing zones, a rinse zone and a dryer, preserving surface quality (Arconic-Köfém Mill Products Hungary Kft, n.d., Internal Document "Nyújtvaegyengetés-zsírtalanítás").

Detailed figure of the Ungerer Line 3 is provided in Annex 5 (A5.1 Figure)

12. Figure: Stretch Leveler components
(Source: Arconic-Köfém (n.d.). Nyújtó – 18. ábra: A leveler szerkezeti elemei. [Internal technical document])



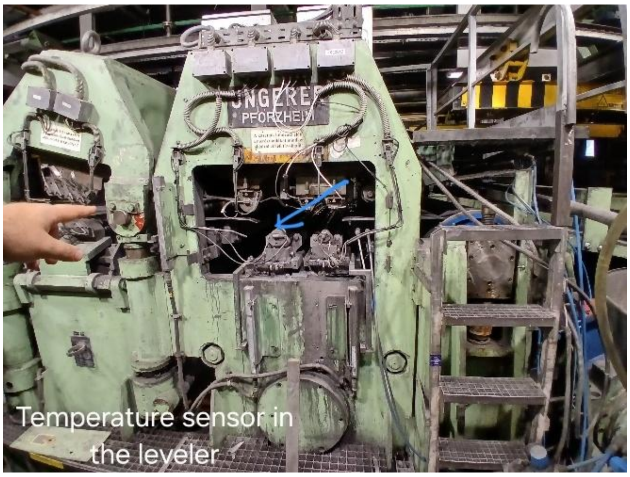
Some of the key operational parameters documented for the line (used to define monitoring constraints and sampling strategy) are thread/feed speed for coil loading ≈ 30 $m \cdot min^{-1}$, maximum continuous processing speeds in degreasing + leveling modes up to 165 $m \cdot min^{-1}$, and material thickness ranges covered by the unit from 0.2 mm up to 3.0 mm depending on the mode. The apparatus enforces stringent flatness and width tolerances (for example, maximum waviness and width tolerances specified in the technical sheet) and maintains set tensions with an accuracy of roughly ±2% under normal operation. These operational envelopes play a crucial role in the selection of sensor types, sampling rates, and most importantly alarm thresholds for vibration and SPM monitoring because they define the rotational speeds and loading regimes that the Leveler's bearings and gearbox will see (Arconic-Köfém Mill Products Hungary Kft, n.d., Internal Document "Nyújtvaegyengetés-zsírtalanítás").

Since the surrounding components directly affect the Leveler's mechanical interactions and operating conditions, it is essential to understand its place in the larger line layout. In the line diagram, which depicts the sequential arrangement of units, the Leveler is installed after the guiding section and before recoiling. Its strategic positioning highlights how important it is to maintain both continuity in production processes as well as process quality of final products.

Annex 5 contains a detailed figure of the Stretch Leveler degreaser unit (A5.2 Figure).

Further close-up on the stretch leveling section shows the location of critical monitoring points. Bearings, gearboxes, and guiding rolls in this section are equipped with SPM shock-pulse and vibration sensors for continuous monitoring of mechanical integrity and lubrication condition.

16. Figure: Temperature Sensor on the Leveler
(Source: Own photo, Arconic Székesfehérvár plant (2025))



15. Figure: SPM unit for Temperature monitoring
(Source: Own photo, Arconic Székesfehérvár plant (2025))

14. Figure: SPM Vibration monitoring sensor on degreaser section
(Source: Own photo, Arconic Székesfehérvár plant (2025))

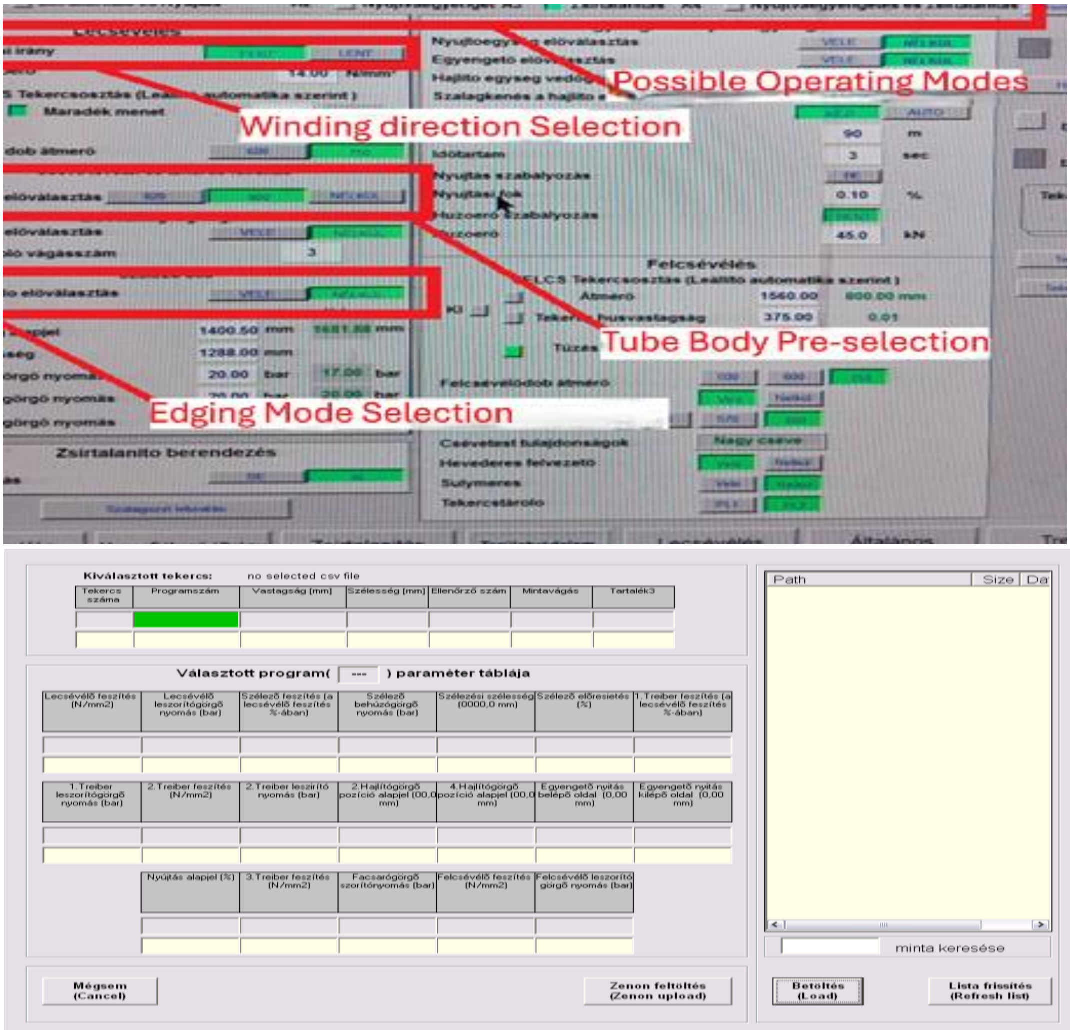
13. Figure: SPM-Vibration monitoring unit for the stretch leveler degreaser
(Source: Own photo, Arconic Székesfehérvár plant (2025))

3.2.1 Operational and Control Data Flow

The coil parameter list is in CSV. It uploads to the control system before every coil run, through an HMI (Zenon screens) operating the PLC supervised Leveler. Within its operation routine, prestart checks (visual inspection, check hydraulic oil levels, waste bin emptied, emergency stop and area protection check) and auxiliary services to the main control panel (hydraulics, drives, lubrication, compressed air and steam) must be switched on.

Because the context of the measurement (for example if the line runs at a given tension or in degreasing mode) is defined within PLC parameters these procedural steps and this parameter upload mechanism are crucial methodologically and as a consequence must be recorded together with any SPM/Condmaster measurements used within this thesis. Stated differently, recorded PLC parameter sets(CSV/Zenon snapshots) are a part of experimental metadata and will be kept together with the measurement database to ensure reproducibility (Arconic-Köfém Mill Products Hungary Kft,n.d.,Internal Document H-KEZ-NEZ-01).

17. Figure: PLC/HMI parameter upload (CSV → Zenon) used for coil
(Source: Arconic Székesfehérvár (2025). Internal Manual H-KEZ-NEZ-01. [Internal manual])



3.3 SPM System at Arconic

3.3.1 Historical Development

The first SPM system was acquired by the enterprise in 1996. A significant upgrade was performed when the Intellinova system having multiplexer technology replaced the old CMS platform in 2013. Tests conducted on other diagnostic systems from competing vendors proved them inadequate since they only catered to vibration measurements and did not address multi-point diagnostics or lubrication (Zsolnai, personal communication, August 2025).

3.3.2 Technologies Used

The methods used in the diagnostic approach include SPM HD, SPM LR/HR HD, Velocity RMS, Acceleration RMS. Very often temperature monitoring is also applied together with the measurements (Zsolnai, personal communication, August 2025). The degreaser section uses the combined reading values of VEL RMS, SPM HD, and LR/HR HD. The VEL RMS parameter detects mechanical faults such as broken Seeger rings at shaft ends, misadjusted rollers, or even a failed coupling. Bearing pitting, incorrectly set pressure levels or lubrication problems can be determined through the SPM HD and LR/HR HD readings. Temperature sensors are also used as auxiliary indicators; increased temperature means lack of lubrication or lateral contact between housing covers and roller bodies. The early fault detection and operational safety are ensured by this combination of temperature and vibration monitoring (Zsolnai, personal communication, October 2025).

The main online hardware at Arconic for SPM is Intellinova Parallel EN. This unit supports high-end, multipoint synchronous condition monitoring of complex rotating machinery. It features parallel, in real-time data acquisition on eight channels for shock pulse or vibration measurements and additional analog-digital inputs for RPM and process signals. The platform further allows wide ranging analytical techniques that include SPM HD, SPM LR/HR (LR/HR HD), FFT-based spectra, HD ENV, and EVAM while complying with international vibration standards such as ISO 2372 and ISO 10816. A detection range extension bearing gears drive train levels achieved single online unit integration of both shock pulse and vibration analyses lubrication mechanical fault diagnostics same measuring point.

A practical example of how these technologies work is the Leveler machine at Arconic's Székesfehérvár plant. The selected measuring points comprise the main drive bearings, gearbox, roller bearings supporting the leveling rolls, gear mesh locations, and main drive couplings. Any measuring point may have a combination of techniques assigned to it; shock-pulse methods (SPM HD or LR) primarily used for diagnosis on bearing and lubrication condition, and vibration-based methods such as EVAM or FFT more generalized mechanical fault detection within the scope of this survey assignment. Mixed assignments can be installed at one point when using multifunction transducers like DuoTech sensor recording both vibration and shock-pulse data simultaneously this possibility has been described in detail in Condmaster®Ruby User Manual. The installation is most suitable for the Leveler, where parameters of mechanical integrity and lubrication quality shall be constantly monitored (SPM Instrument AB, 2023, Internal Manual 72303B; SPM Instrument AB, 2022, Internal Manual 72243B).

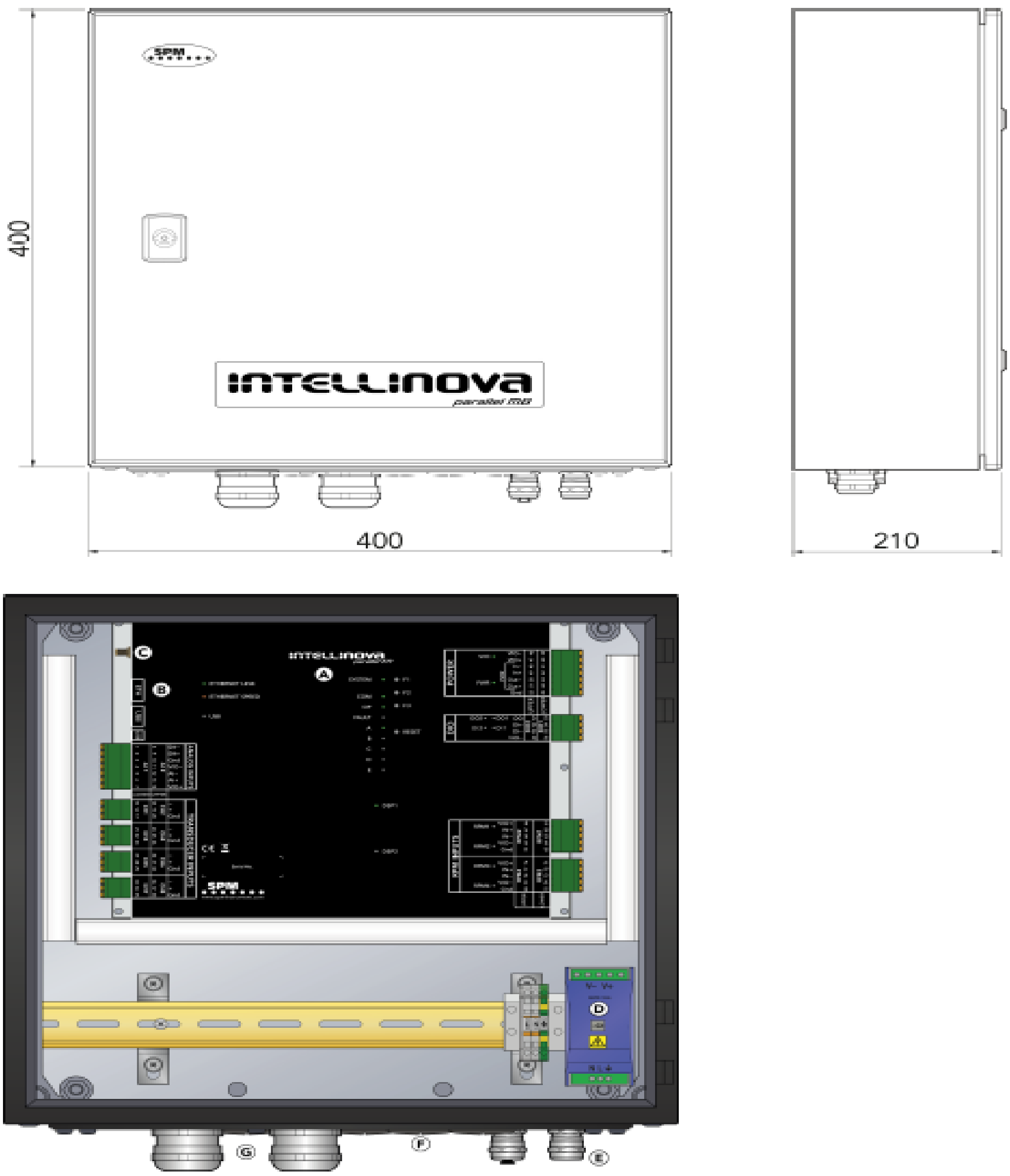
András Zsolnai (personal communication, October 2025) described two different SPM systems at Arconic: The newer parallel system and the traditional multiplexer. The parallel system is now preferred where applicable because it permits several measuring points on one component (like a shaft and a motor) to be checked simultaneously, which is vital in machines with variable speed.

18. Figure: Parallel SPM unit of Main driver
(Source: Own photo, Arconic Székesfehérvár plant (2025))

Another promising development is in wireless systems, which do away with wired installations and allow more freedom in placing sensors as well as reducing costs. Zsolnai emphasized that two basic pillars are needed for enhancement: the continuous education of diagnostic and condition monitoring specialists, and the technical optimization of measurement techniques.

19. Figure: Intellinova Parallel EN front panel and connection layout

(Source: SPM Instrument AB(2022). Internal Manual 72243B, p.5. [Internal manual])



A. System unit INCEN8 with inputs and outputs

B. Network connection, RJ45

C. Wi-Fi antenna connector (INO57 accessory)

D. Power supply unit and terminal blocks mounted on DIN rail

E. Cable inlets, 1 x Pg11 for voltage cable and 1 x M20 for network cable

F. Blind plugs

G. Cable inlets, 2 x Pg29

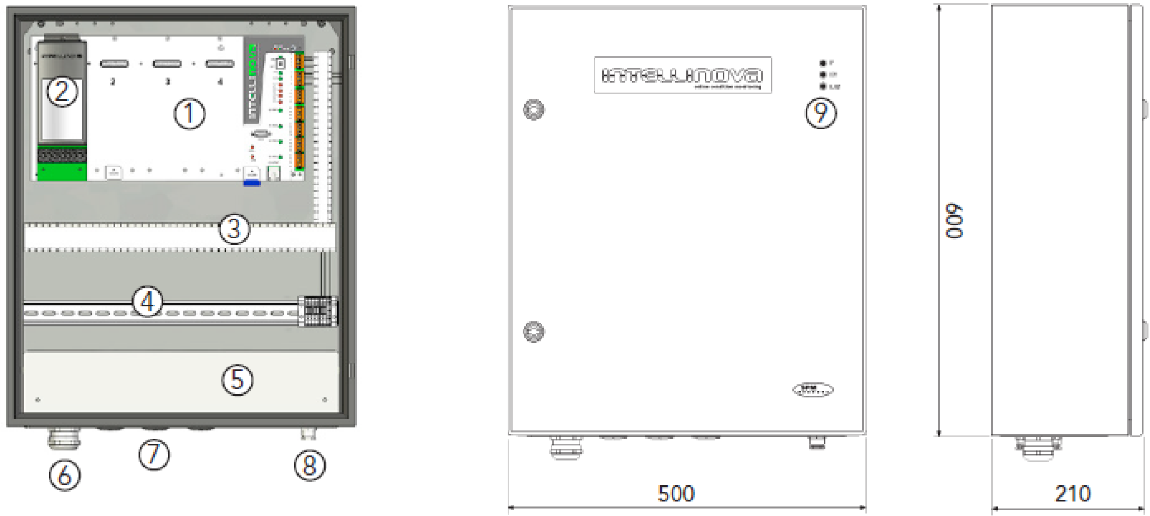
3.3.3 Installation Strategy

An SPM monitoring system installation followed a criticality analysis that incorporated failure rates and repair times, production loss in hours, and the cost implications. Monitoring points were installed on only key machines such as the Leveler is one of them according to these standards (Arconic, 2025, internal company document). According to a logical structure of the steps to be taken already compiled by András Zsolnai (personal communication, October 2025), they are on-site inspection, environmental assessment, possible sensor placements, cable routing, and measurement unit allocation (parallel or multiplexer). In every setup there is Signal type, communication network (LAN, 4G or Wi-Fi) and license management within Condmaster Ruby (Zsolnai, personal communication, October 2025).

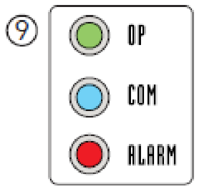
The Intellinova Commander units are physically installed on critical machines such as the Leveler in accordance with SPM’s recommended cabinet and grounding installation procedures. The standard commander unit cabinet (INO18 / IND8) contains an earth rail for proper cable shield termination, is IP rated for harsh environments, and is designed to accept Pg29 cable inlets (eight measuring cables per inlet). For safe handling during mounting and to ensure proper earthing, the commander unit should be withdrawn from the cabinet. Mounting instructions specify M-grade bolts with a tightening torque of approximately 17 to 20 Nm on the cabinet fasteners. Installation instructions detail correct multipair cable preparation and cable shielding guidelines which are critical both against ground loops as well as maintaining high frequency shock signals; connect the shield only at the specified end and make sure that all shields remain isolated inside junction boxes. These were the suggestions that guided the Leveler's sensor placement and cabling at the Székesfehérvár plant (SPM Instrument AB, 2023, Internal Manual 71862B; SPM Instrument AB, 2023, Internal Manual 72301B).

20. Figure: INO18 / Commander cabinet and cable inlet arrangement

(Source: SPM Instrument AB(2022). Internal Manual 71862B, p.4. [Internal manual])

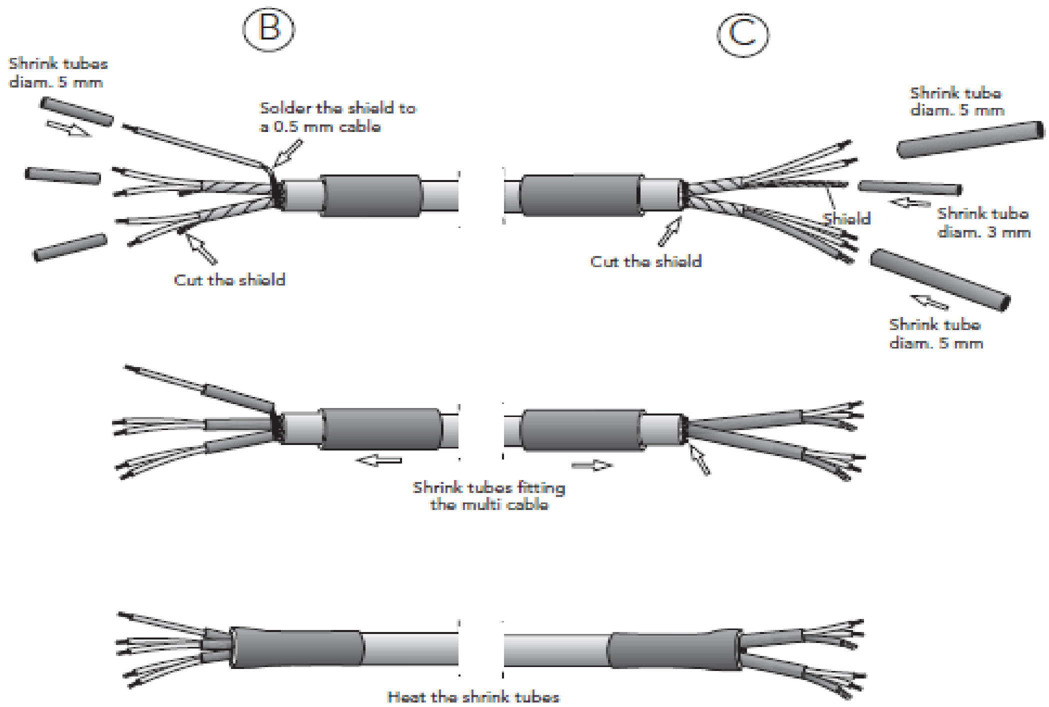


1. Commander Unit INC40
2. Monitoring Unit
3. Cable channels
4. DIN rail with terminal blocks
5. Cover plate
6. Cable inlet Pg29 for 8 measuring cables
7. Blind plugs for additional inlets Pg29
8. Cable inlet Pg11 for power supply and network connection
9. Status LED indicators (option)



21. Figure: Cable preparation and shielding for transducer wiring

(Source: SPM Instrument AB (2022). Internal Manual 71862B, p. 22. [Internal manual])



3.3.4 Installation Strategy environmental constraints and sensor placement considerations

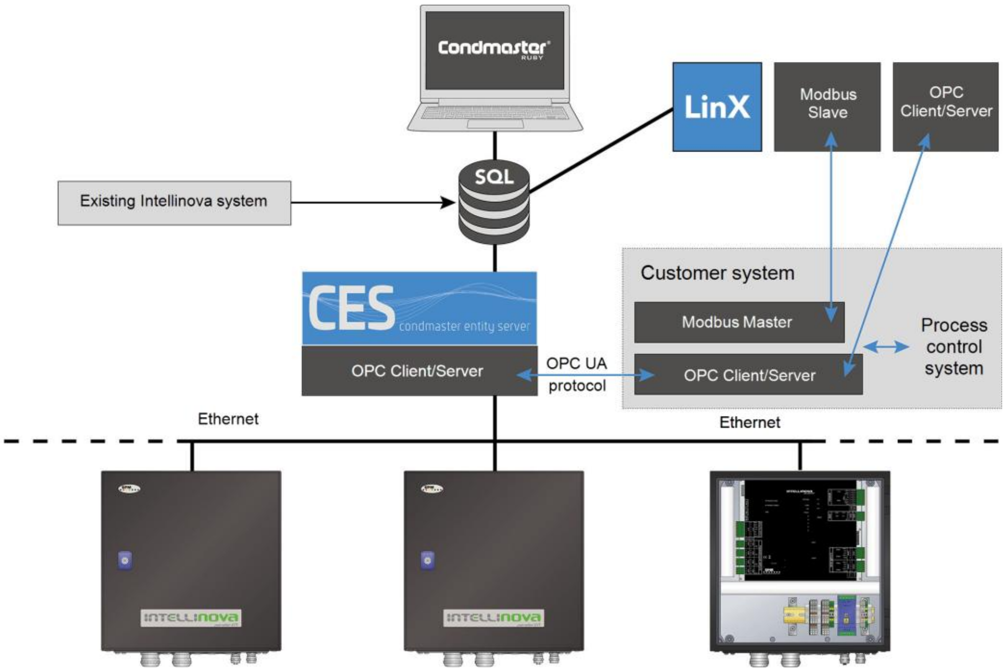
The degreasing and rinse sections of the Leveler operate with compressed air blow-off (up to 5 bar) at strip edges and sprayed alkaline detergent working at high temperatures (wash zones about 85 °C, rinse-dryer zones around 60 °C). Steam utilities are available for heating (technical data indicate saturated steam at about 2.5 bar). These environmental conditions limit the choice and installation mode of sensors (sprays, high local humidity, hot surfaces, chemical exposure); permanent type transducers should be installed as far as possible from direct spray and high temperature areas; connectors and junctions have to be IP rated; cabling has to be routed not to cross steam and condensate paths (installation choice confirmed in the plant documentation) (Arconic-Köfém Mill Products Hungary Kft, n.d., Internal Document "Nyújtvaegyengetés-zsírtalanítás"; Arconic-Köfém Mill Products Hungary Kft, n.d., Internal Document H-KEZ-NEZ-01).

Due to the small size needle roller bearings (5-8 per bearing block) which makes vibration and shock-pulse technically very difficult, SPM monitoring is not directly applied at Leveler and Bender units. Rather, temperature monitoring works as a practical substitute for early fault indication. These components have a modular construction for quick replacement in case of failure (Zsolnai, personal communication, October 2025).

3.3.5 Monitoring and Data Collection

The SPM system is functioning online so continuous measurement is possible. It collects data with different frequencies at measuring points, from one or two times per day to a minimum of five minutes maximum five minutes apart that depends on the condition of the machine mostly exceptions measurement taken once every hour per point (Zsolnai peronal communication August 2025).

22. Figure: Data pipeline between Intellinova, CES/LinX and Condmaster
(Source: SPM Instrument AB (2022). Internal Manual 72243B, p. 4. [Internal manual])

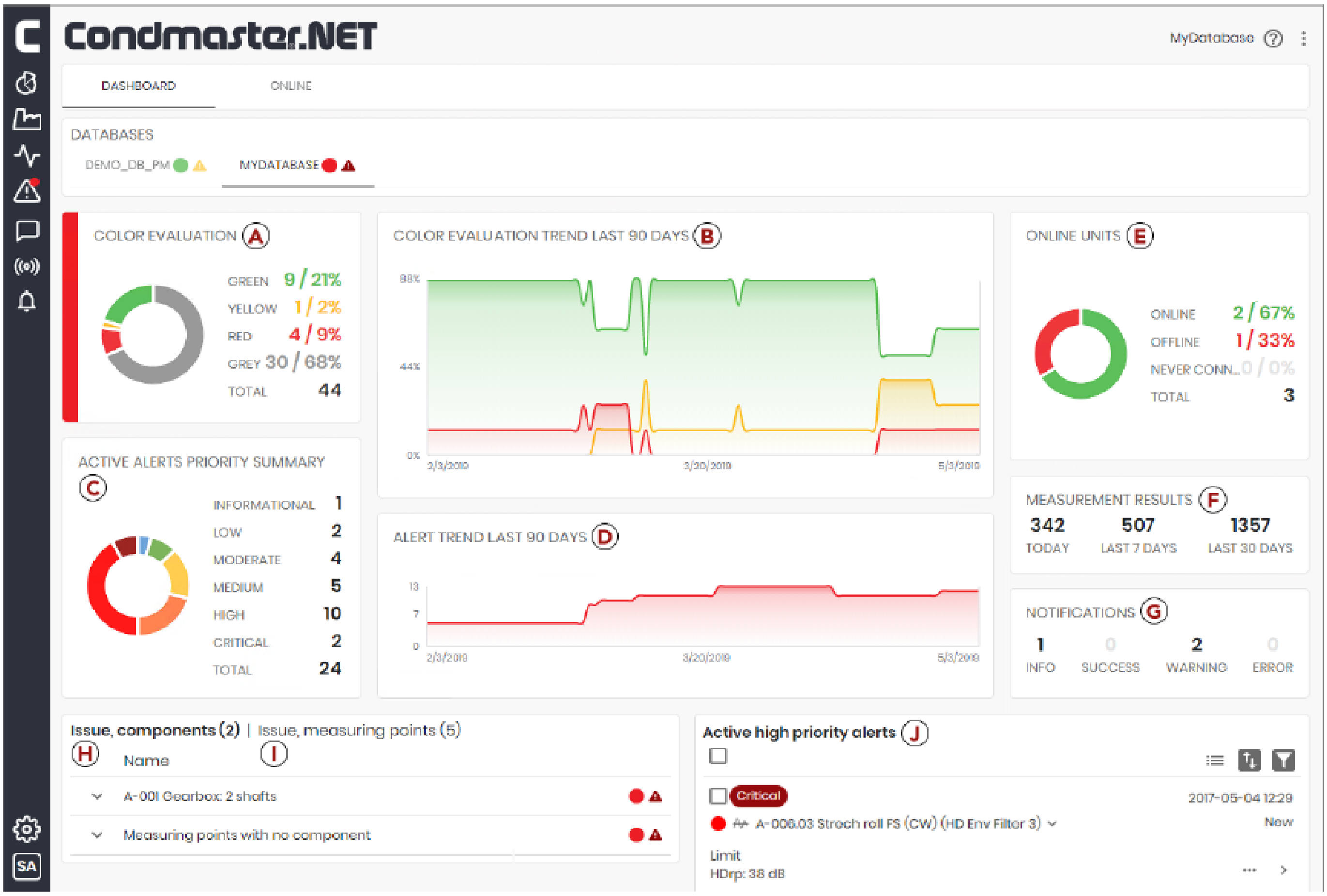


Presently, a 32 channel multiplexer measuring system is utilized in monitoring the Leveler's degreaser unit. Eight of these channels are assigned to four guide rollers (two before and two after the degreaser), while 24 channels cover 12 squeeze roller bearings. The bearing housings have sensors positioned radially for maximizing the detection of shock-pulse and vibration signatures (Zsolnai, personal communication, October 2025).

Through Condmaster Entity Server (CES) and LinX communication modules, Intellinova system units work with Condmaster®Ruby. Condmaster®Ruby sets up the measuring assignments, CES/LinX delivers them to the Intellinova units, and a historical SQL database stores the results where automatic evaluation and color-coded diagnostics take place. To export both evaluated and raw values to process control and asset management systems, the system supports industrial data exchange (OPC UA, OPC DA via LinX, and Modbus TCP). This permits for example the forwarding of alarm parameters to an enterprise maintenance system or plant SCADA. The manuals also strongly emphasize database hygiene which is important when running numerous continuous monitoring points like those on the Leveler line. Conditions, triggers and filters prevent unnecessary growth of data, distinguish between short term and long term storage. (SPM Instrument AB, 2023, Internal Manual 72301B; SPM Instrument AB, 2023, Internal Manual 72303B).

Arconic also uses Condmaster.NET, a web based interface for access to measurement data and diagnostics throughout the company in addition to the local Condmaster®Ruby client. Dashboards in the system contain color-coded condition indicators together with a hierarchical overview of machines. Engineers and managers remotely monitor their machine health; hence this improves departmental communication while reducing reliance on local workstations. The CES Admin Portal ensures all Condmaster applications run on a centralized secured database where system parameters, modules, user permissions are managed (SPM Instrument AB, 2022, Internal Manual 72302B; SPM Instrument AB, 2023, Internal Manual 72304B).

23. Figure: Condmaster.NET dashboard with hierarchical machine overview
(Source: SPM Instrument AB (2023). Internal Manual 72304B, p. 14. [Internal manual])



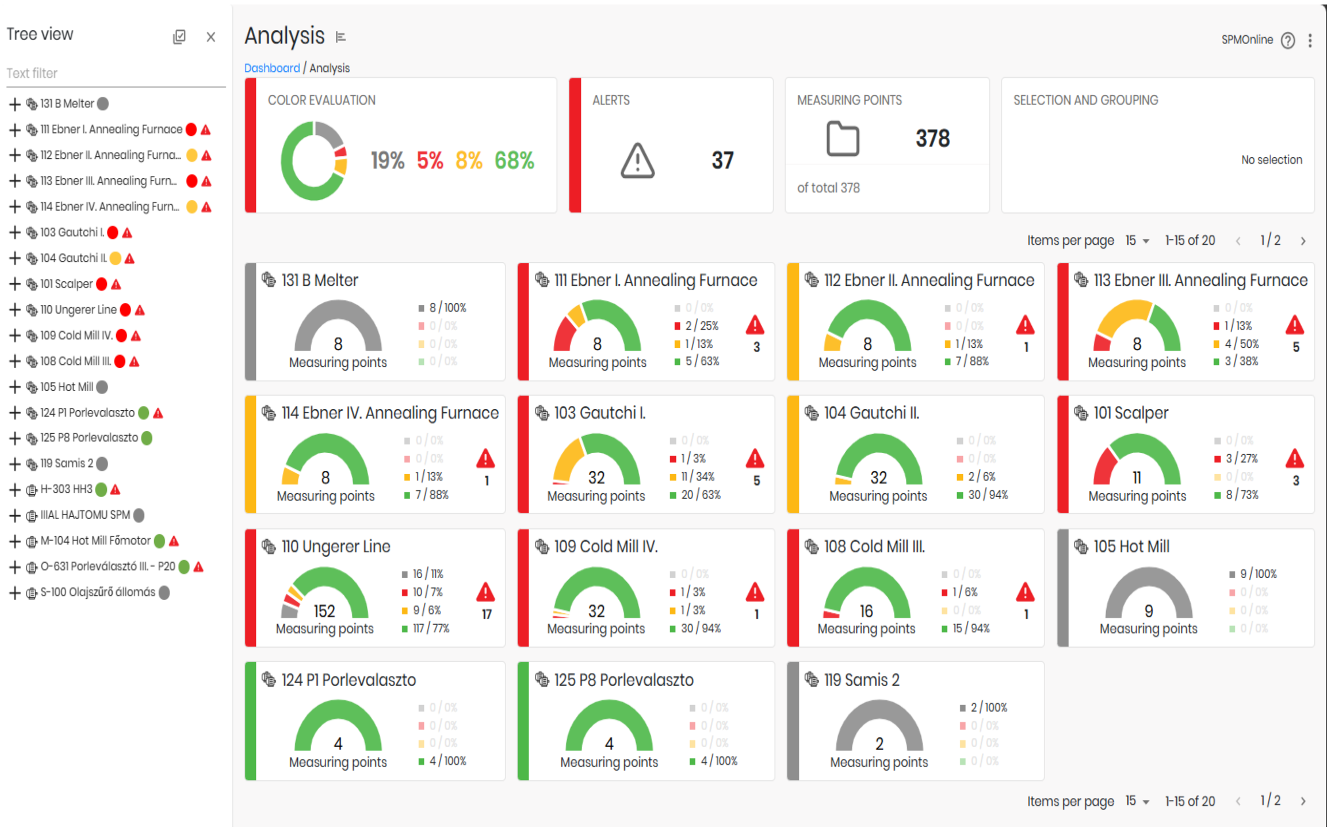
3.3.6 Responsibilities and Alerts

Maintenance managers are responsible for analysis and remedial action while data collection and storage fall under Process Control IT. Alerts appear first on the SPM platform from where they are automatically emailed to concerned staff members. Problems get logged within Oracle eAM (Enterprise Asset Management) system wherein remedial actions get logged and closed once resolved (Zsolnai, personal communication, August 2025).

A maintenance workflow is supported by Condmaster's flexible alerting and evaluation features (alert list, alert limit manager, colored spectrum overviews, and configurable delays). Alarms are raised in Condmaster, can be color-coded by severity, and can be exported to other systems via email notifications or OPC/Modbus. In Arconic's actual operations, this pipeline allows the IT and Process Control teams to centrally log results while maintenance managers go over alerts that have been prioritized and plan corrective actions using the enterprise asset management system. The alert configuration features that enable alarms to be filtered and routed in accordance with the plant's notification protocols are explained in the manuals (SPM Instrument AB, 2023, Internal Manual 72303B; SPM Instrument AB, 2023, Internal Manual 72301B).

Condmaster.NET helps in duty delegation by user role and access rights definition as well. Alarms generated within the Intellinova units are received by Condmaster®Ruby then made visible through Condmaster.NET where a standardized color coding indicates severity levels. List filtering or exportation at any detail level supports Production Managers, IT staff, and Maintenance Engineers to get alarm information at the appropriate detail level. This structure prevents critical fault warnings such as Leveler's gearbox or roller bearings that are supposed to propagate up through organizational levels from being confined only within the maintenance team (SPM Instrument AB, 2023, Internal Manual 72304B).

24. Figure: Alarm list with severity color codes (Condmaster.NET)
(Source: Own photo, Arconic Székesfehérvár plant (2025))



Arconic has organised a daily routine of condition monitoring besides the automatic evaluation and forwarding of alarms by the system. Through the SPM system, each area manager is responsible for checking the conditions of machines within their section. There are distinct colour codes to display the results: green, yellow, and red for normal state, warning state, and alarm state respectively. Temperature, velocity RMS, acceleration RMS together with shock pulse methods such as SPM HD and LR/HR HD are different measurement techniques that always use these same colour indicators. This ensures practising early detection of deviations and emphasises departments sharing responsibility over machine health rather than solely on maintenance team (Arconic, 2023, Internal Document Daily Routine of use the SPM System). Anomalies related to impacts were detected before visible damage, according to diagnostic data from multiplexer channels. The Stretch Leveler line SPM system report (Arconic, 2017) trend and spectral plots clearly display the slow increase in shock-pulse levels before a shaft crack in the guiding roll.

4. Analysis and Discussion

4.1 SPM's Effect on Reliability

After installation of the SPM system, unplanned downtime on all monitored machines reduced by 90%. This performance improvement highlights the effectiveness of integrating vibration and lubrication monitoring into predictive maintenance practices (Zsolnai, personal communication, August 2025).

Several features support operational reliability in the Intellinova/Condmaster design. These comprise internal memory buffering for brief communication outages and on unit buffering plus SD-card based initialization as well as backup. Added to this is the possibility of reactivating system units and reloading saved measurement sets which enhances that detection to action chain that minimized unplanned downtime at Arconic by way of reducing loss of data thereby enabling condition monitoring during network maintenance (SPM Instrument AB, 2023, Internal Manual 72301B; SPM Instrument AB, 2022, Internal Manual 72243B).

4.2 Incorporation into Shutdown and Maintenance Planning-Results

Useful experience was gained in the integration of SPM readings from the degreaser section of the Ungerer Leveler with shutdown planning. The fact that abnormal reading levels could be correlated to a specific mechanical event on the line such as coupling or bearing degradation, through vibration, shock-pulse and temperature data is very handy for maintenance works. Most of these insights have been confirmed by routine inspections which also supported decision bearing replacements (Zsolnai, personal communication, October 2025).

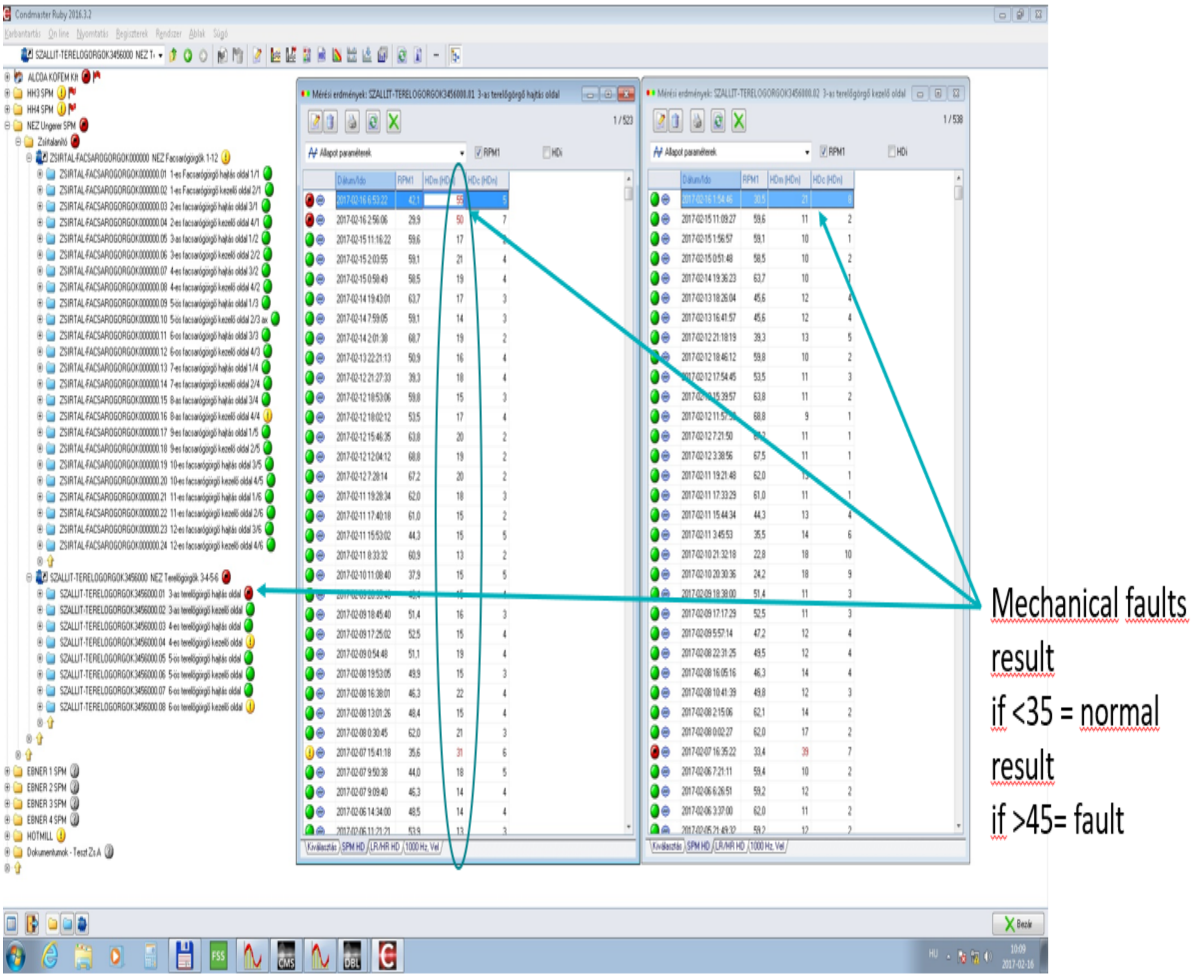
The technical report and diagnostic slides of Ungerer Stretch-Leveler show the operational mode context in which the SPM alarms were raised, together with specific fault scenarios such as bearing, roll weld cracks, and imbalance. When presenting case study data trends, spectra, and corrective actions include a PLC parameter snapshot together with the mode of operation degreasing versus leveling, speed tension set points in which the alarm occurred. This contextual metadata is available from the plant HMI log and explained in the operating manual (Arconic-Köfém Mill Products Hungary Kft, n.d., Internal Document H-KEZ-NEZ-01). SPM alarms are checked whether they can be left for corrective action or if immediate action has to be taken; in this latter case production disruption will be minimized since problems will be rectified during planned shutdowns (Zsolnai, personal communication, August 2025).

A very illustrative case of the effectiveness of the SPM system was found in the Stretch Leveler line at Arconic. The online monitoring system detected anomalous patterns on the drive side guiding roll in 2017, later confirmed to be a shaft crack. Due to this incipient detection, maintenance people could plan a controlled replacement of the component before it broke down completely.

25. Figure: Cracked guiding-roll shaft
(Source: Arconic (2017). Internal Diagnostic Report – Stretch Leveler line SPM system. [Internal diagnostic report]))

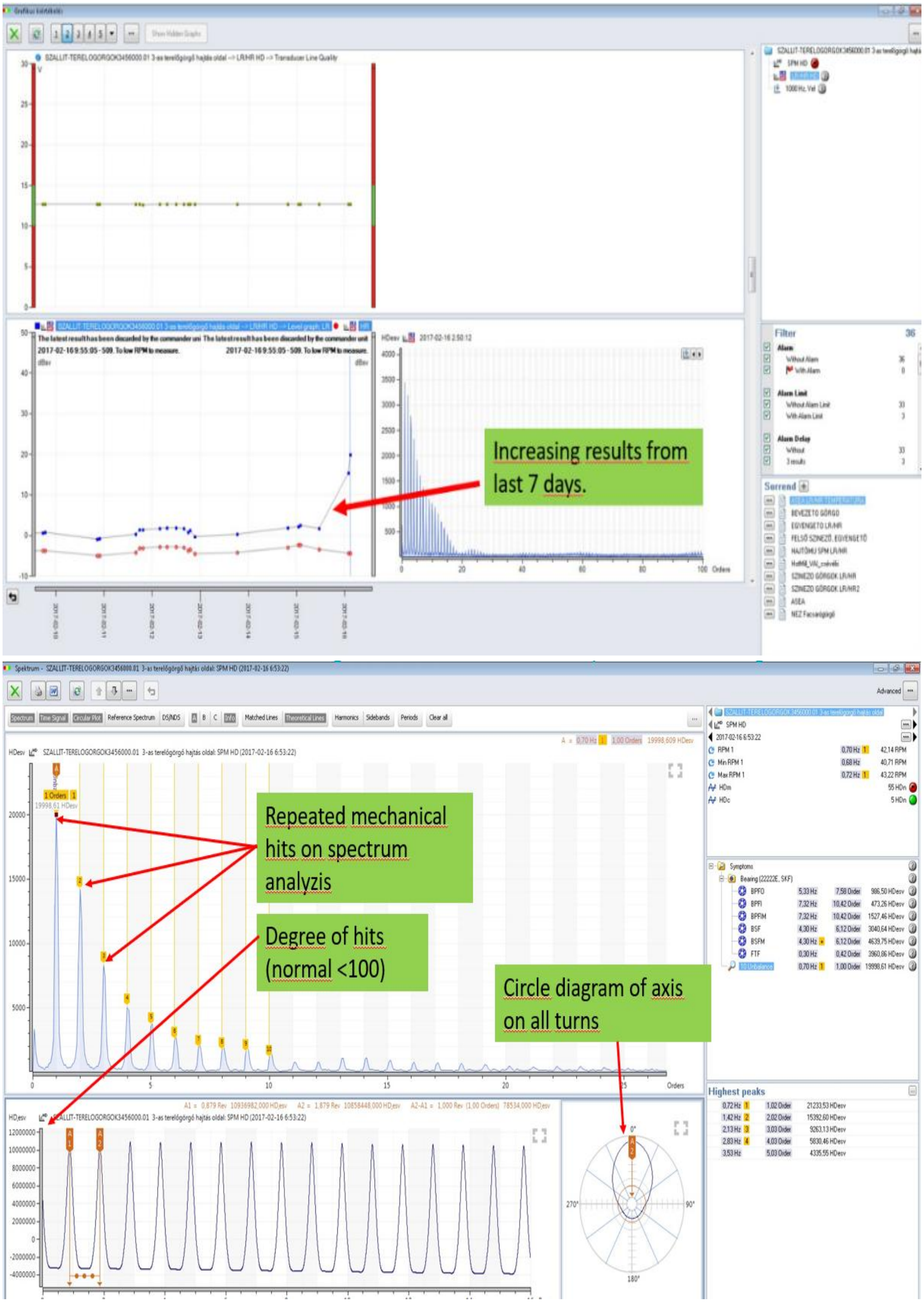
The diagnostic report included the spectral data as well as a trend curve showing gradual degradation leading to the fault. These plots illustrate the manner in which anomalies related to impacts were pre-identified by the SPM system.

26. Figure: Measuring results
(Source: Arconic (2017). Internal Diagnostic Report – Stretch Leveler line SPM system. [Internal diagnostic report])



27. Figure: Shock-pulse trend curve and spectral plot showing progressive increase before failure

(Source: (2017). Internal Diagnostic Report – Stretch Leveler line SPM system. [Internal diagnostic report]))



4.3 ROI (Return on Investment)

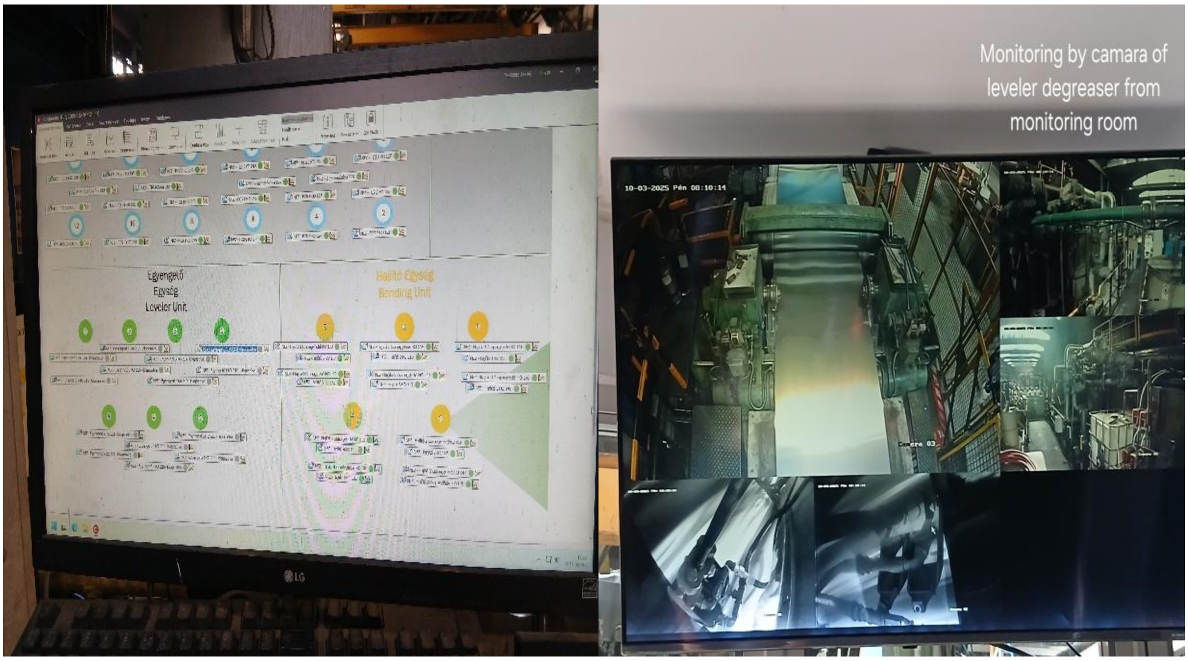
Arconic maintains monitoring of the performance indicators in a very organized way to judge the effectiveness of SPM. In fact, every installation is followed by a monitoring period of two to three years to check if the investment was justified. The return on investment is considered positive whenever the costs resulting from downtime surpass the initial investment. Detected failures are monetized and compared against installation costs (Zsolnai, personal communication, August 2025).

Mean time between failure in lubrication condition in vibration severity is one of the technical KPIs provided by Plant Performer together with economic indicators such as estimated savings due to early fault detection and avoided downtime costs. These figures help to express the Leveler's technical benefits into SPM monitoring's measurable economic value added so that lower maintenance cost and productivity loss due to unscheduled stoppages can be convincingly demonstrated. The Condmaster.NET integration with Plant Performer module enhances assessment on predictive maintenance performance (SPM Instrument AB, 2023, Internal Manual 72304B).

28. Figure: Plant Performer KPI (technical & economic KPIs)
(Source: SPM Instrument AB (2023). Internal Manual 72304B, pp. 35–36. [Internal manual])

The economic analysis makes clear and real the advantages of predictive maintenance. In this particular case, early detection saved Arconic from having to scrap just one coil, additional collateral damage that could have amounted to tens of thousands of euros more, and about 12 hours of unscheduled downtime worth approximately €36,000. A total saving of €50,500 is counted against €41,000 for the installation of the SPM system. This positive return on investment economically justifies the technical dependability terms as well as financial rationale applying predictive maintenance techniques to crucial equipment such as Stretch Leveler in addition to its technical dependability (Arconic; 2017; Internal Document Stretch Leveler line SPM system).

29. Figure: Monitoring room view and Condmaster screen used during anomalies detection (Source: Own photo, Arconic Székesfehérvár plant (2025))



4.4 A Comparative Analysis

The SPM system contains more features from multipoint measurements, recording lubrication conditions, to automatic alarming functions than the normal FFT based vibration analysis. This makes the Leveler machine and other important equipment in the plant more reliable through this integration, hence proving the benefits of hybrid monitoring techniques (Arconic, 2025, internal company document).

Several advantages are stocked up by the Intellinova Parallel EN system over a conventional vibration monitoring system. Features stocked within include: a 125 dB dynamic range, up to 40 kHz frequency ranges supporting parallel multi analyses accurate in both low and high frequency fault signature detections; it is a merged single platform of vibration and shock pulse analyses differing from traditional FFT based methods, compatibility ease with OPC and Modbus protocols for connectivity to plant level SCADA and Enterprise Asset Management systems. All this put together describes perfectly well why since 2013 Arconic Székesfehérvár has been using Intellinova as its main monitoring solution (SPM Instrument AB, 2022, internal manual 72243B).

5 Inferences and Recommendations

5.1 Main Findings

According to the analysis done at the Arconic Székesfehérvár plant, predictive maintenance based on vibration and shock-pulse measurement greatly improves machine reliability as well as maintenance efficiency. The Ungerer Stretch Leveler case showed that by integrating temperature monitoring, vibration velocity (VEL RMS), LR/HR HD, and SPM HD, it is possible to identify early failures which would otherwise go completely unnoticed under normal maintenance schedules.

There is clear proof that impact related abnormalities on a guiding roll shaft were identified weeks prior to physical failure, according to the Stretch Leveler line SPM system diagnostic report (Arconic, 2017). The trend and spectrum plots' gradual increase in shock-pulse amplitudes was a definite sign of shaft or bearing deterioration. In order to prevent collateral damage and an estimated 12 hours of unscheduled downtime, the maintenance team replaced the component during a planned shutdown.

These findings highlight the strategic benefit of predictive maintenance over reactive and preventive maintenance (Mobley, 2002; Ahmad and Kamaruddin, 2012). Sensor data was integrated with the PLC/HMI system to store information in Condmaster software. This enabled technical information flow between maintenance and operations while enhancing accuracy in diagnostics together with effective decision making (SPM Instrument AB, 2023; Zsolnai, personal communication, October 2025).

30. Figure: Ungerer line 3 monitoring point

(Source: Own photo, Arconic Székesfehérvár plant (2025))

5.2 Research Contributions

Linking theoretical models of predictive maintenance to an actual industrial case, this work contributes to both academic and industrial knowledge. It provides evidence that predictive maintenance can generate quantifiable operational and financial benefits when supported by accurate data collection, appropriately placed sensors, and sound organizational practices. Technically, a useful development for PdM applications is the incorporation of multi-parameter monitoring by Ungerer Leveler. With no additional hardware complexity, the installation of mixed measurement points combining vibration and shock pulse data at one place proved to be very successful in identifying mechanical and lubrication related faults (SPM Instrument AB, 2022; SPM Instrument AB, 2023).

The study emphasizes the importance of that data chain from an organizational point of view which connects Oracle eAM, Condmaster, Condmaster.NET and Intellinova. It is this digital infrastructure which proactively enables and supports effective maintenance planning by ensuring alarms and diagnostics results automatically transmitted and logged into the enterprise asset management system (Arconic, 2023; Zsolnai, personal communication, October 2025). Finally, the study brings out human knowledge in predictive maintenance. Despite a high level of automation, skilled professionals who can decipher vibration signatures and pinpoint the physical cause of anomalies are essential to the success of maintenance decisions and accuracy in diagnosis. Even in the era of Industry 4.0, this human technical synergy is still crucial to PdM success (Lee, Bagheri and Kao, 2015).

5.3 Incorporation into Maintenance and Planning

The integration of SPM data into Arconic's maintenance strategy impacted directly the planning and optimization of shutdowns. The interventions could be scheduled precisely when deterioration trends warranted them, instead of adhering to strict time based intervals, by continuously monitoring mechanical and lubrication parameters.

The guiding roll shaft case provided a clear illustration of how a controlled replacement decision was initiated by pre-failure trends thereby increasing machine availability while reducing maintenance costs. To crosscheck that the anomalies were not due to some transient process variation, the collected SPM data was analyzed together with PLC and operational parameters such as line speed and tension. The incorporation of operational context into diagnostic interpretation reduced false positives due to better understanding (Arconic Köfém n.d.; HKEZNEZ01; Zsolnai, personal communication, October 2025) . In addition, integration of SPM results into Oracle eAM and Condmaster.NET enabled easier formal registration of each event thereby supporting benchmarking on performance and history tracking. Predictive maintenance is supportive of the Industry 4.0 principles, connectivity and transparency, intelligent decision making as illustrated by structured communication flow between sensors, analysis software and enterprise databases (SPM Instrument AB, 2023; Lee, Bagheri and Kao, 2015).

5.4 Economic and Operational Impact

There was a clearly measurable return on investment (ROI) for the predictive maintenance system at the Arconic plant. The plant was able to save losses in production, greater than the cost of implementation and operation of the SPM monitoring system, by Ungerer Leveler experiencing just one instance of unplanned shutdown (Arconic, 2017). Apart from measurable cost savings due to predictive maintenance, there were untold intangible benefits such as enhanced confidence in machine health, better safety to workmen, and improved accuracy of maintenance planning.

The long-term benefit is the collection of historical vibration and shock-pulse data that permits the continual refinement of maintenance strategies. As more data becomes available, the system's diagnostic thresholds can be tuned to better reflect the actual operating conditions in the plant. This makes it more accurate in prediction and reduces false alarms (SPM Instrument

AB, 2023; Arconic, 2023). A constant feedback loop like this one is representative of predictive maintenance in its latest evolution as a data-driven discipline aimed at cost efficiency with operational continuity.

5.5 Future Work

A study on how explainable artificial intelligence and machine learning can be incorporated into SPM and Condmaster platforms may be conducted in future research based on this study. Algorithms that recognize patterns between different machines and time horizons improve the accuracy of fault prediction plus response times (Zhao, Yan, Wang and Mao, 2019).
Another fascinating direction is in developing digital twin models of the Ungerer Leveler. Apart from simulating wear patterns, stress distributions, and lubrication conditions, a digital twin could emulate the behavior of a machine in real time. Minimizing false alarms and strengthening predictive analytics, such models would improve technical and financial results.

Another major development is in the increase of wireless sensors. However, as was clear from the interviews of András Zsolnai, rigorous testing and validation of the signals are to be carried out before wireless monitoring would be implemented in such high humidity or electromagnetic interference environments.
Finally, in the long run, a study on knowledge transfer and reliability growth involving systemic return on investment across the total fleet comprising several lines or plants would elucidate effects of predictive maintenance on the entire fleet. Such a study shall also incorporate how predictive maintenance can be helpful in sustainability objectives, specifically waste minimization and energy efficiency in the aluminum industry.

5.6 Conclusion

This thesis demonstrates that predictive maintenance is a core aspect of dependability and competitiveness that should be systematically implemented with modern sensing and analytical technologies. Vibration and shock-pulse monitoring enable maintenance management to move from a reactive and preventive approach into fully data-driven discipline as demonstrated at Ungerer Stretch Leveler in Arconic, Székesfehérvár. The anomaly detection capabilities mechanically signaled through the plant by SPM HD together with LR/HR HD systems allowed interventions to reduce unplanned downtime dramatically, maintenance costs, and secondary failures in very recent references of installation (Arconic, 2017; SPM Instrument AB, 2023).

The findings of the study highlight predictive maintenance as an organizational strategy that links people, technology, and processes within the enterprise and not just a diagnostic technique. Condmaster is integrated with the enterprise asset management system (Oracle eAM). DuoTech sensors are properly positioned. Engineers have proficiency in data interpretation and action planning. This was Arconic's success in deploying the solution (Zsolnai, personal communication, October 2025). Sustainable reliability must be both technically accurate and operationally disciplined. The resulting synergy between human expertise and digital intelligence points to this fact.

The case also empirically proves that predictive maintenance aligns with the broader Industry 4.0 principles, automated data exchange, interconnected systems, and real-time analytics towards production efficiency. Best illustrated as a cyber-physical system is the SPM system and its integration with the plant's PLC and maintenance databases where sensors act as a "nervous system" of the machine continuously transmitting condition data supporting predictive decision making (Lee, Bagheri and Kao, 2015). Through this digital integration, Arconic was able to sustain operational excellence by shifting from a 'fail and fix' mode to 'predict and prevent'.

The results provide continued validity to basic maintenance theories such as those proposed by Mobley (2002), who emphasized the role of predictive methods in improving asset utilization and lifecycle management. Through actual operational improvements in the Ungerer line, where predictive diagnostics directly influenced capital planning and maintenance scheduling, this case study offers not only validation of those theoretical benefits but their quantification as well. Wider industrial implementation signifies success, marking it not just as a technical improvement but an indication of strategic cultural change toward knowledge based maintenance. Predictive maintenance fosters the formulation of common understandings regarding equipment condition between operators and maintainers and promotes cooperation between experts in maintenance and data analysis. This human centered approach ensures that technological innovation, based on improvements in the ways information is collected, analyzed, and used, brings about noticeable reliability enhancements.

Finally, this study once again proves how predictive maintenance becomes more significant in the transformation to sustainable manufacturing. Apart from making the whole process more profitable, PdM also makes it environmentally effective and ensures responsible resource use by maximizing component lifetimes, reducing waste, and lowering unscheduled downtime. Predictive Maintenance is a reflection of the twin objectives of modern industry intelligent, data-driven engineering aimed at operational performance as well as sustainability (Mobley, 2002; Lee, Bagheri and Kao, 2015).

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APPENDICES

Appendix A: Important Technical Details and Ungerer Stretch Leveler Measuring Points

This appendix displays the main monitoring points and parameters set for SPM predictive maintenance at Ungerer Stretch Leveler line in Arconic's plant located in Székesfehérvár. The author collected the information during field visits and from Arconic Diagnostic Report (2017) and internal manuals (SPM Instrument AB, 2022–2023).

Component	Sensor type	Measurement technique	Parameter monitored	Location
Main drive bearings	DuoTech accelerometer	SPM HD + HD ENV vibration	Bearing and lubrication condition	Drive housing
Main gearbox	DuoTech accelerometer	Vibration (FFT/Velocity)	Gear mesh fault detection	Gearbox casing
Leveler rolls	DuoTech accelerometer	SPM HD	Roller bearing impacts and lubrication	Roll supports
Couplings	Vibration transducer	Velocity RMS	Mechanical looseness	Coupling area
Hydraulic unit	Temperature and pressure sensors	Analog 4–20 mA	Fluid pressure and temperature	Hydraulic cabinet
Degreaser section	DuoTech accelerometer	FFT + SPM HD	Roller misalignment and resonance	Degreaser rollers
Stretch unit	DuoTech accelerometer	FFT + Envelope analysis	Shaft condition and balance	Leveler frame

Data acquisition system: *Intellinova Parallel EN* (SPM Instrument AB, 2022). **Software:** *Condmaster.NET* for visualization, trend analysis, and alarm management.

(Source: Compiled by the author based on SPM Instrument AB internal manuals 72243B, 72303B; Arconic, 2017; Interview with András Zsolnai, 2025.)

Appendix B: Synopsis of András Zsolnai's Interviews (Arconic Székesfehérvár Plant, 2025)

This appendix contains the fully transcribed two interviews conducted with András Zsolnai, Maintenance Engineer at Arconic Székesfehérvár plant.

The aim was to obtain detailed organizational and technical knowledge about the SPM condition monitoring system installation, setup, functioning, and its impact on reliability improvement.

B.1 — First Interview (August of 2025)

Plant Overview

Arconic Székesfehérvár FRP Plant, in the center of Hungary, has semi-fabricated aluminum products for building, auto, and home industries. It works with two integrated units. The FRP line (Flat rolled product) processes rolls and finishes the material. Another unit is a Casthouse creating rolling billets.

SPM System Implementation

The plant installed the SPM system for the first time in 1996. A major upgrade was done in 2013 to Intellinova Parallel EN units with multiplexer measurement technology. The system comprises temperature sensors at particular locations apart from SPM HD, SPM LR/HR HD, Vel RMS, and Acc RMS techniques.

Key pieces of equipment include the Scalper, Hot Mill, Stretch Leveler, and Degreaser. A total of 15 SPM systems are installed 12 in FRP and 3 in Casthouse.

Monitoring and Data Collection

The system automatically stores vibration and lubrication measurement values once every hour for each measuring point. Since the system is working online, it gives a possibility to generate an alarm automatically by SMS or e-mail.

Data is being stored by Process Control IT, analyzed by maintenance managers using Condmaster.NET and Oracle eAM platforms for findings and responding to alerts.

Results and Impact

Bearing in mind the implementation of SPM Bearing monitoring Bearing system, unplanned downtime which can be attributed to lubrication has dropped by about 90%. Bearing failures and lubrication problems were clearly identified, and maintenance changed from reactive to predictive.

Payback is measured in two to three years after installation by linking the cost of the system to the losses in production that it prevents.

(Source: Interview with András Zsolnai, August 2025, conducted by the author at Arconic Székesfehérvár Plant.)

B.2 — Second Interview (October 2025)

System Configuration and Limitations

There are two types of SPM systems in use: the traditional multiplexer units and the more modern parallel systems. The parallel system is not yet applied on the leveler due to the bearing arrangement. Temperature sensors are applied for early fault detection since each bearing block contains a number of small needle bearings which are difficult to monitor by vibration.

Installation Process

The installation process includes:

1. Environmental survey and on-site inspection
2. Sensor location selection (maximum 50 m distance)
3. Unit placement and cable routing (parallel or multiplexer)
4. Identifying the required measurement methods (Acc RMS, Vel RMS, LR/HR HD, and SPM HD)
5. IT assessment (LAN, 4G, or Wi-Fi connectivity)
6. Parameter setup, such as lubricant type, bearing info, and rotational speed

Crutial Parameters

For SPM:

- Rotational speed
- Bearing data (manufacturer, type)
- Lubricant type and viscosity

For vibration:

- Rotational speed

- Bearing data for advanced fault identification

Challenges and Recommendations

Main challenges relate to staff competence, cost, and training. Zsolnai highlighted two main pillars to SPM's success:

1. Properly set up measurement methods and systems.
2. Skilled experts.

He promoted users and system manufacturers (such as SPM Instrument AB) working in close cooperation and diagnostic experts receiving continual education. It is based on userfeedback. Wireless and parallel. Wireless lower the installation costand increase themeasurement possibilities. While parallel ensure the measurement of synchronization on avariable speed machine.

Degreaser Section Setup

In the degreaser section, measurements are taken by a 32 channel multiplexer: 8 channels on 4 guide rollers, and 24 channels on 12 squeeze roller bearings.

Sensors that record simultaneously VEL RMS, SPM HD and LR/HR HD are mounted radially on bearing housings.

Further temperature readings indicate either under-lubrication or contact between the housing cover and the roll.

(Source: Interview with András Zsolnai, October 2025, conducted by the author at Arconic Székesfehérvár Plant.)

Appendix C — Author's Field Observations and System Interface Screens

This appendix contains photographic records, and the notes taken by the author during his technical visits to Arconic Székesfehérvár, real installation layouts are also included together with Condmaster.NET displays.

- C.1: Condmaster.NET hierarchical machine overview with alarm color codes.
- C.2: The degreaser section has an SPM vibration monitoring sensor installed.
- C.3: The main driver's parallel SPM unit.
- C.4: Coil parameterization is done via the PLC/HMI parameter upload interface.

(Source: Photographs and screenshots by the author, Arconic Székesfehérvár plant, 2025.)

ANNEXES

Annex 1 — Extracts from the 2017 SPM Diagnostic Report

The “Stretch Leveler Line SPM System Diagnostic Report” (Arconic, 2017) illustrates the development of a bearing fault on the guiding-roll shaft.

Plots and photographic evidence are provided to support how the SPM system indicated the defect trend long before a catastrophic failure, allowing for a planned replacement.

(Source: Arconic, 2017, Internal Diagnostic Report – Stretch Leveler line SPM system.)

Annex 2 — Selected Pages from SPM Instrument Manuals

Selected pages from SPM Instrument AB internal manuals that deal with the setup and functioning of the monitoring system at Arconic are included in this annex:

- **Manual 72243B** – *Intellinova Parallel EN System Guide (2022)*
- **Manual 72303B** – *Intellinova Compact User Manual (2023)*
- **Manual 72304B** – *Condmaster.NET User Guide (2023)*

These documents describe alarm management, configuration parameters, and hardware layout.

(Source: SPM Instrument AB, Internal Manuals, 2022–2023.)

Annex 3 — Excerpt from H-KEZ-NEZ-01 Internal Manual

This is an excerpt from the H-KEZ-NEZ-01 internal operational document describing automation and PLC data flow between Leveler control system and Condmaster monitoring hub (Arconic, 2025).

(Source: Arconic Székesfehérvár, 2025, Internal Manual H-KEZ-NEZ-01.)

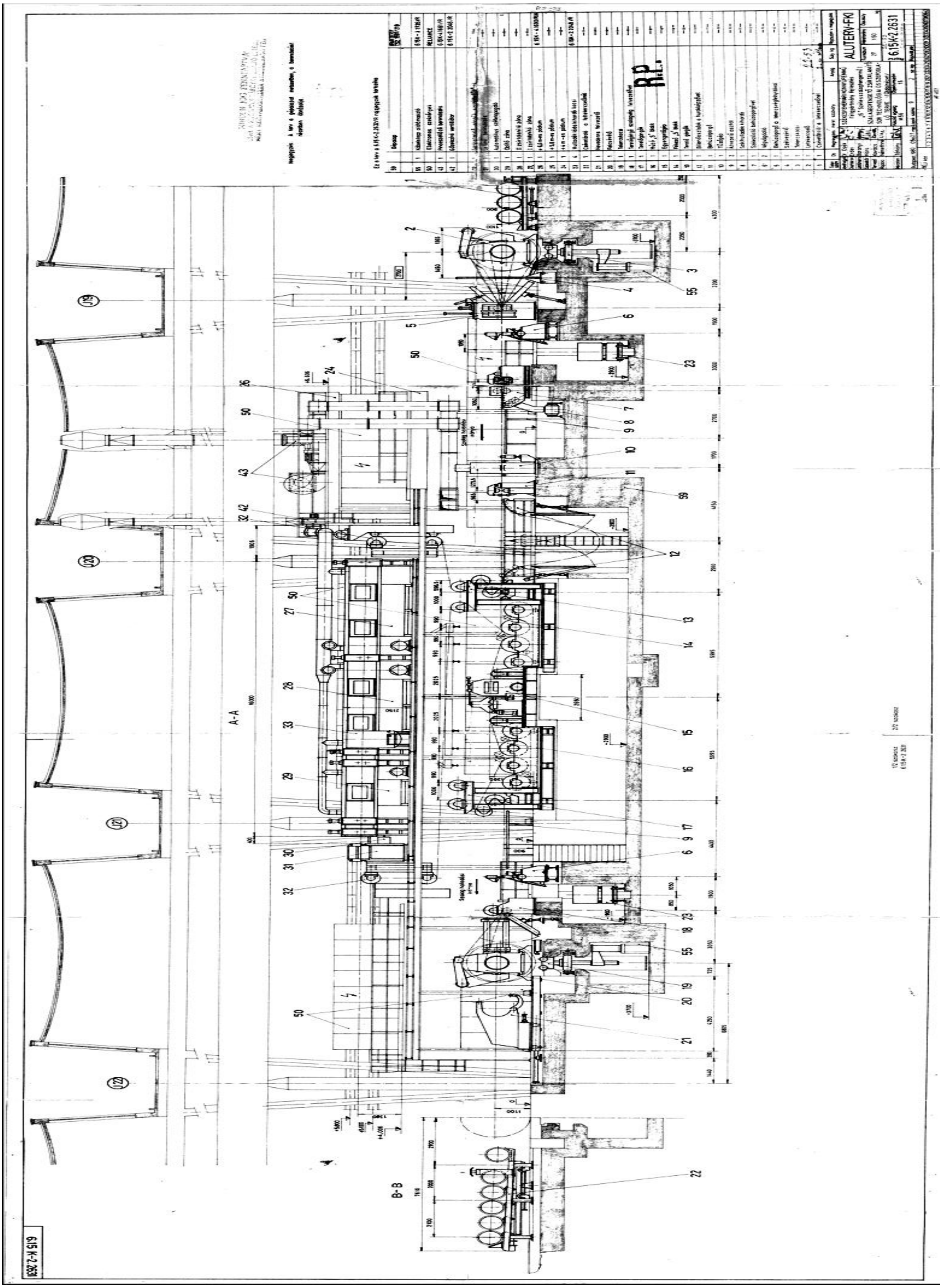
Annex 4 — Nyújtó Technical Document

A technical excerpt describes the Ungerer Stretch Leveler's components and construction. Included are original engineering drawings used as a reference guide to locate sensors and machine components.

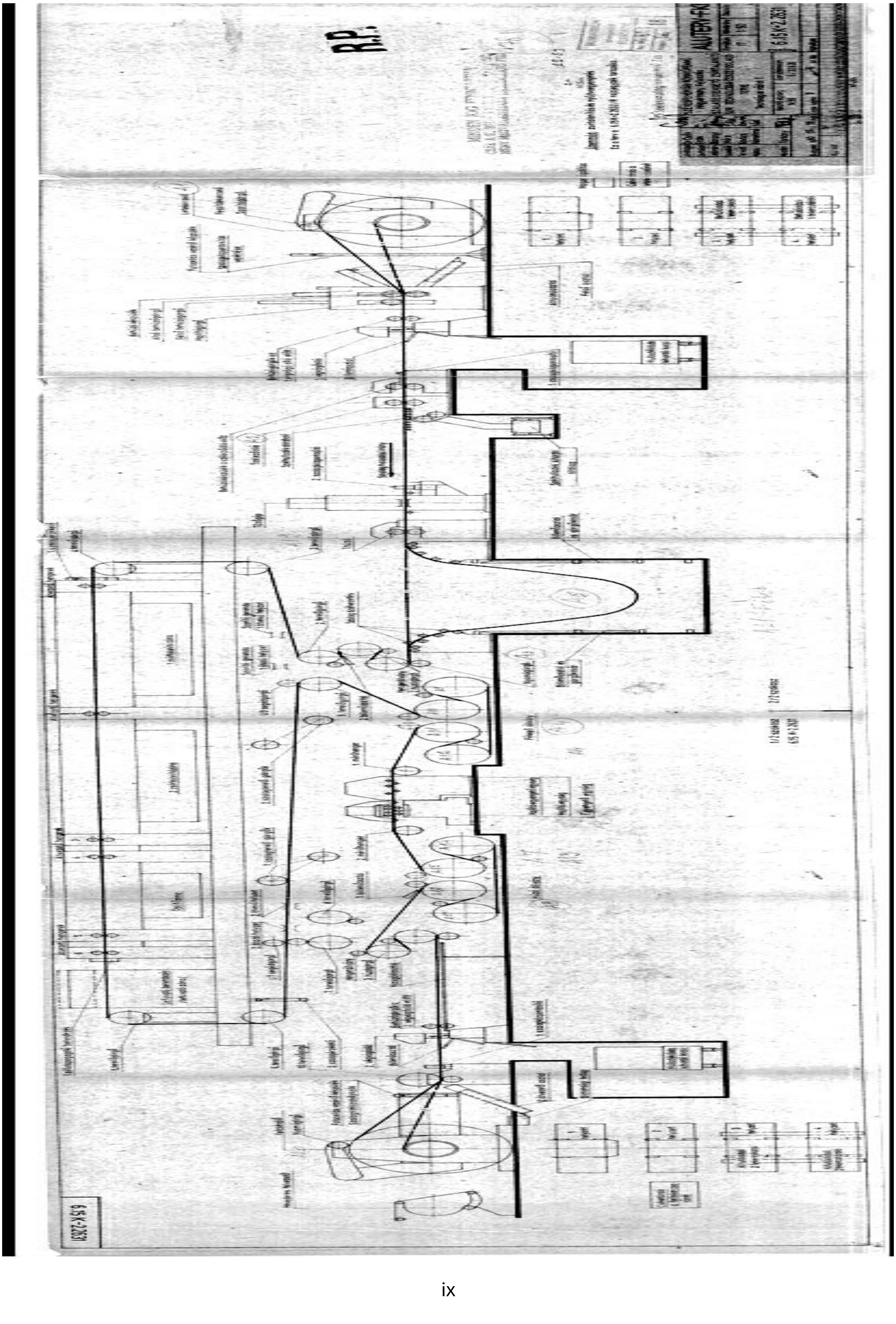
(Source: Arconic-Köfém, n.d., Internal Technical Document “Nyújtó – 18. ábra.”)

Annex 5 – Technical Figures from Arconic Internal Documents

A5.1 Figure: Ungerer Line 3 general layout drawing
(Source: Arconic (n.d.). Ungerer Line 3. [Internal engineering drawing, Doc. No. 6.15-K-2631]. ALUTERV-FKI.)



A5.2 Figure: Stretch leveler degreaser general layout drawing (Source: Arconic (n.d.). Ungerer Line 3. [Internal engineering drawing, Doc. No. 6.15-K-2631]. ALUTERV-FKI.)



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Geovana Fausta Gaspar Gomes (name) (student Neptun code: JCDGUN)
as a consultant, I declare that I have reviewed the final thesis/thesis/dissertation/portfolio[1] and that I have informed the student of the requirements, legal and ethical rules for the correct handling of literary sources.

I recommend / do not recommend[2] the final thesis / dissertation / portfolio to be defended in the final examination.

The thesis contains a state or official secret: yes no*[3]

Date: 2025 year 10. month 27 day

insider consultant

[1] The other types should be deleted while retaining the corresponding thesis type.
[2] The appropriate one should be underlined.
[3] The appropriate one should be underlined.

DECLARATION OF INDEPENDENT SUPERVISOR

As independent supervisor of Geovana Fausta Gaspar Gomes

(name of student) (Neptun code of student: JCDGUN)

I declare, that the student regularly attended the pre-scheduled consultations.

Date: 2025 year 10. month 28 day

independent supervisor

Declaration of Students and Doctoral Candidates on the Use of Artificial Intelligence (AI)”

1. general information:

Name of the student:	Geovana Fausta Gaspar Gomes
Neptun ID:	JCDGUN
Level of program (mark with X):	☒ BSc/BA ☐ MSc/MA ☐ Doctoral School (PhD) ☐ Other: ………………………
Name and code of the subject*:	Mechanical EngineeringB-GOD-N-EN-GEPES
Title of the work:	PdM Strategy via Vb Analysis-Abbreviated

* Not required to be completed in the case of a doctoral dissertation.

2. Declaration on the Use of AI

I, the undersigned, fully aware of my ethical responsibility, make the following declaration:

(Please choose one of the options below!)

☐ A) I have not used any artificial intelligence system or service.

(If you selected this option, completing the subsequent tables is not required.)

☒ B) I have used an artificial intelligence system or service.

(Please fill in the relevant tables!)

3. Details of Artificial Intelligence Usage

TABLE I: Assistant or Minor Usage (e.g., translation, language proofreading, brainstorming, etc.)

(For these uses, attaching the specific prompts and responses is not required.)

Purpose of Use	**Name and Version of the AI Tool Used**	**Affected Section (if not applicable to the entire text)**
Linguistic,grammar and translation of non-English content	QuillBot and Google Gemini	

TABLE II: Significant Content Contribution (e.g., generating an entire figure or a longer text section)

(In these cases, documenting the key prompts used and the raw responses provided by the AI, and attaching them as an appendix to the work, is required.)

Purpose of Use	**Name, Version, and Access Information of the AI Tool Used**	**Exact Number of the Affected Chapter / Figure / Table**	**Entry Number of the Appendix Containing the Prompt Log**

3/A. Additional Rules Prescribed by the Lecturer (if any)

If the instructor or supervisor of the course has established specific rules or expectations regarding the use of AI tools, please summarize them in the field below:

For example: prohibition of AI use for certain types of tasks; only specific tools are permitted; different citation requirements; documentation format, etc.

Rules Prescribed by the Lecturer or Supervisor

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4. Declaration Applicable to All Students:

I declare that I have critically reviewed, edited, and incorporated any content potentially generated by AI in all cases. I take full responsibility for every element of the submitted work, including its originality and scientific validity. I acknowledge that the Hungarian University of Agriculture and Life Sciences may check the submitted work with an artificial intelligence detector and may initiate proceedings if my declaration is found to be false or incomplete.

Place and Date: ……………Gödöllő……………, 2025. ……10…… month …30… day

Geovana F. G. Gomes
……………………………………………………………
Signature of the Student

……………………………………………………………
Signature of the Advisor/Supervisor